Mirror Descent Maximizes Generalized Margin and Can Be Implemented Efficiently

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Abstract

Driven by the empirical success and wide use of deep neural networks, understanding the generalization performance of overparameterized models has become an increasingly popular question. To this end, there has been substantial effort to characterize the implicit bias of the optimization algorithms used, such as gradient descent (GD), and the structural properties of their preferred solutions. This paper answers an open question in this literature: For the classification setting, what solution does mirror descent (MD) converge to? Specifically, motivated by its efficient implementation, we consider the family of mirror descent algorithms with potential function chosen as the p-th power of the ℓ_p-norm, which is an important generalization of GD. We call this algorithm p-GD. For this family, we characterize the solutions it obtains and show that it converges in direction to a *generalized maximum-margin* solution with respect to the ℓ_p-norm for linearly separable classification. While the MD update rule is in general expensive to compute and perhaps not suitable for deep learning, p-GD is fully parallelizable in the same manner as SGD and can be used to train deep neural networks with virtually *no additional computational overhead*. Using comprehensive experiments with both linear and deep neural network models, we demonstrate that p-GD can noticeably affect the structure and the generalization performance of the learned models.

1 Introduction

Overparameterized deep neural networks have enjoyed a tremendous amount of success in a wide range of machine learning applications [Brown et al., 2020, Dosovitskiy et al., 2020, Ramesh et al., 2021, Schrittwieser et al., 2020]. However, as these highly expressive models have the capacity to have multiple solutions that interpolate training data, and not all these solutions perform well on test data, it is important to characterize which of these interpolating solutions the optimization algorithms converge to. Such characterization is important as it helps understand the generalization performance of these models, which is one of the most fundamental questions in machine learning.

Notably, it has been observed that even in the absence of any explicit regularization, the interpolating solutions obtained by the standard gradient-based optimization algorithms, such as (stochastic) gradient descent, tend to generalize well. Recent research has highlighted that such algorithms favor particular types of solutions, i.e., they *implicitly regularize* the learned models. Importantly, such implicit biases are shown to play a crucial role in determining generalization performance, e.g., [Donhauser et al., 2022, Neyshabur et al., 2014, Wilson et al., 2017, Zhang et al., 2021].

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Table 1: **Conceptual summary of our results.** In the case of linear regression, the implicit regularization results are complete; it is shown that mirror descent converges to the interpolating solution that is closest to the initialization. However, such characterization in the classification setting is missing in the literature and this is precisely the goal of this work. In particular, motivated by its practical application, we consider the potential function $\psi(\cdot) = \frac{1}{p}\|\cdot\|_p^p$ and extend the result of the gradient descent to such mirror descents.

	Regression	Classification
Gradient Descent ($\psi(\cdot) = \frac{1}{2}\|\cdot\|_2^2$)	$\operatorname{argmin}_w \|w - w_0\|_2$ s.t. w fits all data [Engl et al., 1996, Thm 6.1]	$\operatorname{argmin}_w \|w\|_2$ s.t. w classifies all data Soudry et al. [2018] Ji and Telgarsky [2019]
Mirror Descent (e.g. $\psi(\cdot) = \frac{1}{p}\|\cdot\|_p^p$)	$\operatorname{argmin}_w \|w - w_0\|_p$ s.t. w fits all data Gunasekar et al. [2018] Azizan and Hassibi [2019a]	$\operatorname{argmin}_w \|w\|_p$ s.t. w classifies all data **This work**

In the literature, the implicit bias of first-order methods is first studied in linear settings since the analysis is more tractable, and also, there have been several theoretical and empirical evidence that certain insights from linear models translate to deep learning, e.g. [Allen-Zhu et al., 2019, Bartlett et al., 2017, Belkin et al., 2019, Jacot et al., 2018, Lyu and Li, 2019, Nakkiran et al., 2021]. In the linear setting, it is easier to establish implicit bias for regression tasks, where square loss is typically used and it attains its minimum at a finite value. For example, the implicit bias of gradient descent (GD) for square loss goes back to Engl et al. [1996]. Beyond GD, analysis of other popular algorithms such as the family of mirror descent (MD), which is an important generalization of GD, is more involved and was established only recently by [Azizan and Hassibi, 2019a, Gunasekar et al., 2018]. Specifically, those works showed that mirror descent converges to the interpolating solution that is closest to the initialization in terms of a Bregman divergence. Thus, the implicit bias in linear regression is relatively well-understood by now.

On the other hand, **in the classification setting, the implicit bias analysis becomes significantly more challenging, and several questions remain open** despite significant progress in the past few years. A key differentiating factor in the classification setting is that the loss function does not attain its minimum at a finite value, and the weights have to grow to infinity. It has been shown that for the logistics loss, the gradient descent iterates converge to the ℓ_2-maximum margin SVM solution in direction [Ji and Telgarsky, 2019, Soudry et al., 2018]. However, such characterizations for mirror descent are missing in the literature. Because it is possible for optimization algorithms to exhibit implicit bias in regression but not in classification (and vice versa) [Gunasekar et al., 2018], resolving this gap of knowledge warrants careful analysis. See Table 1 for a summary.

In this paper, we advance the understanding of the implicit regularization of mirror descent in the classification setting. In particular, inspired by their practicality, we focus on mirror descents with potential function $\psi(\cdot) = \frac{1}{p}\|\cdot\|_p^p$ for $p > 1$. More specifically, such choice of potential results in an update rule that *can be applied coordinate-wise*, in the sense that updating the value at one coordinate does not depend on the values at other coordinates. Thanks to this property, this subclass of mirror descent can be implemented with *no additional computational overhead*, making it much more practical than other algorithms in the literature; see Remark 10 for more details.

Our contributions. In this paper, we make the following contributions:

- We study mirror descent with potential $\frac{1}{p}\|\cdot\|_p^p$ for $p > 1$, which will call *p-norm GD*, and abbreviated as p-GD, as a practical and efficient generalization of the popular gradient descent.
- We show that for separable linear classification with logistics loss, p-GD exhibits implicit regularization by converging in direction to a "generalized" maximum-margin solution with respect to

the ℓ_p norm. More generally, we show that, for monotonically decreasing loss functions, p-GD follows the so-called regularization path, which is defined in Section 2.

- We further investigate the implications of our theoretical findings with a set of experiments. Our experiments involving linear models corroborate our theoretical results, and real-world experiments with deep neural network models and popular datasets suggest that our findings carry over to such nonlinear settings.

Additional related work. We remark that recent works also attempt to accelerate the convergence of gradient descent to its implicit regularization, either by using an aggressive step size schedule [Ji and Telgarsky, 2021, Nacson et al., 2019] or with momentum [Ji et al., 2021]. Further, there have been several results for other optimization methods, including steepest descent, AdaBoost, and various adaptive methods such as RMSProp and Adam [Gunasekar et al., 2018, Rosset et al., 2004, Telgarsky, 2013, Wang et al., 2021]. However, to the best of our knowledge, there is no result for mirror descent in the classification setting.

2 Background and Problem Setting

We are interested in the well-known classification setting. Consider a collection of input-label pairs $\{(x_i, y_i)\}_{i=1}^n \subset \mathbb{R}^d \times \{\pm 1\}$ and a classifier $f_w(x)$, where $w \in \mathcal{W}$. For some *loss function* $\ell : \mathbb{R} \times \{\pm 1\} \to \mathbb{R}$, our goal is to minimize the empirical loss:

$$L(w) = \frac{1}{n} \sum_{i=1}^{n} \ell(y_i \cdot f_w(x_i)).$$

Throughout the paper, we assume that the classification loss function ℓ is decreasing, convex and does not attain its minimum, as in most common loss functions in practice (e.g., logistics loss and exponential loss). Without loss of generality, we assume that $\inf \ell(\cdot) = 0$.

For our theoretical analysis, we consider a linear model, where the models can be expressed by $f_w(x) = w^\top x$ and $w \in \mathbb{R}^d$. We also make the following assumptions about the data. First, since we are mainly interested in the over-parameterized setting where $d > n$, we assume that the data is linearly separable, i.e., there exists $w^* \in \mathbb{R}^d$ s.t. $\operatorname{sign}(\langle w^*,\ x_i \rangle) = y_i$ for all $i \in [n]$. We also assume that the inputs x_i's are bounded. More specifically, for our later purpose, we assume that for $p > 0$, there exists some constant C so that $\max_i \|x_i\|_q < C$, where $1/q + 1/p = 1$.

Preliminaries on mirror descent. The key component of mirror descent is a *potential function*. In this work, we will focus on differentiable and strictly convex potentials defined on the entire domain $\mathbb{R}^n$.[1] We call $\nabla\psi$ the corresponding *mirror map*. Given a potential, the natural notion of "distance" associated with the potential ψ is given by the Bregman divergence.

Definition 1 (Bregman divergence [Bregman, 1967])**.** *For a mirror map ψ, the Bregman divergence $D_\psi(\cdot, \cdot)$ associated to ψ is defined as*

$$D_\psi(x, y) := \psi(x) - \psi(y) - \langle \nabla\psi(y),\ x - y \rangle, \qquad \forall x, y \in \mathbb{R}^n.$$

An important case is the potential $\psi = \frac{\|\cdot\|^2}{2}$, where $\|\cdot\|$ denotes the Euclidean norm. Then, the Bregman divergence becomes $D_\psi(x, y) = \frac{1}{2}\|x - y\|^2$. For more background on Bregman divergence and its properties, see, e.g., [Bauschke et al., 2017, Section 2.2] and [Azizan and Hassibi, 2019b].

Mirror descent (MD) with respect to the mirror map ψ is a generalization of gradient descent where we use Bregman divergence as a measure of distance:

$$w_{t+1} = \operatorname*{argmin}_{w} \left\{ \frac{1}{\eta} D_\psi(w, w_t) + \langle \nabla L(w_t),\ w \rangle \right\} \tag{MD}$$

Equivalently, MD can be written as $\nabla\psi(w_{t+1}) = \nabla\psi(w_t) - \eta\nabla L(w_t)$. We refer readers to [Bubeck, 2015, Figure 4.1] for a nice illustration of mirror descent. Also, see [Juditsky et al., 2011, Section 5.7] for various examples of potentials depending on applications.

[1] In general, the mirror map is a convex function of Legendre type (see, e.g., [Rockafellar, 1970, Section 26]).

One property we will repeatedly use is the following [Azizan and Hassibi, 2019a]:

Lemma 2 (MD identity)**.** *For any $w \in \mathbb{R}^n$, the following identities hold for* MD*:*

$$D_\psi(w, w_t) = D_\psi(w, w_{t+1}) + D_{\psi-\eta L}(w_{t+1}, w_t) + \eta D_L(w, w_t) - \eta L(w) + \eta L(w_{t+1}), \tag{1a}$$

$$= D_\psi(w, w_{t+1}) + D_{\psi-\eta L}(w_{t+1}, w_t) - \eta \langle \nabla L(w_t),\ w - w_t \rangle - \eta L(w_t) + \eta L(w_{t+1}). \tag{1b}$$

Using Lemma 2, we make several new observations and prove the following useful statements.

Lemma 3. *For sufficiently small step size η such that $\psi - \eta L$ is convex, the loss is monotonically decreasing after each iteration of* MD*, i.e., $L(w_{t+1}) \le L(w_t)$.*

Lemma 4. *In a separable linear classification problem, if η is chosen sufficiently small s.t. $\psi - \eta L$ is convex, then we have $L(w_t) \to 0$ as $t \to \infty$. Hence, $\lim_{t\to\infty} \|w_t\| = \infty$ for any norm $\|\cdot\|$.*

The formal proofs of these lemmas can be found in Appendix A.

Remark 5. We can relax the condition in Lemma 3 and 4 such that for a sufficiently small step size η, $\psi - \eta L$ is only locally convex at the iterates w_t. The relaxed condition allows us to analyze losses such as the exponential loss (see, e.g. footnote 2 of Soudry et al. [2018]). This condition can be considered as the mirror descent counterpart to the standard smoothness assumption in the analysis of gradient descent (see Lu et al. [2018]).

Preliminaries on the convergence of linear classifier. As we discussed above, the weights vector w_t diverges for mirror descent. Here the main theoretical question is:

What direction does MD diverge to? In other words, can we characterize $w_t / \|w_t\|$ as $t \to \infty$?

To answer this question, we define two special directions whose importance will be illustrated later.

Definition 6. *The **regularization path** with respect to the ℓ_p-norm is defined as*

$$\bar{w}_p(B) = \operatorname*{argmin}_{\|w\|_p \le B} L(w) \tag{2}$$

*And if the limit $\lim_{B\to\infty} \bar{w}_p(B)/B$ exists, we call it the **regularized direction** and denote it by u_p^{r}.*

Definition 7. *The **margin** γ of the a linear classifier w is defined as $\gamma(w) = \min_{i=1,\dots,n} y_i \langle x_i,\ w \rangle$. The* **max-margin direction** *with respect to the ℓ_p-norm is defined as:*

$$u_p^{\mathsf{m}} := \operatorname*{argmax}_{\|w\|_p \le 1} \left\{ \min_{i=1,\dots,n} y_i \langle x_i,\ w \rangle \right\} \tag{3}$$

And let $\hat{\gamma}_p$ be the optimal value to the equation above.

Note that u_p^{m} is parallel to the hard-margin SVM solution w.r.t. ℓ_p-norm: $\operatorname{argmin}_w \{\|w\|_p : \gamma(w) \ge 1\}$. Prior results had shown that, in linear classification, gradient descent converges in direction.

Theorem 8 (Soudry et al. [2018])**.** *For separable linear classification with logistics loss, the gradient descent iterates with sufficiently small step size converge in direction to u_2^{m}, i.e., $\lim_{t\to\infty} \frac{w_t}{\|w_t\|_2} = u_2^{\mathsf{m}}$.*

Theorem 9 (Ji et al. [2020])**.** *If the regularized direction u_p^{r} with respect to the ℓ_2-norm exists, then the gradient descent iterates with sufficiently small step size converge to the regularized direction u_2^{r}, i.e., $\lim_{t\to\infty} \frac{w_t}{\|w_t\|_2} = u_2^{\mathsf{r}}$.*

3 Mirror Descent with the p-th Power of ℓ_p-norm

In this section, we investigate theoretical properties of the main algorithm of interest, namely mirror descent with $\psi(\cdot) = \frac{1}{p}\|\cdot\|_p^p$ and for $p > 1$. We shall call this algorithm *p-norm GD* because it naturally generalizes gradient descent to ℓ_p geometry, and for conciseness, we will refer to this algorithm by the shorthand p-GD. As noticed by Azizan et al. [2021], this choice of mirror potential is particularly of practical interest because the mirror map $\nabla\psi$ updates becomes *separable* in coordinates and thus can be implemented *coordinate-wise* independent of other coordinates:

$$\forall j \in [d], \quad \begin{cases} w_{t+1}[j] \leftarrow \left|w_t^+[j]\right|^{\frac{1}{p-1}} \cdot \operatorname{sign}\left(w_t^+[j]\right) \\ w_t^+[j] := |w_t[j]|^{p-1}\operatorname{sign}(w_t[j]) - \eta \nabla L(w_t)[j] \end{cases} \tag{p-GD}$$

Furthermore, we can extend upon the observation of Azizan et al. [2021] and derive these identities that allow us to better manipulate p-GD:

$$\langle \nabla \psi(w),\ w \rangle = \operatorname{sign}(w_1) w_1 \cdot |w_1|^{p-1} + \cdots + \operatorname{sign}(w_d) w_d \cdot |w_d|^{p-1} = \|w\|^p \tag{4a}$$

$$D_\psi\left(cw, cw'\right) = |c|^p D_\psi\left(w, w'\right) \quad \forall c \in \mathbb{R}. \tag{4b}$$

Remark 10. Note that the coordinate-wise separability property is not shared among other related algorithms in the literature. For instance, the choice $\psi = \frac{1}{2}\|\cdot\|_q^2$ for $1/p + 1/q = 1$, which is referred to as the p-norm algorithm [Gentile, 2003, Grove et al., 2001] is not fully coordinate-wise separable since it requires computing $\|w_t\|_p$ at each step (see, e.g., [Gentile, 2003, eq. (1)]). Another related algorithm is steepest descent, where the Bregman divergence in MD is replaced with $\|\cdot\|^2$ for general norm $\|\cdot\|$.[2] However, for similar reasons, the update rule is not fully separable.

3.1 Main theoretical results

We extend Theorems 8 and 9 to the setting of p-GD. We will resolve two major obstacles in the analysis of implicit regularization in linear classification:

- Our analysis approaches the classification setting as a limit of the regression implicit bias. This argument gives stronger theoretical justification for utilizing the regularized direction (as employed by Ji et al. [2020]) and partially addresses the concern from Gunasekar et al. [2018] that the implicit bias of regression and classification problems are "fundamentally different."
- On a more technical note, analyzing the implicit bias requires handling the cross terms of the form $\langle \nabla \psi(w),\ w' \rangle$, which lack direct geometric interpretations. We demonstrate that for our potential functions of interest, these terms can be nicely written and can be handled in the analysis.

We begin with the motivation behind the regularized direction, and consider the regression setting in which there exists some weight vector w such that $L(w) = 0$. Then, we can apply Lemma 2 to get

$$D_\psi(w, w_t) = D_\psi(w, w_{t+1}) + D_{\psi - \eta L}(w_{t+1}, w_t) + \eta D_L(w, w_t) + \eta(L(w_{t+1}) - L(w))$$

Since we assumed $L(w) = 0$, the equation above implies that $D_\psi(w, w_t) \geq D_\psi(w, w_{t+1})$ for sufficiently small step-size η. This can be interpreted as MD having a decreasing "potential" of the from $D_\psi\left(w, \cdot\right)$ during each step. Using this property, Azizan and Hassibi [2019a] establishes the implicit bias results of mirror descent in the regression setting.

However, such weight vector w does not exist in the classification setting. One natural workaround would then be to choose a vector w so that $L(w) \leq L(w_t)$ for all $t \leq T$. The following result, which is a generalization of [Ji et al., 2020, Lemma 9], shows that one can in fact choose the reference vector w as a scalar multiple of the regularized direction.

Lemma 11. *If the regularized direction u_p^{r} exists, then $\forall \alpha > 0$, there exists r_α such that for any w with $\|w\|_p > r_\alpha$, we have $L((1+\alpha)\|w\|_p u_p^{\mathsf{r}}) \leq L(w)$.*

However, this does not resolve the issue altogether. Recall from Lemma 4 that the loss approaches 0, and therefore one cannot choose a fixed reference vector w in the limit as $T \to \infty$. But due to the homogeneity of Bregman divergence (4b), we can scale u_p^{r} by a constant factor during each iteration, and, by doing so, we choose the reference vector w to be a "moving target." In other words, the idea behind our analysis is that the classification problem is chasing after a regression one and would behave similar to it in the limit. Let us formalize this idea. We begin with the following inequality:

$$D_\psi\left(c_t u_p^{\mathsf{r}}, w_{t+1}\right) \leq D_\psi\left(c_t u_p^{\mathsf{r}}, w_t\right) - \eta L(w_{t+1}) + \eta L(w_t), \tag{5}$$

where c_t is taken to be $\approx \|w_t\|_p$.[3]

[2] It is also worth noting that steepest descent is not an instance of mirror descent since $\|\cdot\|^2$ is not a Bregman divergence for a general norm $\|\cdot\|$.

[3] To be more precise, we want $c_t = (1+\alpha)\|w_t\|_p$; and reason behind this choice is self-evident after we present Corollary 12.

Now we modify (5) so that it can telescope over different iterations. One way is to add $D_\psi\left(c_{t+1}u_p^{\mathsf{r}}, w_{t+1}\right)$ on both sides of (5) and move $D_\psi\left(c_t u_p^{\mathsf{r}}, w_{t+1}\right)$ to the right-hand side as follows:

$$\begin{aligned}
&D_\psi\left(c_{t+1}u_p^{\mathsf{r}}, w_{t+1}\right)\\
&\le D_\psi\left(c_t u_p^{\mathsf{r}}, w_t\right) - \eta L(w_{t+1}) + \eta L(w_t) + D_\psi\left(c_{t+1}u_p^{\mathsf{r}}, w_{t+1}\right) - D_\psi\left(c_t u_p^{\mathsf{r}}, w_{t+1}\right)\\
&= D_\psi\left(c_t u_p^{\mathsf{r}}, w_t\right) - \eta L(w_{t+1}) + \eta L(w_t) + \psi(c_{t+1}u_p^{\mathsf{r}}) - \psi(c_t u_p^{\mathsf{r}}) - \left\langle \nabla\psi(w_{t+1}),\ (c_{t+1}-c_t)u_p^{\mathsf{r}}\right\rangle
\end{aligned}$$

Summing over $t = 0, \ldots, T-1$ gives us

$$\begin{aligned}
D_\psi\left(c_T u_p^{\mathsf{r}}, w_T\right) \le D_\psi\left(c_0 u_p^{\mathsf{r}}, w_0\right) - \eta L(w_1) + \eta L(w_T) + \psi(c_T u_p^{\mathsf{r}}) - \psi(c_1 u_p^{\mathsf{r}})\\
- \sum_{t=1}^{T-1} \left\langle \nabla\psi(w_{t+1}),\ (c_{t+1}-c_t)u_p^{\mathsf{r}}\right\rangle
\end{aligned} \tag{6}$$

The rest of the argument deals with simplifying quantities that do not cancel under telescoping sum. For instance, in order to deal with $\left\langle \nabla\psi(w_{t+1}),\ u_p^{\mathsf{r}}\right\rangle$, we invoke the MD update rule as follows

$$\left\langle \nabla\psi(w_{t+1}) - \nabla\psi(w_t),\ u_p^{\mathsf{r}}\right\rangle = \left\langle -\eta\nabla L(w_t),\ u_p^{\mathsf{r}}\right\rangle \gtrsim \left\langle -\eta\nabla L(w_t),\ w_t\right\rangle,$$

where the last inequality follows from the intuition that u_p^{r} is the direction along which the loss achieves the smallest value and hence $\nabla L(w_t)$ must point away from u_p^{r}, i.e., it must be that $\left\langle \nabla L(w_t),\ u_p^{\mathsf{r}}\right\rangle \lesssim \left\langle \nabla L(w_t),\ u\right\rangle$ for any direction u. The following result formalizes this intuition.

Corollary 12. *For w so that $\|w\|_p > r_\alpha$, we have $\left\langle \nabla L(w),\ w\right\rangle \ge (1+\alpha)\|w\|_p \left\langle \nabla L(w),\ u_p^{\mathsf{r}}\right\rangle$.*

Proof. This follows from the convexity of L and Lemma 11: $\left\langle \nabla L(w),\ w - (1+\alpha)\|w\|\, u_p^{\mathsf{r}})\right\rangle \ge L(w) - L((1+\alpha)\|w\|\, u_p^{\mathsf{r}}) \ge 0$. □

Now we are left with the terms $\langle -\eta\nabla L(w_t),\ w_t\rangle$. For general potential ψ, the quantity $\langle -\eta\nabla L(w_t),\ w_t\rangle = \langle \nabla\psi(w_{t+1}) - \nabla\psi(w_t),\ w_t\rangle$ cannot be simplified. On the other hand, due to our choice of potential, one can invoke Lemma 2 to lower bound these quantities in terms of $\|w_{t+1}\|_p$ and $\|w_t\|_p$, and this step is detailed in Lemma 18 in Appendix B.2. Once we have established a lower bound on $\left\langle \nabla\psi(w_{t+1}),\ u_p^{\mathsf{r}}\right\rangle$, we can turn (6) entirely into a telescoping sum and unwind the above process to show that $D_\psi\left(u_p^{\mathsf{r}}, w_t/\|w_t\|_p\right)$ must converge to zero in the limit as $t \to \infty$. Putting this all together, we obtain the following result.

Theorem 13. *For a separable linear classification problem, if the regularized direction u_p^{r} exists, then with sufficiently small step size, the iterates of p-GD converge to u_p^{r} in direction:*

$$\lim_{t\to\infty} \frac{w_t}{\|w_t\|_p} = u_p^{\mathsf{r}}. \tag{7}$$

A formal proof of this theorem can be found in Appendix B.3. We note that our proof further simplifies derivations using the separability of the mirror map. The final missing piece would be the existence of the regularized direction. In general, finding the limit direction u_p^{r} would be difficult. Fortunately, we can sometimes appeal to the max-margin direction that is much easier to compute. The following result is a generalization of [Ji et al., 2020, Proposition 10] and shows that for common losses in classification, the regularized direction and the max-margin direction are the same, hence proving the existence of the former.

Proposition 14. *If we have a loss with exponential tail, e.g. $\lim_{z\to\infty} \ell(z)e^{az} = b$, then the regularized direction exists and it is equal to the max-margin direction u_p^{m}.*

The proof of this result can be found in Appendix B.5. Note that many commonly used losses in classification, e.g., logistic loss, have exponential tail.

3.2 Asymptotic convergence rate

In this section, we characterize the rate of convergence in Theorem 13. Following the proof of Theorem 13, one can show the following result in the case of linearly separable data.

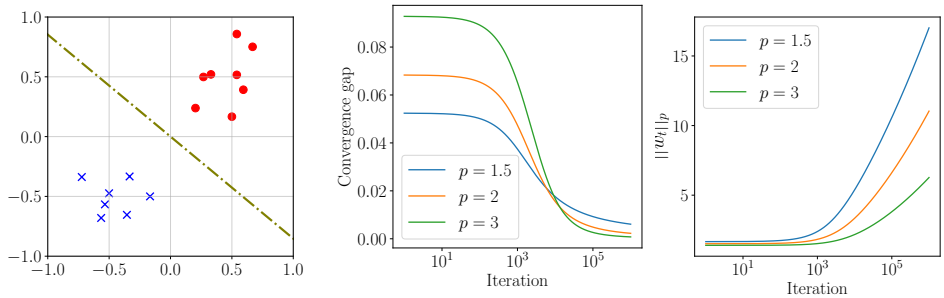

Figure 1: An example of p-GD on randomly generated data with exponential loss and $p = 1.5, 2, 3$. **(1)** The left plot is a scatter plot of the data: $\times$'s and $\bullet$'s denote the two different labels ($y_i = \pm 1$). The dotted line is the ℓ_2 max-margin classifier. For clarity, other ℓ_p max-margin classifiers are omitted from the plot. **(2)** The middle plot shows the rate which the quantity $D_\psi\left(u_p^{\mathsf{r}}, w_t / \|w_t\|_t\right)$ converges to 0. **(3)** The right plot shows how fast the p-norm of w_t growths. We can observe that the asymptotic behaviors of these plots are consistent with Corollary 17.

Corollary 15. *The following rate of convergence holds:* $D_\psi\left(u_p^{\mathsf{r}}, \frac{w_t}{\|w_t\|_p}\right) \in O\left(\|w_t\|_p^{-(p-1)}\right)$.

In order to fully understand the convergence rate, we need to characterize the asymptotic behavior of $\|w_t\|_p$. The next result precisely does that. Recall that we assumed the dataset is bounded so that $\max_i \|x_i\|_q \le C$ for $1/p + 1/q = 1$, and the max-margin direction u_p^{m} satisfies $\langle x_i,\ u_p^{\mathsf{m}} \rangle \ge \hat{\gamma}_p \, \forall i \in [n]$. Then, we have the following bound on $\|w_t\|_p$.

Lemma 16. *For exponential loss $\ell(z) = \exp(-z)$, the asymptotic growth of $\|w_t\|_p$ is contained in $\Theta(\log t)$. In particular, we have*

$$\liminf_{t\to\infty} \|w_t\|_p \ge \frac{1}{C}(\log t - p \log\log t) + O(1) \text{ and } \limsup_{t\to\infty} \|w_t\|_p \le \hat{\gamma}_p^{-1} \frac{p}{p-1} \log t.$$

The proof of this lemma can be found in Appendix C. Similar conclusions can be reached for other losses with exponential tail. Therefore, in such cases, p-GD has poly-logarithmic rate of convergence.

Corollary 17. *For exponential loss, we have convergence rate* $D_\psi\left(u_p^{\mathsf{r}}, \frac{w_t}{\|w_t\|_p}\right) \in O\left(\frac{1}{\log^{p-1}(t)}\right)$.

4 Experiments

In this section, we investigate the behavior and performance of p-GD for various values of p. We naturally pick $p = 2$ that corresponds to gradient descent, Because p-GD does not directly support $p = 1$ and ∞, we choose $p = 1.1$ as a surrogate for ℓ_1, and $p = 10$ as a surrogate for ℓ_∞. We also consider $p = 1.5, 3, 6$ to interpolate these points. This section will present a summary of our results; the complete experimental setup and full results can be found in Appendices E and F.

4.1 Linear classification

Visualization of the convergence of p-GD. To visualize the results of Theorem 13 and Corollary 17, we randomly generated a linearly separable set of 15 points in $\mathbb{R}^2$. We then employed p-GD on this dataset with exponential loss $\ell(z) = \exp(-z)$ and fixed step size $\eta = 10^{-4}$. We ran this experiment for $p = 1.5, 2, 3$ and for 10^6 iterations.

In the illustrations of Figure 1, the mirror descent iterates w_t have unbounded norm and converge in direction to u_p^{m}. These results are consistent with Lemma 4 and with Theorem 13. Moreover, as predicted by Corollary 17, the exact rate of convergence for $D_\psi\left(u_p^{\mathsf{m}}, w_t / \|w_t\|_t\right)$ is poly-logarithmic with respect to the number of iterations. Corollary 17 also indicates that the convergence rate would be faster for larger p due to the larger exponent, and this is consistent with our observation in the second plot of Figure 1. Finally, in the third plot of Figure 1, the norm of the iterates w_t grows at a logarithmic rate, which is the same as the prediction by Lemma 16.

Implicit bias of p-GD in linear classification. We now verify the conclusions of Theorem 13. To this end, we recall that u_p^{m} is parallel to the SVM solution $\operatorname{argmin}_w\{\|w\|_p : \gamma(w) \geq 1\}$. Hence, we can exploit the linearity and rescale any classifier so that its margin is equal to 1. If the prediction of Theorem 13 holds, then for each fixed value of p, the classifier generated by p-GD should have the smallest ℓ_p-norm after rescaling.

To ensure that u_p^{m} are sufficiently different for different values of p, we simulate an over-parameterized setting by randomly select 15 points in $\mathbb{R}^{100}$. We used fixed step size of 10^{-4} and ran 250 thousand iterations for different p's.

Table 2 shows the results for $p = 1.1, 2, 3$ and 10; under each norm, we highlight the smallest classifier in **boldface**. Among the four classifiers we presented, p-GD with $p = 1.1$ has the smallest $\ell_{1.1}$-norm. And similar conclusions hold for $p = 2, 3, 10$. Although p-GD converges to u_p^{m} at a very slow rate, we are able to observe a very strong implicit bias of p-GD classifiers toward their respective ℓ_p geometry in a highly over-parameterized setting. This suggests we should be able to take advantage of the implicit regularization in practice and at a moderate computational cost. Due to space constraints, we defer a more complete result with additional values of p to Appendix F.1.

Table 2: Size of the linear classifiers generated by p-GD (after rescaling) in $\ell_{1.1}, \ell_2, \ell_3$ and ℓ_{10} norms.

	$\ell_{1.1}$	ℓ_2	ℓ_3	ℓ_{10}
$p = 1.1$	**5.670**	1.659	1.100	0.698
$p = 2$	6.447	**1.273**	0.710	0.393
$p = 3$	7.618	1.345	**0.691**	0.318
$p = 10$	9.086	1.520	0.742	**0.281**

4.2 Deep neural networks

Going beyond linear models, we now investigate p-GD in deep-learning settings in its impact on the structure of the learned model and potential implications on the generalization performance. As we had discussed in Section 3, **the implementation of p-GD is straightforward**; to illustrate simplicity of implementation, we provide code snippets in Appendix D. Thus, we are able to effectively experiment with the behaviors p-GD in neural network training. Specifically, we perform a set of experiments on the CIFAR-10 dataset [Krizhevsky et al., 2009]. We use the *stochastic* version of p-GD with different values of p. We choose a variety of networks: VGG [Simonyan and Zisserman, 2014], RESNET [He et al., 2016], MOBILENET [Sandler et al., 2018] and REGNET [Radosavovic et al., 2020].

Implicit bias of p-GD in deep neural networks. Since the notion of margin is not well-defined in this highly nonlinear setting, we instead visualize the impacts of p-GD's implicit regularization on the histogram of weights (in absolute value) in the trained model.

In Figure 2, we report the weight histograms of RESNET-18 models trained under p-GD with $p = 1.1, 2, 3$ and 10. Depending on p, we observe interesting differences between the histograms. Note that the deep network is most sparse when $p = 1.1$ as most weights clustered around 0. Moreover, comparing the maximum weights, one can see that the case of $p = 10$ achieves the smallest value. Another observation is that the network becomes denser as p increases; for instance, there are more weights away from zero for the cases $p = 3, 10$. These overall tendencies are also observed for other deep neural networks; see Appendix F.2.

Generalization performance. We next investigate the generalization performance of networks trained with different p's. To this end, we adopt a fixed selection of hyper-parameters and then train four deep neural network models to 100% training accuracy with p-GD with different p's. As Table 3 shows, interestingly the networks trained by p-GD with $p = 3$ consistently outperform other choices of p's; notably, for MOBILENET and REGNET, the case of $p = 3$ outperforms the others by more than 1%. Somewhat counter-intuitively, the most sparse network trained by p-GD with $p = 1.1$ does not exhibit better generalization performance, but rather shows worse generalization than other values of p. Although these observations are not directly predicted by our theoretical results, we believe that understanding them would establish an important step toward understanding generalization of overparameterized models. Due to space limit, we defer other experimental results to Appendix F.3.

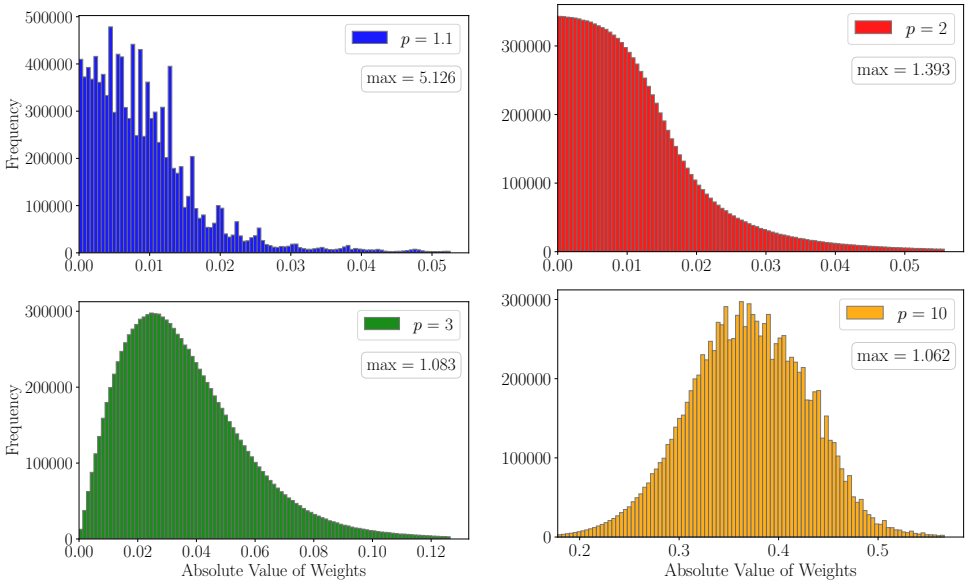

Figure 2: The histogram of weights in RESNET-18 models trained with p-GD for the CIFAR-10 dataset. For clarity, we cropped out the tails and each plot has 100 bins after cropping. The trends of these histograms reflect the implicit biases of p-GD: the distribution of $p = 1.1$ has the most number of weights around zero; and the maximum weight is smallest when $p = 10$.

Table 3: CIFAR-10 test accuracy (%) of p-GD on various deep neural networks. For each deep network and value of p, the average $\pm$ std. dev. over 5 trials are reported. And the best performing value(s) of p for each individual deep network is highlighted in **boldface**.

	VGG-11	RESNET-18	MOBILENET-V2	REGNETX-200MF
$p = 1.1$	88.19 $\pm$ .17	92.63 $\pm$ .12	91.16 $\pm$ .09	91.21 $\pm$ .18
$p = 2$ (SGD)	90.15 $\pm$ .16	**93.90** $\pm$ .14	91.97 $\pm$ .10	92.75 $\pm$ .13
$p = 3$	**90.85** $\pm$ .15	**94.01** $\pm$ .13	**93.23** $\pm$ .26	**94.07** $\pm$ .12
$p = 10$	88.78 $\pm$ .37	93.55 $\pm$ .21	92.60 $\pm$ .22	92.97 $\pm$ .16

IMAGENET experiments. We also perform a similar set of experiments on the IMAGENET dataset [Russakovsky et al., 2015], and these results can be found in Appendix F.4.

5 Conclusion and Future Work

In this paper, we establish an important step towards better understanding implicit bias in the classification setting, by showing that p-GD converges in direction to the generalized regularized/max-margin directions. We also run several experiments to corroborate our main findings along with the practicality of p-GD. The experiments are conducted in various settings: (i) linear models in both low and high dimensions, (ii) real-world data with highly over-parameterized nonlinear models.

We conclude this paper with several important future directions:

- Our analysis holds for $\psi(\cdot) = \|\cdot\|_p^p$, where we argued that this choice is key practical interest due to its efficient algorithmic implementations. It is mathematically interesting to generalize our analysis to other potential functions regardless of practical interest.
- As we discussed in Section 4.2, different choices of p's for our p-GD algorithm result in different generalization performance. It would be interesting to theoretically investigate these results.
- Another interesting question is to further investigate how practical techniques used in training neural networks (such as weight decay and adaptive learning rate) can affect the implicit bias and generalization properties of p-GD.

References

Zeyuan Allen-Zhu, Yuanzhi Li, and Zhao Song. A convergence theory for deep learning via over-parameterization. In *International Conference on Machine Learning*, pages 242–252. PMLR, 2019.

Navid Azizan and Babak Hassibi. Stochastic gradient/mirror descent: Minimax optimality and implicit regularization. In *International Conference on Learning Representations*, 2019a.

Navid Azizan and Babak Hassibi. A stochastic interpretation of stochastic mirror descent: Risk-sensitive optimality. In *2019 IEEE 58th Conference on Decision and Control (CDC)*, pages 3960–3965. IEEE, 2019b.

Navid Azizan, Sahin Lale, and Babak Hassibi. Stochastic mirror descent on overparameterized nonlinear models. *IEEE Transactions on Neural Networks and Learning Systems*, 2021.

Peter L Bartlett, Dylan J Foster, and Matus J Telgarsky. Spectrally-normalized margin bounds for neural networks. *Advances in neural information processing systems*, 30, 2017.

Heinz H Bauschke, Jérôme Bolte, and Marc Teboulle. A descent lemma beyond lipschitz gradient continuity: first-order methods revisited and applications. *Mathematics of Operations Research*, 42(2):330–348, 2017.

Mikhail Belkin, Daniel Hsu, Siyuan Ma, and Soumik Mandal. Reconciling modern machine-learning practice and the classical bias–variance trade-off. *Proceedings of the National Academy of Sciences*, 116(32):15849–15854, 2019.

Lev M. Bregman. The relaxation method of finding the common point of convex sets and its application to the solution of problems in convex programming. *USSR Computational Mathematics and Mathematical Physics*, 7(3):200–217, 1967.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.

Sébastien Bubeck. Convex optimization: algorithms and complexity. *Foundations and Trends® in Machine Learning*, 8(3-4):231–357, 2015.

Konstantin Donhauser, Nicolo Ruggeri, Stefan Stojanovic, and Fanny Yang. Fast rates for noisy interpolation require rethinking the effects of inductive bias. *arXiv preprint arXiv:2203.03597*, 2022.

Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929*, 2020.

Heinz Werner Engl, Martin Hanke, and Andreas Neubauer. *Regularization of inverse problems*, volume 375. Springer Science & Business Media, 1996.

Claudio Gentile. The robustness of the p-norm algorithms. *Machine Learning*, 53(3):265–299, 2003.

Adam J Grove, Nick Littlestone, and Dale Schuurmans. General convergence results for linear discriminant updates. *Machine Learning*, 43(3):173–210, 2001.

Suriya Gunasekar, Jason Lee, Daniel Soudry, and Nathan Srebro. Characterizing implicit bias in terms of optimization geometry. In *International Conference on Machine Learning*, pages 1832–1841. PMLR, 2018.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

Arthur Jacot, Franck Gabriel, and Clément Hongler. Neural tangent kernel: Convergence and generalization in neural networks. *Advances in neural information processing systems*, 31, 2018.

Ziwei Ji and Matus Telgarsky. The implicit bias of gradient descent on nonseparable data. In *Conference on Learning Theory*, pages 1772–1798. PMLR, 2019.

Ziwei Ji and Matus Telgarsky. Characterizing the implicit bias via a primal-dual analysis. In *Algorithmic Learning Theory*, pages 772–804. PMLR, 2021.

Ziwei Ji, Miroslav Dudík, Robert E Schapire, and Matus Telgarsky. Gradient descent follows the regularization path for general losses. In *Conference on Learning Theory*, pages 2109–2136. PMLR, 2020.

Ziwei Ji, Nathan Srebro, and Matus Telgarsky. Fast margin maximization via dual acceleration. In *International Conference on Machine Learning*, pages 4860–4869. PMLR, 2021.

Anatoli Juditsky, Arkadi Nemirovski, et al. First order methods for nonsmooth convex large-scale optimization, i: general purpose methods. *Optimization for Machine Learning*, 30(9):121–148, 2011.

Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009.

Haihao Lu, Robert M Freund, and Yurii Nesterov. Relatively smooth convex optimization by first-order methods, and applications. *SIAM Journal on Optimization*, 28(1):333–354, 2018.

Kaifeng Lyu and Jian Li. Gradient descent maximizes the margin of homogeneous neural networks. In *International Conference on Learning Representations*, 2019.

Mor Shpigel Nacson, Jason Lee, Suriya Gunasekar, Pedro Henrique Pamplona Savarese, Nathan Srebro, and Daniel Soudry. Convergence of gradient descent on separable data. In *The 22nd International Conference on Artificial Intelligence and Statistics*, pages 3420–3428. PMLR, 2019.

Preetum Nakkiran, Gal Kaplun, Yamini Bansal, Tristan Yang, Boaz Barak, and Ilya Sutskever. Deep double descent: Where bigger models and more data hurt. *Journal of Statistical Mechanics: Theory and Experiment*, 2021(12):124003, 2021.

Behnam Neyshabur, Ryota Tomioka, and Nathan Srebro. In search of the real inductive bias: On the role of implicit regularization in deep learning. *arXiv preprint arXiv:1412.6614*, 2014.

Ilija Radosavovic, Raj Prateek Kosaraju, Ross Girshick, Kaiming He, and Piotr Dollár. Designing network design spaces. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10428–10436, 2020.

Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, and Ilya Sutskever. Zero-shot text-to-image generation. In *International Conference on Machine Learning*, pages 8821–8831. PMLR, 2021.

R Tyrrell Rockafellar. *Convex analysis*. Number 28. Princeton University Press, 1970.

Saharon Rosset, Ji Zhu, and Trevor Hastie. Boosting as a regularized path to a maximum margin classifier. *The Journal of Machine Learning Research*, 5:941–973, 2004.

Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, et al. Imagenet large scale visual recognition challenge. *International journal of computer vision*, 115(3):211–252, 2015.

Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4510–4520, 2018.

Julian Schrittwieser, Ioannis Antonoglou, Thomas Hubert, Karen Simonyan, Laurent Sifre, Simon Schmitt, Arthur Guez, Edward Lockhart, Demis Hassabis, Thore Graepel, et al. Mastering atari, go, chess and shogi by planning with a learned model. *Nature*, 588(7839):604–609, 2020.

Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.

Daniel Soudry, Elad Hoffer, Mor Shpigel Nacson, Suriya Gunasekar, and Nathan Srebro. The implicit bias of gradient descent on separable data. *The Journal of Machine Learning Research*, 19(1): 2822–2878, 2018.

Matus Telgarsky. Margins, shrinkage, and boosting. In *International Conference on Machine Learning*, pages 307–315. PMLR, 2013.

Bohan Wang, Qi Meng, Wei Chen, and Tie-Yan Liu. The implicit bias for adaptive optimization algorithms on homogeneous neural networks. In *International Conference on Machine Learning*, pages 10849–10858. PMLR, 2021.

Ashia C Wilson, Rebecca Roelofs, Mitchell Stern, Nati Srebro, and Benjamin Recht. The marginal value of adaptive gradient methods in machine learning. *Advances in neural information processing systems*, 30, 2017.

Chiyuan Zhang, Samy Bengio, Moritz Hardt, Benjamin Recht, and Oriol Vinyals. Understanding deep learning (still) requires rethinking generalization. *Communications of the ACM*, 64(3):107–115, 2021.