Learning-Augmented Private Algorithms for Multiple Quantile Release

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Abstract

When applying differential privacy to sensitive data, we can often improve performance using external information such as other sensitive data, public data, or human priors. We propose to use the learning-augmented algorithms (or algorithms with predictions) framework—previously applied largely to improve time complexity or competitive ratios—as a powerful way of designing and analyzing privacy-preserving methods that can take advantage of such external information to improve utility. This idea is instantiated on the important task of multiple quantile release, for which we derive error guarantees that scale with a natural measure of prediction quality while (almost) recovering state-of-the-art prediction-independent guarantees. Our analysis enjoys several advantages, including minimal assumptions about the data, a natural way of adding robustness, and the provision of useful surrogate losses for two novel "meta" algorithms that learn predictions from other (potentially sensitive) data. We conclude with experiments on challenging tasks demonstrating that learning predictions across one or more instances can lead to large error reductions while preserving privacy.

1. Introduction

The differentially private (DP) release of statistics such as the quantile q of a private dataset $\mathbf{x} \in \mathbb{R}^n$ is an inevitably error-prone task because we are by definition precluded from revealing exact information about the instance at hand (Dwork & Roth, 2014). However, DP instances rarely occur in a vacuum: even in the simplest practical settings, we usually know basic information such as the fact that all individuals have a nonnegative age. Often, the dataset we are considering is drawn from a similar population as a public dataset $\mathbf{z} \in \mathbb{R}^N$ and should thus have similar quantiles, a case known as the *public-private* setting (Liu et al., 2021; Bie et al., 2022). Alternatively, we may be interested in releasing statistics about each of many datasets $\mathbf{x}_1, \ldots, \mathbf{x}_T$; for example, in the cross-silo setting of federated learning (Kairouz et al., 2021b) a group of hospitals may each want to privately release quantile information about their patients. In all of these settings, we might hope to incorporate external information to reduce error, but approaches for doing so tend to be *ad hoc* and assumption-heavy.

We propose that the framework of *learning-augmented algorithms*—a.k.a. *algorithms with predictions* (Mitzenmacher & Vassilvitskii, 2021)—provides the right tools for deriving DP algorithms in this setting, and instantiate this idea for multiple quantile release (Gillenwater et al., 2021; Kaplan et al., 2022). Algorithms with predictions is an expanding field of algorithm design that constructs methods whose instance-dependent performance improves with the accuracy of some prediction about the instance. The goal is to bound the cost $C_{\mathbf{x}}(\mathbf{w})$ of running on instance $\mathbf{x}$ given a prediction $\mathbf{w}$ by some metric $U_{\mathbf{x}}(\mathbf{w})$ of the *quality* of the prediction on that instance. While past work has focused on using predictions to improve metrics related to time, space, and communication complexity, we instead aim to design learning-augmented algorithms whose cost $C_{\mathbf{x}}(\mathbf{w})$ captures the error of some statistic—in our case quantiles—computed privately on instance an $\mathbf{x}$ given a prediction $\mathbf{w}$. We are interested in bounding this cost in terms of the quality of the external information provided to our algorithm, $U_{\mathbf{x}}(\mathbf{w})$.

While incorporating external information into DP is well-studied, c.f. public-private methods and private posterior inference (Dimitrakakis et al., 2017; Geumlek et al., 2017; Seeman et al., 2020), by deriving and analyzing a learning-augmented algorithm for multiple quantiles we show numerous comparative advantages, including:

1. Minimal assumptions about the data, in our case even fewer than needed by the unaugmented baseline.
2. Existing tools for studying the robustness of algorithms to noisy predictions (Lykouris & Vassilvitskii, 2021).
3. Co-designing algorithms with predictions together with methods for *learning* those predictions from data (Khodak et al., 2022), which we show is crucial for both the public-private and sequential release settings.

As part of this analysis we derive a learning-augmented ex-

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tension of the `ApproximateQuantiles` (AQ) method of Kaplan et al. (2022) that (nearly) matches its worst-case guarantees while being much better if a natural measure $U_{\mathbf{x}}(\mathbf{w})$ of prediction quality is small. By studying $U_{\mathbf{x}}$, we make the following contributions to multiple quantiles:

1. The first robust algorithm, even for one quantile, that avoids assuming the data is bounded on some interval, specifically by using a heavy-tailed prior.
2. A provable way of ensuring robustness to poor priors, without losing the consistency of good ones.
3. A novel connection between DP quantiles and censored regression that leads to (a) a public-private release algorithm and (b) a sequential release scheme, both with runtime and error guarantees.

Finally, we integrate these techniques to significantly improve quantile release on several real and synthetic datasets.

2. Augmenting a private algorithm

The basic requirement for a learning-augmented algorithm is that the cost $C_{\mathbf{x}}(\mathbf{w})$ of running it on an instance $\mathbf{x}$ with prediction $\mathbf{w}$ should be upper bounded—usually up to constant or logarithmic factors—by a metric $U_{\mathbf{x}}(\mathbf{w})$ of the quality of the prediction on the instance. We denote this by $C_{\mathbf{x}} \lesssim U_{\mathbf{x}}$. In our work the cost $C_{\mathbf{x}}(\mathbf{w})$ will be the error of a privately released statistic, as compared to some ground truth. We will use the following privacy notion:

Definition 2.1 (Dwork & Roth (2014))**.** *Algorithm $\mathcal{A}$ is (ε, δ)-***differentially private** *if for all subsets S of its range, $\Pr\{\mathcal{A}(\mathbf{x}) \in S\} \leqslant e^{\varepsilon} \Pr\{\mathcal{A}(\tilde{\mathbf{x}}) \in S\} + \delta$ whenever $\mathbf{x} \sim \tilde{\mathbf{x}}$ are* **neighboring***, i.e. they differ in at most one element.*

Using ε-DP to denote $(\varepsilon, 0)$-DP, the broad goal of this work will be to reduce the error $C_{\mathbf{x}}(\mathbf{w})$ of ε-DP multiple quantile release while fixing the privacy level ε. In the rest of this section we derive an upper bound $U_{\mathbf{x}}(\mathbf{w})$ on the performance of $C_{\mathbf{x}}(\mathbf{w})$ in the *single*-quantile case; doing so for multiple quantiles is much more involved and shown in Section D.1.

Given a quantile $q \in (0, 1)$ and a sorted dataset $\mathbf{x} \in \mathbb{R}^n$ of n distinct points, we want to release $o \in [\mathbf{x}_{\lfloor qn \rfloor}, \mathbf{x}_{\lfloor qn \rfloor + 1})$, i.e. such that the proportion of entries less than o is q. As in prior work (Kaplan et al., 2022), the error of o will be the number of points between it and the desired interval:

$$\mathrm{Gap}_q(\mathbf{x}, o) = ||\{i : \mathbf{x}_{[i]} < o\}| - \lfloor qn \rfloor| = |\max_{\mathbf{x}_{[i]} < o} i - \lfloor qn \rfloor| \tag{1}$$

$\mathrm{Gap}_q(\mathbf{x}, o)$ is constant on intervals $I_k = (\mathbf{x}_{[k]}, \mathbf{x}_{[k+1]}]$ in the partition by $\mathbf{x}$ of $\mathbb{R}$ (let $I_0 = (-\infty, \mathbf{x}_{[1]}]$ and $I_n = (\mathbf{x}_{[n]}, \infty)$), so we also say that $\mathrm{Gap}_q(\mathbf{x}, I_k)$ is the same as $\mathrm{Gap}_q(\mathbf{x}, o)$ for some o in the interior of I_k.

For single quantile release we choose perhaps the most natural way of specifying a prediction for a DP algorithm: via the base measure $\mu : \mathbb{R} \mapsto \mathbb{R}_{\geqslant 0}$ of the exponential mechanism:

Theorem 2.1 (McSherry & Talwar (2007))**.** *If the* **utility** *$u(\mathbf{x}, o)$ of an outcome o of a query over dataset $\mathbf{x}$ has* **sensitivity** *$\max_{o, \mathbf{x} \sim \tilde{\mathbf{x}}} |u(\mathbf{x}, o) - u(\tilde{\mathbf{x}}, o)| \leqslant \Delta$ then the* **exponential mechanism***, which releases o w.p. $\propto \exp(\frac{\varepsilon}{2\Delta} u(\mathbf{x}, o))\mu(o)$ for some base measure μ, is ε-DP.*

The utility function we use is $u_q = -\mathrm{Gap}_q$, so since this is constant on each interval I_k the mechanism here is equivalent to sampling k w.p. $\propto \exp(\varepsilon u_q(\mathbf{x}, I_k)/2)\mu(I_k)$ and then sampling o from I_k w.p. $\propto \mu(o)$. While using non-uniform priors for EM is well-studied, the key idea here is to obtain a prediction-dependent bound on the error that reveals a useful measure of the *quality* of the prediction. In particular, running EM in this way yields o that w.p. $\geqslant 1 - \beta$ satisfies

$$\mathrm{Gap}_q(\mathbf{x}, o) \leqslant \frac{2}{\varepsilon} \log \frac{1/\beta}{\Psi_{\mathbf{x}}^{(q,\varepsilon)}(\mu)} \leqslant \frac{2}{\varepsilon} \log \frac{1/\beta}{\Psi_{\mathbf{x}}^{(q)}(\mu)} \tag{2}$$

where $\Psi_{\mathbf{x}}^{(q,\varepsilon)} = \int \exp(-\frac{\varepsilon}{2} \mathrm{Gap}_q(\mathbf{x}, o))\mu(o)do$ is the inner product between the prior and the EM score while $\Psi_{\mathbf{x}}^{(q)} = \lim_{\varepsilon \to \infty} \Psi_{\mathbf{x}}^{(q,\varepsilon)} = \mu((\mathbf{x}_{[\lfloor qn \rfloor]}, \mathbf{x}_{[\lfloor qn \rfloor + 1]}])$ is the probability assigned to the optimal interval (c.f. Lemma D.1).

This suggests two metrics of prediction quality: the negative log-inner-products $U_{\mathbf{x}}^{(q,\varepsilon)}(\mu) = -\log \Psi_{\mathbf{x}}^{(q,\varepsilon)}(\mu)$ and $U_{\mathbf{x}}^{(q)}(\mu) = -\log \Psi_{\mathbf{x}}^{(q)}(\mu)$. Both make intuitive sense: we expect predictions μ that assign a high probability to intervals that the EM score weighs heavily to perform well, and EM assigns the most weight to the optimal interval. There are also many ways that these metrics are useful. For one, in the case of perfect prediction—i.e. if μ assigns probability one to the optimal interval $I_{\lfloor qn \rfloor}$—then $\Psi_{\mathbf{x}}^{(q,\varepsilon)}(\mu) = \Psi_{\mathbf{x}}^{(q)}(\mu) = 1$, yielding an upper bound on the error of only $\frac{2}{\varepsilon} \log \frac{1}{\beta}$. Secondly, as we will see, both are also amenable for analyzing robustness (the mechanism's sensitivity to *incorrect* priors) and learning. A final and important quality is that the guarantees using these metrics hold under no extra assumptions. Between the two, the first metric provides a tighter bound on the utility loss while the second does not depend on ε, which may be desirable.

It is also fruitful to analyze the metrics for specific priors. When $\mathbf{x}$ is in a bounded interval (a, b) and $\mu(o) = \frac{1_{o \in (a,b)}}{b-a}$ is the uniform measure, then $\Psi_{\mathbf{x}}^{(q)}(\mu) \geqslant \frac{\psi_{\mathbf{x}}}{b-a}$, where $\psi_{\mathbf{x}}$ is the minimum distance between entries; thus we recover past bounds, e.g. Kaplan et al. (2022, Lemma A.1), that implicitly use this measure to guarantee $\mathrm{Gap}_q(\mathbf{x}, o) \leqslant \frac{2}{\varepsilon} \log \frac{b-a}{\beta \psi_{\mathbf{x}}}$. Here the support of the uniform distribution is correct by assumption as the data is assumed bounded. However, analyzing $\Psi_{\mathbf{x}}^{(q)}$ also yields a novel way of removing this assumption: if we suspect the data lies in (a, b), we set μ to be the Cauchy prior with location $\frac{a+b}{2}$ and scale $\frac{b-a}{2}$. Even if we are wrong about the interval, there exists an $R > 0$ s.t. the data lies in the interval $(\frac{a+b}{2} \pm R)$, so using the Cauchy yields $\Psi_{\mathbf{x}}^{(q)} \geqslant \frac{2(b-a)\psi_{\mathbf{x}}/\pi}{(b-a)^2 + 4R^2}$ and thus the following guarantee:

Corollary 2.1 (of Lem. D.1)**.** *If the data lies in the interval* $(\frac{a+b}{2} \pm R)$ *and* μ *is the Cauchy measure with location* $\frac{a+b}{2}$ *and scale* $\frac{b-a}{2}$ *then the output of the exponential mechanism satisfies* $\mathrm{Gap}_q(\mathbf{x}, o) \leqslant \frac{2}{\varepsilon} \log\left(\pi \frac{b-a+\frac{4R^2}{b-a}}{2\beta\psi_{\mathbf{x}}}\right)$ *w.p.* $\geqslant 1-\beta$.

If $R = \frac{b-a}{2}$, i.e. we get the interval right, then the bound is only an additive factor $\frac{2}{\varepsilon}\log\pi$ worse than before, but if we are wrong then performance degrades as $\mathcal{O}(\log(1+R^2))$, unlike the $\mathcal{O}(R)$ error of the uniform prior. Note our use of a heavy-tailed distribution here: a sub-exponential density decays too quickly and leads to error $\mathcal{O}(R)$ rather than $\mathcal{O}(\log(1+R^2))$. We can also adapt this technique if we know only a single-sided bound, e.g. if values must be positive, by using an appropriate half-Cauchy distribution.

3. Releasing quantiles across multiple datasets

In the main version of this draft, we consider a *sequential release* variant of the multi-dataset example from the introduction in which the T datasets $\mathbf{x}_1, \dots, \mathbf{x}_T$ arrive one-by-one. For example, they could be generated by a stationary or other process that allows information derived from prior releases to inform predictions of future releases. We also consider a public-private application but relegate it to Section F.2. Note that in this section we use only the ε-independent bound $U_{\mathbf{x}}$, as $U_{\mathbf{x}}^{(\varepsilon)}$ does not yield a convex objective. We also again mainly discuss the single-quantile bound $U_{\mathbf{x}}^{(q)}$ for simplicity, but the general results (c.f. Section F) extend naturally to multiple quantiles, and our experiments also consider the multiple-quantile setting.

Throughout our applications, we will mainly consider a specific class of priors known as *location-scale priors*, which for some measure $f : \mathbb{R} \mapsto \mathbb{R}_{\geqslant 0}$ have form $\mu_{\nu,\sigma}(x) = \frac{1}{\sigma} f\left(\frac{x-\nu}{\sigma}\right)$ for $\nu \in \mathbb{R}$ and $\sigma > 0$. Such families allows us to model both the location of a quantile using $\nu = \langle \mathbf{w}, \mathbf{f}\rangle$—where $\mathbf{w} \in \mathbb{R}^d$ is a linear model from public features $\mathbf{f} \in \mathbb{R}^d$ about the dataset $\mathbf{x} \in \mathbb{R}^n$—and our uncertainty about it using σ, all while staying in reasonable dimensions.

One notable aspect of location-scale priors is that they can be re-parameterized so that the upper bounds $U_{\mathbf{x}}^{(q)}$ are *convex*; this allows the optimal priors to be provably learned using first-order methods. To show this, we make use of a connection between these upper bounds and the likelihood of **censored regression** (Pratt, 1981), which for noise $\xi_i \in \mathbb{R}$ models a relationship between features $\mathbf{f}_i \in \mathbb{R}^d$ and a variable $y_i = \langle \mathbf{w}, \mathbf{f}_i\rangle + \xi_i$ when information about y_i is only provided in terms of an interval $[a_i, b_i)$ containing it (e.g. an individual's income bracket, not their exact income). If ξ_i is from a location-scale distribution with $\nu = 0$ the log-likelihood given datapoints $(a_i, b_i, \mathbf{f}_i)$ is

$$\mathcal{L}_{\{a_i,b_i,\mathbf{f}_i\}_{i=1}^n}(\mathbf{w},\sigma) = \sum_{i=1}^n \log \int_{a_i}^{b_i} \frac{1}{\sigma} f\left(\frac{y - \langle \mathbf{w}, \mathbf{f}_i\rangle}{\sigma}\right) dy \quad (3)$$

Observe that for $a = \mathbf{x}_{[\lfloor qn \rfloor]}$ and $b = \mathbf{x}_{[\lfloor qn \rfloor]+1}$ we have

$$\begin{aligned} U_{\mathbf{x}}^{(q)}(\mu_{\langle \mathbf{w},\mathbf{f}\rangle,\sigma}) &= -\log \mu_{\langle \mathbf{w},\mathbf{f}\rangle,\sigma}((a,b]) \\ &= -\log \int_a^b \frac{1}{\sigma} f\left(\frac{o - \langle \mathbf{w}, \mathbf{f}\rangle}{\sigma}\right) do \end{aligned} \quad (4)$$

which is the negative of $\mathcal{L}_{a,b,\mathbf{f}}(\mathbf{w}, \sigma)$. We thus adopt the reparameterization of Burridge (1981), who showed that (3) is concave w.r.t. $(\mathbf{v}, \phi) = (\frac{\mathbf{w}}{\sigma}, \frac{1}{\sigma})$ whenever f is **log-concave**, a property satisfied by the Gaussian and Laplace families but not the Cauchy. Therefore, for such f we have that $\ell_{\mathbf{x}}^{(q)}(\langle \mathbf{v}, \mathbf{f}\rangle, \phi) = U_{\mathbf{x}}^{(q)}(\mu_{\frac{\langle \mathbf{v},\mathbf{f}\rangle}{\phi}, \frac{1}{\phi}})$ is convex w.r.t. $(\mathbf{v}, \phi)$. For numerical convenience and other reasons (c.f. Section F.1) we use Laplace priors for the rest of this section.

Having established a family of priors, we now turn to the sequential release application. Here we have a sequence of datasets $\mathbf{x}_1, \dots, \mathbf{x}_T$, each with associated *public* features $\mathbf{f}_1, \dots, \mathbf{f}_T \in \mathbb{R}^d$ (e.g. day of the week), and we wish to minimize the average gap $\frac{1}{T}\sum_{t=1}^T \mathrm{Gap}_q(\mathbf{x}_t, o_{t,i})$, whose expectation can be bounded (42) in terms of $\frac{1}{T}\sum_{t=1}^T U_{\mathbf{x}_t}^{(q)}$. For simplicity, we assume individuals do not occur in multiple datasets $\mathbf{x}_t$, e.g. we are releasing the median age of new users of a service. Note the natural way to avoid this assumption is to compose the privacy budgets at each time; empirically our methods are especially useful in the low privacy regime this entails.

Our analysis suggests that we can apply online learning here, e.g. doing the following at each t starting with a prior μ_1:

1. release o_t using the prior μ_t and suffer $\mathrm{Gap}_q(\mathbf{x}_t, o_t)$
2. update to μ_{t+1} using online learning on the loss $\ell_{\mathbf{x}_t}^{(q)}$

Because $\ell_{\mathbf{x}_t}^{(q)}(\theta, \phi) = U_{\mathbf{x}_t}^{(q)}(\mu_{\frac{\theta}{\phi}, \frac{1}{\phi}})$ is convex for Laplace priors, online convex optimization (OCO) (Shalev-Shwartz, 2011) lets us compete with the best prior in hindsight according to the upper bounds $U_{\mathbf{x}_t}^{(q)}(\mu_t)$, or with the best linear map $\mathbf{w}$ to locations $\langle \mathbf{w}, \mathbf{f}_t\rangle$. We can again hedge against poor predictions by mixing with a constant robust distribution.

However, we face the difficulty that online learning on losses $\ell_{\mathbf{x}_t}^{(q)}$ leaks information about $\mathbf{x}_t$. There are two natural solutions. One is to use part of the budget $\varepsilon' < \varepsilon$ on a DP online learner (Jain et al., 2012; Smith & Thakurta, 2013) and hope that the reduction in budget allocated to quantile release is made up for by the improved priors. We can show provable guarantees for this approach using DP-FTRL (Kairouz et al., 2021a) (c.f. Theorem F.5), but in practice it is too noisy to learn competitive priors, except with a lot of stationary data (c.f. Fig. 1 (left)). One issue is that its DP guarantee is too strong, as it it allows swapping out the entire dataset $\mathbf{x}_t$ rather than a single entry. It is unclear if a better sensitivity is possible for $U_{\mathbf{x}_t}$, as changing an entry can flip the sign of the gradient while preserving magnitude. We show (c.f. Lem. E.1) that it is possible

for the ε-dependent bound $U_{\mathbf{x}_t}^{(\varepsilon)}$ over piecewise-constant priors—remarkably sensitivity *decreases* with ε—but that upper bound is non-convex for location-scale families, which are preferable for model learning.

Alternatively, we can replace ℓ with a *proxy* loss $\hat{\ell}$ that does not depend on the data and optimize it using regular OCO. We can do this because $U_{\mathbf{x}_t}^{(q)}$ depends only on the optimal interval $[\mathbf{x}_{t[\lfloor qn \rfloor]}, \mathbf{x}_{t[\lfloor qn \rfloor+1]})$, whose location and size we have (public) estimates for: the former via the quantile estimate o_t and the size is lower-bounded by the underlying data discretization, which we have access to in-practice (e.g. age is reported in years, bicycle trip length in seconds). We use this information to construct proxy losses $\hat{\ell}_{o_t}^{(q)}(\langle \mathbf{v}, \mathbf{f}_t \rangle, \phi)$, which do not depend on $\mathbf{x}_t$ and so be learned with (standard) OCO. Our DP-FTRL analysis (c.f. Theorem F.5) suggested using different step-sizes for the location and scale, so we use the COCOB optimizer (Orabona & Tomassi, 2017) as it provably sets per-coordinate step-sizes without tuning.

We evaluate sequential release on three online tasks, each consisting of a sequence of datasets needing quantiles:

1. Synthetic: each dataset is generated such that the quantiles are fixed linear functions of a random Gaussian feature vector, plus noise.
2. CitiBike: the data are the lengths of a day's bicycle trips, with the date and NYC weather information features.
3. BBC: the data are the Flesch readability scores of the comments on a headline posted to Reddit's `worldnews` forum, with date and headline text information features.

In addition to the proxy approach, which we call `PubProx`, we evaluate static priors—the uniform, Cauchy, and half-Cauchy (if nonnegative)—and an approach we call `PubPrev`, which uses a Laplace prior centered around the previous step's released quantile. Note that using the Uniform is equivalent to `ApproximateQuantiles` (AQ). For both `PubProx` and `PubPrev` we ensure robustness by mixing with a Cauchy (or half-Cauchy, if nonnegative) distribution with coefficient 0.1; this nearly always improves performance for these methods, likely by ensuring their training data is not too noisy. For a theoretical justification of this approach, see Section C.2, and to see its effectiveness, note how in Figure 1 (right) both augmented methods are almost always better when made robust, especially `PubPrev`; in fact, non-robust `PubPrev` is unable to do better than Uniform after around day 1600, when the start of the COVID-19 pandemic significantly affects bicycle trips.

Our main comparisons is time-aggregated performance as a function of ε (c.f. Figs. 2 and 3). All except perhaps Synthetic demonstrate significant improvement by our methods over the Uniform (AQ) baseline, especially at small ε. On Synthetic and CitiBike, both tasks with features for which a linear model should provide some benefit, we see in Figure 2

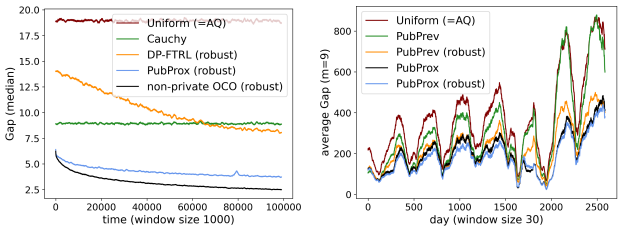

Figure 1. Comparison of sequential release over time on Synthetic (left, $\log_{10}\varepsilon = -1/2$) and CitiBike (right, $\log_{10}\varepsilon = -2$) tasks.

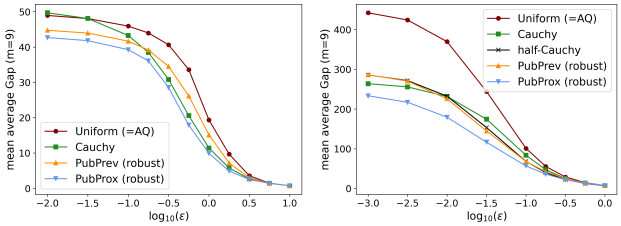

Figure 2. Time-averaged performance of the sequential release of nine quantiles on the Synthetic (left) and CitiBike (right) tasks.

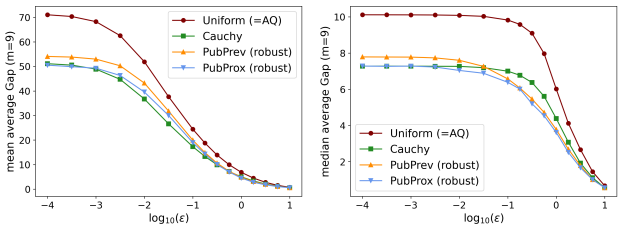

Figure 3. Time-aggregated mean (left) and median (right) performance of sequential release of nine quantiles on the BBC task.

that `PubProx` is indeed the best across all except perhaps the lowest privacy settings. For BBC, Figure 3 reveals a large difference between mean and median performance (note the difference in y-axis scales), with `PubProx` doing best for the typical headline but the Cauchy doing better on-average due to better performance on headlines with many comments. The result suggests that in highly noisy settings, the learning-based scheme should help, but it might not overcome the robustness of a static Cauchy prior in-expectation.

Overall, the results demonstrate the strength of the Cauchy and half-Cauchy priors, both as unbounded substitutes for the Uniform and as a means of robustifying learning-augmented algorithms. They also demonstrate the utility of our upper bound in providing an objective for learning, albeit using proxy data rather the DP online learning: `PubProx` usually does better than `PubPrev` despite using the same information. Overall, `PubProx` performs the best at most privacy levels in all evaluation settings (Synthetic, CitiBike, and BBC) except when the mean is used as the metric for BBC (Fig. 3, left), where it does almost as well as the best. Narrowing the performance gap with non-private OCO (c.f. Fig. 1 (left), where we run COCOB directly on $\ell_{\mathbf{x}_t}^{(q)}$)—remains an important research direction.

References

Agarwal, N. and Singh, K. The price of differential privacy for online learning. In *Proceedings of the 34th International Conference on Machine Learning*, 2017.

Amid, E., Ganesh, A., Mathews, R., Ramaswamy, S., Song, S., Steinke, T., Suriyakumar, V. M., Thakkar, O., and Thakurta, A. Public data-assisted mirror descent for private model training. In *Proceedings of the 39th International Conference on Machine Learning*, 2022.

Anand, K., Ge, R., and Panigrahi, D. Customizing ML predictions for online algorithms. In *Proceedings of the 37th International Conference on Machine Learning*, 2020.

Andrew, G., Thakkar, O., McMahan, H. B., and Ramaswamy, S. Differentially private learning with adaptive clipping. In *Advances in Neural Information Processing Systems*, 2021.

Balcan, M.-F., Khodak, M., Sharma, D., and Talwalkar, A. Learning-to-learn non-convex piecewise-Lipschitz functions. In *Advances in Neural Information Processing Systems*, 2021.

Bamas, E., Maggiori, A., and Svensson, O. The primal-dual method for learning augmented algorithms. In *Advances in Neural Information Processing Systems*, 2020.

Bassily, R., Mohri, M., and Suresh, A. T. Private domain adaptation from a public source. arXiv, 2022.

Bie, A., Kamath, G., and Singhal, V. Private estimation with public data. In *Advances in Neural Information Processing Systems*, 2022.

Biswas, S., Dong, Y., Kamath, G., and Ullman, J. CoinPress: Practical private mean and covariance estimation. In *Advances in Neural Information Processing Systems*, 2020.

Boucheron, S., Lugosi, G., and Massart, P. *Concentration Inequalities: A Nonasymptotic Theory of Independence*. Caledon Press, 2012.

Burridge, J. A note on maximum likelihood estimation for regression models using grouped data. *Journal of the Royal Statistical Society. Series B (Methodological)*, 43 (1):41–45, 1981.

Cesa-Bianchi, N., Conconi, A., and Gentile, C. On the generalization ability of on-line learning algorithms. *IEEE Transactions on Information Theory*, 50(9):2050–2057, 2004.

Chaudhuri, K. and Vinterbo, S. A. A stability-based validation procedure for differentially private machine learning. In *Advances in Neural Information Processing Systems*, 2013.

Chen, J. Y., Silwal, S., Vakilian, A., and Zhang, F. Faster fundamental graph algorithms via learned predictions. In *Proceedings of the 40th International Conference on Machine Learning*, 2022.

Christianson, N., Shen, J., and Wierman, A. Optimal robustness-consistency tradeoffs for learning-augmented metrical task systems. In *Proceedings of the 26th International Conference on Artificial Intelligence and Statistics*, 2023.

Cover, T. M. Universal portfolios. *Mathematical Finance*, 1:1–29, 1991.

Cule, M. and Samworth, R. Theoretical properties of the log-concave maximum likelihood estimator of a multidimensional density. *Electronic Journal of Statistics*, 4: 254–270, 2010.

David, H. A. and Nagaraja, H. N. *Order Statistics*. John Wiley & Sons, Inc., 2003.

Diakonikolas, I., Kontonis, V., Tzamos, C., Vakilian, A., and Zarifis, N. Learning online algorithms with distributional advice. In *Proceedings of the 38th International Conference on Machine Learning*, 2021.

Dimitrakakis, C., Nelson, B., Zhang, Z., Mitrokotsa, A., and Rubinstein, B. I. P. Differential privacy for bayesian inference through posterior sampling, 2017.

Dinitz, M., Im, S., Lavastida, T., Moseley, B., and Vassilvitskii, S. Faster matchings via learned duals. In *Advances in Neural Information Processing Systems*, 2021.

Du, E., Wang, F., and Mitzenmacher, M. Putting the "learning" into learning-augmented algorithms for frequency estimation. In *Proceedings of the 38th International Conference on Machine Learning*, 2021.

Dütting, P., Lattanzi, S., Leme, R. P., and Vassilvitskii, S. Secretaries with advice. In *Proceedings of the 22nd ACM Conference on Economics and Computation*, 2021.

Dwork, C. and Roth, A. The algorithmic foundations of differential privacy. *Foundations and Trends in Theoretical Computer Science*, 9(3-4):211–407, 2014.

Geumlek, J., Song, S., and Chaudhuri, K. Rényi differential privacy mechanisms for posterior sampling. In *Advances in Neural Information Processing Systems*, 2017.

Gillenwater, J., Joseph, M., and Kulesza, A. Differentially private quantiles. In *Proceedings of the 38th International Conference on Machine Learning*, 2021.

Gupta, A., Roth, A., and Ullman, J. Iterative constructions and private data release. In *Theory of Cryptography Conference*, 2012.

Hardt, M. and Rothblum, G. A multiplicative weights mechanism for privacy-preserving data analysis. In *51st Annual IEEE Symposium on Foundations of Computer Science*, 2010.

Hazan, E., Agarwal, A., and Kale, S. Logarithmic regret algorithms for online convex optimization. *Machine Learning*, 69:169–192, 2007.

Indyk, P., Mallmann-Trenn, F., Mitrović, S., and Rubinfeld, R. Online page migration with ML advice. In *Proceedings of the 25th International Conference on Artificial Intelligence and Statistics*, 2022.

Jain, P., Kothari, P., and Thakurta, A. Differentially private online learning. In *Proceedings of the 25th Annual Conference on Learning Theory*, 2012.

Jiang, Z., Panigrahi, D., and Sun, K. Online algorithms for weighted paging with predictions. In *Proceedings of the 47th International Colloquium on Automata, Languages, and Programming*, 2020.

Kairouz, P., McMahan, B., Song, S., Thakkar, O., Thakurta, A., and Xu, Z. Practical and private (deep) learning without sampling or shuffling. In *Proceedings of the 38th International Conference on Machine Learning*, 2021a.

Kairouz, P., McMahan, H. B., Avent, B., Bellet, A., Bennis, M., Bhagoji, A. N., Bonawitz, K., Charles, Z., Cormode, G., Cummings, R., D'Oliveira, R. G. L., Rouayheb, S. E., Evans, D., Gardner, J., Garrett, Z., Gascón, A., Ghazi, B., Gibbons, P. B., Gruteser, M., Harchaoui, Z., He, C., He, L., Huo, Z., Hutchinson, B., Hsu, J., Jaggi, M., Javidi, T., Joshi, G., Khodak, M., Konečný, J., Korolova, A., Koushanfar, F., Koyejo, S., Lepoint, T., Liu, Y., Mittal, P., Mohri, M., Nock, R., Özgür, A., Pagh, R., Raykova, M., Qi, H., Ramage, D., Raskar, R., Song, D., Song, W., Stich, S. U., Sun, Z., Suresh, A. T., Tramèr, F., Vepakomma, P., Wang, J., Xiong, L., Xu, Z., Yang, Q., Yu, F. X., Yu, H., and Zhao, S. Advances and open problems in federated learning. *Foundations and Trends in Machine Learning*, 14:1–210, 2021b.

Kaplan, H., Schnapp, S., and Stemmer, U. Differentially private approximate quantiles. In *Proceedings of the 39th International Conference on Machine Learning*, 2022.

Khodak, M., Balcan, M.-F., Talwalkar, A., and Vassilvitskii, S. Learning predictions for algorithms with predictions. In *Advances in Neural Information Processing Systems*, 2022.

Kivinen, J. and Warmuth, M. K. Exponentiated gradient versus gradient descent for linear predictors. *Information and Computation*, 132:1–63, 1997.

Kohavi, R. Scaling up the accuracy of Naive-Bayes classifiers: a decision-tree hybrid. In *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining*, 1996.

Kraska, T., Beutel, A., Chi, E. H., Dean, J., and Polyzotis, N. The case for learned index structures. In *Proceedings of the 2018 International Conference on Management of Data*, 2018.

Kumar, R., Purohit, M., and Svitkina, Z. Improving online algorithms via ML predictions. In *Advances in Neural Information Processing Systems*, 2018.

Lattanzi, S., Lavastida, T., Moseley, B., and Vassilvitskii, S. Online scheduling via learned weights. In *Proceedings of the 2020 ACM-SIAM Symposium on Discrete Algorithms*, 2020.

Li, T., Zaheer, M., Reddi, S., and Smith, V. Private adaptive optimization with side information. In *Proceedings of the 39th International Conference on Machine Learning*, 2022.

Lindermayr, A. and Megow, N. Permutation predictions for non-clairvoyant scheduling. In *Proceedings of the 34th ACM Symposium on Parallelism in Algorithms and Architectures*, 2022.

Liu, T., Vietri, G., Steinke, T., Ullman, J., and Wu, Z. S. Leveraging public data for practical private query release. In *Proceedings of the 38th International Conference on Machine Learning*, 2021.

Liu, Z., Chen, Y., Bash, C., Wierman, A., Gmach, D., Wang, Z., Marwah, M., and Hyser, C. Renewable and cooling aware workload management for sustainable data centers. In *ACM SIGMETRICS Performance Evaluation Review*, 2012.

Loper, E. and Bird, S. NLTK: The natural language toolkit. arXiv, 2002.

Lykouris, T. and Vassilvitskii, S. Competitive caching with machine learned advice. *Journal of the ACM*, 68(4), 2021.

McMahan, H. B. A survey of algorithms and analysis for adaptive online learning. *Journal of Machine Learning Research*, 18, 2017.

McSherry, F. and Talwar, K. Mechanism design via differential privacy. In *Proceedings of the 48th Annual IEEE Symposium on Foundations of Computer Science*, 2007.

Mitzenmacher, M. and Vassilvitskii, S. Algorithms with predictions. In Roughgarden, T. (ed.), *Beyond the Worst-Case Analysis of Algorithms*. Cambridge University Press, Cambridge, UK, 2021.

Orabona, F. and Tomassi, T. Training deep networks without learning rates through coin betting. In *Advances in Neural Information Processing Systems*, 2017.

Pennington, J., Socher, R., and Manning, C. D. GloVe: Global vectors for word representation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing*, 2014.

Pratt, J. W. Concavity of the log likelihood. *Journal of the American Statistical Association*, 76(373):103–106, 1981.

Rohatgi, D. Near-optimal bounds for online caching with machine learned advice. In *Proceedings of the 2020 ACM-SIAM Symposium on Discrete Algorithms*, 2020.

Roughgarden, T. *Beyond Worst-Case Analysis of Algorithms*. Cambridge University Press, 2020.

Sakaue, S. and Oki, T. Discrete-convex-analysis-based framework for warm-starting algorithms with predictions. In *Advances in Neural Information Processing Systems*, 2022.

Scully, Z., Grosof, I., and Mitzenmacher, M. Uniform bounds for scheduling with job size estimates. In *Proceedings of the 13th Innovations in Theoretical Computer Science Conference*, 2022.

Seeman, J., Slavkovic, A., and Reimherr, M. Private posterior inference consistent with public information: A case study in small area estimation from synthetic census data. In *Proceedings of the International Conference on Privacy in Statistical Databases*, 2020.

Shalev-Shwartz, S. Online learning and online convex optimization. *Foundations and Trends in Machine Learning*, 4(2):107–194, 2011.

Smith, A. and Thakurta, A. (Nearly) optimal algorithms for private online learning in full-information and bandit settings. In *Advances in Neural Information Processing Systems*, 2013.

Wan, M. and McAuley, J. J. Item recommendation on monotonic behavior chains. In *Proceedings of the 12th ACM Conference on Recommender Systems*, 2018.

Yu, C., Shi, G., Chung, S.-J., Yue, Y., and Wierman, A. Competitive control with delayed imperfect information. In *Proceedings of the American Control Conference*, 2022.

Zinkevich, M. Online convex programming and generalized infinitesimal gradient ascent. In *Proceedings of the 20th International Conference on Machine Learning*, 2003.

A. Related work

There has been significant work on incorporating external information to improve DP methods. A major line of work is the public-private framework, where we have access to public data that is related in some way to the private data (Liu et al., 2021; Amid et al., 2022; Li et al., 2022; Bie et al., 2022; Bassily et al., 2022). The use of public data can be viewed as using a prediction, but such work starts by making (often strong) distributional assumptions on the public and private data; we instead derive instance-dependent upper bounds with minimal assumptions that we then apply to such public-private settings. Furthermore, our framework allows us to ensure robustness to poor predictions without distributional assumptions, and to derive learning algorithms using training data that may itself be sensitive. Another approach is to treat DP mechanisms (e.g. the exponential) as Bayesian posterior sampling (Dimitrakakis et al., 2017; Geumlek et al., 2017; Seeman et al., 2020). Our work can be viewed as an adaptation where we give explicit prior-dependent utility bounds. To our knowledge, no such guarantees exist in the literature. Moreover, while our focus is quantile estimation, the predictions-based framework that we advocate is much broader, as many DP methods—including for multiple quantiles—combine multiple queries that must be considered jointly.

Our approach for augmenting DP with external information centers the algorithms with predictions framework. Motivated by practical success (Liu et al., 2012; Kraska et al., 2018) and as a type of beyond-worst-case analysis (Roughgarden, 2020), algorithms in this framework have targeted a wide variety of cost measures, e.g. competitive ratios in online algorithms (Anand et al., 2020; Bamas et al., 2020; Diakonikolas et al., 2021; Dütting et al., 2021; Indyk et al., 2022; Yu et al., 2022; Christianson et al., 2023; Jiang et al., 2020; Kumar et al., 2018; Lykouris & Vassilvitskii, 2021; Rohatgi, 2020), space complexity in streaming algorithms (Du et al., 2021), and time complexity in graph algorithms (Dinitz et al., 2021; Chen et al., 2022; Sakaue & Oki, 2022) and distributed systems (Lattanzi et al., 2020; Lindermayr & Megow, 2022; Scully et al., 2022). We make use of existing techniques from this literature, including robustness-consistency tradeoffs (Lykouris & Vassilvitskii, 2021) and the online learning of predictions (Khodak et al., 2022). Tuning DP algorithms has been an important topic in private machine learning, e.g. for hyperparameter tuning (Chaudhuri & Vinterbo, 2013) and federated learning (Andrew et al., 2021), but these have not to our knowledge considered incorporating per-instance predictions.

The specific task we focus on is DP quantiles, a well-studied problem (Gillenwater et al., 2021; Kaplan et al., 2022), but we are not aware of work adding outside information. We also make the important contribution of an effective method for removing data-boundedness assumptions. Our algorithm builds upon the state-of-the-art work of Kaplan et al. (2022), which is also our main source for empirical comparison.

B. Problem formulation

A good guarantee for a learning-augmented algorithm will have several important properties that formally separate its performance from naive upper bounds $U_{\mathbf{x}} \gtrsim C_{\mathbf{x}}$. The first, *consistency*, requires it to be a reasonable indicator of strong performance in the limit of perfect prediction:

Definition B.1. *A learning-augmented guarantee $C_{\mathbf{x}} \lesssim U_{\mathbf{x}}$ is $c_{\mathbf{x}}$-**consistent** if $C_{\mathbf{x}}(\mathbf{w}) \leqslant c_{\mathbf{x}}$ whenever $U_{\mathbf{x}}(\mathbf{w}) = 0$.*

Here $c_{\mathbf{x}}$ is prediction-independent and should depend weakly or not at all on problem difficulty (for quantiles, the minimum separation between data points). Consistency is often presented via a tradeoff with *robustness* (Lykouris & Vassilvitskii, 2021), which guarantees some level of performance ifthe prediction is bad, similar to a standard worst-case bound:

Definition B.2. *A learning-augmented guarantee $C_{\mathbf{x}} \lesssim U_{\mathbf{x}}$ is $r_{\mathbf{x}}$-**robust** if it implies $C_{\mathbf{x}}(\mathbf{w}) \leqslant r_{\mathbf{x}}$ for all predictions $\mathbf{w}$.*

Unlike consistency, robustness usually depends strongly on the difficulty of the instance $\mathbf{x}$, with the goal being to not do much worse than a prediction-free approach. Note that the latter is trivially robust but not (meaningfully) consistent, since it ignores the prediction; this makes clear the need for considering the two properties via tradeoff between them.

As discussed further in Section C.2, this existing language for quantifying robustness is one of the advantages of using the framework of learning-augmented algorithms for incorporating external information into DP methods. We report robustness-consistency trade-offs for our quantile release algorithms in the same section.

A last desirable property of the prediction quality measure $U_{\mathbf{x}}(\mathbf{w})$ is that it should be useful for making good predictions. One way to formalize this is to require $U_{\mathbf{x}_t}$ to be *learnable* from multiple instances $\mathbf{x}_t$. For example, we could ask for *online* learnability, i.e. the existence of an algorithm that makes predictions $\mathbf{w}_t \in W$ in some action space W given instances $\mathbf{x}_1, \ldots, \mathbf{x}_{t-1}$ whose *regret* is sublinear in T:

Definition B.3. *The* **regret** *of actions $\mathbf{w}_1, \ldots, \mathbf{w}_T \in W$ on the sequence of functions $U_{\mathbf{x}_1}, \ldots, U_{\mathbf{x}_T}$ is $\max_{\mathbf{w} \in W} \sum_{t=1}^{T} U_{\mathbf{x}_t}(\mathbf{w}_t) - U_{\mathbf{x}_t}(\mathbf{w})$.*

Sublinear regret implies average prediction quality as good as that of the optimal prediction in hindsight, up to an additive term that vanishes as $T \to \infty$. Since $U_{\mathbf{x}_t}$ roughly upper-bounds the error $C_{\mathbf{x}_t}$, this means that asymptotically the average error is governed by the average prediction quality $\min_{\mathbf{w}\in W} \frac{1}{T}\sum_{t=1}^{T} U_{\mathbf{x}_t}(\mathbf{w})$ of the optimal $\mathbf{w} \in W$. A crucial observation here is that sublinear regret can often be obtained by making the function $U_{\mathbf{x}}$ amenable to familiar gradient-based online convex optimization methods such as online gradient descent (Khodak et al., 2022). Doing so also enables instance-dependent linear prediction: setting $\mathbf{w}_t$ using a learned function of some instance features $\mathbf{f}_t$.

We demonstrate the usefulness of both learning and robustness-consistency analysis in two applications where it is reasonable to have external information about the sensitive dataset(s). In the **public-private** setting, the prediction $\mathbf{w}$ is obtained from a public dataset $\mathbf{x}'$ that is assumed to be similar to $\mathbf{x}$ but is not subject to privacy-protection. In **sequential release**, we privately release information about each dataset in a sequence $\mathbf{x}_1, \dots, \mathbf{x}_T$; the release at time t can depend on $\mathbf{x}_t$ and on a prediction $\mathbf{w}_t$, which can be derived (privately) from past observations. In Section 3 we show that sequential release can be posed directly as a private online learning problem, while the public-private setting can be approached via online-to-batch conversion (Cesa-Bianchi et al., 2004). Both are thus directly enabled by treating the prediction quality measures $U_{\mathbf{x}_t}$ as surrogate objectives for the actual cost functions $C_{\mathbf{x}}$ and applying standard optimization techniques (Khodak et al., 2022).

C. Utility of learning-augmented algorithms

In Sections 2 and D.1 we derive a data-dependent function $U_{\mathbf{x}}^{(\varepsilon)} = -\log \Psi_{\mathbf{x}}^{(\varepsilon)}$ that upper bounds the error of quantile release using priors $\mu_1, \dots, \mu_m$. As in the single-quantile case, we can construct a looser, ε-independent upper bound

$$U_{\mathbf{x}} = -\log \Psi_{\mathbf{x}} = \log \sum_{i=1}^{m} e^{U_{\mathbf{x}}^{(q_i)}} \geqslant U_{\mathbf{x}}^{(\varepsilon)} \tag{5}$$

using the harmonic mean $\Psi_{\mathbf{x}}$ of $\Psi_{\mathbf{x}}^{(q_i)}$. We next summarize the usefulness of these upper bounds for understanding and applying DP methods with external information. Note that all three aspects below are crucial in our experiments.

C.1. Minimal assumptions and new insights

Our guarantees require no extra data assumptions: in-fact, the first outcome of our analysis was *removing* a boundedness assumption. This contrasts with past public-private work (Liu et al., 2021; Bie et al., 2022), which makes distributional assumptions, and is why we can apply these results to two very distinct settings in Section 3.

C.2. Ensuring robustness

While we incorporate external information into DP-algorithms because we hope to improve performance, if not done carefully it may lead to worse results. For example, a quantile prior concentrated away from the data may have error depending linearly on the distance to the optimal interval. Ideally an algorithm that uses a prediction will be robust, i.e. revert back to worst-case guarantees if the prediction is poor, without significantly sacrificing consistency, i.e. performing well if the prediction is good.

Using the formalization of these properties in Definitions B.1 and B.2, algorithms with predictions provides a convenient way to deploy them by *parameterizing* the robustness-consistency tradeoff, in which methods are designed to be $r_{\mathbf{x}}(\lambda)$-robust and $c_{\mathbf{x}}(\lambda)$-consistent for a user-specified parameter $\lambda \in [0, 1]$ (Bamas et al., 2020; Lykouris & Vassilvitskii, 2021). For quantiles, we can obtain an elegant parameterized tradeoff by interpolating prediction priors with a "robust" prior. In particular, since $\Psi_{\mathbf{x}}^{(q,\varepsilon)}$ is linear we can pick ρ to be a trusted prior such as the uniform or Cauchy and for any prediction μ use $\mu^{(\lambda)} = (1-\lambda)\mu + \lambda\rho$ instead. Setting $\Psi_{\mathbf{x}}^{(q,\varepsilon)}(\mu^{(\lambda)}) = (1-\lambda)\Psi_{\mathbf{x}}^{(q,\varepsilon)}(\mu) + \lambda\Psi_{\mathbf{x}}^{(q,\varepsilon)}(\rho)$ in (2) yields:

Corollary C.1 (of Lem. D.1; c.f. Cor. E.1)**.** *For quantile q, applying EM with prior $\mu^{(\lambda)} = (1-\lambda)\mu + \lambda\rho$ is $\left(\frac{2}{\varepsilon}\log\frac{1/\beta}{\lambda\Psi_{\mathbf{x}}^{(q,\varepsilon)}(\rho)}\right)$-robust and $\left(\frac{2}{\varepsilon}\log\frac{1/\beta}{1-\lambda}\right)$-consistent.*

Thus w.h.p. error is simultaneously at most $\frac{2}{\varepsilon}\log\frac{1}{\lambda}$ worse than that of only using the robust prior ρ and we only have error $\frac{2}{\varepsilon}\log\frac{1/\beta}{1-\lambda}$ if the prediction μ is perfect, i.e. if it is only supported on the optimal interval. This is easy to extend to the multiple-quantile metric $-\log\Psi_{\mathbf{x}}^{(\varepsilon)}$. In fact, we can even interpolate between the $\mathrm{polylog}(m)$ prediction-free guarantee of past work and our learning-augmented guarantee with the worse dependence on m; thus if the prediction is not good enough to overcome this worse rate we can still ensure that we do not do much worse than the original guarantee.

Corollary C.2 (of Lem. D.2 & Thm. D.3; c.f. Cor. E.2)**.** *If we run binary AQ on data in the interval* $(\frac{a+b}{2} \pm R)$ *for unknown* $R > 0$ *and use the prior* $\mu_i^{(\lambda)} = (1-\lambda)\mu + \lambda\rho$ *for each* q_i*, where* ρ *is Cauchy* $(\frac{a+b}{2}, \frac{b-a}{2})$*, then the algorithm is* $\left(\frac{2}{\varepsilon}\lceil\log_2 m\rceil^2 \log\left(\pi m \frac{b-a+\frac{4R^2}{b-a}}{2\lambda\beta\psi_{\mathbf{x}}}\right)\right)$*-robust and* $\left(\frac{2}{\varepsilon}\phi^{\log_2 m}\lceil\log_2 m\rceil \log\frac{m/\beta}{1-\lambda}\right)$*-consistent.*

These results show the advantage of our framework in designing algorithms that make robust use of possibly noisy predictions. Notably, related public-private work that studies robustness still assumes source and target data are Gaussian (Bie et al., 2022), whereas we make no distributional assumptions. We demonstrate the importance of this robustness technique throughout our experiments in Section 3.

C.3. Learning

A last important use for prior-dependent bounds is as surrogate objectives for optimization. As we show in Section 3, being able to learn across upper bounds $U_{\mathbf{x}_1}, \dots, U_{\mathbf{x}_T}$ of a sequence of (possibly sensitive) datasets $\mathbf{x}_t$ is useful for both the public-private and sequential release. Algorithms with predictions guarantees are often sufficiently nice to do this using off-the-shelf online learning (Khodak et al., 2022), a property that largely holds for our upper bounds as well.

Most saliently, the bound $U_{\mathbf{x}}^{(q,\varepsilon)} = -\log \Psi_{\mathbf{x}}^{(q,\varepsilon)}$ is a convex function of an inner product $\Psi_{\mathbf{x}}^{(q,\varepsilon)}$ between the EM score and the prior μ; thus by discretizing one can learn over a large family of piecewise-constant priors, which themselves Lipschitz priors over a bounded domain. The same is true of the multiple quantile bound $U_{\mathbf{x}}^{(\varepsilon)}$ because it is the log-sum-exp over $U_{\mathbf{x}}^{(q_i,\varepsilon_i)}$ and thus also convex. Thus in theory we can (privately) online learn the sequence $U_{\mathbf{x}_t}^{(\varepsilon)}$ with low-regret w.r.t. any set of m Lipschitz priors (c.f. Theorem E.2). However, in-practice we may not want to learn in the high dimensions needed by the discretization, and rather than fixed priors we may wish to learn a mapping from dataset-specific features. In Section 3 we thus focus on learning the less-expressive family of location-scale models.

D. Section 2 details

D.1. Releasing multiple quantiles

To simultaneously estimate quantiles $q_1, \dots, q_m$ we adapt the `ApproximateQuantiles` method of (Kaplan et al., 2022), which assigns each q_i to a node in a binary tree and, starting from the root, uses EM with the uniform prior to estimate a quantile before sending the data below the outcome o to its left child and the data above o to its right child. Thus each entry is only involved in $\lceil\log_2 m\rceil$ exponential mechanisms, and so for data in (a, b) the maximum Gap_{q_i} across quantiles is $\mathcal{O}\left(\frac{\log^2 m}{\varepsilon}\log\frac{m(b-a)}{\beta\psi_{\mathbf{x}}}\right)$, which is much better than the naive bound of a linear function of m.

Given one prior μ_i for each q_i, a naive extension of (2) gets a similar $\mathrm{polylog}(m)$ bound (c.f. Lem D.2); notably we extend the Cauchy-unboundedness result to multiple quantiles (c.f. Cor. D.1). However the upper bound is not a deterministic function of μ_i, as it depends on restrictions of $\mathbf{x}$ and μ_i to subsets (o_j, o_k) of the domain induced by the outcomes of EM for quantiles q_j and q_k earlier in the tree. It thus does not encode a direct relationship between the prediction and instance data and is less amenable for learning.

We instead want guarantees depending on a more natural metric, e.g. one aggregating $\Psi_{\mathbf{x}}^{(q_i,\varepsilon_i)}(\mu_i)$ from the previous section across pairs (q_i, μ_i). The core issue is that the data splitting makes the probability assigned by a prior μ_i to data outside the interval (o_j, o_k) induced by the outcomes of quantiles q_j and q_k earlier in the tree not affect the distribution of o_i. One way to handle this is to assign this probability mass to the edges of (o_j, o_k), rather than the more natural conditional approach of `ApproximateQuantiles`. We refer to this as "edge-based prior adaptation" and use it to bound $\mathrm{Gap}_{\max} = \max_i \mathrm{Gap}_{q_i}(\mathbf{x}, o_i)$ via the harmonic mean $\Psi_{\mathbf{x}}^{(\varepsilon)}$ of the inner products $\Psi_{\mathbf{x}}^{(q_i,\varepsilon_i)}(\mu_i)$:

Theorem D.1 (c.f. Thm. D.3)**.** *If* $m = 2^k - 1$ *for some* k*, quantiles* $q_1, \dots, q_m$ *are uniformly spaced, and for each we have a prior* $\mu_i : \mathbb{R} \mapsto \mathbb{R}_{\geqslant 0}$*, then running* `ApproximateQuantiles` *with edge-based prior adaptation (c.f. Algorithm 2) is* ε*-DP, and w.p.* $\geqslant 1-\beta$

$$\mathrm{Gap}_{\max} \leqslant \frac{2}{\varepsilon}\phi^{\log_2(m+1)}\lceil\log_2(m+1)\rceil \log\frac{m/\beta}{\Psi_{\mathbf{x}}^{(\varepsilon)}} \qquad \textit{for}\Psi_{\mathbf{x}}^{(\varepsilon)} = \left(\sum_{i=1}^{m}\frac{1/m}{\Psi_{\mathbf{x}}^{(q_i,\varepsilon_i)}(\mu_i)}\right)^{-1} \tag{6}$$

Here $\varepsilon_i = \frac{\varepsilon}{\lceil\log_2(m+1)\rceil}$ *and* $\phi = \frac{1+\sqrt{5}}{2}$ *is the golden ratio.*

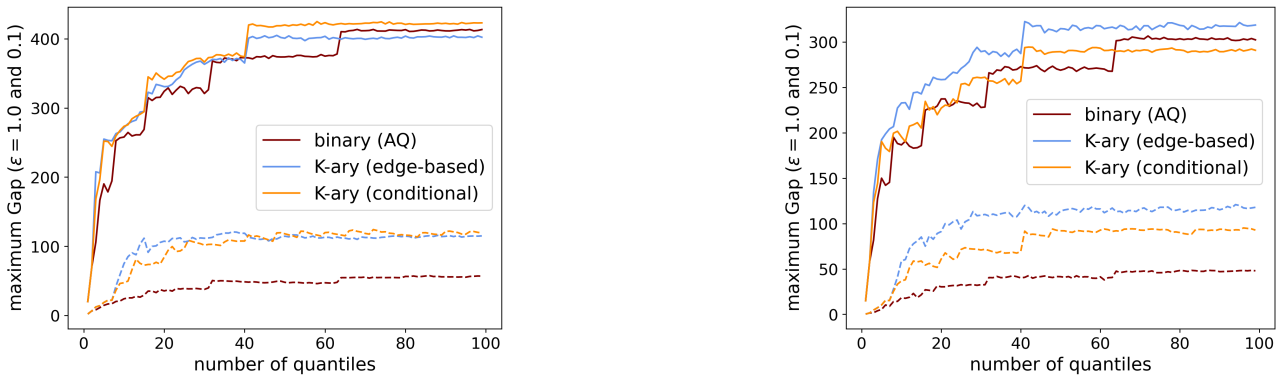

Figure 4. Maximum gap as a function of m for different variants of AQ when using the Uniform prior, evaluated on 1000 samples from a standard Gaussian (left) and the Adult "age" dataset (right). The dashed and solid lines correspond to $\varepsilon = 1$ and 0.1, respectively.

The golden ratio is due to a Fibonacci-type recurrence bounding the maximum Gap_{q_i} at each depth of the tree. $\Psi_{\mathbf{x}}^{(\varepsilon)}$ depends only on $\mathbf{x}$ and predictions μ_i, and it yields a nice error metric $U_{\mathbf{x}}^{(\varepsilon)} = -\log \Psi_{\mathbf{x}}^{(\varepsilon)} = \log \sum_{i=1}^{m} e^{U_{\mathbf{x}}^{(q_i,\varepsilon_i)}}$. However, the dependence of the error on m is worse than of `ApproximateQuantiles`, as $\phi^{\log_2 m}$ is roughly $\mathcal{O}(m^{0.7})$. The bound is still sublinear and thus better than the naive baseline of running EM m times.

The $\tilde{\mathcal{O}}(\phi^{\log_2 m})$ dependence results from error compounding across depths of the tree, so we can try to reduce depth by going from a binary to a K-ary tree. This involves running EM $K-1$ times at each node—and paying $K-1$ more in budget—to split the data into K subsets; the resulting estimates may also be out of order. However, by showing that sorting them back into order does not increase the error and then controlling the maximum Gap_{q_i} at each depth via another recurrence relation, we prove the following:

Theorem D.2 (c.f. Thm. D.4)**.** *For any $q_1, \ldots, q_m$, using $K = \lceil \exp(\sqrt{\log 2 \log(m+1)}) \rceil$ and edge-based adaptation guarantees ε-DP and w.p. $\geqslant 1-\beta$ has* $\mathrm{Gap}_{\max} \leqslant \frac{2\pi^2}{\varepsilon} \exp\left(2\sqrt{\log(2)\log(m+1)}\right) \log \frac{m/\beta}{\Psi_{\mathbf{x}}^{(\varepsilon)}}$.

The rate in m is both sub-polynomial and super-poly-logarithmic ($o(m^\alpha)$ and $\omega(\log^\alpha m)\ \forall\ \alpha > 0$); while asymptotically worse than the prediction-free original result (Kaplan et al., 2022), for almost any practical value of m (e.g. $m \in [3, 10^{12}]$) it does not exceed a small constant (e.g. nine) times $\log^3 m$. Thus if the error $-\log \Psi_{\mathbf{x}}^{(\varepsilon)}$ of the prediction is small—i.e. the inner products between priors and EM scores are large on (harmonic) average—then we may do much better with this approach.

We compare K-ary AQ with edge-based adaptation to regular AQ on two datasets in Figure 4. The original is better at higher ε but similar or worse at higher privacy. We also find that conditional adaptation is only better on discretized data that can have repetitions, a case where neither method provides guarantees. Overall, we find that our prior-dependent analysis covers a useful algorithm, but for consistency with past work and due to its better performance at high ε we will focus on the original binary approach in experiments.

D.2. Quantile estimation via a prediction-dependent prior

The base measure μ of DP mechanisms such as the exponential is the starting point of many approaches to incorporating external information, especially ones focused on Bayesian posterior sampling (Dimitrakakis et al., 2017; Geumlek et al., 2017; Seeman et al., 2020); while it is also our approach to single-quantile estimation with predictions, a key difference here is the focus on utility guarantees depending on both the prediction and instance, which is missing from this past work. In the quantile problem, given a quantile q and a sorted dataset $\mathbf{x} \in \mathbb{R}^n$ of n distinct points, the goal is to release a number o that upper bounds exactly $\lfloor qn \rfloor$ of the entries. A natural error metric, $\mathrm{Gap}_q(\mathbf{x}, o)$, is the number of entries between the released number o and $\lfloor qn \rfloor$, and we can show that prediction-dependent bound using astraightforward application of EM with utility $-\mathrm{Gap}_q$:

Lemma D.1. *Releasing $o \in \mathbb{R}$ w.p. $\propto \exp(-\varepsilon \operatorname{Gap}_q(\mathbf{x}, o)/2)\mu(o)$ is ε-DP, and w.p. $1-\beta$*

$$\operatorname{Gap}_q(\mathbf{x}, o) \leqslant \frac{2}{\varepsilon}\left(\log\frac{1}{\beta} - \log \Psi_{\mathbf{x}}^{(q,\varepsilon)}(\mu)\right) \leqslant \frac{2}{\varepsilon}\left(\log\frac{1}{\beta} - \log \Psi_{\mathbf{x}}^{(q)}(\mu)\right) \tag{7}$$

where $\Psi_{\mathbf{x}}^{(q,\varepsilon)}(\mu) = \sum_{i=0}^{n} \exp(-\varepsilon \operatorname{Gap}_q(\mathbf{x}, I_i)/2)\mu(I_i) = \int \exp(-\varepsilon \operatorname{Gap}_q(\mathbf{x}, o)/2)\mu(o)do$ is the inner product between μ and the exponential score while $\Psi_{\mathbf{x}}^{(q)}(\mu) = \mu(I_{\lfloor qn \rfloor})$ is the measure of the optimal interval (note $\max_k u_q(\mathbf{x}, I_k) = -\operatorname{Gap}_q(\mathbf{x}, I_{\lfloor qn \rfloor}) = 0$ and so $\Psi_{\mathbf{x}}^{(q)}(\mu) \leqslant \Psi_{\mathbf{x}}^{(q,\varepsilon)}(\mu)\ \forall\ \varepsilon > 0$).

Proof. ε-DP follows from u_q having sensitivity one and the guarantee of EM with base measure μ (McSherry & Talwar, 2007, Theorem 6). For the error, since we sample an interval I_k and then sample $o \in I_k$ we have

$$\begin{aligned}\Pr\{\operatorname{Gap}_q(\mathbf{x}, o) \geqslant \gamma\} = \Pr\{u_q(\mathbf{x}, I_k) \leqslant -\gamma\} &= \sum_{j=0}^{n} \Pr\{k = j\} 1_{u_q(\mathbf{x}, I_j) \leqslant -\gamma} \\ &\leqslant \sum_{j=0}^{n} \frac{\exp(-\frac{\varepsilon\gamma}{2})\mu(I_j)}{\sum_{i=0}^{n} \exp(\frac{\varepsilon}{2} u_q(\mathbf{x}, I_i))\mu(I_i)} \leqslant \frac{\exp(-\frac{\varepsilon\gamma}{2})}{\Psi_{\mathbf{x}}^{(q,\varepsilon)}(\mu)}\end{aligned} \tag{8}$$

The result follows by substituting β for the failure probability and solving for γ. □

We can also analyze the error metrics in this bound for specific measures μ. In particular, if the points are in a bounded interval (a, b) and we use the uniform measure $\mu(o) = 1_{o \in (a,b)}/(b-a)$ then $\Psi_{\mathbf{x}}^{(q,\varepsilon)}(\mu) \geqslant \frac{\psi_{\mathbf{x}}}{b-a}$, where $\psi_{\mathbf{x}} = \min_k \mathbf{x}_{[k+1]} - \mathbf{x}_{[k]}$, and we exactly recover the standard bound of $\frac{2}{\varepsilon}\log\frac{b-a}{\beta\psi_{\mathbf{x}}}$, e.g. the one in (Kaplan et al., 2022, Lemma A.1) (indeed their analysis implicitly uses this measure). However, our approach also allows us to remove the boundedness assumption, which itself can be viewed as a type of prediction, as one needs external information to assume that the data, or at least the quantile, lies within the interval (a, b). Taking this view, we can use the prediction to set the location $\nu \in \mathbb{R}$ and scale $\sigma > 0$ of a Cauchy prior $\mu_{\nu,\sigma}(o) = \sigma/(\pi(\sigma^2 + (o-\nu)^2))$ without committing to (a, b) actually containing the data. Since we know that the optimal interval $(\mathbf{x}_{[\lfloor qn \rfloor]}, \mathbf{x}_{[\lfloor qn \rfloor+1]}]$ is a subset of $(\frac{a+b}{2} \pm R)$ for some $R > 0$, setting $\nu = \frac{a+b}{2}$ and $\sigma = \frac{b-a}{2}$ yields

$$\Psi_{\mathbf{x}}^{(q)}(\mu_{\nu,\sigma}) \geqslant \frac{\sigma}{\pi}\frac{\mathbf{x}_{[\lfloor qn \rfloor+1]} - \mathbf{x}_{[\lfloor qn \rfloor]}}{\sigma^2 + \max_{k \in \{\lfloor qn \rfloor, \lfloor qn \rfloor+1\}}(\nu - \mathbf{x}_{[k]})^2} \geqslant \frac{\sigma}{\pi}\min_k \frac{\mathbf{x}_{[k+1]} - \mathbf{x}_{[k]}}{\sigma^2 + R^2} \geqslant \frac{2(b-a)\psi_{\mathbf{x}}/\pi}{(b-a)^2 + 4R^2} \tag{9}$$

If $R = \frac{b-a}{2}$, i.e. we get the interval containing the data correct, then substituting the above into Lemma D.1 recovers the guarantee of the uniform prior up to an additive factor $\frac{2}{\varepsilon}\log\pi$. However, whereas for the uniform prior we have no performance guarantees if the interval is incorrect, using the Cauchy prior the performance degrades gracefully as the error (R) grows. While this first result can be viewed as designing a better prediction-free algorithm, it can also be viewed as making more robust use of the external information about the interval containing the data.

D.3. Multiple-quantile release using multiple priors

To estimate $m > 1$ quantiles $q_1, \ldots, q_m$ at once, we adapt the recursive approach of (Kaplan et al., 2022), whose method `ApproximateQuantiles` implicitly constructs a binary tree with a quantile q_i at each node and uses the exponential mechanism to compute the quantile $\tilde{q}_i = (q_i - \underline{q}_i)/(\overline{q}_i - \underline{q}_i)$ of the dataset $\hat{\mathbf{x}}_i$ of points in the original dataset $\mathbf{x}$ restricted to the interval $(\hat{a}_i, \hat{b}_i)$; here $\underline{q}_i < q_i$ and $\overline{q}_i > q_i$ are quantiles appearing earlier in the tree whose respective estimates $\hat{a}_i$ and $\hat{b}_i$ determine the sub-interval (if there is no earlier quantile on the left and/or right of q_i we use $\underline{q}_i = 0, \hat{a}_i = a$ and/or $\overline{q}_i = 1, \hat{b}_i = b$). Because each datapoint only participates in $\mathcal{O}(\log_2 m)$ exponential mechanisms, the approach is able to run each mechanism with budget $\Omega(\varepsilon/\log_2 m)$ and thus only suffer error logarithmic in the number of quantiles m, a significant improvement upon running one EM with budget ε/m on the entire dataset for each quantile, which has error $\mathcal{O}(m)$ in the number of quantiles.

We can apply prior-dependent guarantees to `ApproximateQuantiles`—pseudocode for a generalized version of which is provided in Algorithm 2—by recognizing that implicitly the method assigns a uniform prior μ_i to each quantile q_i and then running EM with the *conditional* prior $\hat{\mu}_i$ restricted to the interval $[\hat{a}_i, \hat{b}_i]$ determined by earlier quantiles in the binary

tree. An extension of the argument in Equation 8 (c.f. Lemma D.2) then yields a bound on the error of the estimate o_i returned for quantile q_i in terms of the prior-EM inner-product computed with this conditional prior $\hat{\mu}_i$ over the subset $\hat{\mathbf{x}}_i$:

$$\Pr\{\mathrm{Gap}_{q_i}(\mathbf{x}, o_i) \geqslant \gamma\} \leqslant \frac{\exp\left(\frac{\varepsilon_i}{2}(\hat{\gamma}_i - \gamma)\right)}{\Psi^{(\tilde{q}_i,\varepsilon_i)}_{\hat{\mathbf{x}}_i}(\hat{\mu}_i)} \qquad \text{for} \qquad \hat{\gamma}_i = (1-\tilde{q}_i)\,\mathrm{Gap}_{\underline{q}_i}(\mathbf{x}, \hat{a}_i) + \tilde{q}_i\,\mathrm{Gap}_{\overline{q}_i}(\mathbf{x}, \hat{b}_i) \tag{10}$$

Note that the error is offset by a weighted combination $\hat{\gamma}_i$ of the errors of the estimates of quantiles earlier in the tree. Controlling this error allows us to bound the maximum error of any quantile via the harmonic mean of the inner products between the exponential scores and conditional priors:

Lemma D.2. *Algorithm 2 with $K = 2$ and $\varepsilon_i = \varepsilon/\lceil\log_2 m\rceil$ $\forall\, i$ is ε-DP and w.p. $\geqslant 1-\beta$ has*

$$\max_i \mathrm{Gap}_{q_i}(\mathbf{x}, o_i) \leqslant \frac{2}{\varepsilon}\lceil\log_2 m\rceil^2 \log\frac{m}{\beta\hat{\Psi}^{(\varepsilon)}_{\mathbf{x}}} \qquad \textit{for} \qquad \hat{\Psi}^{(\varepsilon)}_{\mathbf{x}} = \left(\sum_{i=1}^{m} \frac{1/m}{\Psi^{(\tilde{q}_i,\varepsilon_i)}_{\hat{\mathbf{x}}_i}(\hat{\mu}_i)}\right)^{-1} \tag{11}$$

Proof. The privacy guarantee follows as in (Kaplan et al., 2022, Lemma 3.1). Setting the above probability bound (10) to $\frac{\beta\hat{\Psi}^{(\varepsilon)}_{\mathbf{x}}}{m\Psi^{(\varepsilon_i)}_{\tilde{q}_i}(\hat{\mathbf{x}}_i,\hat{\mu}_i)}$ for each i we have w.p. $\geqslant 1-\beta$ that $\mathrm{Gap}_{q_i}(\mathbf{x}, o_i) \leqslant \frac{2}{\bar{\varepsilon}}\log\frac{m}{\beta\hat{\Psi}^{(\varepsilon)}_{\mathbf{x}}} + \hat{\gamma}_i\ \forall\, i$. Now let k_i be the depth of quantile q_i in the tree. If $k_i = 1$ then i is the root node so $\hat{\gamma}_i = 0$ and we have $\mathrm{Gap}_{q_i}(\mathbf{x}, o_i) \leqslant \frac{2}{\bar{\varepsilon}}\log\frac{m}{\beta\hat{\Psi}^{(\varepsilon)}_{\mathbf{x}}}$. To make an inductive argument, we assume $\mathrm{Gap}_{q_i}(\mathbf{x}, o_i) \leqslant \frac{2k}{\bar{\varepsilon}}\log\frac{m}{\beta\hat{\Psi}^{(\varepsilon)}}\ \forall\, i$ s.t. $k_i \leqslant k$, and so for any i s.t. $k_i = k+1$ we have that

$$\mathrm{Gap}_{q_i}(\mathbf{x}, o_i) \leqslant \frac{2}{\bar{\varepsilon}}\log\frac{m}{\beta\hat{\Psi}^{(\varepsilon)}_{\mathbf{x}}} + (1-\tilde{q}_i)\,\mathrm{Gap}_{\underline{q}_i}(\mathbf{x}, \hat{a}_i) + \tilde{q}_i\,\mathrm{Gap}_{\overline{q}_i}(\mathbf{x}, \hat{b}_i) \leqslant \frac{2(k+1)}{\bar{\varepsilon}}\log\frac{m}{\beta\hat{\Psi}^{(\varepsilon)}_{\mathbf{x}}} \tag{12}$$

Thus $\mathrm{Gap}_{q_i}(\mathbf{x}, o_i) \leqslant \frac{2k_i}{\bar{\varepsilon}}\log\frac{m}{\beta\hat{\Psi}^{(\varepsilon)}_{\mathbf{x}}}\ \forall\, i$, so using $k_i \leqslant \lceil\log_2 m\rceil$ and $\bar{\varepsilon} = \frac{\varepsilon}{\lceil\log_2 m\rceil}$ yields the result. □

Setting $\hat{\mu}_i$ to be uniform on $[\hat{a}_i, \hat{b}_i]$ exactly recovers both the algorithm and guarantee of (Kaplan et al., 2022, Theorem 3.3). As before, we can also extend the algorithm to the infinite interval:

Corollary D.1. *If all priors are Cauchy with location $\frac{a+b}{2}$ and scale $\frac{b-a}{2}$ and the data lies in the interval $(\frac{a+b}{2} \pm R)$ then w.p. $\geqslant 1-\beta$ the maximum error is at most $\frac{2}{\varepsilon}\lceil\log_2 m\rceil^2 \log\left(\pi m \frac{b-a+\frac{4R^2}{b-a}}{2\beta\psi_{\mathbf{x}}}\right)$.*

However, while this demonstrates the usefulness of Lemma D.2 for obtaining robust priors on infinite intervals, the associated prediction measure $\hat{\Psi}^{(\varepsilon)}_{\mathbf{x}}$ is imperfect because it is non-deterministic: its value depends on the random execution of the algorithm, specifically on the data subsets $\hat{\mathbf{x}}_i$ and priors $\hat{\mu}_i$, which for i not at the root of the tree are affected by the DP mechanisms of i's ancestor nodes. In addition to not being given fully specified by the prediction and data, this makes $\hat{\Psi}^{(\varepsilon)}$ difficult to use as an objective for learning. A natural more desirable prediction metric is the harmonic mean of the inner products between the exponential scores and *original* priors μ_i over the *original* dataset $\mathbf{x}$, i.e. the direct generalization of our approach for single quantiles.

Unfortunately, the conditional restriction of μ_i to the interval $[\hat{a}_i, \hat{b}_i]$ removes the influence of probabilities assigned to intervals between points *not* in this interval. To solve this, we propose a different *edge*-restriction of μ_i that assigns probabilities $\mu_i((-\infty, \hat{a}_i))$ and $\mu_i((\hat{b}_i, \infty))$ of being outside the interval $[\hat{a}_i, \hat{b}_i]$ to atoms on its edges $\hat{a}_i$ and $\hat{b}_i$, respectively. Despite not using any information from points outside $\hat{\mathbf{x}}_i$, this approach puts probabilities assigned to intervals outside $[\hat{a}_i, \hat{b}_i]$ to the edge closest to them, allowing us to extend the previous probability bound (10) to depend on the original prior-EM inner-product (c.f. Lemma G.3):

$$\Pr\{\mathrm{Gap}_{q_i}(\mathbf{x}, o_i) \geqslant \gamma\} \leqslant \exp(\varepsilon(\hat{\gamma}_i - \gamma/2))/\Psi^{(q_i,\varepsilon_i)}_{\mathbf{x}}(\mu_i) \tag{13}$$

However, the stronger dependence of this bound on errors $\hat{\gamma}_i$ earlier in the tree lead to an $\tilde{\mathcal{O}}(\phi^{\log_2 m}) = \mathcal{O}(m^{0.7})$ dependence on m, where $\phi = \frac{1+\sqrt{5}}{2}$ is the golden ratio:

Theorem D.3. *If the quantiles are uniform negative powers of two then Algorithm 2 with $K = 2$, edge-based prior adaptation, and $\varepsilon_i = \varepsilon/\lceil\log_2(m+1)\rceil$ $\forall\, i$ is ε-DP and w.p. $\geqslant 1-\beta$ has*

$$\max_i \mathrm{Gap}_{q_i}(\mathbf{x}, o_i) \leqslant \frac{2}{\varepsilon}\phi^{\log_2(m+1)}\lceil\log_2(m+1)\rceil \log\frac{m}{\beta\Psi^{(\varepsilon)}_{\mathbf{x}}} \qquad \textit{for} \qquad \Psi^{(\varepsilon)}_{\mathbf{x}} = \left(\sum_{i=1}^{m} \frac{1/m}{\Psi^{(q_i,\varepsilon_i)}_{\mathbf{x}}(\mu_i)}\right)^{-1} \tag{14}$$

Proof. Since $\tilde{q}_i = 1/2 \; \forall \; i$, setting the new probability bound equal to $\frac{\beta\Psi_{\mathbf{x}}^{(\varepsilon)}}{m\Psi_{\mathbf{x}}^{(q_i\varepsilon_i)}(\mu_i)}$ yields that w.p. $\geqslant 1-\beta$

$$\mathrm{Gap}_{q_i}(\mathbf{x}, o_i) \leqslant \frac{2}{\bar{\varepsilon}} \log \frac{m}{\beta\Psi_{\mathbf{x}}^{(\varepsilon)}} + 2\hat{\gamma}_i = \frac{2}{\bar{\varepsilon}} \log \frac{m}{\beta\Psi_{\mathbf{x}}^{(\varepsilon)}} + \mathrm{Gap}_{\underline{q}_i}(\mathbf{x}, \hat{a}_i) + \mathrm{Gap}_{\overline{q}_i}(\mathbf{x}, \hat{b}_i) \; \forall \; i \tag{15}$$

If for each $k \leqslant \lceil \log_2 m \rceil$ we define E_k to be the maximum error of any quantile of at most depth k in the tree then since one of $\underline{q}_i$ and $\overline{q}_i$ is at depth at least one less than q_i and the other is at depth at least two less than q_i we have $E_k \leqslant \frac{2A_k}{\bar{\varepsilon}} \log \frac{m}{\beta\Psi_{\mathbf{x}}^{(\varepsilon)}}$ for recurrent relation $A_k = 1 + A_{k-1} + A_{k-2}$ with $A_0 = 0$ and $A_1 = 1$. Since $A_k = F_{k+1} - 1$ for Fibonacci sequence $F_j = \frac{\phi^j - (1-\phi)^j}{\sqrt{5}}$, we have

$$\max_i \mathrm{Gap}_{q_i}(\mathbf{x}, o_i) = \max_k E_k \leqslant \frac{2\phi^{\lceil \log_2(m+1) \rceil + 1}}{\bar{\varepsilon}\sqrt{5}} \log \frac{m}{\beta\Psi_{\mathbf{x}}^{(\varepsilon)}} = \frac{2\phi^{\lceil \log_2(m+1) \rceil + 1}}{\varepsilon\sqrt{5}} \lceil \log_2(m+1) \rceil \log \frac{m}{\beta\Psi_{\mathbf{x}}^{(\varepsilon)}} \tag{16}$$

□

Thus while we have obtained a performance guarantee depending only on the prediction and the data via the harmonic mean $\Psi_{\mathbf{x}}^{(\varepsilon)}$ of the true prior-EM inner-products, the dependence on m is now polynomial. Note that it is still sublinear, which means it is better than the naive baseline of running m independent exponential mechanisms. Still, we can do much better—in-fact asymptotically better than any power of m—by recognizing that the main issue is the compounding error induced by successive errors to the boundaries of sub-intervals. We can reduce this by reducing the depth of the tree using a K-ary rather than binary tree and instead paying $K-1$ times the privacy budget at each depth in order to naively release values for $K-1$ quantiles. This can introduce out-of-order quantiles, but by Lemma G.4 swapping any two out-of-order quantiles does not increase the maximum error and so this issue can be solved by sorting the $K-1$ quantiles before using them to split the data. We thus have the following prediction-dependent performance bound for multiple quantiles:

Theorem D.4. *If we run Algorithm 2 with* $K = \lceil \exp(\sqrt{\log 2 \log(m+1)}) \rceil$*, edge-based adaptation, and* $\varepsilon_i = \frac{\bar{\varepsilon}}{k_i^p}$ *for some power* $p > 1$*,* k_i *the depth of* q_i *in the* K*-ary tree, and* $\bar{\varepsilon} = \frac{\varepsilon}{K-1} \left(\sum_{k=1}^{\lceil \log_K(m+1) \rceil} \frac{1}{k^p} \right)^{-1}$*, then the result satisfies* ε*-DP and w.p.* $\geqslant 1-\beta$ *we have* $\max_i \mathrm{Gap}_{q_i}(\mathbf{x}, o_i) \leqslant \frac{2\pi^2}{\varepsilon} \exp\left(2\sqrt{\log(2)\log(m+1)}\right) \log \frac{m}{\beta\Psi_{\mathbf{x}}^{(\varepsilon)}}$ *if* $p = 2$ *and more generally* $\max_i \mathrm{Gap}_{q_i}(\mathbf{x}, o_i) \leqslant \frac{c_p}{\varepsilon} \exp\left(2\sqrt{\log(2)\log(m+1)}\right) \log \frac{m}{\beta\Psi_{\mathbf{x}}^{(\varepsilon)}}$*, where* c_p *depends only on* p*.*

Proof. The privacy guarantee follows as in (Kaplan et al., 2022, Lemma 3.1) except before each split we compute $K-1$ quantiles with $K-1$ times less budget. As in the previous proof, we have w.p. $\geqslant 1-\beta$ that

$$\mathrm{Gap}_{q_i}(\mathbf{x}, o_i) \leqslant \frac{2}{\varepsilon_i} \log \frac{m}{\beta\Psi_{\mathbf{x}}^{(\varepsilon)}} + 2\hat{\gamma}_i = \frac{2k_i^2}{\bar{\varepsilon}} \log \frac{m}{\beta\Psi_{\mathbf{x}}^{(\varepsilon)}} + 2(1-\tilde{q}_i)\,\mathrm{Gap}_{\underline{q}_i}(\mathbf{x}, \hat{a}_i) + 2\tilde{q}_i\,\mathrm{Gap}_{\overline{q}_i}(\mathbf{x}, \hat{b}_i) \; \forall \; i \tag{17}$$

If for each $k \leqslant \lceil \log_K(m+1) \rceil$ we define E_k to be the maximum error of any quantile of at most depth k in the tree then since both $\underline{q}_i$ and $\overline{q}_i$ are at depth at least one less than q_i we have $E_k \leqslant \frac{2A_k}{\bar{\varepsilon}} \log \frac{m}{\beta\Psi_{\mathbf{x}}^{(\varepsilon)}}$, where $A_k = k^p + 2A_{k-1}$ and $A_1 = 1$. For the case of $p = 2$, $A_k \leqslant 6 \cdot 2^k$ and $1/\bar{\varepsilon} = \frac{K-1}{\varepsilon} \sum_{k=1}^{\lceil \log_K(m+1) \rceil} \frac{1}{k^2} \leqslant \frac{\pi^2}{6\varepsilon}(K-1)$ so we have that

$$\max_i \mathrm{Gap}_{q_i}(\mathbf{x}, o_i) = \max_k E_k \leqslant \frac{12}{\bar{\varepsilon}} 2^{\lceil \log_K(m+1) \rceil} \log \frac{m}{\beta\Psi_{\mathbf{x}}^{(\varepsilon)}} \leqslant \frac{2\pi^2}{\varepsilon}(K-1)2^{\lceil \log_K(m+1) \rceil} \log \frac{m}{\beta\Psi_{\mathbf{x}}^{(\varepsilon)}} \tag{18}$$

Substituting $K = \lceil \exp(\sqrt{\log 2 \log(m+1)}) \rceil$ and simplifying yields the result. For $p > 1$, $A_k \leqslant 2^{k-2}\left(2 + \Phi\left(\frac{1}{2}, -p, 2\right)\right)$, where Φ is the Lerch transcendent, and $1/\bar{\varepsilon} \leqslant \frac{K-1}{\varepsilon}\zeta(p)$, where ζ is the Riemann zeta function. Therefore

$$\max_i \mathrm{Gap}_{q_i}(\mathbf{x}, o_i) = \max_k E_k \leqslant \frac{2^{\lceil \log_K(m+1) \rceil}}{2\bar{\varepsilon}} \left(2 + \Phi\left(\frac{1}{2}, -p, 2\right)\right) \log \frac{m}{\beta\Psi_{\mathbf{x}}^{(\varepsilon)}} \leqslant \frac{c_p}{\varepsilon}(K-1)2^{\lceil \log_K(m+1) \rceil} \log \frac{m}{\beta\Psi_{\mathbf{x}}^{(\varepsilon)}} \tag{19}$$

for $c_p = \left(1 + \Phi\left(\frac{1}{2}, -p, 2\right)/2\right)\zeta(p)$. □

Similarly to Theorem D.3, the proof establishes a recurrence relationship between the maximum errors at each depth. Note that in addition to the K-ary tree this bound uses depth-dependent budgeting to remove a $\mathcal{O}(\log_2 m)$-factor; the constant depending upon the parameter $p > 1$ of the latter has a minimum of roughly 8.42 at $p \approx 1.6$. As discussed before, the new dependence $\tilde{\mathcal{O}}\left(\exp\left(2\sqrt{\log(2)\log(m+1)}\right)\right)$ on m is sub-polynomial, i.e $o(m^\alpha)\ \forall\ \alpha > 0$. While it is also super-polylogarithmic, its shape for any practical value of m is roughly $\mathcal{O}(\log_2^2 m)$, making the result of interest as a justification for the negative log-inner-product performance metric.

D.4. Experimental details

For the experiments in Section 2, specifically Figures 6, we evaluate three variants of the algorithm on data drawn from a standard Gaussian distribution and from the Adult "age" dataset (Kohavi, 1996). In both cases we use 1000 samples and run each experiment 40 times, reporting the average performance. As we do for all datasets, we use reasonable guesses of mean, scale, and bounds on each dataset to set priors. As in this section we report the Uniform, we need to specify its range; for Gaussian we use $[-10, 10]$, while for "age" we use $[10, 120]$.

The original AQ algorithm of Kaplan et al. (2022) is now fully specified. We test two variants of our K-ary modification: one with edge-based adaptation, and the other using the original conditional adaptation. For both cases we set K as a function of m according to the formula in Theorem D.2, and we set the power p of the depth-dependent budget discounting to 1.5, which is close to the theoretically optimal value of around 1.6 (c.f. Thm D.4).

E. Section C details

E.1. Robustness-consistency tradeoffs

While prediction-dependent guarantees work well if the prediction is accurate, without safeguards they may perform catastrophically poorly if the prediction is incorrect. Quantiles provide a prime demonstration of the importance of robustness, as using priors allows for approaches that may assign very little probability to the interval containing the quantile. For example, if one is confident that it has a specific value $x \in (a, b)$ one can specify a more concentrated prior, e.g. the Laplace distribution around x. Alternatively, if one believes the data is drawn i.i.d. from some a known distribution then μ can be constructed via its CDF using order statistics (David & Nagaraja, 2003, Equation 2.1.5). These reasonable approaches can result in distributions with exponential or high-order-polynomial tails, using which directly may work poorly if the prediction is incorrect.

Luckily, for our negative log-inner-product error metric it is straightforward to show a parameterized robustness-consistency tradeoff by simply mixing the prediction prior μ with a robust prior ρ:

Corollary E.1. *For any prior $\mu : \mathbb{R} \mapsto \mathbb{R}_{\geqslant 0}$, robust prior $\rho : \mathbb{R} \mapsto \mathbb{R}_{\geqslant 0}$, and robustness parameter $\lambda \in [0, 1]$, releasing $o \in \mathbb{R}$ w.p. $\propto \exp(-\varepsilon\, \mathrm{Gap}_q(\mathbf{x}, o)/2)\mu^{(\lambda)}(o)$ for $\mu^{(\lambda)} = (1-\lambda)\mu + \lambda\rho$ is $\left(\frac{2}{\varepsilon}\log\frac{1/\beta}{\lambda\Psi_{\mathbf{x}}^{(q,\varepsilon)}(\rho)}\right)$-robust and $\left(\frac{2}{\varepsilon}\log\frac{1/\beta}{1-\lambda}\right)$-consistent w.p. $\geqslant 1-\beta$.*

Proof. Apply Lemma D.1 and linearity of $\Psi_{\mathbf{x}}^{(q,\varepsilon)}(\mu^{(\lambda)}) = (1-\lambda)\Psi_{\mathbf{x}}^{(q,\varepsilon)}(\mu) + \lambda\Psi_{\mathbf{x}}^{(q,\varepsilon)}(\rho)$. □

Thus if the interval is finite and we set ρ to be the uniform prior, using $\mu^{(\lambda)}$ in the algorithm will have a high probability guarantee at most $\frac{2}{\varepsilon}\log\frac{1}{\lambda}$-worse than the prediction-free guarantee of Kaplan et al. (2022, Lemma A.1), no matter how poor μ is for the data, while also guaranteeing w.p. $\geqslant 1-\beta$ that the error will be at most $\frac{2}{\varepsilon}\log\frac{1/\beta}{1-\lambda}$ if μ is perfect. A similar result holds for the case of an infinite interval if we instead use a Cauchy prior. Corollary E.1 demonstrates the usefulness of the algorithms with predictions framework for not only quantifying improvement in utility using external information but also for making the resulting DP algorithms robust to prediction noise.

The above argument for single-quantiles is straightforward to extend to the negative log of the harmonic means of the inner products. In-fact for the binary case with uniform quantiles we can trade-off between $\mathrm{polylog}(m)$-guarantees similar to those of Kaplan et al. (2022) and our prediction-dependent bounds:

Corollary E.2. *Consider priors $\mu_1, \dots, \mu_m : \mathbb{R} \mapsto \mathbb{R}_{\geqslant 0}$, Cauchy prior $\rho : \mathbb{R} \mapsto \mathbb{R}_{\geqslant 0}$ with location $\frac{a+b}{2}$ and scale $\frac{b-a}{2}$, and robustness parameter $\lambda \in [0,1]$. Then running Algorithm 2 on quantiles that are uniform negative powers of two with $K = 2$, edge-based prior adaptation, $\varepsilon_i = \bar{\varepsilon} = \varepsilon/\lceil \log_2 m \rceil \ \forall\ i$, and priors $\mu_i^{(\lambda)} = \lambda\rho + (1-\lambda)\mu_i \ \forall\ i$ is $\left(\frac{2}{\varepsilon}\lceil \log_2 m \rceil^2 \log\left(\pi m \frac{b-a+\frac{4R^2}{b-a}}{2\lambda\beta\psi_{\mathbf{x}}}\right)\right)$-robust and $\left(\frac{2}{\varepsilon}\phi^{\log_2 m}\lceil \log_2 m \rceil \log\frac{m/\beta}{1-\lambda}\right)$-consistent w.p. $\geqslant 1-\beta$.*

Proof. Apply Lemma D.2, Theorem D.3, and the linearity of inner products making up $\hat{\Psi}_{\mathbf{x}}^{(\varepsilon)}$ and $\Psi_{\mathbf{x}}^{(\varepsilon)}$. □

E.2. Learning predictions, privately

Past work, e.g. the public-private framework (Liu et al., 2021; Bassily et al., 2022; Bie et al., 2022), has often focused on domain adaptation-type learning where we adapt a public source to private target. We avoid assuming access to large quantities of i.i.d. public data and instead assume numerous tasks that can have sensitive data and may be adversarially generated. As discussed before, this is the online setting where we see loss functions defined by a sequence of datasets $\mathbf{x}_1, \dots, \mathbf{x}_T$ and aim to compete with best fixed prediction in-hindsight. Note such a guarantee can also be converted into excess risk bounds (c.f. Appendix H.1).

E.2.1. Non-Euclidean DP-FTRL

Because the optimization domain is not well-described by the ℓ_2-ball, we are able to obtain significant savings in dependence on the dimension and in some cases even in the number of instances T by extending the DP-FTRL algorithm of (Kairouz et al., 2021a) to use non-Euclidean regularizers, as in Algorithm 1. For this we prove the following regret guarantee:

Theorem E.1. *Let $\theta_1, \dots, \theta_T$ be the outputs of Algorithm 1 using a regularizer $\phi : \Theta \mapsto \mathbb{R}$ that is strongly-convex w.r.t. $\|\cdot\|$. Suppose $\forall\ t \in [T]$ that $\ell_{\mathbf{x}_t}(\cdot)$ is L-Lipschitz w.r.t. $\|\cdot\|$ and its gradient has ℓ_2-sensitivity Δ_2. Then w.p. $\geqslant 1-\beta'$ we have $\forall\ \theta^* \in \Theta$ that*

$$\sum_{t=1}^{T} \ell(\theta_t; \mathbf{x}_t) - \ell(\theta^*; \mathbf{x}_t) \leqslant \frac{\phi(\theta^*) - \phi(\theta_1)}{\eta} + \eta L\left(L + \left(G + C\sqrt{2\log\frac{T}{\beta'}}\right)\sigma\Delta_2\sqrt{\lceil \log_2 T \rceil}\right)T \tag{20}$$

where $G = \mathbb{E}_{\mathbf{z}\sim\mathcal{N}(\mathbf{0}_p, \mathbf{I}_p)} \sup_{\|\mathbf{y}\|\leqslant 1}\langle \mathbf{z}, \mathbf{y}\rangle = \mathbb{E}_{\mathbf{z}\sim\mathcal{N}(\mathbf{0}_p,1)}\|\mathbf{z}\|_*$ is the Gaussian width of the unit $\|\cdot\|$-ball and C is the Lipschitz constant of $\|\cdot\|_*$ w.r.t. $\|\cdot\|_2$. Furthermore, for any $\varepsilon' \leqslant 2\log\frac{1}{\delta'}$, setting $\sigma = \frac{1}{\varepsilon'}\sqrt{2\lceil \log_2 T \rceil \log\frac{1}{\delta'}}$ makes the algorithm (ε', δ')-DP.

Proof. The privacy guarantee follows from past results for tree aggregation (Smith & Thakurta, 2013; Kairouz et al., 2021a). For all $t \in [T]$ we use the shorthand $\nabla_t = \nabla_\theta \ell_{\mathbf{x}_t}(\theta_t)$; we can then define $\tilde{\theta}_t = \arg\min_{\theta\in\Theta} \phi(\theta) + \eta\sum_{s=1}^{t}\langle \nabla_s, \theta\rangle$ and $\mathbf{b}_t = \mathbf{g}_t - \sum_{s=1}^{t}\nabla_s$. Then

$$\begin{aligned}
\sum_{t=1}^{T} \ell_{\mathbf{x}_t}(\theta_t) - \ell_{\mathbf{x}_t}(\theta^*) \leqslant \sum_{t=1}^{T}\langle \nabla_t, \theta_t - \theta^*\rangle &= \sum_{t=1}^{T}\langle \nabla_t, \tilde{\theta}_t - \theta^*\rangle + \sum_{t=1}^{T}\langle \nabla_t, \theta_t - \tilde{\theta}_t\rangle \\
&\leqslant \frac{\phi(\theta^*) - \phi(\theta_1)}{\eta} + \eta\sum_{t=1}^{T}\|\nabla_t\|_*^2 + \sum_{t=1}^{T}\|\nabla_t\|_*\|\tilde{\theta}_t - \theta_t\| \\
&\leqslant \frac{\phi(\theta^*) - \phi(\theta_1)}{\eta} + \eta L\left(LT + \sum_{t=1}^{T}\|\mathbf{b}_t\|_*\right)
\end{aligned} \tag{21}$$

where the first inequality follows from the standard linear approximation in online convex optimization (Zinkevich, 2003), the second by the regret guarantee for online mirror descent (Shalev-Shwartz, 2011, Theorem 2.15), and the last by applying McMahan (2017, Lemma 7) with $\phi_1(\cdot) = \phi(\cdot) + \eta\sum_{s=1}^{t}\langle \nabla_s, \cdot\rangle$, $\psi(\cdot) = \eta\langle \mathbf{b}_t, \cdot\rangle$, and $\phi_2(\cdot) = \phi(\cdot) + \eta\langle \mathbf{g}_t, \cdot\rangle$, yielding $\|\tilde{\theta}_t - \theta_t\| \leqslant \eta\|\mathbf{b}_t\|_* \ \forall\ t \in [T]$. The final guarantee follows by observing that the tree aggregation protocol adds noise $\mathbf{b}_t \sim \mathcal{N}(\mathbf{0}_p, \sigma^2\Delta_2^2\lceil \log_2 t \rceil)$ to each prefix sum and applying the Gaussian concentration of Lipschitz functions (Boucheron et al., 2012, Theorem 5.6). □

Algorithm 1: Non-Euclidean DP-FTRL. For the `InitializeTree`, `AddToTree`, and `GetSum` subroutines see Kairouz et al. (2021a, Section B.1).

Input: Datasets $\mathbf{x}_1, \dots, \mathbf{x}_T$ arriving in a stream in arbitrary order, domain $\Theta \subset \mathbb{R}^p$, step-size $\eta > 0$, noise scale $\sigma > 0$, ℓ_2-sensitivity $\Delta_2 > 0$, regularizer $\phi : \Theta \mapsto \mathbb{R}$

$\mathbf{g}_1 \leftarrow \mathbf{0}_p$

$\mathcal{T} \leftarrow$`InitializeTree`(T, σ^2, Δ_2) `// start tree aggregation`

for $t = 1, \dots, T$ **do**

  $\theta_t \leftarrow \arg\min_{\theta \in \Theta} \phi(\theta) + \eta \langle \mathbf{g}_t, \theta \rangle$

  suffer $\ell_{\mathbf{x}_t}(\theta_t)$

  $\mathcal{T} \leftarrow$`AddToTree`$(\mathcal{T}, t, \nabla_\theta \ell_{\mathbf{x}_t}(\theta_t))$ `// add gradient to tree`

  $\mathbf{g}_{t+1} \leftarrow$`GetSum`$(\mathcal{T}, t)$ `// estimate` $\sum_{s=1}^{t} \nabla_\theta \ell_{\mathbf{x}_s}(\theta_s)$

The above proof of this result follows that of the Euclidean case, which can be recovered by setting $G = \mathcal{O}(\sqrt{d})$, $C = 1$, and $\Delta_2 = \mathcal{O}(L)$.[1] In addition to the Lipschitz constants L, a key term that can lead to improvement is the Gaussian width G of the unit $\|\cdot\|$-ball, which for the Euclidean case is $\mathcal{O}(\sqrt{d})$ but e.g. for $\|\cdot\| = \|\cdot\|_1$ is $\mathcal{O}(\sqrt{\log d})$. Note that a related dependence on the Laplace width of Θ appears in Agarwal & Singh (2017, Theorem 3.1), although their guarantee only holds for linear losses and is not obviously extendable. Thus Theorem E.1 may be of independent interest for DP online learning.

E.2.2. Learning priors for one or more quantiles

We now turn to learning priors $\mu_t = \left(\mu_{t[1]}, \cdots, \mu_{t[m]}\right)$ to privately estimate m quantiles $q_1, \dots, q_m$ on each of a sequence of T datasets $\mathbf{x}_t$. We will aim to set $\mu_1, \dots, \mu_T$ s.t. if at each time t we run Algorithm 2 with privacy $\varepsilon > 0$ then the guarantees given by Lemmas D.3 and D.4 will be asymptotically at least as good as those of the best set of measures in $\mathcal{F}^m$, where $\mathcal{F}$ is some class of measures on the finite interval (a, b). The latter we will assume to be known and bounded. Note that in this section almost all single-quantile results follow from setting $m = 1$, so we study it jointly with learning for multiple quantiles.

Ignoring constants, the loss functions implied by our prediction-dependent upper bounds for multiple-quantiles are the following negative log-harmonic sums of prior-EM inner-products:

$$U_{\mathbf{x}_t}^{(\varepsilon)}(\mu) = \log \sum_{i=1}^{m} \frac{1}{\Psi_{\mathbf{x}_t}^{(q_i, \varepsilon_i)}(\mu_{[i]})} = \log \sum_{i=1}^{m} \frac{1}{\int_a^b \exp(-\varepsilon_i \operatorname{Gap}_{q_i}(\mathbf{x}_t, o)/2) \mu_{[i]}(o) do} \tag{22}$$

We focus on minimizing regret $\max_{\mu \in \mathcal{F}^m} \sum_{t=1}^{T} U_{\mathbf{x}_t}^{(\varepsilon)}(\mu_t) - U_{\mathbf{x}_t}^{(\varepsilon)}(\mu)$ over these losses for priors $\mu_{[i]}$ in a class $\mathcal{F}_{V,d}$ of probability measures that are piecewise V-Lipschitz over each of d intervals uniformly partitioning $[a, b)$. This is chosen because it covers the class $\mathcal{F}_{V,1}$ of V-Lipschitz measures and the class of $\mathcal{F}_{0,d}$ of discrete measures that are constant on each of the d intervals. The latter can be parameterized by $\mathbf{W} \in \triangle_d^m$, so that the losses have the form $U_{\mathbf{x}_t}^{(\varepsilon)}(\mu_{\mathbf{W}}) = \log \sum_{i=1}^{m} \langle \mathbf{s}_{t,i}, \mathbf{W}_{[i]} \rangle^{-1}$ for $\mathbf{s}_{t,i} \in \mathbb{R}_{\geqslant 0}^d$. This can be seen by setting $\mathbf{s}_{t,i[j]} = \frac{d}{b-a} \int_{a + \frac{b-a}{d}(j-1)}^{a + \frac{b-a}{d} j} \exp(-\varepsilon_i \operatorname{Gap}_{q_i}(\mathbf{x}_t, o)/2) do$ and $\mu_{\mathbf{W}_{[i]}}(o) = \frac{d}{b-a} \mathbf{W}_{[i,j]}$ over the interval $\left[a + \frac{b-a}{d}(j-1), a + \frac{b-a}{d} j\right)$. Finally, for $\lambda \in [0, 1]$ we also let $\mathcal{F}^{(\lambda)} = \{(1-\lambda)\mu + \frac{\lambda}{b-a} : \mu \in \mathcal{F}\}$ denote the class of mixtures of measures $\mu \in \mathcal{F}$ with the uniform measure.

As detailed in Appendix H.2, losses of the form $-\log\langle \mathbf{s}_t, \cdot \rangle$, i.e. those above when $m = 1$, have been studied in (non-private) online learning (Hazan et al., 2007; Balcan et al., 2021). However, specialized approaches, e.g. those taking advantage exp-concavity, are not obviously implementable via prefix sums of gradients, the standard approach to private online learning (Smith & Thakurta, 2013; Agarwal & Singh, 2017; Kairouz et al., 2021a). Still, we can at least use the fact that we are optimizing over a product of simplices to improve the dimension-dependence by applying Non-Euclidean DP-FTRL with entropic regularizer $\phi(\mathbf{W}) = m\langle \mathbf{W}, \log \mathbf{W} \rangle$, which yields an m-way exponentiated gradient (EG) update (Kivinen & Warmuth, 1997). To apply its guarantee for the problem of learning priors for quantile estimation, we need to bound the sensitivity of the gradients $\nabla_{\mathbf{W}} U_{\mathbf{x}_t}^{(\varepsilon)}(\mu_{\mathbf{W}})$ to changes in the underlying datasets $\mathbf{x}_t$. This is often done via a bound on the gradient norm, which in our case is unbounded near the boundary of the simplex. We thus restrict to γ-robust priors for some

[1] As of this writing, the most recent arXiv version of Kairouz et al. (2021a, Theorem C.1) has a typo leading to missing a Lipschitz constant in the bound, confirmed via correspondence with the authors.

$\gamma \in (0,1]$ by constraining $\mathbf{W} \in \triangle_d^m$ to have entries lower bounded by γ/d—a domain where $\|\nabla_{\mathbf{W}} U_{\mathbf{x}_t}^{(\varepsilon)}(\mu_{\mathbf{W}})\|_1 \leqslant d/\gamma$ (c.f. Lemma H.1)—and bounding the resulting approximation error; we are not aware of even a non-private approach that avoids this except by taking advantage of exp-concavity (Hazan et al., 2007).

We thus have a bound of $2d/\gamma$ on the ℓ_2-sensitivity. However, this may be too loose since it allows for changing the entire dataset $\mathbf{x}_t$, whereas we are only interested in changing one entry. Indeed, for small ε we can obtain a tighter bound:

Lemma E.1. *The ℓ_2-sensitivity of $\nabla_{\mathbf{w}} U_{\mathbf{x}_t}^{(\varepsilon)}(\mu_{\mathbf{w}})$ is $\frac{d}{\gamma}\min\{2, e^{\tilde{\varepsilon}_m} - 1\}$, where $\tilde{\varepsilon}_m = (1 + 1_{m>1})\max_i \varepsilon_i$.*

Proof for $m = 1$; c.f. Appendix H.2.1. Let $\tilde{\mathbf{x}}_t$ be a neighboring dataset of $\mathbf{x}_t$ and let $U_{\tilde{\mathbf{x}}_t}^{(\varepsilon)}(\mu_{\mathbf{W}}) = -\log\langle \tilde{\mathbf{s}}_t, \mathbf{w}\rangle$ be the corresponding loss. Note that $\max_{o\in[a,b]} |\operatorname{Gap}_q(\mathbf{x}_t, o) - \operatorname{Gap}_q(\tilde{\mathbf{x}}_t, o)| \leqslant 1$ so

$$\tilde{\mathbf{s}}_{t[j]} = \int_{a+\frac{b-a}{d}(j-1)}^{a+\frac{b-a}{d}j} \exp\left(-\frac{\varepsilon}{2}\operatorname{Gap}_q(\tilde{\mathbf{x}}_t, o)\right) do \in e^{\pm\frac{\varepsilon}{2}} \int_{a+\frac{b-a}{d}(j-1)}^{a+\frac{b-a}{d}j} \exp\left(-\frac{\varepsilon}{2}\operatorname{Gap}_q(\mathbf{x}_t, o)\right) do = e^{\pm\frac{\varepsilon}{2}}\mathbf{s}_{t[j]} \tag{23}$$

Therefore since $m = 1$ we denote $\mathbf{w} = \mathbf{W}_{[1]}$, $\mathbf{s}_t = \mathbf{s}_{t,1}$, and $\tilde{\mathbf{s}}_t = \tilde{\mathbf{s}}_{t,1}$ and have

$$\begin{aligned}\|\nabla_{\mathbf{w}} U_{\mathbf{x}_t}^{(\varepsilon)}(\mu_{\mathbf{w}}) - \nabla_{\mathbf{w}} U_{\tilde{\mathbf{x}}_t}^{(\varepsilon)}(\mu_{\mathbf{w}})\|_2 &= \sqrt{\sum_{j=1}^d \left(\frac{\mathbf{s}_{t[j]}}{\langle \mathbf{s}_t, \mathbf{w}\rangle} - \frac{\tilde{\mathbf{s}}_{t[j]}}{\langle \tilde{\mathbf{s}}_t, \mathbf{w}\rangle}\right)^2} = \sqrt{\sum_{j=1}^d \frac{\mathbf{s}_{t[j]}^2}{\langle \mathbf{s}_t, \mathbf{w}\rangle^2}\left(1 - \frac{\tilde{\mathbf{s}}_{t[j]}\langle \mathbf{s}_t, \mathbf{w}\rangle}{\mathbf{s}_{t[j]}\langle \tilde{\mathbf{s}}_t, \mathbf{w}\rangle}\right)^2} \\ &\leqslant \|\nabla_{\mathbf{w}} U_{\mathbf{x}_t}^{(\varepsilon)}(\mu_{\mathbf{w}})\|_1 \max_j |1 - \kappa_j|\end{aligned} \tag{24}$$

where $\kappa_j = \frac{\tilde{\mathbf{s}}_{t[j]}\langle \mathbf{s}_t, \mathbf{w}\rangle}{\mathbf{s}_{t[j]}\langle \tilde{\mathbf{s}}_t, \mathbf{w}\rangle} \in \frac{\mathbf{s}_{t[j]}\exp(\pm\frac{\varepsilon}{2})\langle \mathbf{s}_t, \mathbf{w}\rangle}{\mathbf{s}_{t[j]}\langle \mathbf{s}_t, \mathbf{w}\rangle\exp(\pm\frac{\varepsilon}{2})} \in \exp(\pm\varepsilon)$ by Equation 23. The result follows by taking the minimum with the bound on the Euclidean norm of the gradient (Lemma H.1). □

Since $e^\varepsilon - 1 \leqslant 2\varepsilon$ for $\varepsilon \in (0, 1.25]$, for small ε this allows us to add less noise in DP-FTRL. With this sensitivity bound, we apply Algorithm 1 using the entropic regularizer to obtain the following result:

Theorem E.2. *For $d \geqslant 2, \gamma \in (0, 1/2]$ if we run Algorithm 1 on $U_{\mathbf{x}_t}^{(\varepsilon)}(\mu_{\mathbf{W}}) = \log\sum_{i=1}^m \frac{1}{\Psi_{\mathbf{x}_t}^{(q_i,\varepsilon_i)}(\mu_{\mathbf{W}})}$ over γ-robust priors with step-size $\eta = \frac{\gamma m}{d}\sqrt{\frac{\log(d)/T}{1+\left(2\sqrt{\log(md)}+\sqrt{2\log\frac{T}{\beta'}}\right)\sigma\sqrt{\lceil\log_2 T\rceil}\min\{1,\tilde{\varepsilon}_m\}}}$ and regularizer $\phi(\mathbf{W}) = m\langle \mathbf{W}, \log\mathbf{W}\rangle$ then for any $V \geqslant 0$, $\lambda \in [0,1]$, and $\beta' \in (0,1]$ we will have regret*

$$\begin{aligned}\max_{\mu_{[i]}\in\mathcal{F}_{V,d}^{(\lambda)}} \sum_{t=1}^T U_{\mathbf{x}_t}^{(\varepsilon)}(\mu_{\mathbf{W}_t}) - U_{\mathbf{x}_t}^{(\varepsilon)}(\mu) &\leqslant \frac{VmT}{\gamma d\bar{\psi}}(b-a)^3 + 2\max\{\gamma - \lambda, 0\}T\log 2 \\ &+ \frac{2md}{\gamma}\sqrt{\left(1 + \left(4\sqrt{\log(md)} + 2\sqrt{2\log\frac{T}{\beta'}}\right)\sigma\sqrt{\lceil\log_2 T\rceil}\min\{1,\tilde{\varepsilon}_m\}\right)T\log d}\end{aligned} \tag{25}$$

w.p. $\geqslant 1 - \beta'$, where $\bar{\psi}$ is the harmonic mean of $\psi_{\mathbf{x}_t} = \min_k \mathbf{x}_{t[k+1]} - \mathbf{x}_{t[k]}$ and $\tilde{\varepsilon}_m = (1 + 1_{m>1})\max_i \varepsilon_i$. For any $\varepsilon' \leqslant 2\log\frac{1}{\delta'}$ setting $\sigma = \frac{1}{\varepsilon'}\sqrt{2\lceil\log_2 T\rceil\log\frac{1}{\delta'}}$ makes this procedure (ε', δ')-DP.

Proof. For set of γ-robust priors ρ s.t. $\rho_{[i]} = \min\{1-\gamma+\lambda, 1\}\mu_{[i]} + \frac{\max\{\gamma-\lambda,0\}}{b-a}$ and $\mathbf{W} \in \triangle_d^m$ s.t. $\mathbf{W}_{[i,j]} = \frac{b-a}{d}\int_{a+\frac{b-a}{d}(j-1)}^{a+\frac{b-a}{d}j} \rho_{[i]}(o)do$ we can divide the regret into three components:

$$\sum_{t=1}^{T} U_{\mathbf{x}_t}^{(\varepsilon)}(\mu_{\mathbf{W}_t}) - U_{\mathbf{x}_t}^{(\varepsilon)}(\mu) = \sum_{t=1}^{T} U_{\mathbf{x}_t}^{(\varepsilon)}(\mu_{\mathbf{W}_t}) - U_{\mathbf{x}_t}^{(\varepsilon)}(\mu_{\mathbf{W}}) + \sum_{t=1}^{T} U_{\mathbf{x}_t}^{(\varepsilon)}(\mu_{\mathbf{W}}) - U_{\mathbf{x}_t}^{(\varepsilon)}(\rho) + \sum_{t=1}^{T} U_{\mathbf{x}_t}^{(\varepsilon)}(\rho) - U_{\mathbf{x}_t}^{(\varepsilon)}(\mu) \quad (26)$$

The first summation is the regret of DP-FTRL with regularizer ϕ, which is strongly convex w.r.t. $\|\cdot\|_1$. The Gaussian width of its unit ball is $2\sqrt{\log(md)}$, by Lemma H.1 the losses are $\frac{d}{\gamma}$-Lipschitz w.r.t. $\|\cdot\|_1$, and by Lemma E.1 the ℓ_2-sensitivity is $\Delta_2 = \frac{d}{\gamma}\min\{2, e^{\tilde{\varepsilon}_m} - 1\} \leqslant \frac{2d}{\gamma}\min\{1, \tilde{\varepsilon}_m\}$, so applying Theorem E.1 yields the bound $\frac{m^2\log d}{\eta} + \frac{\eta d^2 T}{\gamma^2}\left(1 + \left(4\sqrt{\log d} + 2\sqrt{2\log\frac{T}{\beta'}}\right)\sigma\sqrt{\lceil\log_2 T\rceil}\min\{1,\varepsilon\}\right)$. The second summation is a sum over the errors due to discretization, where we have

$$\begin{aligned}
\sum_{t=1}^{T} U_{\mathbf{x}_t}^{(\varepsilon)}(\mu_{\mathbf{W}}) - U_{\mathbf{x}_t}^{(\varepsilon)}(\rho) &= \sum_{t=1}^{T} \log \sum_{i=1}^{m} \langle \mathbf{s}_{t,i}, \mathbf{W}_{[i]}\rangle^{-1} - \log \sum_{i=1}^{m} \frac{1}{\int_a^b \exp(-\varepsilon_i \operatorname{Gap}_{q_i}(\mathbf{x}_t, o)/2)\rho_{[i]}(o)do} \\
&\leqslant \sum_{t=1}^{T}\sum_{i=1}^{m} \frac{\int_a^b \exp(-\frac{\varepsilon_i}{2}\operatorname{Gap}_{q_i}(\mathbf{x}_t, o))\rho_{[i]}(o)do - \langle \mathbf{s}_{t,i}, \mathbf{W}_{[i]}\rangle}{\langle \mathbf{s}_{t,i}, \mathbf{W}_{[i]}\rangle} \\
&\leqslant \sum_{t=1}^{T}\sum_{i=1}^{m} \frac{\sum_{j=1}^{d}\int_{a+\frac{b-a}{d}(j-1)}^{a+\frac{b-a}{d}j} \exp(-\frac{\varepsilon_i}{2}\operatorname{Gap}_{q_i}(\mathbf{x}_t, o))(\rho_{[i]}(o) - \mu_{\mathbf{W}_{[i]}}(o))do}{\gamma\psi_{\mathbf{x}_t}/(b-a)} \\
&\leqslant \sum_{t=1}^{T}\sum_{i=1}^{m} \frac{\sum_{j=1}^{d}\int_{a+\frac{b-a}{d}(j-1)}^{a+\frac{b-a}{d}j} |\rho_{[i]}(o) - \rho_{[i]}(o_{i,j})|do}{\gamma\psi_{\mathbf{x}_t}/(b-a)} \leqslant \frac{VmT}{\gamma d\bar{\psi}}(b-a)^3
\end{aligned} \quad (27)$$

where the first inequality follows by concavity, the second by using the definition of $\mathbf{W}$ to see that $\langle \mathbf{s}_{t,i}, \mathbf{W}_{[i]}\rangle = \int_a^b \exp(-\frac{\varepsilon_i}{2}\operatorname{Gap}_{q_i}(\mathbf{x}_t, o))\mu_{\mathbf{W}_{[i]}}(o)do \geqslant \frac{\gamma\psi_{\mathbf{x}_t}}{b-a}$, the third by Hölder's inequality and the mean value theorem for some $o_{i,j} \in (a+\frac{b-a}{d}(j-1), a+\frac{b-a}{d}j)$, and the fourth by the Lipschitzness of $\rho_{[i]} \in \mathcal{F}_{V,d}^{(\gamma)}$. The third summation is a sum over the errors due to γ-robustness, with the result following by $U_{\mathbf{x}_t}^{(\varepsilon)}(\rho) - U_{\mathbf{x}_t}^{(\varepsilon)}(\mu) \leqslant U_{\mathbf{x}_t}^{(\varepsilon)}(\mu) - \log(1-\max\{\gamma-\lambda,0\}) - U_{\mathbf{x}_t}^{(\varepsilon)}(\mu) \leqslant 2\max\{\gamma-\lambda, 0\}\log 2$. □

Note that in the case of $V > 0$ or $\lambda = 0$ we will need to set $d = \omega_T(1)$ or $\gamma = o_T(1)$ in order to obtain sublinear regret. Thus for these more difficult classes our extension of DP-FTRL to non-Euclidean regularizers yields improved rates, as in the Euclidean case the first term has an extra $\sqrt[4]{d}$-factor. The following provides some specific upper bounds derived from Theorem E.2:

Corollary E.3. *For each of the following classes of priors there exist settings of d (where needed) and $\gamma > 0$ in Theorem E.2 that guarantee obtain the following regret w.p. $\geqslant 1-\beta'$:*

1. *λ-robust and discrete $\mu_{[i]} \in \mathcal{F}_{0,d}^{(\lambda)}$:* $\tilde{\mathcal{O}}\left(\frac{dm}{\lambda}\sqrt{\left(1 + \frac{\min\{1,\tilde{\varepsilon}_m\}}{\varepsilon'}\right)T}\right)$
2. *λ-robust and V-Lipschitz $\mu_{[i]} \in \mathcal{F}_{V,1}^{(\lambda)}$:* $\tilde{\mathcal{O}}\left(\frac{m}{\lambda}\sqrt{\frac{V}{\bar{\psi}}}\sqrt[4]{\left(1 + \frac{\min\{1,\tilde{\varepsilon}_m\}}{\varepsilon'}\right)T^3}\right)$
3. *discrete $\mu_{[i]} \in \mathcal{F}_{0,d}$:* $\tilde{\mathcal{O}}\left(\sqrt{dm}\sqrt[4]{\left(1 + \frac{\min\{1,\tilde{\varepsilon}_m\}}{\varepsilon'}\right)T^3}\right)$
4. *V-Lipschitz $\mu_{[i]} \in \mathcal{F}_{V,1}$:* $\tilde{\mathcal{O}}\left(\sqrt{m}\sqrt[4]{\frac{V}{\bar{\psi}}}\sqrt[8]{\left(1 + \frac{\min\{1,\tilde{\varepsilon}_m\}}{\varepsilon'}\right)T^7}\right)$

Thus competing with λ-robust priors with discrete PDFs enjoys the fastest regret rate of $\tilde{\mathcal{O}}(\sqrt{T})$, while either removing robustness or competing with any V-Lipschitz prior has regret $\tilde{\mathcal{O}}(T^{3/4})$, and doing both has regret $\tilde{\mathcal{O}}(T^{7/8})$. When comparing to Lipschitz priors we also incur a dependence on the inverse of minimum datapoint separation, which may be small. A notable aspect of all the bounds is that the regret *improves* with small ε due to the sensitivity analysis in Lemma E.1; indeed for $\varepsilon = \mathcal{O}(\varepsilon')$ the regret bound only has a $\mathcal{O}(\log \frac{1}{\delta'})$-dependence on the privacy guarantee. Finally, for λ-robust priors we can also apply the $\log \frac{b-a}{\lambda\psi}$-boundedness of $-\log \Psi_{\mathbf{x}}^{(q,\varepsilon)}(\mu)$ and standard online-to-batch conversion (e.g. Cesa-Bianchi et al. (2004, Proposition 1) to obtain the following sample complexity guarantee:

Corollary E.4. *For any $\alpha > 0$ and distribution $\mathcal{D}$ over finite datasets $\mathbf{x}$ of ψ-separated points from (a, b), if we run the algorithm in Theorem E.2 on $T = \Omega\left(\frac{\log \frac{1}{\beta'}}{\alpha^2}\left(\frac{d^2m^2}{\lambda^2}\left(1 + \frac{\min\{1,\tilde{\varepsilon}_m\}}{\varepsilon'}\right) + \log^2 \frac{1}{\lambda\psi}\right)\right)$ i.i.d. samples from $\mathcal{D}$ then w.p. $\geqslant 1 - \beta'$ the average $\hat{\mathbf{W}} = \frac{1}{T}\sum_{t=1}^{T} \mathbf{W}_t$ of the resulting iterates satisfies $\mathbb{E}_{\mathbf{x}\sim\mathcal{D}} \log \sum_{i=1}^{m} \frac{1}{\Psi_{\mathbf{x}}^{(q_i,\varepsilon_i)}(\mu_{\hat{\mathbf{W}}_{[i]}})} \leqslant \min_{\mu_{[i]}\in\mathcal{F}_{0,d}^{(\lambda)}} \mathbb{E}_{\mathbf{x}\sim\mathcal{D}} \log \sum_{i=1}^{m} \frac{1}{\Psi_{\mathbf{x}}^{(q_i,\varepsilon_i)}(\mu_{[i]})} + \alpha$. For α-suboptimality w.r.t. $\mu_{[i]} \in \mathcal{F}_{V,1}^{(\lambda)}$ the sample complexity is $\Omega\left(\frac{\log \frac{1}{\beta'}}{\alpha^2}\left(\frac{V^2m^2}{\lambda^4\psi^2\alpha^2}\left(1 + \frac{\min\{1,\tilde{\varepsilon}_m\}}{\varepsilon'}\right) + \log^2 \frac{1}{\lambda\psi}\right)\right)$.*

F. Section 3 details

F.1. Location-scale families

A location-scale model is a distribution parameterized by a location $\nu \in \mathbb{R}$ and scale $\sigma \in \mathbb{R}_{\geqslant 0}$ whose density has the form $\mu_{\nu,\sigma}(x) = \frac{1}{\sigma} f\left(\frac{x-\nu}{\sigma}\right)$ for some centered probability measure $f : \mathbb{R} \mapsto \mathbb{R}_{\geqslant 0}$. Unfortunately, we show that no log-concave f is robust, in the sense that for any $R > 0$ there exists a dataset of points in the interval $(\theta \pm R)^n$ s.t. $U_{\mathbf{x}}^{(q)}(\mu_{\theta,1}) = \Omega(R)$ (rather than $\mathcal{O}(\log(1+R^2))$ as shown for the Cauchy family in Corollary 2.1). On the other hand, log-concave location-scale families are the only ones for which $U_{\mathbf{x}}^{(q)}$ is convex, both for the original parameterization and that of Burridge (1981). We record these facts in the following theorem:

Theorem F.1 (c.f. Thm. F.2)**.** *Let $\mu_{\nu,\sigma}$ be a location-scale family associated with a continuous measure $f : \mathbb{R} \mapsto \mathbb{R}_{\geqslant 0}$.*

1. *If f is log-concave then $\exists\, a, b > 0$ s.t. for any $R > 0$, $\psi \in (0, \frac{R}{2n}]$, $q \geqslant \frac{1}{n}$, and $\theta \in \mathbb{R}$ there exists $\mathbf{x} \in (\theta \pm R)^n$ with $\min_i \mathbf{x}_{[i+1]} - \mathbf{x}_{[i]} = \psi$ s.t. $U_{\mathbf{x}}^{(q)}(\mu_{\theta,1}) = aR + \log \frac{b}{\psi}$.*
2. *If f is not log-concave then there exists $\mathbf{x} \in \mathbb{R}^n$ with $\min_i \mathbf{x}_{[i+1]} - \mathbf{x}_{[i]} > 0$ s.t. $U_{\mathbf{x}}^{(q)}(\mu_{\theta,1})$ is non-convex in θ.*

Note the latter dataset is not degenerate: for f strictly log-convex over $[a, b]$, any $\mathbf{x}$ whose optimal interval has length $< \frac{b-a}{2}$ has non-convex $U_{\mathbf{x}}^{(q)}(\mu_{\theta,1}) = -\log \Psi_{\mathbf{x}}^{(q)}(\mu_{\theta,1})$.

We must thus choose between having a robust location-scale family like the Cauchy or an easy-to-optimize log-concave one. As we can ensure robustness of the learned prior *post-hoc* using the approach of Section C.2, we choose the latter. Specifically, we use the Laplace prior, as it is in some sense the most robust log-concave distribution (it has loss $\Theta(R)$ if $\mathbf{x} \in (\theta \pm R)^n$, whereas e.g. the Gaussian has loss $\Theta(R^2)$) and because it yields a numerically stable closed-form expression (37) for $\ell_{\mathbf{x}}^{(q)}(\theta, \phi)$ (unlike e.g. the Gaussian).

F.1.1. Impossibility of simultaneous robustness and convexity

Theorem F.2. *Let $f : \mathbb{R} \mapsto \mathbb{R}_{\geqslant 0}$ be a centered probability measure and for each $\theta \in \Theta$ define $\mu_\theta(x) = f(x - \theta)$.*

1. *If f is continuous then $U_{\mathbf{x}}(\mu_\theta)$ is convex in θ for all sorted dataset $\mathbf{x} \in \mathbb{R}^n$ if and only if f is log-concave.*
2. *There exist constants $a, b > 0$ s.t. for any $r > 0$, $\psi \in (0, \frac{R}{2n}]$, $q \geqslant \frac{1}{n}$, and $\theta \in \mathbb{R}$ there exists a sorted dataset $\mathbf{x} \in (\theta \pm R)^n$ with $\min_{i\in[n-1]} \mathbf{x}_{[i+1]} - \mathbf{x}_{[i]} = \psi$ s.t. $U_{\mathbf{x}}^{(q)}(\mu_\theta) = aR + \log \frac{b}{\psi}$.*

Proof. For the first direction of the first result, consider any $\theta, \theta' \in \mathbb{R}$ and $\lambda \in [0,1]$. We have that

$$U^{(q)}_{*x}(\mu_{\lambda\theta+(1-\lambda)\theta'}) - \left(\lambda U^{(q)}_{\mathbf{x}}(\mu_\theta) - (1-\lambda)\log U^{(q)}_{\mathbf{x}}(\mu_{\theta'}\right) = \log \frac{\Psi^{(q)}_{\mathbf{x}}(\mu_\theta)^\lambda \Psi^{(q)}_{\mathbf{x}}(\mu_{\theta'})^{1-\lambda}}{\Psi^{(q)}_{\mathbf{x}}\mu_{\lambda\theta+(1-\lambda)\theta'})} \tag{28}$$

so it suffices to show that $\Psi_{\mathbf{x}}(q)(\mu_{\lambda\theta+(1-\lambda)\theta'}) \geqslant \Psi^{(q)}_{\mathbf{x}}(\mu_\theta)^\lambda \Psi^{(q)}_{\mathbf{x}}(\mu_{\theta'})^{1-\lambda}$. By the log-concavity of f we have

$$\mu_{\lambda\theta+(1-\lambda)\theta'}(\lambda x + (1-\lambda)y) = f(\lambda(x-\theta) + (1-\lambda)(y-\theta')) \geqslant f(x-\theta)^\lambda f(y-\theta')^{1-\lambda} = \mu_\theta(x)^\lambda \mu_{\theta'}(y)^{1-\lambda} \tag{29}$$

for all $x, y \in \mathbb{R}$. Therefore by the Prékopa-Leindler inequality we have that

$$\begin{aligned}\Psi^{(q)}_{\mathbf{x}}(\mu_{\lambda\theta+(1-\lambda)\theta'}) = \int_{\mathbf{x}_{[\lfloor qn\rfloor]}}^{\mathbf{x}_{[\lfloor qn\rfloor+1]}} \mu_{\lambda\theta+(1-\lambda)\theta'}(x)dx &\geqslant \left(\int_{\mathbf{x}_{[\lfloor qn\rfloor]}}^{\mathbf{x}_{[\lfloor qn\rfloor+1]}} \mu_\theta(x)dx\right)^\lambda \left(\int_{\mathbf{x}_{[\lfloor qn\rfloor]}}^{\mathbf{x}_{[\lfloor qn\rfloor+1]}} \mu_{\theta'}(x)dx\right)^{1-\lambda} \\ &= \Psi_{\mathbf{x}}(q)(\mu_\theta)^\lambda \Psi^{(q)}_{\mathbf{x}}(\mu_{\theta'})^{1-\lambda}\end{aligned} \tag{30}$$

For the second direction, by assumption $\exists\ a < c, b > c$ s.t. $\sqrt{f(x)f(y)} > f(\frac{x+y}{2})\ \forall\ x, y \in [a,b]$, i.e. f is strictly log-convex on $[a,b]$. Let $\mathbf{x} \in \mathbb{R}^n$ be any dataset s.t. $\mathbf{x}_{[\lfloor qn\rfloor+1]} - \mathbf{x}_{[\lfloor qn\rfloor]} \leqslant \frac{b-a}{2}$ and set $\theta = \mathbf{x}_{[\lfloor qn\rfloor]} - a$, $\theta' = \mathbf{x}_{[\lfloor qn\rfloor]} - \frac{a+b}{2}$. Then we have

$$\begin{aligned}\sqrt{\int_{\mathbf{x}_{[\lfloor qn\rfloor]}}^{\mathbf{x}_{[\lfloor qn\rfloor+1]}} \mu_\theta(x)dx \int_{\mathbf{x}_{[\lfloor qn\rfloor]}}^{\mathbf{x}_{[\lfloor qn\rfloor+1]}} \mu_{\theta'}(x)dx} &= \sqrt{\int_{\mathbf{x}_{[\lfloor qn\rfloor]}}^{\mathbf{x}_{[\lfloor qn\rfloor+1]}} \sqrt{\mu_\theta(x)}^2 dx \int_{\mathbf{x}_{[\lfloor qn\rfloor]}}^{\mathbf{x}_{[\lfloor qn\rfloor+1]}} \sqrt{\mu_{\theta'}(x)}^2 dx} \\ &\geqslant \int_{\mathbf{x}_{[\lfloor qn\rfloor]}}^{\mathbf{x}_{[\lfloor qn\rfloor+1]}} \sqrt{\mu_\theta(x)\mu_{\theta'}(x)}dx \\ &= \int_{\mathbf{x}_{[\lfloor qn\rfloor]}}^{\mathbf{x}_{[\lfloor qn\rfloor+1]}} \sqrt{f(x-\theta)f(x-\theta')}dx \\ &> \int_{\mathbf{x}_{[\lfloor qn\rfloor]}}^{\mathbf{x}_{[\lfloor qn\rfloor+1]}} f\left(x - \frac{\theta+\theta'}{2}\right)dx = \int_{\mathbf{x}_{[\lfloor qn\rfloor]}}^{\mathbf{x}_{[\lfloor qn\rfloor+1]}} \mu_{\frac{\theta+\theta'}{2}}(x)dx\end{aligned} \tag{31}$$

where the first inequality is Hölder's and the second is due to the strict log-convexity of f on $[a,b]$. Taking the logarithm of both sides followed by their negatives completes the proof.

Finally, for the second result, since f is centered and log-concave, by Cule & Samworth (2010, Lemma 1) there exist constants $C, c > 0$ s.t. $\mu_\theta(x) \leqslant C\exp(-c|x-\theta|)\ \forall\ \theta \in \mathbb{R}$. Let $\mathbf{x} = \begin{pmatrix}\theta + R - n\psi & \theta + R - (n-1)\psi & \cdots & \theta + R - 2\psi & \theta + R - \psi\end{pmatrix}$, so that $|\mathbf{x}_{[\lfloor qn\rfloor]} - \theta| \geqslant |\mathbf{x}_{[1]} - \theta| = R - n\psi \geqslant \frac{R}{2}$. Then

$$\Psi^{(q)}_{\mathbf{x}}(\mu_\theta) = \int_{\mathbf{x}_{[\lfloor qn\rfloor]}}^{\mathbf{x}_{[\lfloor qn\rfloor+1]}} \mu_\theta(x)dx \leqslant C\psi\exp(-c|\mathbf{x}_{[\lfloor qn\rfloor]} - \theta|) \leqslant C\psi\exp(-cR/2) \tag{32}$$

so $U^{(q)}_{\mathbf{x}}(\mu) = -\log\Psi^{(q)}_{\mathbf{x}}(\mu_\theta) \geqslant \log\frac{1}{C\psi} + \frac{cR}{2}$. □

Variants of the first result have been shown in the censored regression literature (Burridge, 1981; Pratt, 1981). In fact, Burridge (1981) shows convexity of $U^{(q)}_{\mathbf{x}}(\mu_{\frac{\langle \mathbf{v},\mathbf{f}\rangle}{\phi}, \frac{1}{\phi}})$ w.r.t. $(\mathbf{v}, \phi) \in \mathbb{R}^d \times \mathbb{R}_{>0}$, i.e. simultaneous learning of a feature map and inverse scale. Convexity of $U_{\mathbf{x}} = -\log\Psi_{\mathbf{x}} = \log\sum_{i=1}^m \frac{1}{\Psi^{(q_i)}_{\mathbf{x}}} = \log\sum_{i=1}^m \exp(-\log\Psi^{(q_i)}_{\mathbf{x}})$ follows because $\log\sum_{i=1}^m e^{x_i}$ is convex and non-decreasing in each argument. Note that for the converse direction, the dataset $\mathbf{x}$ is not a degenerate case; in-fact if f is strictly log-convex over an interval $[a,b]$ then any dataset whose optimal interval has length smaller than $\frac{b-a}{2}$ will yield a non-convex $U^{(q)}_{\mathbf{x}}(\mu_\theta)$.

F.1.2. The case of the Laplacian

For the Laplace prior with $a = \mathbf{x}_{[\lfloor qn \rfloor]}$ and $b = \mathbf{x}_{[\lfloor qn \rfloor+1]}$ we have

$$\begin{aligned} &-\log \Psi_{\mathbf{x}}^{(q)}(\mu_{\frac{\theta}{\phi},\frac{1}{\phi}}) \\ &\quad = \log 2 - \log\left(\operatorname{sign}\left(b-\frac{\theta}{\phi}\right)\left(1-\exp\left(-\left|b-\frac{\theta}{\phi}\right|\phi\right)\right) - \operatorname{sign}\left(a-\frac{\theta}{\phi}\right)\left(1-\exp\left(-\left|a-\frac{\theta}{\phi}\right|\phi\right)\right)\right) \end{aligned} \tag{33}$$

For $\theta < a\phi$ this simplifies to

$$\log 2 - \log\left(e^{\theta-a\phi} - e^{\theta-b\phi}\right) = \log 2 - \log\left((e^{\frac{b-a}{2}\phi} - e^{\frac{a-b}{2}\phi})e^{\theta-\frac{a+b}{2}\phi}\right) = \left|\theta - \frac{a+b}{2}\phi\right| - \log\left(\sinh\left(\frac{b-a}{2}\phi\right)\right) \tag{34}$$

and similarly for $\theta > b\phi$ it becomes

$$\log 2 - \log\left(e^{b\phi-\theta} - e^{a\phi-\theta}\right) = \log 2 - \log\left((e^{\frac{b-a}{2}\phi} - e^{\frac{a-b}{2}\phi})e^{\frac{a+b}{2}\phi-\theta}\right) = \left|\frac{a+b}{2}\phi - \theta\right| - \log\left(\sinh\left(\frac{b-a}{2}\phi\right)\right) \tag{35}$$

On the other hand for $\theta \in [a\phi, b\phi]$ it is

$$\begin{aligned} \log 2 - \log\left(2 - e^{-|b\phi-\theta|} - e^{-|a\phi-\theta|}\right) &= \log 2 - \log\left(2 - e^{\theta-b\phi} - e^{a\phi-\theta}\right) \\ &= \log 2 - \log\left(e^{-\frac{b-a}{2}\phi}\left(2e^{\frac{b-a}{2}\phi} - e^{\theta-\frac{a+b}{2}\phi} - e^{\frac{a+b}{2}\phi-\theta}\right)\right) \\ &= \frac{b-a}{2}\phi + \log 2 - \log\left(2e^{\frac{b-a}{2}\phi} - e^{\theta-\frac{a+b}{2}\phi} - e^{\frac{a+b}{2}\phi-\theta}\right) \\ &= \frac{b-a}{2}\phi - \log\left(e^{\frac{b-a}{2}\phi} - \cosh\left(\theta - \frac{a+b}{2}\phi\right)\right) \end{aligned} \tag{36}$$

Thus we have

$$U_{\mathbf{x}}^{(q)}(\mu_{\frac{\theta}{\phi},\frac{1}{\phi}}) = \begin{cases} \frac{b-a}{2}\phi - \log\left(\exp\left(\frac{b-a}{2}\phi\right) - \cosh\left(\theta - \frac{a+b}{2}\phi\right)\right) & \text{if} \quad \theta \in [a\phi, b\phi] \\ \left|\theta - \frac{a+b}{2}\phi\right| - \log\left(\sinh\left(\frac{b-a}{2}\phi\right)\right) & \text{else} \end{cases} \tag{37}$$

Suppose $\mathbf{x} \in [\pm B]^n$ and has the optimal interval has separation $\psi > 0$, $\frac{\theta}{\phi} \in [\pm B]$, and $\frac{1}{\phi} \in [\sigma_{\min}, \sigma_{\max}]$. Then $\phi \in [1/\sigma_{\max}, 1/\sigma_{\min}]$ and $\theta \in [\pm B/\sigma_{\min}]$, and so

$$U_{\mathbf{x}}^{(q)}(\mu_{\frac{\theta}{\phi},\frac{1}{\phi}}) \leqslant \frac{2B}{\sigma_{\min}} + \log\frac{2\sigma_{\max}}{\psi} \tag{38}$$

For $\theta \notin [a\phi, b\phi]$, the derivative w.r.t. θ always has magnitude 1. Within the interval, the derivative w.r.t. θ is $-\frac{\sinh(\frac{a+b}{2}\phi-\theta)}{\exp(\frac{b-a}{2}\phi)-\cosh(\theta-\frac{a+b}{2}\phi)}$, which attains its extrema at the endpoints $a\phi$ and $b\phi$, where its magnitude is also 1. Outside the interval, the derivative w.r.t. ϕ has magnitude

$$\begin{aligned} \left|\frac{a+b}{2}\operatorname{sign}\left(\frac{a+b}{2}\phi-\theta\right) - \frac{b-a}{2}\coth\left(\frac{b-a}{2}\phi\right)\right| &\leqslant \frac{|a+b|}{2} + \frac{b-a}{2}\coth\left(\frac{b-a}{2}\phi\right) \\ &\leqslant \frac{|a+b|}{2} + \frac{b-a}{2}\left(\frac{2/\phi}{(b-a)}+1\right) = \frac{|a+b|}{2} + \frac{b-a}{2} + \frac{1}{\phi} \end{aligned} \tag{39}$$

while inside the interval the derivative w.r.t. ϕ is $\frac{b-a}{2} - \frac{(b-a)\exp(\frac{b-a}{2}\phi)-(a+b)\sinh(\frac{a+b}{2}\phi-\theta)}{2\left(\exp(\frac{b-a}{2}\phi)-\cosh(\frac{a+b}{2}\phi-\theta)\right)}$, which again attains its extrema at the endpoints $a\phi$ and $b\phi$, yielding magnitudes

$$\frac{b-a}{2} + \frac{b-a}{2}\left(\coth\left(\frac{b-a}{2}\phi\right)+1\right) + \frac{|a+b|}{2} \leqslant \frac{b-a}{2}\left(\frac{2/\phi}{(b-a)}+3\right) + \frac{|a+b|}{2} \leqslant \frac{1}{\phi} + \frac{3}{2}(b-a) + \frac{|a+b|}{2} \tag{40}$$

Thus we have

$$|\partial_\theta U_{\mathbf{x}}^{(q)}(\mu_{\frac{\theta}{\phi},\frac{1}{\phi}})| \leqslant 1 \qquad \text{and} \qquad |\partial_\phi U_{\mathbf{x}}^{(q)}(\mu_{\frac{\theta}{\phi},\frac{1}{\phi}})| \leqslant 4B + \sigma_{\max} \tag{41}$$

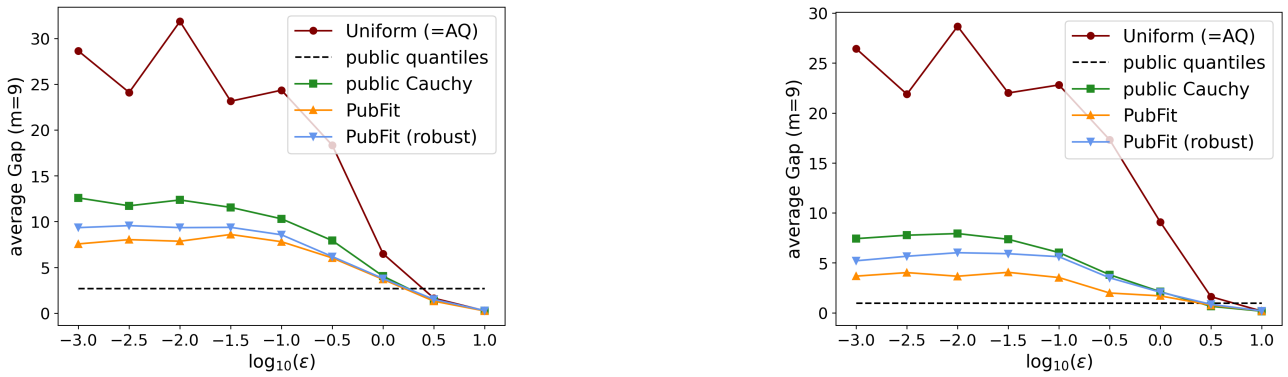

Figure 5. Public-private release of nine quantiles using one hundred samples from the Adult age (left) and hours (right) datasets. The public data is the Adult training set while private data is test.

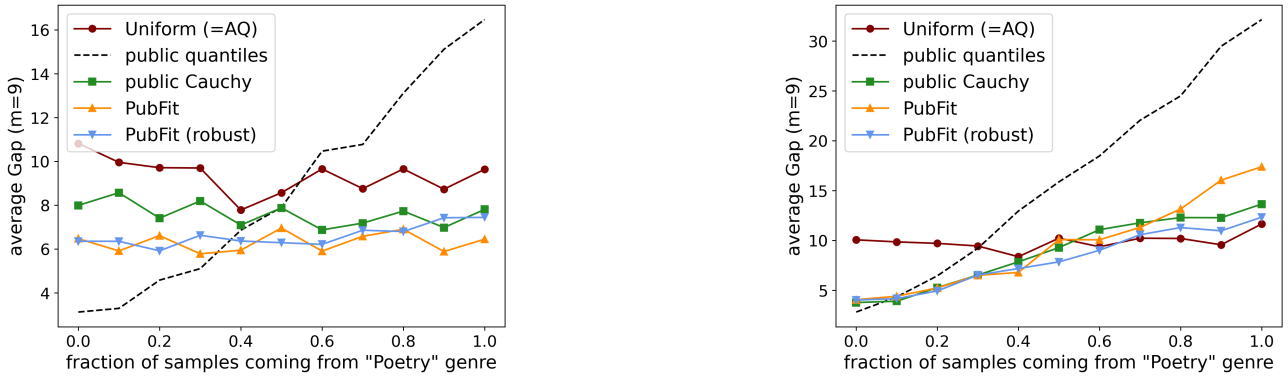

Figure 6. Public-private release of nine quantiles on one hundred samples from the Goodreads rating (left) and page count (right) datasets, with $\varepsilon = 1$. The public data is the "History" genre while private data is sampled from a mixture of it and "Poetry."

F.2. Augmenting quantile release using public data

We turn to two applications that depend on optimizing upper bounds $\ell_{\mathbf{x}}^{(q)}(\theta, \phi)$ on the performance of quantile release using the Laplace prior with scale $\frac{1}{\phi}$ and location $\frac{\theta}{\phi}$. While our final objective is small Gap_q, we will mainly discuss optimizing $\ell_{\mathbf{x}}^{(q)} = U_{\mathbf{x}}^{(q)}$, or its expectation if $\mathbf{x}$ is drawn from some distribution. In the former case this directly bounds (w.h.p.) the cost of multiple quantile release via the theoretical results in Section 2 because $U_{\mathbf{x}} \geqslant -\log \Psi_{\mathbf{x}}^{(\varepsilon)}$, while a bound on $\mathbb{E}_{\mathbf{x}} U_{\mathbf{x}}$ can bound $\mathbb{E}\,\mathrm{Gap}_{\max}$ by setting β. For example, $\beta = \frac{2\pi^2}{\varepsilon n} \exp(2\sqrt{\log(2)\log(m+1)})$ in Theorem D.2 implies $\mathrm{Gap}_{\max}$ has expectation at most

$$\mathcal{O}\left(\exp\left(2\sqrt{\log(2)\log(m+1)}\right)\frac{\log(\varepsilon m n) + \mathbb{E}_{\mathbf{x}} U_{\mathbf{x}}}{\varepsilon}\right) \tag{42}$$

Our first application is the frequently studied setting where we have a large public dataset $\mathbf{x}' \in \mathbb{R}^N$ and want to use it to improve the release of statistics of a smaller private dataset $\mathbf{x} \in \mathbb{R}^n$. To apply our quantile release method, we must use $\mathbf{x}'$ to construct a prior μ' for each that makes $U_{\mathbf{x}}^{(q)}(\mu')$ small. If the entries of $\mathbf{x}$ and $\mathbf{x}'$ are sampled i.i.d. from similar distributions $\mathcal{D}$ and $\mathcal{D}'$, respectively, the convexity of $U_{\mathbf{x}}^{(q)}$ suggests using stochastic optimization find a prior μ that approximately minimizes the expectation $\mathbb{E}_{\mathbf{z}\sim\mathcal{D}'^n} U_{\mathbf{z}}(\mu)$ using samples of size n drawn from $\mathbf{x}'$. We provide a guarantee for a variant of this generic approach that runs online gradient descent (OGD) with separate learning rates for θ and ϕ on samples drawn without replacement from $\mathbf{x}'$:

Theorem F.3 (c.f. Thm. F.4)**.** *If $\mathcal{D}$ and $\mathcal{D}'$ have bounded densities with bounded support then there exists an algorithm optimizing $U_{\mathbf{x}'_t}$ over T datasets $\mathbf{x}'_t$ of size n drawn from $\mathbf{x}' \in \mathbb{R}^N$ without replacement that runs in time $\mathcal{O}(mN)$ and returns a set μ' of m Laplace priors s.t. w.h.p.*

$$\mathbb{E}_{\mathbf{x}\sim\mathcal{D}^n} U_{\mathbf{x}}(\mu') \leqslant \min_{\mu\in\mathrm{Lap}^m_{B,\sigma_{\min},\sigma_{\max}}} \mathbb{E}_{\mathbf{x}\sim\mathcal{D}^n} U_{\mathbf{x}}(\mu) + \tilde{\mathcal{O}}\left(\mathrm{TV}_q(\mathcal{D},\mathcal{D}') + \sqrt{\frac{mn}{N}}\right) \tag{43}$$

where $\mathrm{Lap}_{B,\sigma_{\min},\sigma_{\max}}$ is the set of Laplace priors with locations in $[\pm B]$ and scales in $[\sigma_{\min},\sigma_{\max}]$ and $\mathrm{TV}_q(\mathcal{D},\mathcal{D}')$ is the total variation distance between the joint distributions of the order statistics $\left\{(\mathbf{x}_{[\lfloor q_i n\rfloor]}, \mathbf{x}_{[\lfloor q_i n\rfloor+1]})\right\}_{i=1}^m$ for $\mathbf{x}\sim\mathcal{D}^n$ and $\left\{(\mathbf{x}'_{[\lfloor q_i n\rfloor]}, \mathbf{x}'_{[\lfloor q_i n\rfloor+1]})\right\}_{i=1}^m$ for $\mathbf{x}'\sim\mathcal{D}'^n$.

For $N \gg mn$, the suboptimality of μ' for the upper bound $U_{\mathbf{x}}$ will depend on the statistical distance between the quantile intervals of $\mathcal{D}$ and $\mathcal{D}'$: even if $\mathcal{D}$ and $\mathcal{D}'$ are dissimilar, similar order statistic distributions will ensure good performance. Note, as in Section C.2, we can hedge against large $\mathrm{TV}_q(\mathcal{D},\mathcal{D}')$ by mixing the output μ' with a robust prior.

We evaluate this approach, which we call *Public Fit* or `PubFit`, on Adult (Kohavi, 1996) and Goodreads (Wan & McAuley, 2018), both used previously for DP quantiles (Gillenwater et al., 2021; Kaplan et al., 2022). Because our guarantees improve with different step-sizes for θ and ϕ, we use COCOB (Orabona & Tomassi, 2017) as `PubFit`'s stochastic solver. We also test a robust version where its output is mixed with a half-Cauchy distribution, and three baselines: the Uniform prior, just using the quantiles of the public data (`public quantiles`), and using the public quantiles to set the location parameters of m Cauchy priors (`public Cauchy`).

Adult tests the $\mathcal{D}=\mathcal{D}'$ case, with its "train" set the public dataset and a hundred samples from "test" as private. Figure 5 shows that `public quantiles` does best at small ε, as is expected with no distribution shift, but it cannot adapt to the empirical distribution of a small number of private points, and so is worse at $\varepsilon > 1$. Among the rest, `PubFit` is most similar to `public-quantiles` at small ε but still does well at large ε.

We use the Goodreads "History" and "Poetry" genres to evaluate under distribution shift by fitting on all but a small fraction of data from the former and releasing quantiles of samples from varying mixtures of the two datasets. As expected, the performance of `public quantiles` deteriorates with more samples from "Poetry." For book ratings, `PubFit` is best among the remaining methods, but without much change with distribution shift, possibly due to an incomplete fit of the data. For page counts, the `PubFit` methods and `public Cauchy` both do as well as `public-quantiles` when most data is from "History," but `PubFit (robust)` deteriorates least—and much less than regular `PubFit`—as the distribution shifts. This highlights the importance of robustness analysis, and suggest the former as a good method to start with, as it takes advantage of similar public and private distributions (Fig. 5) while never doing much worse than the default method (Uniform) when the the distributions are dissimilar (Fig. 6).

F.2.1. Guarantees

Theorem F.4. *Suppose for $N \geqslant n$ we have a private dataset $\mathbf{x}\sim\mathcal{D}^n$ and a public dataset $\mathbf{x}'\sim\mathcal{D}'^N$, both drawn from κ-bounded distributions over $[\pm B]$. Use i.i.d. draws from the public dataset to construct $T=\lfloor N/n\rfloor$ datasets $\mathbf{x}'_t\sim\mathcal{D}'^n$ and run online gradient descent on the resulting losses $\ell_{\mathbf{x}'_t}(\theta,\psi) = \mathrm{LSE}_i(\ell^{(q_i)}_{\mathbf{x}'_t}(\theta_{[i]},\phi_{[i]}))$ over the parameter space $\theta\in[\pm B/\sigma_{\min}]^m$ starting at $\theta=\mathbf{0}_m$ and $\phi\in[1/\sigma_{\max},1/\sigma_{\min}]^m$ starting at the midpoint, with stepsize $B\sqrt{\frac{m}{T}}$ for θ and $\frac{\sigma_{\max}-\sigma_{\min}}{4B+\sigma_{\max}}\sqrt{\frac{m}{T}}$ for ϕ, obtaining iterates $(\theta_1,\phi_1),\ldots,(\theta_T,\phi_T)$. Return the priors $\mu_i = \mu_{\bar\theta_{[i]},\frac{1}{\bar\phi_{[i]}}}$ for $\bar\theta=\frac{1}{T}\sum_{t=1}^T\theta_t$ and $\bar\phi=\frac{1}{T}\sum_{t=1}^T\phi_t$ the average of these iterates. Then $\mu'=\begin{pmatrix}\mu_1 & \cdots & \mu_m\end{pmatrix}$ satisfies*

$$\begin{aligned}\mathbb{E}_{\mathbf{x}\sim\mathcal{D}^n} U_{\mathbf{x}}(\mu') \leqslant \min_{\mu\in\mathrm{Lap}^m_{B,\sigma_{\min},\sigma_{\max}}} \mathbb{E}_{\mathbf{x}\sim\mathcal{D}^n} U_{\mathbf{x}}(\mu) &+ 2\left(\frac{2B}{\sigma_{\min}} + \log\frac{4\kappa m(n+1)N\sigma_{\max}}{\beta'}\right)\mathrm{TV}_q(\mathcal{D},\mathcal{D}') \\ &+ (B+4B\sigma_{\max}+\sigma^2_{\max})\sqrt{\frac{m(n+1)}{N}} + 2\left(\frac{4B}{\sigma_{\min}} + \log\frac{4\kappa m(n+1)N\sigma_{\max}}{\beta'}\right)\sqrt{\frac{2(n+1)}{N}\log\frac{4}{\beta'}} \\ &+ \frac{(n+1)\beta'}{N}\left(3+\frac{4B}{\sigma_{\min}} + 4\log\frac{2\kappa(n+1)N\sqrt{2m\sigma_{\max}}}{\beta'}\right)\end{aligned} \tag{44}$$

where $\mathrm{Lap}_{B,\sigma_{\min},\sigma_{\max}}$ is the set of Laplace priors with locations in $[\pm B]$ and scales in $[\sigma_{\min},\sigma_{\max}]$.

Proof. Define ${\mathcal{D}'_\psi}^n$ to be the conditional distribution over $\mathbf{z} \sim {\mathcal{D}'}^n$ s.t. $\psi_\mathbf{z} \geqslant \psi$, with associated density $\rho'_\psi(\mathbf{z}) = \frac{\rho'(\mathbf{z})1_{\psi_\mathbf{z} \geqslant \psi}}{1-p'_\psi}$, where $p'_\psi = \int_{\psi_\mathbf{z} < \psi} \rho'(\mathbf{z}) \leqslant \kappa n^2 \psi$. Then we have for any $\mu^* \in \mathrm{Lap}^m_{B,\sigma_{\min},\sigma_{\max}}$ that

$$\begin{aligned}
\mathbb{E}_{\mathbf{z}\sim\mathcal{D}^n} U_\mathbf{x}(\mu') &= \mathbb{E}_{\mathbf{z}\sim\mathcal{D}^n} U_\mathbf{z}(\mu') - \mathbb{E}_{\mathbf{z}\sim{\mathcal{D}'}^n} U_\mathbf{z}(\mu') + \mathbb{E}_{\mathbf{z}\sim{\mathcal{D}'}^n} U_\mathbf{z}(\mu') - \mathbb{E}_{\mathbf{z}\sim{\mathcal{D}'_\psi}^n} U_\mathbf{z}(\mu') + \mathbb{E}_{\mathbf{z}\sim{\mathcal{D}'_\psi}^n} U_\mathbf{z}(\mu') \\
&\leqslant \int U_\mathbf{z}(\mu')(\rho(\mathbf{z}) - \rho'(\mathbf{z})) + \int U_\mathbf{z}(\mu')(\rho'(\mathbf{z}) - \rho'_\psi(\mathbf{x})) + \mathbb{E}_{\mathbf{z}\sim{\mathcal{D}'_\psi}^n} U_\mathbf{z}(\mu^*) + \mathcal{E}_\psi \\
&\leqslant \mathbb{E}_{\mathbf{z}\sim\mathcal{D}^n} U_\mathbf{x}(\mu^*) + \int (U_\mathbf{z}(\mu') + U_\mathbf{x}(\mu^*))|\rho(\mathbf{z}) - \rho'(\mathbf{x})| + \int (U_\mathbf{z}(\mu') + U_\mathbf{z}(\mu^*))|\rho'(\mathbf{z}) - \rho'_\psi(\mathbf{z})| + \mathcal{E}_\psi
\end{aligned} \tag{45}$$

where $\mathcal{E}_\psi$ is the error of running online gradient descent with the specified step-sizes on samples $\mathbf{z}'_t \sim {\mathcal{D}'_\psi}^n$ for $t = 1, \ldots, T$. Now if $\mathbf{z}$ has entries drawn i.i.d. from a κ-bounded distribution $\mathcal{D}^n$ (or ${\mathcal{D}'}^n$), then we have that

$$\int_0^\psi \rho_{\psi_\mathbf{z}}(y)dy = \Pr(\psi_\mathbf{z} \leqslant \psi : \mathbf{z} \sim \mathcal{D}^n) \leqslant n(n-1) \max_{z\in\mathbb{R}} \Pr(|z - z'| \leqslant \psi : z' \sim \mathcal{D}) \leqslant \kappa n^2 \psi \tag{46}$$

where $\rho_{\psi_\mathbf{z}}$ is the density of $\psi_\mathbf{z}$ for $\mathbf{z} \sim \mathcal{D}^n$ (not to be confused with the conditional density ρ_ψ over $\mathbf{z}$); the same holds for the analog $\rho'_{\psi_\mathbf{z}}$ for ${\mathcal{D}'}^n$. Since this holds for all $\psi \geqslant 0$ and $\log \frac{1}{y}$ is monotonically decreasing on $y > 0$, this means the worst-case measure that $\rho_{\psi_\mathbf{z}}$ can be is constant over $[0, \psi]$ and thus $\int_0^\psi \rho_{\psi_\mathbf{z}}(y) \log \frac{1}{y} dy \leqslant \kappa n^2 \int_0^\psi \log \frac{1}{y} dy = \kappa n^2 \psi(1 + \log \frac{1}{\psi})$, and similarly for $\rho'_{\psi_\mathbf{z}}$. We then bound the first integral, noting that $U_\mathbf{z} = \mathrm{LSE}_i(U_\mathbf{z}^{(q_i)}) \leqslant \max_i U_\mathbf{z}^{(q_i)} + \log m \leqslant \frac{2B}{\sigma_{\min}} + \log \frac{2m\sigma_{\max}}{\psi_\mathbf{z}}$ and that the r.v. $\psi_\mathbf{z}$ depends only on the joint distribution over the order statistics of $\mathcal{D}^n$ and ${\mathcal{D}'}^n$:

$$\begin{aligned}
\int (U_\mathbf{z}(\mu') + U_\mathbf{z}(\mu^*))|\rho(\mathbf{z}) - \rho'(\mathbf{z})| &\leqslant \int \left(\frac{2B}{\sigma_{\min}} + \log \frac{2m\sigma_{\max}}{\psi_\mathbf{z}}\right) |\rho(\mathbf{z}) - \rho'(\mathbf{z})| \\
&\leqslant 2\left(\frac{2B}{\sigma_{\min}} + \log \frac{2m\sigma_{\max}}{\psi}\right) \mathrm{TV}_q(\mathcal{D}, \mathcal{D}') + \int_{\psi_\mathbf{z} < \psi} |\rho(\mathbf{z}) - \rho'(\mathbf{z})| \log \frac{1}{\psi_\mathbf{z}} \\
&\leqslant 2\left(\frac{2B}{\sigma_{\min}} + \log \frac{2m\sigma_{\max}}{\psi}\right) \mathrm{TV}_q(\mathcal{D}, \mathcal{D}') + \int_0^\psi (\rho_{\psi_\mathbf{z}}(y) + \rho'_{\psi_\mathbf{z}}(y)) \log \frac{1}{y} dy \\
&\leqslant 2\left(\frac{2B}{\sigma_{\min}} + \log \frac{2m\sigma_{\max}}{\psi}\right) \mathrm{TV}_q(\mathcal{D}, \mathcal{D}') + 2\kappa n^2 \psi \left(1 + \log \frac{1}{\psi}\right)
\end{aligned} \tag{47}$$

For the second integral we have for $p'_\psi = \int_{\psi_\mathbf{z} < \psi} \rho'(\mathbf{z}) \leqslant \kappa n^2 \psi$ that

$$\begin{aligned}
&\int (U_\mathbf{z}(\mu') + U_\mathbf{z}(\mu^*))|\rho'(\mathbf{z}) - \rho'_\psi(\mathbf{z})| \\
&= \int_{\psi_\mathbf{z} \geqslant \psi} (U_\mathbf{x}(\mu') + U_\mathbf{z}(\mu^*)) \left|\rho'(\mathbf{z}) - \frac{\rho'(\mathbf{z})}{1 - p'_\psi}\right| + \int_{\psi_\mathbf{z} < \psi} (U_\mathbf{z}(\mu') + U_\mathbf{z}(\mu^*))\rho'(\mathbf{z}) \\
&= \frac{2p'_\psi}{1 - p'_\psi} \int_{\psi_\mathbf{z} \geqslant \psi} \left(\frac{2B}{\sigma_{\min}} + \log \frac{2m\sigma_{\max}}{\psi}\right) \rho'(\mathbf{z}) + \int_{\psi_\mathbf{z} < \psi} \left(\frac{2B}{\sigma_{\min}} + \log \frac{2m\sigma_{\max}}{\psi_\mathbf{z}}\right) \rho'(\mathbf{z}) \\
&= 2p'_\psi \left(\frac{4B}{\sigma_{\min}} + \log \frac{4m^2\sigma_{\max}^2}{\psi}\right) + \int_{\psi_\mathbf{z} < \psi} \rho'(\mathbf{z}) \log \frac{1}{\psi_\mathbf{z}} \\
&\leqslant 2\kappa n^2 \psi \left(\frac{4B}{\sigma_{\min}} + \log \frac{4m^2\sigma_{\max}^2}{\psi}\right) + \kappa n^2 \psi \left(1 + \log \frac{1}{\psi}\right)
\end{aligned} \tag{48}$$

Finally, we bound $\mathcal{E}_\psi$. By κ-boundedness of $\mathcal{D}'$, the probability that $\exists\, t \in [T]$ s.t. $\psi_{\mathbf{z}'_t} < \psi\ \forall\, t \in [T]$ is at most $\kappa n^2 T \psi$, so if we set $\psi = \frac{\beta'}{2\kappa n^2 T}$ then w.p. $\geqslant 1 - \beta'/2$ the sampling $\mathbf{z}'_t$ from $\mathbf{x}'$ as specified is equivalent to rejection sampling from ${\mathcal{D}'_\psi}^n$, on which the functions $U_\mathbf{z}$ are bounded by $\frac{2B}{\sigma_{\min}} + \log \frac{2m\sigma_{\max}}{\psi}$. Therefore with probability $\geqslant 1 - \beta'/2$ by Shalev-Shwartz (2011, Theorem 2.21) and Theorem H.1 we have that w.p. $1 - \beta'/2$

$$\begin{aligned}\mathcal{E}_\psi &\leqslant (B + (\sigma_{\max} - \sigma_{\min})(4B + \sigma_{\max}))\sqrt{\frac{m}{T}} + 2\left(\frac{4B}{\sigma_{\min}} + \log\frac{2m\sigma_{\max}}{\psi}\right)\sqrt{\frac{2}{T}\log\frac{4}{\beta'}} \\ &= (B + 4B\sigma_{\max} + \sigma_{\max}^2)\sqrt{\frac{m(n+1)}{N}} + 2\left(\frac{4B}{\sigma_{\min}} + \log\frac{2m\sigma_{\max}}{\psi}\right)\sqrt{\frac{2(n+1)}{N}\log\frac{4}{\beta'}}\end{aligned} \tag{49}$$

Combining terms and substituting the selected value for ψ yields the result. □

F.2.2. Experimental details

For our public-private experiments we evaluate several methods on the Adult ("age" and "hours" categories) and Goodreads ("rating" and "page count" categories). For the former we use the train set as the public data, while for the latter we use the "History" genre as the public data and the "Poetry" genre as the private data (Wan & McAuley, 2018). The public data are used to fit Laplace location and scale parameters using the COCOB optimizer run until progress stops. We use the implementation here: `https://github.com/anandsaha/nips.cocob.pytorch`. All evaluations are averages of forty trials.

We use the following reasonable guesses for locations ν, scales σ, and quantile ranges $[a, b]$ for these distributions:

- age: $\nu = 40$, $\sigma = 5$, $a = 10$, $b = 120$
- hours: $\nu = 40$, $\sigma = 2$, $a = 0$, $b = 168$
- rating: $\nu = 2.5$, $\sigma = 0.5$, $a = 0$, $b = 5$
- page count: $\nu = 200$, $\sigma = 25$, $a = 0$, $b = \frac{1000}{1-q}$

Note that, here and elsewhere, using q-dependent range for b only helps the Uniform prior, which is the baseline. The scales σ are used to set the scale parameter of the Cauchy distribution for `public quantiles`—its location is fixed by the public quantiles. Meanwhile the locations ν are used to set to *scale* parameter of the half-Cauchy prior used to mix with `PubFit` for robustness (using coefficient 0.1 on the robust prior). We choose this prior because the data are all nonnegative.

F.3. Sequential release

Sequential release can be done with provable guarantees by applying DP-FTRL (Kairouz et al., 2021a), again using two different step-sizes:

Theorem F.5 (c.f. Thm. F.6)**.** *Consider a sequence of datasets $\mathbf{x}_t \in [\pm B]^{n_t}$ with bounded features $\mathbf{f}_t$ and suppose we set Laplace priors $\mu_{t,i} = \mu_{\frac{\langle \mathbf{v}_{t,i}, \mathbf{f}_t\rangle}{\phi_{t,i}}, \frac{1}{\phi_{t,i}}}$ via two DP-FTRL algorithms applied separately to the variables $\mathbf{v}_i$ and ϕ_i of the losses $\ell_{\mathbf{x}_t}(\langle \mathbf{v}_i, \mathbf{f}_t\rangle, \phi_i)$ with budgets $\frac{\varepsilon'}{2}$, with respective step-sizes $\tilde{\Theta}\left(\sqrt{\frac{\varepsilon'}{\sigma_{\min}^2 T}\sqrt{\frac{m}{d}}}\right)$ and $\tilde{\Theta}\left(\sqrt{\frac{\varepsilon'\sqrt{m}}{\sigma_{\min}^2\sigma_{\max}^2 T}}\right)$. This is (ε', δ')-DP and w.h.p. has regret*

$$\frac{1}{T}\sum_{t=1}^{T} U_{\mathbf{x}_t}(\mu_t) - \min_{\substack{\mathbf{w}_i \in [\pm B]^d \\ \sigma_i \in [\sigma_{\min}, \sigma_{\max}]}} \frac{1}{T}\sum_{t=1}^{T} U_{\mathbf{x}_t}(\mu_{\langle \mathbf{w}_i, \mathbf{f}_t\rangle, \sigma_i}) = \tilde{\mathcal{O}}\left(\frac{d^{\frac{3}{4}} + \sigma_{\max}}{\sigma_{\min}}\sqrt{\frac{m}{\varepsilon' T}\sqrt{m\log\frac{2}{\delta'}}}\right) \tag{50}$$

Thus we can do as well as any sequence of Laplace priors μ_t with locations determined by a fixed linear map from $\mathbf{f}_t$, up to a term that decreases at rate $\tilde{\mathcal{O}}(\frac{1}{\sqrt{T}})$. Furthermore, running quantile release with budget $\varepsilon - \varepsilon'$ ensures (ε, δ')-DP for each dataset $\mathbf{x}_t$. Note that using different step-sizes allows us to separate the difficulty of learning a d-dimensional linear map from the difficulty of learning a scale parameter of magnitude at most $\sigma_{\max}$.

F.3.1. GUARANTEES

Theorem F.6. *Consider a sequence of datasets $\mathbf{x}_t \in [\pm R]^{n_t}$ and associated feature vectors $\mathbf{f}_t \in [\pm F]^d$. Suppose we set the component priors $\mu_{t,i}$ of μ_t as the Laplace distributions $\mu_{t,i} = \mu_{\frac{\langle \mathbf{v}_{t,i}, \mathbf{f}_t \rangle}{\phi_{t,i}}, \frac{1}{\phi_{t,i}}}$, where $\mathbf{v}_{t,i} \in [\pm B/\sigma_{\min}]^d$ and $\phi_i \in [1/\sigma_{\max}, 1/\sigma_{\min}]$ are determined by separate runs of DP-FTRL with budgets $(\varepsilon'/2, \delta'/2)$ and step-sizes $\eta_1 = \frac{B}{F\sigma_{\min}} \sqrt{\frac{2m\varepsilon_1'}{\lceil \log_2(T+1) \rceil T \left(1 + \sqrt{2md \log \frac{T}{\beta'} \log \frac{1}{\delta'}}\right)}}$, and $\eta_2 = \frac{1/\sigma_{\min}}{B + \sigma_{\max}} \sqrt{\frac{m\varepsilon_2'}{2\lceil \log_2(T+1) \rceil T \left(1 + \sqrt{2m \log \frac{T}{\beta'} \log \frac{1}{\delta'}}\right)}}$. Then we have regret*

$$\max_{\substack{\mathbf{w}_i \in [\pm B]^d \\ \sigma_i \in [\sigma_{\min}, \sigma_{\max}]}} \sum_{t=1}^{T} U_{\mathbf{x}_t}(\mu_t) - U_{\mathbf{x}_t}(\mu_{\langle \mathbf{w}_i, \mathbf{f}_t \rangle, \sigma_i}) \leqslant \frac{B(F+1) + \sigma_{\max}}{\sigma_{\min}} \sqrt{md\lceil \log_2(T+1) \rceil T \left(4 + \frac{8}{\varepsilon'} \sqrt{2md \log \frac{T}{\beta'} \log \frac{2}{\delta'}}\right)} \tag{51}$$

For sufficiently small ε' (including $\varepsilon' \leqslant 1$) we can instead simplify the regret to

$$\frac{4}{\sigma_{\min}} \left(BFd^{\frac{3}{4}} + B + \sigma_{\max}\right) \sqrt{\frac{m\lceil \log_2(T+1) \rceil T}{\varepsilon'} \sqrt{2m \log \frac{T}{\beta'} \log \frac{2}{\delta'}}} \tag{52}$$

Proof. Note that

$$\sum_{j=1}^{m} \|\nabla_{\mathbf{v}_j} \operatorname{LSE}_i(\ell^{(q_i)}_{\mathbf{x}_t, \mathbf{f}_t})\|_2^2 \leqslant \|\mathbf{f}_t\|_2^2 \sum_{j=1}^{m} \left(\frac{\exp(\ell^{(q_j)}_{\mathbf{x}_t, \mathbf{f}_t})}{\sum_{i=1}^{m} \exp(\ell^{(q_i)}_{\mathbf{x}_t, \mathbf{f}_t})} \right)^2 \leqslant F^2 d \tag{53}$$

and

$$\sum_{j=1}^{m} (\partial_{\phi_j} \operatorname{LSE}_i(\ell^{(q_i)}_{\mathbf{x}_t, \mathbf{f}_t}))^2 \leqslant (4B + \sigma_{\max})^2 \sum_{j=1}^{m} \left(\frac{\exp(\ell^{(q_j)}_{\mathbf{x}_t, \mathbf{f}_t})}{\sum_{i=1}^{m} \exp(\ell^{(q_i)}_{\mathbf{x}_t, \mathbf{f}_t})} \right)^2 \leqslant (4B + \sigma_{\max})^2 \tag{54}$$

and so applying Theorem E.1 twice with the assumed budgets and step-sizes yields

$$\begin{aligned}
\max_{\substack{\mathbf{w}_i \in [\pm B]^d \\ \sigma_i \in [\sigma_{\min}, \sigma_{\max}]}} \sum_{t=1}^{T} U_{\mathbf{x}_t}(\mu_t) - U_{\mathbf{x}_t}(\mu_{\langle \mathbf{w}_i, \mathbf{f}_t \rangle, \sigma_i}) &= \max_{\substack{\mathbf{v}_i \in [\pm \frac{B}{\sigma_{\min}}]^d \\ \phi_i \in [\frac{1}{\sigma_{\max}}, \frac{1}{\sigma_{\min}}]}} \sum_{t=1}^{T} \operatorname{LSE}_i(\ell^{(q_i)}_{\mathbf{x}_t, \mathbf{f}_t}(\mathbf{v}_{t,i}, \phi_{t,i})) - \operatorname{LSE}_i(\ell^{(q_i)}_{\mathbf{x}_t, \mathbf{f}_t}(\mathbf{v}_i, \phi_i)) \\
&\leqslant \sum_{i=1}^{m} \frac{\|\mathbf{v}_{1,i} - \mathbf{v}_i\|_2^2}{2\eta_1} + \eta_1 \lceil \log_2(T+1) \rceil T \left(1 + \frac{2}{\varepsilon'} \sqrt{2md \log \frac{T}{\beta'} \log \frac{2}{\delta'}}\right) \sum_{j=1}^{m} \|\nabla_{\mathbf{v}_j} \operatorname{LSE}_i(\ell^{(q_i)}_{\mathbf{x}_t, \mathbf{f}_t})\|_2^2 \\
&\quad + \sum_{i=1}^{m} \frac{(\phi_{1,i} - \phi_i)^2}{2\eta_2} + \eta_2 \lceil \log_2(T+1) \rceil T \left(1 + \frac{2}{\varepsilon'} \sqrt{2m \log \frac{T}{\beta'} \log \frac{2}{\delta'}}\right) \sum_{j=1}^{m} (\partial_{\phi_j} \operatorname{LSE}_i(\ell^{(q_i)}_{\mathbf{x}_t, \mathbf{f}_t}))^2 \\
&\leqslant \frac{2B^2 md}{\eta_1 \sigma_{\min}^2} + \eta_1 \lceil \log_2(T+1) \rceil T F^2 d \left(1 + \frac{2}{\varepsilon'} \sqrt{2md \log \frac{T}{\beta'} \log \frac{2}{\delta'}}\right) \\
&\quad + \frac{m}{2\eta_2 \sigma_{\min}^2} + \eta_2 \lceil \log_2(T+1) \rceil T (B + \sigma_{\max})^2 \left(1 + \frac{2}{\varepsilon'} \sqrt{2m \log \frac{T}{\beta'} \log \frac{2}{\delta'}}\right) \\
&\leqslant \frac{2BF}{\sigma_{\min}} \sqrt{2md \lceil \log_2(T+1) \rceil T \left(1 + \frac{2}{\varepsilon'} \sqrt{2md \log \frac{T}{\beta'} \log \frac{2}{\delta'}}\right)} \\
&\quad + \frac{2}{\sigma_{\min}} (B + \sigma_{\max}) \sqrt{2m \lceil \log_2(T+1) \rceil T \left(1 + \frac{2}{\varepsilon'} \sqrt{2m \log \frac{T}{\beta'} \log \frac{2}{\delta'}}\right)} \\
&\leqslant \frac{2}{\sigma_{\min}} (B(F+1) + \sigma_{\max}) \sqrt{md \lceil \log_2(T+1) \rceil T \left(1 + \frac{2}{\varepsilon'} \sqrt{2md \log \frac{T}{\beta'} \log \frac{2}{\delta'}}\right)}
\end{aligned} \tag{55}$$

□

F.3.2. Experimental details

For sequential release we consider the following tasks:

- Synthetic is a stationary dataset generation scheme in which we randomly sample a one standard Gaussian vector $\mathbf{a}$ for each feature dimension (we use ten) and another $\mathbf{b}$ of size $m+2$, which we sort. On each day t of T we sample the public feature vector $\mathbf{f}_t$, also from a standard normal, and the "ground truth" quantiles q_i on that day are then set by $\langle \mathbf{a}, \mathbf{f}_t \rangle + \mathbf{b}_{[i+1]}$. We generate the actual data by sampling from the uniform distributions on $[\langle \mathbf{a}, \mathbf{f}_t \rangle + \mathbf{b}_{[i]}, \langle \mathbf{a}, \mathbf{f}_t \rangle + \mathbf{b}_{[i+1]}]$. The number of points we sample is determined by $\lfloor 100/(m+1) \rfloor$ plus different Poisson-distributed random variable for each; in the "noiseless" setting used in Figure 1 (left) the Poisson's scale is zero, so the "ground truth" quantiles are correct for the dataset, while for Figure 2 (left) we use a Poisson with scale five. For the noiseless setting we use 100K timesteps, while for the noisy setting we use 2500.
- CitiBike consists of data downloaded from here: `https://s3.amazonaws.com/tripdata/index.html`, We take the period from September 2015 through November 2022, which is roughly 2500 days, although days with less than ten trips—seemingly data errors—are ignored. For each day we include a feature vector containing seven dimensions for the day of the week, one dimension for a sinusoidal encoding of the day of the year, and six weather features from the Central Park station downloaded from here `https://www.ncei.noaa.gov/cdo-web/`, specifically average wind speed, precipitation, snowfall, snow depth, maximum temperature, and minimum temperature. These are scaled to lie within similar ranges.
- BBC consists of Reddit's `worldnews` corpus downloaded from here: `https://zissou.infosci.cornell.edu/convokit/datasets/subreddit-corpus/corpus-zipped/`. We find all conversations corresponding to a post of a BBC article, specified by the domain `bbc.co.uk`, and collect those with at least ten comments. We compute the Flesch readability score of each comment using the package here `https://github.com/textstat/textstat`. The datasets for computing quantiles are then the collection of scores for each headline; the size is roughly 10K, corresponding to articles between 2008 and 2018. As features we combine a seven-dimensional day-of-the-week encoding, sinusoidal features for the day of the year and the time of day of the post, information about the post itself (whether it is gilded, its own Flesch score, and the number of tokens), and finally a 25-dimensional embedding of the title, set using a normalized sum of GloVe embeddings (Pennington et al., 2014) of the tokens, excluding English stop-words via NLTK (Loper & Bird, 2002).

We again use reasonable guesses of data information to set the static priors, and to initialized the learning schemes.

- Synthetic: $\nu = 0, \sigma = 1, a = -100, b = 100$
- CitiBike: $\nu = 10, \sigma = 1, a = 0, b = 50/(1-q)$
- BBC: $\nu = 50, \sigma = 10, a = -100 - 100/(1-q), b = 100 + 100q$

We use a and b for the static Uniform distributions, ν and σ for the static Cauchy distributions, in the case of nonnegative data (CitiBike) we use ν for the *scale* of the half-Cauchy distribution, and for the learning schemes we initialize their Laplace priors to be centered at ν with scale σ. We again use the COCOB optimizer for non-private and proxy learning, and for robustness we mix with the Cauchy (or half-Cauchy for nonnegative data) with coefficient 0.1 on the robust prior. For the `PubPrev` method, we set its scale using σ. For DP-FTRL, we heavily tune it to show the possibility of learning on the synthetic task; the implementation is adapted from the one here: `https://github.com/google-research/DP-FTRL`. All results are reported as averages over forty trials.

G. Additional proofs for multiple quantile release

Lemma G.1. *In Algorithm 2, for any $i \in [m]$ we have*

1. $\mathrm{Gap}_{\tilde{q}_i}(\hat{\mathbf{x}}_i, o) \leqslant \mathrm{Gap}_{q_i}(\mathbf{x}, o) + \hat{\gamma}_i \;\forall\, o \in \mathbb{R}$
2. $\mathrm{Gap}_{q_i}(\mathbf{x}, o) \leqslant \mathrm{Gap}_{\tilde{q}_i}(\hat{\mathbf{x}}_i, o) + \hat{\gamma}_i \;\forall\, o \in [\hat{a}_i, \hat{b}_i]$

where $\hat{\gamma}_i = (1-\tilde{q}_i)\,\mathrm{Gap}_{\underline{q}_i}(\mathbf{x}, \hat{a}_i) + \tilde{q}_i\,\mathrm{Gap}_{\overline{q}_i}(\mathbf{x}, \hat{b}_i)$.

Proof. For $o \in [\hat{a}_i, \hat{b}_i]$ we apply the triangle inequality twice to get

$$\begin{aligned}
\mathrm{Gap}_{\tilde{q}_i}(\hat{\mathbf{x}}_i, o) &= |\max_{\hat{\mathbf{x}}_{[j]}<o} j - \lfloor \tilde{q}_i \hat{n}_i \rfloor| \\
&= |\max_{\hat{\mathbf{x}}_{[j]}<o} j + \max_{\mathbf{x}_{[j]}<\hat{a}_i} j - \lfloor q_i n \rfloor + \lfloor q_i n \rfloor - \max_{\mathbf{x}_{[j]}<\hat{a}_i} j - \lfloor \tilde{q}_i \hat{n}_i \rfloor| \\
&\leqslant \mathrm{Gap}_{q_i}(\mathbf{x}, o) + \left| \lfloor \tilde{q}_i(\lfloor \overline{q}_i n \rfloor - \lfloor \underline{q}_i n \rfloor) \rfloor + \lfloor \underline{q}_i n \rfloor - \max_{\mathbf{x}_{[j]}<\hat{a}_i} j - \lfloor \tilde{q}_i (\max_{\mathbf{x}_{[j]}<\hat{b}_i} j - \max_{\mathbf{x}_{[j]}<\hat{a}_i} j) \rfloor \right| \\
&\leqslant \mathrm{Gap}_{q_i}(\mathbf{x}, o) + (1-\tilde{q}_i)\,\mathrm{Gap}_{\underline{q}_i}(\mathbf{x}, \hat{a}_i) + \tilde{q}_i\,\mathrm{Gap}_{\overline{q}_i}(\mathbf{x}, \hat{b}_i)
\end{aligned} \tag{56}$$

and again to get

$$\begin{aligned}
\mathrm{Gap}_{q_i}(\mathbf{x}, o) &= |\max_{\mathbf{x}_{[j]}<o} j - \lfloor q_i n \rfloor| \\
&= |\max_{\hat{\mathbf{x}}_{[j]}<o} j + \max_{\mathbf{x}_{[j]}<\hat{a}_i} j - \lfloor \tilde{q}_i \hat{n}_i \rfloor + \lfloor \tilde{q}_i \hat{n}_i \rfloor - \lfloor q_i n \rfloor| \\
&\leqslant \mathrm{Gap}_{\tilde{q}_i}(\hat{\mathbf{x}}_i, o) + \left| \max_{\mathbf{x}_{[j]}<\hat{a}_i} j - \lfloor \tilde{q}_i (\max_{\mathbf{x}_{[j]}<\hat{b}_i} j + \max_{\mathbf{x}_{[j]}<\hat{a}_i} j) \rfloor - \lfloor \tilde{q}_i (\lfloor \overline{q}_i n \rfloor - \lfloor \underline{q}_i n \rfloor) \rfloor - \lfloor \underline{q}_i n \rfloor \right| \\
&\leqslant \mathrm{Gap}_{\tilde{q}_i}(\hat{\mathbf{x}}_i, o) + (1-\tilde{q}_i)\,\mathrm{Gap}_{\underline{q}_i}(\mathbf{x}, \hat{a}_i) + \tilde{q}_i\,\mathrm{Gap}_{\overline{q}_i}(\mathbf{x}, \hat{b}_i)
\end{aligned} \tag{57}$$

For $o < \hat{a}_i$ we use the fact that $\max_{\mathbf{x}_{[j]}<o} j \leqslant \max_{\mathbf{x}_{[j]}<\hat{a}_i} j$ and the triangle inequality to get

$$\begin{aligned}
\mathrm{Gap}_{\tilde{q}_i}(\hat{\mathbf{x}}_i, o) &= \lfloor \tilde{q}_i \hat{n}_i \rfloor \\
&= \lfloor \tilde{q}_i (\max_{\mathbf{x}_{[j]}<\hat{b}_i} j - \max_{\mathbf{x}_{[j]}<\hat{a}_i} j) \rfloor \\
&\leqslant \lfloor \tilde{q}_i \max_{\mathbf{x}_{[j]}<\hat{b}_i} j \rfloor + \lfloor (1-\tilde{q}_i) \max_{\mathbf{x}_{[j]}<\hat{a}_i} j \rfloor - \max_{\mathbf{x}_{[j]}<o} j \\
&= \lfloor \tilde{q}_i \max_{\mathbf{x}_{[j]}<\hat{b}_i} j \rfloor + \lfloor (1-\tilde{q}_i) \max_{\mathbf{x}_{[j]}<\hat{a}_i} j \rfloor - \max_{\mathbf{x}_{[j]}<o} j + \lfloor q_i n \rfloor| - \lfloor \tilde{q}_i (\lfloor \overline{q}_i n \rfloor - \lfloor \underline{q}_i n \rfloor) \rfloor - \lfloor \underline{q}_i n \rfloor \\
&\leqslant \mathrm{Gap}_{q_i}(\mathbf{x}, o) + (1-\tilde{q}_i)\,\mathrm{Gap}_{\underline{q}_i}(\mathbf{x}, \hat{a}_i) + \tilde{q}_i\,\mathrm{Gap}_{\overline{q}_i}(\mathbf{x}, \hat{b}_i)
\end{aligned} \tag{58}$$

For $o > \hat{b}_i$ we use the fact that $\max_{\mathbf{x}_{[j]}<\hat{b}_i} j \leqslant \max_{\mathbf{x}_{[j]}<o} j$ and the triangle inequality to get

$$\begin{aligned}
\mathrm{Gap}_{\tilde{q}_i}(\hat{\mathbf{x}}_i, o) &= \lfloor (1-\tilde{q}_i) \hat{n}_i \rfloor \\
&= \lfloor (1-\tilde{q}_i) (\max_{\mathbf{x}_{[j]}<\hat{b}_i} j - \max_{\mathbf{x}_{[j]}<\hat{a}_i} j) \rfloor \\
&\leqslant \max_{\mathbf{x}_{[j]}<o} j - \lfloor \tilde{q}_i \max_{\mathbf{x}_{[j]}<\hat{b}_i} j - \lfloor (1-\tilde{q}_i) \max_{\mathbf{x}_{[j]}<\hat{a}_i} j \\
&= \max_{\mathbf{x}_{[j]}<o} j - \lfloor \tilde{q}_i \max_{\mathbf{x}_{[j]}<\hat{b}_i} j - \lfloor (1-\tilde{q}_i) \max_{\mathbf{x}_{[j]}<\hat{a}_i} j - \lfloor q_i n \rfloor + \lfloor \tilde{q}_i (\lfloor \overline{q}_i n \rfloor - \lfloor \underline{q}_i n \rfloor) \rfloor + \lfloor \underline{q}_i n \rfloor \\
&\leqslant \mathrm{Gap}_{q_i}(\mathbf{x}, o) + (1-\tilde{q}_i)\,\mathrm{Gap}_{\underline{q}_i}(\mathbf{x}, \hat{a}_i) + \tilde{q}_i\,\mathrm{Gap}_{\overline{q}_i}(\mathbf{x}, \hat{b}_i)
\end{aligned} \tag{59}$$

□

Lemma G.2. *For any $\gamma > 0$ the estimate o_i of the quantile q_i by Algorithm 2 satisfies*

$$Pr\{\mathrm{Gap}_{q_i}(\mathbf{x}, o_i) \geqslant \gamma\} \leqslant \frac{\exp\left(\varepsilon_i(\hat{\gamma}_i - \gamma)/2\right)}{\Psi_{\hat{\mathbf{x}}_i}^{(\tilde{q}_i, \varepsilon_i)}(\hat{\mu}_i)} \tag{60}$$

Proof. We use k_i to denote the interval $\hat{I}_k^{(j)}$ sampled at index i in the algorithm and note that o_i corresponds to the released number o at that index. Since $o_i \in [\hat{a}_i, \hat{b}_i]$, applying Lemma G.1 yields

$$\begin{aligned}
\Pr\{\mathrm{Gap}_{q_i}(\mathbf{x}, o_i) \geqslant \gamma\} &= \sum_{j=0}^{\hat{n}_i} \Pr\{k_i = j\} 1_{\mathrm{Gap}_{q_i}(\mathbf{x}, \hat{I}_j^{(i)}) \geqslant \gamma} \\
&= \sum_{j=0}^{n_i} \frac{\exp(-\varepsilon\, \mathrm{Gap}_{\tilde{q}_i}(\hat{\mathbf{x}}_i, \hat{I}_j^{(i)})/2) \hat{\mu}_i(\hat{I}_j^{(i)}) 1_{\mathrm{Gap}_{q_i}(\mathbf{x}, \hat{I}_j^{(i)}) \geqslant \gamma}}{\sum_{l=0}^{\hat{n}_i} \exp(\varepsilon u_{\tilde{q}_i}(\hat{\mathbf{x}}_i, \hat{I}_l^{(i)})/2) \hat{\mu}_i(\hat{I}_l)} \\
&\leqslant \frac{\exp(\varepsilon \hat{\gamma}_i/2)}{\Psi_{\hat{\mathbf{x}}_i}^{(\tilde{q}_i, \varepsilon_i)}(\hat{\mu}_i)} \sum_{j=0}^{n_i} \exp(-\varepsilon\, \mathrm{Gap}_{q_i}(\mathbf{x}, \hat{I}_j^{(i)})/2) \hat{\mu}_i(\hat{I}_j^{(i)}) 1_{\mathrm{Gap}_{q_i}(\mathbf{x}, \hat{I}_j^{(i)}) \geqslant \gamma} \\
&\leqslant \frac{\exp(\varepsilon(\hat{\gamma}_i - \gamma)/2)}{\Psi_{\hat{\mathbf{x}}_i}^{(\tilde{q}_i, \varepsilon_i)}(\hat{\mu}_i)}
\end{aligned} \tag{61}$$

□

Lemma G.3. *For any $\gamma > 0$ the estimate o_i of the quantile q_i by Algorithm 2 with edge-based prior adaptation satisfies*

$$\Pr\{\mathrm{Gap}_{q_i}(\mathbf{x}, o_i) \geqslant \gamma\} \leqslant \frac{\exp(\varepsilon(\hat{\gamma}_i - \gamma/2))}{\Psi_{\mathbf{x}}^{(q_i, \varepsilon_i)}(\mu_i)} \tag{62}$$

Proof. Applying Lemma G.1 yields the following lower bound on $\Psi_{\tilde{q}_i}^{(\varepsilon_i)}(\hat{\mathbf{x}}_i, \hat{\mu}_i)$:

$$\begin{aligned}
\sum_{l=0}^{\hat{n}_i} \exp(\varepsilon u_{\tilde{q}_i}(\hat{\mathbf{x}}_i, \hat{I}_l^{(i)})/2) \hat{\mu}_i(\hat{I}_l^{(i)}) &= \exp(\varepsilon u_{\tilde{q}_i}(\hat{\mathbf{x}}_i, \hat{I}_0^{(i)})/2) \mu_i((-\infty, \hat{a}_i]) + \exp(\varepsilon u_{\tilde{q}_i}(\hat{\mathbf{x}}_i, \hat{I}_{\hat{n}_i}^{(i)})/2) \mu_i([\hat{b}_i, \infty)) \\
&\quad + \sum_{l=0}^{\hat{n}_i} \exp(\varepsilon u_{\tilde{q}_i}(\hat{\mathbf{x}}_i, \hat{I}_l^{(i)})/2) \mu_i(\hat{I}_l) \\
&= \sum_{l=0}^{\max_{\mathbf{x}_{[j]} < \hat{a}_i} j} \exp(-\varepsilon\, \mathrm{Gap}_{\tilde{q}_i}(\hat{\mathbf{x}}_i, I_l \cap (-\infty, \hat{a}_i])/2) \mu_i(I_l \cap (-\infty, \hat{a}_i]) \\
&\quad + \sum_{l=\max_{\mathbf{x}_{[j]} < \hat{b}_i} j}^{n} \exp(-\varepsilon\, \mathrm{Gap}_{\tilde{q}_i}(\hat{\mathbf{x}}_i, I_l \cap [\hat{b}_i, \infty))/2) \mu_i(I_l \cap [\hat{b}_i, \infty)) \\
&\quad + \sum_{l=\max_{\mathbf{x}_{[j]} < \hat{a}_i} j}^{\max_{\mathbf{x}_{[j]} < \hat{b}_i} j} \exp(-\varepsilon\, \mathrm{Gap}_{\tilde{q}_i}(\hat{\mathbf{x}}_i, I_l \cap [\hat{a}_i, \hat{b}_i]) \mu_i(I_l \cap [\hat{a}_i, \hat{b}_i]) \\
&\geqslant \Psi_{\mathbf{x}}^{(q_i, \varepsilon_i)}(\mu_i) \exp(-\varepsilon \hat{\gamma}_i/2)
\end{aligned} \tag{63}$$

Substituting into Lemma D.2 yields the result. □

Lemma G.4. *Suppose $q_0 < q_1$ are two quantiles and $o_0 > o_1$. Then*

$$\max_{i=0,1} \mathrm{Gap}_{q_i}(\mathbf{x}, o_i) \geqslant \max_{i=0,1} \mathrm{Gap}_{q_i}(\mathbf{x}, o_{1-i}) \tag{64}$$

Proof. We consider four cases. If $\lfloor q_0|\mathbf{x}|\rfloor \leqslant \max_{\mathbf{x}_{[j]}<o_1} j$ and $\lfloor q_1|X|\rfloor \leqslant \max_{\mathbf{x}_{[j]}<o_0} j$ then

$$\lfloor q_0|\mathbf{x}|\rfloor \leqslant \min\{\lfloor q_1|\mathbf{x}|\rfloor, \max_{\mathbf{x}_{[j]}<o_1} j\} \leqslant \max\{\lfloor q_1|\mathbf{x}|\rfloor, \max_{\mathbf{x}_{[j]}<o_1} j\} \leqslant \max_{\mathbf{x}_{[j]}<o_0} j \tag{65}$$

and so

$$\max_{i=0,1} \mathrm{Gap}_{q_i}(\mathbf{x}, o_i) = \max_{\mathbf{x}_{[j]}<o_0} j - \lfloor q_0|\mathbf{x}|\rfloor \geqslant \max_{i=0,1} \mathrm{Gap}_{q_i}(X, o_{i-1}) \tag{66}$$

If $\lfloor q_0|X|\rfloor \leqslant \max_{\mathbf{x}_{[j]}<o_1} j$ and $\lfloor q_1|\mathbf{x}|\rfloor > \max_{\mathbf{x}_{[j]}<o_0} j$ then

$$\lfloor q_0|\mathbf{x}|\rfloor \leqslant \max_{\mathbf{x}_{[j]}<o_1} j \leqslant \max_{\mathbf{x}_{[j]}<o_0} j < \lfloor q_1|\mathbf{x}|\rfloor \tag{67}$$

and so both improve after swapping. If $\lfloor q_0|\mathbf{x}|\rfloor > \max_{\mathbf{x}_{[j]}<o_1} j$ and $\lfloor q_1|\mathbf{x}|\rfloor > \max_{\mathbf{x}_{[j]}<o_0} j$ then

$$\max_{\mathbf{x}_{[j]}<o_1} j \leqslant \min\{\lfloor q_0|\mathbf{x}|\rfloor, \max_{\mathbf{x}_{[j]}<o_0} j\} \leqslant \max\{\lfloor q_0|\mathbf{x}|\rfloor, \max_{\mathbf{x}_{[j]}<o_0} j\} \leqslant \lfloor q_1|\mathbf{x}|\rfloor \tag{68}$$

and so

$$\max_{i=0,1} \mathrm{Gap}_{q_i}(\mathbf{x}, o_i) = \max_{\mathbf{x}_{[j]}<o_1} j - \lfloor q_1|\mathbf{x}|\rfloor \geqslant \max_{i=0,1} \mathrm{Gap}_{q_i}(\mathbf{x}, o_{i-1}) \tag{69}$$

Finally, if $\lfloor q_0|\mathbf{x}|\rfloor > \max_{\mathbf{x}_{[j]}<o_1} j$ and $\lfloor q_1|\mathbf{x}|\rfloor \leqslant \max_{\mathbf{x}_{[j]}<o_0} j$ then

$$\max_{\mathbf{x}_{[j]}<o_1} j < \lfloor q_0|\mathbf{x}|\rfloor \leqslant \lfloor q_1|\mathbf{x}|\rfloor \leqslant \max_{\mathbf{x}_{[j]}<o_0} j \tag{70}$$

so swapping will make the new largest error for each quantile at most as large as the other quantile's current error. □

H. Additional proofs for online learning

H.1. Online-to-batch conversion

Theorem H.1. *Suppose an online algorithm sees a sequence $\ell_{\mathbf{x}_1}(\cdot), \dots, \ell_{\mathbf{x}_T}(\cdot) : \Theta \mapsto [0, B]$ of convex losses whose data $\mathbf{x}_1, \dots, \mathbf{x}_T$ are drawn i.i.d. from some distribution $\mathcal{D}$, and let $\theta_1, \dots, \theta_T$ be its predictions. If $\max_{\theta\in\Theta} \sum_{t=1}^T \ell_{\mathbf{x}_t}(\theta_t) - \ell_{\mathbf{x}_t}(\theta) \leqslant R_T$, $\hat{\theta} = \frac{1}{T}\sum_{t=1}^T \theta_t$, and $T = \Omega\left(T_\alpha + \frac{B^2}{\alpha^2}\log\frac{1}{\beta'}\right)$ for $T_\alpha = \min_{2R_T \leqslant T\alpha} T$, then w.p. $\geqslant 1-\beta'$*

$$\mathbb{E}_{\mathbf{x}\sim\mathcal{D}}\ell_{\mathbf{x}}(\hat{\theta}) \leqslant \min_{\theta\in\Theta} \mathbb{E}_{\mathbf{x}\sim\mathcal{D}}\ell_{\mathbf{x}}(\theta) + \alpha \tag{71}$$

Proof. This is a formalization of a standard procedure; we follow the argument in Khodak et al. (2022, Lemma A.1). Applying Jensen's inequality, Cesa-Bianchi et al. (2004, Proposition 1), the assumption that regret is $\leqslant R_T$, and Hoeffding's inequality yields

$$\begin{aligned}\mathbb{E}_{\mathbf{x}\sim\mathcal{D}}\ell_{\mathbf{x}}(\hat{\theta}) \leqslant \frac{1}{T}\sum_{t=1}^T \mathbb{E}_{\mathbf{x}\sim\mathcal{D}}\ell_{\mathbf{x}}(\theta_t) \leqslant \frac{1}{T}\sum_{t=1}^T \ell_{\mathbf{x}_t}(\theta_t) + B\sqrt{\frac{2}{T}\log\frac{2}{\beta'}} &\leqslant \min_{\theta\in\Theta}\frac{1}{T}\sum_{t=1}^T \ell_{\mathbf{x}_t}(\theta) + \frac{R_T}{T} + B\sqrt{\frac{2}{T}\log\frac{2}{\beta'}} \\ &\leqslant \min_{\theta\in\Theta}\mathbb{E}_{\mathbf{x}\sim\mathcal{D}}\ell_{\mathbf{x}}(\theta) + \frac{R_T}{T} + 2B\sqrt{\frac{2}{T}\log\frac{2}{\beta'}}\end{aligned} \tag{72}$$

w.p. $\geqslant 1-\beta'$. Substituting the lower bound on T yields the result. □

H.2. Negative log-inner-product losses

For functions of the form $f_t(\mu) = -\log\int_a^b s_t(o)\mu(o)do$, Balcan et al. (2021) showed $\tilde{\mathcal{O}}(T^{3/4})$ regret for the case $s_t(o) \in \{0,1\}\ \forall\ o \in [a,b]$ using a variant of exponentiated gradient with a dynamic discretization. Notably their algorithm can be extended to (non-privately) learn $-\log\Psi^{(q)}_{\mathbf{x}_t}(\mu)$, since s_t in this case is one on the optimal interval and zero elsewhere. However, the changing discretization and dependence of the analysis on the range of s_t suggests it may be difficult to privatize their approach. The discretized form $-\log\langle \mathbf{s}_t, \mathbf{w}\rangle$ is more heavily studied, arising in portfolio management (Cover, 1991). It enjoys the exp-concavity property, leading to $\mathcal{O}(d\log T)$ regret using the EWOO method (Hazan et al., 2007). However, EWOO requires maintaining and sampling from a distribution defined by a product of inner products, which is inefficient and similarly difficult to privatize. Other algorithms, e.g. adaptive FTAL (Hazan et al., 2007), also attain logarithmic regret for exp-concave functions, but the only private variant we know of is non-adaptive and only guarantees $\mathcal{O}(\sqrt{T})$-regret for non-strongly-convex losses (Smith & Thakurta, 2013). The adaptivity, which is itself data-dependent, seems critical for taking advantage of exp-concavity.

Lemma H.1. *If $f_t(\mu_{\mathbf{W}}) = -\log\sum_{i=1}^m \frac{1/m}{\langle \mathbf{s}_{t,i}, \mathbf{W}_{[i]}\rangle}$ for $\mathbf{s}_{t,i} \in \mathbb{R}^d_{\geqslant 0}$ then $\|\nabla_{\mathbf{W}} f_t(\mu_{\mathbf{W}})\|_1 \leqslant d/\gamma\ \forall\ \mathbf{W} \in \triangle_d^m$ s.t. $\mathbf{W}_{[i,j]} \geqslant \gamma/d\ \forall\ i,j$ for some $\gamma \in (0,1]$.*

Proof.

$$\begin{aligned}\|\nabla_{\mathbf{W}} f_t(\mu_{\mathbf{W}})\|_1 = \sum_{i=1}^m \|\nabla_{\mathbf{W}_{[i]}} f_t(\mu_{\mathbf{W}})\|_1 &= \left(\sum_{i=1}^m \frac{1}{\langle \mathbf{s}_{t,i}, \mathbf{W}_{[i]}\rangle}\right)^{-1} \sum_{i=1}^m\sum_{j=1}^d \frac{\mathbf{s}_{t,i[j]}}{\langle \mathbf{s}_{t,i}, \mathbf{W}_{[i]}\rangle^2} \\ &\leqslant \left(\sum_{i=1}^m \frac{1}{\langle \mathbf{s}_{t,i}, \mathbf{W}_{[i]}\rangle}\right)^{-1} \sum_{i=1}^m \frac{1}{\langle \mathbf{s}_{t,i}, \mathbf{W}_{[i]} \odot \mathbf{W}_{[i]}\rangle} \leqslant d/\gamma\end{aligned} \tag{73}$$

where the first inequality follows by Sedrakyan's inequality and the second by $\mathbf{W}_{[i,j]} \geqslant \gamma/d$. □

H.2.1. Proof of Lemma E.1 for $m > 1$

Proof. Let $\tilde{\mathbf{x}}_t$ be a neighboring dataset of $\mathbf{x}_t$ constructed by adding or removing a single element, and let $U^{(\varepsilon)}_{\tilde{\mathbf{x}}_t}$ be the corresponding loss function. We note that changing from $\mathbf{x}_t$ to $\tilde{\mathbf{x}}_t$ changes the value of $\mathrm{Gap}_{q_i}(\mathbf{x}_t, o)$ at any point $o \in [a, b]$ by at most ± 1 and so the value of the exponential score at any point $o \in [a, b]$ is changed by at most a multiplicative factor $\exp(-\varepsilon_i/2)$ in either direction. Therefore

$$\begin{aligned}\tilde{\mathbf{s}}_{t,i[j]} &= \int_{a+\frac{b-a}{d}(j-1)}^{a+\frac{b-a}{d}j} \exp(-\varepsilon_i \,\mathrm{Gap}_{q_i}(\tilde{\mathbf{x}}_t, o)/2)do \\ &\in \exp(\pm\varepsilon_i/2) \int_{a+\frac{b-a}{d}(j-1)}^{a+\frac{b-a}{d}j} \exp(-\varepsilon_i \,\mathrm{Gap}_{q_i}(\mathbf{x}_t, o)/2)do = \exp(\pm\varepsilon_i/2)\mathbf{s}_{t,i[j]}\end{aligned} \tag{74}$$

where $\pm$ indicates the interval between values.

$$\begin{aligned}&\|\nabla_{\mathbf{W}} U^{(\varepsilon)}_{\mathbf{x}_t}(\mathbf{W}) - \nabla_{\mathbf{W}} U^{(\varepsilon)}_{\tilde{\mathbf{x}}_t}(\mathbf{W})\|_F \\ &\quad= \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{d}\left(\left(\sum_{i'=1}^{m}\frac{1}{\langle \mathbf{s}_{t,i'}, \mathbf{W}_{[i']}\rangle}\right)^{-1}\frac{\mathbf{s}_{t,i[j]}}{\langle \mathbf{s}_{t,i}, \mathbf{W}_{[i]}\rangle^2} - \left(\sum_{i'=1}^{m}\frac{1}{\langle \tilde{\mathbf{s}}_{t,i'}, \mathbf{W}_{[i']}\rangle}\right)^{-1}\frac{\tilde{\mathbf{s}}_{t,i[j]}}{\langle \tilde{\mathbf{s}}_{t,i}, \mathbf{W}_{[i]}\rangle^2}\right)^2} \\ &\quad= \left(\sum_{i'=1}^{m}\frac{1}{\langle \mathbf{s}_{t,i'}, \mathbf{W}_{[i']}\rangle}\right)^{-1}\sqrt{\sum_{i=1}^{m}\sum_{j=1}^{d}\left(\frac{\mathbf{s}_{t,i[j]}}{\langle \mathbf{s}_{t,i}, \mathbf{W}_{[i]}\rangle^2} - \frac{\tilde{\mathbf{s}}_{t,i[j]}}{\langle \tilde{\mathbf{s}}_{t,i}, \mathbf{W}_{[i]}\rangle^2}\frac{\sum_{i'=1}^{m}\frac{1}{\langle \mathbf{s}_{t,i'}, \mathbf{W}_{[i']}\rangle}}{\sum_{i'=1}^{m}\frac{1}{\langle \tilde{\mathbf{s}}_{t,i'}, \mathbf{W}_{[i']}\rangle}}\right)^2} \\ &\quad= \left(\sum_{i'=1}^{m}\frac{1}{\langle \mathbf{s}_{t,i'}, \mathbf{W}_{[i']}\rangle}\right)^{-1}\sqrt{\sum_{i=1}^{m}\sum_{j=1}^{d}\frac{\mathbf{s}_{t,i[j]}^2}{\langle \mathbf{W}_{t,i}, \mathbf{W}_{[i]}\rangle^4}\left(1 - \frac{\langle \mathbf{g}_{t,i}, \mathbf{x}_{[i]}\rangle^2}{\langle \tilde{\mathbf{s}}_{t,i}, \mathbf{W}_{[i]}\rangle^2}\frac{\sum_{i'=1}^{m}\frac{\tilde{\mathbf{s}}_{t,i[j]}}{\langle \mathbf{s}_{t,i'}, \mathbf{W}_{[i']}\rangle}}{\sum_{i'=1}^{m}\frac{\mathbf{s}_{t,i[j]}}{\langle \tilde{\mathbf{s}}_{t,i'}, \mathbf{W}_{[i']}\rangle}}\right)^2} \\ &\quad\leqslant \left(\sum_{i'=1}^{m}\frac{1}{\langle \mathbf{s}_{t,i'}, \mathbf{W}_{[i']}\rangle}\right)^{-1}\sum_{i=1}^{m}\sum_{j=1}^{d}\frac{\mathbf{s}_{t,i[j]}}{\langle \mathbf{s}_{t,i}, \mathbf{W}_{[i]}\rangle^2}|1-\kappa_{i,j}| \leqslant \frac{d}{\gamma}\max_{i,j}|1-\kappa_{i,j}|\end{aligned} \tag{75}$$

where we have

$$\kappa_{i,j} = \frac{\langle \mathbf{s}_{t,i}, \mathbf{W}_{[i]}\rangle^2}{\langle \tilde{\mathbf{s}}_{t,i}, \mathbf{x}_{[i]}\rangle^2}\frac{\sum_{i'=1}^{m}\frac{\tilde{\mathbf{s}}_{t,i[j]}}{\langle \mathbf{s}_{t,i'}, \mathbf{W}_{[i']}\rangle}}{\sum_{i'=1}^{m}\frac{\mathbf{s}_{t,i[j]}}{\langle \tilde{\mathbf{s}}_{t,i'}, \mathbf{W}_{[i']}\rangle}} \in \frac{\langle \mathbf{s}_{t,i}, \mathbf{W}_{[i]}\rangle^2}{\langle \mathbf{s}_{t,i}, \mathbf{W}_{[i]}\rangle^2\exp(\pm\varepsilon_i)}\frac{\sum_{i'=1}^{m}\frac{\mathbf{s}_{t,i[j]}\exp(\pm\frac{\varepsilon_{i'}}{2})}{\langle \mathbf{s}_{t,i'}, \mathbf{W}_{[i']}\rangle}}{\sum_{i'=1}^{m}\frac{\mathbf{s}_{t,i[j]}}{\langle \mathbf{s}_{t,i'}, \mathbf{W}_{[i']}\rangle\exp(\pm\frac{\varepsilon_{i'}}{2})}} = \exp(\pm 2\max_i \varepsilon_i) \tag{76}$$

Substituting into the previous inequality and taking the minimum with the ℓ_1 bound on the gradient of the losses from Lemma H.1 yields the result. □

H.2.2. Settings of γ and d for Corollary E.3

1. λ-robust and discrete $\mu_{[i]} \in \mathcal{F}^{(\lambda)}_{0,d}$: $\gamma = \lambda$
2. λ-robust and V-Lipschitz $\mu_{[i]} \in \mathcal{F}^{(\lambda)}_{V,1}$: $\gamma = \lambda$ and $d = \left\lceil \sqrt{\frac{V(b-a)^3}{\bar{\psi}}\sqrt{\left(1 + \frac{\min\{1,\tilde{\varepsilon}_m\}}{\varepsilon'}\right)T}} \right\rceil$
3. discrete $\mu_{[i]} \in \mathcal{F}_{0,d}$: $\gamma = \sqrt{md}\sqrt[4]{\frac{1+\min\{1,\tilde{\varepsilon}_m\}/\varepsilon'}{T}}$
4. V-Lipschitz $\mu_{[i]} \in \mathcal{F}_{V,1}$: $\gamma = \sqrt{m}\sqrt[4]{\frac{V(b-a)^3}{\bar{\psi}}}\sqrt[8]{\frac{1+\min\{1,\tilde{\varepsilon}_m\}/\varepsilon'}{T}}$ and $d = \left\lceil \sqrt{\frac{V(b-a)^3}{\bar{\psi}}\sqrt{\left(1 + \frac{\min\{1,\tilde{\varepsilon}_m\}}{\varepsilon'}\right)T}} \right\rceil$

Algorithm 2: `ApproximateQuantiles` with predictions

Input: sorted unrepeated data $\mathbf{x} \in (a,b)^n$, ordered quantiles $q_1, \ldots, q_m \in (0,1)$,
priors $\mu_1, \ldots, \mu_m : \mathbb{R} \mapsto \mathbb{R}_{\geqslant 0}$, prior adaptation rule $r \in$ {`conditional`, `edge`},
privacy parameters $\varepsilon_1, \ldots, \varepsilon_m > 0$, branching factor $K \geqslant 2$

`// runs single-quantile algorithm on datapoints` $\hat{\mathbf{x}}$

Method `quantile` ($\hat{\mathbf{x}}$, q, ε, μ) **:**

  Output: $o \in (a,b)$ w.p. $\propto \exp(-\varepsilon \operatorname{Gap}_q(\hat{\mathbf{x}}, o)/2)\mu(o)$

Method `recurse` ($\mathbf{j}$, $\underline{q}$, $\overline{q}$, $\hat{a}$, $\hat{b}$) **:**

  `// determines` $K-1$ `indices` $\mathbf{i}$ `whose quantiles to compute at this node`

  if $|\mathbf{j}| \geqslant K$ **then**

    $\mathbf{i} \leftarrow \left(\mathbf{j}_{[\lceil |\mathbf{j}|/K \rceil]}, \cdots, \mathbf{j}_{[\lceil (K-1)|\mathbf{j}|/K \rceil]}\right)$

  else

    $\mathbf{i} \leftarrow \mathbf{j}$

  `// restricts dataset to the interval` $(\hat{a}, \hat{b})$

  $\underline{k}_{\mathbf{i}} \leftarrow \min_{\mathbf{x}_{[k]} > \hat{a}} k$

  $\overline{k}_{\mathbf{i}} \leftarrow \max_{\mathbf{x}_{[k]} < \hat{b}} k$

  $\hat{\mathbf{x}}_{\mathbf{i}} \leftarrow \left(\mathbf{x}_{[\underline{k}_{\mathbf{i}}]}, \cdots, \mathbf{x}_{[\overline{k}_{\mathbf{i}}]}\right)$

  `// sets relative quantiles` $\tilde{q}_i$ `and restricts priors to the interval` $[\hat{a}, \hat{b}]$

  for $j = 1, \ldots, |\mathbf{i}|$ **do**

    $\tilde{q}_{\mathbf{i}_{[j]}} \leftarrow (q_{\mathbf{i}_{[j]}} - \underline{q})/(\overline{q} - \underline{q})$

    if $r =$ `conditional` **then**

      $\hat{\mu}_{\mathbf{i}_{[j]}}(o) \leftarrow \frac{\mu_{\mathbf{i}_{[j]}}(o)}{\mu_{\mathbf{i}_{[j]}}([\hat{a},\hat{b}])} 1_{o \in [\hat{a},\hat{b}]}$

    else

      $\hat{\mu}_{\mathbf{i}_{[j]}}(o) \leftarrow \mu_{\mathbf{i}_{[j]}}(o) 1_{o \in (\hat{a},\hat{b})} + \mu_{\mathbf{i}_{[j]}}((-\infty, \hat{a}])\delta(o - \hat{a}) + \mu_{\mathbf{i}_{[j]}}([\hat{b}, \infty))\delta(o - \hat{b})$

  `// computes` $K-1$ `quantiles` $\mathbf{o}_{\mathbf{i}}$ `and sorts the results`

  $\mathbf{o}_{\mathbf{i}} \leftarrow \left(\texttt{quantile}\left(\hat{\mathbf{x}}_{\mathbf{i}}, \tilde{q}_{\mathbf{i}_{[1]}}, \varepsilon_{\mathbf{i}_{[1]}}/|\mathbf{i}|, \hat{\mu}_{\mathbf{i}_{[1]}}\right), \cdots, \texttt{quantile}\left(\hat{\mathbf{x}}_{\mathbf{i}}, \tilde{q}_{\mathbf{i}_{[|\mathbf{i}|]}}, \varepsilon_{\mathbf{i}_{[|\mathbf{i}|]}}/|\mathbf{i}|, \hat{\mu}_{\mathbf{i}_{[|\mathbf{i}|]}}\right)\right)$

  $\mathbf{o}_{\mathbf{i}} \leftarrow \texttt{sort}(\mathbf{o}_{\mathbf{i}})$

  `// recursively computes remaining indices on the` K `intervals induced by` $\mathbf{o}_{\mathbf{i}}$

  if $|\mathbf{j}| < K$ **then**

    $\mathbf{o} \leftarrow \mathbf{o}_i$

  else

    $\mathbf{o} \leftarrow \texttt{concat}\left(\texttt{recurse}\left(\left(\mathbf{j}_{[1]}, \cdots, \mathbf{j}_{[\lceil |\mathbf{j}|/K \rceil - 1]}\right), \underline{q}, q_{\mathbf{i}_{[1]}}, \hat{a}, \mathbf{o}_{[1]}\right), \left(\mathbf{o}_{[1]}\right)\right)$

    for $j = 2, \ldots, |\mathbf{i}|$ **do**

      $\mathbf{o} \leftarrow \texttt{concat}\left(\mathbf{o}, \texttt{recurse}\left(\left(\mathbf{j}_{[\lceil (j-1)|\mathbf{j}|/K \rceil + 1]}, \cdots, \mathbf{j}_{[\lceil j|\mathbf{j}|/K \rceil - 1]}\right), q_{\mathbf{i}_{[j-1]}}, q_{\mathbf{i}_{[j]}}, \mathbf{o}_{[j-1]}, \mathbf{o}_{[j]}\right)\right)$

      $\mathbf{o} \leftarrow \texttt{concat}\left(\mathbf{o}, \left(\mathbf{o}_{[j]}\right)\right)$

    $\mathbf{o} \leftarrow \texttt{concat}\left(\mathbf{o}, \texttt{recurse}\left(\left(\mathbf{j}_{[\lceil (K-1)|\mathbf{j}|/K \rceil + 1]}, \cdots, \mathbf{j}_{[|\mathbf{j}|]}\right), q_{\mathbf{i}_{[K-1]}}, \overline{q}, \mathbf{o}_{[K-1]}, \hat{b}\right)\right)$

  Output: $\mathbf{o}$

Output: `recurse` $\left(\left(1, \cdots, m\right), 0, 1, -\infty, \infty\right)$