The Shape of Generalization through the Lens of Norm-based Capacity Control

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Abstract

Understanding how the test risk scales with model complexity is a central question in machine learning. Classical theory is challenged by the learning curves observed for large over-parametrized deep networks. Capacity measures based on parameter count typically fail to account for these empirical observations. To tackle this challenge, we consider norm-based capacity measures and develop our study for random features based estimators, widely used as simplified theoretical models for more complex networks. In this context, we provide a precise characterization of how the estimator's norm concentrates and how it governs the associated test error. Our results show that the predicted learning curve admits a phase transition from under- to over-parameterization, but no double descent behavior. This confirms that more classical U-shaped behavior is recovered considering appropriate capacity measures based on models norms rather than size. From a technical point of view, we leverage deterministic equivalence as the key tool and further develop new deterministic quantities which are of independent interest.

1. Introduction

How the test risk scales with the data size and model size is always a central question in machine learning, both empirically and theoretically. This is characterized as the shape of *generalization*, i.e., learning curves, that can be formulated as classical U-shaped curves [48], double descent [5], and scaling laws [24, 53].

In these learning curves, the model size, i.e., the number of parameters, provides a basic measure of the capacity of a machine learning (ML) model. However it is well known that model size cannot describe the "true" model capacity [2, 57], especially for over-parameterized neural networks [4, 56] and large language models (LLMs) [7]. The focus on the number of parameters results in an inaccurate characterization of the learning curve, and consequently, an improper data-parameter configuration in practice. For instance, even for the same architecture (model size), the learning curve can be totally different, e.g., double descent may disappear [35, 36]. A natural question raises that: *What is the shape of generalization under the lens of a suitable model capacity than model size?*

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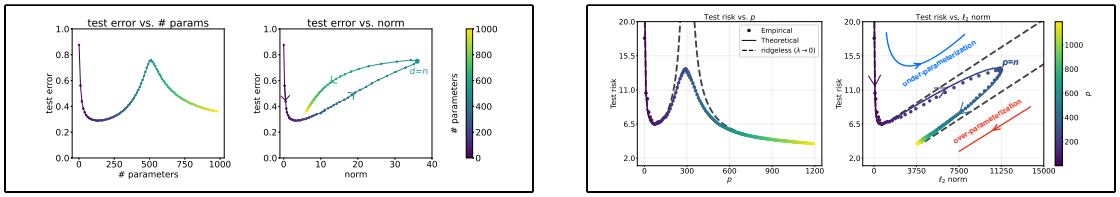

(a) Empirical observations from Figure 8.12 of [39]

(b) Our theory

Figure 1: Fig. 1(a) presents previous empirical observations from [39, Fig. 8.12] in the random feature model. Fig. 1(b) precisely characterize the learning curve from our theory and perfectly matches our experiments (shown by points) with training data $\{(\boldsymbol{x}_i, y_i)\}_{i=1}^n$, with $n = 300$, sub-sampled from the MNIST [26] with $d = 748$. The feature map is defined as $\varphi(\boldsymbol{x}, \boldsymbol{w}) = erf(\langle \boldsymbol{x}, \boldsymbol{w} \rangle)$ with random initialization $\boldsymbol{w} \sim \mathcal{N}(0, \boldsymbol{I})$. Note that whether the curve is finally lower than before is different between Fig. 1(a) and Fig. 1(b), mainly because of data, see more discussion in Appendix I.3.

In a ML model, its parameters can be represented as vectors, matrices, or tensors, and hence the model size is characterized by their dimensions. However, to evaluate the "size" of parameters, a more suitable metric is their norm. This is termed as *normed based capacity*, a perspective pioneered in the classical results indicated by [2]. Indeed, norm based capacity/complexity are widely considered to be more effective in characterizing generalization behavior; see e.g. [14, 29, 38, 46] and references therein. For instance, path-norm based model capacity empirically demonstrates a quite strong correlation to generalization while other metrics of model capacity may not [23]. Additionally, minimum norm-based solution received much attention as a possible way to understand the learning performance of over-parameterized neural networks in the interpolation regime; see e.g. [4, 27, 36, 49, 56].

Empirical observations on the learning curve under norm-based capacity have been discussed in the lecture notes [39, Fig. 8.12], as shown in Fig. 1(a): when changing the model capacity from model size to parameters' norm, the learning curve is changed from double descent to a "φ"-shaped curve. However, a precise mathematical framework on obtaining/understanding this curve is still lacking. The goal of this paper is to investigate this curve by addressing the following fundamental question:

What is the relationship between test risk and norm-based model capacity, and how can it be precisely characterized?

In this work, we take the first step toward answering this question, as illustrated in Fig. 1(b). Compared to the classical double descent curve w.r.t. model size p, we quantitatively characterize the relationship: test risk *vs.* norm-based capacity. Our theoretical predictions (shown as curves) precisely predict the empirical results (shown as points). More broadly, our results address how the learning curve behaves under more suitable model capacities—specifically, whether classical phenomena such as the U-shaped curve, double descent, or scaling laws persist or are fundamentally altered. We believe this opens the door to rethinking the role of model capacity and the nature of learning curves (e.g., scaling laws) in the era of LLMs.

Table 1: Summary of our main results for RFMs on deterministic equivalents and their relationship.

Type	Results	Regularization	Deterministic equivalents N	Relationship between R and N
Deterministic equivalence	Theorem 2	$\lambda > 0$	Asymptotic	-
	Theorem 30	$\lambda \to 0$	Asymptotic	-
	Theorem 36	$\lambda > 0$	Non-asymptotic	-
Relationship	Theorem 31	$\lambda \to 0$	-	Over-parameterized regime
	Theorem 37	$\lambda \to 0$	-	Under $\boldsymbol{\Lambda} = \boldsymbol{I}_m$ $(n < m < \infty)$
	Theorem 33	$\lambda \to 0$	-	Under Theorem 32 (power-law)
	Theorem 34	$\lambda > 0$	-	Under Theorem 32 (power-law)

2. Contributions

We consider linear and random features models (RFMs) regression to precisely characterize the relationship between the test risk and the capacity measured by the estimator's norm. The key technical tool we leverage is the *deterministic equivalence* technique from random matrix theory [9, 12], where the test risk $\mathcal{R}$ (depending on data $\boldsymbol{X}$, target function f^*, and the regularization parameter λ) can be well approximated by a deterministic quantity R (with data size n and model size p), i.e.,

$$\mathcal{R}(\boldsymbol{X}, f_*, \lambda) = (1+\mathcal{O}(n^{-1/2})+\mathcal{O}(p^{-1/2}))\cdot \mathsf{R}(\boldsymbol{\Sigma}, f_*, \lambda_*)\,, \quad \textit{asymptotically} \text{ or } \textit{non-asymptotically}$$

where $\mathsf{R}(\boldsymbol{\Sigma}, f_*, \lambda_*)$ is the exact deterministic characterization only depends on $f^\star$, expected data covariance $\boldsymbol{\Sigma}$, "re-scaled" regularization parameter λ, or other deterministic quantities. In our work, we aim to build the deterministic equivalents N of the estimator's ℓ_2 norm $\mathcal{N}$, both *asymptotically* and *non-asymptotically*, and derive a corresponding relationship between R and N, allowing a precise characterization, i.e.

Our target

$$\mathcal{N}(\boldsymbol{X}, f_*, \lambda) = (1+\mathcal{O}(n^{-1/2})+\mathcal{O}(p^{-1/2}))\cdot\mathsf{N}(\boldsymbol{\Sigma}, f_*, \lambda_*) \implies \mathsf{R} = g(\mathsf{N}) \text{ for some function } g.$$

The main results are given by Table 1 for RFMs, which covers random features ridge regression as well as min-norm estimator ($\lambda = 0$). Results for linear regression are deferred to Appendix D due to page limit. Deriving results N on norm-based capacity is more chandelling than for test risk. This is because, we need to explore ***new deterministic quantities***, which are of independent interest and more broadly useful. Specifically, we derive the deterministic equivalents w.r.t. $\mathrm{Tr}(\boldsymbol{A}\boldsymbol{X}^\top\boldsymbol{X}(\boldsymbol{X}^\top\boldsymbol{X}+\lambda)^{-1})$ for any positive semi-definite (PSD) matrix $\boldsymbol{A}$ while previous work only handled $\boldsymbol{A} := \boldsymbol{I}$ [1, 12, 33]. Moreover, non-asymptotic results, those valid for finite $n, p = \Omega(1)$ rather than in the asymptotic regime $n, p \to \infty$, on norm-based capacity require more technical conditions. In particular, they involve non-asymptotic bounds on *deterministic equivalents of differences between random quantities*. Due to the complexity of the formulations, we present these results in the appendix.

After that, we establish the characterization of $\mathsf{R} = g(\mathsf{N})$ under isotropic features and further illustrate the scaling law under classical power law scaling assumptions. The derivation requires non-trivial calculation and integral approximation by eliminating the model size p.

3. Main results

Random features models (RFMs) [28, 43] can be regarded as two-layer neural networks with $f(\boldsymbol{x};\boldsymbol{a}) = \frac{1}{\sqrt{p}}\sum_{j=1}^{p} a_j\varphi(\boldsymbol{x},\boldsymbol{w}_j)$, where $\varphi : \mathbb{R}^d \times \mathbb{R}^d \to \mathbb{R}$ is a nonlinear activation function. The first-layer parameters $\{\boldsymbol{w}_i\}_{i=1}^p$ are sampled i.i.d. from a probability measure $\mu_{\boldsymbol{w}}$ and kept unchanged during training. We only train $\boldsymbol{a}$ by solving the following random features ridge regression

$$\hat{\boldsymbol{a}} := \arg\min_{\boldsymbol{a}\in\mathbb{R}^p}\left\{\sum_{i=1}^{n}(y_i - f(\boldsymbol{x}_i;\boldsymbol{a}))^2 + \lambda\|\boldsymbol{a}\|_2^2\right\} = \left(\boldsymbol{Z}^\top\boldsymbol{Z} + \lambda\boldsymbol{I}_p\right)^{-1}\boldsymbol{Z}^\top\boldsymbol{y}\,, \quad \boldsymbol{Z}\in\mathbb{R}^{n\times p}\,, \tag{1}$$

where the feature matrix is $[\boldsymbol{Z}]_{ij} = p^{-1/2}\varphi(\boldsymbol{x}_i;\boldsymbol{w}_j)$ and $\lambda \geq 0$ is the regularization parameter. We also consider min-ℓ_2-norm solution ($\lambda = 0$), i.e., $\hat{\boldsymbol{a}}_{\min} = \arg\min_{\boldsymbol{a}}\|\boldsymbol{a}\|_2, s.t. \boldsymbol{Z}\boldsymbol{a} = \boldsymbol{y}$.

To mathematically characterize the phenomena in Fig. 1 under norm-based capacity, in this section, we firstly derive the bias-variance decomposition for the norm $\mathbb{E}_\varepsilon\|\hat{\boldsymbol{a}}\|_2^2 =: \mathcal{N}_\lambda^{RFM} = \mathcal{B}_{\mathcal{N},\lambda}^{RFM} + \mathcal{V}_{\mathcal{N},\lambda}^{RFM}$ (with definition later), then relate $\mathcal{B}_{\mathcal{N},\lambda}^{RFM}$ and $\mathcal{V}_{\mathcal{N},\lambda}^{RFM}$ to their respective deterministic equivalents $\mathsf{B}_{\mathsf{N},\lambda}^{RFM}$ and $\mathsf{V}_{\mathsf{N},\lambda}^{RFM}$. We need the following assumption for derivation.

Assumption 1 (Concentration of the eigenfunctions [12]) *Recall the random vectors $\boldsymbol{\psi} := (\xi_k\psi_k(\boldsymbol{x}))_{k\geq 1}$ and $\boldsymbol{\phi} := (\xi_k\phi_k(\boldsymbol{w}))_{k\geq 1}$. There exists $C_* > 0$ such that for any PSD matrix $\boldsymbol{A}\in\mathbb{R}^{\infty\times\infty}$ with $\mathrm{Tr}(\boldsymbol{\Lambda}\boldsymbol{A}) < \infty$ and any $t \geq 0$, we have*

$$\mathbb{P}\left(\left|\boldsymbol{\psi}^\top\boldsymbol{A}\boldsymbol{\psi} - \mathrm{Tr}(\boldsymbol{\Lambda}\boldsymbol{A})\right| \geq t\|\boldsymbol{\Lambda}^{1/2}\boldsymbol{A}\boldsymbol{\Lambda}^{1/2}\|_{\mathbf{F}}\right) \leq C_* e^{-\frac{t}{C_*}},$$
$$\mathbb{P}\left(\left|\boldsymbol{\phi}^\top\boldsymbol{A}\boldsymbol{\phi} - \mathrm{Tr}(\boldsymbol{\Lambda}\boldsymbol{A})\right| \geq t\|\boldsymbol{\Lambda}^{1/2}\boldsymbol{A}\boldsymbol{\Lambda}^{1/2}\|_{\mathbf{F}}\right) \leq C_* e^{-\frac{t}{C_*}}.$$

This assumptions holds for sub-Gaussian distributions and more generally, distributions that satisfy a log-Sobolev or convex Lipschitz concentration inequality [9]. Next we present the deterministic equivalence results of $\mathcal{N}_\lambda^{RFM}$, deferring the proof to Appendix G.1.

Theorem 2 (Deterministic equivalence of $\mathcal{N}_\lambda^{RFM}$) *The bias-variance decomposition of RFM's norm $\mathbb{E}_\varepsilon\|\hat{\boldsymbol{a}}\|_2^2$ is given by $\mathbb{E}_\varepsilon\|\hat{\boldsymbol{a}}\|_2^2 =: \mathcal{N}_\lambda^{RFM} = \mathcal{B}_{\mathcal{N},\lambda}^{RFM} + \mathcal{V}_{\mathcal{N},\lambda}^{RFM}$. Under Assumption 1, we have the following asymptotic deterministic equivalents $\mathcal{B}_{\mathcal{N},\lambda}^{RFM} \sim \mathsf{B}_{\mathsf{N},\lambda}^{RFM}$, $\mathcal{V}_{\mathcal{N},\lambda}^{RFM} \sim \mathsf{V}_{\mathsf{N},\lambda}^{RFM}$ and thus $\mathcal{N}_\lambda^{RFM} \sim \mathsf{N}_\lambda^{RFM} := \mathsf{B}_{\mathsf{N},\lambda}^{RFM} + \mathsf{V}_{\mathsf{N},\lambda}^{RFM}$*

$$\mathsf{B}_{\mathsf{N},\lambda}^{RFM} := \frac{p\langle\boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}\boldsymbol{\theta}_*\rangle}{p - \mathrm{Tr}\left(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}\right)} + \frac{p\chi(\nu_2)}{n}\cdot\underbrace{\frac{\nu_2^2\left[\langle\boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}\boldsymbol{\theta}_*\rangle + \chi(\nu_2)\langle\boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}\boldsymbol{\theta}_*\rangle\right]}{1-\Upsilon(\nu_1,\nu_2)}}_{\mathsf{B}_{\mathsf{R},\lambda}^{RFM}},$$

$$\mathsf{V}_{\mathsf{N},\lambda}^{RFM} := \frac{p\chi(\nu_2)}{n\Upsilon(\nu_1,\nu_2)}\cdot\underbrace{\frac{\sigma^2\Upsilon(\nu_1,\nu_2)}{1-\Upsilon(\nu_1,\nu_2)}}_{\mathsf{V}_{\mathsf{R},\lambda}^{RFM}}. \tag{2}$$

Remark: This theorem establishes asymptotic equivalence; a more complex non-asymptotic analysis is developed in Appendix G.2. Numerical validation is provided through experiments on synthetic and real-world datasets in Appendix J.1 and Appendix J.2, respectively.

By comparing Eq. (4) and Eq. (2) via deterministic equivalence, we conclude that

- Bias: the test risk's bias is the the second term of $\mathsf{B}_{\mathsf{N},\lambda}^{\mathrm{RFM}}$ (see the red area in Eq. (2)) with a rescaled factor $\frac{p\chi(\nu_2)}{n}$.
- Variance: we find that the variance term of the norm $\mathsf{V}_{\mathsf{N},\lambda}^{\mathrm{RFM}}$ equals the variance term of the test risk $\mathsf{V}_{\mathsf{R},\lambda}^{\mathrm{RFM}}$ (see the blue area in Eq. (2)) multiplied by a factor $\frac{p\chi(\nu_2)}{n\Upsilon(\nu_1,\nu_2)}$.

Hence norm-based capacity (on the second layer) suffices to characterize the test risk in RFMs. However, **other classical metrics** of model capacity, e.g., effective dimension [57], Smoother [11], capture the variance component of test risk but contain no information about the target function $\boldsymbol{\theta}^*$, and thus cannot fully characterize generalization. In summary, ***norm-based capacity suffices to characterize generalization, whereas effective dimension and smoother do not.*** By giving the deterministic equivalents of the norm, we are ready to plot the learning curve under norm-based capacity, see Fig. 1(*b*) for illustration. In some special cases, the mathematical formulation of learning curves can be given. For example, in Appendix F.2, we take the example of min-ℓ_2-norm interpolator, and precisely characterize the learning curve by reshaping scaling laws.

4. Findings and conclusion

We have the following findings and conclusion from the above characterization.

- **Norm-based capacity suffices to characterize generalization, whereas effective dimension and smoother do not:** Our results on deterministic equivalence demonstrate that the estimator's norm includes the information of the test risk's bias and variance[1], respectively. In contrast, typical model capacity, e.g., effective dimension [57] and smoother [11] can only characterize the test risk's variance and thus are insufficient to characterize generalization.

- **Phase transition exists but double descent does not exist:** There exists a phase transition from under- to over-parameterized regime, as shown in Fig. 1(*b*). In the under-parameterized regime, we still observe the same U-shaped curve, whether we consider the norm N or model size p as the model capacity. This curve can be precisely described as a hyperbola for the min-norm interpolator (linear regression) under isotropic features.

  But in the over-parameterized regime, when the norm N increases, the test risk R also increases (almost linearly if the regularization is small). This differs from double descent: when the model size p increases, the test risk decreases. Our empirical results on Fig. 1 verify this theoretical prediction. More importantly, this curve aligns more with classical statistical intuition—a U-shaped curve—rather than the double descent phenomenon. We conclude that ***with suitably chosen model capacity, the learning curve more closely follows a U-shape curve than a double descent***, potentially observable in more complex models and real-world datasets, see Appendices J.2 and J.3, respectively.

- **Scaling law is not monotone in norm-based capacity:** We study the scaling law of RFMs under norm-based capacity in a multiplication style by taking model size $p := n^q$ ($q \geq 0$), leading to $\mathsf{R} = Cn^{-a}\mathsf{N}^b$ with $a \geq 0$, $b \in \mathbb{R}$, and $C > 0$. Note that $b \in \mathbb{R}$ can be positive or negative, resulting in different behaviors of R. This differs from the classical scaling law that is monotonically decreasing in the model size.

1. Strictly speaking, it also requires knowing whether the model is under-parameterized or over-parameterized, as the self-consistent equations differ between these two regimes.

- **Controlling norm-based capacity can be achieved by the tuned regularization parameter λ:** Norm-based capacity appears less intuitive used in practice when compared to model size. Our results demonstrate that the norm decreases monotonically with increasing λ, and in both under- and over-parameterized regimes. Accordingly, such one-to-one correspondence allows for controlling norm via λ, related to the known L-curve [19].

We emphasize that we do *not* claim that ℓ_2 norm-based capacity (or other norm-based capacity) is the best metric of model capacity. Rather, this work aims to show how the test risk behaves when a more suitable model capacity than model size is used to measure capacity. For completeness, we discuss other metrics of model capacity and experiments on real-world datasets in Appendix J.

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Appendix A. Notations

In this paper we generally adopt the following convention. Caligraphic letters (e.g., $\mathcal{N}_\lambda, \mathcal{R}_\lambda, \mathcal{B}_{\mathcal{N},\lambda}, \mathcal{V}_{\mathcal{R},\lambda},$) denote random quantities, and upright letters (e.g., N_λ, R_λ, $\mathsf{B}_{\mathsf{N},\lambda}$, $\mathsf{V}_{\mathsf{R},\lambda}$) denote their deterministic equivalents. The letters N, R, B, V above (in any font) signify quantities related to the solution norm, test risk, bias, and variance, respectively. With λ denoting the ℓ_2-regularization parameter, setting $\lambda = 0$ corresponds to the min-norm interpolator. The superscripts ^{LS} and ^{RFM} denote quantities defined for linear regression and random feature regression, respectively.

We denote by γ the ratio between the parameter size and the data size, i.e., $\gamma := d/n$ in ridge regression and $\gamma := p/n$ in RFMs. For asymptotic results, we adopt the notation $u \sim v$, meaning that the ratio u/v tends to one as the dimensions n, d (p for RFMs) tend to infinity. Table 2 summarizes the notations used throughout the main text and appendices.

Table 2: Core notations used the main text and appendix.

Notation	Dimension(s)	Definition
$\mathcal{N}_{\lambda}^{\mathrm{L}S}$	-	The ℓ_2 norm of the linear regression estimator under regularization λ for linear regression
$\mathcal{B}_{\mathcal{N},\lambda}^{\mathrm{L}S}$	-	The bias of $\mathcal{N}_{\lambda}^{\mathrm{L}S}$
$\mathcal{V}_{\mathcal{N},\lambda}^{\mathrm{L}S}$	-	The variance of $\mathcal{N}_{\lambda}^{\mathrm{L}S}$
$\mathsf{N}_{\lambda}^{\mathrm{L}S}$	-	The deterministic equivalent of $\mathcal{N}_{\lambda}^{\mathrm{L}S}$
$\mathsf{B}_{\mathsf{N},\lambda}^{\mathrm{L}S}$	-	The deterministic equivalent of $\mathcal{B}_{\mathcal{N},\lambda}^{\mathrm{L}S}$
$\mathsf{V}_{\mathsf{N},\lambda}^{\mathrm{L}S}$	-	The deterministic equivalent of $\mathcal{V}_{\mathcal{N},\lambda}^{\mathrm{L}S}$
$\lVert\boldsymbol{v}\rVert_2$	-	Euclidean norms of vectors $\boldsymbol{v}$
$\lVert\boldsymbol{v}\rVert_{\boldsymbol{\Sigma}}$	-	$\sqrt{\boldsymbol{v}^\top\boldsymbol{\Sigma}\boldsymbol{v}}$
n	-	Number of training samples
d	-	Dimension of the data for linear regression
p	-	Number of features for random feature model
λ	-	Regularization parameter
λ_*	-	Effective regularization parameter for linear ridge regression
ν_1 , ν_2	-	Effective regularization parameters for random feature ridge regression
$\sigma_k(\boldsymbol{M})$	-	The k-th eigenvalue of $\boldsymbol{M}$
$\boldsymbol{x}$	$\mathbb{R}^d$	The data vector
$\boldsymbol{X}$	$\mathbb{R}^{n\times d}$	The data matrix
$\boldsymbol{\Sigma}$	$\mathbb{R}^{d\times d}$	The covariance matrix of $\boldsymbol{x}$
y	$\mathbb{R}$	The label
$\boldsymbol{y}$	$\mathbb{R}^n$	The label vector
$\boldsymbol{\beta}_*$	$\mathbb{R}^d$	The target function for linear regression
$\hat{\boldsymbol{\beta}}$	$\mathbb{R}^d$	The estimator of ridge regression model
$\hat{\boldsymbol{\beta}}_{\min}$	$\mathbb{R}^d$	The min-ℓ_2-norm estimator of ridge regression model
ε	$\mathbb{R}$	The noise
ε_i	$\mathbb{R}$	The i-th noise
$\boldsymbol{\varepsilon}$	$\mathbb{R}^n$	The noise vector
σ^2	$\mathbb{R}$	The variance of the noise
$\boldsymbol{w}_i$	$\mathbb{R}^d$	The i-th weight vector for random feature model
$\varphi(\cdot;\cdot)$	-	Nonlinear activation function for random feature model
$\boldsymbol{z}_i$	$\mathbb{R}^p$	The i-th feature for random feature model
$\boldsymbol{Z}$	$\mathbb{R}^{n\times p}$	Feature matrix for random feature model
$\hat{\boldsymbol{a}}$	$\mathbb{R}^p$	The estimator of random feature ridge regression model
$\hat{\boldsymbol{a}}_{\min}$	$\mathbb{R}^p$	The min-ℓ_2-norm estimator of random feature ridge regression model
$f_*(\cdot)$	-	The target function
$\mu_{\boldsymbol{x}}$	-	The distribution of $\boldsymbol{x}$
$\mu_{\boldsymbol{w}}$	-	The distribution of $\boldsymbol{w}$
$\mathbb{T}$	-	An integral operator defined by $(\mathbb{T}f)(\boldsymbol{w}) := \int_{\mathbb{R}^d}\varphi(\boldsymbol{x};\boldsymbol{w})f(\boldsymbol{x})\mathrm{d}\mu_{\boldsymbol{x}}\,,\quad \forall f\in L_2(\mu_{\boldsymbol{x}})$
$\mathcal{V}$	-	The image of $\mathbb{T}$
ξ_k	$\mathbb{R}$	The k-th eigenvalue of $\mathbb{T}$, defined by $\mathbb{T}=\sum_{k=1}^{\infty}\xi_k\psi_k\phi_k^*$
ψ_k	-	The k-th eigenfunction of $\mathbb{T}$ in the space $L_2(\mu_{\boldsymbol{x}})$, defined by the decomposition $\mathbb{T}=\sum_{k=1}^{\infty}\xi_k\psi_k\phi_k^*$
ϕ_k	-	The k-th eigenfunction of $\mathbb{T}$ in the space $\mathcal{V}$, defined by the decomposition $\mathbb{T}=\sum_{k=1}^{\infty}\xi_k\psi_k\phi_k^*$
$\boldsymbol{\Lambda}$	$\mathbb{R}^{\infty\times\infty}$	The spectral matrix of $\mathbb{T}$, $\boldsymbol{\Lambda}=\mathrm{diag}(\xi_1^2,\xi_2^2,\ldots)\in\mathbb{R}^{\infty\times\infty}$
$\boldsymbol{g}_i$	$\mathbb{R}^{\infty}$	$\boldsymbol{g}_i := (\psi_k(\boldsymbol{x}_i))_{k\geq 1}$
$\boldsymbol{f}_i$	$\mathbb{R}^{\infty}$	$\boldsymbol{f}_i := (\xi_k\phi_k(\boldsymbol{w}_i))_{k\geq 1}$
$\boldsymbol{G}$	$\mathbb{R}^{n\times\infty}$	$\boldsymbol{G}:=[\boldsymbol{g}_1,\ldots,\boldsymbol{g}_n]^\top\in\mathbb{R}^{n\times\infty}$ with $\boldsymbol{g}_i := (\psi_k(\boldsymbol{x}_i))_{k\geq 1}$
$\boldsymbol{F}$	$\mathbb{R}^{p\times\infty}$	$\boldsymbol{F}:=[\boldsymbol{f}_1,\ldots,\boldsymbol{f}_p]^\top\in\mathbb{R}^{p\times\infty}$
$\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}$	$\mathbb{R}^{p\times p}$	$\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}} := \mathbb{E}_{\boldsymbol{z}}[\boldsymbol{z}\boldsymbol{z}^\top\vert\boldsymbol{F}] = \frac{1}{p}\boldsymbol{F}\boldsymbol{F}^\top\in\mathbb{R}^{p\times p}$
$\boldsymbol{\theta}_{*,k}$	$\mathbb{R}$	The coefficients associated with the eigenfunction ψ_k in the expansion of $f_*(\boldsymbol{x})=\sum_{k\geq 1}\boldsymbol{\theta}_{*,k}\psi_k(\boldsymbol{x})$
$\boldsymbol{\theta}_*$	$\mathbb{R}^{\infty}$	$\boldsymbol{\theta}_* = (\boldsymbol{\theta}_{*,k})_{k\geq 1}$

[1] Replacing $\mathcal{N}$ with $\mathcal{R}$ (N with R), we get the notations associated to the test risk.
[2] Replacing λ with 0, we get the notations associated to the min-ℓ_2-norm solution.
[3] Replacing $\mathrm{L}S$ with $\mathrm{R}FM$, we get the notations associated to random feature regression.

Appendix B. Related work and Preliminaries

B.1. Related work

The relationship between the test risk, the data size, and the model size is classically characterized by the U-shaped curve [48]: larger models tend to overfit. This can not explain the success of deep

learning (with even more parameters than data), leading to a new concept: double descent [5], where the test risk has a second descent when transitioning from under- to over-parameterized regimes. Moreover recent scaling law [24] shows that the test risk is monotonically decreasing with model size, typically in the under-parameterized regime for LLMs.

Model capacity metrics: Beyond model size as a capacity measure, there is considerable effort to define alternative capacity measures, e.g, degrees of freedom from statistics [15, 16, 41], effective dimension/rank [3, 57], smoother [11], flatness [42], as well as norm-based capacity [29, 38]. The norm's asymptotic characterization is given in specific settings [22] but the risk-norm relationship is not directly studied. Besides, training strategies can be also explained as implicit regularization [37, 55], affecting the model capacity as well. We refer to the survey [23] for details.

Deterministic equivalents: Random matrix theory (RMT) provides powerful mathematical tools to precisely characterize the relationship between the test risk $\mathcal{R}$ and n, p, d via deterministic equivalence, in an asymptotic regime ($n, p, d \to \infty$, [1, 18, 31, 51, 54]), or non-asymptotic regime [9, 20, 33]. We refer the reader to [10] for further details. Complementary to RMT approaches, techniques from statistical physics are also possible to derive the deterministic equivalence, e.g., replica methods [6, 17, 30] and dynamical mean field theory [25, 32, 34].

B.2. Preliminaries

We provide an overview of the preliminary results used in this work. For self-contained completeness, we include results on asymptotic deterministic equivalence in Appendix B.3, results on ridge regression in Appendix B.4, and results on random feature ridge regression in Appendix B.5. Additionally, Appendix B.6 presents results on non-asymptotic deterministic equivalence, along with definitions of quantities required for these results. Finally, Appendix B.7 introduces key results for deriving the scaling law.

Here we give an overview of RFMs via deterministic equivalents here for better understanding.

Random features models (RFMs) [28, 43] can be regarded as two-layer neural networks with $f(\boldsymbol{x}; \boldsymbol{a}) = \frac{1}{\sqrt{p}} \sum_{j=1}^{p} a_j \varphi(\boldsymbol{x}, \boldsymbol{w}_j)$, where $\varphi : \mathbb{R}^d \times \mathbb{R}^d \to \mathbb{R}$ is a nonlinear activation function. The first-layer parameters $\{\boldsymbol{w}_i\}_{i=1}^p$ are sampled i.i.d. from a probability measure $\mu_{\boldsymbol{w}}$ and kept unchanged during training. We only train $\boldsymbol{a}$ by solving the following random features ridge regression

$$\hat{\boldsymbol{a}} := \arg\min_{\boldsymbol{a} \in \mathbb{R}^p} \left\{ \sum_{i=1}^{n} (y_i - f(\boldsymbol{x}_i; \boldsymbol{a}))^2 + \lambda \|\boldsymbol{a}\|_2^2 \right\} = \left(\boldsymbol{Z}^\top \boldsymbol{Z} + \lambda \mathbf{I}_p \right)^{-1} \boldsymbol{Z}^\top \boldsymbol{y}\,, \quad \boldsymbol{Z} \in \mathbb{R}^{n \times p}\,, \tag{3}$$

where the feature matrix is $[\boldsymbol{Z}]_{ij} = p^{-1/2} \varphi(\boldsymbol{x}_i; \boldsymbol{w}_j)$ and $\lambda \geq 0$ is the regularization parameter. We also consider min-ℓ_2-norm solution ($\lambda = 0$), i.e., $\hat{\boldsymbol{a}}_{\min} = \arg\min_{\boldsymbol{a}} \|\boldsymbol{a}\|_2, s.t. \boldsymbol{Z}\boldsymbol{a} = \boldsymbol{y}$.

Following [12], under proper assumptions on φ (e.g., bounded, squared-integrable), we can define a compact integral operator $\mathbb{T} : L^2(\mu_{\boldsymbol{x}}) \to \mathcal{V} \subseteq L^2(\mu_{\boldsymbol{w}})$ for any $f \in L_2(\mu_{\boldsymbol{x}})$ such that

$$(\mathbb{T} f)(\boldsymbol{w}) := \int_{\mathbb{R}^d} \varphi(\boldsymbol{x}; \boldsymbol{w}) f(\boldsymbol{x}) \mathrm{d}\mu_{\boldsymbol{x}}\,, \quad \mathbb{T} = \sum_{k=1}^{\infty} \xi_k \psi_k \phi_k^*\,,$$

where $(\xi_k)_{k \geq 1} \subseteq \mathbb{R}$ are the eigenvalues and $(\psi_k)_{k \geq 1}$ and $(\phi_k)_{k \geq 1}$ are orthonormal bases of $L^2(\mu_{\boldsymbol{x}})$ and $\mathcal{V}$ for spectral decomposition respectively. We denote $\boldsymbol{\Lambda} := \mathrm{diag}(\xi_1^2, \xi_2^2, \ldots) \in \mathbb{R}^{\infty \times \infty}$ and assume all eigenvalues are non-zero and arranged in non-increasing order.

Accordingly, the covariate feature matrix can be represented as $\boldsymbol{G} := [\boldsymbol{g}_1, \ldots, \boldsymbol{g}_n]^\mathsf{T} \in \mathbb{R}^{n\times\infty}$ with $\boldsymbol{g}_i := (\psi_k(\boldsymbol{x}_i))_{k\geq 1}$ and the weight feature matrix is $\boldsymbol{F} := [\boldsymbol{f}_1, \ldots, \boldsymbol{f}_p]^\mathsf{T} \in \mathbb{R}^{p\times\infty}$ with $\boldsymbol{f}_j := (\xi_k \phi_k(\boldsymbol{w}_j))_{k\geq 1}$. Then the feature matrix can be denoted by $\boldsymbol{Z} = \frac{1}{\sqrt{p}}\boldsymbol{G}\boldsymbol{F}^\mathsf{T} \in \mathbb{R}^{n\times p}$. Note that $\boldsymbol{f}$ has covariance matrix $\mathbb{E}[\boldsymbol{f}\boldsymbol{f}^\mathsf{T}] = \boldsymbol{\Lambda}$, and we further introduce $\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}} := \mathbb{E}_{\boldsymbol{z}}[\boldsymbol{z}\boldsymbol{z}^\mathsf{T}|\boldsymbol{F}] = \frac{1}{p}\boldsymbol{F}\boldsymbol{F}^\mathsf{T} \in \mathbb{R}^{p\times p}$.

Assuming that $f_* \in L^2(\mu_{\boldsymbol{x}})$ admits $f_*(\boldsymbol{x}) = \sum_{k\geq 1} \boldsymbol{\theta}_{*,k}\psi_k(\boldsymbol{x})$, we have a bias-variance decomposition of the excess risk

$$\mathcal{R}^{\mathrm{RFM}} := \mathbb{E}_\varepsilon \left\| \boldsymbol{\theta}_* - \frac{1}{\sqrt{p}}\boldsymbol{F}^\mathsf{T}\hat{\boldsymbol{a}} \right\|_2^2 = \left\| \boldsymbol{\theta}_* - \frac{1}{\sqrt{p}}\boldsymbol{F}^\mathsf{T}\mathbb{E}_\varepsilon[\hat{\boldsymbol{a}}] \right\|_2^2 + \mathrm{Tr}\left(\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}\mathrm{Cov}_\varepsilon(\hat{\boldsymbol{a}})\right),$$

where the first RHS term is the *bias*, denoted by $\mathcal{B}^{\mathrm{RFM}}_{\mathcal{R},\lambda}$, and the second term is the *variance*, denoted by $\mathcal{V}^{\mathrm{RFM}}_{\mathcal{R},\lambda}$. Similarly, under proper assumptions (to be detailed later), they admit the following deterministic equivalents, asymptotically [47] and non-asymptotically [12]

$$\begin{aligned}
\mathcal{B}^{\mathrm{RFM}}_{\mathcal{R},\lambda} &\sim \mathsf{B}^{\mathrm{RFM}}_{\mathsf{R},\lambda} := \frac{\nu_2^2}{1-\Upsilon(\nu_1,\nu_2)}\left[\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2\mathbf{I})^{-2}\boldsymbol{\theta}_*\rangle + \chi(\nu_2)\langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2\mathbf{I})^{-2}\boldsymbol{\theta}_*\rangle\right], \\
\mathcal{V}^{\mathrm{RFM}}_{\mathcal{R},\lambda} &\sim \mathsf{V}^{\mathrm{RFM}}_{\mathsf{R},\lambda} := \frac{\sigma^2\Upsilon(\nu_1,\nu_2)}{1-\Upsilon(\nu_1,\nu_2)},
\end{aligned} \tag{4}$$

where (ν_1, ν_2) satisfy the self-consistent equations

$$n - \frac{\lambda}{\nu_1} = \mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2\mathbf{I})^{-1}), \quad p - \frac{p\nu_1}{\nu_2} = \mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2\mathbf{I})^{-1}), \tag{5}$$

and $\Upsilon(\nu_1,\nu_2)$ and $\chi(\nu_2)$ are defined as

$$\Upsilon(\nu_1,\nu_2) := \frac{p}{n}\left[\left(1-\frac{\nu_1}{\nu_2}\right)^2 + \left(\frac{\nu_1}{\nu_2}\right)^2 \frac{\mathrm{Tr}\left(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\nu_2)^{-2}\right)}{p - \mathrm{Tr}\left(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\nu_2)^{-2}\right)}\right], \quad \chi(\nu_2) := \frac{\mathrm{Tr}\left(\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}\right)}{p - \mathrm{Tr}\left(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\nu_2)^{-2}\right)}.$$

B.3. Asymptotic deterministic equivalence

For the ease of description, we include preliminary results on asymptotic deterministic equivalence here. In fact, these assumptions and results can be recovered from non-asymptotic results, e.g., [33].

For linear regression, the asymptotic deterministic equivalence aim to find $\mathcal{B}^{\mathrm{LS}}_{\mathcal{R},\lambda} \sim \mathsf{B}^{\mathrm{LS}}_{\mathsf{R},\lambda}$, $\mathcal{V}^{\mathrm{LS}}_{\mathcal{R},\lambda} \sim \mathsf{V}^{\mathrm{LS}}_{\mathsf{R},\lambda}$, where $\mathsf{B}^{\mathrm{LS}}_{\mathsf{R},\lambda}$ and $\mathsf{V}^{\mathrm{LS}}_{\mathsf{R},\lambda}$ are some deterministic quantities. For asymptotic results, a series of assumptions in high-dimensional statistics via random matrix theory are required, on well-behaved data, spectral properties of $\boldsymbol{\Sigma}$ under nonlinear transformation in high-dimensional regime. We put the assumption from [1] here that are also widely used in previous literature [13, 45].

Assumption 3 *[1, Well-behaved data] We assume that:*

(A1) *The sample size n and dimension d grow to infinity with $\frac{d}{n} \to \gamma > 0$.*

(A2) *$\boldsymbol{X} = \boldsymbol{T}\boldsymbol{\Sigma}^{1/2}$, where $\boldsymbol{T} \in \mathbb{R}^{n\times d}$ has i.i.d. sub-Gaussian entries with zero mean and unit variance.*

(A3) *$\boldsymbol{\Sigma}$ is invertible with $\|\boldsymbol{\Sigma}\|_{op} < \infty$ and its spectral measure $\frac{1}{d}\sum_{i=1}^{d}\delta_{\sigma_i}$ converges to a compactly supported probability distribution μ on $\mathbb{R}^+$.*

(A4) *$\|\boldsymbol{\beta}_*\|_2 < \infty$ and the measure $\sum_{i=1}^{d}(\boldsymbol{v}_i^\top\boldsymbol{\beta}_*)^2\delta_{\sigma_i}$ converges to a measure ν with bounded mass, where $\boldsymbol{v}_i$ is the unit-norm eigenvector of $\boldsymbol{\Sigma}$ related to its respective eigenvalue σ_i.*

Definition 4 (Effective regularization) *For n, $\boldsymbol{\Sigma}$, and $\lambda \geq 0$, we define the* effective regularization *λ_* to be the unique non-negative solution to the self-consistent equation*

$$n - \frac{\lambda}{\lambda_*} \sim \mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*)^{-1}). \tag{6}$$

Definition 5 (Degrees of freedom)

$$\mathrm{d}f_1(\lambda_*) := \mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*)^{-1}), \quad \mathrm{d}f_2(\lambda_*) := \mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*)^{-2}).$$

Proposition 6 *[1, Restatement of Proposition 1] Assume **(A1), (A2), (A3)**, we consider $\boldsymbol{A}$ and $\boldsymbol{B}$ with bounded operator norm, admitting the convergence of the empirical measures, i.e., $\sum_{i=1}^{d}\boldsymbol{v}_i^\top\boldsymbol{A}\boldsymbol{v}_i \cdot \delta_{\sigma_i} \to \nu_A$ and $\sum_{i=1}^{d}\boldsymbol{v}_i^\top\boldsymbol{B}\boldsymbol{v}_i \cdot \delta_{\sigma_i} \to \nu_B$ with bounded total variation, respectively. Then, for $\lambda \geq 0$, with λ_* satisfying Eq. (6), we have the following **a**symptotic deterministic equivalence*

$$\mathrm{Tr}(\boldsymbol{A}\boldsymbol{X}^\top\boldsymbol{X}(\boldsymbol{X}^\top\boldsymbol{X}+\lambda)^{-1}) \sim \mathrm{Tr}(\boldsymbol{A}\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*)^{-1}), \tag{7}$$

$$\begin{aligned}\mathrm{Tr}(\boldsymbol{A}\boldsymbol{X}^\top\boldsymbol{X}(\boldsymbol{X}^\top\boldsymbol{X}+\lambda)^{-1}\boldsymbol{B}\boldsymbol{X}^\top\boldsymbol{X}(\boldsymbol{X}^\top\boldsymbol{X}+\lambda)^{-1}) &\sim \mathrm{Tr}(\boldsymbol{A}\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*)^{-1}\boldsymbol{B}\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*)^{-1}) \\ &+\lambda_*^2\mathrm{Tr}(\boldsymbol{A}(\boldsymbol{\Sigma}+\lambda_*)^{-2}\boldsymbol{\Sigma})\cdot\mathrm{Tr}(\boldsymbol{B}(\boldsymbol{\Sigma}+\lambda_*)^{-2}\boldsymbol{\Sigma})\cdot\frac{1}{n-\mathrm{d}f_2(\lambda_*)},\end{aligned} \tag{8}$$

$$\mathrm{Tr}(\boldsymbol{A}(\boldsymbol{X}^\top\boldsymbol{X}+\lambda)^{-1}) \sim \frac{\lambda_*}{\lambda}\mathrm{Tr}(\boldsymbol{A}(\boldsymbol{\Sigma}+\lambda_*)^{-1}), \tag{9}$$

$$\begin{aligned}\mathrm{Tr}(\boldsymbol{A}(\boldsymbol{X}^\top\boldsymbol{X}+\lambda)^{-1}\boldsymbol{B}(\boldsymbol{X}^\top\boldsymbol{X}+\lambda)^{-1}) &\sim \frac{\lambda_*^2}{\lambda^2}\mathrm{Tr}(\boldsymbol{A}(\boldsymbol{\Sigma}+\lambda_*)^{-1}\boldsymbol{B}(\boldsymbol{\Sigma}+\lambda_*)^{-1}) \\ &+\frac{\lambda_*^2}{\lambda^2}\mathrm{Tr}(\boldsymbol{A}(\boldsymbol{\Sigma}+\lambda_*)^{-2}\boldsymbol{\Sigma})\cdot\mathrm{Tr}(\boldsymbol{B}(\boldsymbol{\Sigma}+\lambda_*)^{-2}\boldsymbol{\Sigma})\cdot\frac{1}{n-\mathrm{d}f_2(\lambda_*)}.\end{aligned} \tag{10}$$

Proposition 7 *[1, Restatement of Proposition 2] Assume **(A1), (A2), (A3)**, we consider $\boldsymbol{A}$ and $\boldsymbol{B}$ with bounded operator norm, admitting the convergence of the empirical measures, i.e., $\sum_{i=1}^{d}\boldsymbol{v}_i^\top\boldsymbol{A}\boldsymbol{v}_i \cdot \delta_{\sigma_i} \to \nu_A$ and $\sum_{i=1}^{d}\boldsymbol{v}_i^\top\boldsymbol{B}\boldsymbol{v}_i \cdot \delta_{\sigma_i} \to \nu_B$ with bounded total variation, respectively. Then, for $\lambda \in \mathbb{C}\boldsymbol{a}ckslash\mathbb{R}_+$, with λ_* satisfying Eq. (6), we have the following **a**symptotic deterministic equivalence*

$$\mathrm{Tr}(\boldsymbol{A}\boldsymbol{T}^\top(\boldsymbol{T}\boldsymbol{\Sigma}\boldsymbol{T}^\top+\lambda)^{-1}\boldsymbol{T}) \sim \mathrm{Tr}(\boldsymbol{A}(\boldsymbol{\Sigma}+\lambda_*)^{-1}), \tag{11}$$

$$\begin{aligned}\mathrm{Tr}(\boldsymbol{A}\boldsymbol{T}^\top(\boldsymbol{T}\boldsymbol{\Sigma}\boldsymbol{T}^\top+\lambda)^{-1}\boldsymbol{T}\boldsymbol{B}\boldsymbol{T}^\top(\boldsymbol{T}\boldsymbol{\Sigma}\boldsymbol{T}^\top+\lambda)^{-1}\boldsymbol{T}) &\sim \mathrm{Tr}(\boldsymbol{A}(\boldsymbol{\Sigma}+\lambda_*)^{-1}\boldsymbol{B}(\boldsymbol{\Sigma}+\lambda_*)^{-1}) \\ &+\lambda_*^2\mathrm{Tr}(\boldsymbol{A}(\boldsymbol{\Sigma}+\lambda_*)^{-2})\cdot\mathrm{Tr}(\boldsymbol{B}(\boldsymbol{\Sigma}+\lambda_*)^{-2})\cdot\frac{1}{n-\mathrm{d}f_2(\lambda_*)}.\end{aligned} \tag{12}$$

Note that the results in Theorem 6, 7 still hold even for the random features model. We will explain this in details in Appendix G.

B.4. Deterministic equivalence for ridge regression

We consider n samples $\{\boldsymbol{x}_i\}_{i=1}^n$ sampled i.i.d. from a distribution $\mu_{\boldsymbol{x}}$ over $\mathbb{R}^d$ with covariance matrix $\boldsymbol{\Sigma} := \mathbb{E}[\boldsymbol{x}\boldsymbol{x}^\top] \in \mathbb{R}^{d\times d}$. The label y_i is generated by a linear target function parameterized by $\boldsymbol{\beta}_* \in \mathbb{R}^d$, i.e., $y_i = \boldsymbol{x}_i^\top \boldsymbol{\beta}_* + \varepsilon_i$, where ε_i is additive noise independent of $\boldsymbol{x}_i$ satisfying $\mathbb{E}[\varepsilon_i] = 0$ and $\mathrm{var}(\varepsilon_i) = \sigma^2$. We can write the model in a compact form as $\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta}_* + \boldsymbol{\varepsilon}$, where the data matrix as $\boldsymbol{X} \in \mathbb{R}^{n\times d}$, the label vector $\boldsymbol{y} \in \mathbb{R}^n$, and the noise vector as $\boldsymbol{\varepsilon} \in \mathbb{R}^n$. The estimator of ridge regression is given by $\hat{\boldsymbol{\beta}} = \left(\boldsymbol{X}^\top\boldsymbol{X} + \lambda\boldsymbol{I}\right)^{-1}\boldsymbol{X}^\top\boldsymbol{y}$. We also consider min-$\ell_2$-norm solution in the over-parameterized regime, i.e., $\hat{\boldsymbol{\beta}}_{\min} = \arg\min_{\boldsymbol{\beta}} \|\boldsymbol{\beta}\|_2$, s.t. $\boldsymbol{X}\boldsymbol{\beta} = \boldsymbol{y}$. The excess risk of $\hat{\boldsymbol{\beta}}$ admits a bias-variance decomposition

$$\mathcal{R}^{\mathrm{LS}} := \mathbb{E}_\varepsilon\|\boldsymbol{\beta}_* - \hat{\boldsymbol{\beta}}\|_{\boldsymbol{\Sigma}}^2 = \|\boldsymbol{\beta}_* - \mathbb{E}_\varepsilon[\hat{\boldsymbol{\beta}}]\|_{\boldsymbol{\Sigma}}^2 + \mathrm{Tr}(\boldsymbol{\Sigma}\mathrm{Cov}_\varepsilon(\hat{\boldsymbol{\beta}}))\,,$$

where the first RHS term is the *bias*, denoted by $\mathcal{B}_{\mathcal{R},\lambda}^{\mathrm{LS}}$, and the second term is the *variance*, denoted by $\mathcal{V}_{\mathcal{R},\lambda}^{\mathrm{LS}}$. Accordingly, the bias-variance decomposition is given by

$$\mathcal{B}_{\mathcal{R},\lambda}^{\mathrm{LS}} := \|\boldsymbol{\beta}_* - \mathbb{E}_\varepsilon[\hat{\boldsymbol{\beta}}]\|_{\boldsymbol{\Sigma}}^2 = \lambda^2\langle\boldsymbol{\beta}_*, (\boldsymbol{X}^\top\boldsymbol{X} + \lambda\boldsymbol{I})^{-1}\boldsymbol{\Sigma}(\boldsymbol{X}^\top\boldsymbol{X} + \lambda\boldsymbol{I})^{-1}\boldsymbol{\beta}_*\rangle\,, \tag{13}$$

$$\mathcal{V}_{\mathcal{R},\lambda}^{\mathrm{LS}} := \mathrm{Tr}\left(\boldsymbol{\Sigma}\mathrm{Cov}_\varepsilon(\hat{\boldsymbol{\beta}})\right) = \sigma^2\mathrm{Tr}(\boldsymbol{\Sigma}\boldsymbol{X}^\top\boldsymbol{X}(\boldsymbol{X}^\top\boldsymbol{X} + \lambda\boldsymbol{I})^{-2})\,. \tag{14}$$

Under proper assumptions (to be detailed later), we have the following deterministic equivalents, asymptotically [1] and non-asymptotically [9]

$$\mathcal{B}_{\mathcal{R},\lambda}^{\mathrm{LS}} \sim \mathsf{B}_{\mathsf{R},\lambda}^{\mathrm{LS}} := \frac{\lambda_*^2\langle\boldsymbol{\beta}_*, \boldsymbol{\Sigma}(\boldsymbol{\Sigma} + \lambda_*\mathbf{I})^{-2}\boldsymbol{\beta}_*\rangle}{1 - n^{-1}\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma} + \lambda_*\mathbf{I})^{-2})}\,, \quad \mathcal{V}_{\mathcal{R},\lambda}^{\mathrm{LS}} \sim \mathsf{V}_{\mathsf{R},\lambda}^{\mathrm{LS}} := \frac{\sigma^2\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma} + \lambda_*\mathbf{I})^{-2})}{n - \mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma} + \lambda_*\mathbf{I})^{-2})}\,, \tag{15}$$

where λ_* is the non-negative solution to the self-consistent equation $n - \frac{\lambda}{\lambda_*} = \mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma} + \lambda_*\mathbf{I})^{-1})$.

Accordingly, the risk admits the following deterministic equivalents via bias-variance decomposition.

Proposition 8 *[1, Restatement of Proposition 3] Given the bias variance decomposition in Eq. (13) and Eq. (14), $\boldsymbol{X}$, $\boldsymbol{\Sigma}$ and $\boldsymbol{\beta}_*$ satisfy Theorem 3, we have the following asymptotic deterministic equivalents $\mathcal{R}_\lambda^{LS} \sim \mathsf{R}_\lambda^{LS} := \mathsf{B}_{\mathsf{R},\lambda}^{LS} + \mathsf{V}_{\mathsf{R},\lambda}^{LS}$ such that $\mathcal{B}_{\mathcal{R},\lambda}^{LS} \sim \mathsf{B}_{\mathsf{R},\lambda}^{LS}$, $\mathcal{V}_{\mathcal{R},\lambda}^{LS} \sim \mathsf{V}_{\mathsf{R},\lambda}^{LS}$, where $\mathsf{B}_{\mathsf{R},\lambda}^{LS}$ and $\mathsf{V}_{\mathsf{R},\lambda}^{LS}$ are defined by Eq. (15).*

Proposition 9 *[1, Restatement of results in Sec 5] Under the same assumption as Theorem 8, for the minimum ℓ_2-norm estimator $\hat{\boldsymbol{\beta}}_{\min}$, we have for the under-parameterized regime ($d < n$):*

$$\mathcal{B}_{\mathcal{R},0}^{LS} = 0, \quad \mathcal{V}_{\mathcal{R},0}^{LS} \sim \sigma^2\frac{d}{n-d}\,.$$

In the over-parameterized regime ($d > n$), we have

$$\mathcal{B}_{\mathcal{R},0}^{LS} \sim \frac{\lambda_n^2\langle\boldsymbol{\beta}_*, \boldsymbol{\Sigma}(\boldsymbol{\Sigma} + \lambda_n\boldsymbol{I})^{-2}\boldsymbol{\beta}_*\rangle}{1 - n^{-1}\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma} + \lambda_n\boldsymbol{I})^{-2})}\,, \qquad \mathcal{V}_{\mathcal{R},0}^{LS} \sim \frac{\sigma^2\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma} + \lambda_n\boldsymbol{I})^{-2})}{n - \mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma} + \lambda_n\boldsymbol{I})^{-2})}\,,$$

where λ_n defined by $\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma} + \lambda_n\boldsymbol{I})^{-1}) \sim n$.

B.5. Deterministic equivalence for random feature ridge regression

Recall Eq. (3), the parameter $\boldsymbol{a}$ can be learned by the following empirical risk minimization with an ℓ_2 regularization

$$\hat{\boldsymbol{a}} := \underset{\boldsymbol{a}\in\mathbb{R}^p}{\arg\min}\left\{\sum_{i=1}^{n}\left(y_i - \frac{1}{\sqrt{p}}\sum_{j=1}^{p}\boldsymbol{a}_j\varphi(\boldsymbol{x},\boldsymbol{w}_j)\right)^2 + \lambda\|\boldsymbol{a}\|_2^2\right\} = (\boldsymbol{Z}^\top\boldsymbol{Z}+\lambda\boldsymbol{I})^{-1}\boldsymbol{Z}^\top\boldsymbol{y}\,.$$

Assuming that the target function $f_* \in L^2(\mu_{\boldsymbol{x}})$ admits $f_*(\boldsymbol{x}) = \sum_{k\geq 1}\boldsymbol{\theta}_{*,k}\psi_k(\boldsymbol{x})$, the excess risk $\mathcal{R}^{\mathrm{RFM}} := \mathbb{E}_\varepsilon\left\|\boldsymbol{\theta}_* - \frac{\boldsymbol{F}^\top\hat{\boldsymbol{a}}}{\sqrt{p}}\right\|_2^2$ admits the following bias-variance decomposition

$$\mathcal{B}_{\mathcal{R},\lambda}^{\mathrm{RFM}} := \left\|\boldsymbol{\theta}_* - \frac{\boldsymbol{F}^\top\mathbb{E}_\varepsilon[\hat{\boldsymbol{a}}]}{\sqrt{p}}\right\|_2^2 = \left\|\boldsymbol{\theta}_* - p^{-1/2}\boldsymbol{F}^\top(\boldsymbol{Z}^\top\boldsymbol{Z}+\lambda\boldsymbol{I})^{-1}\boldsymbol{Z}^\top\boldsymbol{G}\boldsymbol{\theta}_*\right\|_2^2\,, \tag{16}$$

$$\mathcal{V}_{\mathcal{R},\lambda}^{\mathrm{RFM}} := \mathrm{Tr}\left(\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}\mathrm{Cov}_\varepsilon(\hat{\boldsymbol{a}})\right) = \sigma^2\mathrm{Tr}(\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}\boldsymbol{Z}^\top\boldsymbol{Z}(\boldsymbol{Z}^\top\boldsymbol{Z}+\lambda\boldsymbol{I})^{-2})\,. \tag{17}$$

Accordingly, the risk admits the following deterministic equivalents via bias-variance decomposition.

Proposition 10 *[12, Asymptotic version of Theorem 3.3] Given the bias variance decomposition in Eq. (16) and Eq. (17), under Theorem 1, we have the following asymptotic deterministic equivalents* $\mathcal{R}_\lambda^{RFM} \sim \mathsf{R}_\lambda^{RFM} := \mathsf{B}_{\mathsf{R},\lambda}^{RFM} + \mathsf{V}_{\mathsf{R},\lambda}^{RFM}$ *such that* $\mathcal{B}_{\mathcal{R},\lambda}^{RFM} \sim \mathsf{B}_{\mathsf{R},\lambda}^{RFM}$, $\mathcal{V}_{\mathcal{R},\lambda}^{RFM} \sim \mathsf{V}_{\mathsf{R},\lambda}^{RFM}$, *where* $\mathsf{B}_{\mathsf{R},\lambda}^{RFM}$ *and* $\mathsf{V}_{\mathsf{R},\lambda}^{RFM}$ *are defined by Eq. (4).*

Note that the above results are delivered in a non-asymptotic way [12], but more notations and technical assumptions are required. We give an overview of non-asymptotic deterministic equivalence as below.

B.6. Non-asymptotic deterministic equivalence

Regarding non-asymptotic results, we require a series of notations and assumptions. We give a brief introduction here for self-completeness. More details can be found in [9, 12, 33].

Given $\boldsymbol{x} \in \mathbb{R}^d$ with $d \in \mathbb{N}$, the associated covariance matrix is given by $\boldsymbol{\Sigma} = \mathbb{E}[\boldsymbol{x}\boldsymbol{x}^\top]$. We denote the eigenvalue of $\boldsymbol{\Sigma}$ in non-increasing order as $\sigma_1 \geq \sigma_2 \geq \sigma_3 \geq \cdots \geq \sigma_d$.

We introduce the non-asymptotic version of Eq. (6) as below.

Definition 11 (Effective regularization) *Given n, $\boldsymbol{\Sigma}$, and $\lambda \geq 0$, the* effective regularization λ_* *is defined as the unique non-negative solution of the following self-consistent equation*

$$n - \frac{\lambda}{\lambda_*} = \mathrm{Tr}\big(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*)^{-1}\big).$$

Remark: Existence and uniqueness of λ_* are guaranteed since the left-hand side of the equation is monotonically increasing in λ_*, while the right-hand side is monotonically decreasing.

In the next, we introduce the following definitions on "effective dimension", a metric to describe the model capacity, widely used in statistical learning theory.

Define $r_{\boldsymbol{\Sigma}}(k) := \frac{\mathrm{Tr}(\boldsymbol{\Sigma}_{\geq k})}{\|\boldsymbol{\Sigma}_{\geq k}\|_{op}} = \frac{\sum_{j=k}^d \sigma_j}{\sigma_k}$ as the intrinsic dimension, we require the following definition

$$\rho_\lambda(n) := 1 + \frac{n\sigma_{\lfloor \eta_* \cdot n \rfloor}}{\lambda} \left\{ 1 + \frac{r_{\boldsymbol{\Sigma}}(\lfloor \eta_* \cdot n \rfloor) \vee n}{n} \log \left(r_{\boldsymbol{\Sigma}}(\lfloor \eta_* \cdot n \rfloor) \vee n \right) \right\}, \tag{18}$$

where $\eta_* \in (0, 1/2)$ is a constant that will only depend on C_* defined in Theorem 22. And we used the convention that $\sigma_{\lfloor \eta_* \cdot n \rfloor} = 0$ if $\lfloor \eta_* \cdot n \rfloor > d$.

In this section we consider functionals that depend on $\boldsymbol{X}$ and deterministic matrices. For a general PSD matrix $\boldsymbol{A} \in \mathbb{R}^{d \times d}$, define the functionals

$$\Phi_1(\boldsymbol{X}; \boldsymbol{A}, \lambda) := \mathrm{Tr}\left(\boldsymbol{A}\boldsymbol{\Sigma}^{1/2}(\boldsymbol{X}^\top \boldsymbol{X} + \lambda)^{-1}\boldsymbol{\Sigma}^{1/2} \right), \tag{19}$$

$$\Phi_2(\boldsymbol{X}; \boldsymbol{A}, \lambda) := \mathrm{Tr}\left(\boldsymbol{A}\boldsymbol{X}^\top \boldsymbol{X}(\boldsymbol{X}^\top \boldsymbol{X} + \lambda)^{-1} \right), \tag{20}$$

$$\Phi_3(\boldsymbol{X}; \boldsymbol{A}, \lambda) := \mathrm{Tr}\left(\boldsymbol{A}\boldsymbol{\Sigma}^{1/2}(\boldsymbol{X}^\top \boldsymbol{X} + \lambda)^{-1}\boldsymbol{\Sigma}(\boldsymbol{X}^\top \boldsymbol{X} + \lambda)^{-1}\boldsymbol{\Sigma}^{1/2} \right), \tag{21}$$

$$\Phi_4(\boldsymbol{X}; \boldsymbol{A}, \lambda) := \mathrm{Tr}\left(\boldsymbol{A}\boldsymbol{\Sigma}^{1/2}(\boldsymbol{X}^\top \boldsymbol{X} + \lambda)^{-1}\frac{\boldsymbol{X}^\top \boldsymbol{X}}{n}(\boldsymbol{X}^\top \boldsymbol{X} + \lambda)^{-1}\boldsymbol{\Sigma}^{1/2} \right). \tag{22}$$

These functionals can be approximated through quantities that scale proportionally to

$$\Psi_1(\lambda_*; \boldsymbol{A}) := \mathrm{Tr}\left(\boldsymbol{A}\boldsymbol{\Sigma}(\boldsymbol{\Sigma} + \lambda_* \boldsymbol{I})^{-1} \right), \tag{23}$$

$$\Psi_2(\lambda_*; \boldsymbol{A}) := \frac{1}{n} \cdot \frac{\mathrm{Tr}\left(\boldsymbol{A}\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma} + \lambda_* \boldsymbol{I})^{-2} \right)}{n - \mathrm{Tr}\left(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma} + \lambda_* \boldsymbol{I})^{-2} \right)}. \tag{24}$$

The following theorem gathers the approximation guarantees for the different functionals stated above, and is obtained by modifying [12, Theorem A.2]. We generalize Eq. (27) for any PSD matrix $\boldsymbol{A}$, which will be required for our results on the deterministic equivalence of ℓ_2 norm. The proof can be found in Appendix C.

Theorem 12 (Dimension-free deterministic equivalents, Theorem A.2 of [12]) *Assume the features $\{\boldsymbol{x}_i\}_{i \in [n]}$ satisfy Theorem 22 with a constant $C_* > 0$. Then for any $D, K > 0$, there exist constants $\eta_* \in (0, 1/2)$, $C_{D,K} > 0$ and $C_{*,D,K} > 0$ ensuring the following property holds. For any $n \geq C_{D,K}$ and $\lambda > 0$, if the following condition is satisfied:*

$$\lambda \cdot \rho_\lambda(n) \geq \|\boldsymbol{\Sigma}\|_{\mathrm{op}} \cdot n^{-K}, \quad \rho_\lambda(n)^{5/2} \log^{3/2}(n) \leq K\sqrt{n}, \tag{25}$$

then for any PSD matrix $\boldsymbol{A}$, with probability at least $1 - n^{-D}$, we have that

$$|\Phi_1(\boldsymbol{X}; \boldsymbol{A}, \lambda) - \frac{\lambda_*}{\lambda}\Psi_1(\lambda_*; \boldsymbol{A})| \leq C_{*,D,K}\frac{\rho_\lambda(n)^{5/2}\log^{3/2}(n)}{\sqrt{n}} \cdot \frac{\lambda_*}{\lambda}\Psi_1(\lambda_*; \boldsymbol{A}), \tag{26}$$

$$|\Phi_2(\boldsymbol{X}; \boldsymbol{I}, \lambda) - \Psi_1(\lambda_*; \boldsymbol{I})| \leq C_{*,D,K}\frac{\rho_\lambda(n)^{4}\log^{3/2}(n)}{\sqrt{n}}\Psi_1(\lambda_*; \boldsymbol{I}), \tag{27}$$

$$|\Phi_3(\boldsymbol{X}; \boldsymbol{A}, \lambda) - \left(\frac{n\lambda_*}{\lambda}\right)^2 \Psi_2(\lambda_*; \boldsymbol{A})| \leq C_{*,D,K}\frac{\rho_\lambda(n)^{6}\log^{5/2}(n)}{\sqrt{n}} \cdot \left(\frac{n\lambda_*}{\lambda}\right)^2 \Psi_2(\lambda_*; \boldsymbol{A}), \tag{28}$$

$$|\Phi_4(\boldsymbol{X}; \boldsymbol{A}, \lambda) - \Psi_2(\lambda_*; \boldsymbol{A})| \leq C_{*,D,K}\frac{\rho_\lambda(n)^{6}\log^{3/2}(n)}{\sqrt{n}}\Psi_2(\lambda_*; \boldsymbol{A}). \tag{29}$$

Next, we present some of the concepts to be used in deriving random feature ridge regression. Similar to how ridge regression depends on λ_*, as defined in Theorem 11, the deterministic equivalence of random feature ridge regression relies on ν_1 and ν_2, which are the solutions to the coupled equations

$$n - \frac{\lambda}{\nu_1} = \mathrm{Tr}\left(\mathbf{\Lambda}(\mathbf{\Lambda}+\nu_2)^{-1}\right), \quad p - \frac{p\nu_1}{\nu_2} = \mathrm{Tr}\left(\mathbf{\Lambda}(\mathbf{\Lambda}+\nu_2)^{-1}\right). \tag{30}$$

Writing ν_1 as a function of ν_2 produces the equations as below

$$1+\frac{n}{p}-\sqrt{\left(1-\frac{n}{p}\right)^2+4\frac{\lambda}{p\nu_2}} = \frac{2}{p}\mathrm{Tr}\left(\mathbf{\Lambda}(\mathbf{\Lambda}+\nu_2)^{-1}\right), \nu_1 := \frac{\nu_2}{2}\left[1-\frac{n}{p}+\sqrt{\left(1-\frac{n}{p}\right)^2+4\frac{\lambda}{p\nu_2}}\right]. \tag{31}$$

For random features, our results also depend on the capacity of $\mathbf{\Lambda}$. Recall the definition of $r_{\mathbf{\Lambda}}(k) := \frac{\mathrm{Tr}(\mathbf{\Lambda}\geq k)}{\|\mathbf{\Lambda}\geq k\|_{op}}$ as the intrinsic dimension of $\mathbf{\Lambda}$ at level k, we sequentially define the following quantities that can be found in [12, 33].

$$M_{\mathbf{\Lambda}}(k) = 1 + \frac{r_{\mathbf{\Lambda}}(\lfloor \eta_* \cdot k \rfloor) \vee k}{k} \log\left(r_{\mathbf{\Lambda}}(\lfloor \eta_* \cdot k \rfloor) \vee k\right), \tag{32}$$

$$\rho_\kappa(p) = 1 + \frac{p \cdot \xi^2_{\lfloor \eta_* \cdot p \rfloor}}{\kappa} M_{\mathbf{\Lambda}}(p), \tag{33}$$

$$\widetilde{\rho}_\kappa(n,p) = 1 + \mathbb{1}\{n \leq p/\eta_*\} \cdot \left\{\frac{n\xi^2_{\lfloor \eta_* \cdot n \rfloor}}{\kappa} + \frac{n}{p} \cdot \rho_\kappa(p)\right\} M_{\mathbf{\Lambda}}(n), \tag{34}$$

where the constant $\eta_* \in (0, 1/2)$ only depends on C_* introduced in Assumption 1.

For an integer $\mathsf{m} \in \mathbb{N}$, we split the covariance matrix $\mathbf{\Lambda}$ into low degree part and high degree part as

$$\mathbf{\Lambda}_0 := \mathrm{diag}(\xi_1^2, \xi_2^2, \ldots, \xi_{\mathsf{m}}^2), \quad \mathbf{\Lambda}_+ := \mathrm{diag}(\xi_{\mathsf{m}+1}^2, \xi_{\mathsf{m}+2}^2, \ldots).$$

After we define the high degree feature covariance $\mathbf{\Lambda}_+$, we can define the function $\gamma(\kappa) := \kappa + \mathrm{Tr}(\mathbf{\Lambda}_+)$. To simplify the statement, we assume that we can choose m such that $p^2\xi^2_{\mathsf{m}+1} \leq \gamma(p\lambda/n)$, which is always satisfied under Theorem 1. For convenience, we will further denote

$$\gamma_+ := \gamma(p\nu_1), \qquad \gamma_\lambda := \gamma(p\lambda/n). \tag{35}$$

For random feature ridge regression, we will first demonstrate that the ℓ_2 norm concentrates around a quantity that depends only on $\widehat{\mathbf{\Lambda}}_{\boldsymbol{F}}$. To this end, we define the following functionals with respect to $\boldsymbol{Z}$.

$$\begin{aligned}\Phi_3(\boldsymbol{Z};\boldsymbol{A},\kappa) &:= \mathrm{Tr}\left(\boldsymbol{A}\widehat{\mathbf{\Lambda}}_{\boldsymbol{F}}^{1/2}(\boldsymbol{Z}^\top\boldsymbol{Z}+\kappa)^{-1}\widehat{\mathbf{\Lambda}}_{\boldsymbol{F}}(\boldsymbol{Z}^\top\boldsymbol{Z}+\kappa)^{-1}\widehat{\mathbf{\Lambda}}_{\boldsymbol{F}}^{1/2}\right),\\ \Phi_4(\boldsymbol{Z};\boldsymbol{A},\kappa) &:= \mathrm{Tr}\left(\boldsymbol{A}\widehat{\mathbf{\Lambda}}_{\boldsymbol{F}}^{1/2}(\boldsymbol{Z}^\top\boldsymbol{Z}+\kappa)^{-1}\frac{\boldsymbol{Z}^\top\boldsymbol{Z}}{n}(\boldsymbol{Z}^\top\boldsymbol{Z}+\kappa)^{-1}\widehat{\mathbf{\Lambda}}_{\boldsymbol{F}}^{1/2}\right).\end{aligned} \tag{36}$$

Given that $\boldsymbol{Z}$ consists of i.i.d. rows with covariance $\widehat{\mathbf{\Lambda}}_{\boldsymbol{F}} = \boldsymbol{F}\boldsymbol{F}^\top/p$, we will demonstrate that the aforementioned functionals can be approximated by those of $\boldsymbol{F}$, which, in turn, can be represented using the following functionals:

$$\begin{aligned}\widetilde{\Phi}_5(\boldsymbol{F};\boldsymbol{A},\kappa) &:= \frac{1}{n}\cdot\frac{\widetilde{\Phi}_6(\boldsymbol{F};\boldsymbol{A},\kappa)}{n-\widetilde{\Phi}_6(\boldsymbol{F};\boldsymbol{I},\kappa)},\\ \widetilde{\Phi}_6(\boldsymbol{F};\boldsymbol{A},\kappa) &:= \mathrm{Tr}\left(\boldsymbol{A}(\boldsymbol{F}\boldsymbol{F}^\top)^2(\boldsymbol{F}\boldsymbol{F}^\top+\kappa)^{-2}\right).\end{aligned} \tag{37}$$

Proposition 13 (Deterministic equivalents for $\Phi(\boldsymbol{Z})$ conditional on $\boldsymbol{F}$, Proposition B.6 of [12]) *Assume $\{\boldsymbol{z}_i\}_{i\in[n]}$ and $\{\boldsymbol{f}\}_{i\in[p]}$ satisfy Theorem 1 with a constant $C_*>0$, and $\boldsymbol{F}\in\mathcal{A}_{\boldsymbol{F}}$ defined in [12, Eq. (79)]. Then for any $D,K>0$, there exist constants $\eta_*\in(0,1/2)$, $C_{D,K}>0$ and $C_{*,D,K}>0$ ensuring the following property holds. Let $\rho_\kappa(p)$ and $\tilde{\rho}_\kappa(n,p)$ be defined as per Eq. (33) and Eq. (34), γ_+ be defined as Eq. (35). For any $n\geq C_{D,K}$ and $\lambda>0$, if the following condition is satisfied:*

$$\lambda\geq n^{-K}\,,\qquad \widetilde{\rho}_\lambda(n,p)^{5/2}\log^{3/2}(n)\leq K\sqrt{n}\,,\qquad \widetilde{\rho}_\lambda(n,p)^2\cdot\rho_{\gamma_+}(p)^{5/2}\log^3(p)\leq K\sqrt{p}\,,$$

then for any PSD matrix $\boldsymbol{A}\in\mathbb{R}^{p\times p}$ (independent of $\boldsymbol{Z}$ conditional on $\boldsymbol{F}$), we have with probability at least $1-n^{-D}$ that

$$\left|\Phi_3(\boldsymbol{Z};\boldsymbol{A},\lambda)-\left(\frac{n\nu_1}{\lambda}\right)^2\widetilde{\Phi}_5(\boldsymbol{F};\boldsymbol{A},p\nu_1)\right|\leq C_{*,D,K}\cdot\mathcal{E}_1(n,p)\cdot\left(\frac{n\nu_1}{\lambda}\right)^2\widetilde{\Phi}_5(\boldsymbol{F};\boldsymbol{A},p\nu_1), \tag{38}$$

$$\left|\Phi_4(\boldsymbol{Z};\boldsymbol{A},\lambda)-\widetilde{\Phi}_5(\boldsymbol{F};\boldsymbol{A},p\nu_1)\right|\leq C_{*,D,K}\cdot\mathcal{E}_1(n,p)\cdot\widetilde{\Phi}_5(\boldsymbol{F};\boldsymbol{A},p\nu_1), \tag{39}$$

where the rate $\mathcal{E}_1(n,p)$ is given by $\mathcal{E}_1(n,p):=\frac{\widetilde{\rho}_\lambda(n,p)^6\log^{5/2}(n)}{\sqrt{n}}+\frac{\widetilde{\rho}_\lambda(n,p)^2\cdot\rho_{\gamma_+}(p)^{5/2}\log^3(p)}{\sqrt{p}}$.

B.7. Scaling law

For the derivation of the scaling law, we use the results in [12, Appendix D]. We define $T^s_{\delta,\gamma}(\nu)$ as

$$T^s_{\delta,\gamma}(\nu):=\sum_{k=1}^{\infty}\frac{k^{-s-\delta\alpha}}{(k^{-\alpha}+\nu)^\gamma}\,,\quad s\in 0,1,\ 0\leq\delta\leq\gamma.$$

Under Theorem 32, according to [12, Appendix D], we have the following results

$$T^s_{\delta\gamma}(\nu)=O\left(\nu^{1/\alpha[s-1+\alpha(\delta-\gamma)]\wedge 0}\right). \tag{40}$$

Next, we present some rates of the quantities used in the deterministic equivalence of random feature ridge regression. The rate of ν_2 is given by

$$\nu_2\approx O\left(n^{-\alpha(1\wedge q\wedge \ell/\alpha)}\right), \tag{41}$$

and in particular, for $\Upsilon(\nu_1,\nu_2)$ and $\chi(\nu_2)$, we have

$$1-\Upsilon(\nu_1,\nu_2)=O(1)\,, \tag{42}$$

$$\chi(\nu_2)=n^{-q}O\left(\nu_2^{-1-1/\alpha}\right). \tag{43}$$

Appendix C. Proofs on additional non-asymptotic deterministic equivalents

In this section, we aim to generalize Eq. (27) for any PSD matrix $\boldsymbol{A}$, i.e.

$$\left|\Phi_2(\boldsymbol{X};\boldsymbol{A}) - \Psi_2(\mu_*;\boldsymbol{A})\right| \leq \widetilde{\mathcal{O}}(n^{-\frac{1}{2}}) \cdot \Psi_2(\mu_*;\boldsymbol{A}),$$

that is required to derive our non-asymptotic deterministic equivalence for the bias term of the ℓ_2 norm.

By introducing a change of variable $\mu_* := \mu_*(\lambda) = \lambda/\lambda_*$, we find that μ_* satisfies the following fixed-point equation:

$$\mu_* = \frac{n}{1 + \mathrm{T}r(\boldsymbol{\Sigma}(\mu_*\boldsymbol{\Sigma} + \lambda)^{-1})}. \tag{44}$$

We define $\boldsymbol{t}$ and $\boldsymbol{T}$ as follows

$$\boldsymbol{t} = \boldsymbol{\Sigma}^{-1/2}\boldsymbol{x}, \quad \boldsymbol{T} = \boldsymbol{X}\boldsymbol{\Sigma}^{-1/2}.$$

And the following resolvents are also defined

$$\boldsymbol{R} := (\boldsymbol{X}^\top\boldsymbol{X} + \lambda)^{-1}, \quad \overline{\boldsymbol{R}} := (\mu_*\boldsymbol{\Sigma} + \lambda)^{-1}, \quad \boldsymbol{M} := \boldsymbol{\Sigma}^{1/2}\boldsymbol{R}\boldsymbol{\Sigma}^{1/2}, \quad \overline{\boldsymbol{M}} := \boldsymbol{\Sigma}^{1/2}\overline{\boldsymbol{R}}\boldsymbol{\Sigma}^{1/2}.$$

Since the proof relies on a leave-one-out argument, we define $\boldsymbol{X}_- \in \mathbb{R}^{(n-1)\times d}$ as the data matrix obtained by removing one data. We also introduce the associated resolvent and rescaled resolvent:

$$\boldsymbol{R}_- := (\boldsymbol{X}_-^\top\boldsymbol{X}_- + \lambda)^{-1}, \overline{\boldsymbol{R}}_- := \left(\frac{n}{1+\kappa}\boldsymbol{\Sigma} + \lambda\right)^{-1}, \boldsymbol{M}_- := \boldsymbol{\Sigma}^{1/2}\boldsymbol{R}_-\boldsymbol{\Sigma}^{1/2}, \overline{\boldsymbol{M}}_- := \boldsymbol{\Sigma}^{1/2}\overline{\boldsymbol{R}}_-\boldsymbol{\Sigma}^{1/2},$$

where $\kappa = \mathbb{E}[\mathrm{T}r(\boldsymbol{M}_-)]$.

For the sake of narrative convenience, we introduce a functional used in [33]

$$\Psi_1(\mu_*;\boldsymbol{A}) := \mathrm{T}r(\boldsymbol{A}\boldsymbol{\Sigma}(\mu_*\boldsymbol{\Sigma} + \lambda)^{-1}).$$

Next, we give the proof of Eq. (27). We consider the functional

$$\Phi_2(\boldsymbol{X};\boldsymbol{A}) = \mathrm{T}r(\boldsymbol{A}\boldsymbol{\Sigma}^{-1/2}\boldsymbol{X}^\top\boldsymbol{X}(\boldsymbol{X}^\top\boldsymbol{X} + \lambda)^{-1}\boldsymbol{\Sigma}^{1/2}) = \mathrm{T}r(\boldsymbol{A}\boldsymbol{T}^\top\boldsymbol{T}\boldsymbol{M}).$$

Remark: Note that, to align more closely with the proof in [33], the $\Phi_2(\boldsymbol{X};\boldsymbol{A})$ defined here differs slightly from the $\Phi_2(\boldsymbol{X};\boldsymbol{A},\lambda)$ in Eq. (27). However, the two definitions are equivalent if we take $\boldsymbol{A}$ here as $\boldsymbol{A} = \boldsymbol{\Sigma}^{-1/2}\boldsymbol{B}\boldsymbol{\Sigma}^{1/2}$, which recovers the formulation in Eq. (27).

We show that $\Phi_2(\boldsymbol{X};\boldsymbol{A})$ is well approximated by the following deterministic equivalent:

$$\Psi_2(\mu_*;\boldsymbol{A}) = \mathrm{T}r(\boldsymbol{A}\mu_*\boldsymbol{\Sigma}(\mu_*\boldsymbol{\Sigma} + \lambda)^{-1}) = \mathrm{T}r(\boldsymbol{A}\boldsymbol{\Sigma}(\boldsymbol{\Sigma} + \lambda_*)^{-1}).$$

Theorem 14 (Deterministic equivalent for $\mathrm{T}r(\boldsymbol{A}\boldsymbol{T}^\top\boldsymbol{T}\boldsymbol{M})$) *Assume the features $\{\boldsymbol{x}_i\}_{i\in[n]}$ satisfy Theorem 22 with a constant $C_* > 0$. Then for any $D, K > 0$, there exist constants $\eta \in (0, 1/2)$, $C_{D,K} > 0$, and $C_{*,D,K} > 0$ ensuring the following property holds. For any $n \geq C_{D,K}$ and $\lambda > 0$, if the following condition is satisfied:*

$$\lambda \cdot \rho_\lambda(n) \geq n^{-K}, \qquad \rho_\lambda(n)^2 \log^{\frac{3}{2}}(n) \leq K\sqrt{n}, \tag{45}$$

then for any PSD matrix $\boldsymbol{A}$, with probability at least $1 - n^{-D}$, we have that

$$\left|\Phi_2(\boldsymbol{X};\boldsymbol{A}) - \Psi_2(\mu_*;\boldsymbol{A})\right| \leq C_{*,D,K}\frac{\rho_\lambda(n)^4\log^{\frac{3}{2}}(n)}{\sqrt{n}}\Psi_2(\mu_*;\boldsymbol{A}). \tag{46}$$

Remark: Theorem 14 generalizes Eq. (27). Note that there are some differences between ρ_λ as defined in Eq. (18) and ν_λ as defined in [33]. However, based on the discussion in [12, Appendix A], ν_λ can be easily adjusted to match ρ_λ. Therefore, while we follow the argument in [33], we use ρ_λ directly in this work to minimize additional notation.

Following the approach outlined in [33], our proof involves separately bounding the deterministic and martingale components. This is accomplished in the following two propositions.

Proposition 15 (Deterministic part of $\mathrm{Tr}(\boldsymbol{A}\boldsymbol{T}^\top\boldsymbol{T}\boldsymbol{M})$) *Under the same assumption as Theorem 14, there exist constants C_K and $C_{*,K}$, such that for all $n \geq C_K$ and $\lambda > 0$ satisfying Eq. (45), and for any PSD matrix $\boldsymbol{A}$, we have*

$$\left|\mathbb{E}[\Phi_2(\boldsymbol{X};\boldsymbol{A})] - \Psi_2(\mu_*;\boldsymbol{A})\right| \leq C_{*,K}\frac{\rho_\lambda(n)^4}{\sqrt{n}}\Psi_2(\mu_*;\boldsymbol{A}). \tag{47}$$

Proposition 16 (Martingale part of $\mathrm{Tr}(\boldsymbol{A}\boldsymbol{T}^\top\boldsymbol{T}\boldsymbol{M})$) *Under the same assumption as Theorem 14, there exist constants $C_{K,D}$ and $C_{*,D,K}$, such that for all $n \geq C_{K,D}$ and $\lambda > 0$ satisfying Eq. (45), and for any PSD matrix $\boldsymbol{A}$, we have with probability at least $1 - n^{-D}$ that*

$$\left|\Phi_2(\boldsymbol{X};\boldsymbol{A}) - \mathbb{E}[\Phi_2(\boldsymbol{X};\boldsymbol{A})]\right| \leq C_{*,D,K}\frac{\rho_\lambda(n)^3\log^{\frac{3}{2}}(n)}{\sqrt{n}}\Psi_2(\mu_*;\boldsymbol{A}). \tag{48}$$

Theorem 14 is obtained by combining the bounds (47) and (48). Next, we prove the two propositions above separately.

Proof [Proof of Proposition 15] First, by Sherman-Morrison identity

$$\boldsymbol{M} = \boldsymbol{M}_- - \frac{\boldsymbol{M}_-\boldsymbol{t}\boldsymbol{t}^\top\boldsymbol{M}_-}{1+\boldsymbol{t}^\top\boldsymbol{M}_-\boldsymbol{t}}, \quad \text{and} \quad \boldsymbol{M}\boldsymbol{t} = \frac{\boldsymbol{M}_-\boldsymbol{t}}{1+\boldsymbol{t}^\top\boldsymbol{M}_-\boldsymbol{t}},$$

we decompose $\mathbb{E}[\Phi_2(\boldsymbol{X};\boldsymbol{A})]$ as

$$\begin{aligned}\mathbb{E}\left[\mathrm{Tr}(\boldsymbol{A}\boldsymbol{T}^\top\boldsymbol{T}\boldsymbol{M})\right] &= n\mathbb{E}\left[\frac{\boldsymbol{t}^\top\boldsymbol{M}_-\boldsymbol{A}\boldsymbol{t}}{1+S}\right] \\ &= n\frac{\mathbb{E}[\mathrm{Tr}(\boldsymbol{A}\boldsymbol{M}_-)]}{1+\kappa} + n\mathbb{E}\left[\frac{\kappa - S}{(1+\kappa)(1+S)}\boldsymbol{t}^\top\boldsymbol{M}_-\boldsymbol{A}\boldsymbol{t}\right],\end{aligned}$$

where we denoted $S = \boldsymbol{t}^\top\boldsymbol{M}_-\boldsymbol{t}$. Therefore, bounding the following two terms is sufficient

$$\begin{aligned}&|\mathbb{E}[\Phi_2(\boldsymbol{X};\boldsymbol{A})] - \Psi_2(\mu_*;\boldsymbol{A})| \\ \leq &\left|\frac{n\mathbb{E}[\mathrm{Tr}(\boldsymbol{A}\boldsymbol{M}_-)]}{1+\kappa} - \Psi_2(\mu_*;\boldsymbol{A})\right| + \left|n\mathbb{E}\left[\frac{\kappa - S}{(1+\kappa)(1+S)}\boldsymbol{t}^\top\boldsymbol{M}_-\boldsymbol{A}\boldsymbol{t}\right]\right|.\end{aligned} \tag{49}$$

For the first term, recall that $\tilde{\mu}_*$ is the solution of the equation (44) where we replaced n by $n-1$, and $\tilde{\mu}_- := n/(1+\kappa)$. By [33, Proposition 2], we have

$$|\mathbb{E}[\mathrm{Tr}(\boldsymbol{A}\boldsymbol{M}_-)] - \Psi_1(\tilde{\mu}_*;\boldsymbol{A})| \leq \mathcal{E}^{(\mathsf{D})}_{1,n-1}\cdot\Psi_1(\tilde{\mu}_*;\boldsymbol{A}),$$

where $\mathcal{E}^{(\mathsf{D})}_{1,n-1} = C_{*,K}\frac{\rho_\lambda(n)^{5/2}}{\sqrt{n-1}}$. For $n \geq C$, we have $\mathcal{E}^{(\mathsf{D})}_{1,n-1} \leq C\mathcal{E}^{(\mathsf{D})}_{1,n}$ and by [33, Lemma 3], we have

$$|\Psi_1(\tilde{\mu}_*;\boldsymbol{A}) - \Psi_1(\mu_*;\boldsymbol{A})| \leq C\frac{\rho_\lambda(n)}{n}\Psi_1(\mu_*;\boldsymbol{A}).$$

Combining the above bounds, we obtain

$$|\mathbb{E}[\mathrm{Tr}(\boldsymbol{A}\boldsymbol{M}_-)] - \Psi_1(\mu_*; \boldsymbol{A})| \le \mathcal{E}_{1,n}^{(\mathsf{D})} \cdot \Psi_1(\mu_*; \boldsymbol{A}) \,.$$

Furthermore, from the proof of [33, Proposition 4, Claim 3], we have

$$\frac{|\mu_* - \tilde{\mu}_-|}{\tilde{\mu}_-} \le C_{*,K} \frac{\rho_\lambda(n)^{5/2}}{\sqrt{n}}.$$

Then we conclude that

$$\begin{aligned}
|\mu_* - \tilde{\mu}_-| &\le C_{*,K} \frac{\rho_\lambda(n)^{5/2}}{\sqrt{n}} \cdot \tilde{\mu}_- \\
&\le C_{*,K} \frac{\rho_\lambda(n)^{5/2}}{\sqrt{n}} \cdot \left(1 + C_{*,K} \frac{\rho_\lambda(n)^{5/2}}{\sqrt{n}}\right) \mu_* \\
&\le C_{*,K} \frac{\rho_\lambda(n)^{5/2}}{\sqrt{n}} \cdot \mu_*,
\end{aligned}$$

where we use condition (45) in the last inequality.

Combining this inequality with the previous bounds, we obtain

$$\begin{aligned}
\left| \frac{n\mathbb{E}[\mathrm{Tr}(\boldsymbol{A}\boldsymbol{M}_-)]}{1+\kappa} - \Psi_2(\mu_*; \boldsymbol{A}) \right| &= |\tilde{\mu}_- \mathbb{E}[\mathrm{Tr}(\boldsymbol{A}\boldsymbol{M}_-)] - \mu_* \Psi_1(\mu_*; \boldsymbol{A})| \\
&\le \tilde{\mu}_- \, |\mathbb{E}[\mathrm{Tr}(\boldsymbol{A}\boldsymbol{M}_-)] - \Psi_1(\mu_*; \boldsymbol{A})| + \frac{|\tilde{\mu}_- - \mu_*|}{\mu_*} \cdot \mu_* \Psi_1(\mu_*; \boldsymbol{A}) \\
&\le C\mathcal{E}_{1,n}^{(\mathsf{D})} \cdot \mu_* \Psi_1(\mu_*; \boldsymbol{A}) \\
&= C\mathcal{E}_{1,n}^{(\mathsf{D})} \cdot \Psi_2(\mu_*; \boldsymbol{A}) \,.
\end{aligned}$$

In the next, we aim to estimate the second term in Eq. (49). Here we can reduce $\boldsymbol{A}$ to be a rank-one matrix $\boldsymbol{A} := \boldsymbol{v}\boldsymbol{v}^\top$ following [33, Eq. (77)]. We simply apply Hölder's inequality and obtain

$$\begin{aligned}
& n \left| \mathbb{E}\left[\frac{\kappa - S}{(1+\kappa)(1+S)} \boldsymbol{t}^\top \boldsymbol{M}_- \boldsymbol{A} \boldsymbol{t} \right] \right| \\
&= n\mathbb{E}\left[\left| \frac{\kappa - S}{(1+\kappa)(1+S)} \boldsymbol{t}^\top \boldsymbol{M}_- \boldsymbol{v}\boldsymbol{v}^\top \boldsymbol{t} \right| \right] \\
&\le n\mathbb{E}_{\boldsymbol{M}_-} \left[\mathbb{E}_{\boldsymbol{t}} \left[(\kappa - S)^2 \right]^{1/2} \mathbb{E}_{\boldsymbol{t}} \left[(\boldsymbol{t}^\top \boldsymbol{M}_- \boldsymbol{v}\boldsymbol{v}^\top \boldsymbol{t})^2 \right]^{1/2} \right] \\
&\le n\mathbb{E}_{\boldsymbol{M}_-} \left[\mathbb{E}_{\boldsymbol{t}} \left[(\kappa - S)^2 \right] \right]^{1/2} \mathbb{E}_{\boldsymbol{M}_-} \left[\mathbb{E}_{\boldsymbol{t}} \left[(\boldsymbol{t}^\top \boldsymbol{M}_- \boldsymbol{v}\boldsymbol{v}^\top \boldsymbol{t})^2 \right] \right]^{1/2} \\
&\le n\mathbb{E}_{\boldsymbol{M}_-} \left[\mathbb{E}_{\boldsymbol{t}} \left[(\kappa - S)^2 \right] \right]^{1/2} \mathbb{E}_{\boldsymbol{M}_-} \left[\mathbb{E}_{\boldsymbol{t}} \left[(\boldsymbol{t}^\top \boldsymbol{M}_- \boldsymbol{v})^4 \right]^{1/2} \mathbb{E}_{\boldsymbol{t}} \left[(\boldsymbol{v}^\top \boldsymbol{t})^4 \right]^{1/2} \right]^{1/2} .
\end{aligned}$$

Each of these terms can be bounded, according to the proof of [33, Proposition 2], for the first term, we get

$$\mathbb{E}_{\boldsymbol{M}_-} \left[\mathbb{E}_{\boldsymbol{t}} \left[(\boldsymbol{t}^\top \boldsymbol{M}_- \boldsymbol{t} - \kappa)^2 \right] \right]^{1/2} \le C_{*,K} \frac{\rho_\lambda(n)}{\sqrt{n}}.$$

For the second term, first according to [33, Lemma 2], we have

$$\mathbb{E}_{\boldsymbol{t}}\left[(\boldsymbol{t}^\top \boldsymbol{M}_- \boldsymbol{v})^4\right]^{1/2} \le C_{*,K}\boldsymbol{v}^\top \boldsymbol{M}_-^2 \boldsymbol{v}\,,$$

$$\mathbb{E}_{\boldsymbol{t}}\left[(\boldsymbol{v}^\top \boldsymbol{t})^4\right]^{1/2} \le C_{*,K}\boldsymbol{v}^\top \boldsymbol{v}\,.$$

Thus we have

$$\begin{aligned}\mathbb{E}_{\boldsymbol{M}_-}\left[\mathbb{E}_{\boldsymbol{t}}\left[(\boldsymbol{t}^\top \boldsymbol{M}_- \boldsymbol{v})^4\right]^{1/2}\mathbb{E}_{\boldsymbol{t}}\left[(\boldsymbol{v}^\top \boldsymbol{t})^4\right]^{1/2}\right]^{1/2} &\le \mathbb{E}_{\boldsymbol{M}_-}\left[C_{*,K}\boldsymbol{v}^\top \boldsymbol{M}_-^2 \boldsymbol{v}\boldsymbol{v}^\top \boldsymbol{v}\right]^{1/2} \\ &= C_{*,K}\mathbb{E}_{\boldsymbol{M}_-}\left[\mathrm{T}r(\boldsymbol{A}\boldsymbol{M}_-^2\boldsymbol{A})\right]^{1/2}.\end{aligned}$$

Then according to [33, Lemma 4.(b)], we have

$$\mathbb{E}_{\boldsymbol{M}_-}\left[\mathrm{T}r(\boldsymbol{A}\boldsymbol{M}_-^2\boldsymbol{A})\right] \le C_{*,K}\rho_\lambda^2(n)\mathrm{T}r(\boldsymbol{A}\overline{\boldsymbol{M}}_-^2\boldsymbol{A}) = C_{*,K}\rho_\lambda^2(n)\mathrm{T}r(\boldsymbol{A}\overline{\boldsymbol{M}}_-)^2,$$

where the last inequality holds due to $\boldsymbol{A}\overline{\boldsymbol{M}}_-$ being a rank-1 matrix. Combining the bounds for the second term, we have

$$\mathbb{E}_{\boldsymbol{M}_-}\left[\mathbb{E}_{\boldsymbol{t}}\left[(\boldsymbol{t}^\top \boldsymbol{M}_- \boldsymbol{v})^4\right]^{1/2}\mathbb{E}_{\boldsymbol{t}}\left[(\boldsymbol{v}^\top \boldsymbol{t})^4\right]^{1/2}\right]^{1/2} \le C_{*,K}\rho_\lambda(n)\mathrm{T}r(\boldsymbol{A}\overline{\boldsymbol{M}}_-) \le C_{*,K}\rho_\lambda^2(n)\mathrm{T}r(\boldsymbol{A}\overline{\boldsymbol{M}}).$$

By combining the above bounds for the first and second term, we have

$$\begin{aligned}n\left|\mathbb{E}\left[\frac{\kappa - S}{(1+\kappa)(1+S)}\boldsymbol{T}^\top \boldsymbol{M}_- \boldsymbol{A}\boldsymbol{T}\right]\right| &\le C_{*,K}\frac{\rho_\lambda^3(n)}{\sqrt{n}}n\mathrm{T}r(\boldsymbol{A}\overline{\boldsymbol{M}}) \\ &\le C_{*,K}\frac{\rho_\lambda^4(n)}{\sqrt{n}}\mu_*\mathrm{T}r(\boldsymbol{A}\overline{\boldsymbol{M}}),\end{aligned}$$

where we use $\mu_* = \frac{n}{1+\mathrm{T}r(\overline{\boldsymbol{M}})} \ge \frac{n}{2\rho_\lambda(n)}$ according to [33, Lemma 3] in the last inequality.

Combining the above bounds concludes the proof. ■

Proof [Proof of Proposition Theorem 16] The martingale argument follows a similar approach to the proofs of [33, Propositions 3 and 5]. The key remaining steps are to adjust Step 2 in [33, Proposition 3] and establish high-probability bounds for each term in the martingale difference sequence.

We rewrite this term as a martingale difference sequence

$$S_n := \mathrm{T}r(\boldsymbol{A}\boldsymbol{T}^\top\boldsymbol{T}\boldsymbol{M}) - \mathbb{E}[\mathrm{T}r(\boldsymbol{A}\boldsymbol{T}^\top\boldsymbol{T}\boldsymbol{M})] = \sum_{i=1}^n (\mathbb{E}_i - \mathbb{E}_{i-1})\,\mathrm{T}r(\boldsymbol{A}\boldsymbol{T}^\top\boldsymbol{T}\boldsymbol{M}) =: \sum_{i=1}^n \Delta_i\,,$$

where $\mathbb{E}_i$ is denoted as the expectation over $\{\boldsymbol{x}_{i+1}, \cdots, \boldsymbol{x}_n\}$.

We show below that $|\Delta_i| \le R$ with probability at least $1 - n^{-D}$ with

$$R = C_{*,D,K}\frac{\rho_\lambda(n)^2\log(n)}{n}\Psi_2(\mu_*; \boldsymbol{A}). \tag{50}$$

For Step 3 and bounding $\mathbb{E}_{i-1}[\Delta_i \mathbb{1}_{\Delta_i \notin [-R,R]}]$, observe that with probability at least $1 - n^{-D}$, by [33, Lemma 4.(b)]

$$\begin{aligned}
\mathbb{E}_{i-1}[\Delta_i^2]^{1/2} &\leq 2\mathbb{E}_{i-1}\left[\frac{(\boldsymbol{t}^\top \boldsymbol{M}_- \boldsymbol{A}\boldsymbol{t})^2}{(1+S)^2}\right]^{1/2} \\
&\leq C_{*,D,K}\frac{\rho_\lambda(n)^3 \log^{1/2}(n)}{n}\mu_* \mathrm{Tr}(\boldsymbol{A}\overline{\boldsymbol{M}}) \\
&\leq C_{*,D,K}\frac{\rho_\lambda(n)^3 \log^{1/2}(n)}{n}\Psi_2(\mu_*; \boldsymbol{A}).
\end{aligned}$$

We establish a high-probability bound for Δ_i by first decomposing it and strategically adding and subtracting carefully chosen terms. Observing that

$$\Delta_i = (\mathbb{E}_i - \mathbb{E}_{i-1})\,\mathrm{Tr}(\boldsymbol{A}\boldsymbol{T}^\top \boldsymbol{T}\boldsymbol{M}) = (\mathbb{E}_i - \mathbb{E}_{i-1})\left(\mathrm{Tr}(\boldsymbol{A}\boldsymbol{T}^\top \boldsymbol{T}\boldsymbol{M}) - \mathrm{Tr}(\boldsymbol{A}\boldsymbol{T}_i^\top \boldsymbol{T}_i\boldsymbol{M}_i)\right),$$

where $\boldsymbol{M}_i$ is the rescaled resolvent removes $\boldsymbol{x}_i$, and we used that $\mathbb{E}_i\left[\boldsymbol{A}\boldsymbol{T}_i^\top \boldsymbol{T}_i\boldsymbol{M}_i\right] = \mathbb{E}_{i-1}\left[\boldsymbol{A}\boldsymbol{T}_i^\top \boldsymbol{T}_i\boldsymbol{M}_i\right]$, and we'll write (recall that $S_i = \boldsymbol{t}_i^\top \boldsymbol{M}_i\boldsymbol{t}_i$)

$$\begin{aligned}
\mathrm{Tr}(\boldsymbol{A}\boldsymbol{T}^\top \boldsymbol{T}\boldsymbol{M}) - \mathrm{Tr}(\boldsymbol{A}\boldsymbol{T}_i^\top \boldsymbol{T}_i\boldsymbol{M}_i) &= \mathrm{Tr}(\boldsymbol{A}(\boldsymbol{t}_i\boldsymbol{t}_i^\top + \boldsymbol{T}_i^\top \boldsymbol{T}_i)\boldsymbol{M}) - \mathrm{Tr}(\boldsymbol{A}\boldsymbol{T}_i^\top \boldsymbol{T}_i\boldsymbol{M}_i) \\
&= \boldsymbol{t}_i^\top \boldsymbol{M}\boldsymbol{A}\boldsymbol{t}_i + \mathrm{Tr}(\boldsymbol{A}\boldsymbol{T}_i^\top \boldsymbol{T}_i\boldsymbol{M}) - \mathrm{Tr}(\boldsymbol{A}\boldsymbol{T}_i^\top \boldsymbol{T}_i\boldsymbol{M}_i) \\
&= \frac{1}{(1+S_i)}\left\{\boldsymbol{t}_i^\top \boldsymbol{M}_i\boldsymbol{A}\boldsymbol{t}_i - \mathrm{Tr}(\boldsymbol{A}\boldsymbol{T}_i^\top \boldsymbol{T}_i\boldsymbol{M}_i\boldsymbol{t}_i\boldsymbol{t}_i^\top \boldsymbol{M}_i)\right\} \\
&= \frac{1}{(1+S_i)}\mathrm{Tr}(\boldsymbol{t}_i\boldsymbol{t}_i^\top \boldsymbol{M}_i\boldsymbol{A}(\boldsymbol{I} - \boldsymbol{T}_i^\top \boldsymbol{T}_i\boldsymbol{M}_i)).
\end{aligned}$$

Observing that

$$\boldsymbol{I} - \boldsymbol{T}_i^\top \boldsymbol{T}_i\boldsymbol{M}_i = \lambda\boldsymbol{\Sigma}^{-1}\boldsymbol{M}_i,$$

we can write for $j \in \{i-1, i\}$, with probability at least $1 - n^{-D}$,

$$\begin{aligned}
\left|\mathbb{E}_j\left[\frac{1}{(1+S_i)}\mathrm{Tr}(\boldsymbol{t}_i\boldsymbol{t}_i^\top \boldsymbol{M}_i\boldsymbol{A}(\boldsymbol{I} - \boldsymbol{T}_i^\top \boldsymbol{T}_i\boldsymbol{M}_i))\right]\right| &\leq \lambda\mathbb{E}_j\left[|\boldsymbol{t}_i^\top \boldsymbol{M}_i\boldsymbol{A}\boldsymbol{\Sigma}^{-1}\boldsymbol{M}_i\boldsymbol{t}_i|\right] \\
&\leq \mathbb{E}_j\left[|\boldsymbol{t}_i^\top \boldsymbol{M}_i\boldsymbol{A}\boldsymbol{t}_i|\right] \\
&\leq C_{*,D}\log(n)\mathbb{E}_j\left[\mathrm{Tr}(\boldsymbol{A}\boldsymbol{M}_i)\right] \\
&\leq C_{*,D}\rho_\lambda(n)\log(n)\mathrm{Tr}(\boldsymbol{A}\overline{\boldsymbol{M}}) \\
&\leq C_{*,D}\frac{\rho_\lambda(n)^2\log(n)}{n}\mu_*\mathrm{Tr}(\boldsymbol{A}\overline{\boldsymbol{M}}) \\
&= C_{*,D}\frac{\rho_\lambda(n)^2\log(n)}{n}\Psi_2(\mu_*; \boldsymbol{A}),
\end{aligned}$$

where we used that $\boldsymbol{M}_i \preceq \boldsymbol{\Sigma}/\lambda$ by definition in the second inequality, [33, Lemma 4.(b)] in the fourth inequality, and $\mu_* = \frac{n}{1+\mathrm{Tr}(\overline{\boldsymbol{M}})} \geq \frac{n}{2\rho_\lambda(n)}$ in the last inequality.

Applying a union bound and adjusting the choice of D, we conclude that with probability at least $1 - n^{-D}$, the following holds for all $i \in [n]$:

$$|\Delta_i| \leq C_{*,D,K}\frac{\rho_\lambda(n)^2\log(n)}{n}\Psi_2(\mu_*; \boldsymbol{A}).$$

■

Appendix D. Main results and proofs for linear regression

In this section, we study the asymptotic and non-asymptotic deterministic equivalent of the (ridge/ridgeless) estimator norm for linear regression. Based on these results, we are able to mathematically characterize the test risk under norm-based capacity. Table 3 presents the main results for linear regression.

Table 3: Summary of our main results for **Linear Regression**.

Type	Results	Regularization	Deterministic equivalents N	Relationship between R and N
Deterministic equivalence	Theorem 20	$\lambda > 0$	Asymptotic	-
	Theorem 21	$\lambda \to 0$	Asymptotic	-
	Theorem 24	$\lambda > 0$	Non-asymptotic	-
Relationship	Theorem 25	$\lambda > 0$	-	Under $\boldsymbol{\Sigma} = \boldsymbol{I}_d$
	Theorem 27	$\lambda \to 0$	-	Under-parameterized regime
	Theorem 26	$\lambda \to 0$	-	Under $\boldsymbol{\Sigma} = \boldsymbol{I}_d$
	Theorem 29	$\lambda \to 0$	-	Under Theorem 28 (power-law)

To deliver our results, we need the following lemma for the bias-variance decomposition of the estimator's norm.

Lemma 17 (Bias-variance decomposition of $\mathcal{N}_\lambda^{\mathrm{LS}}$) *We have the bias-variance decomposition* $\mathbb{E}_\varepsilon \|\hat{\boldsymbol{\beta}}\|_2^2 =: \mathcal{N}_\lambda^{LS} = \mathcal{B}_{\mathcal{N},\lambda}^{LS} + \mathcal{V}_{\mathcal{N},\lambda}^{LS}$, *where* $\mathcal{B}_{\mathcal{N},\lambda}^{LS}$ *and* $\mathcal{V}_{\mathcal{N},\lambda}^{LS}$ *are defined as*

$$\mathcal{B}_{\mathcal{N},\lambda}^{LS} := \langle \boldsymbol{\beta}_*, (\boldsymbol{X}^\top \boldsymbol{X})^2 (\boldsymbol{X}^\top \boldsymbol{X} + \lambda \boldsymbol{I})^{-2} \boldsymbol{\beta}_* \rangle \,, \quad \mathcal{V}_{\mathcal{N},\lambda}^{LS} := \sigma^2 \mathrm{Tr}(\boldsymbol{X}^\top \boldsymbol{X} (\boldsymbol{X}^\top \boldsymbol{X} + \lambda \boldsymbol{I})^{-2}) \,.$$

And we present the proof of Theorem 17 as below.

Proof [Proof of Theorem 17] Here we give the bias-variance decomposition of $\mathbb{E}_\varepsilon \|\hat{\boldsymbol{\beta}}\|_2^2$. The formulation of $\mathbb{E}_\varepsilon \|\hat{\boldsymbol{\beta}}\|_2^2$ is given by

$$\mathbb{E}_\varepsilon \|\hat{\boldsymbol{\beta}}\|_2^2 = \| \left(\boldsymbol{X}^\top \boldsymbol{X} + \lambda \boldsymbol{I} \right)^{-1} \boldsymbol{X}^\top \boldsymbol{y} \|_2^2 \,,$$

which can be decomposed as

$$\begin{aligned}
\mathbb{E}_\varepsilon \|\hat{\boldsymbol{\beta}}\|_2^2 &= \mathbb{E}_\varepsilon \| \left(\boldsymbol{X}^\top \boldsymbol{X} + \lambda \boldsymbol{I} \right)^{-1} \boldsymbol{X}^\top (\boldsymbol{X} \boldsymbol{\beta}_* + \boldsymbol{\varepsilon}) \|_2^2 \\
&= \| \left(\boldsymbol{X}^\top \boldsymbol{X} + \lambda \boldsymbol{I} \right)^{-1} \boldsymbol{X}^\top \boldsymbol{X} \boldsymbol{\beta}_* \|_2^2 + \mathbb{E}_\varepsilon \| \left(\boldsymbol{X}^\top \boldsymbol{X} + \lambda \boldsymbol{I} \right)^{-1} \boldsymbol{X}^\top \boldsymbol{\varepsilon} \|_2^2 \\
&= \langle \boldsymbol{\beta}_*, (\boldsymbol{X}^\top \boldsymbol{X})^2 (\boldsymbol{X}^\top \boldsymbol{X} + \lambda \boldsymbol{I})^{-2} \boldsymbol{\beta}_* \rangle + \sigma^2 \mathrm{Tr}(\boldsymbol{X}^\top \boldsymbol{X} (\boldsymbol{X}^\top \boldsymbol{X} + \lambda \boldsymbol{I})^{-2}) \\
&=: \mathcal{B}_{\mathcal{N},\lambda}^{\mathrm{LS}} + \mathcal{V}_{\mathcal{N},\lambda}^{\mathrm{LS}} \,.
\end{aligned}$$

Accordingly, we can see that it shares the similar spirit with the bias-variance decomposition. ■

Our first goal is to relate $\mathcal{B}_{\mathcal{N},\lambda}^{\mathrm{LS}}$ and $\mathcal{V}_{\mathcal{N},\lambda}^{\mathrm{LS}}$ to their respective deterministic equivalents. And next, we will present the results for both asymptotic and non-asymptotic regime separately.

D.1. Asymptotic deterministic equivalence for ridge regression

In this section, we establish the asymptotic approximation guarantees for linear regression, focusing on the relationships between the ℓ_2 norm of the estimator and its deterministic equivalent. These results can be recovered by our non-asymptotic results, but we put them here just for completeness.

Before presenting the results on deterministic equivalence for ridge regression and their proofs, we begin by introducing a couple of useful corollaries from Theorems 6 and 7.

Corollary 18 *Under the same condition of Theorem 6, we have*

$$\mathrm{Tr}(\boldsymbol{A}\boldsymbol{X}^\top\boldsymbol{X}(\boldsymbol{X}^\top\boldsymbol{X}+\lambda)^{-2}) \sim \frac{\mathrm{Tr}(\boldsymbol{A}\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})}{n-\mathrm{d}f_2(\lambda_*)}\,. \tag{51}$$

Specifically, if $\boldsymbol{A}=\boldsymbol{\Sigma}$, we have

$$\mathrm{Tr}(\boldsymbol{\Sigma}\boldsymbol{X}^\top\boldsymbol{X}(\boldsymbol{X}^\top\boldsymbol{X}+\lambda)^{-2}) \sim \frac{\mathrm{d}f_2(\lambda_*)}{n-\mathrm{d}f_2(\lambda_*)}\,. \tag{52}$$

Corollary 19 *Under the same condition of Theorem 7, we have*

$$\mathrm{Tr}(\boldsymbol{A}\boldsymbol{T}^\top(\boldsymbol{T}\boldsymbol{\Sigma}\boldsymbol{T}^\top+\lambda)^{-2}\boldsymbol{T}) \sim \frac{\mathrm{Tr}(\boldsymbol{A}(\boldsymbol{\Sigma}+\lambda_*)^{-2})}{n-\mathrm{d}f_2(\lambda_*)}\,. \tag{53}$$

Using the equation

$$\mathrm{Tr}(\boldsymbol{A}\boldsymbol{X}^\top\boldsymbol{X}(\boldsymbol{X}^\top\boldsymbol{X}+\lambda)^{-2}) = \frac{1}{\lambda}\left(\mathrm{Tr}(\boldsymbol{A}\boldsymbol{X}^\top\boldsymbol{X}(\boldsymbol{X}^\top\boldsymbol{X}+\lambda)^{-1}) - \mathrm{Tr}(\boldsymbol{A}(\boldsymbol{X}^\top\boldsymbol{X})^2(\boldsymbol{X}^\top\boldsymbol{X}+\lambda)^{-2})\right)\,,$$

we can directly obtain Theorems 18 and 19 from Theorems 6 and 7.

Now we are ready to derive the deterministic equivalence, i.e., $\mathbb{E}_\varepsilon\|\hat{\boldsymbol{\beta}}\|_2^2$, under the bias-variance decomposition. Our results can handle ridge estimator $\hat{\boldsymbol{\beta}}$ in Theorem 20 and interpolator $\hat{\boldsymbol{\beta}}_{\min}$ in Theorem 21, respectively.

Proposition 20 (Asymptotic deterministic equivalence of $\mathcal{N}_\lambda^{LS}$.) *Given the bias variance decomposition of $\mathbb{E}_\varepsilon\|\hat{\boldsymbol{\beta}}\|_2^2$ in Theorem 17, under Theorem 3, we have the following asymptotic deterministic equivalents $\mathcal{N}_\lambda^{LS} \sim \mathsf{N}_\lambda^{LS} := \mathsf{B}_{\mathsf{N},\lambda}^{LS} + \mathsf{V}_{\mathsf{N},\lambda}^{LS}$ such that $\mathcal{B}_{\mathcal{N},\lambda}^{LS} \sim \mathsf{B}_{\mathsf{N},\lambda}^{LS}$, $\mathcal{V}_{\mathcal{N},\lambda}^{LS} \sim \mathsf{V}_{\mathsf{N},\lambda}^{LS}$, where these quantities are from Theorem 17 and Eq. (54).*

$$\mathsf{B}_{\mathsf{N},\lambda}^{LS} := \langle\boldsymbol{\beta}_*, \boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2}\boldsymbol{\beta}_*\rangle + \frac{\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})}{n}\cdot\underbrace{\frac{\lambda_*^2\langle\boldsymbol{\beta}_*, \boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2}\boldsymbol{\beta}_*\rangle}{1-n^{-1}\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})}}_{\mathsf{B}_{\mathsf{R},\lambda}^{LS}}\,,$$

$$\mathsf{V}_{\mathsf{N},\lambda}^{LS} := \frac{\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})}{\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})}\cdot\underbrace{\frac{\sigma^2\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})}{n-\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})}}_{\mathsf{V}_{\mathsf{R},\lambda}^{LS}}\,. \tag{54}$$

We remark that, by checking Eq. (15) and Eq. (54), norm-based capacity suffices to characterize generalization while effective dimension can not, where effective dimension is defined as $\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-1})$ [57] or similar formulation, e.g., $\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})$.

- Bias: for the bias term, we find that the second term of $\mathsf{B}^{\mathrm{L}S}_{\mathsf{N},\lambda}$ rescales $\mathsf{B}^{\mathrm{L}S}_{\mathsf{R},\lambda}$ in Eq. (15) by a factor $\frac{\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})}{n}$.
- Variance: we find that the variance term of the norm $\mathsf{V}^{\mathrm{L}S}_{\mathsf{N},\lambda}$ equals the variance term of the test risk $\mathsf{V}^{\mathrm{L}S}_{\mathsf{R},\lambda}$ in Eq. (15) multiplied by a factor $\frac{\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})}{\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})}$. That means, under isotropic features $\boldsymbol{\Sigma}=\boldsymbol{I}_d$, they are the same.

Accordingly, the norm-based capacity is able to characterize the bias and variance of the excess risk. We provide a quantitative analysis of this relationship in **??** D.3.2. Below, we present the proof of Theorem 20.

Proof [Proof of Theorem 20] We give the asymptotic deterministic equivalents for $\mathcal{B}^{\mathrm{L}S}_{\mathcal{N},\lambda}$ and $\mathcal{V}^{\mathrm{L}S}_{\mathcal{N},\lambda}$, respectively. For the bias term $\mathcal{B}^{\mathrm{L}S}_{\mathcal{N},\lambda}$, we use Eq. (8) by taking $\boldsymbol{A}=\boldsymbol{\beta}_*\boldsymbol{\beta}_*^\top$ and $\boldsymbol{B}=\boldsymbol{I}$ and thus obtain

$$\begin{aligned}
\mathcal{B}^{\mathrm{L}S}_{\mathcal{N},\lambda} &= \langle \boldsymbol{\beta}_*, (\boldsymbol{X}^\top\boldsymbol{X})^2(\boldsymbol{X}^\top\boldsymbol{X}+\lambda\boldsymbol{I})^{-2}\boldsymbol{\beta}_*\rangle \\
&= \mathrm{Tr}(\boldsymbol{\beta}_*\boldsymbol{\beta}_*^\top(\boldsymbol{X}^\top\boldsymbol{X})^2(\boldsymbol{X}^\top\boldsymbol{X}+\lambda\boldsymbol{I})^{-2}) \\
&\sim \mathrm{Tr}(\boldsymbol{\beta}_*\boldsymbol{\beta}_*^\top\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2}) \\
&\quad + \lambda_*^2\mathrm{Tr}(\boldsymbol{\beta}_*\boldsymbol{\beta}_*^\top\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})\cdot\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})\cdot\frac{1}{n-\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})} \\
&= \langle\boldsymbol{\beta}_*, \boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2}\boldsymbol{\beta}_*\rangle + \frac{\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})}{n}\cdot\frac{\lambda_*^2\langle\boldsymbol{\beta}_*,\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2}\boldsymbol{\beta}_*\rangle}{1-n^{-1}\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})} \\
&=: \mathsf{B}^{\mathrm{L}S}_{\mathsf{N},\lambda}\,.
\end{aligned}$$

For the variance term $\mathcal{V}^{\mathrm{L}S}_{\mathcal{N}}$, we use Eq. (51) by taking $\boldsymbol{A}=\boldsymbol{I}$ and obtain

$$\mathcal{V}^{\mathrm{L}S}_{\mathcal{N}} = \sigma^2\mathrm{Tr}(\boldsymbol{X}^\top\boldsymbol{X}(\boldsymbol{X}^\top\boldsymbol{X}+\lambda\boldsymbol{I})^{-2}) \sim \frac{\sigma^2\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})}{n-\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})} =: \mathsf{V}^{\mathrm{L}S}_{\mathsf{N},\lambda}\,.$$

■

The deterministic equivalent of the norm for the min-ℓ_2-norm estimator. We have the following results on the characterization of the deterministic equivalence of $\|\hat{\boldsymbol{\beta}}_{\min}\|_2$.

Corollary 21 (Asymptotic deterministic equivalence of the norm of interpolator) *Under Theorem 3, for the minimum ℓ_2-norm estimator $\hat{\boldsymbol{\beta}}_{\min}$, we have the following deterministic equivalence: for the under-parameterized regime ($d<n$), we have*

$$\mathcal{B}^{LS}_{\mathcal{N},0} = \|\boldsymbol{\beta}_*\|_2^2\,, \quad \mathcal{V}^{LS}_{\mathcal{N},0} \sim \frac{\sigma^2}{n-d}\mathrm{Tr}(\boldsymbol{\Sigma}^{-1})\,.$$

In the over-parameterized regime ($d>n$), we have

$$\begin{aligned}
\mathcal{B}^{LS}_{\mathcal{N},0} &\sim \langle\boldsymbol{\beta}_*, \boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n\boldsymbol{I})^{-1}\boldsymbol{\beta}_*\rangle\,, \\
\mathcal{V}^{LS}_{\mathcal{N},0} &\sim \frac{\sigma^2\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n\boldsymbol{I})^{-2})}{n-\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n\boldsymbol{I})^{-2})} = \frac{\sigma^2}{\lambda_n}\,,
\end{aligned}$$

where λ_n is defined by $\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n\boldsymbol{I})^{-1})\sim n$.

Remark: The asymptotic behavior of λ_* differs between the under-parameterized and over-parameterized regimes as $\lambda \to 0$, though the ridge regression estimator $\hat{\boldsymbol{\beta}}$ converges to the min-ℓ_2-norm estimator $\hat{\boldsymbol{\beta}}_{\min}$. To be specific, in the under-parameterized regime, λ_* converges to 0 as $\lambda \to 0$; while in the over-parameterized regime, λ_* converges to a constant that admits $\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-1}) \sim n$ when $\lambda \to 0$. Accordingly, for the minimum ℓ_2-norm estimator, it is necessary to analyze the two regimes separately. And we show that the solution λ_n to the self-consistent equation $\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-1}) \sim n$ can be obtained from the variance $\mathsf{V}_{\mathsf{N},0}^{\mathrm{L}S} = \sigma^2/\lambda_n$.

Proof [Proof of Theorem 21] We separate the results in the under-parameterized and over-parameterized regimes.

In the under-parameterized regime ($d < n$), for minimum norm estimator $\hat{\boldsymbol{\beta}}_{\min}$, we have (for $\boldsymbol{X}^\top \boldsymbol{X}$ is invertible)

$$\hat{\boldsymbol{\beta}}_{\min} = \left(\boldsymbol{X}^\top \boldsymbol{X}\right)^{-1} \boldsymbol{X}^\top \boldsymbol{y} = \left(\boldsymbol{X}^\top \boldsymbol{X}\right)^{-1} \boldsymbol{X}^\top (\boldsymbol{X}\boldsymbol{\beta}_* + \boldsymbol{\varepsilon}) = \boldsymbol{\beta}_* + \left(\boldsymbol{X}^\top \boldsymbol{X}\right)^{-1} \boldsymbol{X}^\top \boldsymbol{\varepsilon}\,.$$

Accordingly, we can directly obtain the bias-variance decomposition as well as their deterministic equivalents

$$\mathcal{B}_{\mathcal{N},0}^{\mathrm{L}S} = \|\boldsymbol{\beta}_*\|_2^2\,, \quad \mathcal{V}_{\mathcal{N},0}^{\mathrm{L}S} = \sigma^2 \mathrm{Tr}(\boldsymbol{X}^\top \boldsymbol{X}(\boldsymbol{X}^\top \boldsymbol{X})^{-2}) \sim \sigma^2 \frac{\mathrm{Tr}(\boldsymbol{\Sigma}^{-1})}{n-d}\,,$$

where we use Eq. (51) and take $\lambda \to 0$ for the variance term.

In the over-parameterized regime ($d > n$), we take the limit $\lambda \to 0$ within ridge regression and use Theorem 20. Define λ_n as $\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-1}) \sim n$, we have for the bias term

$$\begin{aligned}
\mathcal{B}_{\mathcal{N},0}^{\mathrm{L}S} &\sim \langle \boldsymbol{\beta}_*, \boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2}\boldsymbol{\beta}_*\rangle + \frac{\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2})}{n} \cdot \frac{\lambda_n^2 \langle \boldsymbol{\beta}_*, \boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2}\boldsymbol{\beta}_*\rangle}{1 - n^{-1}\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2})} \\
&= \langle \boldsymbol{\beta}_*, \boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-1}\boldsymbol{\beta}_*\rangle - \lambda_n \langle \boldsymbol{\beta}_*, \boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2}\boldsymbol{\beta}_*\rangle \\
&\quad + \frac{\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2})}{n} \cdot \frac{\lambda_n^2 \langle \boldsymbol{\beta}_*, \boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2}\boldsymbol{\beta}_*\rangle}{1 - n^{-1}\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2})} \\
&= \langle \boldsymbol{\beta}_*, \boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-1}\boldsymbol{\beta}_*\rangle\,.
\end{aligned}$$

For the variance term, we have

$$\mathcal{V}_{\mathcal{N},0}^{\mathrm{L}S} \sim \frac{\sigma^2 \mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2})}{n - \mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2})}\,.$$

Finally we conclude the proof. ■

D.2. Non-asymptotic analysis on the deterministic equivalents of estimator's norm

To derive the non-asymptotic results, we make the following assumption on well-behaved data.

Assumption 22 (Data concentration [33]) *There exist $C_* > 0$ such that for any PSD matrix $\boldsymbol{A} \in \mathbb{R}^{d\times d}$ with $\mathrm{Tr}(\boldsymbol{\Sigma}\boldsymbol{A}) < \infty$ and $t \geq 0$, we have*

$$\mathbb{P}\left(\left|\boldsymbol{X}^\top \boldsymbol{A}\boldsymbol{X} - \mathrm{Tr}(\boldsymbol{\Sigma}\boldsymbol{A})\right| \geq t\|\boldsymbol{\Sigma}^{1/2}\boldsymbol{A}\boldsymbol{\Sigma}^{1/2}\|_{\mathrm{F}}\right) \leq C_* e^{-\frac{t}{C_*}}\,.$$

Assumption 23 ([12]) *There exists $C > 1$*

$$\frac{\langle \boldsymbol{\beta}_*, \boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*)^{-1}\boldsymbol{\beta}_*\rangle}{\langle \boldsymbol{\beta}_*, \boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*)^{-2}\boldsymbol{\beta}_*\rangle} \leq C\,.$$

Remark: This assumption holds in many settings of interest, such as power law assumptions like those in Theorem 28, since under this assumption the numerator and denominator are bounded sums of finite terms. It is a technical assumption used to address the difference between two deterministic equivalents that are needed in our work for norm-based capacity. In fact, this assumption is used for RFMs in [12] as the authors also face with the issue on the difference between two deterministic equivalents.

Based on the above two assumptions, we are ready to deliver the following result, our results can also numerically validated by Fig. 11 in Appendix J.2.

Theorem 24 (Deterministic equivalents of the ℓ_2-norm of the estimator.) *Assume well-behaved data $\{\boldsymbol{x}_i\}_{i=1}^n$ satisfy Theorem 22 and Theorem 23. Then for any $D, K > 0$, there exist constants $\eta_* \in (0, 1/2)$ and $C_{*,D,K} > 0$ ensuring the following property holds. For any $n \geq C_{*,D,K}$, $\lambda > 0$, if the following condition is satisfied:*

$$\lambda \geq n^{-K}\,, \quad \rho_\lambda(n)^{5/2}\log^{3/2}(n) \leq K\sqrt{n}\,,$$

then with probability at least $1 - n^{-D}$, we have that

$$\left|\mathcal{B}^{LS}_{\mathcal{N},\lambda} - \mathsf{B}^{LS}_{\mathsf{N},\lambda}\right| \leq C_{x,D,K}\frac{\rho_\lambda(n)^6\log^{3/2}(n)}{\sqrt{n}}\mathsf{B}^{LS}_{\mathsf{N},\lambda}\,,$$
$$\left|\mathcal{V}^{LS}_{\mathcal{N},\lambda} - \mathsf{V}^{LS}_{\mathsf{N},\lambda}\right| \leq C_{x,D,K}\frac{\rho_\lambda(n)^6\log^{3/2}(n)}{\sqrt{n}}\mathsf{V}^{LS}_{\mathsf{N},\lambda}\,.$$

Next, we give the proof of Theorem 20 below.

Proof [Proof of Theorem 24] **P**art 1: Deterministic equivalents for the bias term.

Here we prove the deterministic equivalents of $\mathcal{B}^{\text{LS}}_{\mathcal{N},\lambda}$ and $\mathcal{V}^{\text{LS}}_{\mathcal{N},\lambda}$. First, we decompose $\mathcal{B}^{\text{LS}}_{\mathcal{N},\lambda}$ into

$$\begin{aligned}\mathcal{B}^{\text{LS}}_{\mathcal{N},\lambda} &= \mathrm{T}r\left(\boldsymbol{\beta}_*\boldsymbol{\beta}_*^\top\boldsymbol{X}^\top\boldsymbol{X}(\boldsymbol{X}^\top\boldsymbol{X}+\lambda)^{-1}\right) - \lambda\mathrm{T}r\left(\boldsymbol{\beta}_*\boldsymbol{\beta}_*^\top\boldsymbol{X}^\top\boldsymbol{X}(\boldsymbol{X}^\top\boldsymbol{X}+\lambda)^{-2}\right),\\ &= \Phi_2(\boldsymbol{X};\tilde{\boldsymbol{A}}_1,\lambda) - n\lambda\Phi_4(\boldsymbol{X};\tilde{\boldsymbol{A}}_2,\lambda)\,,\end{aligned}$$

where $\tilde{\boldsymbol{A}}_1 := \boldsymbol{\beta}_*\boldsymbol{\beta}_*^\top$, $\tilde{\boldsymbol{A}}_2 := \boldsymbol{\Sigma}^{-1/2}\boldsymbol{\beta}_*\boldsymbol{\beta}_*^\top\boldsymbol{\Sigma}^{-1/2}$. Therefore, using Theorem 12, with probability at least $1 - n^{-D}$, we have

$$\left|\Phi_2(\boldsymbol{X};\tilde{\boldsymbol{A}}_1,\lambda) - \Psi_1(\lambda_*;\tilde{\boldsymbol{A}}_1)\right| \leq C_{x,D,K}\frac{\rho_\lambda(n)^{5/2}\log^{3/2}(n)}{\sqrt{n}}\Psi_1(\lambda_*;\tilde{\boldsymbol{A}}_1)\,,$$
$$\left|n\lambda\Phi_4(\boldsymbol{X};\tilde{\boldsymbol{A}}_2,\lambda) - n\lambda\Psi_2(\lambda_*;\tilde{\boldsymbol{A}}_2)\right| \leq C_{x,D,K}\frac{\rho_\lambda(n)^6\log^{3/2}(n)}{\sqrt{n}}n\lambda\Psi_2(\lambda_*;\tilde{\boldsymbol{A}}_2)\,.$$

Combining the above bounds, we deduce that

$$\begin{aligned}&\left|\mathcal{B}^{\text{LS}}_{\mathcal{N},\lambda} - \left(\Psi_1(\lambda_*;\tilde{\boldsymbol{A}}_1) - n\lambda\Psi_2(\lambda_*;\tilde{\boldsymbol{A}}_2)\right)\right|\\ &\leq C_{x,D,K}\frac{\rho_\lambda(n)^6\log^{3/2}(n)}{\sqrt{n}}\left(\Psi_1(\lambda_*;\tilde{\boldsymbol{A}}_1) + n\lambda\Psi_2(\lambda_*;\tilde{\boldsymbol{A}}_2)\right).\end{aligned}$$

Note that

$$\Psi_1(\lambda_*; \tilde{\boldsymbol{A}}_1) - n\lambda\Psi_2(\lambda_*; \tilde{\boldsymbol{A}}_2) = \mathsf{B}^{\mathrm{LS}}_{\mathsf{N},\lambda}\,.$$

For $n\lambda\Psi_2(\lambda_*; \tilde{\boldsymbol{A}}_2)$, recall that $\Psi_2(\lambda_*; \boldsymbol{A}) := \frac{1}{n}\frac{\mathrm{Tr}(\boldsymbol{A}\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})}{n-\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})}$, and according to Theorem 11 and Theorem 23, we have

$$\begin{aligned}
n\lambda\Psi_2(\lambda_*; \tilde{\boldsymbol{A}}_2) &= \lambda\frac{\mathrm{Tr}(\boldsymbol{\beta}_*\boldsymbol{\beta}_*^\top\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})}{n-\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})} \\
&\le \lambda_*\mathrm{Tr}(\boldsymbol{\beta}_*\boldsymbol{\beta}_*^\top\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2}) \\
&= \mathrm{Tr}(\boldsymbol{\beta}_*\boldsymbol{\beta}_*^\top\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-1}) - \mathrm{Tr}(\boldsymbol{\beta}_*\boldsymbol{\beta}_*^\top\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2}) \\
&\le \left(1-\frac{1}{C}\right)\mathrm{Tr}(\boldsymbol{\beta}_*\boldsymbol{\beta}_*^\top\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*)^{-1})\,,
\end{aligned}$$

and therefore

$$\begin{aligned}
\Psi_1(\lambda_*; \tilde{\boldsymbol{A}}_1) + n\lambda\Psi_2(\lambda_*; \tilde{\boldsymbol{A}}_2) &\le \left(2-\frac{1}{C}\right)\mathrm{Tr}(\boldsymbol{\beta}_*\boldsymbol{\beta}_*^\top\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*)^{-1}) \\
&\le (2C-1)\,\frac{1}{C}\mathrm{Tr}(\boldsymbol{\beta}_*\boldsymbol{\beta}_*^\top\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_*)^{-1}) \\
&\le (2C-1)\left(\Psi_1(\lambda_*; \tilde{\boldsymbol{A}}_1) - n\lambda\Psi_2(\lambda_*; \tilde{\boldsymbol{A}}_2)\right).
\end{aligned}$$

Then we conclude that

$$\left|\mathcal{B}^{\mathrm{LS}}_{\mathcal{N},\lambda} - \mathsf{B}^{\mathrm{LS}}_{\mathsf{N},\lambda}\right| \le C_{x,D,K}\frac{\rho_\lambda(n)^6\log^{3/2}(n)}{\sqrt{n}}\mathsf{B}^{\mathrm{LS}}_{\mathsf{N},\lambda},$$

with probability at least $1-n^{-D}$.

Part 2: Deterministic equivalents for the variance term. Next, we prove the deterministic equivalent of $\mathcal{V}^{\mathrm{LS}}_{\mathcal{N},\lambda}$. First, note that $\mathcal{V}^{\mathrm{LS}}_{\mathcal{N},\lambda}$ can be written in terms of the functional $\Phi_4(\boldsymbol{X}; \boldsymbol{A}, \lambda)$ defined in Eq. (22)

$$\mathcal{V}^{\mathrm{LS}}_{\mathcal{N},\lambda} = n\sigma_\varepsilon^2\Phi_4(\boldsymbol{X}; \boldsymbol{\Sigma}^{-1}, \lambda)\,.$$

Thus, under the assumptions, we can apply Theorem 12 to obtain that with probability at least $1-n^{-D}$

$$\left|n\sigma_\varepsilon^2\Phi_4(\boldsymbol{X}; \boldsymbol{\Sigma}^{-1}, \lambda) - n\sigma_\varepsilon^2\Psi_2(\lambda_*; \boldsymbol{\Sigma}^{-1})\right| \le C_{x,D,K}\frac{\rho_\lambda(n)^6\log^{3/2}(n)}{\sqrt{n}}n\sigma_\varepsilon^2\Psi_2(\lambda_*; \boldsymbol{\Sigma}^{-1})\,.$$

Recall that $\Psi_2(\lambda_*; \boldsymbol{A}) := \frac{1}{n}\frac{\mathrm{Tr}(\boldsymbol{A}\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})}{n-\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_*\boldsymbol{I})^{-2})}$, then we have

$$\left|\mathcal{V}^{\mathrm{LS}}_{\mathcal{N},\lambda} - \mathsf{V}^{\mathrm{LS}}_{\mathsf{N},\lambda}\right| \le C_{x,D,K}\frac{\rho_\lambda(n)^6\log^{3/2}(n)}{\sqrt{n}}\mathsf{V}^{\mathrm{LS}}_{\mathsf{N},\lambda}\,,$$

with probability at least $1-n^{-D}$. ■

D.3. Characterization of learning curves

By deriving deterministic equivalents for the norm in linear regression, we can now analyze learning curves through the lens of norm-based capacity. In certain cases, these learning curves can even be expressed in closed form.

In this section, we first examine the general characteristics of learning curves from a norm-based capacity perspective in **??** D.3.1. We then provide a precise characterization of these curves in **??** D.3.2.

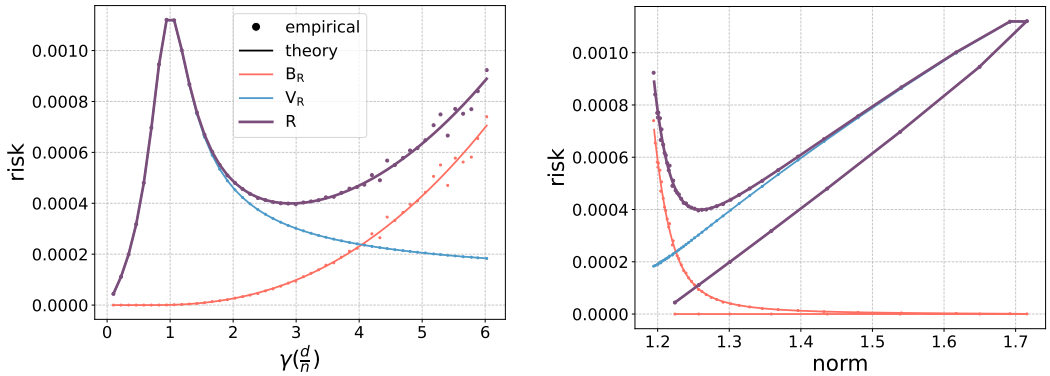
D.3.1. THE SHAPE DESCRIPTION OF LEARNING CURVES

We plot the bias and variance components of the test risk over $\gamma := \frac{d}{n}$ and norm, see Fig. 2(*a*) and Fig. 2(*b*), respectively. Note that, our theory (shown in curve) can precisely predict experimental results (shown by points).

Fig. 2(*a*) reveals a clear bias-variance tradeoff in the over-parameterized regime (where $\gamma > 1$, as shown in the right portion of Fig. 2(*a*)). Specifically, we observe that: *i)* The bias exhibits a strictly increasing relationship with the parameter γ. *ii)* The variance demonstrates a corresponding strictly decreasing trend.

However, in the under-parameterized regime ($\gamma < 1$), both bias and variance increase monotonically with γ, therefore the bias-variance tradeoff does not exist. In particular, for the min-ℓ_2-norm interpolator, since the bias equals 0, the risk is entirely composed of variance.

Because the self-consistent equation differs between the under- and over-parameterized regimes, the learning curve plotted against the norm (see Fig. 2(*b*)) is not single-valued—this is due to the phase transition between regimes. Specifically, a single norm value can correspond to two distinct error levels, depending on whether the model is under- or over-parameterized. However, when examined separately, each regime displays a one-to-one relationship between test risk and norm.



(*a*) Test risk vs. γ ($\frac{d}{n}$)

(*b*) Test risk vs. Norm

Figure 2: The relationship between the test risk R, norm N, their bias and variance (B_R, V_R, B_N, V_N), and the ratio $\gamma := \frac{d}{n}$ for linear regression model. Training data $\{(\boldsymbol{x}_i, y_i)\}_{i\in[n]}$, $d = 1000$, sampled from a linear model $y_i = \boldsymbol{x}_i^\top \boldsymbol{\beta}_* + \varepsilon_i$, $\sigma^2 = 0.0004$, $\boldsymbol{x}_i \sim \mathcal{N}(0, \boldsymbol{\Sigma})$, with $\sigma_k(\boldsymbol{\Sigma}) = k^{-1}$, $\boldsymbol{\beta}_{*,k} = k^{-3/2}$. The ridge $\lambda = 0.005$. Note that in the under-parameterized regime ($d < n$), the bias of the test risk is zero.

D.3.2. MATHEMATICAL FORMULATION OF LEARNING CURVES

In this section, we give the mathematical formulation of learning curves in several settings of interest. First we give some concrete examples on the relationship between R and N in terms of isotropic features.

Proposition 25 (Isotropic features for ridge regression, see Fig. 3) *Consider covariance matrix* $\boldsymbol{\Sigma} = \boldsymbol{I}_d$*, the deterministic equivalents* R_λ^{LS} *and* N_λ^{LS} *satisfy*

$$\left(\|\boldsymbol{\beta}_*\|_2^2 - \mathsf{R}_\lambda^{LS} - \mathsf{N}_\lambda^{LS}\right)\left(\|\boldsymbol{\beta}_*\|_2^2 + \mathsf{R}_\lambda^{LS} - \mathsf{N}_\lambda^{LS}\right)^2 d + 2\|\boldsymbol{\beta}_*\|_2^2\left(\left(\|\boldsymbol{\beta}_*\|_2^2 + \mathsf{R}_\lambda^{LS} - \mathsf{N}_\lambda^{LS}\right)^2 - 4\|\boldsymbol{\beta}_*\|_2^2\mathsf{R}_\lambda^{LS}\right)\lambda = 2\left(\left(\mathsf{R}_\lambda^{LS} - \mathsf{N}_\lambda^{LS}\right)^2 - \|\boldsymbol{\beta}_*\|_2^4\right) d\sigma^2 .$$

Remark: R_λ^{LS} and N_λ^{LS} formulates a third-order polynomial. When $\lambda \to \infty$, it degenerates to $\mathsf{R}_\lambda^{LS} = (\|\boldsymbol{\beta}_*\|_2 - \sqrt{\mathsf{N}_\lambda^{LS}})^2$ when $\mathsf{N}_\lambda^{LS} \leq \|\boldsymbol{\beta}_*\|_2^2$. Hence R_λ^{LS} is monotonically decreasing with respect to N_λ^{LS}, empirically verified by Fig. 3. Besides, if we take $\lambda = \frac{d\sigma^2}{\|\boldsymbol{\beta}_*\|_2^2}$, which is the **o**ptimal regularization parameter discussed in [35, 51], the relationship in Theorem 25 will become $\mathsf{R}_\lambda^{LS} = \|\boldsymbol{\beta}_*\|_2^2 - \mathsf{N}_\lambda^{LS}$, which corresponds to a straight line. This is empirically shown in Fig. 3 with $\lambda = 50$. In addition to isotropic features, we further examine the relationship under the power-law assumption for the data.

Apart from sufficiently large λ and optimal λ mentioned before, below we consider min-ℓ_2-norm estimator. Note that when $\lambda \to 0$, the ridge regression estimator $\hat{\boldsymbol{\beta}}$ converges to the min-ℓ_2-norm estimator $\hat{\boldsymbol{\beta}}_{\min}$. However, the behavior of λ_* differs between the under-parameterized and over-parameterized regimes as $\lambda \to 0$. Thus, the min-ℓ_2-norm estimator requires **s**eparate analysis of the two regimes.

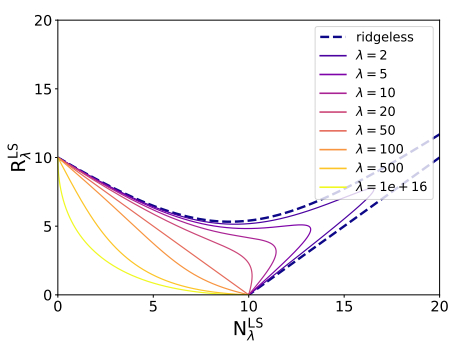


Figure 3: Relationship between R_λ^{LS} and N_λ^{LS} under the linear model $y_i = \boldsymbol{x}_i^\top \boldsymbol{\beta}_* + \varepsilon_i$, with $d = 500$, $\boldsymbol{\Sigma} = \boldsymbol{I}_d$, $\|\boldsymbol{\beta}_*\|_2^2 = 10$, and $\sigma^2 = 1$. The dashed line corresponds to the ridgeless regression curve.

Proof [Proof of Theorem 25] According to the formulation of $\mathsf{B}_{\mathsf{N},\lambda}^{LS}$ and $\mathsf{V}_{\mathsf{N},\lambda}^{LS}$ in Eq. (54), for $\boldsymbol{\Sigma} = \boldsymbol{I}_d$, we have

$$\mathsf{B}_{\mathsf{N},\lambda}^{LS} = \frac{1}{(1+\lambda_*)^2}\|\boldsymbol{\beta}_*\|_2^2 + \frac{d}{n(1+\lambda_*)^2} \cdot \frac{\lambda_*^2 \frac{1}{(1+\lambda_*)^2}\|\boldsymbol{\beta}_*\|_2^2}{1 - \frac{d}{n(1+\lambda_*)^2}}, \quad \mathsf{V}_{\mathsf{N},\lambda}^{LS} = \frac{\sigma^2 \frac{d}{(1+\lambda_*)^2}}{n - \frac{d}{(1+\lambda_*)^2}},$$

$$\mathsf{N}_\lambda^{LS} = \frac{d}{(1+\lambda_*)^2}\|\boldsymbol{\beta}_*\|_2^2 + \frac{d}{n(1+\lambda_*)^2} \cdot \frac{\lambda_*^2 \frac{d}{(1+\lambda_*)^2}\|\boldsymbol{\beta}_*\|_2^2}{1 - \frac{d}{n(1+\lambda_*)^2}} + \frac{\sigma^2 \frac{d}{(1+\lambda_*)^2}}{n - \frac{d}{(1+\lambda_*)^2}},$$

where λ_* admits a closed-form solution

$$\lambda_* = \frac{d + \lambda - n + \sqrt{4\lambda n + (n - d - \lambda)^2}}{2n}\,.$$

Recall the formulation $\mathsf{B}^{LS}_{\mathsf{R},\lambda}$ and $\mathsf{V}^{LS}_{\mathsf{R},\lambda}$ (for test risk) in Eq. (15), for $\boldsymbol{\Sigma} = \boldsymbol{I}_d$, we have

$$\mathsf{B}^{LS}_{\mathsf{R},\lambda} = \frac{\lambda_*^2 \frac{1}{(1+\lambda_*)^2}\|\boldsymbol{\beta}_*\|_2^2}{1 - \frac{d}{n(1+\lambda_*)^2}}\,, \quad \mathsf{V}^{LS}_{\mathsf{R},\lambda} = \frac{\sigma^2 \frac{d}{(1+\lambda_*)^2}}{n - \frac{d}{(1+\lambda_*)^2}}\,, \quad \mathsf{R}^{LS}_{\lambda} = \frac{\lambda_*^2 \frac{d}{(1+\lambda_*)^2}\|\boldsymbol{\beta}_*\|_2^2}{1 - \frac{d}{n(1+\lambda_*)^2}} + \frac{\sigma^2 \frac{d}{(1+\lambda_*)^2}}{n - \frac{d}{(1+\lambda_*)^2}}\,.$$

Accordingly, to establish the relationship between $\mathsf{R}^{LS}_{\lambda}$ and $\mathsf{N}^{LS}_{\lambda}$, we combine their formulation and eliminate n to obtain[2]

$$\begin{aligned} 2((\mathsf{R}^{LS}_{\lambda} - \mathsf{N}^{LS}_{\lambda})^2 - \|\boldsymbol{\beta}_*\|_2^4)d\sigma^2 &= (\|\boldsymbol{\beta}_*\|_2^2 - \mathsf{R}^{LS}_{\lambda} - \mathsf{N}^{LS}_{\lambda})(\|\boldsymbol{\beta}_*\|_2^2 + \mathsf{R}^{LS}_{\lambda} - \mathsf{N}^{LS}_{\lambda})^2 d \\ &\quad + 2\|\boldsymbol{\beta}_*\|_2^2((\|\boldsymbol{\beta}_*\|_2^2 + \mathsf{R}^{LS}_{\lambda} - \mathsf{N}^{LS}_{\lambda})^2 - 4\|\boldsymbol{\beta}_*\|_2^2 \mathsf{R}^{LS}_{\lambda})\lambda\,. \end{aligned}$$

■

Corollary 26 (Isotropic features for min-ℓ_2-norm interpolator, see Fig. 3) *Consider covariance matrix $\boldsymbol{\Sigma} = \boldsymbol{I}_d$, the relationship between R^{LS}_0 and N^{LS}_0 from under-parameterized to over-parameterized regimes admit*

$$\mathsf{R}^{LS}_0 = \begin{cases} \mathsf{N}^{LS}_0 - \|\boldsymbol{\beta}_*\|_2^2\,, & \textit{if } d < n \textit{ (under-parameterized)}; \\ \sqrt{\left[\mathsf{N}^{LS}_0 - (\|\boldsymbol{\beta}_*\|_2^2 - \sigma^2)\right]^2 + 4\|\boldsymbol{\beta}_*\|_2^2\sigma^2} - \sigma^2\,, & \textit{o/w}\,. \end{cases}$$

For the variance part of R^{LS}_0 and N^{LS}_0, we have $\mathsf{V}^{LS}_{\mathsf{R},0} = \mathsf{V}^{LS}_{\mathsf{N},0}$; For the respective bias part, we have $\mathsf{B}^{LS}_{\mathsf{R},0} + \mathsf{B}^{LS}_{\mathsf{N},0} = \|\boldsymbol{\beta}_*\|_2^2$.

Remark: In the under-parameterized regime, the test error R^{LS}_0 is a linear function of the norm N^{LS}_0. In the over-parameterized regime, R^{LS}_0 and N^{LS}_0 formulates a rectangular hyperbola: R^{LS}_0 decreases with N^{LS}_0 if $\mathsf{N}^{LS}_0 < \|\boldsymbol{\beta}_*\|_2^2 - \sigma^2$ while R^{LS}_0 increases with N^{LS}_0 if $\mathsf{N}^{LS}_0 > \|\boldsymbol{\beta}_*\|_2^2 - \sigma^2$.

Proof [Proof of Theorem 26] According to Theorem 9 and Theorem 21, for minimum ℓ_2-norm estimator and $\boldsymbol{\Sigma} = \boldsymbol{I}_d$, for the under-parameterized regime ($d < n$), we have

$$\mathsf{B}^{LS}_{\mathsf{R},0} = 0\,, \quad \mathsf{V}^{LS}_{\mathsf{R},0} = \frac{\sigma^2 d}{n-d}\,; \qquad \mathsf{B}^{LS}_{\mathsf{N},0} = \|\boldsymbol{\beta}_*\|_2^2\,, \quad \mathsf{V}^{LS}_{\mathsf{N},0} = \frac{\sigma^2 d}{n-d}\,.$$

From these expressions, we can conclude that

$$\mathsf{R}^{LS}_0 = \mathsf{B}^{LS}_{\mathsf{R},0} + \mathsf{V}^{LS}_{\mathsf{R},0} = \frac{\sigma^2 d}{n-d}\,; \qquad \mathsf{N}^{LS}_0 = \mathsf{B}^{LS}_{\mathsf{N},0} + \mathsf{V}^{LS}_{\mathsf{N},0} = \|\boldsymbol{\beta}_*\|_2^2 + \frac{\sigma^2 d}{n-d}\,.$$

Finally, in the under-parameterized regime, it follows that

$$\mathsf{R}^{LS}_0 = \mathsf{N}^{LS}_0 - \|\boldsymbol{\beta}_*\|_2^2\,.$$

2. Due to the complexity of the calculations, we use Mathematica Wolfram to eliminate n. The same approach is applied later whenever n or p elimination is required.

In the over-parameterized regime ($d > n$), the effective regularization λ_* will have an explicit formulation as $\lambda_* = \frac{d-n}{n}$, thus for the bias and variance of the test error, we have

$$\mathsf{B}_{\mathsf{R},0}^{\mathrm{L}S} = \frac{\lambda_n^2 \langle \boldsymbol{\beta}_*, \boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2}\boldsymbol{\beta}_*\rangle}{1-n^{-1}\mathrm{T}r(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n)^{-2})} = \frac{\lambda_n^2 \frac{1}{(1+\lambda_n)^2}\|\boldsymbol{\beta}_*\|_2^2}{1-\frac{1}{n}\frac{d}{(1+\lambda_n)^2}} = \|\boldsymbol{\beta}_*\|_2^2 \frac{d-n}{d}\,,$$

$$\mathsf{V}_{\mathsf{R},0}^{\mathrm{L}S} = \frac{\sigma^2 \mathrm{T}r(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2})}{n-\mathrm{T}r(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2})} = \frac{\sigma^2 \frac{d}{(1+\lambda_n)^2}}{n-\frac{d}{(1+\lambda_n)^2}} = \sigma^2 \frac{n}{d-n}\,,$$

and combining the bias and variance, we have

$$\mathsf{R}_0^{\mathrm{L}S} = \mathsf{B}_{\mathsf{R},0}^{\mathrm{L}S} + \mathsf{V}_{\mathsf{R},0}^{\mathrm{L}S} = \|\boldsymbol{\beta}_*\|_2^2 \frac{d-n}{d} + \sigma^2 \frac{n}{d-n}\,. \tag{55}$$

For the bias and variance of the norm, we have

$$\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S} = \langle \boldsymbol{\beta}_*, \boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-1}\boldsymbol{\beta}_*\rangle = \frac{1}{1+\lambda_n}\|\boldsymbol{\beta}_*\|_2^2 = \|\boldsymbol{\beta}_*\|_2^2 \frac{n}{d}\,,$$

$$\mathsf{V}_{\mathsf{N},0}^{\mathrm{L}S} = \frac{\sigma \mathrm{T}r(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2})}{n-\mathrm{T}r(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2})} = \frac{\sigma^2 \frac{d}{(1+\lambda_n)^2}}{n-\frac{d}{(1+\lambda_n)^2}} = \sigma^2 \frac{n}{d-n}\,,$$

and combining the bias and variance, we have

$$\mathsf{N}_0^{\mathrm{L}S} = \mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S} + \mathsf{V}_{\mathsf{N},0}^{\mathrm{L}S} = \|\boldsymbol{\beta}_*\|_2^2 \frac{n}{d} + \sigma^2 \frac{n}{d-n}\,. \tag{56}$$

Finally, combining Eq. (55) and Eq. (56), we eliminate n and thus obtain

$$\mathsf{R}_0^{\mathrm{L}S} = \sqrt{(\mathsf{N}_0^{\mathrm{L}S})^2 - 2(\|\boldsymbol{\beta}_*\|_2^2 - \sigma^2)\mathsf{N}_0^{\mathrm{L}S} + (\|\boldsymbol{\beta}_*\|_2^2 + \sigma^2)^2} - \sigma^2\,.$$

By taking the derivative of $\mathsf{R}_0^{\mathrm{L}S}$ with respect to $\mathsf{N}_0^{\mathrm{L}S}$, we get

$$\frac{\partial \mathsf{R}_0^{\mathrm{L}S}}{\partial \mathsf{N}_0^{\mathrm{L}S}} = \frac{\mathsf{N}_0^{\mathrm{L}S} - (\|\boldsymbol{\beta}_*\|_2^2 - \sigma^2)}{\sqrt{(\mathsf{N}_0^{\mathrm{L}S})^2 - 2(\|\boldsymbol{\beta}_*\|_2^2 - \sigma^2)\mathsf{N}_0^{\mathrm{L}S} + (\|\boldsymbol{\beta}_*\|_2^2 + \sigma^2)^2}}\,.$$

From the derivative function, we observe that $\mathsf{R}_0^{\mathrm{L}S}$ decreases monotonically with $\mathsf{N}_0^{\mathrm{L}S}$ when $\mathsf{N}_0^{\mathrm{L}S} < \|\boldsymbol{\beta}_*\|_2^2 - \sigma^2$, and increases monotonically with $\mathsf{N}_0^{\mathrm{L}S}$ when $\mathsf{N}_0^{\mathrm{L}S} > \|\boldsymbol{\beta}_*\|_2^2 - \sigma^2$. ■

Relationship for min-ℓ_2-norm interpolator in the under-parameterized regime. Next, we consider the min-norm estimator, and we find that for the min-norm estimator, in the under-parameterized regime, the relationship between risk and norm is linear, and this linearity is independent of the data distribution.

Proposition 27 (Relationship for min-ℓ_2-norm interpolator in the under-parameterized regime) *The deterministic equivalents R_0^{LS} and N_0^{LS}, in under-parameterized regimes ($d < n$) admit the linear relationship*

$$\mathsf{R}_0^{LS} = d\left(\mathsf{N}_0^{LS} - \|\boldsymbol{\beta}_*\|_2^2\right)/\mathrm{T}r(\boldsymbol{\Sigma}^{-1})\,.$$

Proof [Proof of Theorem 27] According to Theorem 9 and Theorem 21, for minimum ℓ_2-norm estimator, in the under-parameterized regime ($d < n$), we have

$$\mathsf{B}_{\mathsf{R},0}^{\mathrm{L}S} = 0\,, \quad \mathsf{V}_{\mathsf{R},0}^{\mathrm{L}S} = \frac{\sigma^2 d}{n-d}\,; \qquad \mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S} = \|\boldsymbol{\beta}_*\|_2^2\,, \quad \mathsf{V}_{\mathsf{N},0}^{\mathrm{L}S} = \frac{\sigma^2 \mathrm{Tr}(\boldsymbol{\Sigma}^{-1})}{n-d}\,.$$

From these expressions, we can conclude that

$$\mathsf{R}_0^{\mathrm{L}S} = \mathsf{B}_{\mathsf{R},0}^{\mathrm{L}S} + \mathsf{V}_{\mathsf{R},0}^{\mathrm{L}S} = \frac{\sigma^2 d}{n-d}\,; \qquad \mathsf{N}_0^{\mathrm{L}S} = \mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S} + \mathsf{V}_{\mathsf{N},0}^{\mathrm{L}S} = \|\boldsymbol{\beta}_*\|_2^2 + \frac{\sigma^2 \mathrm{Tr}(\boldsymbol{\Sigma}^{-1})}{n-d}\,.$$

Finally, combing the above equation and eliminate n, in the under-parameterized regime, it follows that

$$\mathsf{R}_0^{\mathrm{L}S} = \frac{d}{\mathrm{Tr}(\boldsymbol{\Sigma}^{-1})}\left(\mathsf{N}_0^{\mathrm{L}S} - \|\boldsymbol{\beta}_*\|_2^2\right)\,. \tag{57}$$

■

The relationship in the over-parameterized regime is more complicated. We present it in the special case of isotropic features in Theorem 26 of Theorem 25, and we also give an approximation in Theorem 29 under the power-law assumption.

Assumption 28 (Power-law assumption) *For the covariance matrix $\boldsymbol{\Sigma}$ and the target function $\boldsymbol{\beta}_*$, we assume that $\sigma_k(\boldsymbol{\Sigma}) = k^{-\alpha}, \alpha > 0$ and $\boldsymbol{\beta}_{*,k} = k^{-\alpha\beta/2}, \beta \in \mathbb{R}$.*

This assumption is close to classical source condition and capacity condition [8] and is similarly used in [40, Assumption 1].

Relationship under power-law assumption. Instead of assuming $\boldsymbol{\Sigma} = \boldsymbol{I}_d$, we next consider power-law features in Theorem 28 and characterize the relationship.

Proposition 29 (Power-law features for min-ℓ_2 norm estimator) *Under Theorem 28, in the over-parameterized regime ($d > n$), we consider some special cases for analytic formulation: if $\alpha = 1$ and $\beta = 0$, when $n \to d$, we have*[3]

$$\mathsf{V}_{\mathsf{R},0}^{LS} \approx \frac{2(\mathsf{V}_{\mathsf{N},0}^{LS})^2}{d\mathsf{V}_{\mathsf{N},0}^{LS} - d^2\sigma^2}\,, \quad \mathsf{B}_{\mathsf{R},0}^{LS} \approx \frac{2\mathsf{B}_{\mathsf{N},0}^{LS}(d - \mathsf{B}_{\mathsf{N},0}^{LS})}{d^2}\,.$$

Remark: The relationship between $\mathsf{R}_0^{\mathrm{L}S}$ and $\mathsf{N}_0^{\mathrm{L}S}$ is still linear in the under-parameterized regime, but is quite complex in the over-parameterized regime.

Proof [Proof of Theorem 29] In the over-parameterized regime ($d > n$), according to Theorem 9 and Theorem 21, under Theorem 28, we have

$$\begin{aligned}
\mathsf{B}_{\mathsf{R},0}^{\mathrm{L}S} &= \frac{\lambda_n^2 \langle \boldsymbol{\beta}_*, \boldsymbol{\Sigma}(\boldsymbol{\Sigma} + \lambda_n \boldsymbol{I})^{-2}\boldsymbol{\beta}_*\rangle}{1 - n^{-1}\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma} + \lambda_n \boldsymbol{I})^{-2})} = \frac{\lambda_n^2 \mathrm{Tr}(\boldsymbol{\Sigma}^{1+\beta}(\boldsymbol{\Sigma} + \lambda_n \boldsymbol{I})^{-2})}{1 - n^{-1}\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma} + \lambda_n \boldsymbol{I})^{-2})}\,,\\
\mathsf{V}_{\mathsf{R},0}^{\mathrm{L}S} &= \frac{\sigma^2 \mathrm{Tr}\left(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma} + \lambda_n \boldsymbol{I})^{-2}\right)}{n - \mathrm{Tr}\left(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma} + \lambda_n \boldsymbol{I})^{-2}\right)}\,,\\
\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S} &= \langle \boldsymbol{\beta}_*, \boldsymbol{\Sigma}(\boldsymbol{\Sigma} + \lambda_n \boldsymbol{I})^{-1}\boldsymbol{\beta}_*\rangle = \mathrm{Tr}(\boldsymbol{\Sigma}^{1+\beta}(\boldsymbol{\Sigma} + \lambda_n \boldsymbol{I})^{-1})\,,\\
\mathsf{V}_{\mathsf{N},0}^{\mathrm{L}S} &= \frac{\sigma^2 \mathrm{Tr}\left(\boldsymbol{\Sigma}(\boldsymbol{\Sigma} + \lambda_n \boldsymbol{I})^{-2}\right)}{n - \mathrm{Tr}\left(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma} + \lambda_n \boldsymbol{I})^{-2}\right)}\,.
\end{aligned}$$

3. The symbol $\approx$ here represents two types of approximations: i) approximation for self-consistent equations; ii) Taylor approximation of logarithmic function around zero (related to $n \to d$).

To compute these quantities, here we introduce the following continuum approximations to eigensums.

$$\int_1^{d+1} \frac{k^{-\alpha}}{k^{-\alpha}+\lambda_n}\,\mathrm{d}k \le \mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n)^{-1}) = \sum_{i=1}^{d} \frac{\sigma_i}{\sigma_i+\lambda_n} \le \int_0^{d} \frac{k^{-\alpha}}{k^{-\alpha}+\lambda_n}\,\mathrm{d}k\,, \tag{58}$$

due to the fact that the integrand is non-increasing function of k. Similarly, we also have

$$\int_1^{d+1} \frac{k^{-2\alpha}}{(k^{-\alpha}+\lambda_n)^2}\,\mathrm{d}k \le \mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n)^{-2}) = \sum_{i=1}^{d} \frac{\sigma_i^2}{(\sigma_i+\lambda_n)^2} \le \int_0^{d} \frac{k^{-2\alpha}}{(k^{-\alpha}+\lambda_n)^2}\,\mathrm{d}k\,. \tag{59}$$

We consider some special cases that are useful for discussion. When $\alpha = 1$, we have

$$\frac{\log(1+d\lambda_n+\lambda_n)-\log(1+\lambda_n)}{\lambda_n} \le \mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n)^{-1}) \le \frac{\log(1+d\lambda_n)}{\lambda_n}\,, \tag{60}$$

$$\frac{d+1}{\lambda_n d+\lambda_n+1} - \frac{1}{\lambda_n+1} \le \mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n)^{-2}) = \sum_{i=1}^{d} \frac{\sigma_i^2}{(\sigma_i+\lambda_n)^2} \le \frac{d}{1+d\lambda_n}\,. \tag{61}$$

Recall that λ_n is defined by $\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n\boldsymbol{I})^{-1}) = n$. Using Eq. (58), we have

$$\frac{\log(1+d\lambda_n)}{\lambda_n} \approx n.$$

Observe that as $n \to d$, $\lambda_n \to 0$, allowing us to apply a Taylor expansion:

$$\frac{\log(1+d\lambda_n)}{\lambda_n} \approx \frac{d\lambda_n - \frac{1}{2}(d\lambda_n)^2}{\lambda_n} = d - \frac{1}{2}d^2\lambda_n.$$

Based on this approximation, λ_n can be expressed as

$$\lambda_n \approx \frac{2(d-n)}{d^2}.$$

In the following discussion, we consider the case $n \to d$. Thus, we have the approximation

$$\mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n)^{-1}) \approx n\,, \quad \mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n)^{-2}) \approx \frac{d}{1+d\lambda_n}\,.$$

Then we have

$$\mathsf{V}_{\mathsf{R},0}^{\mathrm{L}S} = \frac{\sigma^2\mathrm{Tr}\left(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n\boldsymbol{I})^{-2}\right)}{n-\mathrm{Tr}\left(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n\boldsymbol{I})^{-2}\right)} \approx \frac{\sigma^2\frac{d}{1+d\lambda_n}}{n-\frac{d}{1+d\lambda_n}} = \frac{\sigma^2 d}{n+d(n\lambda_n-1)}\,,$$

$$\mathsf{V}_{\mathsf{N},0}^{\mathrm{L}S} = \frac{\sigma^2\mathrm{Tr}\left(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n\boldsymbol{I})^{-2}\right)}{n-\mathrm{Tr}\left(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n\boldsymbol{I})^{-2}\right)} \approx \frac{\sigma^2\frac{1}{\lambda_n}(d-\frac{1}{2}d^2\lambda_n-\frac{d}{1+d\lambda_n})}{n-\frac{d}{1+d\lambda_n}} = \frac{\sigma^2 d^2(d\lambda_n-1)}{2(n+d(n\lambda_n-1))}\,.$$

Use these two formulation to eliminate n, we obtain

$$\mathsf{V}_{\mathsf{R},0}^{\mathrm{L}S} \approx \frac{2(\mathsf{V}_{\mathsf{N},0}^{\mathrm{L}S})^2}{d\mathsf{V}_{\mathsf{N},0}^{\mathrm{L}S} - d^2\sigma^2}\,.$$

Next we discuss the situation under different β.

For $\beta = 0$, we have

$$\mathsf{B}_{\mathsf{R},0}^{\mathrm{L}S} = \frac{\lambda_n^2 \mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2})}{1 - n^{-1}\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2})} \approx \frac{\lambda_n(d - \frac{1}{2}d^2\lambda_n - \frac{d}{1+d\lambda_n})}{1 - \frac{d}{n(1+d\lambda_n)}} = n\lambda_n \,,$$

$$\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S} = \mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-1}) \approx d - \frac{1}{2}d^2\lambda_n \,,$$

Use these two formulation to eliminate n, we obtain

$$\mathsf{B}_{\mathsf{R},0}^{\mathrm{L}S} \approx \frac{2\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S}(d - \mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S})}{d^2} \,.$$

For $\beta = 1$, we have

$$\mathsf{B}_{\mathsf{R},0}^{\mathrm{L}S} = \frac{\lambda_n^2 \mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2})}{1 - n^{-1}\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2})} \approx \frac{\lambda_n^2 \frac{d}{1+d\lambda_n}}{1 - \frac{d}{n(1+d\lambda_n)}} = \frac{nd\lambda_n^2}{n(1+d\lambda_n) - d} \,,$$

$$\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S} = \mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-1}) = \mathrm{Tr}(\boldsymbol{\Sigma}) - \lambda_n \mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-1}) \approx \mathrm{Tr}(\boldsymbol{\Sigma}) - n\lambda_n \,.$$

Use these two formulation to eliminate n, we obtain

$$\mathsf{B}_{\mathsf{R},0}^{\mathrm{L}S} \approx \frac{2\sqrt{(\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S})^2 - 2\mathrm{Tr}(\boldsymbol{\Sigma})\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S} + \mathrm{Tr}(\boldsymbol{\Sigma})^2}}{\sqrt{d^2 + 2d^2\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S} - 2d^2\mathrm{Tr}(\boldsymbol{\Sigma})}} = \frac{2(\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S} - \mathrm{Tr}(\boldsymbol{\Sigma}))}{d\sqrt{1 + 2\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S} - 2\mathrm{Tr}(\boldsymbol{\Sigma})}} \,.$$

For $\beta = -1$, we need to use another two continuum approximations to eigensums

$$\mathrm{Tr}((\boldsymbol{\Sigma}+\lambda_n)^{-1}) = \sum_{i=1}^{d} \frac{1}{\sigma_i + \lambda_n} \approx \int_0^d \frac{1}{k^{-\alpha} + \lambda_n}\,\mathrm{d}k = \frac{d\lambda_n - \log(1+d\lambda_n)}{\lambda_n^2} \,,$$

$$\mathrm{Tr}((\boldsymbol{\Sigma}+\lambda_n)^{-2}) = \sum_{i=1}^{d} \frac{1}{(\sigma_i + \lambda_n)^2} \approx \int_0^d \frac{1}{(k^{-\alpha} + \lambda_n)^2}\,\mathrm{d}k = \frac{\frac{d\lambda_n(2+d\lambda_n)}{1+d\lambda_n} - 2\log(1+d\lambda_n)}{\lambda_n^3} \,.$$

Once again, we apply the Taylor expansion, but this time expanding to the third order

$$\log(1+d\lambda_n) \approx d\lambda_n - \frac{1}{2}(d\lambda_n)^2 + \frac{1}{3}(d\lambda_n)^3 \,.$$

Then we have

$$\mathrm{Tr}((\boldsymbol{\Sigma}+\lambda_n)^{-1}) \approx \frac{d\lambda_n - \log(1+d\lambda_n)}{\lambda_n^2} \approx \frac{1}{2}d^2 - \frac{1}{3}d^3\lambda_n \,,$$

$$\mathrm{Tr}((\boldsymbol{\Sigma}+\lambda_n)^{-2}) \approx \frac{\frac{d\lambda_n(2+d\lambda_n)}{1+d\lambda_n} - 2\log(1+d\lambda_n)}{\lambda_n^3} = \frac{\frac{1}{3}d^3 - \frac{2}{3}d^4\lambda_n}{1+d\lambda_n} \,.$$

Using the approximation sated above, we have

$$\mathsf{B}_{\mathsf{R},0}^{\mathrm{L}S} = \frac{\lambda_n^2 \mathrm{Tr}((\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2})}{1 - n^{-1}\mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-2})} \approx \frac{\lambda_n^2\left((\frac{1}{3}d^3 - \frac{2}{3}d^4\lambda_n)/(1+d\lambda_n)\right)}{1 - \frac{d}{n(1+d\lambda_n)}} \,,$$

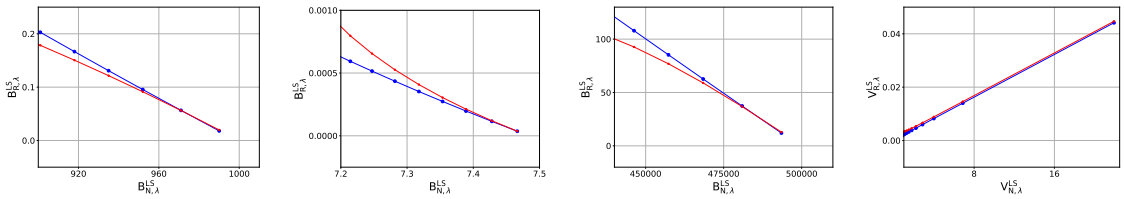
$$\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S} = \mathrm{Tr}((\boldsymbol{\Sigma}+\lambda_n \boldsymbol{I})^{-1}) = \frac{1}{2}d^2 - \frac{1}{3}d^3\lambda_n \,.$$

Use these two formulation to eliminate n, we obtain

$$\mathsf{B}_{\mathsf{R},0}^{\mathrm{L}S} \approx \frac{216(\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S})^4 - 324d^2(\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S})^3 + 126d^4(\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S})^2 + d^6\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S} - 5d^8}{2d^5(6\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S} - d^2)}.$$

■

Here we present some experimental results to check the relationship between $\mathsf{B}_{\mathsf{R},0}^{\mathrm{L}S}$ and $\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S}$, as well as $\mathsf{V}_{\mathsf{R},0}^{\mathrm{L}S}$ and $\mathsf{V}_{\mathsf{N},0}^{\mathrm{L}S}$, see Fig. 4. We can see that our approximate relationship on variance (see the red line in Fig. 4(*d*)) provides the precise estimation. For the bias (see the left three figures of Fig. 4), our approximate relationship is accurate if $\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S}$ is large.



(*a*) $\beta = 0$ (*b*) $\beta = 1$ (*c*) $\beta = -1$ (*d*) $\mathsf{V}_{\mathsf{R},0}^{\mathrm{L}S}$ vs. $\mathsf{V}_{\mathsf{N},0}^{\mathrm{L}S}$

Figure 4: The left three figures (a) (b) (c) show the relationship between $\mathsf{B}_{\mathsf{R},0}^{\mathrm{L}S}$ and $\mathsf{B}_{\mathsf{N},0}^{\mathrm{L}S}$ when $\alpha = 1$ and β takes on different values. The figure (d) shows the relationship between $\mathsf{V}_{\mathsf{R},0}^{\mathrm{L}S}$ and $\mathsf{V}_{\mathsf{N},0}^{\mathrm{L}S}$ when $\alpha = 1$. The blue line is the relationship obtained by deterministic equivalent experiments, and the red line is the approximate relationship we give.

Appendix E. Deterministic equivalents under norm-based capacity

Here we present more results and discussion on Theorem 2.

Norm-based capacity over different layers: In RFMs, if we use the norm of the first layer, i.e., $\|\boldsymbol{W}\|_{\mathrm{F}}$ as model capacity, we will obtain a reshaped double descent curve as Fig. 15. This is because, the first layer's parameters are with random Gaussian initialization and then untrained, we directly have $\mathbb{E}[\|\boldsymbol{W}\|_{\mathrm{F}}] = \sqrt{2} \cdot \Gamma(\frac{dp+1}{2})/\Gamma(\frac{dp}{2}) \approx \sqrt{dp - \frac{1}{2}}$, increasing with p. For two-layer neural networks with both trained layers, path norm is empirically verified as the most suitable (data-independent) model capacity for neural networks. We find that the curve aligns more closely with the norm-based capacity in RFMs of the second-layer parameters, rather than that of the first layer, see more discussion in Appendix J.3.

For better illustration, we consider a special case of Theorem 2, the min-norm estimator ($\lambda = 0$), which will be used later, and derive its deterministic equivalence; see the proof in Appendix G.1.

Corollary 30 (Asymptotic deterministic equivalence of $\mathsf{N}_0^{\mathbf{R}FM}$) *Under Theorem 1, for the min-ℓ_2-norm estimator $\hat{\boldsymbol{a}}_{\min}$, in the under-parameterized regime ($p < n$), we have*

$$\mathcal{B}_{\mathcal{N},0}^{RFM} \sim \frac{p\langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda} + \lambda_p \boldsymbol{I})^{-2}\boldsymbol{\theta}_*\rangle}{n - \mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda} + \lambda_p \boldsymbol{I})^{-2})} + \frac{p\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda} + \lambda_p \boldsymbol{I})^{-1}\boldsymbol{\theta}_*\rangle}{n - p}, \quad \mathcal{V}_{\mathcal{N},0}^{RFM} \sim \frac{\sigma^2 p}{\lambda_p(n-p)},$$

where λ_p is from $\mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\lambda_p\boldsymbol{I})^{-1}) \sim p$. In the over-parameterized regime ($p > n$), we have

$$\mathcal{B}_{\mathcal{N},0}^{RFM} \sim \frac{p\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-1}\boldsymbol{\theta}_*\rangle}{p-n}, \quad \mathcal{V}_{\mathcal{N},0}^{RFM} \sim \frac{\sigma^2 p}{\lambda_n(p-n)},$$

where λ_n is defined by $\mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\lambda_n\boldsymbol{I})^{-1}) \sim n$.

Remark: $\mathcal{V}_{\mathcal{N},0}^{\mathrm{R}FM}$ admits the similar formulation in under-/over-parameterized regimes but differs in λ_n and λ_p. An interesting point to note is that, in the over-parameterized regime, λ_n is a constant when n constant. Therefore, $\mathcal{B}_{\mathcal{N},0}^{\mathrm{R}FM}$ and $\mathcal{V}_{\mathcal{N},0}^{\mathrm{R}FM}$ are proportional to each other.

We need to analyze RFMs separately in the under-/over-parameterized regimes when $\lambda \to 0$, leading to different self-consistent equations in these two settings.

- In the under-parameterized regime, ν_1 converges to 0, and ν_2 converges to a value λ_p satisfying $\mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\lambda_p\boldsymbol{I})^{-1}) = p$.
- In the over-parameterized regime, ν_2 converges to a constant λ_n satisfying $\mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\lambda_n\boldsymbol{I})^{-1}) = n$, and ν_1 converges to $\nu_2(1-{}^{n}\!/_{p})$.

These differing asymptotic behaviors of ν_1 and ν_2 between the two regimes enable a more precise characterization of the risk–norm relationship, which will be described in the next section.

Appendix F. Characterization of learning curves

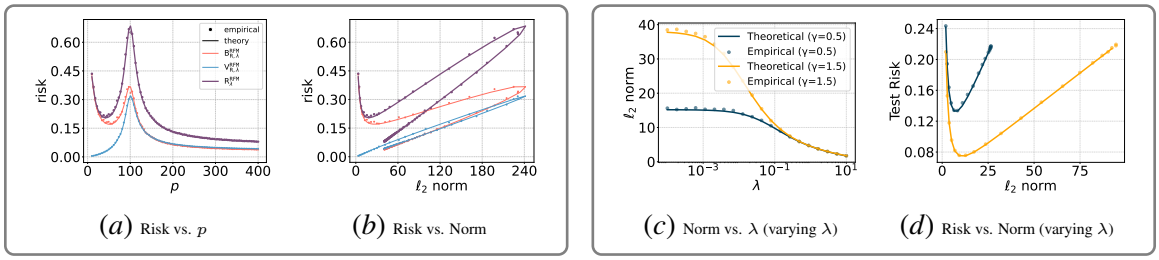
By giving the deterministic equivalents of the norm, we are ready to plot the learning curve under norm-based capacity, see Fig. 1(*b*) for illustration. In some special cases, the mathematical formulation of learning curves can be given. Accordingly, in this section, we firstly discuss the shape of learning curves from the lens of norm-based capacity in Appendix F.1. Then we take the example of min-ℓ_2-norm interpolator, and precisely characterize the learning curve by reshaping scaling laws in Appendix F.2.

F.1. The shape description of learning curves

Here we conduct the bias-variance decomposition, and track how bias and variance behave w.r.t. model size, norm, and the regularization parameter λ, as shown in Fig. 5, which will provide a more detailed description and understanding on learning curves.

Reshape bias-variance trade-offs and double descent: We plot the bias and variance components of the test risk over model size p and norm, see Fig. 5(*a*) and Fig. 5(*b*), respectively. Note that, our theory (shown in curve) can precisely predict experimental results (shown by points). Fig. 5(*a*) aligns closely with [31, Figure 6] on the double descent when increasing the model size p from the under- to over-parameterized regimes. However, even in the classical under-parameterized setting, the conventional bias-variance trade-off no longer holds: the bias follows a U-shaped curve, whereas the variance grows monotonically. This was discussed recently by [44, 50] on "whether we should remove bias-variance trade-offs from ML textbooks".

When examining bias-variance vs. norm (see Fig. 5(*b*)), we observe that: *i)* in the under-parameterized regime, bias exhibits a U-shaped dependence on norm, while variance increases monotonically. This result matches with that for model size in Fig. 5(*a*); *ii)* in the over-parameterized regime, both bias and variance increase monotonically with norm. These findings reshape the traditional understanding of bias-variance trade-offs and double descent.



(a) Risk vs. p (b) Risk vs. Norm (c) Norm vs. λ (varying λ) (d) Risk vs. Norm (varying λ)

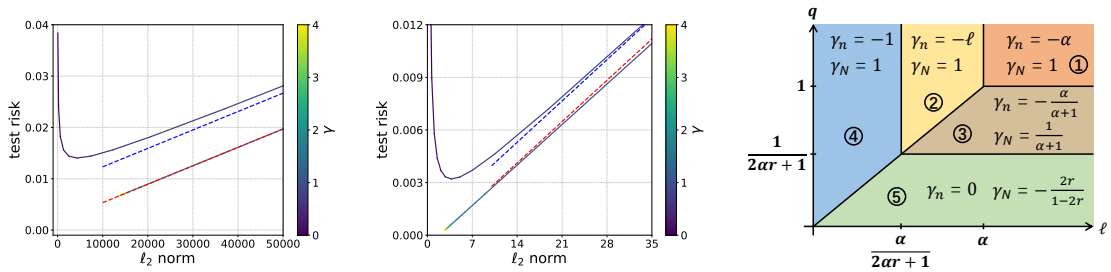
Figure 5: The curves of bias and variance in RFMs are over model size p in Fig. 5(a) and over norm $\mathbb{E}_\varepsilon\|\hat{\boldsymbol{a}}\|_2^2$ in Fig. 5(b), respectively. Fig. 5(c) establishes a one-to-one correspondence between the norm and λ for a fixed p across varying λ values. Fig. 5(d) examines the relationship between risk and norm under the same conditions. Training data $\{(\boldsymbol{x}_i, y_i)\}_{i\in[n]}$, $n = 100$, sampled from the model $y_i = \boldsymbol{g}_i^\top \boldsymbol{\theta}_* + \varepsilon_i$, $\sigma^2 = 0.04$, $\boldsymbol{g}_i \sim \mathcal{N}(0, \boldsymbol{I})$, $\boldsymbol{f}_i \sim \mathcal{N}(0, \boldsymbol{\Lambda})$, with $\xi_k^2(\boldsymbol{\Lambda}) = k^{-3/2}$ and $\boldsymbol{\theta}_{*,k} = k^{-1}$.

Since the self-consistent equation differs from under-parameterized to over-parameterized regimes, the learning curve plotted against the norm (see Fig. 1(b) and Fig. 5(d)) is not **single-valued** because of such phase transition: a single norm value may correspond to two distinct error levels in the under- and over-parameterized regimes. However, when analyzed separately, each regime exhibits a one-to-one relationship between test risk and norm. Notably, our analytical and empirical findings suggest that i) sufficient over-parameterization is always better than under-parameterization in terms of lower test risk, which also coincides with [47]. ii) More importantly, this curve aligns more with classical statistical intuition—a U-shaped curve—rather than the double descent phenomenon. We conclude that ***with suitably chosen model capacity, the learning curve more closely follows a U-shape than a double descent***. We conjecture that this behavior is universal in more complex models and real-world datasets; see Appendices J.2 and J.3 for details.

Control the norm via regularization. Norm-based capacity appears less intuitive used in practice when compared to model size. To control model norm, one can either fix the regularization parameter and vary the model size p or fix p and constrain the weight norm, The latter approach is mathematically equivalent to tuning the regularization parameter λ in random feature ridge regression, as evidenced by the equivalence to the constrained optimization problem: $\min_{\boldsymbol{\beta}} \|\boldsymbol{y} - \boldsymbol{Z}\boldsymbol{a}\|^2 \quad \text{s.t.} \quad \|\boldsymbol{a}\|_2 = B$. This yields a ridge-type solution: $\hat{\boldsymbol{a}} = (\boldsymbol{Z}^\top \boldsymbol{Z} + \lambda \boldsymbol{I})^{-1} \boldsymbol{Z}^\top \boldsymbol{y} \quad \text{subject to} \quad \|\hat{\boldsymbol{a}}\|_2 = B$, where λ is uniquely determined by the norm constraint B (with $\partial\|\hat{\boldsymbol{a}}\|_2^2/\partial\lambda < 0$ guaranteeing a one-to-one mapping). We empirically verified this in the random feature model by fixing the training sample size n and ratio γ, and varying λ to control the estimator norm. As shown in Fig. 5(c) (under-parameterized with $\gamma = 0.5$) and Fig. 5(d) (over-parameterized with $\gamma = 1.5$), the norm decreases monotonically with increasing λ, and in both under- and over-parameterized regimes, the test risk exhibits a U-shaped dependence on norm capacity, consistent with the known L-curve behavior [19]. Further discussion can be found in Appendix I.1.

F.2. Mathematical formulation of learning curves

Firstly, we show that the risk-norm relationship is **linear** in over-parameterized regime, see the proof in Appendix G.3.



(*a*) $\alpha = 2.5, r = 0.2$ (*b*) $\alpha = 1.5, r = 0.8$ (*c*) Scaling law

Figure 6: Fig. 6(*a*) and Fig. 6(*b*): Validation of Theorem 33. The solid line represents the result of the deterministic equivalents, well approximated by the red dashed line of Eq. (63) in the over-parameterized regime, and the blue dashed line of Eq. (63) when $p \to n$ in the under-parameterized regime. **Fig. 6(*c*): The value of exponents γ_n and γ_{N} in different regions (divided by q and ℓ) for $r \in (0, \frac{1}{2})$. Variance dominated region is colored by orange, yellow and brown, bias dominated region is colored by blue and green.**

Proposition 31 (Linear learning curve) *The deterministic equivalents R_0^{RFM} and N_0^{RFM}, in over-parameterized regimes ($p > n$) admit the linear relationship with the constant slope λ_n*

$$\mathsf{R}_0^{RFM} = \lambda_n \mathsf{N}_0^{RFM} + C_{\boldsymbol{\theta}_*, \boldsymbol{\Lambda}, n, \sigma}\,, \tag{62}$$

where λ_n satisfying $\mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda} + \lambda_n \boldsymbol{I})^{-1}) \sim n$ and $C_{\boldsymbol{\theta}_*, \boldsymbol{\Lambda}, n, \sigma}$ are two constants independent of p but dependent on $\boldsymbol{\theta}_*$, $\boldsymbol{\Lambda}$, n, and σ, as defined in Appendix G.3.

Remark: Characterizing the relationship between risk and norm for ridge estimators ($\lambda > 0$) becomes particularly challenging. As shown in Eq. (5), the parameters p, λ, ν_1, and ν_2 are intricately coupled, making it extremely difficult to solve for ν_1 and ν_2—let alone derive an explicit (even approximate) relationship between risk and norm. In the case of linear regression, a complete description of the risk-norm relationship under ridge regularization can be established, as presented in Appendix D.

The relationship in the under-parameterized regime is also complicated as well. We consider the special case of isotropic features in Theorem 37 and give an approximation in Theorem 33 under the power-law assumption, given as below.

Assumption 32 (Power-law, [12]) *We assume that $\{\xi_k^2\}_{k=1}^{\infty}$ in $\boldsymbol{\Lambda}$ and $\boldsymbol{\theta}_*$ satisfy*

$$\xi_k^2 = k^{-\alpha}, \quad \theta_{*,k} = k^{-\frac{1+2\alpha\tau}{2}}\,, \text{with } \alpha > 1,\ r > 0\,.$$

The assumption coincides with the source condition $\|\boldsymbol{\Lambda}^{-r}\boldsymbol{\theta}_*\|_2 < \infty$ ($r > 0$) and capacity condition $\mathrm{Tr}(\boldsymbol{\Lambda}^{1/\alpha}) < \infty$ ($\alpha > 1$) [8]. Under power-law, we need to handle the self-consistent equations to approximate the infinite summation. We have the following approximation.

Corollary 33 (Relationship for min-ℓ_2 norm interpolator under power law) *Under Theorem 32, the deterministic equivalents R_0^{RFM} and N_0^{RFM} admit [4] the following relationship with $C_{n,\alpha,r,1} <$*

4. The symbol $\approx$ here denotes using an integral to approximate an infinite sum when calculating $\mathrm{Tr}(\cdot)$.

$C_{n,\alpha,r,2}$

$$\mathsf{R}_0^{RFM} \approx (n/C_\alpha)^{-\alpha} + \begin{cases} C_{n,\alpha,r,1} & \text{if } p > n\,, \\ C_{n,\alpha,r,2} & \text{if } p \to n^-\,. \end{cases} \tag{63}$$

where $C_{n,\alpha,r,1(2)}$ are constants (see Appendix G.3 for details) that only depend on n, α and r. The notation $p \to n^-$ means that p approaches to n in the under-parameterized regime ($p < n$).

Remark: In the over-parameterized regime, the relationship between R_0^{RFM} and N_0^{RFM} is a monotonically increasing linear function, with a growth rate controlled by the factor decaying with n. In the under-parameterized regime, as $p \to n$ (which also leads to R_0^{RFM} and $\mathsf{N}_0^{RFM} \to \infty$), R_0^{RFM} still grows linearly w.r.t N_0^{RFM}, with the same growth rate factor decaying with n. Furthermore, since $C_{n,\alpha,r,1} < C_{n,\alpha,r,2}$, the test risk curve shows that over-parameterization is better than under-parameterization. This approximation is also empirically verified to be precise in Fig. 6.

To study scaling law, we follow the same setting of [12] by choosing $p = n^q$ and $\lambda = n^{-(\ell-1)}$ with $q, l \geq 0$. We have the scaling law as below; see the proof in Appendix H.

Proposition 34 *Under Theorem 32, for $r \in (0, \frac{1}{2})$, taking $p = n^q$ and $\lambda = n^{-(\ell-1)}$ with $q, l \geq 0$, we formulate the scaling law under norm-based capacity in different areas as*

$$\mathsf{R}_\lambda^{RFM} = \Theta\left(n^{\gamma_n} \cdot \left(\mathsf{N}_\lambda^{RFM}\right)^{\gamma_\mathsf{N}}\right)\,, \quad \gamma_n \leq 0, \;\; \gamma_\mathsf{N} \in \mathbb{R}\,,$$

where the rate $\{\gamma_n, \gamma_\mathsf{N}\}$ in different areas is given in Fig. 6(c).

Remark: In all regions of Fig. 6(*c*), $\gamma_n \leq 0$, which aligns with the classical scaling law—that increasing the number of training samples leads to a reduction in test risk. As for γ_N, in regions ①, ②, ③, and ④, $\gamma_\mathsf{N} > 0$, indicating that when q is large (i.e., p is large), the test risk increases monotonically with the norm. In contrast, in region ⑤, $\gamma_\mathsf{N} < 0$, meaning that when q is small (i.e., p is small), the risk decreases monotonically with the norm. This again resembles the traditional U-shaped curve. These findings highlight the dual role of model norm in generalization: while a larger norm can be beneficial in low-complexity regimes, it becomes detrimental when the model is already sufficiently complex.

Appendix G. Proofs for random feature ridge regression

In this section, we provide the proof of deterministic equivalence for random feature ridge regression in both the asymptotic (Appendix G.1) and non-asymptotic (Appendix G.2) settings. Additionally, we provide the proof of the relationship between test risk and the ℓ_2 norm given in the main text, as detailed in Appendix G.3.

Though the results [1] are for linear regression, we can still use the results for RFMs, which requires some knowledge from Eqs. (26) and (27).

We firstly confirm that Theorem 3 in Appendix B.3, used to derive all asymptotic results, can be replaced by the Hanson-Wright assumption employed in the non-asymptotic analysis. It is evident that Eqs. (7) and (9) are obtained directly by taking the limits of Eqs. (26) and (27) as $n \to \infty$.

Additionally, a key step in the proof of Eqs. (8) and (10) in [1] involves showing that Δ is almost surely negligible, where Δ is defined as

$$\Delta = \frac{1}{n}\sum_{i=1}^{n} \frac{\boldsymbol{x}_i \boldsymbol{x}_i^\top (\widehat{\boldsymbol{\Sigma}}_{-i} - z\boldsymbol{I})^{-1} - \boldsymbol{\Sigma}(\widehat{\boldsymbol{\Sigma}} - z\boldsymbol{I})^{-1}}{1 + \boldsymbol{x}_i^\top (n\widehat{\boldsymbol{\Sigma}}_{-i} - nz\boldsymbol{I})^{-1}\boldsymbol{x}_i}\,,$$

with $\widehat{\boldsymbol{\Sigma}} = \frac{1}{n}\sum_{i=1}^{n} \boldsymbol{x}_i\boldsymbol{x}_i^\top$, $\widehat{\boldsymbol{\Sigma}}_{-i} = \frac{1}{n}\sum_{j\neq i} \boldsymbol{x}_j\boldsymbol{x}_j^\top$, and $z \in \mathbb{R}$.

In the analysis of [1], the negligibility of Δ arises from the assumption that the components of $\boldsymbol{x}_i$ follow a sub-Gaussian distribution, which leads to the Hanson-Wright inequality

$$\mathbb{P}\left[\left|\boldsymbol{x}_i^\top \boldsymbol{x}_i - \operatorname{tr}(\boldsymbol{\Sigma})\right| \leq c\left(t\|\boldsymbol{\Sigma}\|_{\mathrm{op}} + \sqrt{t}\|\boldsymbol{\Sigma}\|_F\right)\right] \geq 1 - 2e^{-t}.$$

In this way, Theorem 22 is also sufficient to establish the negligibility of Δ.

After obtaining Eqs. (7) and (9) and the negligibility of Δ, we can follow the argument of [1] and derive the rest asymptotic deterministic equivalence.

Finally, with these observations, we can eliminate the reliance on Theorem 3 and instead rely solely on Theorem 22 to derive all the asymptotic results.

G.1. Asymptotic deterministic equivalence for random features ridge regression

In this section, we establish the asymptotic approximation guarantees for random feature regression in terms of its ℓ_2-norm based capacity. Before presenting the proof of Theorem 2, we firstly give the proof of the bias-variance decomposition.

Proof Here we give the bias-variance decomposition of $\mathbb{E}_\varepsilon\|\hat{\boldsymbol{a}}\|_2^2$. The formulation of $\mathbb{E}_\varepsilon\|\hat{\boldsymbol{a}}\|_2^2$ is given by

$$\mathbb{E}_\varepsilon\|\hat{\boldsymbol{a}}\|_2^2 = \mathbb{E}_\varepsilon\|(\boldsymbol{Z}^\top\boldsymbol{Z} + \lambda\boldsymbol{I})^{-1}\boldsymbol{Z}^\top\boldsymbol{y}\|_2^2\,,$$

which admits a similar bias-variance decomposition

$$\begin{aligned}
\mathbb{E}_\varepsilon\|\hat{\boldsymbol{a}}\|_2^2 &= \mathbb{E}_\varepsilon\|(\boldsymbol{Z}^\top\boldsymbol{Z} + \lambda\boldsymbol{I})^{-1}\boldsymbol{Z}^\top(\boldsymbol{G}\boldsymbol{\theta}_* + \boldsymbol{\varepsilon})\|_2^2 \\
&= \|(\boldsymbol{Z}^\top\boldsymbol{Z} + \lambda\boldsymbol{I})^{-1}\boldsymbol{Z}^\top\boldsymbol{G}\boldsymbol{\theta}_*\|_2^2 + \mathbb{E}_\varepsilon\|(\boldsymbol{Z}^\top\boldsymbol{Z} + \lambda\boldsymbol{I})^{-1}\boldsymbol{Z}^\top\boldsymbol{\varepsilon}\|_2^2 \\
&= \langle\boldsymbol{\theta}_*, \boldsymbol{G}^\top\boldsymbol{Z}(\boldsymbol{Z}^\top\boldsymbol{Z} + \lambda\boldsymbol{I})^{-2}\boldsymbol{Z}^\top\boldsymbol{G}\boldsymbol{\theta}_*\rangle + \sigma^2\mathrm{Tr}\left(\boldsymbol{Z}^\top\boldsymbol{Z}(\boldsymbol{Z}^\top\boldsymbol{Z} + \lambda\boldsymbol{I})^{-2}\right) \\
&=: \mathcal{B}_{\mathcal{N},\lambda}^{\mathrm{RFM}} + \mathcal{V}_{\mathcal{N},\lambda}^{\mathrm{RFM}}\,.
\end{aligned}$$

Accordingly, we conclude the proof. ■

Now we are ready to present the proof of Theorem 2 as below.

Proof [Proof of Theorem 2] We give the asymptotic deterministic equivalents for the norm from the bias $\mathcal{B}_{\mathcal{N},\lambda}^{\mathrm{RFM}}$ and variance $\mathcal{V}_{\mathcal{N},\lambda}^{\mathrm{RFM}}$, respectively. We provide asymptotic expansions in two steps, by first considering the deterministic equivalent over $\boldsymbol{G}$, and then over $\boldsymbol{F}$.

Under Theorem 1, we can apply Theorems 6, 7, 18 and 19 directly in the proof below.

Deterministic equivalent over $\boldsymbol{G}$: For the bias term, we use Eq. (12) in Theorem 7 with $\boldsymbol{T} = \boldsymbol{G}$, $\boldsymbol{\Sigma} = \boldsymbol{F}^\top\boldsymbol{F}$, $\boldsymbol{A} = \boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top$ and $\boldsymbol{B} = \boldsymbol{F}^\top\boldsymbol{F}$ and obtain

$$\begin{aligned}
\mathcal{B}_{\mathcal{N},\lambda}^{\mathrm{RFM}} &= \langle\boldsymbol{\theta}_*, \boldsymbol{G}^\top\boldsymbol{Z}(\boldsymbol{Z}^\top\boldsymbol{Z} + \lambda\boldsymbol{I})^{-2}\boldsymbol{Z}^\top\boldsymbol{G}\boldsymbol{\theta}_*\rangle \\
&= \mathrm{Tr}(\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top\boldsymbol{Z}(\boldsymbol{Z}^\top\boldsymbol{Z} + \lambda\boldsymbol{I})^{-2}\boldsymbol{Z}^\top\boldsymbol{G}\boldsymbol{\theta}_*) \\
&= p\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{F}^\top\boldsymbol{F}\boldsymbol{G}^\top + p\lambda\boldsymbol{I})^{-1}\boldsymbol{G}\boldsymbol{F}^\top\boldsymbol{F}\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{F}^\top\boldsymbol{F}\boldsymbol{G}^\top + p\lambda\boldsymbol{I})^{-1}\boldsymbol{G}) \\
&\sim p\underbrace{\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top(\boldsymbol{F}^\top\boldsymbol{F} + \nu_1\boldsymbol{I})^{-1}\boldsymbol{F}^\top\boldsymbol{F}(\boldsymbol{F}^\top\boldsymbol{F} + \nu_1\boldsymbol{I})^{-1})}_{\mathrm{I}_1} \\
&\quad + p\nu_1^2\underbrace{\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top(\boldsymbol{F}^\top\boldsymbol{F} + \nu_1\boldsymbol{I})^{-2})}_{:=I_2}\cdot\underbrace{\mathrm{Tr}(\boldsymbol{F}^\top\boldsymbol{F}(\boldsymbol{F}^\top\boldsymbol{F} + \nu_1\boldsymbol{I})^{-2})}_{:=I_3}\cdot\frac{1}{n - \widehat{\mathrm{d}f}_2(\nu_1)}\,,
\end{aligned} \tag{64}$$

where ν_1 defined by $\nu_1(1-\frac{1}{n}\widehat{\mathrm{d}f}_1(\nu_1)) \sim \frac{p\lambda}{n}$, $\widehat{\mathrm{d}f}_1(\nu_1)$ and $\widehat{\mathrm{d}f}_2(\nu_1)$ are degrees of freedom associated to $\boldsymbol{F}^\top \boldsymbol{F}$ in Theorem 5.

For the variance term, we use Eq. (53) with $\boldsymbol{T} = \boldsymbol{G}$ in Theorem 7, $\boldsymbol{A} = \boldsymbol{F}^\top \boldsymbol{F}$, $\boldsymbol{\Sigma} = \boldsymbol{F}^\top \boldsymbol{F}$ and obtain

$$\begin{aligned}
\mathcal{V}_{\mathcal{N},\lambda}^{\mathrm{RFM}} &= \sigma^2 \mathrm{Tr}\left(\boldsymbol{Z}^\top \boldsymbol{Z}(\boldsymbol{Z}^\top \boldsymbol{Z} + \lambda \boldsymbol{I})^{-2}\right) = \sigma^2 \mathrm{Tr}\left(\boldsymbol{Z}\boldsymbol{Z}^\top (\boldsymbol{Z}\boldsymbol{Z}^\top + \lambda \boldsymbol{I})^{-2}\right) \\
&= \sigma^2 p \mathrm{Tr}\left(\boldsymbol{G}\boldsymbol{F}^\top \boldsymbol{F}\boldsymbol{G}^\top (\boldsymbol{G}\boldsymbol{F}^\top \boldsymbol{F}\boldsymbol{G}^\top + p\lambda \boldsymbol{I})^{-2}\right) \\
&\sim \sigma^2 p \frac{\mathrm{Tr}(\boldsymbol{F}^\top \boldsymbol{F}(\boldsymbol{F}^\top \boldsymbol{F} + \nu_1 \boldsymbol{I})^{-2})}{n - \widehat{\mathrm{d}f}_2(\nu_1)} .
\end{aligned}$$

Deterministic equivalent over $\boldsymbol{F}$: In the next, we aim to eliminate the randomness over $\boldsymbol{F}$ in Eq. (64) from the bias part. First our result depends on the asymptotic equivalents for $\widehat{\mathrm{d}f}_1(\nu_1)$ and $\widehat{\mathrm{d}f}_2(\nu_1)$. For $\widehat{\mathrm{d}f}_1(\nu_1)$, we use Eq. (7) in Theorem 6 with $\boldsymbol{X} = \boldsymbol{F}$ and obtain

$$\widehat{\mathrm{d}f}_1(\nu_1) = \mathrm{Tr}(\boldsymbol{F}^\top \boldsymbol{F}(\boldsymbol{F}^\top \boldsymbol{F} + \nu_1 \boldsymbol{I})^{-1}) \sim \mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda} + \nu_2 \boldsymbol{I})^{-1}) = \mathrm{d}f_1(\nu_2) ,$$

where ν_2 defined by $\nu_2(1 - \frac{1}{p}\mathrm{d}f_1(\nu_2)) \sim \frac{\nu_1}{p}$. Hence ν_1 can be defined by $\nu_1(1 - \frac{1}{n}\mathrm{d}f_1(\nu_2)) \sim \frac{p\lambda}{n}$ from Eq. (5).

For $\widehat{\mathrm{d}f}_2(\nu_1)$, we use Eq. (8) in Theorem 6 with $\boldsymbol{X} = \boldsymbol{F}$, $\boldsymbol{A} = \boldsymbol{B} = \boldsymbol{I}$ and obtain

$$\begin{aligned}
\widehat{\mathrm{d}f}_2(\nu_1) =\ & \mathrm{Tr}(\boldsymbol{F}^\top \boldsymbol{F}(\boldsymbol{F}^\top \boldsymbol{F} + \nu_1 \boldsymbol{I})^{-1} \boldsymbol{F}^\top \boldsymbol{F}(\boldsymbol{F}^\top \boldsymbol{F} + \nu_1 \boldsymbol{I})^{-1}) \\
\sim\ & \mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda} + \nu_2 \boldsymbol{I})^{-2}) + \nu_2^2 \mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda} + \nu_2 \boldsymbol{I})^{-2}) \cdot \mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda} + \nu_2 \boldsymbol{I})^{-2}) \cdot \frac{1}{p - \mathrm{d}f_2(\nu_2)} \\
=:\ & n\Upsilon(\nu_1, \nu_2) .
\end{aligned} \tag{65}$$

For $I_3 := \mathrm{Tr}(\boldsymbol{F}^\top \boldsymbol{F}(\boldsymbol{F}^\top \boldsymbol{F} + \nu_1 \boldsymbol{I})^{-2})$, we use Eq. (51) with $\boldsymbol{X} = \boldsymbol{F}$ and obtain

$$\mathrm{Tr}(\boldsymbol{F}^\top \boldsymbol{F}(\boldsymbol{F}^\top \boldsymbol{F} + \nu_1 \boldsymbol{I})^{-2}) \sim \mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda} + \nu_2 \boldsymbol{I})^{-2}) \cdot \frac{1}{p - \mathrm{d}f_2(\nu_2)} . \tag{66}$$

Then we use Eq. (51) again with $\boldsymbol{X} = \boldsymbol{F}$, $\boldsymbol{A} = \boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top$ to obtain the deterministic equivalent of I_1

$$\begin{aligned}
\mathrm{Tr}(\boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top (\boldsymbol{F}^\top \boldsymbol{F} + \nu_1 \boldsymbol{I})^{-1} \boldsymbol{F}^\top \boldsymbol{F}(\boldsymbol{F}^\top \boldsymbol{F} + \nu_1 \boldsymbol{I})^{-1}) &= \mathrm{Tr}(\boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top \boldsymbol{F}^\top \boldsymbol{F}(\boldsymbol{F}^\top \boldsymbol{F} + \nu_1 \boldsymbol{I})^{-2}) \\
&\sim \mathrm{Tr}(\boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top \boldsymbol{\Lambda}(\boldsymbol{\Lambda} + \nu_2 \boldsymbol{I})^{-2}) \cdot \frac{1}{p - \mathrm{d}f_2(\nu_2)} \\
&= \boldsymbol{\theta}_*^\top \boldsymbol{\Lambda}(\boldsymbol{\Lambda} + \nu_2 \boldsymbol{I})^{-2} \boldsymbol{\theta}_* \cdot \frac{1}{p - \mathrm{d}f_2(\nu_2)} .
\end{aligned}$$

Further, for I_2, use Eq. (10) with $\boldsymbol{A} = \boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top$ and $\boldsymbol{B} = \boldsymbol{I}$, we obtain

$$\begin{aligned}
\mathrm{Tr}(\boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top (\boldsymbol{F}^\top \boldsymbol{F} + \nu_1 \boldsymbol{I})^{-2}) \sim\ & \frac{\nu_2^2}{\nu_1^2} \mathrm{Tr}(\boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top (\boldsymbol{\Lambda} + \nu_2 \boldsymbol{I})^{-2}) \\
& + \frac{\nu_2^2}{\nu_1^2} \mathrm{Tr}(\boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top (\boldsymbol{\Lambda} + \nu_2 \boldsymbol{I})^{-2} \boldsymbol{\Lambda}) \cdot \mathrm{Tr}((\boldsymbol{\Lambda} + \nu_2 \boldsymbol{I})^{-2} \boldsymbol{\Lambda}) \cdot \frac{1}{p - \mathrm{d}f_2(\nu_2)} .
\end{aligned}$$

Finally, combine the above equivalents, for the bias, we obtain

$$
\begin{aligned}
\mathcal{B}_{\mathcal{N},\lambda}^{\mathrm{RFM}} &\sim p\boldsymbol{\theta}_*^\top \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}\boldsymbol{\theta}_* \cdot \frac{1}{p-\mathrm{d}f_2(\nu_2)} \\
&\quad + p\nu_1^2\left(\frac{\nu_2^2}{\nu_1^2}\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top(\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}) + \frac{\nu_2^2}{\nu_1^2}\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top(\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}\boldsymbol{\Lambda}) \cdot \frac{\mathrm{Tr}((\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}\boldsymbol{\Lambda})}{p-\mathrm{d}f_2(\nu_2)}\right) \\
&\quad \cdot \mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}) \cdot \frac{1}{p-\mathrm{d}f_2(\nu_2)} \cdot \frac{1}{n-n\Upsilon(\nu_1,\nu_2)} \\
&= p\boldsymbol{\theta}_*^\top \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}\boldsymbol{\theta}_* \cdot \frac{1}{p-\mathrm{d}f_2(\nu_2)} \\
&\quad + \frac{p}{n}\left(\nu_2^2\boldsymbol{\theta}_*^\top(\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}\boldsymbol{\theta}_* + \nu_2^2\boldsymbol{\theta}_*^\top\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}\boldsymbol{\theta}_* \cdot \frac{\mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2})}{p-\mathrm{d}f_2(\nu_2)}\right) \\
&\quad \cdot \mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}) \cdot \frac{1}{p-\mathrm{d}f_2(\nu_2)} \cdot \frac{1}{1-\Upsilon(\nu_1,\nu_2)} \\
&= \frac{p\langle\boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}\boldsymbol{\theta}_*\rangle}{p-\mathrm{Tr}\left(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}\right)} \\
&\quad + \frac{p\chi(\nu_2)}{n} \cdot \frac{\nu_2^2\left[\langle\boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}\boldsymbol{\theta}_*\rangle + \chi(\nu_2)\langle\boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}\boldsymbol{\theta}_*\rangle\right]}{1-\Upsilon(\nu_1,\nu_2)}\,.
\end{aligned}
$$

Similarly, for the variance, using Eq. (65) and Eq. (66) for I_3, we have

$$
\begin{aligned}
\mathcal{V}_{\mathcal{N},\lambda}^{\mathrm{RFM}} &\sim \sigma^2 p\mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2\boldsymbol{I})^{-2}) \cdot \frac{1}{p-\mathrm{d}f_2(\nu_2)} \cdot \frac{1}{n-n\Upsilon(\nu_1,\nu_2)} \\
&\sim \sigma^2 \frac{\frac{p}{n}\chi(\nu_2)}{1-\Upsilon(\nu_1,\nu_2)}\,.
\end{aligned}
$$

Accordingly, we finish the proof. ■

In the next, we present the proof for min-ℓ_2-norm interpolator under RFMs.

Proof [Proof of Theorem 30] Similar to linear regression, we separate the two regimes $p < n$ and $p > n$ as well. For both of them, we provide asymptotic expansions in two steps, first with respect to $\boldsymbol{G}$ and then $\boldsymbol{F}$ in the under-parameterized regime and vice-versa for the over-parameterized regime.

Under-parameterized regime: Deterministic equivalent over $\boldsymbol{G}$ For the variance term, we can use Eq. (53) with $\boldsymbol{T} = \boldsymbol{G}$, $\boldsymbol{\Sigma} = \boldsymbol{F}^\top\boldsymbol{F}$, $\boldsymbol{A} = \boldsymbol{F}^\top\boldsymbol{F}$ and obtain

$$
\begin{aligned}
\mathcal{V}_{\mathcal{N},0}^{\mathrm{RFM}} &= \sigma^2 \cdot \mathrm{Tr}(\boldsymbol{Z}^\top\boldsymbol{Z}(\boldsymbol{Z}^\top\boldsymbol{Z}+\lambda\boldsymbol{I})^{-2}) \\
&= \sigma^2 \cdot p\mathrm{Tr}(\boldsymbol{F}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{F}^\top(\boldsymbol{F}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{F}^\top+p\lambda\boldsymbol{I})^{-2}) \\
&= \sigma^2 \cdot p\mathrm{Tr}(\boldsymbol{F}^\top\boldsymbol{F}\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{F}^\top\boldsymbol{F}\boldsymbol{G}^\top+p\lambda\boldsymbol{I})^{-2}\boldsymbol{G}) \\
&\sim \sigma^2 \cdot p\mathrm{Tr}(\boldsymbol{F}^\top\boldsymbol{F}(\boldsymbol{F}^\top\boldsymbol{F}+\tilde{\lambda}\boldsymbol{I})^{-2}) \cdot \frac{1}{n-p} \\
&\sim \sigma^2 \cdot \mathrm{Tr}((\boldsymbol{F}\boldsymbol{F}^\top)^{-1}) \cdot \frac{p}{n-p}\,,
\end{aligned}
$$

where $\tilde{\lambda}$ is defined by

$$
\tilde{\lambda}(1-\frac{1}{n}\widetilde{\mathrm{d}f}_1(\tilde{\lambda})) \sim \frac{p\lambda}{n}\,, \tag{67}
$$

where $\widetilde{\mathrm{d}f}_1(\tilde{\lambda})$ and $\widetilde{\mathrm{d}f}_2(\tilde{\lambda})$ are degrees of freedom associated to $\boldsymbol{F}^\top\boldsymbol{F}$. In the under-parameterized regime ($p < n$), when λ goes to zero, we have $\tilde{\lambda} \to 0$ and $\widetilde{\mathrm{d}f}_2(\tilde{\lambda}) \to p$ [1].

For the bias term, we use Eq. (12) with $\boldsymbol{T} = \boldsymbol{G}$, $\boldsymbol{\Sigma} = \boldsymbol{F}^\top\boldsymbol{F}$, $\boldsymbol{A} = \boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top$, $\boldsymbol{B} = \boldsymbol{F}^\top\boldsymbol{F}$ and then obtain

$$\begin{aligned}
\mathcal{B}_{\mathcal{N},0}^{\mathrm{RFM}} &= \mathrm{Tr}(\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top\boldsymbol{Z}(\boldsymbol{Z}^\top\boldsymbol{Z}+\lambda\boldsymbol{I})^{-2}\boldsymbol{Z}^\top\boldsymbol{G}\boldsymbol{\theta}_*) \\
&= p\mathrm{Tr}(\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{F}^\top(\boldsymbol{F}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{F}^\top+p\lambda\boldsymbol{I})^{-2}\boldsymbol{F}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\theta}_*) \\
&= p\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{F}^\top\boldsymbol{F}\boldsymbol{G}^\top+p\lambda\boldsymbol{I})^{-1}\boldsymbol{G}\boldsymbol{F}^\top\boldsymbol{F}\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{F}^\top\boldsymbol{F}\boldsymbol{G}^\top+p\lambda\boldsymbol{I})^{-1}\boldsymbol{G}) \\
&\sim p\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top(\boldsymbol{F}^\top\boldsymbol{F}+\tilde{\lambda}\boldsymbol{I})^{-1}\boldsymbol{F}^\top\boldsymbol{F}(\boldsymbol{F}^\top\boldsymbol{F}+\tilde{\lambda}\boldsymbol{I})^{-1}) \\
&\quad + p\tilde{\lambda}^2\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top(\boldsymbol{F}^\top\boldsymbol{F}+\tilde{\lambda}\boldsymbol{I})^{-2})\cdot\mathrm{Tr}(\boldsymbol{F}^\top\boldsymbol{F}(\boldsymbol{F}^\top\boldsymbol{F}+\tilde{\lambda}\boldsymbol{I})^{-2})\cdot\frac{1}{n-p} \\
&\sim p\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{F}^\top(\boldsymbol{F}\boldsymbol{F}^\top)^{-2}\boldsymbol{F}) + p\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top(\boldsymbol{I}-\boldsymbol{F}^\top(\boldsymbol{F}\boldsymbol{F}^\top)^{-1}\boldsymbol{F}))\cdot\mathrm{Tr}((\boldsymbol{F}\boldsymbol{F}^\top)^{-1})\cdot\frac{1}{n-p}\,.
\end{aligned}$$

In the next, we are ready to eliminate the randomness over $\boldsymbol{F}$.

Under-parameterized regime: deterministic equivalent over $\boldsymbol{F}$ For the variance term, from [1, Sec 3.2] we know that $1/\lambda_p$ is almost surely the limit of $\mathrm{Tr}((\boldsymbol{F}\boldsymbol{F}^\top)^{-1})$, thus we have

$$\mathrm{Tr}((\boldsymbol{F}\boldsymbol{F}^\top)^{-1}) \sim \frac{1}{\lambda_p}\,,$$

where λ_p defined by $\mathrm{d}f_1(\lambda_p) = p$, where $\mathrm{d}f_1(\lambda_p)$ and $\mathrm{d}f_2(\lambda_p)$ are degrees of freedom associated to $\boldsymbol{\Lambda}$. Hence we can obtain

$$\mathcal{V}_{\mathcal{N},0}^{\mathrm{RFM}} \sim \sigma^2\cdot\frac{1}{\lambda_p}\cdot\frac{p}{n-p} = \frac{\sigma^2 p}{\lambda_p(n-p)}\,.$$

For the bias term, denote $\boldsymbol{D} := \boldsymbol{F}\boldsymbol{\Lambda}^{-1/2}$, we first use Eq. (53) with $\boldsymbol{T} = \boldsymbol{D}$, $\boldsymbol{\Sigma} = \boldsymbol{\Lambda}$, $\boldsymbol{A} = \boldsymbol{\Lambda}^{1/2}\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{\Lambda}^{1/2}$ and obtain the deterministic equivalent of the first term in $\mathcal{B}_{\mathcal{N},0}^{\mathrm{RFM}}$

$$\begin{aligned}
\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{F}^\top(\boldsymbol{F}\boldsymbol{F}^\top)^{-2}\boldsymbol{F}) &= \mathrm{Tr}(\boldsymbol{\Lambda}^{1/2}\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{\Lambda}^{1/2}\boldsymbol{D}^\top(\boldsymbol{D}\boldsymbol{\Lambda}\boldsymbol{D}^\top)^{-2}\boldsymbol{D}) \\
&\sim \mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\lambda_p)^{-2})\cdot\frac{1}{n-\mathrm{d}f_2(\lambda_p)}\,.
\end{aligned}$$

Then we use Eq. (12) with $\boldsymbol{T} = \boldsymbol{D}$, $\boldsymbol{\Sigma} = \boldsymbol{\Lambda}$, $\boldsymbol{A} = \boldsymbol{\Lambda}^{1/2}\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{\Lambda}^{1/2}$ and obtain

$$\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{F}^\top(\boldsymbol{F}\boldsymbol{F}^\top)^{-1}\boldsymbol{F}) = \mathrm{Tr}(\boldsymbol{\Lambda}^{1/2}\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{\Lambda}^{1/2}\boldsymbol{D}^\top(\boldsymbol{D}\boldsymbol{\Lambda}\boldsymbol{D}^\top)^{-1}\boldsymbol{D}) \sim \mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\lambda_p)^{-1})\,,$$

Then the deterministic equivalent of the second term in $\mathcal{B}_{\mathcal{N},0}^{\mathrm{RFM}}$ is given by

$$\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top(\boldsymbol{I}-\boldsymbol{F}^\top(\boldsymbol{F}\boldsymbol{F}^\top)^{-1}\boldsymbol{F})) \sim \lambda_p\boldsymbol{\theta}_*^\top(\boldsymbol{\Lambda}+\lambda_p)^{-1}\boldsymbol{\theta}_*.$$

Finally, combine the above equivalents and we have

$$\begin{aligned}
\mathcal{B}_{\mathcal{N},0}^{\mathrm{RFM}} &\sim \boldsymbol{\theta}_*^\top\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\lambda_p)^{-2}\boldsymbol{\theta}_*\cdot\frac{p}{n-\mathrm{d}f_2(\lambda_p)} + \boldsymbol{\theta}_*^\top(\boldsymbol{\Lambda}+\lambda_p)^{-1}\boldsymbol{\theta}_*\cdot\frac{p}{n-p} \\
&= \frac{p\langle\boldsymbol{\theta}_*,\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\lambda_p)^{-2}\boldsymbol{\theta}_*\rangle}{n-\mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n\boldsymbol{I})^{-2})} + \frac{p\langle\boldsymbol{\theta}_*,(\boldsymbol{\Lambda}+\lambda_p)^{-1}\boldsymbol{\theta}_*\rangle}{n-p}\,.
\end{aligned}$$

Over-parameterized regime: deterministic equivalent over $\boldsymbol{F}$ Denote $\boldsymbol{K} := \boldsymbol{\Lambda}^{1/2}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\Lambda}^{1/2}$, for the variance term, we use Eq. (53) with $\boldsymbol{T} = \boldsymbol{D}$, $\boldsymbol{\Sigma} = \boldsymbol{A} = \boldsymbol{K}$ and obtain

$$\begin{aligned}
\mathcal{V}_{\mathcal{N},0}^{\mathrm{RFM}} &= \sigma^2 \cdot p\mathrm{Tr}(\boldsymbol{F}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{F}^\top(\boldsymbol{F}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{F}^\top + p\lambda\boldsymbol{I})^{-2}) \\
&= \sigma^2 \cdot p\mathrm{Tr}(\boldsymbol{K}\boldsymbol{D}^\top(\boldsymbol{D}\boldsymbol{K}\boldsymbol{D}^\top + p\lambda\boldsymbol{I})^{-2}\boldsymbol{D}) \\
&\sim \sigma^2 \cdot p\mathrm{Tr}(\boldsymbol{K}(\boldsymbol{K} + \hat{\lambda}\boldsymbol{I})^{-2}) \cdot \frac{1}{p-n} \\
&\sim \sigma^2 \cdot \mathrm{Tr}((\boldsymbol{G}\boldsymbol{\Lambda}\boldsymbol{G}^\top)^{-1}) \cdot \frac{p}{p-n}\,,
\end{aligned}$$

where $\hat{\lambda}$ is defined by

$$\hat{\lambda}(1 - \frac{1}{n}\widehat{\mathrm{d}f}_1(\hat{\lambda})) \sim \frac{p\lambda}{n}\,, \tag{68}$$

where $\widehat{\mathrm{d}f}_1(\hat{\lambda})$ and $\widehat{\mathrm{d}f}_2(\hat{\lambda})$ are degrees of freedom associated to $\boldsymbol{K}$. In the over-parameterized regime ($p > n$), when λ goes to zero, we have $\hat{\lambda} \to 0$ and $\widehat{\mathrm{d}f}_2(\hat{\lambda}) \to n$ [1].

For the bias term, we use Eq. (53) with $\boldsymbol{T} = \boldsymbol{D}$, $\boldsymbol{\Sigma} = \boldsymbol{K}$, $\boldsymbol{A} = \boldsymbol{\Lambda}^{1/2}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\Lambda}^{1/2}$ and obtain

$$\begin{aligned}
\mathcal{B}_{\mathcal{N},0}^{\mathrm{RFM}} &= p\mathrm{Tr}(\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{F}^\top(\boldsymbol{F}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{F}^\top + p\lambda\boldsymbol{I})^{-2}\boldsymbol{F}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\theta}_*) \\
&= p\mathrm{Tr}(\boldsymbol{\Lambda}^{1/2}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\Lambda}^{1/2}\boldsymbol{D}(\boldsymbol{D}\boldsymbol{K}\boldsymbol{D}^\top + p\lambda\boldsymbol{I})^{-2}\boldsymbol{D}) \\
&\sim p\mathrm{Tr}(\boldsymbol{\Lambda}^{1/2}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\Lambda}^{1/2}(\boldsymbol{K} + \hat{\lambda}\boldsymbol{I})^{-2}) \cdot \frac{1}{p-n} \\
&\sim \mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{\Lambda}\boldsymbol{G}^\top)^{-1}\boldsymbol{G}) \cdot \frac{p}{p-n}\,.
\end{aligned}$$

Over-parameterized regime: deterministic equivalent over $\boldsymbol{G}$ For the variance term, we have

$$\mathcal{V}_{\mathcal{N},0}^{\mathrm{RFM}} \sim \sigma^2 \cdot \frac{1}{\lambda_n} \cdot \frac{p}{p-n} = \frac{\sigma^2 p}{\lambda_n(p-n)}.$$

For the bias term, we have

$$\begin{aligned}
\mathcal{B}_{\mathcal{N},0}^{\mathrm{RFM}} &\sim \mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top(\boldsymbol{\Lambda} + \lambda_n)^{-1}) \cdot \frac{p}{p-n} \\
&= \boldsymbol{\theta}_*^\top(\boldsymbol{\Lambda} + \lambda_n)^{-1}\boldsymbol{\theta}_* \cdot \frac{p}{p-n} \\
&= \frac{p\langle\boldsymbol{\theta}_*, (\boldsymbol{\Lambda} + \lambda_n)^{-1}\boldsymbol{\theta}_*\rangle}{p-n}\,.
\end{aligned}$$

Finally, we conclude the proof. ■

To build the connection between the test risk and norm for the min-ℓ_2-norm estimator for random features regression, we also need the deterministic equivalent of the test risk as below.

Proposition 35 (Asymptotic deterministic equivalence of the test risk of the min-ℓ_2-norm interpolator) *Under Theorem 1, for the minimum ℓ_2-norm estimator $\hat{\mathbf{a}}_{\min}$, we have the following deterministic equivalence: for the under-parameterized regime ($p < n$), we have*

$$\mathcal{B}_{\mathcal{R},0}^{\mathrm{RFM}} \sim \frac{n\lambda_p\langle\boldsymbol{\theta}_*, (\boldsymbol{\Lambda} + \lambda_p\boldsymbol{I})^{-1}\boldsymbol{\theta}_*\rangle}{n-p}\,, \quad \mathcal{V}_{\mathcal{R},0}^{\mathrm{RFM}} \sim \frac{\sigma^2 p}{n-p}\,,$$

where λ_p is defined by $\mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\lambda_p \boldsymbol{I})^{-1}) \sim p$. In the over-parameterized regime ($p > n$), we have

$$\mathcal{B}_{\mathcal{R},0}^{\mathrm{RFM}} \sim \frac{n\lambda_n^2 \langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2}\boldsymbol{\theta}_*\rangle}{n - \mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2})} + \frac{n\lambda_n \langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-1}\boldsymbol{\theta}_*\rangle}{p-n},$$
$$\mathcal{V}_{\mathcal{R},0}^{\mathrm{RFM}} \sim \frac{\sigma^2 \mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2})}{n - \mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2})} + \frac{\sigma^2 n}{p-n},$$

where λ_n is defined by $\mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-1}) \sim n$.

Proof [Proof of Theorem 35] For the proof, we separate the two regimes $p < n$ and $p > n$. For both of them, we provide asymptotic expansions in two steps, first with respect to $\boldsymbol{G}$ and then $\boldsymbol{F}$ in the under-parameterized regime and vice-versa for the over-parameterized regime.

Under-parameterized regime: deterministic equivalent over $\boldsymbol{G}$ For the variance term, in the under-parameterized regime, when $\lambda \to 0$, the variance term will become $\mathcal{V}_{\mathcal{R},0}^{\mathrm{RFM}} = \sigma^2 \cdot \mathrm{Tr}(\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}(\boldsymbol{Z}^\top \boldsymbol{Z})^{-1})$. Accordingly, using [1, Eq. (12)], we have

$$\begin{aligned}
\mathcal{V}_{\mathcal{R},0}^{\mathrm{RFM}} &= \sigma^2 \cdot \mathrm{Tr}(\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}(\boldsymbol{Z}^\top \boldsymbol{Z})^{-1}) \\
&= \sigma^2 \cdot \mathrm{Tr}(\boldsymbol{F}\boldsymbol{F}^\top(\boldsymbol{F}\boldsymbol{G}^\top \boldsymbol{G}\boldsymbol{F}^\top)^{-1}) \\
&\sim \frac{\sigma^2}{n-p} \cdot \mathrm{Tr}(\boldsymbol{F}\boldsymbol{F}^\top(\boldsymbol{F}\boldsymbol{F}^\top)^{-1}) \\
&= \frac{\sigma^2 p}{n-p}.
\end{aligned}$$

For the bias term, it can be decomposed into

$$\begin{aligned}
\mathcal{B}_{\mathcal{R},0}^{\mathrm{RFM}} &= \|\boldsymbol{\theta}_* - p^{-1/2}\boldsymbol{F}^\top(\boldsymbol{Z}^\top \boldsymbol{Z}+\lambda \boldsymbol{I})^{-1}\boldsymbol{Z}^\top \boldsymbol{G}\boldsymbol{\theta}_*\|_2^2 \\
&= \boldsymbol{\theta}_*^\top \boldsymbol{\theta}_* - 2p^{-1/2}\boldsymbol{\theta}_*^\top \boldsymbol{F}^\top(\boldsymbol{Z}^\top \boldsymbol{Z}+\lambda \boldsymbol{I})^{-1}\boldsymbol{Z}^\top \boldsymbol{G}\boldsymbol{\theta}_* \\
&\quad + \boldsymbol{\theta}_*^\top \boldsymbol{G}^\top \boldsymbol{Z}(\boldsymbol{Z}^\top \boldsymbol{Z}+\lambda \boldsymbol{I})^{-1}\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}(\boldsymbol{Z}^\top \boldsymbol{Z}+\lambda \boldsymbol{I})^{-1}\boldsymbol{Z}^\top \boldsymbol{G}\boldsymbol{\theta}_*.
\end{aligned}$$

For the second term: $p^{-1/2}\boldsymbol{\theta}_*^\top \boldsymbol{F}^\top(\boldsymbol{Z}^\top \boldsymbol{Z}+\lambda \boldsymbol{I})^{-1}\boldsymbol{Z}^\top \boldsymbol{G}\boldsymbol{\theta}_*$, we can use Eq. (11) with $\boldsymbol{T} = \boldsymbol{G}$, $\boldsymbol{\Sigma} = \boldsymbol{F}^\top \boldsymbol{F}$, $\boldsymbol{A} = \boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top \boldsymbol{F}^\top \boldsymbol{F}$ and obtain

$$\begin{aligned}
p^{-1/2}\boldsymbol{\theta}_*^\top \boldsymbol{F}^\top(\boldsymbol{Z}^\top \boldsymbol{Z}+\lambda \boldsymbol{I})^{-1}\boldsymbol{Z}^\top \boldsymbol{G}\boldsymbol{\theta}_* &= \mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top \boldsymbol{F}^\top \boldsymbol{F}\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{F}^\top \boldsymbol{F}\boldsymbol{G}^\top + p\lambda \boldsymbol{I})^{-1}\boldsymbol{G}) \\
&\sim \mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top \boldsymbol{F}^\top \boldsymbol{F}(\boldsymbol{F}^\top \boldsymbol{F}+\tilde{\lambda}\boldsymbol{I})^{-1}) \\
&\sim \mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top \boldsymbol{F}^\top(\boldsymbol{F}\boldsymbol{F}^\top)^{-1}\boldsymbol{F}),
\end{aligned}$$

where the implicit regularization parameter $\tilde{\lambda}$ is defined by Eq. (67).

For the third term: $\boldsymbol{\theta}_*^\top \boldsymbol{G}^\top \boldsymbol{Z}(\boldsymbol{Z}^\top \boldsymbol{Z} + \lambda \boldsymbol{I})^{-1} \widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}} (\boldsymbol{Z}^\top \boldsymbol{Z} + \lambda \boldsymbol{I})^{-1} \boldsymbol{Z}^\top \boldsymbol{G} \boldsymbol{\theta}_*$, we can use Eq. (12) with $\boldsymbol{T} = \boldsymbol{G}$, $\boldsymbol{\Sigma} = \boldsymbol{F}^\top \boldsymbol{F}$, $\boldsymbol{A} = \boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top$, $\boldsymbol{B} = \boldsymbol{F}^\top \boldsymbol{F} \boldsymbol{F}^\top \boldsymbol{F}$ and obtain

$$
\begin{aligned}
&\boldsymbol{\theta}_*^\top \boldsymbol{G}^\top \boldsymbol{Z}(\boldsymbol{Z}^\top \boldsymbol{Z} + \lambda \boldsymbol{I})^{-1} \widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}} (\boldsymbol{Z}^\top \boldsymbol{Z} + \lambda \boldsymbol{I})^{-1} \boldsymbol{Z}^\top \boldsymbol{G} \boldsymbol{\theta}_* \\
&= \mathrm{Tr}(\boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top \boldsymbol{G}^\top \boldsymbol{G} \boldsymbol{F}^\top (\boldsymbol{F} \boldsymbol{G}^\top \boldsymbol{G} \boldsymbol{F}^\top + p\lambda \boldsymbol{I})^{-1} \boldsymbol{F} \boldsymbol{F}^\top (\boldsymbol{F} \boldsymbol{G}^\top \boldsymbol{G} \boldsymbol{F}^\top + p\lambda \boldsymbol{I})^{-1} \boldsymbol{F} \boldsymbol{G}^\top \boldsymbol{G}) \\
&= \mathrm{Tr}(\boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top \boldsymbol{G}^\top (\boldsymbol{G} \boldsymbol{F}^\top \boldsymbol{F} \boldsymbol{G}^\top + p\lambda \boldsymbol{I})^{-1} \boldsymbol{G} \boldsymbol{F}^\top \boldsymbol{F} \boldsymbol{F}^\top \boldsymbol{F} \boldsymbol{G}^\top (\boldsymbol{G} \boldsymbol{F}^\top \boldsymbol{F} \boldsymbol{G}^\top + p\lambda \boldsymbol{I})^{-1} \boldsymbol{G}) \\
&\sim \mathrm{Tr}(\boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top (\boldsymbol{F}^\top \boldsymbol{F} + \tilde{\lambda} \boldsymbol{I})^{-1} \boldsymbol{F}^\top \boldsymbol{F} \boldsymbol{F}^\top \boldsymbol{F} (\boldsymbol{F}^\top \boldsymbol{F} + \tilde{\lambda} \boldsymbol{I})^{-1}) \\
&\quad + \tilde{\lambda}^2 \mathrm{Tr}(\boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top (\boldsymbol{F}^\top \boldsymbol{F} + \tilde{\lambda} \boldsymbol{I})^{-2}) \cdot \mathrm{Tr}(\boldsymbol{F}^\top \boldsymbol{F} \boldsymbol{F}^\top \boldsymbol{F} (\boldsymbol{F}^\top \boldsymbol{F} + \tilde{\lambda} \boldsymbol{I})^{-2}) \cdot \frac{1}{n-p} \\
&\sim \mathrm{Tr}(\boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top \boldsymbol{F}^\top (\boldsymbol{F} \boldsymbol{F}^\top)^{-1} \boldsymbol{F}) + \mathrm{Tr}(\boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top (\boldsymbol{I} - \boldsymbol{F}^\top (\boldsymbol{F} \boldsymbol{F}^\top)^{-1} \boldsymbol{F})) \cdot \frac{p}{n-p} \,.
\end{aligned}
$$

Combining the above equivalents, we have

$$
\begin{aligned}
\mathcal{B}_{\mathcal{R},0}^{\mathrm{RFM}} &= \boldsymbol{\theta}_*^\top \boldsymbol{\theta}_* - \mathrm{Tr}(\boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top \boldsymbol{F}^\top (\boldsymbol{F} \boldsymbol{F}^\top)^{-1} \boldsymbol{F}) + \mathrm{Tr}(\boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top (\boldsymbol{I} - \boldsymbol{F}^\top (\boldsymbol{F} \boldsymbol{F}^\top)^{-1} \boldsymbol{F})) \cdot \frac{p}{n-p} \\
&= \boldsymbol{\theta}_*^\top \boldsymbol{\theta}_* \cdot \frac{n}{n-p} - \mathrm{Tr}(\boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top \boldsymbol{F}^\top (\boldsymbol{F} \boldsymbol{F}^\top)^{-1} \boldsymbol{F}) \cdot \frac{n}{n-p} \,.
\end{aligned}
$$

Under-parameterized regime: deterministic equivalent over $\boldsymbol{F}$ For the bias term, we can use Eq. (11) with $\boldsymbol{T} = \boldsymbol{D} := \boldsymbol{F} \boldsymbol{\Lambda}^{-1/2}$, $\boldsymbol{A} = \boldsymbol{\Lambda}^{1/2} \boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top \boldsymbol{\Lambda}^{1/2}$ and obtain

$$
\begin{aligned}
\mathrm{Tr}(\boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top \boldsymbol{F}^\top (\boldsymbol{F} \boldsymbol{F}^\top)^{-1} \boldsymbol{F}) &= \mathrm{Tr}(\boldsymbol{\Lambda}^{1/2} \boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top \boldsymbol{\Lambda}^{1/2} \boldsymbol{D}^\top (\boldsymbol{D} \boldsymbol{\Lambda} \boldsymbol{D}^\top)^{-1} \boldsymbol{D}) \\
&\sim \mathrm{Tr}(\boldsymbol{\Lambda}^{1/2} \boldsymbol{\theta}_* \boldsymbol{\theta}_*^\top \boldsymbol{\Lambda}^{1/2} (\boldsymbol{\Lambda} + \lambda_p)^{-1}) \\
&= \boldsymbol{\theta}_*^\top \boldsymbol{\Lambda} (\boldsymbol{\Lambda} + \lambda_p)^{-1} \boldsymbol{\theta}_* \,.
\end{aligned}
$$

Thus, we finally obtain

$$
\begin{aligned}
\mathcal{B}_{\mathcal{R},0}^{\mathrm{RFM}} &\sim \boldsymbol{\theta}_*^\top \boldsymbol{\theta}_* \cdot \frac{n}{n-p} - \boldsymbol{\theta}_*^\top \boldsymbol{\Lambda} (\boldsymbol{\Lambda} + \lambda_p)^{-1} \boldsymbol{\theta}_* \cdot \frac{n}{n-p} \\
&= \lambda_p \boldsymbol{\theta}_*^\top (\boldsymbol{\Lambda} + \lambda_p)^{-1} \boldsymbol{\theta}_* \cdot \frac{n}{n-p} \\
&= \frac{n \lambda_p \langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda} + \lambda_p \boldsymbol{I})^{-1} \boldsymbol{\theta}_* \rangle}{n-p} \,.
\end{aligned}
$$

Over-parameterized regime: deterministic equivalent over $\boldsymbol{F}$ For the variance term, with $\boldsymbol{D} := \boldsymbol{F} \boldsymbol{\Lambda}^{-1/2}$ and $\boldsymbol{K} := \boldsymbol{\Lambda}^{1/2} \boldsymbol{G}^\top \boldsymbol{G} \boldsymbol{\Lambda}^{1/2}$ we can obtain

$$
\begin{aligned}
\mathcal{V}_{\mathcal{R},0}^{\mathrm{RFM}} &= \sigma^2 \cdot \mathrm{Tr}(\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}} \boldsymbol{Z}^\top \boldsymbol{Z} (\boldsymbol{Z}^\top \boldsymbol{Z} + \lambda \boldsymbol{I})^{-2}) \\
&= \sigma^2 \cdot \mathrm{Tr}(\boldsymbol{F} \boldsymbol{F}^\top \boldsymbol{F} \boldsymbol{G}^\top \boldsymbol{G} \boldsymbol{F}^\top (\boldsymbol{F} \boldsymbol{G}^\top \boldsymbol{G} \boldsymbol{F}^\top + p\lambda \boldsymbol{I})^{-2}) \\
&= \sigma^2 \cdot \mathrm{Tr}(\boldsymbol{D} \boldsymbol{\Lambda} \boldsymbol{D}^\top \boldsymbol{D} \boldsymbol{\Lambda}^{1/2} \boldsymbol{G}^\top \boldsymbol{G} \boldsymbol{\Lambda}^{1/2} \boldsymbol{D}^\top (\boldsymbol{D} \boldsymbol{\Lambda}^{1/2} \boldsymbol{G}^\top \boldsymbol{G} \boldsymbol{\Lambda}^{1/2} \boldsymbol{D}^\top + p\lambda \boldsymbol{I})^{-2}) \\
&= \sigma^2 \cdot \mathrm{Tr}(\boldsymbol{\Lambda} \boldsymbol{D}^\top (\boldsymbol{D} \boldsymbol{K} \boldsymbol{D}^\top + p\lambda \boldsymbol{I})^{-1} \boldsymbol{D} \boldsymbol{K} \boldsymbol{D}^\top (\boldsymbol{D} \boldsymbol{K} \boldsymbol{D}^\top + p\lambda \boldsymbol{I})^{-1} \boldsymbol{D}) \,,
\end{aligned}
$$

then we directly use Eq. (12) with $\boldsymbol{T} = \boldsymbol{D}$, $\boldsymbol{\Sigma} = \boldsymbol{K}$, $\boldsymbol{A} = \boldsymbol{\Lambda}$, $\boldsymbol{B} = \boldsymbol{K}$ and obtain

$$
\begin{aligned}
&\mathrm{Tr}(\boldsymbol{\Lambda} \boldsymbol{D}^\top (\boldsymbol{D} \boldsymbol{K} \boldsymbol{D}^\top + p\lambda \boldsymbol{I})^{-1} \boldsymbol{D} \boldsymbol{K} \boldsymbol{D}^\top (\boldsymbol{D} \boldsymbol{K} \boldsymbol{D}^\top + p\lambda \boldsymbol{I})^{-1} \boldsymbol{D}) \\
&\sim \mathrm{Tr}(\boldsymbol{\Lambda} (\boldsymbol{K} + \hat{\lambda} \boldsymbol{I})^{-1} \boldsymbol{K} (\boldsymbol{K} + \hat{\lambda} \boldsymbol{I})^{-1}) + \hat{\lambda}^2 \mathrm{Tr}(\boldsymbol{\Lambda} (\boldsymbol{K} + \hat{\lambda} \boldsymbol{I})^{-2}) \cdot \mathrm{Tr}(\boldsymbol{K} (\boldsymbol{K} + \hat{\lambda} \boldsymbol{I})^{-2}) \cdot \frac{1}{p-n} \\
&\sim \mathrm{Tr}(\boldsymbol{\Lambda}^2 \boldsymbol{G}^\top (\boldsymbol{G} \boldsymbol{\Lambda} \boldsymbol{G}^\top)^{-2} \boldsymbol{G}) + \mathrm{Tr}(\boldsymbol{\Lambda} (\boldsymbol{I} - \boldsymbol{\Lambda}^{1/2} \boldsymbol{G}^\top (\boldsymbol{G} \boldsymbol{\Lambda} \boldsymbol{G}^\top)^{-1} \boldsymbol{G} \boldsymbol{\Lambda}^{1/2})) \cdot \mathrm{Tr}((\boldsymbol{G} \boldsymbol{\Lambda} \boldsymbol{G}^\top)^{-1}) \cdot \frac{1}{p-n} \,,
\end{aligned}
$$

where the implicit regularization parameter $\hat{\lambda}$ is defined by Eq. (68).

For the bias term, first we have

$$\begin{aligned} p^{-1/2}\boldsymbol{\theta}_*^\top \boldsymbol{F}^\top(\boldsymbol{Z}^\top\boldsymbol{Z}+\lambda\boldsymbol{I})^{-1}\boldsymbol{Z}^\top\boldsymbol{G}\boldsymbol{\theta}_* &= \mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{F}^\top(\boldsymbol{F}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{F}^\top+p\lambda\boldsymbol{I})^{-1}\boldsymbol{F}\boldsymbol{G}^\top\boldsymbol{G}) \\ &= \mathrm{Tr}(\boldsymbol{\Lambda}^{1/2}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{\Lambda}^{1/2}\boldsymbol{D}^\top(\boldsymbol{D}\boldsymbol{K}\boldsymbol{D}^\top+p\lambda\boldsymbol{I})^{-1}\boldsymbol{D})\,, \end{aligned}$$

then we use Eq. (11) with $\boldsymbol{T}=\boldsymbol{D}$, $\boldsymbol{\Sigma}=\boldsymbol{K}$, $\boldsymbol{A}=\boldsymbol{\Lambda}^{1/2}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{\Lambda}^{1/2}$ and obtain

$$\mathrm{Tr}(\boldsymbol{\Lambda}^{1/2}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{\Lambda}^{1/2}\boldsymbol{D}^\top(\boldsymbol{D}\boldsymbol{K}\boldsymbol{D}^\top+p\lambda\boldsymbol{I})^{-1}\boldsymbol{D}) \sim \mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{\Lambda}\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{\Lambda}\boldsymbol{G}^\top)^{-1}\boldsymbol{G})\,.$$

Furthermore, we use Eq. (12) with $\boldsymbol{T}=\boldsymbol{D}$, $\boldsymbol{\Sigma}=\boldsymbol{K}$, $\boldsymbol{A}=\boldsymbol{\Lambda}^{1/2}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\Lambda}^{1/2}$, $\boldsymbol{B}=\boldsymbol{\Lambda}$ and obtain

$$\begin{aligned} &\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top\boldsymbol{Z}(\boldsymbol{Z}^\top\boldsymbol{Z}+\lambda\boldsymbol{I})^{-1}\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}(\boldsymbol{Z}^\top\boldsymbol{Z}+\lambda\boldsymbol{I})^{-1}\boldsymbol{Z}^\top\boldsymbol{G}\boldsymbol{\theta}_* \\ &= \mathrm{Tr}(\boldsymbol{\Lambda}^{1/2}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\Lambda}^{1/2}\boldsymbol{D}^\top(\boldsymbol{D}\boldsymbol{K}\boldsymbol{D}^\top+p\lambda\boldsymbol{I})^{-1}\boldsymbol{D}\boldsymbol{\Lambda}\boldsymbol{D}^\top(\boldsymbol{D}\boldsymbol{K}\boldsymbol{D}^\top+p\lambda\boldsymbol{I})^{-1}\boldsymbol{D}) \\ &\sim \mathrm{Tr}(\boldsymbol{\Lambda}^{1/2}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\Lambda}^{1/2}(\boldsymbol{K}+\hat{\lambda}\boldsymbol{I})^{-1}\boldsymbol{\Lambda}(\boldsymbol{K}+\hat{\lambda}\boldsymbol{I})^{-1}) \\ &\quad+\hat{\lambda}^2\mathrm{Tr}(\boldsymbol{\Lambda}^{1/2}\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top\boldsymbol{G}\boldsymbol{\Lambda}^{1/2}(\boldsymbol{K}+\hat{\lambda}\boldsymbol{I})^{-2})\cdot\mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{K}+\hat{\lambda}\boldsymbol{I})^{-2})\cdot\frac{1}{p-n} \\ &\sim \mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{\Lambda}\boldsymbol{G}^\top)^{-1}\boldsymbol{G}\boldsymbol{\Lambda}^2\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{\Lambda}\boldsymbol{G}^\top)^{-1}\boldsymbol{G}) \\ &\quad+\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{\Lambda}\boldsymbol{G}^\top)^{-1}\boldsymbol{G})\cdot\mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{I}-\boldsymbol{\Lambda}^{1/2}\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{\Lambda}\boldsymbol{G}^\top)^{-1}\boldsymbol{G}\boldsymbol{\Lambda}^{1/2}))\cdot\frac{1}{p-n}\,. \end{aligned}$$

In the next, we are ready to eliminate the randomness over $\boldsymbol{G}$.

Over-parameterized regime: deterministic equivalent over $\boldsymbol{G}$ For the variance term, we use Eq. (53) to obtain

$$\mathrm{Tr}(\boldsymbol{\Lambda}^2\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{\Lambda}\boldsymbol{G}^\top)^{-2}\boldsymbol{G}) \sim \frac{\mathrm{d}f_2(\lambda_n)}{n-\mathrm{d}f_2(\lambda_n)}\,.$$

Then we use Eq. (11) to obtain

$$\mathrm{Tr}(\boldsymbol{\Lambda}^2\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{\Lambda}\boldsymbol{G}^\top)^{-1}\boldsymbol{G}) \sim \mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n)^{-1}),$$

where λ_n is defined by $\mathrm{d}f_1(\lambda_n)=n$. Hence we have

$$\mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{I}-\boldsymbol{\Lambda}^{1/2}\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{\Lambda}\boldsymbol{G}^\top)^{-1}\boldsymbol{G}\boldsymbol{\Lambda}^{1/2})) \sim n\lambda_n.$$

Combine the above equivalents, we have

$$\begin{aligned} \mathcal{V}_{\mathcal{R},0}^{\mathrm{RFM}} &\sim \sigma^2\cdot\frac{\mathrm{d}f_2(\lambda_n)}{n-\mathrm{d}f_2(\lambda_n)}+\sigma^2\cdot\frac{n}{p-n} \\ &= \frac{\sigma^2\mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n\boldsymbol{I})^{-2})}{n-\mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n\boldsymbol{I})^{-2})}+\frac{\sigma^2 n}{p-n}\,. \end{aligned}$$

For the bias term, we first use Eq. (11) to obtain

$$\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{\Lambda}\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{\Lambda}\boldsymbol{G}^\top)^{-1}\boldsymbol{G}) \sim \mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\lambda_n)^{-1})\,.$$

Moreover, we use Eq. (12) to obtain

$$\begin{aligned}&\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{\Lambda}\boldsymbol{G}^\top)^{-1}\boldsymbol{G}\boldsymbol{\Lambda}^2\boldsymbol{G}^\top(\boldsymbol{G}\boldsymbol{\Lambda}\boldsymbol{G}^\top)^{-1}\boldsymbol{G})\\ \sim\ &\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n)^{-2})+\lambda_n^2\cdot\mathrm{Tr}(\boldsymbol{\theta}_*\boldsymbol{\theta}_*^\top(\boldsymbol{\Lambda}+\lambda_n)^{-2})\cdot\frac{\mathrm{d}f_2(\lambda_n)}{n-\mathrm{d}f_2(\lambda_n)}.\end{aligned}$$

Accordingly, we finally conclude that

$$\begin{aligned}\mathcal{B}_{\mathcal{R},0}^{\mathrm{RFM}}&\sim\lambda_n^2\boldsymbol{\theta}_*^\top(\boldsymbol{\Lambda}+\lambda_n\boldsymbol{I})^{-2}\boldsymbol{\theta}_*\cdot\frac{n}{n-\mathrm{d}f_2(\lambda_n)}+\lambda_n\boldsymbol{\theta}_*^\top(\boldsymbol{\Lambda}+\lambda_n\boldsymbol{I})^{-1}\boldsymbol{\theta}_*\cdot\frac{n}{p-n}\\ &=\frac{n\lambda_n^2\langle\boldsymbol{\theta}_*,(\boldsymbol{\Lambda}+\lambda_n\boldsymbol{I})^{-2}\boldsymbol{\theta}_*\rangle}{n-\mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n\boldsymbol{I})^{-2})}+\frac{n\lambda_n\langle\boldsymbol{\theta}_*,(\boldsymbol{\Lambda}+\lambda_n\boldsymbol{I})^{-1}\boldsymbol{\theta}_*\rangle}{p-n}.\end{aligned}$$

■

G.2. Non-asymptotic deterministic equivalence for random features ridge regression

Here we present the proof for the non-asymptotic results on the variance and then discuss the related results on bias due to the insufficient deterministic equivalence.

G.2.1. PROOF ON THE VARIANCE TERM

Theorem 36 (Deterministic equivalence of variance part of the ℓ_2 norm) *Assume the features $\{\boldsymbol{z}_i\}_{i\in[n]}$ and $\{\boldsymbol{f}_j\}_{j\in[p]}$ satisfy Theorem 1 with a constant $C_*>0$. Then for any $D,K>0$, there exist constant $\eta_*\in(0,1/2)$ and $C_{*,D,K}>0$ ensuring the following property holds. For any $n,p\geq C_{*,D,K}$, $\lambda>0$, if the following condition is satisfied:*

$$\lambda\geq n^{-K},\quad \gamma_\lambda\geq p^{-K},\quad \widetilde{\rho}_\lambda(n,p)^{5/2}\log^{3/2}(n)\leq K\sqrt{n},\quad \widetilde{\rho}_\lambda(n,p)^2\cdot\rho_{\gamma_+}(p)^7\log^4(p)\leq K\sqrt{p},$$

then with probability at least $1-n^{-D}-p^{-D}$, we have that

$$\left|\mathcal{V}_{\mathcal{N},\lambda}^{\mathrm{RFM}}-\mathsf{V}_{\mathsf{N},\lambda}^{\mathrm{RFM}}\right|\leq C_{x,D,K}\cdot\mathcal{E}_V(n,p)\cdot\mathsf{V}_{\mathsf{N},\lambda}^{\mathrm{RFM}}.$$

where the approximation rate is given by

$$\mathcal{E}_V(n,p):=\frac{\widetilde{\rho}_\lambda(n,p)^6\log^{5/2}(n)}{\sqrt{n}}+\frac{\widetilde{\rho}_\lambda(n,p)^2\cdot\rho_{\gamma_+}(p)^7\log^3(p)}{\sqrt{p}}.$$

Proof [Proof of Theorem 36] First, note that $\mathcal{V}_{\mathcal{N},\lambda}^{\mathrm{RFM}}$ can be written in terms of the functional Φ_4 defined in Eq. (36):

$$\mathcal{V}_{\mathcal{N},\lambda}^{\mathrm{RFM}}=\sigma^2\cdot n\Phi_4(\boldsymbol{Z};\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}^{-1},\lambda).$$

Recall that $\mathcal{A}_{\mathcal{F}}$ is the event defined in [12, Eq. (79)]. Under the assumptions, we have

$$\mathbb{P}(\mathcal{A}_{\mathcal{F}})\geq 1-p^{-D}.$$

Hence, applying Theorem 13 for $\boldsymbol{F}\in\mathcal{A}_{\mathcal{F}}$ and via union bound, we obtain that with probability at least $1-p^{-D}-n^{-D}$,

$$\left|n\Phi_4(\boldsymbol{Z};\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}^{-1},\lambda)-n\widetilde{\Phi}_5(\boldsymbol{F};\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}^{-1},p\nu_1)\right|\leq C_{*,D,K}\cdot\mathcal{E}_1(p,n)\cdot n\widetilde{\Phi}_5(\boldsymbol{F};\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}^{-1},p\nu_1),\qquad(69)$$

and we recall the expressions

$$n\widetilde{\Phi}_5(\boldsymbol{F};\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}^{-1},p\nu_1)=\frac{\widetilde{\Phi}_6(\boldsymbol{F};\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}^{-1},p\nu_1)}{n-\widetilde{\Phi}_6(\boldsymbol{F};\boldsymbol{I},p\nu_1)},\qquad \widetilde{\Phi}_6(\boldsymbol{F};\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}^{-1},p\nu_1)=p\mathrm{Tr}\big(\boldsymbol{F}\boldsymbol{F}^\top(\boldsymbol{F}\boldsymbol{F}^\top+p\nu_1)^{-2}\big).$$

From [12, Lemma B.11], we have with probability at least $1-p^{-D}$

$$\left|p\mathrm{Tr}(\boldsymbol{F}\boldsymbol{F}^\top(\boldsymbol{F}\boldsymbol{F}^\top+p\nu_1)^{-2})-p^2\Psi_3(\nu_2;\boldsymbol{\Lambda}^{-1})\right|\leq C_{*,D,K}\cdot\rho_{\gamma_+}(p)\cdot\mathcal{E}_3(p)\cdot p^2\Psi_3(\nu_2;\boldsymbol{\Lambda}^{-1}),$$

where the approximation rate $\mathcal{E}_3(p)$ is given by

$$\mathcal{E}_3(p):=\frac{\rho_{\gamma_+}(p)^6\log^3(p)}{\sqrt{p}}.$$

Furthermore, from the proof of [12, Theorem B.12], we have with probability at least $1-p^{-D}$,

$$\left|(1-n^{-1}\widetilde{\Phi}_6(\boldsymbol{F};\boldsymbol{I},p\nu_1))^{-1}-(1-\Upsilon(\nu_1,\nu_2))^{-1}\right|\leq C_{*,D,K}\cdot\widetilde{\rho}_\lambda(n,p)\rho_{\gamma_+}(p)\mathcal{E}_3(p)\cdot(1-\Upsilon(\nu_1,\nu_2))^{-1}.$$

Combining those two bounds, we obtain

$$\left|\frac{\widetilde{\Phi}_6(\boldsymbol{F};\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}^{-1},p\nu_1)}{n-\widetilde{\Phi}_6(\boldsymbol{F};\boldsymbol{I},p\nu_1)}-\frac{p^2\Psi_3(\nu_2;\boldsymbol{\Lambda}^{-1})}{n-n\Upsilon(\nu_1,\nu_2)}\right|\leq C_{*,D,K}\cdot\widetilde{\rho}_\lambda(n,p)\rho_{\gamma_+}(p)\mathcal{E}_3(p)\cdot\frac{p^2\Psi_3(\nu_2;\boldsymbol{\Lambda}^{-1})}{n-n\Upsilon(\nu_1,\nu_2)}.$$

Finally, we can combine this bound with Eq. (69) to obtain via union bound that with probability at least $1-n^{-D}-p^{-D}$,

$$\left|n\Phi_4(\boldsymbol{Z};\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}^{-1},\lambda)-\frac{p^2\Psi_3(\nu_2;\boldsymbol{\Lambda}^{-1})}{n-n\Upsilon(\nu_1,\nu_2)}\right|\leq C_{*,D,K}\left\{\mathcal{E}_1(p,n)+\widetilde{\rho}_\lambda(n,p)\rho_{\gamma_+}(p)\mathcal{E}_3(p)\right\}\frac{p^2\Psi_3(\nu_2;\boldsymbol{\Lambda}^{-1})}{n-n\Upsilon(\nu_1,\nu_2)}.$$

Replacing the rate $\mathcal{E}_j$ by their expressions conclude the proof of this theorem. ■

G.2.2. DISCUSSION ON THE BIAS TERM

We present the deterministic equivalence of the bias term as an informal result, without a Existing deterministic equivalence results appear insufficient to directly establish this desired bias result. While we believe this is doable under additional assumptions, a complete proof is beyond the scope of this paper..

In the proof of the bias term, deterministic equivalences for functionals of the form

$$\mathrm{Tr}\left(\boldsymbol{A}\left(\boldsymbol{X}^\top\boldsymbol{X}\right)^2(\boldsymbol{X}^\top\boldsymbol{X}+\lambda)^{-2}\right)$$

are required. However, such equivalences are currently unavailable, necessitating the introduction of technical assumptions to leverage the deterministic equivalences of $\Phi_2(\boldsymbol{X};\boldsymbol{A},\lambda)$ and $\Phi_4(\boldsymbol{X};\boldsymbol{A},\lambda)$.

Furthermore, the proof of the bias term in [12] suggests that deriving deterministic equivalences for the bias of the ℓ_2 norm, analogous to [12, Proposition B.7], is also required but remains unresolved.

Addressing these gaps in deterministic equivalence is an important direction for future work, particularly to establish rigorous proofs for the currently missing results.

G.3. Proofs on relationship between test risk and ℓ_2 norm of random feature ridge regression estimator

To derive the relationship between test risk and norm for the random feature model, we first examine the linear relationship in the over-parameterized regime. Next, we analyze the case where $\boldsymbol{\Lambda} = \boldsymbol{I}_m$ with $n < m < \infty$ (finite rank), followed by the relationship under the power-law assumption.

G.3.1. PROOF FOR MIN-NORM INTERPOLATOR IN THE OVER-PARAMETERIZED REGIME

According to the formulation in Theorem 30 and Theorem 35, we have for the under-parameterized regime ($p < n$), we have

$$\mathcal{B}_{\mathcal{N},0}^{\mathrm{RFM}} \sim \mathsf{B}_{\mathsf{N},0}^{\mathrm{RFM}} = \frac{p\langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\lambda_p \boldsymbol{I})^{-2}\boldsymbol{\theta}_*\rangle}{n - \mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_p \boldsymbol{I})^{-2})} + \frac{p\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\lambda_p \boldsymbol{I})^{-1}\boldsymbol{\theta}_*\rangle}{n-p},$$
$$\mathcal{V}_{\mathcal{N},0}^{\mathrm{RFM}} \sim \mathsf{V}_{\mathsf{N},0}^{\mathrm{RFM}} = \frac{\sigma^2 p}{\lambda_p(n-p)},$$

$$\mathcal{B}_{\mathcal{R},0}^{\mathrm{RFM}} \sim \mathsf{B}_{\mathsf{R},0}^{\mathrm{RFM}} = \frac{n\lambda_p\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\lambda_p \boldsymbol{I})^{-1}\boldsymbol{\theta}_*\rangle}{n-p}, \quad \mathcal{V}_{\mathcal{R},0}^{\mathrm{RFM}} \sim \mathsf{V}_{\mathsf{R},0}^{\mathrm{RFM}} = \frac{\sigma^2 p}{n-p}.$$

In the over-parameterized regime ($p > n$), we have

$$\mathcal{B}_{\mathcal{N},0}^{\mathrm{RFM}} \sim \mathsf{B}_{\mathsf{N},0}^{\mathrm{RFM}} = \frac{p\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-1}\boldsymbol{\theta}_*\rangle}{p-n}, \quad \mathcal{V}_{\mathcal{N},0}^{\mathrm{RFM}} \sim \mathsf{V}_{\mathsf{N},0}^{\mathrm{RFM}} = \frac{\sigma^2 p}{\lambda_n(p-n)},$$

$$\mathcal{B}_{\mathcal{R},0}^{\mathrm{RFM}} \sim \mathsf{B}_{\mathsf{R},0}^{\mathrm{RFM}} = \frac{n\lambda_n^2\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2}\boldsymbol{\theta}_*\rangle}{n - \mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2})} + \frac{n\lambda_n\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-1}\boldsymbol{\theta}_*\rangle}{p-n},$$
$$\mathcal{V}_{\mathcal{R},0}^{\mathrm{RFM}} \sim \mathsf{V}_{\mathsf{R},0}^{\mathrm{RFM}} = \frac{\sigma^2\mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2})}{n - \mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2})} + \frac{\sigma^2 n}{p-n}.$$

With these formulations we can introduce the relationship between test risk and norm in the over-parameterized regime as follows.

Proof [Proof of Theorem 31] In the over-parameterized regime ($p > n$), we have

$$\mathsf{N}_0^{\mathrm{RFM}} = \mathsf{B}_{\mathsf{N},0}^{\mathrm{RFM}} + \mathsf{V}_{\mathsf{N},0}^{\mathrm{RFM}} = \frac{p\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-1}\boldsymbol{\theta}_*\rangle}{p-n} + \frac{\sigma^2 p}{\lambda_n(p-n)} = \left[\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-1}\boldsymbol{\theta}_*\rangle + \frac{\sigma^2}{\lambda_n}\right]\frac{p}{p-n}.$$

$$\begin{aligned}\mathsf{R}_0^{\mathrm{RFM}} =& \frac{n\lambda_n^2\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2}\boldsymbol{\theta}_*\rangle}{n - \mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2})} + \frac{n\lambda_n\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-1}\boldsymbol{\theta}_*\rangle}{p-n} + \frac{\sigma^2\mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2})}{n - \mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2})} + \frac{\sigma^2 n}{p-n}\\ =& \frac{n\lambda_n^2\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2}\boldsymbol{\theta}_*\rangle + \sigma^2\mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2})}{n - \mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2})} + \left[n\lambda_n\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-1}\boldsymbol{\theta}_*\rangle + \sigma^2 n\right]\frac{1}{p-n}.\end{aligned}$$

Then we eliminate p and obtain that the deterministic equivalents of the estimator's test risk and norm, $\mathsf{R}_0^{\mathrm{RFM}}$ and $\mathsf{N}_0^{\mathrm{RFM}}$, in over-parameterized regimes ($p > n$) admit

$$\mathsf{R}_0^{\mathrm{RFM}} = \lambda_n \mathsf{N}_0^{\mathrm{RFM}} - \left[\lambda_n\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-1}\boldsymbol{\theta}_*\rangle + \sigma^2\right] + \frac{n\lambda_n^2\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2}\boldsymbol{\theta}_*\rangle + \sigma^2\mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2})}{n - \mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\lambda_n \boldsymbol{I})^{-2})}.$$

■

G.3.2. ISOTROPIC FEATURES WITH FINITE RANK

Corollary 37 (Isotropic features for min-ℓ_2-norm interpolator) *Consider covariance matrix $\mathbf{\Lambda} = \boldsymbol{I}_m$ ($n < m < \infty$), in the over-parameterized regime ($p > n$), the deterministic equivalents R_0^{RFM} and N_0^{RFM} specifies the linear relationship in Eq. (62) as $\mathsf{R}_0^{RFM} = \frac{m-n}{n}\mathsf{N}_0^{RFM} + \frac{2n-m}{m-n}\sigma^2$. While in the under-parameterized regime ($p < n$), we focus on bias and variance separately*

$$\textit{Variance: } \left(\mathsf{V}_{\mathsf{R},0}^{RFM}\right)^2 = \frac{m-n}{n}\mathsf{V}_{\mathsf{R},0}^{RFM}\mathsf{V}_{\mathsf{N},0}^{RFM} + \frac{m\sigma^2}{n}\mathsf{V}_{\mathsf{N},0}^{RFM},$$

$$\begin{aligned}\textit{Bias: } &(m-n)\mathsf{B}_{\mathsf{N},0}^{RFM}(m\mathsf{B}_{\mathsf{R},0}^{RFM} - n\|\boldsymbol{\theta}_*\|_2^2)(m(\mathsf{B}_{\mathsf{R},0}^{RFM})^2 - n\|\boldsymbol{\theta}_*\|_2^4)\\ &= nm(\mathsf{B}_{\mathsf{R},0}^{RFM} - \|\boldsymbol{\theta}_*\|_2^2)^2[m(\mathsf{B}_{\mathsf{R},0}^{RFM})^2 + n\|\boldsymbol{\theta}_*\|_2^2\mathsf{B}_{\mathsf{R},0}^{RFM} - 2n\|\boldsymbol{\theta}_*\|_2^4].\end{aligned}$$

Remark: In the under-parameterized regime, $\mathsf{V}_{\mathsf{R},0}^{RFM}$ and $\mathsf{V}_{\mathsf{N},0}^{RFM}$ are related by a hyperbola, the asymptote of which is $\mathsf{V}_{\mathsf{R},0}^{RFM} = \frac{m-n}{n}\mathsf{V}_{\mathsf{N},0}^{RFM} + \frac{m}{m-n}\sigma^2$. Further, for $p \to n$, we have $\mathsf{B}_{\mathsf{R},0}^{RFM} \approx \frac{m-n}{n}\mathsf{B}_{\mathsf{R},0}^{RFM} + \frac{2(m-n)}{m}\|\boldsymbol{\theta}_*\|_2^2$, see discussion in Appendix G.3.

Next we present the proof of Theorem 37 with $\mathbf{\Lambda} = \boldsymbol{I}_m$.

Proof [Proof of Theorem 37] Here we consider the case where $\mathbf{\Lambda} = \boldsymbol{I}_m$. Under this condition, the definitions of λ_p and λ_n above are simplified to $\frac{m}{1+\lambda_p} = p$ and $\frac{m}{1+\lambda_n} = n$, respectively. Consequently, λ_p and λ_n have explicit expressions given by $\lambda_p = \frac{m-p}{p}$ and $\lambda_n = \frac{m-n}{n}$, respectively.

First, in the over-parameterized regime ($p > n$), we have

$$\mathsf{B}_{\mathsf{N},0}^{RFM} = \frac{p\frac{1}{1+\lambda_n}\|\boldsymbol{\theta}_*\|_2^2}{p-n} = \frac{np}{m(p-n)}\|\boldsymbol{\theta}_*\|_2^2, \quad \mathsf{V}_{\mathsf{N},0}^{RFM} = \frac{\sigma^2 p}{\lambda_n(p-n)} = \frac{\sigma^2 np}{(m-n)(p-n)}.$$

$$\begin{aligned}\mathsf{B}_{\mathsf{R},0}^{RFM} =& \frac{n\lambda_n^2\frac{1}{(1+\lambda_n)^2}\|\boldsymbol{\theta}_*\|_2^2}{n - \frac{m}{(1+\lambda_n)^2}} + \frac{n\lambda_n\frac{1}{1+\lambda_n}\|\boldsymbol{\theta}_*\|_2^2}{p-n} = \frac{p(m-n)}{m(p-n)}\|\boldsymbol{\theta}_*\|_2^2,\\ \mathsf{V}_{\mathsf{R},0}^{RFM} =& \frac{\sigma^2\frac{m}{(1+\lambda_n)^2}}{n - \frac{m}{(1+\lambda_n)^2}} + \frac{\sigma^2 n}{p-n} = \frac{\sigma^2 n}{m-n} + \frac{\sigma^2 n}{p-n}.\end{aligned}$$

We eliminate p and obtain that the relationship between $\mathsf{V}_{\mathsf{R},0}^{RFM}$ and $\mathsf{V}_{\mathsf{N},0}^{RFM}$ is

$$\mathsf{V}_{\mathsf{R},0}^{RFM} = \frac{m-n}{n}\mathsf{V}_{\mathsf{N},0}^{RFM} + \frac{2n-m}{m-n}\sigma^2.$$

similarly, the relationship between $\mathsf{B}_{\mathsf{R},0}^{RFM}$ and $\mathsf{B}_{\mathsf{N},0}^{RFM}$ is

$$\mathsf{B}_{\mathsf{R},0}^{RFM} = \frac{m-n}{n}\mathsf{B}_{\mathsf{N},0}^{RFM}.$$

Combining the above two relationship, we obtain the relationship between test risk R_0^{RFM} and norm N_0^{RFM} as

$$\mathsf{R}_0^{RFM} = \frac{m-n}{n}\mathsf{N}_0^{RFM} + \frac{2n-m}{m-n}\sigma^2.$$

Accordingly, in the under-parameterized regime ($p < n$), we have

$$\begin{aligned}
\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} =& \frac{p\frac{1}{(1+\lambda_p)^2}\|\boldsymbol{\theta}_*\|_2^2}{n-\frac{m}{(1+\lambda_p)^2}} + \frac{p\frac{1}{1+\lambda_p}\|\boldsymbol{\theta}_*\|_2^2}{n-p} = \frac{p}{m}\left(\frac{p^2}{nm-p^2}+\frac{p}{n-p}\right)\|\boldsymbol{\theta}_*\|_2^2\,,\\
\mathsf{V}_{\mathsf{N},0}^{\mathrm{R}FM} =& \frac{\sigma^2 p}{\lambda_p(p-n)} = \frac{\sigma^2 p^2}{(m-p)(n-p)}\,.
\end{aligned}$$

$$\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} = \frac{n\lambda_p\frac{1}{1+\lambda_p}\|\boldsymbol{\theta}_*\|_2^2}{n-p} = \frac{n(m-p)}{m(n-p)}\|\boldsymbol{\theta}_*\|_2^2\,,\quad \mathsf{V}_{\mathsf{R},0}^{\mathrm{R}FM} = \frac{\sigma^2 p}{n-p}\,.$$

Then we eliminate p and obtain that, in the under-parameterized regime ($p < n$), the relationship between $\mathsf{V}_{\mathsf{R},0}^{\mathrm{R}FM}$ and $\mathsf{V}_{\mathsf{N},0}^{\mathrm{R}FM}$ is

$$\mathsf{V}_{\mathsf{R},0}^{\mathrm{R}FM} = \frac{(m-n)\mathsf{V}_{\mathsf{N},0}^{\mathrm{R}FM} + \sqrt{(m-n)^2(\mathsf{V}_{\mathsf{N},0}^{\mathrm{R}FM})^2 + 4nm\sigma^2\mathsf{V}_{\mathsf{N},0}^{\mathrm{R}FM}}}{2n}\,,$$

which can be further simplified as a hyperbolic function

$$\left(\mathsf{V}_{\mathsf{R},0}^{\mathrm{R}FM}\right)^2 = \frac{m-n}{n}\mathsf{V}_{\mathsf{R},0}^{\mathrm{R}FM}\mathsf{V}_{\mathsf{N},0}^{\mathrm{R}FM} + \frac{m\sigma^2}{n}\mathsf{V}_{\mathsf{N},0}^{\mathrm{R}FM}\,,$$

and the asymptote of this hyperbola is $\mathsf{V}_{\mathsf{R},0}^{\mathrm{R}FM} = \frac{m-n}{n}\mathsf{V}_{\mathsf{N},0}^{\mathrm{R}FM} + \frac{m}{m-n}\sigma^2$.

Besides, we eliminate p and obtain the relationship between $\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM}$ and $\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM}$ as

$$\begin{aligned}
&\frac{\|\boldsymbol{\theta}_*\|_2^6 n^2\left(2\|\boldsymbol{\theta}_*\|_2^2 + \mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} - \frac{\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} n}{m}\right)}{m} = (\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM})^4 n + (\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM})^2\|\boldsymbol{\theta}_*\|_2^2 n\left(\|\boldsymbol{\theta}_*\|_2^2 + \mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} - \frac{4\|\boldsymbol{\theta}_*\|_2^2 n}{m} - \frac{\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} n}{m}\right)\\
&+ \mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM}\|\boldsymbol{\theta}_*\|_2^4 n\left(\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} + \frac{5\|\boldsymbol{\theta}_*\|_2^2 n}{m} - \frac{\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} n}{m}\right) + (\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM})^3\left(-\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} m - 2\|\boldsymbol{\theta}_*\|_2^2 n + \mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} n + \frac{\|\boldsymbol{\theta}_*\|_2^2 n^2}{m}\right),
\end{aligned}$$

which can be simplified to

$$\begin{aligned}
&\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM}(m-n)(m\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} - n\|\boldsymbol{\theta}_*\|_2^2)(m(\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM})^2 - n\|\boldsymbol{\theta}_*\|_2^4)\\
&= nm(\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} - \|\boldsymbol{\theta}_*\|_2^2)^2(m(\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM})^2 - 2n\|\boldsymbol{\theta}_*\|_2^4 + n\|\boldsymbol{\theta}_*\|_2^2\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM})\,.
\end{aligned}$$

We can find that in this case, the relationship can be easily written as

$$\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} = \frac{nm(\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} - \|\boldsymbol{\theta}_*\|_2^2)^2(m(\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM})^2 - 2n\|\boldsymbol{\theta}_*\|_2^4 + n\|\boldsymbol{\theta}_*\|_2^2\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM})}{(m-n)(m\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} - n\|\boldsymbol{\theta}_*\|_2^2)(m(\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM})^2 - n\|\boldsymbol{\theta}_*\|_2^4)}\,.$$

Next we will show that when $p \to n$, which also implies that $\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} \to \infty$ and $\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} \to \infty$, this relationship is approximately linear.

Recall that the relationship between $\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM}$ and $\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM}$ is given by $\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} = \frac{(m-n)}{n}\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM}$, and is equivalent to $\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} = \frac{n}{(m-n)}\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} := f(\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM})$. We then do a difference and get

$$\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} - f(\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM}) = \frac{nm(\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} - \|\boldsymbol{\theta}_*\|_2^2)^2(m(\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM})^2 - 2n\|\boldsymbol{\theta}_*\|_2^4 + n\|\boldsymbol{\theta}_*\|_2^2\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM})}{(m-n)(m\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} - n\|\boldsymbol{\theta}_*\|_2^2)(m(\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM})^2 - n\|\boldsymbol{\theta}_*\|_2^4)} - \frac{n}{m-n}\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM}\,,$$

then take $\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} \to \infty$ and we get

$$\lim_{\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} \to \infty} \mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} - f(\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM}) = -\frac{2n}{m}\|\boldsymbol{\theta}_*\|_2^2 .$$

Finally, organizing this equation and we get

$$\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} \approx \frac{m-n}{n}\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} + \frac{2(m-n)}{m}\|\boldsymbol{\theta}_*\|_2^2 .$$

■

G.3.3. PROOF ON FEATURES UNDER POWER LAW ASSUMPTION

Proof [Proof of Theorem 33] First, we use integral approximation to give approximations to some quantities commonly used in deterministic equivalence to prepare for the subsequent derivations.

According to the integral approximation in [47, Lemma 1], we have

$$\mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-1}) \approx C_1 \nu_2^{-\frac{1}{\alpha}},\ \mathrm{Tr}(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\nu_2)^{-2}) \approx C_2 \nu_2^{-\frac{1}{\alpha}},\ \mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}) \approx (C_1 - C_2)\nu_2^{-\frac{1}{\alpha}-1}, \quad (70)$$

where C_1 and C_2 are

$$C_1 = \frac{\pi}{\alpha \sin(\pi/\alpha)}, \quad C_2 = \frac{\pi(\alpha-1)}{\alpha^2 \sin(\pi/\alpha)}, \quad \text{with } C_1 > C_2 . \quad (71)$$

Besides, according to definition of $T(\nu)$ Appendix B.7, we have

$$\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2)^{-1}\boldsymbol{\theta}_* \rangle = T_{2r,1}^1(\nu_2) \approx C_3 \nu_2^{(2r-1)\wedge 0},$$
$$\langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_* \rangle = T_{2r+1,2}^1(\nu_2) \approx C_4 \nu_2^{(2r-1)\wedge 0}.$$

When $r \in (0, \frac{1}{2})$, according to the integral approximation, we have

$$C_3 = \frac{\pi}{\alpha \sin(2\pi r)}, \quad C_4 = \frac{2\pi r}{\alpha \sin(2\pi r)}, \quad \text{with } C_3 > C_4. \quad (72)$$

Otherwise, if $r \in [\frac{1}{2}, \infty)$, we have

$$\frac{1}{\alpha(2r-1)} < C_3 < \frac{1}{\alpha(2r-1)} + 1, \quad \frac{1}{\alpha(2r-1)} < C_4 < \frac{1}{\alpha(2r-1)} + 1, \quad \text{with } C_3 > C_4.$$

For $\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_* \rangle$, we have to discuss its approximation in the case $r \in (0, \frac{1}{2})$, $r \in [\frac{1}{2}, 1)$ and $r \in [\frac{1}{2}, \infty)$ separately.

$$\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_* \rangle \approx \begin{cases} (C_3 - C_4)\nu_2^{2r-2}, & \text{if } r \in (0, \frac{1}{2}) ; \\ C_5 \nu_2^{2r-2}, & \text{if } r \in [\frac{1}{2}, 1) ; \\ C_6, & \text{if } r \in [1, \infty) , \end{cases}$$

where $\frac{1}{2\alpha(r-1)} < C_6 < \frac{1}{2\alpha(r-1)} + 1$.

With the results of the integral approximation above, we next derive the relationship between $\mathsf{R}_0^{\mathrm{R}FM}$ and $\mathsf{N}_0^{\mathrm{R}FM}$ separately in over-parameterized regime ($p > n$) and under-parameterized regime ($p < n$).

The relationship in over-parameterized regime ($p > n$) According to the self-consistent equation

$$1 + \frac{n}{p} - \sqrt{\left(1 - \frac{n}{p}\right)^2 + \frac{4\lambda}{p\nu_2}} = \frac{2}{p} \operatorname{Tr}\left(\mathbf{\Lambda}\left(\mathbf{\Lambda} + \nu_2\right)^{-1}\right),$$

$$\nu_1 = \frac{\nu_2}{2}\left[1 - \frac{n}{p} + \sqrt{\left(1 - \frac{n}{p}\right)^2 + \frac{4\lambda}{p\nu_2}}\right],$$

In the over-parameterized regime ($p > n$), as $\lambda \to 0$, for the first equation, $\frac{4\lambda}{p\nu_2}$ will approach 0, and $\operatorname{Tr}(\mathbf{\Lambda}(\mathbf{\Lambda} + \nu_2)^{-1})$ will converge to n. Consequently, by Eq. (70), ν_2 will converge to the constant $(\frac{n}{C_1})^{-\alpha}$. Furthermore, from the second equation, ν_1 will converge to $\nu_2(1 - \frac{n}{p})$. Thus, according to Eq. (70), we have

$$\operatorname{Tr}(\mathbf{\Lambda}(\mathbf{\Lambda} + \nu_2)^{-1}) \approx n, \quad \operatorname{Tr}(\mathbf{\Lambda}^2(\mathbf{\Lambda} + \nu_2)^{-2}) \approx \frac{C_2}{C_1} n, \quad \operatorname{Tr}(\mathbf{\Lambda}(\mathbf{\Lambda} + \nu_2)^{-2}) \approx (C_1 - C_2)(\frac{n}{C_1})^{\alpha+1}.$$

Thus, in the over-parameterized regime

$$\begin{aligned}
\Upsilon(\nu_1, \nu_2) &= \frac{p}{n}\left[\left(1 - \frac{\nu_1}{\nu_2}\right)^2 + \left(\frac{\nu_1}{\nu_2}\right)^2 \frac{\operatorname{Tr}\left(\mathbf{\Lambda}^2(\mathbf{\Lambda} + \nu_2)^{-2}\right)}{p - \operatorname{Tr}\left(\mathbf{\Lambda}^2(\mathbf{\Lambda} + \nu_2)^{-2}\right)}\right] \\
&\approx \frac{p}{n}\left[\left(\frac{n}{p}\right)^2 + \left(1 - \frac{n}{p}\right)^2 \frac{\operatorname{Tr}\left(\mathbf{\Lambda}^2(\mathbf{\Lambda} + \nu_2)^{-2}\right)}{p - \operatorname{Tr}\left(\mathbf{\Lambda}^2(\mathbf{\Lambda} + \nu_2)^{-2}\right)}\right] \\
&\approx \frac{\frac{C_2}{C_1}p - 2\frac{C_2}{C_1}n + n}{p - \frac{C_2}{C_1}n},
\end{aligned}$$

$$\chi(\nu_2) = \frac{\operatorname{Tr}(\mathbf{\Lambda}(\mathbf{\Lambda} + \nu_2)^{-2})}{p - \operatorname{Tr}(\mathbf{\Lambda}^2(\mathbf{\Lambda} + \nu_2)^{-2})} \approx \frac{(C_1 - C_2)(\frac{n}{C_1})^{\alpha+1}}{p - \frac{C_2}{C_1}n}.$$

According to the approximation, we have the deterministic equivalents of variance terms

$$\begin{aligned}
\mathsf{V}_{\mathsf{R},0}^{\mathbb{R}FM} &= \sigma^2 \frac{\Upsilon(\nu_1, \nu_2)}{1 - \Upsilon(\nu_1, \nu_2)} \approx \sigma^2 \frac{(C_1 - 2C_2)n + C_2 p}{(C_1 - C_2)(p - n)}, \\
\mathsf{V}_{\mathsf{N},0}^{\mathbb{R}FM} &= \sigma^2 \frac{p}{n} \frac{\chi(\nu_2)}{1 - \Upsilon(\nu_1, \nu_2)} \approx \sigma^2 \frac{(\frac{n}{C_1})^{\alpha} p}{p - n}.
\end{aligned}$$

Then recall Eq. (71), we eliminate p and obtain

$$\mathsf{V}_{\mathsf{R},0}^{\mathbb{R}FM} \approx \left(\frac{n}{C_1}\right)^{-\alpha} \mathsf{V}_{\mathsf{N},0}^{\mathbb{R}FM} + \sigma^2 \frac{2C_2 - C_1}{C_1 - C_2} = \left(\frac{n}{C_1}\right)^{-\alpha} \mathsf{V}_{\mathsf{N},0}^{\mathbb{R}FM} + \sigma^2(\alpha - 2). \tag{73}$$

For the bias terms, due to the varying approximation behaviors of the quantities containing $\boldsymbol{\theta}_*$ for different values of r, we have to discuss their approximations in the conditions $r \in (0, \frac{1}{2})$, $r \in [\frac{1}{2}, 1)$ and $r \in [\frac{1}{2}, \infty)$ separately.

Condition 1: $r \in (0, \frac{1}{2})$

$$
\begin{aligned}
\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} &= \frac{\nu_2^2}{1-\Upsilon(\nu_1,\nu_2)} \left[\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_* \rangle + \chi(\nu_2) \langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_* \rangle \right] \\
&\approx \frac{\left(\frac{n}{C_1}\right)^{-2\alpha r} ((C_1C_4 - C_2C_3)n + C_1(C_3-C_4)p)}{(C1-C2)(p-n)}, \\
\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} &= \frac{\nu_2}{\nu_1} \langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2)^{-1}\boldsymbol{\theta}_* \rangle - \frac{\lambda}{n}\frac{\nu_2^2}{\nu_1^2} \frac{\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_* \rangle + \chi(\nu_2) \langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_* \rangle}{1-\Upsilon(\nu_1,\nu_2)} \\
&\approx \frac{\nu_2}{\nu_1} \langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2)^{-1}\boldsymbol{\theta}_* \rangle \\
&\approx \frac{\left(\frac{n}{C_1}\right)^{-\alpha(2r-1)} C_3 p}{p-n}.
\end{aligned}
$$

Then we eliminate p and obtain

$$
\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} \approx \left(\frac{n}{C_1}\right)^{-\alpha} \mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} + \left(\frac{n}{C_1}\right)^{-2\alpha r} \frac{C_2C_3 - C_1C_4}{C_1 - C_2}\,. \tag{74}
$$

Condition 2: $r \in [\frac{1}{2}, 1)$

$$
\begin{aligned}
\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} &= \frac{\nu_2^2}{1-\Upsilon(\nu_1,\nu_2)} \left[\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_* \rangle + \chi(\nu_2) \langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_* \rangle \right] \\
&\approx \frac{\left(\frac{n}{C_1}\right)^{-\alpha} \left(C_1 \left(C_4 n + C_5 \left(\frac{n}{C_1}\right)^{-\alpha(2r-1)} p \right) - C_2 n \left(C_4 + C_5 \left(\frac{n}{C_1}\right)^{-\alpha(2r-1)} \right) \right)}{(C1-C2)(p-n)}, \\
\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} &= \langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_* \rangle \cdot \frac{p}{p - \mathrm{d}f_2(\nu_2)} \\
&\quad + \frac{p}{n}\nu_2^2 \left(\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_* \rangle + \chi(\nu_2) \langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_* \rangle \right) \cdot \frac{\chi(\nu_2)}{1-\Upsilon(\nu_1,\nu_2)} \\
&\approx \frac{\left(C_4 + C_5 \left(\frac{n}{C_1}\right)^{-\alpha(2r-1)} \right) p}{p-n}\,.
\end{aligned}
$$

Then we eliminate p and obtain

$$
\begin{aligned}
\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} &\approx \left(\frac{n}{C_1}\right)^{-\alpha} \mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} + \left(\frac{n}{C_1}\right)^{-\alpha} \frac{-C_1C_4 + C_2C_4 + C_2C_5 \left(\frac{n}{C_1}\right)^{-\alpha(2r-1)}}{C_1 - C_2} \\
&\approx \left(\frac{n}{C_1}\right)^{-\alpha} \mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} - \left(\frac{n}{C_1}\right)^{-\alpha} C_4\,.
\end{aligned}
$$

The last "$\approx$" holds because $\left(\frac{n}{C_1}\right)^{-\alpha(2r-1)} = o(1)$.

Condition 3: $r \in [1, \infty)$

$$
\begin{aligned}
\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} &= \frac{\nu_2^2}{1-\Upsilon(\nu_1,\nu_2)}\left[\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_*\rangle + \chi(\nu_2)\langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_*\rangle\right] \\
&\approx \frac{\left(\frac{n}{C_1}\right)^{-2\alpha}\left(C_1\left(C_4 n\left(\frac{n}{C_1}\right)^{\alpha} + C_6 p\right) - C_2 n\left(C_6 + C_4\left(\frac{n}{C_1}\right)^{\alpha}\right)\right)}{(C1-C2)(p-n)}, \\
\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} &= \langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_*\rangle \cdot \frac{p}{p-\mathrm{d}f_2(\nu_2)} \\
&\quad + \frac{p}{n}\nu_2^2\left(\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_*\rangle + \chi(\nu_2)\langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_*\rangle\right)\cdot\frac{\chi(\nu_2)}{1-\Upsilon(\nu_1,\nu_2)} \\
&\approx \frac{\left(C_4 + C_6\left(\frac{n}{C_1}\right)^{-\alpha}\right)p}{p-n}.
\end{aligned}
$$

Then we eliminate p and obtain

$$
\begin{aligned}
\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} &\approx \left(\frac{n}{C_1}\right)^{-\alpha}\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} + \left(\frac{n}{C_1}\right)^{-\alpha}\frac{-C_1C_4 + C_2C_4 + C_2C_6\left(\frac{n}{C_1}\right)^{-\alpha}}{C_1-C_2} \\
&\approx \left(\frac{n}{C_1}\right)^{-\alpha}\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} - \left(\frac{n}{C_1}\right)^{-\alpha}C_4\,.
\end{aligned}
$$

The last "$\approx$" holds because $\left(\frac{n}{C_1}\right)^{-\alpha(2r-1)} = o(1)$.

Combining the above condition $r \in [\frac{1}{2}, 1)$ and $r \in [1, \infty)$, we have for $r \in [\frac{1}{2}, \infty)$

$$
\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} \approx \left(\frac{n}{C_1}\right)^{-\alpha}\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} - \left(\frac{n}{C_1}\right)^{-\alpha}C_4\,. \tag{75}
$$

From Eqs. (73) to (75), we know that the relationship between $\mathsf{R}_0^{\mathrm{R}FM}$ and $\mathsf{N}_0^{\mathrm{R}FM}$ in the over-parameterized regime can be written as

$$
\mathsf{R}_0^{\mathrm{R}FM} \approx (n/C_\alpha)^{-\alpha}\,\mathsf{N}_0^{\mathrm{R}FM} + C_{n,\alpha,r,1}\,.
$$

The relationship in under-parameterized regime ($p < n$) While in the under-parameterized regime ($p < n$), When $\lambda \to 0$, $\mathrm{Tr}(\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-1})$ will converge to p, which means ν_2 will converge to $(\frac{p}{C_1})^{-\alpha}$ and ν_1 will converge to 0, with $\frac{\lambda}{\nu_1} \to n-p$.

Accordingly, in the under-parameterized regime

$$
\Upsilon(\nu_1,\nu_2) = \frac{p}{n}\left[\left(1-\frac{\nu_1}{\nu_2}\right)^2 + \left(\frac{\nu_1}{\nu_2}\right)^2\frac{\mathrm{Tr}\left(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\nu_2)^{-2}\right)}{p-\mathrm{Tr}\left(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\nu_2)^{-2}\right)}\right] \to \frac{p}{n}\,,
$$

$$
\chi(\nu_2) = \frac{\mathrm{Tr}\left(\boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}\right)}{p-\mathrm{Tr}\left(\boldsymbol{\Lambda}^2(\boldsymbol{\Lambda}+\nu_2)^{-2}\right)} \to \frac{1}{\nu_2} \approx (\frac{p}{C_1})^{\alpha}\,.
$$

Then we can further obtain that, for the variance

$$\mathsf{V}_{\mathsf{R},0}^{\mathbb{R}FM} = \sigma^2 \frac{\Upsilon(\nu_1,\nu_2)}{1-\Upsilon(\nu_1,\nu_2)} \approx \sigma^2 \frac{p}{n-p},$$
$$\mathsf{V}_{\mathsf{N},0}^{\mathbb{R}FM} = \sigma^2 \frac{p}{n} \frac{\chi(\nu_2)}{1-\Upsilon(\nu_1,\nu_2)} \approx \sigma^2 C_1^{-\alpha} \frac{p^{\alpha+1}}{n-p}.$$

For the relationship in the under-parameterized regime, we separately consider two cases, i.e. $p \ll n$ and $p \to n$.

First, we derive the relationship in the under-parameterized regime ($p < n$) as $p \to n$, based on the relationship in the over-parameterized regime. Recall the relationship between $\mathsf{V}_{\mathsf{R},0}^{\mathbb{R}FM}$ and $\mathsf{V}_{\mathsf{N},0}^{\mathbb{R}FM}$ in the over-parameterized regime, as presented in Eq. (73), given by

$$\mathsf{V}_{\mathsf{R},0}^{\mathbb{R}FM} \approx \left(\frac{n}{C_1}\right)^{-\alpha} \mathsf{V}_{\mathsf{N},0}^{\mathbb{R}FM} + \sigma^2(\alpha-2) =: h(\mathsf{V}_{\mathsf{N},0}^{\mathbb{R}FM}).$$

Substituting the expression for $\mathsf{V}_{\mathsf{N},0}^{\mathbb{R}FM}$ in the under-parameterized regime into this relationship, we obtain

$$\mathsf{V}_{\mathsf{R},0}^{\mathbb{R}FM} \approx \left(\frac{n}{C_1}\right)^{-\alpha} \sigma^2 C_1^{-\alpha} \frac{p^{\alpha+1}}{n-p} + \sigma^2(\alpha-2),$$

then we compute $\mathsf{V}_{\mathsf{R},0}^{\mathbb{R}FM} - h(\mathsf{V}_{\mathsf{N},0}^{\mathbb{R}FM})$ and obtain

$$\begin{aligned}\mathsf{V}_{\mathsf{R},0}^{\mathbb{R}FM} - h(\mathsf{V}_{\mathsf{N},0}^{\mathbb{R}FM}) &= \sigma^2 \frac{p}{n-p} - \left(\frac{n}{C_1}\right)^{-\alpha} \sigma^2 C_1^{-\alpha} \frac{p^{\alpha+1}}{n-p} - \sigma^2(\alpha-2) \\ &= \sigma^2 \left(\frac{p - p^{\alpha+1} n^{-\alpha}}{n-p}\right) - \sigma^2(\alpha-2).\end{aligned}$$

Taking limits on the left and right sides of the equation, we get

$$\lim_{p\to n} \left(\mathsf{V}_{\mathsf{R},0}^{\mathbb{R}FM} - h(\mathsf{V}_{\mathsf{N},0}^{\mathbb{R}FM})\right) = 2\sigma^2.$$

Then when $p \to n$, we have

$$\mathsf{V}_{\mathsf{R},0}^{\mathbb{R}FM} \approx \left(\frac{n}{C_1}\right)^{-\alpha} \mathsf{V}_{\mathsf{N},0}^{\mathbb{R}FM} + \sigma^2\alpha. \tag{76}$$

For $p \ll n$, we have $\frac{1}{n-p} \approx \frac{1}{n}$, then

$$\mathsf{V}_{\mathsf{R},0}^{\mathbb{R}FM} = \sigma^2 \frac{\Upsilon(\nu_1,\nu_2)}{1-\Upsilon(\nu_1,\nu_2)} \approx \sigma^2 \frac{p}{n},$$
$$\mathsf{V}_{\mathsf{N},0}^{\mathbb{R}FM} = \sigma^2 \frac{p}{n} \frac{\chi(\nu_2)}{1-\Upsilon(\nu_1,\nu_2)} \approx \sigma^2 C_1^{-\alpha} \frac{p^{\alpha+1}}{n}.$$

Eliminate p and we have

$$\mathsf{V}_{\mathsf{R},0}^{\mathbb{R}FM} \approx \left(\sigma^2\right)^{\frac{\alpha}{\alpha+1}} C_1^{\frac{\alpha}{\alpha+1}} \left(\mathsf{V}_{\mathsf{R},0}^{\mathbb{R}FM}\right)^{\frac{1}{\alpha+1}}.$$

Next, for the bias term we have

$$
\begin{aligned}
\mathsf{B}_{\mathsf{R},0}^{\mathbb{R}FM} &= \frac{\nu_2^2}{1-\Upsilon(\nu_1,\nu_2)}\left[\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_*\rangle + \chi(\nu_2)\langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_*\rangle\right] \\
&\approx \frac{\nu_2}{1-\Upsilon(\nu_1,\nu_2)}\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2)^{-1}\boldsymbol{\theta}_*\rangle \\
&\approx \frac{n}{n-p}C_3\nu_2^{2r\wedge 1}. \\
\mathsf{B}_{\mathsf{N},0}^{\mathbb{R}FM} &= p\langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_*\rangle \cdot \frac{1}{p-\mathrm{d}f_2(\nu_2)} \\
&\quad + \frac{p}{n}\chi(\nu_2)\frac{\nu_2^2}{1-\Upsilon(\nu_1,\nu_2)}\left[\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_*\rangle + \chi(\nu_2)\langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_*\rangle\right] \\
&\approx p\langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_*\rangle \cdot \frac{1}{p-\mathrm{d}f_2(\nu_2)} + \frac{p}{n}\chi(\nu_2)\frac{\nu_2}{1-\Upsilon(\nu_1,\nu_2)}\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2)^{-1}\boldsymbol{\theta}_*\rangle \\
&\approx \frac{p}{p-\frac{C_2}{C_1}p}C_4\nu_2^{(2r-1)\wedge 0} + \frac{p}{n-p}C_3\nu_2^{(2r-1)\wedge 0} \\
&\approx \left(\frac{C_1C_4}{C_1-C_2} + \frac{p}{n-p}C_3\right)\nu_2^{(2r-1)\wedge 0}.
\end{aligned}
$$

Then we use the approximation $\nu_2 \approx (\frac{p}{C_1})^{-\alpha}$ and obtain

$$
\mathsf{B}_{\mathsf{R},0}^{\mathbb{R}FM} \approx \frac{n}{n-p}C_3\nu_2^{2r\wedge 1} \approx \frac{n}{n-p}C_3\left(\frac{p}{C_1}\right)^{-\alpha(2r\wedge 1)},
$$

$$
\mathsf{B}_{\mathsf{N},0}^{\mathbb{R}FM} \approx \left(\frac{C_1C_4}{C_1-C_2} + \frac{p}{n-p}C_3\right)\nu_2^{(2r-1)\wedge 0} \approx \left(\frac{C_1C_4}{C_1-C_2} + \frac{p}{n-p}C_3\right)\left(\frac{p}{C_1}\right)^{-\alpha[(2r-1)\wedge 0]}.
$$

Similarly to the bias term, we derive the relationship in the under-parameterized regime ($p < n$) as $p \to n$, based on the relationship in the over-parameterized regime. And we discuss the relationship when $r \in (0, \frac{1}{2})$ and $r \in [\frac{1}{2}, \infty)$ separately.

Condition 1: $r \in (0, \frac{1}{2})$**.** Recall the relationship between $\mathsf{B}_{\mathsf{R},0}^{\mathbb{R}FM}$ and $\mathsf{B}_{\mathsf{N},0}^{\mathbb{R}FM}$ in the over-parameterized regime, as presented in Eq. (74), given by:

$$
\mathsf{B}_{\mathsf{R},0}^{\mathbb{R}FM} = \left(\frac{n}{C_1}\right)^{-\alpha}\mathsf{B}_{\mathsf{N},0}^{\mathbb{R}FM} + \left(\frac{n}{C_1}\right)^{-2\alpha r}\frac{C_2C_3-C_1C_4}{C_1-C_2} =: f(\mathsf{B}_{\mathsf{N},0}^{\mathbb{R}FM}).
$$

Substituting the expression for $\mathsf{B}_{\mathsf{N},0}^{\mathbb{R}FM}$ in the under-parameterized regime into this relationship, we obtain:

$$
f(\mathsf{B}_{\mathsf{N},0}^{\mathbb{R}FM}) = \left(\frac{n}{C_1}\right)^{-\alpha}\left(\frac{C_1C_4}{C_1-C_2} + \frac{p}{n-p}C_3\right)\left(\frac{p}{C_1}\right)^{-\alpha(2r-1)} + \left(\frac{n}{C_1}\right)^{-2\alpha r}\frac{C_2C_3-C_1C_4}{C_1-C_2},
$$

then we compute $\mathsf{B}_{\mathsf{R},0}^{\mathbb{R}FM} - f(\mathsf{B}_{\mathsf{N},0}^{\mathbb{R}FM})$ and obtain

$$
\begin{aligned}
\mathsf{B}_{\mathsf{R},0}^{\mathbb{R}FM} - f(\mathsf{B}_{\mathsf{N},0}^{\mathbb{R}FM}) = C_1^{2\alpha r}\Big(&\frac{n}{n-p}C_3p^{-2\alpha r} - \frac{C_1C_4}{C_1-C_2}p^{-\alpha(2r-1)}n^{-\alpha} \\
&- \frac{p}{n-p}C_3p^{-\alpha(2r-1)}n^{-\alpha} - \frac{C_2C_3-C_1C_4}{C_1-C_2}n^{-2\alpha r}\Big).
\end{aligned}
$$

To simplify this equation, we begin by computing $\frac{n}{n-p}C_3p^{-2\alpha r} - \frac{p}{n-p}C_3p^{-\alpha(2r-1)}n^{-\alpha}$ and obtain

$$\begin{aligned}\frac{n}{n-p}C_3p^{-2\alpha r} - \frac{p}{n-p}C_3p^{-\alpha(2r-1)}n^{-\alpha} &= C_3p^{-\alpha(2r-1)}\left(\frac{n}{n-p}p^{-\alpha} - \frac{p}{n-p}n^{-\alpha}\right)\\ &= C_3p^{-\alpha(2r-1)}\frac{np^{-\alpha}-pn^{-\alpha}}{n-p},\end{aligned}$$

where $\frac{np^{-\alpha}-pn^{-\alpha}}{n-p}$ is monotonically decreasing in p (monotonicity can be obtained by simple derivatives), and by applying L'Hôpital's rule, we have:

$$\lim_{p\to n}\frac{np^{-\alpha}-pn^{-\alpha}}{n-p} = \lim_{p\to n}\frac{-\alpha np^{-\alpha-1}-n^{-\alpha}}{-1} = (\alpha+1)n^{-\alpha}.$$

Thus we have

$$\lim_{p\to n} C_3p^{-\alpha(2r-1)}\frac{np^{-\alpha}-pn^{-\alpha}}{n-p} = (\alpha+1)C_3n^{-2\alpha r}.$$

Thus we have

$$\begin{aligned}&\lim_{p\to n} C_1^{2\alpha r}\Big(C_3p^{-\alpha(2r-1)}\frac{np^{-\alpha}-pn^{-\alpha}}{n-p} - \frac{C_1C_4}{C_1-C_2}p^{-\alpha(2r-1)}n^{-\alpha} - \frac{C_2C_3-C_1C_4}{C_1-C_2}n^{-2\alpha r}\Big)\\ &= C_1^{2\alpha r}\Big((\alpha+1)C_3n^{-2\alpha r} - \frac{C_1C_4}{C_1-C_2}n^{-2\alpha r} - \frac{C_2C_3-C_1C_4}{C_1-C_2}n^{-2\alpha r}\Big)\\ &= C_1^{2\alpha r}C_3n^{-2\alpha r}\Big((\alpha+1) - \frac{C_2}{C_1-C_2}\Big).\end{aligned}$$

Recall that from Eq. (71) we have

$$C_1 = \frac{\pi}{\alpha\sin(\pi/\alpha)}, \quad C_2 = \frac{\pi(\alpha-1)}{\alpha^2\sin(\pi/\alpha)},$$

thus

$$(\alpha+1) - \frac{C_2}{C_1-C_2} = (\alpha+1) - \frac{\frac{\pi(\alpha-1)}{\alpha^2\sin(\pi/\alpha)}}{\frac{\pi}{\alpha\sin(\pi/\alpha)} - \frac{\pi(\alpha-1)}{\alpha^2\sin(\pi/\alpha)}} = 2.$$

Finally, we have

$$\lim_{p\to n}\left(\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} - f(\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM})\right) = 2C_1^{2\alpha r}C_3n^{-2\alpha r} = 2C_3\left(\frac{n}{C_1}\right)^{-2\alpha r},$$

and then the relationship between $\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM}$ and $\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM}$ is

$$\begin{aligned}\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} &\approx \left(\frac{n}{C_1}\right)^{-\alpha}\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} + \left(\frac{n}{C_1}\right)^{-2\alpha r}\frac{C_2C_3-C_1C_4}{C_1-C_2} + 2C_3\left(\frac{n}{C_1}\right)^{-2\alpha r}\\ &\approx \left(\frac{n}{C_1}\right)^{-\alpha}\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} + \left(\frac{n}{C_1}\right)^{-2\alpha r}\frac{2C_1C_3-C_2C_3-C_1C_4}{C_1-C_2}.\end{aligned} \tag{77}$$

Condition 2: $r \in [\frac{1}{2}, \infty)$**.** In this condition, the approximation of $\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM}$ and $\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM}$ can be simplified to

$$\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} \approx \frac{n}{n-p} C_3 \nu_2^{2r\wedge 1} \approx \frac{n}{n-p} C_3 \left(\frac{p}{C_1}\right)^{-\alpha(2r\wedge 1)} = \frac{n}{n-p} C_3 \left(\frac{p}{C_1}\right)^{-\alpha},$$

$$\begin{aligned}\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} &\approx \left(\frac{C_1 C_4}{C_1 - C_2} + \frac{p}{n-p} C_3\right) \nu_2^{(2r-1)\wedge 0} \\ &\approx \left(\frac{C_1 C_4}{C_1 - C_2} + \frac{p}{n-p} C_3\right) \left(\frac{p}{C_1}\right)^{-\alpha[(2r-1)\wedge 0]} \\ &= \frac{C_1 C_4}{C_1 - C_2} + \frac{p}{n-p} C_3 \,.\end{aligned}$$

Recall the relationship between $\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM}$ and $\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM}$ in the over-parameterized regime is presented in Eq. (75), given by:

$$\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} \approx \left(\frac{n}{C_1}\right)^{-\alpha} \mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} - \left(\frac{n}{C_1}\right)^{-\alpha} C_4 =: g(\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM}) \,.$$

Substituting the expression for $\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM}$ in the under-parameterized regime into this relationship, we obtain:

$$g(\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM}) = \left(\frac{n}{C_1}\right)^{-\alpha} \left(\frac{C_1 C_4}{C_1 - C_2} + \frac{p}{n-p} C_3\right) - \left(\frac{n}{C_1}\right)^{-\alpha} C_4 \,,$$

then we compute $\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} - g(\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM})$ and obtain

$$\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} - g(\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM}) = C_3 C_1^{\alpha} \frac{np^{-\alpha} - pn^{-\alpha}}{n-p} - \left(\frac{n}{C_1}\right)^{-\alpha} \left(\frac{C_2 C_4}{C_1 - C_2}\right) .$$

Thus we have

$$\begin{aligned}\lim_{p\to n} \left(\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} - f(\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM})\right) &= \left(\frac{n}{C_1}\right)^{-\alpha} \left((\alpha+1)C_3 - \frac{C_2 C_4}{C_1 - C_2}\right) \\ &\approx \left(\frac{n}{C_1}\right)^{-\alpha} \left((\alpha+1)C_4 - \frac{C_2}{C_1 - C_2} C_4\right) \\ &= \left(\frac{n}{C_1}\right)^{-\alpha} 2C_4 \,,\end{aligned}$$

and the relationship between $\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM}$ and $\mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM}$ is

$$\begin{aligned}\mathsf{B}_{\mathsf{R},0}^{\mathrm{R}FM} &\approx \left(\frac{n}{C_1}\right)^{-\alpha} \mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} - \left(\frac{n}{C_1}\right)^{-\alpha} C_4 + \left(\frac{n}{C_1}\right)^{-\alpha} 2C_4 \\ &\approx \left(\frac{n}{C_1}\right)^{-\alpha} \mathsf{B}_{\mathsf{N},0}^{\mathrm{R}FM} + \left(\frac{n}{C_1}\right)^{-\alpha} C_4 \,.\end{aligned} \tag{78}$$

When $p \ll n$, we discuss cases $r \in (0, \frac{1}{2})$ and $r \in (\frac{1}{2}, \infty)$ separately.

If $r \in (0, \frac{1}{2})$, we have $\frac{n}{n-p} \approx 1$ and $\frac{p}{n-p} \approx 0$, then

$$\mathsf{B}_{\mathsf{R},0}^{\mathbb{R}FM} \approx C_3 \nu_2^{2r \wedge 1} \approx C_3 \left(\frac{p}{C_1}\right)^{-\alpha 2r},$$

$$\mathsf{B}_{\mathsf{N},0}^{\mathbb{R}FM} \approx \frac{C_1 C_4}{C_1 - C_2} \nu_2^{(2r-1)\wedge 0} \approx \frac{C_1 C_4}{C_1 - C_2} \left(\frac{p}{C_1}\right)^{-\alpha(2r-1)}.$$

Then we eliminate p and obtain

$$\mathsf{B}_{\mathsf{R},0}^{\mathbb{R}FM} \approx C_3 \left(\frac{C_1 - C_2}{C_1 C_4}\right)^{2r/(2r-1)} \left(\mathsf{B}_{\mathsf{N},0}^{\mathbb{R}FM}\right)^{2r/(2r-1)}.$$

If $2r \geq 1$, we have

$$\mathsf{B}_{\mathsf{R},0}^{\mathbb{R}FM} \approx \frac{n}{n-p} C_3 \nu_2 \approx \frac{n}{n-p} C_3 \left(\frac{p}{C_1}\right)^{-\alpha},$$

$$\mathsf{B}_{\mathsf{N},0}^{\mathbb{R}FM} \approx \frac{C_1 C_4}{C_1 - C_2} + \frac{p}{n-p} C_3.$$

Then we eliminate p and obtain

$$\mathsf{B}_{\mathsf{R},0}^{\mathbb{R}FM} \approx \left(\frac{C_1 C_3 - C_2 C_3 - C_1 C_4}{C_1 - C_2} + \mathsf{B}_{\mathsf{N},0}^{\mathbb{R}FM}\right) \left(\frac{n\left(\mathsf{B}_{\mathsf{N},0}^{\mathbb{R}FM} - \frac{C_1 C_4}{C_1 - C_2}\right)}{C_1\left(C_3 + \mathsf{B}_{\mathsf{N},0}^{\mathbb{R}FM} - \frac{C_1 C_4}{C_1 - C_2}\right)}\right)^{-\alpha}.$$

From Eqs. (76) to (78), we know that the relationship between $\mathsf{R}_0^{\mathbb{R}FM}$ and $\mathsf{N}_0^{\mathbb{R}FM}$ in the under-parameterized regime when $p \to n$ can be written as

$$\mathsf{R}_0^{\mathbb{R}FM} \approx \left(n/C_\alpha\right)^{-\alpha} \mathsf{N}_0^{\mathbb{R}FM} + C_{n,\alpha,r,2}\,.$$

■

Appendix H. Scaling laws

To derive the scaling laws based on norm-based capacity, we first give the decay rate of the ℓ_2 norm w.r.t. n.

The rate of the deterministic equivalent of the random feature ridge regression estimator's ℓ_2 norm is given by

$$\mathsf{N}_\lambda^{\mathbb{R}FM} = \Theta\left(n^{-\gamma_{\mathsf{B}_{\mathsf{N},\lambda}^{\mathbb{R}FM}}} + \sigma^2 n^{-\gamma_{\mathsf{V}_{\mathsf{N},\lambda}^{\mathbb{R}FM}}}\right) = \Theta\left(n^{-\gamma_{\mathsf{N}_\lambda^{\mathbb{R}FM}}}\right),$$

where $\gamma_{\mathsf{N}_\lambda^{\mathbb{R}FM}} := \gamma_{\mathsf{B}_{\mathsf{N},\lambda}^{\mathbb{R}FM}} \wedge \gamma_{\mathsf{V}_{\mathsf{N},\lambda}^{\mathbb{R}FM}}$ for $\sigma^2 \neq 0$.

H.1. Variance term

Using Eqs. (41) to (43), we have

$$\begin{aligned}\mathsf{V}_{\mathsf{N},\lambda}^{\mathrm{R}FM} &= \sigma^2 \frac{p}{n} \frac{\chi(\nu_2)}{1-\Upsilon(\nu_1,\nu_2)} = n^{q-1} n^{-q} O\left(\nu_2^{-1-1/\alpha}\right) \\ &= O\left(n^{-(1-(\alpha+1)(1\wedge q\wedge \ell/\alpha))}\right).\end{aligned}$$

Hence, the variance term of the norm decays with n with rate

$$\gamma_{\mathsf{V}_{\mathsf{N},\lambda}^{\mathrm{R}FM}}(\ell,q) = 1-(\alpha+1)\left(\frac{\ell}{\alpha}\wedge q\wedge 1\right).$$

H.2. Bias term

First, one could notice, using the integral approximation and Eqs. (40) and (41), that

$$\frac{p}{p-\mathrm{d}f_2(\nu_2)} = \left(1+n^{-q}O\left(\nu_2^{-1/\alpha}\right)\right) = \left(1+O\left(n^{-q}n^{(1\wedge q\wedge \ell/\alpha)}\right)\right) = O\left(1\right).$$

Thus for the bias term, using Eqs. (40) to (43) we have

$$\begin{aligned}\mathsf{B}_{\mathsf{N},\lambda}^{\mathrm{R}FM} &= \langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_*\rangle \cdot \frac{p}{p-\mathrm{d}f_2(\nu_2)} \\ &\quad + \frac{p}{n}\nu_2^2\left(\langle \boldsymbol{\theta}_*, (\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_*\rangle + \chi(\nu_2)\langle \boldsymbol{\theta}_*, \boldsymbol{\Lambda}(\boldsymbol{\Lambda}+\nu_2)^{-2}\boldsymbol{\theta}_*\rangle\right)\cdot \frac{\chi(\nu_2)}{1-\Upsilon(\nu_1,\nu_2)} \\ &= T_{2r+1,2}^1(\nu_2) + n^{q-1}\nu_2^2\left(T_{2r,2}^1(\nu_2)+\chi(\nu_2)T_{2r+1,2}^1(\nu_2)\right)\chi(\nu_2) \\ &= \nu_2^{(2r-1)\wedge 0} + n^{q-1}\nu_2^2 O\left(\nu_2^{(2r-2)\wedge 0} + n^{-q}\nu_2^{-1-1/\alpha+(2r-1)\wedge 0}\right) n^{-q} O\left(\nu_2^{-1-1/\alpha}\right) \\ &= \nu_2^{(2r-1)\wedge 0} + n^{-1} O\left(\nu_2^{2r\wedge 2} + n^{-q}\nu_2^{-1/\alpha+2r\wedge 1}\right) O\left(\nu_2^{-1-1/\alpha}\right) \\ &= O\left(n^{-\alpha(1\wedge q\wedge \ell/\alpha)[(2r-1)\wedge 0]}\right) \\ &\quad + O\left(n^{-\alpha(1\wedge q\wedge \ell/\alpha)[(2r-1)\wedge 1]+(1\wedge q\wedge \ell/\alpha)-1} + n^{-\alpha(1\wedge q\wedge \ell/\alpha)[(2r-1)\wedge 0]+2(1\wedge q\wedge \ell/\alpha)-1-q}\right) \\ &= O\left(n^{-\alpha(1\wedge q\wedge \ell/\alpha)[(2r-1)\wedge 0]} + n^{-\alpha(1\wedge q\wedge \ell/\alpha)[(2r-1)\wedge 1]+(1\wedge q\wedge \ell/\alpha)-1}\right) \\ &= O\left(n^{-\alpha(1\wedge q\wedge \ell/\alpha)[(2r-1)\wedge 0]}\right).\end{aligned}$$

Hence, the bias term of the norm decays with n with rate

$$\gamma_{\mathsf{B}_{\mathsf{N},\lambda}^{\mathrm{R}FM}}(\ell,q) = \alpha\left(1\wedge q\wedge \ell/\alpha\right)\left[(2r-1)\wedge 0\right].$$

Recalling that we have

$$\gamma_{\mathsf{N}_{\lambda}^{\mathrm{R}FM}} := \gamma_{\mathsf{B}_{\mathsf{N},\lambda}^{\mathrm{R}FM}} \wedge \gamma_{\mathsf{V}_{\mathsf{N},\lambda}^{\mathrm{R}FM}},$$

according to which, we obtain the norm exponent $\gamma_{\mathsf{N}_{\lambda}^{\mathrm{R}FM}}$ as a function of ℓ and q, showing in Fig. 7. As observed in Fig. 7, $\gamma_{\mathsf{N}_{\lambda}^{\mathrm{R}FM}}$ is non-positive across all regions, indicating that the norm either increases or remains constant with n in every case.

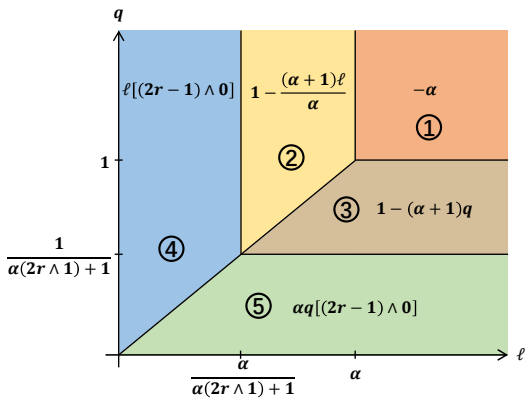


Figure 7: The norm rate $\gamma_{\mathsf{N}_\lambda^{\mathrm{R}FM}}$ as a function of (ℓ, q). Variance dominated region is colored by orange, yellow and brown, bias dominated region is colored by blue and green.

Next for the condition $r \in (0, \frac{1}{2})$, we derive the scaling law under norm-based capacity.

Region 1: $\ell > \alpha$ **and** $q > 1$ In this region, according to [12, Corollary 4.1], we have

$$\mathsf{R}_\lambda^{\mathrm{R}FM} = \Theta\left(n^{-0}\right) = \Theta\left(1\right) ,$$

and according to Fig. 7, we have

$$\mathsf{N}_\lambda^{\mathrm{R}FM} = \Theta\left(n^{\alpha}\right) ,$$

combing the above rate, we can obtain that

$$\mathsf{R}_\lambda^{\mathrm{R}FM} = \Theta\left(n^{-\alpha} \cdot \mathsf{N}_\lambda^{\mathrm{R}FM}\right) .$$

Region 2: $\frac{\alpha}{2\alpha r+1} < \ell < \alpha$ **and** $q > \frac{\ell}{\alpha}$ In this region, according to [12, Corollary 4.1], we have

$$\mathsf{R}_\lambda^{\mathrm{R}FM} = \Theta\left(n^{-\left(1-\frac{\ell}{\alpha}\right)}\right) ,$$

and according to Fig. 7, we have

$$\mathsf{N}_\lambda^{\mathrm{R}FM} = \Theta\left(n^{-\left(1-\frac{(\alpha+1)\ell}{\alpha}\right)}\right) ,$$

combing the above rate, we can obtain that

$$\mathsf{R}_\lambda^{\mathrm{R}FM} = \Theta\left(n^{-\ell} \cdot \mathsf{N}_\lambda^{\mathrm{R}FM}\right) .$$

Region 3: $\frac{1}{2\alpha r+1} < q < 1$ **and** $q < \frac{\ell}{\alpha}$ In this region, according to [12, Corollary 4.1], we have

$$\mathsf{R}_\lambda^{\mathrm{R}FM} = \Theta\left(n^{-(1-q)}\right) ,$$

and according to Fig. 7, we have

$$\mathsf{N}_\lambda^{\mathrm{R}FM} = \Theta\left(n^{-(1-(\alpha+1)q)}\right) ,$$

combing the above rate and eliminate q, we can obtain that

$$\mathsf{R}_\lambda^{\mathrm{R}FM} = \Theta\left(n^{-\frac{\alpha}{\alpha+1}} \cdot \left(\mathsf{N}_\lambda^{\mathrm{R}FM}\right)^{\frac{1}{\alpha+1}}\right) .$$

Region 4: $\ell < \frac{\alpha}{2\alpha r+1}$ **and** $q > \frac{\ell}{\alpha}$ In this region, according to [12, Corollary 4.1], we have

$$\mathsf{R}_\lambda^{\mathrm{R}FM} = \Theta\left(n^{-2\ell r}\right) ,$$

and according to Fig. 7, we have

$$\mathsf{N}_\lambda^{\mathrm{R}FM} = \Theta\left(n^{-\ell(2r-1)}\right) ,$$

combing the above rate, we can obtain that

$$\mathsf{R}_\lambda^{\mathrm{R}FM} = \Theta\left(n^{-1} \cdot \mathsf{N}_\lambda^{\mathrm{R}FM}\right) .$$

Region 5: $q < \frac{1}{2\alpha r+1}$ **and** $q < \frac{\ell}{\alpha}$ In this region, according to [12, Corollary 4.1], we have

$$\mathsf{R}_\lambda^{\mathrm{R}FM} = \Theta\left(n^{-2\alpha q r}\right) ,$$

and according to Fig. 7, we have

$$\mathsf{N}_\lambda^{\mathrm{R}FM} = \Theta\left(n^{-\alpha q(2r-1)}\right) ,$$

combing the above rate, we can obtain that

$$\mathsf{R}_\lambda^{\mathrm{R}FM} = \Theta\left(n^{0} \cdot \left(\mathsf{N}_\lambda^{\mathrm{R}FM}\right)^{-\frac{2r}{1-2r}}\right) .$$

Appendix I. Discussion

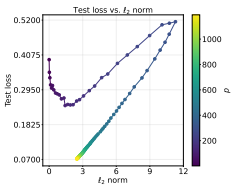
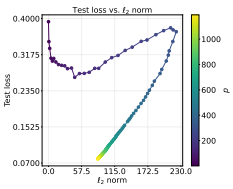
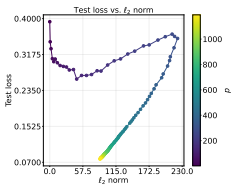
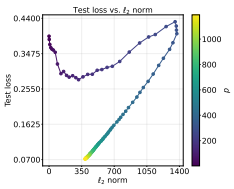
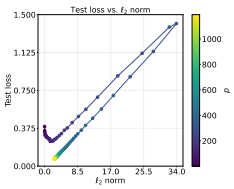
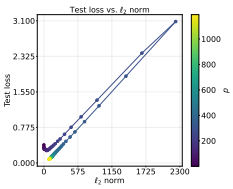
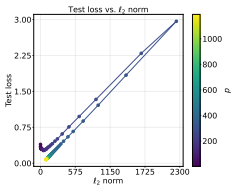
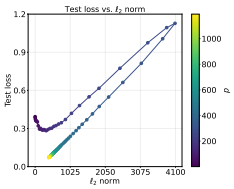
In this section, we discuss several issues related to the shape of generalization curves, norm control, and model complexity. In Appendix I.1, we examine the shape of generalization curves under various settings, emphasizing when theoretical predictions align with or diverge from empirical observations, particularly across synthetic and real-world datasets. In Appendix I.2, we analyze a practical approach to modifying norm by fixing the parameter count and imposing a norm constraint, and demonstrate its equivalence to adjusting the regularization strength. Finally, in Appendix I.3, we compare norm-based capacity with alternative complexity measures, including smoother-based metrics and degrees of freedom, and highlight their limitations in capturing test risk behavior.

I.1. Discussion on the shape of the generalization curve in Fig. 1

As illustrated in Fig. 1(*a*), and based on empirical observations from [39, Figure 8.12], the test risk in the over-parameterized regime initially exceeds that of the under-parameterized regime. However, as over-parameterization increases, the test risk begins to decrease. Eventually, in a sufficiently over-parameterized regime, the test risk becomes lower than in the under-parameterized case—indicating that sufficient over-parameterization can outperform under-parameterization.

In contrast, our experimental results in Fig. 1(*b*) reveal a slightly different behavior: the learning curve in the over-parameterized regime consistently remains below its under-parameterized counterpart throughout. This phenomenon presents an intriguing contrast, and the central question we address in this section is: What underlying factors cause this fundamental difference in behavior - where in

Table 4: Generalization curves (test loss *vs.* ℓ_2 norm) under different activation functions in RFMs. Training data $\{(\boldsymbol{x}_i, y_i)\}_{i\in[n]}$ are generated from a teacher-student model $y_i = \tanh(\langle \boldsymbol{\beta}, \boldsymbol{x}_i \rangle)$, where $\boldsymbol{x}_i \sim$ i.i.d. $\mathcal{N}(\mathbf{0}, \boldsymbol{I}_d)$ with $d = 100$. The number of training samples is fixed at $n = 300$. The random feature map is defined as $\varphi(\boldsymbol{x}, \boldsymbol{w}) = \varphi(\langle \boldsymbol{w}, \boldsymbol{x} \rangle)$ with random Gaussian initialization $\boldsymbol{w} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{I}_d)$, where the activation function $\varphi(\cdot)$ is chosen from `ReLU`, `erf`, `tanh`, or `sigmoid`.

	ReLU	erf	tanh	sigmoid
With ridge				
	$\lambda = 0.1$	$\lambda = 0.01$	$\lambda = 0.1$	$\lambda = 0.1$
Ridgeless				
	$\lambda = 0.01$	$\lambda = 10^{-4}$	$\lambda = 10^{-4}$	$\lambda = 10^{-4}$

some cases the over-parameterized curve initially above then crosses the under-parameterized curve, while in others it stays strictly lower?

We first conduct experiments on synthetic datasets to validate our theoretical findings. We generate training samples $\{(\boldsymbol{x}_i, y_i)\}_{i\in[n]}$ using a teacher-student model: $y_i = \tanh(\langle \boldsymbol{\beta}, \boldsymbol{x}_i \rangle)$, where input features $\boldsymbol{x}_i \overset{i.i.d}{\sim} \mathcal{N}(\mathbf{0}, \boldsymbol{I}_d)$ with dimension $d = 100$. As demonstrated in Table 4, our experimental results reveal that when the input features follow Gaussian distribution, the test loss curves in the over-parameterized regime consistently lie below those in the under-parameterized regime, regardless of the activation functions or ridge parameter values. This observation aligns perfectly with our theoretical predictions.

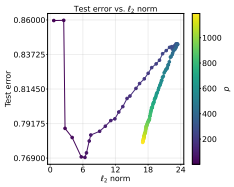
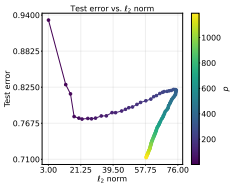
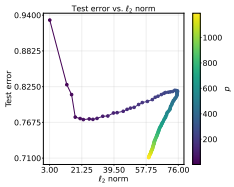
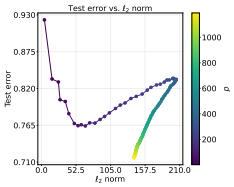
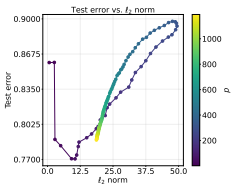
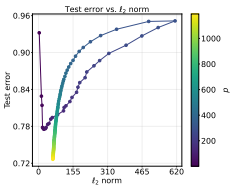
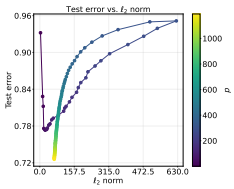
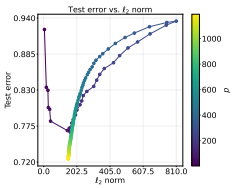
We further conducted experiments on the FashionMNIST data set [52]. In this practical setting, we observed a discrepancy between our experimental results and theoretical predictions.

As in Table 5, for cases with substantial ridge regularization, the test error curves in the over-parameterized regime remained below those in the under-parameterized regime, consistent with our synthetic data experiments. However, in the ridgeless case (corresponding to minimum-ℓ_2-norm interpolators), we discovered a different phenomenon:

- Initially, the over-parameterized regime exhibited higher test error than the under-parameterized regime.
- As the number of parameters p increased, the over-parameterized curve crossed under the under-parameterized curve. And this interaction formed a distinctive φ-shaped learning curve.

We attribute this behavior to the non-Gaussian distribution of input images $\boldsymbol{x}$ in FashionMNIST, which may violates our theoretical assumption like Theorem 1.

Table 5: Generalization curves (test error *vs.* ℓ_2 norm) under different activation functions. Training data $\{(\boldsymbol{x}_i, y_i)\}_{i\in[n]}$ are sampled from the **FashionMNIST** data set [52], with input vectors normalized and flattened to $[-1,1]^d$ for $d = 748$. The random feature map is defined as $\varphi(\boldsymbol{x}, \boldsymbol{w}) = \varphi(\langle \boldsymbol{w}, \boldsymbol{x}\rangle)$ with random Gaussian initialization $\boldsymbol{w} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I}_d)$, where the activation function $\varphi(\cdot)$ is chosen from `ReLU`, `erf`, `tanh`, or `sigmoid`. The number of training samples is fixed at $n = 300$.

	ReLU	erf	tanh	sigmoid
With ridge				
	$\lambda = 10^{-4}$	$\lambda = 10^{-4}$	$\lambda = 10^{-4}$	$\lambda = 10^{-3}$
Ridgeless				
	$\lambda = 10^{-8}$	$\lambda = 10^{-8}$	$\lambda = 10^{-8}$	$\lambda = 10^{-8}$

In summary, while our theoretical framework may not fully capture the generalization behavior when the dataset or activation functions deviate significantly from our assumptions, this does not undermine the core contributions of our work. When the data is well-behaved and aligns with our assumptions, our theory provides a highly accurate and effective characterization of the generalization curves under norm-based capacity control in the under-parameterized regime.

I.2. Discussion on approaches to modifying the norm

Regarding approaches to controlling model norm, one method involves fixing the regularization strength while varying the model parameter count p, which serves as the primary focus of this paper. Alternatively, one can fix p and constrain the weight norm to specific magnitudes. We later show that this approach is mathematically equivalent to fixing the parameter count while varying the regularization strength. In this section, we primarily focus on the latter approach.

We consider the problem of minimizing the squared loss under an ℓ_2-norm constraint on the coefficients:

$$\min_{\boldsymbol{a}} \|\boldsymbol{y} - \boldsymbol{Z}\boldsymbol{a}\|^2 \quad \text{subject to} \quad \|\boldsymbol{a}\|_2^2 = B^2.$$

To incorporate the constraint, we introduce a Lagrange multiplier λ and define the Lagrangian:

$$\mathcal{L}(\boldsymbol{a}, \lambda) = \|\boldsymbol{y} - \boldsymbol{Z}\boldsymbol{a}\|^2 + \lambda \left(\|\boldsymbol{a}\|_2^2 - B^2\right).$$

Taking the gradient of $\mathcal{L}$ with respect to $\boldsymbol{a}$ and setting it to zero yields the first-order optimality condition:

$$\nabla_{\boldsymbol{a}} \mathcal{L} = -2\boldsymbol{Z}^\top \boldsymbol{y} + 2\boldsymbol{Z}^\top \boldsymbol{Z}\boldsymbol{a} + 2\lambda \boldsymbol{a} = \boldsymbol{0}.$$

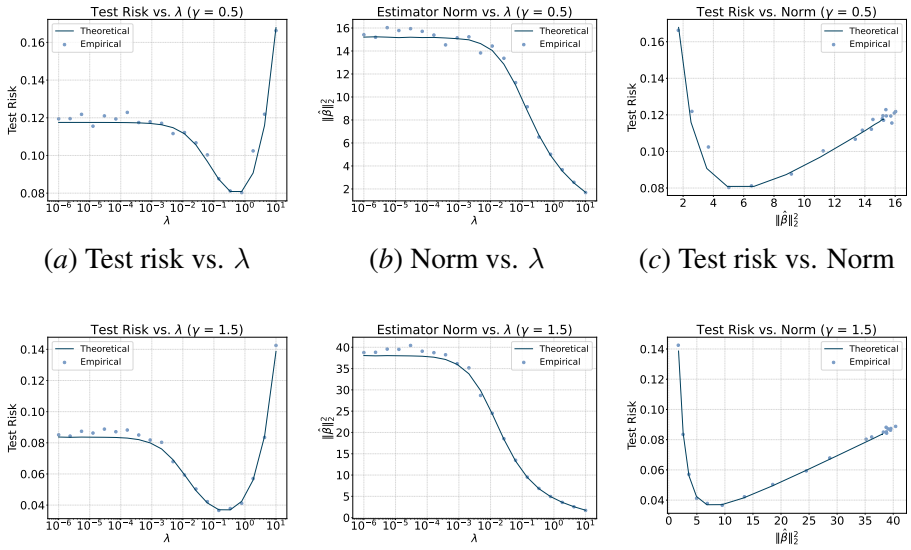
Solving this equation gives the solution:

$$\hat{\boldsymbol{a}} = (\boldsymbol{Z}^\top \boldsymbol{Z} + \lambda I)^{-1} \boldsymbol{Z}^\top \boldsymbol{y}, \quad \text{subject to} \quad \|\hat{\boldsymbol{a}}\|_2^2 = B^2.$$

Relation to Ridge Regression: The solution resembles ridge regression, but λ is chosen to strictly satisfy $\|\hat{\boldsymbol{a}}\|_2 = B$ rather than being a hyperparameter. λ corresponds one-to-one with B, since λ and $\|\hat{\boldsymbol{a}}\|_2^2$ are in one-to-one correspondence if $\lambda \geq 0$ ($\frac{\partial \|\hat{\boldsymbol{a}}\|_2^2}{\partial \lambda} = -2\boldsymbol{y}^\top \boldsymbol{Z}(\boldsymbol{Z}^\top \boldsymbol{Z} + \lambda \boldsymbol{I})^{-3} \boldsymbol{Z}^\top \boldsymbol{y} \leq 0$). Therefore, we can say that changing the constraint B (the restriction on $\|\boldsymbol{a}\|_2$) is equivalent to changing the regularization strength λ.

We conducted experiments on the random feature model by fixing the number of training samples and the aspect ratio γ, and varying the regularization parameter λ to control the norm of the estimator. We then plotted the curves showing the relationships among test risk, norm, and λ as in Fig. 8 (Figs. 8(*a*) to 8(*c*) for under-parameterized regimes and Figs. 8(*d*) to 8(*f*) for over-parameterized regimes). We can find that the norm is monotonically decreasing with the increasing λ, see Figs. 8(*b*) and 8(*e*). In fact, the relationship between the estimator's norm and the regularization parameter is called L-curve [19]. in both under- and over-parameterized ($\lambda < 1$ or $\lambda > 1$), the test risk is always a U-shaped curve of the regularization parameter λ or norm, see Figs. 8(*a*) and 8(*c*) and Figs. 8(*d*) and 8(*f*), respectively.

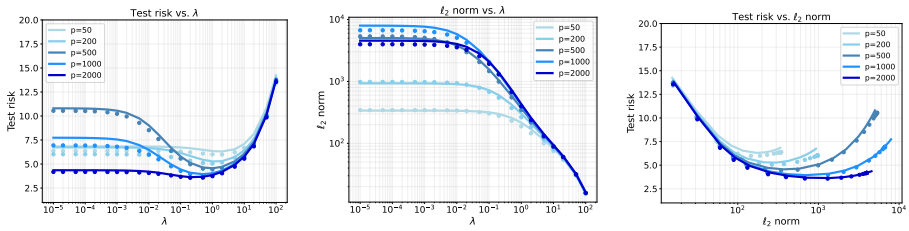
To validate these observations on real data, we also conducted complementary experiments using the MNIST data set [26]. As shown in Fig. 9, all of the above phenomena persist.



(*a*) Test risk vs. λ (*b*) Norm vs. λ (*c*) Test risk vs. Norm

(*d*) Test risk vs. λ (*e*) Norm vs. λ (*f*) Test risk vs. Norm

Figure 8: Relationship between test risk, ℓ_2 norm, and λ for different $\gamma = \frac{p}{n}$ for random feature ridge regression. Points in these figures are given by our experimental results, centering around the curves given by deterministic equivalents we derive. Training data $\{(\boldsymbol{x}_i, y_i)\}_{i \in [n]}$, $n = 100$, sampled from the model $y_i = \boldsymbol{g}_i^\top \boldsymbol{\theta}_* + \varepsilon_i$, $\sigma^2 = 0.01$, $\boldsymbol{g}_i \sim \mathcal{N}(0, \boldsymbol{I})$, $\boldsymbol{f}_i \sim \mathcal{N}(0, \boldsymbol{\Lambda})$ ($\boldsymbol{g}_i$ and $\boldsymbol{f}_i$ is defined in **??**), with $\xi_k^2(\boldsymbol{\Lambda}) = k^{-3/2}$ and $\boldsymbol{\theta}_{*,k} = k^{-11/10}$, given by $\alpha = 1.5$, $r = 0.4$ in Theorem 32.



(*a*) Test risk vs. λ (*b*) Norm vs. λ (*c*) Test risk vs. Norm

Figure 9: Relationship between test risk, ℓ_2 norm, and λ for different $\gamma = \frac{p}{n}$ for random feature ridge regression. Points in these figures are given by our experimental results, centering around the curves given by deterministic equivalents we derive. Training data $\{(\boldsymbol{x}_i, y_i)\}_{i\in[n]}$, $n = 300$, sub-sampled from the **MNIST** data set [26], with feature map given by $\varphi(\boldsymbol{x}, \boldsymbol{w}) = \mathrm{erf}(\langle \boldsymbol{x}, \boldsymbol{w}\rangle)$ and $\boldsymbol{w} \sim \mathcal{N}(0, \boldsymbol{I})$.

I.3. Discussion with other model capacities

In this section, we discuss two other model capacities: *generalized effective number of parameters* and *degrees of freedom*, which are widely used to describe a model's generalization ability. From this discussion, we conclude that these two capacities are less suitable compared to norm-based model capacity.

Generalized Effective Number of Parameters: The authors [11] assess model complexity from the perspective of smoother by introducing a variance-based effective-parameter measure, termed the **g**eneralized effective number of parameters. In the context of ridge regression, this measure is given by

$$p_{\hat{\boldsymbol{s}}}^{\text{test}} = \frac{n}{|\mathcal{I}_{\text{test}}|} \sum_{j\in\mathcal{I}_{\text{test}}} \|\boldsymbol{x}_j^{\text{test}}(\boldsymbol{X}^\top\boldsymbol{X} + \lambda)^{-1}\boldsymbol{X}^\top\|_2^2\,,$$

where $\{\boldsymbol{x}_j^{\text{test}}\}_{j\in\mathcal{I}_{\text{test}}}$ is the set of test inputs. Taking the expectation with respect to the test set yields

$$p_{\hat{\boldsymbol{s}}}^{\text{test}} = n\mathbb{E}_{\boldsymbol{x}_j^{\text{test}}}\|\boldsymbol{x}_j^{\text{test}}(\boldsymbol{X}^\top\boldsymbol{X} + \lambda)^{-1}\boldsymbol{X}^\top\|_2^2 = n\mathrm{Tr}(\boldsymbol{\Sigma}\boldsymbol{X}^\top\boldsymbol{X}(\boldsymbol{X}^\top\boldsymbol{X} + \lambda)^{-2})\,,$$

which corresponds to the variance of the test risk $\mathcal{V}_{\mathcal{R}}^{\mathrm{LS}}$ scaled by the factor $\frac{n}{\sigma^2}$.

For the random feature ridge regression, the generalized effective number of parameters can be similarly given by

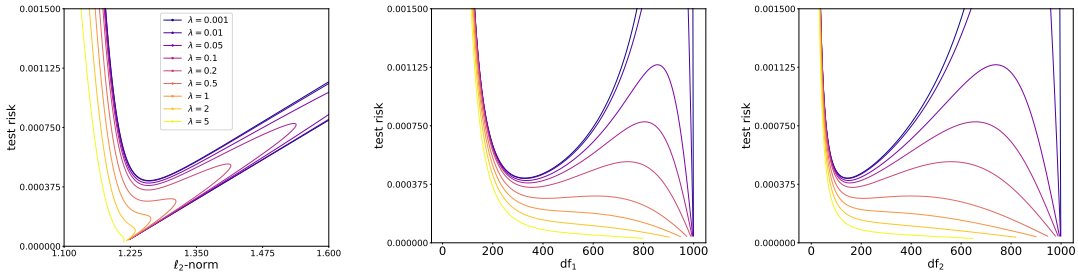
$$p_{\hat{\boldsymbol{s}}}^{\text{test}} = n\mathbb{E}_{\boldsymbol{z}_j^{\text{test}}}\|\boldsymbol{z}_j^{\text{test}}(\boldsymbol{Z}^\top\boldsymbol{Z} + \lambda)^{-1}\boldsymbol{Z}^\top\|_2^2 = n\mathrm{Tr}(\widehat{\boldsymbol{\Lambda}}_{\boldsymbol{F}}\boldsymbol{Z}^\top\boldsymbol{Z}(\boldsymbol{Z}^\top\boldsymbol{Z} + \lambda)^{-2})\,,$$

which corresponds to the variance of the test risk $\mathcal{V}_{\mathcal{R}}^{\mathrm{RFM}}$ scaled by the factor $\frac{n}{\sigma^2}$.

The connection between variance and $p_{\hat{\boldsymbol{s}}}^{\text{test}}$ enables it to effectively capture the variance of test risk. However, due to the lack of information about the target function (without label information y), this model capacity cannot fully describe the behavior of test risk, as it neglects the bias component. This limitation becomes apparent when the test risk is dominated by bias.

Degrees of freedom For linear ridge regression, another measure of model capacity, known as the "degrees of freedom" [1, 8, 21], is defined as

$$\mathrm{d}f_1(\lambda_*) := \mathrm{Tr}(\boldsymbol{\Sigma}(\boldsymbol{\Sigma} + \lambda_*)^{-1})\,, \quad \mathrm{d}f_2(\lambda_*) := \mathrm{Tr}(\boldsymbol{\Sigma}^2(\boldsymbol{\Sigma} + \lambda_*)^{-2})\,.$$



(a) Test Risk vs. Norm (b) Test Risk vs. $\mathrm{d}f_1$ (c) Test Risk vs. $\mathrm{d}f_2$

Figure 10: Relationship between test risk and different model capacities. Training data $\{(\boldsymbol{x}_i, y_i)\}_{i\in[n]}$, $d = 1000$, sampled from a linear model $y_i = \boldsymbol{x}_i^\top \boldsymbol{\beta}_* + \varepsilon_i$, $\sigma^2 = 0.0004$, $\boldsymbol{x}_i \sim \mathcal{N}(0, \boldsymbol{\Sigma})$, with $\sigma_k(\boldsymbol{\Sigma}) = k^{-1}$, $\boldsymbol{\beta}_{*,k} = k^{-3/2}$.

$\mathrm{d}f_1(\lambda_*)$ and $\mathrm{d}f_2(\lambda_*)$ measures the number of "effective" parameters the model can fit. As the regularization strength λ increases, model complexity decreases. From Theorem 11, we have $n - \frac{\lambda}{\lambda_*} = \mathrm{T}r(\boldsymbol{\Sigma}(\boldsymbol{\Sigma} + \lambda_*)^{-1})$, implying that an increase in λ raises λ_*, leading to a reduction in $\mathrm{d}f_1(\lambda_*)$ and $\mathrm{d}f_2(\lambda_*)$. This suggests that degrees of freedom can, to some extent, represent model complexity.

However, it is worth noting that since in linear ridge regression we only vary the number of training data n, according to the self-consistent equation $n - \frac{\lambda}{\lambda_*} = \mathrm{T}r(\boldsymbol{\Sigma}(\boldsymbol{\Sigma} + \lambda_*)^{-1})$ we can tell that λ_* decreases monotonically as n increases, which leads to $\mathrm{d}f_1$ and $\mathrm{d}f_2$ increasing monotonically as n increases. This monotonic relationship with n suggests that when using degrees of freedom as a measure of model capacity, the double descent phenomenon still exists, as the effective capacity of the model continues to increase even beyond the interpolation threshold.

Similar to the generalized effective number of parameters mentioned above, these degrees of freedom also lack information about the target function, making them insufficient for accurately capturing the model's generalization ability.

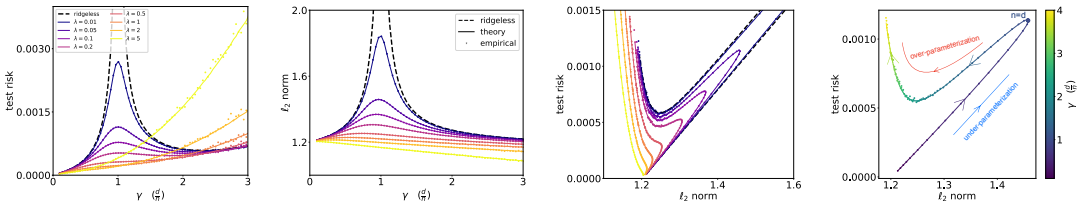
Fig. 10 illustrates the relationship between test risk and different model capacity for linear ridge regression. It shows that double descent persists for degrees of freedom $\mathrm{d}f_1$ and $\mathrm{d}f_2$, indicating that degrees of freedom is not an appropriate measure of model capacity.

Appendix J. Experiment

To systematically validate our theoretical findings, we conduct a comprehensive empirical study across three distinct settings: (1) synthetic datasets (Appendix J.1), (2) real-world datasets (MNIST[26]/FashionMNIST[52]) with random features (Appendix J.2), and (3) two-layer neural networks with various norm-based capacity measures (Appendix J.3). All experiments can be conducted on a standard laptops with 16 GB memory.

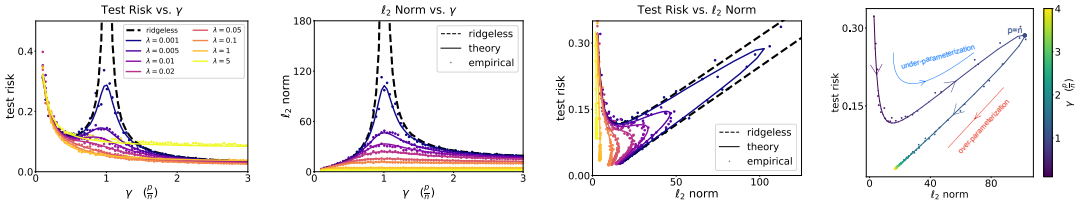
J.1. Experiment on synthetic dataset

To validate our theoretical framework, we conduct comprehensive experiments on synthetic datasets on linear regression in Fig. 11 and RFMs in Fig. 12, respectively. The strong agreement between theoretical predictions and empirical results confirms the accuracy of our theoretical analysis.



(a) Test Risk vs. $\gamma := d/n$ (b) ℓ_2 norm vs. γ (c) Test Risk vs. ℓ_2 norm (d) Risk vs. norm ($\lambda = 0.05$)

Figure 11: Results for the ridge regression estimator. Points in these four figures are given by our experimental results, and the curves are given by our theoretical results via deterministic equivalents. Training data $\{(\boldsymbol{x}_i, y_i)\}_{i\in[n]}$, $d = 1000$, sampled from a linear model $y_i = \boldsymbol{x}_i^\top \boldsymbol{\beta}_* + \varepsilon_i$, $\sigma^2 = 0.0004$, $\boldsymbol{x}_i \sim \mathcal{N}(0, \boldsymbol{\Sigma})$, with $\sigma_k(\boldsymbol{\Sigma}) = k^{-1}$, $\boldsymbol{\beta}_{*,k} = k^{-3/2}$.



(a) Test Risk vs. $\gamma := p/n$ (b) ℓ_2 norm vs. γ (c) Test Risk vs. ℓ_2 norm (d) Risk vs. norm ($\lambda = 0.001$)

Figure 12: Relationship between test risk, ratio $\gamma := p/n$, and ℓ_2 norm of the random feature ridge regression estimator (the regularization parameter is defined in **??**). Points in these four figures are given by our experimental results, centering around the curves given by deterministic equivalents we derive. Training data $\{(\boldsymbol{x}_i, y_i)\}_{i\in[n]}$, $n = 100$, sampled from the model $y_i = \boldsymbol{g}_i^\top \boldsymbol{\theta}_* + \varepsilon_i$, $\sigma^2 = 0.01$, $\boldsymbol{g}_i \sim \mathcal{N}(0, \boldsymbol{I})$, $\boldsymbol{f}_i \sim \mathcal{N}(0, \boldsymbol{\Lambda})$ ($\boldsymbol{g}_i$ and $\boldsymbol{f}_i$ is defined in **??**), with $\xi_k^2(\boldsymbol{\Lambda}) = k^{-3/2}$ and $\boldsymbol{\theta}_{*,k} = k^{-11/10}$, given by $\alpha = 1.5$, $r = 0.4$ in Theorem 32.

J.2. Experiment on real-world dataset

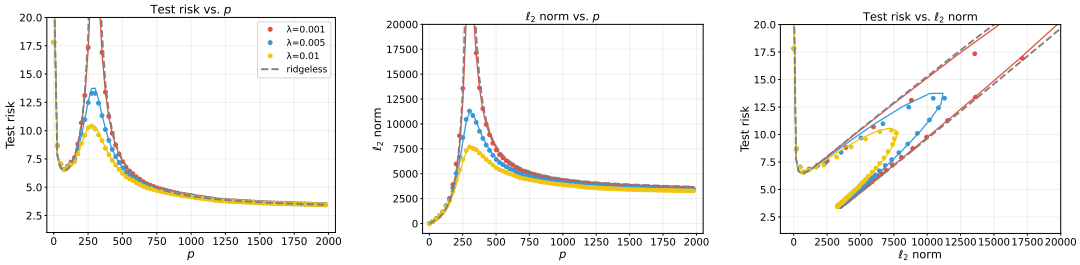
To complement the synthetic experiments presented in Appendix J.1, we additionally conducted experiments on the **MNIST** (Fig. 13) and **FashionMNIST** (Fig. 14) datasets [26, 52]. We applied the empirical diagonalization procedure introduced in [12, Algorithm 1] to estimate the key quantities $\boldsymbol{\Lambda}$ and $\boldsymbol{\theta}_*$ required for our analysis. The results on these real-world datasets are largely consistent with those observed on the synthetic data: in the under-parameterized regime, the curve of test risk versus norm exhibits a U-shape, while in the over-parameterized regime, the test risk increases monotonically with the norm and is approximately linear for ridge-less regression.

Notably, our random features model can be interpreted as a two-layer neural network with fixed first-layer weights $\boldsymbol{W}$, where the random features $\varphi(\boldsymbol{x}, \boldsymbol{w}_i)$ correspond to the hidden layer activations. This connection motivates our investigation of the Frobenius norm $\|\boldsymbol{W}\|_{\mathrm{F}}$ in Fig. 15, which captures the effective capacity of the frozen hidden layer. Furthermore, Fig. 16 examines the path norm—a natural complexity measure for neural networks that sums over all input-output paths and is defined as

$$\mu_{\text{path-norm}} = \sum_{j=1}^{p} a_j^2 \|\boldsymbol{w}_j\|_2^2 \,.$$

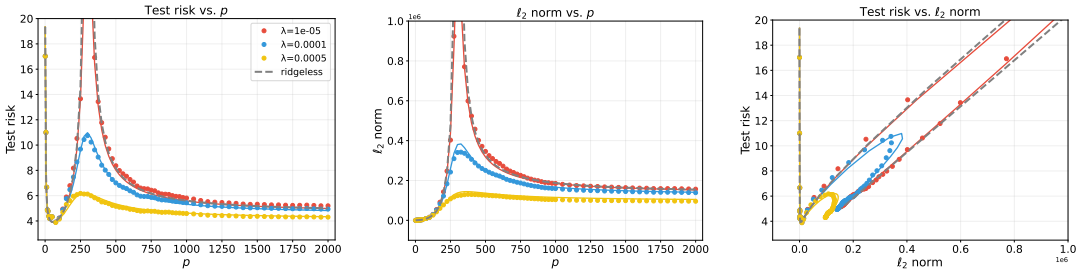
This quantity can be interpreted as the product of the norms of the first-layer and second-layer weights. Prior empirical work by [23] demonstrates that among various norm-based complexity measures, the path norm shows the strongest correlation with generalization performance in neural networks. Motivated by this finding, we investigate the relationship between test risk and path norm in our setting.

Comparing Fig. 13, Fig. 15, and Fig. 16, we observe that the test risk curve aligns more closely with the norm-based capacity of the second-layer parameters in the random feature model, rather than with that of the first-layer weights. Therefore, it is meaningful to study the relationship between the test risk and the norm of the RFM estimator, i.e., the second-layer parameters, as this quantity plays a central role in determining the model's effective capacity and generalization behavior.



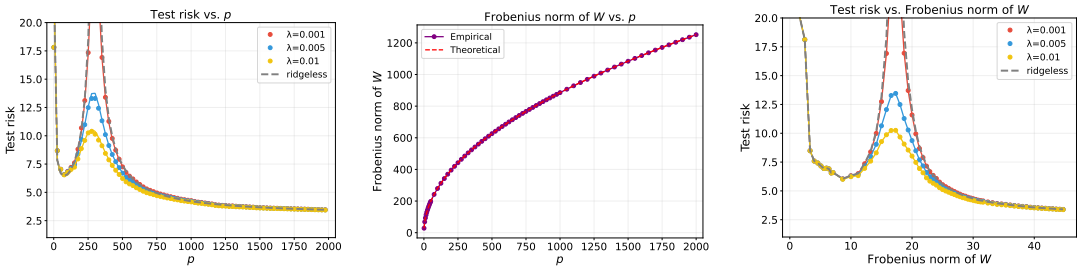
(a) Test risk vs. p (b) ℓ_2 norm vs. p (c) Test risk vs. ℓ_2 norm

Figure 13: The relationship between test risk, ℓ_2 norm and the number of features p. Solid lines are obtained from the deterministic equivalent, and points are numerical simulations, with the different curves denoting different regularization strengths. Training data $\{(\boldsymbol{x}_i, y_i)\}_{i\in[n]}$, $n = 300$, sub-sampled from the **MNIST** data set [26], with feature map given by $\varphi(\boldsymbol{x}, \boldsymbol{w}) = erf(\langle \boldsymbol{x}, \boldsymbol{w}\rangle)$ and $\boldsymbol{w} \sim \mathcal{N}(0, \boldsymbol{I}/d)$, where $d = 748$.



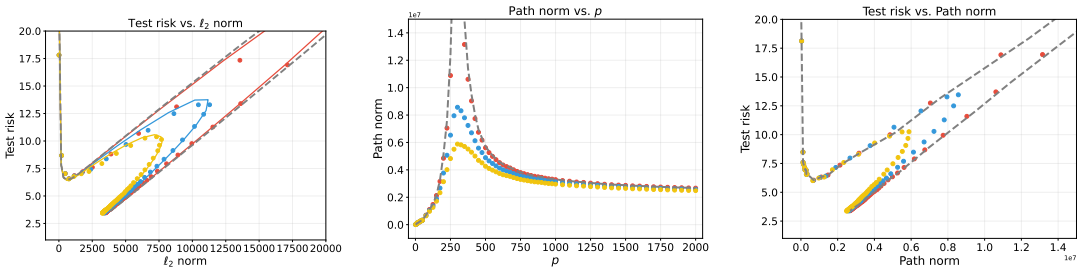
(a) Test risk vs. p (b) Norm vs. p (c) Test risk vs. Norm

Figure 14: The relationship between test risk, ℓ_2 norm and the number of features p. Solid lines are obtained from the deterministic equivalent, and points are numerical simulations, with the different curves denoting different regularization strengths. Training data $\{(\boldsymbol{x}_i, y_i)\}_{i\in[n]}$, $n = 300$, sub-sampled from the **FashionMNIST** data set [52], with feature map given by $\varphi(\boldsymbol{x}, \boldsymbol{w}) = erf(\langle \boldsymbol{x}, \boldsymbol{w}\rangle)$ and $\boldsymbol{w} \sim \mathcal{N}(0, \boldsymbol{I}/d)$, where $d = 748$.



(*a*) Test risk vs. p (*b*) Frobenius norm vs. p (*c*) Test risk vs. Frobenius norm

Figure 15: The relationship between test risk, Frobenius norm of $\boldsymbol{W}$ (the weights in the **hidden layer**) and the number of features p. Training data $\{(\boldsymbol{x}_i, y_i)\}_{i\in[n]}$, $n = 300$, sub-sampled from the MNIST data set [26], with feature map given by $\varphi(\boldsymbol{x}, \boldsymbol{w}) = erf(\langle \boldsymbol{x}, \boldsymbol{w}\rangle)$ and $\boldsymbol{w} \sim \mathcal{N}(0, \boldsymbol{I}/d)$, where $d = 748$.



(*a*) Test risk vs. p (*b*) Path norm vs. p (*c*) Test risk vs. Path norm

Figure 16: The relationship between test risk, Path norm and the number of features p. Training data $\{(\boldsymbol{x}_i, y_i)\}_{i\in[n]}$, $n = 300$, sub-sampled from the MNIST data set [26], with feature map given by $\varphi(\boldsymbol{x}, \boldsymbol{w}) = erf(\langle \boldsymbol{x}, \boldsymbol{w}\rangle)$ and $\boldsymbol{w} \sim \mathcal{N}(0, \boldsymbol{I}/d)$, where $d = 748$.

J.3. Norm-based capacity in two-layer neural networks

In this section, we investigate the relationship between test loss and different norm-based capacities for two-layer fully connected neural networks. Specifically, we evaluate four norm-based capacities: **Frobenius norm**, **Frobenius distance**, **spectral complexity**, and **path norm**. Our empirical results indicate that the path norm is the most suitable model capacity among these three norm-based capacities, which coincides with [23].

In our experiments, we use a balanced subset of the MNIST data set [26], consisting of 4,000 training samples from all the 10 classes. To simulate real-world noisy data, a noise level η is introduced, meaning $\eta \cdot 100\%$ of the training labels are randomly corrupted.

The model is chosen as a two-layer fully connected neural network with parameters including a bias term. The network is initialized using the Xavier initialization scheme and trained using the Stochastic Gradient Descent (SGD) optimizer with a learning rate of 0.1 and momentum of 0.95 over 2,000 epochs. During training, a batch size of 128 is used.

To control model complexity, we vary the number of neurons in the hidden layer, thereby adjusting the number of model parameters. To ensure the robustness of the results, each experiment

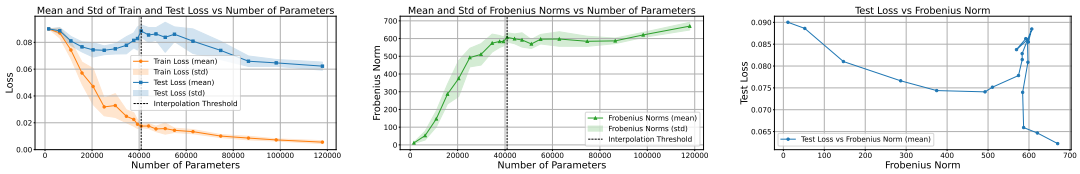
is repeated 10 times for each hidden layer dimension. The model's performance is evaluated using the Mean Squared Error (MSE) loss on both the training and test sets.

Frobenius norm: The parameter Frobenius norm is defined as for such two-layer neural networks

$$\mu_{\text{fro}}(f_{\boldsymbol{w}}) = \sum_{j=1}^{2} \|\boldsymbol{W}_j\|_{\text{F}}^2 \,,$$

where $\boldsymbol{W}_j$ is the parameter matrix of layer j.

Fig. 17 illustrates the relationship between test loss, Frobenius norm μ_{fro}, and the number of parameters p. As the number of model parameters increases, the test loss exhibits the typical double descent phenomenon. However, the Frobenius norm consistently increases monotonically (with a slowdown in the growth rate in the over-parameterized regime). Consequently, when using the Frobenius norm as a measure of model capacity, the double descent phenomenon remains observable.



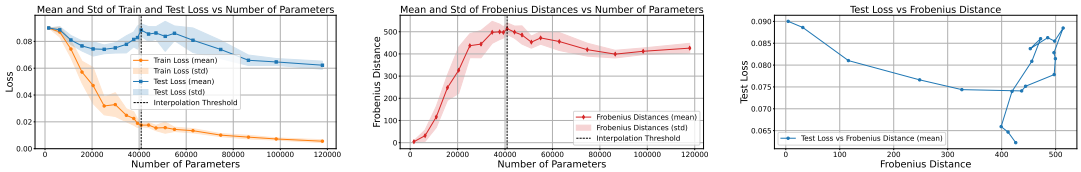
(a) Test (training) Loss vs. p (b) μ_{fro} vs. p (c) Test Loss vs. μ_{fro}

Figure 17: Experiments on two-layer fully connected neural networks with noise level $\eta = 0.2$. The **left** figure shows the relationship between test (training) loss and the number of the parameters p. The **middle** figure shows the relationship between the Frobenius norm μ_{fro} and p. The **right** figure shows the relationship between the test loss and μ_{fro}.

Frobenius distance: The Frobenius distance is defined as for such two-layer neural networks

$$\mu_{\text{fro-dis}}(f_{\boldsymbol{w}}) = \sum_{j=1}^{2} \|\boldsymbol{W}_j - \boldsymbol{W}_j^0\|_{\text{F}}^2 \,,$$

where $\boldsymbol{W}_j^0$ is the initialization of $\boldsymbol{W}_j^0$.



(a) Test (training) Loss vs. p (b) $\mu_{\text{fro-dis}}$ vs. p (c) Test Loss vs. $\mu_{\text{fro-dis}}$

Figure 18: Experiments on two-layer fully connected neural networks with noise level $\eta = 0.2$. The **left** figure is the same as Fig. 17(a). The **middle** figure shows the relationship between the Frobenius distance $\mu_{\text{fro-dis}}$ and p. The **right** figure shows the relationship between the test loss and $\mu_{\text{fro-dis}}$.

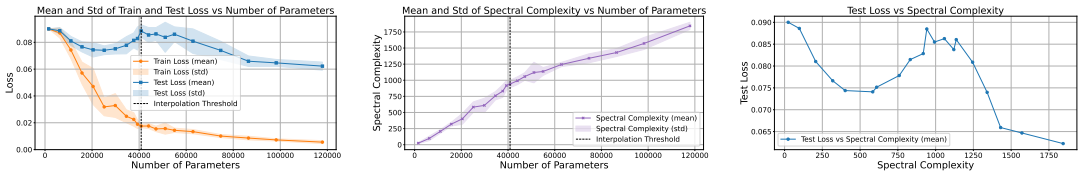
Fig. 18 illustrates the relationship between test loss, Frobenius distance μ_{fro}, and the number of parameters p. Different from Frobenius norm, Frobenius distance monotonically increases in the

under-parameterized regime, but shows a decrease in the over-parameterized regime. However, since the change of Frobenius distance in the over-parameterized regime is gentle and even eventually appears to rise, using Frobenius distance as the model capacity does not reflect the generalization capacity of the model.

Spectral complexity: The spectral complexity is defined as for such two-layer neural networks

$$\mu_{\text{spec}}(f_{\boldsymbol{w}}) = \left(\prod_{i=1}^{2} \|\boldsymbol{W}_i\|\right)\left(\sum_{i=1}^{2} \frac{\|\boldsymbol{W}_i\|_{2,1}^{2/3}}{\|\boldsymbol{W}_i\|^{2/3}}\right)^{3/2},$$

where $\|\cdot\|$ denote the spectral norm, and $\|\cdot\|_{p,q}$ denotes the (p,q)-norm of a matrix, defined as $\|\boldsymbol{M}\|_{p,q} := \|\left(\|\boldsymbol{M}_{:,1}\|_p, \cdots, \|\boldsymbol{M}_{:,m}\|_p\right)\|_q$ for $\boldsymbol{M} \in \mathbb{R}^{d\times m}$.



(a) Test (training) Loss vs. p (b) μ_{spec} vs. p (c) Test Loss vs. μ_{spec}

Figure 19: Experiments on two-layer fully connected neural networks with noise level $\eta = 0.2$. The **left** figure is the same as Fig. 17(a). The **middle** figure shows the relationship between the path norm μ_{spec} and p. The **right** figure shows the relationship between the test loss and μ_{spec}.

Fig. 19 illustrates the relationship between test loss, Spectral complexity μ_{spec}, and the number of parameters p. We can see that μ_{spec} increases monotonically with p, so the same double descent phenomenon occurs with spectral complexity as model capacity.

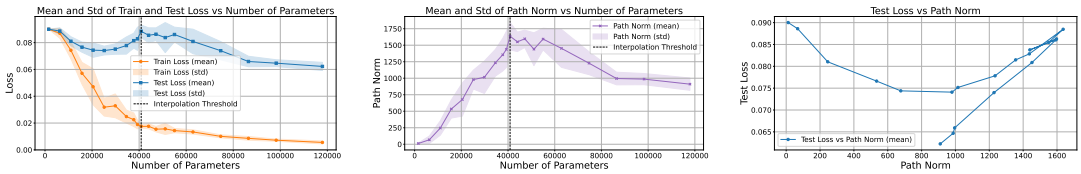
Path norm: The path norm is defined as

$$\mu_{\text{path-norm}}(f_{\boldsymbol{w}}) = \sum_i f_{\boldsymbol{w}^2}(\mathbf{1})[i],$$

where $\boldsymbol{w}^2 = \boldsymbol{w} \circ \boldsymbol{w}$ is the element-wise square of the parameters, and $\mathbf{1}$ for all-one vector. The path norm represents the sum of the outputs of the neural network after squaring all the parameters and inputting the all-one vector.

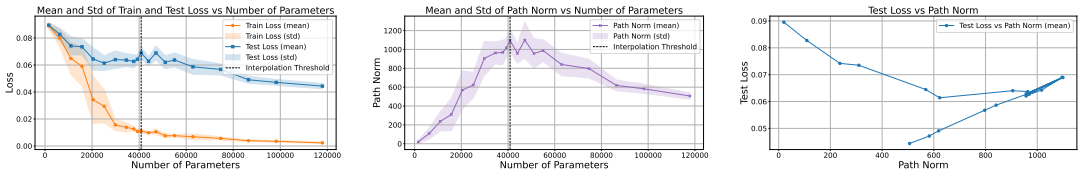
Fig. 20 illustrates the relationship between test loss, Path norm μ_{path}, and the number of parameters p. Path norm increases monotonically in the under-parameterized regime and decreases monotonically in the over-parameterized regime. This behavior resembles that of the ℓ_2 norm of random feature estimators. Additionally, the relationship between test loss and path norm forms a U-shaped curve in the under-parameterized regime and increases monotonically in the over-parameterized regime. This pattern is strikingly similar to the relationship between test loss and the ℓ_2 norm in random feature models.

Besides, we also conduct experiments with the noise level $\eta = 0.1$ and $\eta = 0.3$ in Figs. 21 and 22, respectively. We can see that, when the noise level increases, we observe stronger peaks in the test loss for double descent. However, the trend of test loss is similar at different noise levels with Path norm $\mu_{\text{path-norm}}$ as the model capacity, i.e., it shows a U-shape at the under-parameterized regime and an almost linear relationship at the over-parameterized regime.



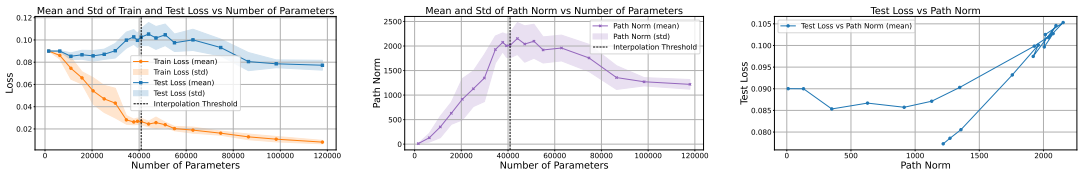
(a) Test (training) Loss vs. p (b) $\mu_{\text{path-norm}}$ vs. p (c) Test Loss vs. $\mu_{\text{path-norm}}$

Figure 20: Experiments on two-layer fully connected neural networks with noise level $\eta = 0.2$. The **left** figure is the same as Fig. 17(a). The **middle** figure shows the relationship between the path norm $\mu_{\text{path-norm}}$ and p. The **right** figure shows the relationship between the test loss and the path norm.



(a) Test (training) Loss vs. p (b) $\mu_{\text{path-norm}}$ vs. p (c) Test Loss vs. $\mu_{\text{path-norm}}$

Figure 21: Experiments on two-layer fully connected neural networks with noise level $\eta = 0.1$.



(a) Test (training) Loss vs. p (b) $\mu_{\text{path-norm}}$ vs. p (c) Test Loss vs. $\mu_{\text{path-norm}}$

Figure 22: Experiments on two-layer fully connected neural networks with noise level $\eta = 0.3$.

These observations demonstrates the relationship between the test loss and norm, which is general, not limited to RFMs in the main text.