OPTIMAL GUARANTEES FOR VARIATIONAL AUDITING OF RÉNYI DIFFERENTIAL PRIVACY

Anonymous authors
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ABSTRACT

We study black-box auditing for machine learning algorithms that claim Rényi differential privacy (RDP) guarantees. We introduce an auditing framework, based on hypothesis testing, that directly estimates Rényi divergence between neighboring executions using the Donsker–Varadhan (DV) variational estimator. Our analysis yields explicit and non-asymptotic confidence intervals for RDP auditing via class-restricted DV estimators, separating statistical estimation error from algorithmic privacy leakage. We prove matching minimax lower bounds showing that, up to logarithmic factors, our sample-complexity guarantees are information-theoretically optimal, thereby establishing the *first* optimal guarantees for variational auditing of RDP. Empirically, we instantiate our framework for auditing DP-SGD in a fully **black-box** setting. Across MNIST and CIFAR-10, and over a wide range of privacy regimes, our auditors produce a strong overall improvement on empirical RDP lower bounds compared to prior state-of-the-art black-box methods *especially at small and moderate Rényi orders* where accurate auditing is most challenging.

1 INTRODUCTION

Differential privacy (DP) has become the de facto standard for providing rigorous privacy guarantees in machine learning (Dwork et al., 2006b;a). Modern private learning algorithms, most notably differentially private stochastic gradient descent (DP-SGD), are routinely deployed with privacy guarantees, expressed in terms of *Rényi differential privacy* (RDP), due to its tight composition guarantees and its central role in state-of-the-art privacy accounting (Abadi et al., 2016; Mironov, 2017). Yet, as DP systems transition from theory to practice, a fundamental question has become increasingly urgent: *How can we reliably verify, from finite empirical observations, that a learning algorithm actually satisfies its claimed privacy guarantees?*

This question has given rise to a rapidly growing literature on *privacy auditing* (Jagielski et al., 2020; Steinke et al., 2023). Empirical audits are used to estimate privacy leakage by distinguishing outputs of a learning algorithm on neighboring datasets, thereby producing lower bounds on the true privacy parameters (Ding et al., 2018). Such audits play a critical role in diagnosing implementation bugs, assessing how tight the theoretical analysis is, and building trust in deployed private learning systems (Dwork et al., 2019; Alabi et al., 2025). However, despite this progress, theoretical foundations of privacy auditing remain incomplete, particularly for RDP.

The gap between empirical auditing and RDP guarantees Most existing auditing methods are tailored to the original (pure and approximate) DP definitions and rely on specific attack constructions such as membership inference and data poisoning (Ding et al., 2018; Jagielski et al., 2020). While effective, these approaches could lack finite-sample guarantees that cleanly separate estimation error from algorithmic privacy leakage. In particular, it is currently unclear how accurately RDP parameters can be estimated from finite samples, whether existing methods are optimal within some class of estimators, and how auditing error should scale with model complexity.

Black-box privacy auditing Tight audits for DP-SGD exist in the white-box auditing setting where an adversary can observe and update intermediate gradients (Nasr et al., 2023). In contrast, in this work we consider a black-box auditing setting, where an adversary can only insert an input canary and observe a (post-processing of a) final trained model. We achieve tighter audits than previous

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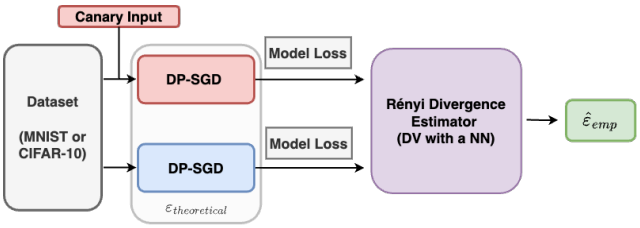

Figure 1: Auditing procedure in Algorithm 3.

works, (Jagielski et al., 2020; Nasr et al., 2023; Steinke et al., 2023; Muthu Selva Annamalai & De Cristofaro, 2024). We follow the method in (Muthu Selva Annamalai & De Cristofaro, 2024) of crafting worst-case initial model parameters, since DP-SGD's privacy is unaffected by the choice of initial parameters before private training and is still considered black-box DP auditing. The approach to doing so by pretraining on a separate part of the dataset is described in Section 4. In short, this worst-case initialization makes training as sensitive as possible to whether the canary is present, leading to a greater Rényi divergence in model outputs trained with and without the canary for us.

Our approach: Hypothesis testing via the variational Rényi divergence In this work, we introduce a *new framework for auditing Rényi differentially private mechanisms* based on hypothesis testing. We utilize the Donsker-Varadhan (DV) variational representation of the Rényi divergence. We view privacy auditing as a statistical estimation problem: given samples from the output distributions of a mechanism evaluated on neighboring datasets, the auditor seeks to estimate (or certify a lower bound on) the corresponding Rényi divergence using the DV representation. This perspective allows us to directly connect empirical auditing to formal definitions of RDP, without relying on specific attacks or asymptotic approximations. Our analysis yields explicit, non-asymptotic confidence intervals for class-restricted Rényi divergence estimates obtained via DV-based variational objectives. These guarantees hold uniformly over parameterized critic classes and make precise the dependence on sample size, Rényi order, and function-class complexity. We can obtain statistically valid RDP audits with controlled Type-I error, converting empirical evidence into privacy violation certificates.

This paper develops a rigorous, non-asymptotic framework for auditing RDP using variational (DV-based) estimators. **Our contributions are summarized as follows:** (i) We are the *first* to directly audit Rényi differential privacy, establishing a state-of-the-art black-box privacy auditing method to estimate the Rényi divergence between neighboring dataset mechanism outputs. Our Rényi divergence estimation methods between loss distributions trained with and loss distributions trained without a canary use a variational representation approach with neural networks to estimate a lower bound. (ii) We introduce a framework, based on hypothesis testing, for auditing RDP via variational Rényi divergence (Section 3.1). We derive explicit, non-asymptotic confidence intervals for DV-based Rényi divergence estimators over restricted critic classes (Theorem 2 and Corollary 3). We provide matching lower bounds, establishing the optimality of our auditing guarantees (Theorem 3), showing that, up to logarithmic and constant factors, the sample complexity in Theorem 2 is minimax optimal. (iii) We validate our theory empirically on private machine learning systems, demonstrating accurate and robust RDP audits in practice (Section 4). Compared to state-of-the-art black-box auditors, our work yields empirical estimates that significantly improve over prior work.

1.1 Related Work

A growing body of work studies how to empirically *audit* DP machine learning algorithms by estimating privacy leakage from observed outputs of the algorithms (Shokri et al., 2017; Annamalai et al., 2024; Muthu Selva Annamalai & De Cristofaro, 2024; Ding et al., 2018; Guan et al., 2023; Ye et al., 2022; Kong et al., 2024). Earlier work introduced data poisoning attacks as a way to audit DP-SGD, demonstrating empirical lower bounds on the privacy parameters can substantially exceed naive theoretical analysis (Jagielski et al., 2020). Subsequent works refined this line of research by improving tightness, reducing the number of required training runs, or adapting to different threat models: Nasr et al. (2023) proposed tight auditing schemes that exploit knowledge of the underlying DP mechanism to dramatically reduce sampling complexity whereas Steinke et al. (2023); Mahloujifar

et al. (2024) showed that meaningful DP audits can be performed using a single training run by exploiting connections between DP and generalization. While these approaches can be effective in practice, they primarily focus on pure or approximate DP guarantees. In contrast, our work targets *Rényi differential privacy* and develops a principled distribution-free statistical framework that yields *finite-sample confidence intervals* and *minimax-optimal guarantees* for variational auditing of Rényi divergence directly.

Several works aim to detect DP violations or compute empirical lower bounds on privacy parameters (Ding et al., 2018; Guan et al., 2023; Ye et al., 2022). Ding et al. (2018) extend previous formulations of DP in terms of hypothesis tests (Kairouz et al., 2016; 2015) in order to detect counterexamples to DP, whereas DP-Finder (Bichsel et al., 2018) is used to search for DP violations as a sampling-and-optimization problem. These tools are powerful for debugging and falsifying incorrect implementations, but they are not designed to provide tight, sample-valid confidence bounds for *correct* algorithms, nor do they address RDP auditing or optimality guarantees. Our approach is complementary: rather than searching for explicit counterexamples, we characterize the *best possible accuracy* of any auditor via information-theoretic lower bounds, thereby establishing fundamental limits for RDP auditing.

There have been several previous works on variational representations of information-theoretic divergences (Donsker & Varadhan, 1983; Anantharam, 2018) and more recently on approximating a lower bound via neural networks with the most prominent being mutual information neural estimation (MINE) (Belghazi et al., 2018). Recent applications (Esfahanizadeh et al., 2023; Kim et al., 2024; 2025) use these networks to perform security and privacy analyses. Our work is the first to not only perform an empirical DP audit using these divergences, but also validate the findings with theoretical confidence bounds for both the DP estimate and lower bound estimate through neural networks.

2 Preliminaries and Background

2.1 Rényi Divergence Definition and Estimation

Definition 1 (Rényi divergence)**.** *The Rényi divergence of order $\alpha > 1$ between two probability distributions P and Q defined over $\mathbb{R}$ is $D_\alpha(P \,\|\, Q) = \frac{1}{\alpha-1} \log \mathbb{E}_{x\sim Q}\left[\left(\frac{P(x)}{Q(x)}\right)^\alpha\right]$, where all logarithms are natural; $P(x)$ and $Q(x)$ denote densities with respect to a common reference measure.*

Measuring the Rényi divergence and other information-theoretic divergences (such as Kullback-Leibler) has presented a challenge in high-dimensional random variables until recently. The previous work of Donsker & Varadhan (1983) presented a variational form of the KL divergence as a supremum over functions, later extended to the Rényi divergence by Anantharam (2018). The idea here is to use neural networks to approximate the supremum of the class of functions, and use that approximation to calculate a lower bound of divergences (Belghazi et al., 2018; Birrell et al., 2021).

Definition 2 (Variational representations of Rényi divergence)**.** *Let P and Q be probability measures on $(\Omega, \mathcal{M})$, $Q \ll P$, and $\alpha \in \mathbb{R}$, $\alpha \neq 0, 1$. Then for any set of functions, Γ, with $\mathcal{M}_b(\Omega) \subset \Gamma \subset \mathcal{M}(\Omega)$ (where $\mathcal{M}(\Omega)$ denotes the set of all real-valued measurable functions on Ω) we have $R_\alpha(Q\|P) = \sup_{g\in\Gamma}\left\{\frac{1}{\alpha-1}\log\left[\int e^{(\alpha-1)g}\, dQ\right] - \frac{1}{\alpha}\log\left[\int e^{\alpha g}\, dP\right]\right\}$ or $= \sup_{g\in\Gamma}\{\frac{1}{\alpha-1}\log \mathbb{E}_{X\sim Q}\left[e^{(\alpha-1)g(X)}\right] - \frac{1}{\alpha}\log \mathbb{E}_{Y\sim P}\left[e^{\alpha g(Y)}\right]\}$.*

To convert to the traditional Rényi divergence, the measure must be scaled by α so $\boldsymbol{D_\alpha(P||Q) = \alpha R_\alpha(P||Q)}$. Throughout the work we refer to the variational expression above as R_α and the true Rényi divergence as D_α. Much like Birrell et al. (2021), we parameterize the variational function class with a neural network and optimize the resulting sample-based objective via stochastic gradient descent. For improved numerical stability, we use mini-batching and exponential moving average (EMA) from MINE (Belghazi et al., 2018). EMA is a running average that mixes the current observation with a previous EMA providing stronger stability and less variance. Mini-batching allows us to optimize using Monte Carlo estimates of expectations, but can have bias and high variance due to the exponential terms in the loss functions. This issue is even more prevalent if one estimates the Rényi divergence with an order of α. In attempts to remedy the bias and variance we follow MINE's approach of maintaining an EMA that averages the exponent term over several mini batches and therefore stabilizes the resulting stochastic gradients. This is especially helpful when

Input: Order $\alpha > 1$, minibatch size b, EMA rate $\beta \in (0, 1)$, step size η
Output: Lower-bound estimate $R_\alpha^\Theta(Q\|P)$
$\theta \leftarrow$ initialize statistics network parameters
$m_Q \leftarrow 0; \quad m_P \leftarrow 0$
repeat
  Draw b minibatch samples from Q: $x^{(1)}, \ldots, x^{(b)} \sim Q$
  Draw b minibatch samples from P: $y^{(1)}, \ldots, y^{(b)} \sim P$
  Evaluate the lower-bound:

$$\mathcal{V}(\theta) \leftarrow \frac{1}{\alpha - 1} \log\Big(\frac{1}{b}\sum_{i=1}^{b} e^{(\alpha-1)T_\theta(x^{(i)})}\Big) - \frac{1}{\alpha}\log\Big(\frac{1}{b}\sum_{i=1}^{b} e^{\alpha T_\theta(y^{(i)})}\Big)$$

  Evaluate bias corrected gradients (e.g., moving average):
  $\widetilde{G}(\theta) \leftarrow \widetilde{\nabla}_\theta \mathcal{V}(\theta)$
  Update the statistics network parameters (gradient ascent): $\theta \leftarrow \theta + \eta\, \widetilde{G}(\theta)$
until *convergence*

Algorithm 1: DV-Rényi Divergence Estimation

estimating at a large order of α for a Rényi divergence. Variants using this formula in (Birrell et al., 2021) demonstrate a high mean squared error at larger α's, so we limit our experimental evaluation for the auditor to $\alpha \in (1, 2]$, a regime in which the estimator remains relatively accurate.

For our neural network, we choose $\Gamma_\Theta := \{ T_\theta : \Omega \to \mathbb{R} \ : \ \theta \in \Theta \} \subseteq \Gamma$, parametrized by a deep neural network with parameters $\theta \in \Theta$, the statistics network. We obtain the lower bound: $R_\alpha(Q\|P) \geq R_\alpha^\Theta(Q\|P)$, where $R_\alpha^\Theta(Q\|P) = \sup_{\theta\in\Theta} \left\{ \frac{1}{\alpha-1} \log \mathbb{E}_Q\left[e^{(\alpha-1)T_\theta}\right] - \frac{1}{\alpha}\log \mathbb{E}_P\left[e^{\alpha T_\theta}\right] \right\}$. The implementation for our Rényi divergence estimator is Algorithm 1. The proof for the formula can be found in Section 6.2 of (Birrell et al., 2021). Theoretical properties follow those in (Birrell et al., 2021; Belghazi et al., 2018), with specific analysis for DP included in later sections.

2.2 Differential Privacy

We now introduce DP and RDP. We define (ε, δ)- differential privacy (Dwork et al., 2006b;a) as follows.

Definition 3 (Differential Privacy)**.** *A randomized privacy mechanism $M : \mathcal{D} \to \mathcal{R}$ satisfies (ε, δ)-DP if for any adjacent $D, D' \in \mathcal{D}$ and any measurable $S \subseteq \mathcal{R}$ it holds that*

$$\Pr\big[M(D) \in S\big] \leq e^\varepsilon \Pr\big[M(D') \in S\big] + \delta,$$

where $0 \leq \delta \leq 1$.

Definition 4 (Rényi differential privacy)**.** *A randomized privacy mechanism $M : \mathcal{D} \to \mathcal{R}$ satisfies $(\alpha, \varepsilon_\alpha)$ Rényi-DP (Mironov, 2017) if for any adjacent $D, D' \in \mathcal{D}$ it holds that*

$$D_\alpha\big(M(D) \,\|\, M(D')\big) \leq \varepsilon_\alpha.$$

Note that as mentioned above, $\alpha \to \infty$ satisfies ε differential privacy. Further, we can then convert from RDP to (ε, δ)-DP using the formula provided in Proposition 3 in (Mironov, 2017). For a mechanism that satisfies $(\alpha, \varepsilon_\alpha)$ RDP, the mechanism also satisfies $(\varepsilon_\alpha + \frac{\log 1/\delta}{\alpha-1}, \delta)$-DP for $0 \leq \delta \leq 1$.

Since the Rényi Divergence is not symmetric, one takes the supremum of the divergence of all neighboring datasets mechanism outputs to see if the mechanism satisfies $(\alpha, \varepsilon_\alpha)$-RDP.

2.3 Hypothesis Testing and Statistical Estimation

As shown in prior works, we would like to frame our auditing result as a statistical estimation problem with a bounded estimation on the privacy parameters.

To begin, we start by viewing this in terms of hypothesis testing. Our null hypothesis is we have a privacy mechanism $M : \mathcal{D} \to \mathcal{R}$ that for any adjacent $D, D' \in \mathcal{D}$, satisfies $(\alpha, \varepsilon_\alpha)$-RDP if

Input : $x \in \mathcal{X}^n$
Model : Loss function $f : \mathbb{R}^d \times \mathcal{X} \to \mathbb{R}$
Parameters : number of iterations $\ell \geq 1$; clipping threshold $c > 0$; noise multiplier $\sigma > 0$; sampling probability $q \in (0, 1]$; learning rate $\eta > 0$

Initialize $w^0 \in \mathbb{R}^d$.
for $t = 1, \ldots, \ell$ **do**
  Sample $S^t \subseteq [n]$ with each $i \in [n]$ included independently with probability q.
  Compute per-example gradients $g_i^t \leftarrow \nabla_{w^{t-1}} f\big(w^{t-1}, x_i\big)$ for all $i \in S^t$.
  Clip $\hat{g}_i^t \leftarrow \min\Big\{1,\ \frac{c}{\|g_i^t\|_2}\Big\}\, g_i^t$ for all $i \in S^t$.
  Sample $\xi^t \sim \mathcal{N}\big(0,\ \sigma^2 c^2 I\big)$.
  Aggregate $\tilde{g}^t \leftarrow \xi^t + \sum_{i \in S^t} \hat{g}_i^t$.
  Update $w^t \leftarrow w^{t-1} - \eta \cdot \tilde{g}^t$.
end
return $w^0, w^1, \ldots, w^\ell$

Algorithm 2: DP-SGD — Differentially Private Stochastic Gradient Descent (Abadi et al., 2016)

$D_\alpha\big(M(D) \,\|\, M(D')\big) \leq \varepsilon_\alpha$. Our audit's goal is to test this hypothesis by running algorithm M. The output of the algorithm is $\widehat{R}_\alpha$. If M satisfies $(\alpha, \varepsilon_\alpha)$-RDP, with probability $1 - \beta$ we have $\widehat{R}_\alpha \leq \varepsilon_\alpha$. To view this in terms of hypothesis testing, start with the null hypothesis that the output of M satisfies $(\alpha, \varepsilon_{\text{null}})$-RDP. Let the hypothesis test's rejection set be $T_{\varepsilon,\alpha,\beta}$. If the null hypothesis is rejected, then we have a lower bound at $\widehat{R}_\alpha$. To convert between hypothesis testing and statistical estimation, consider the following lemma.

Lemma 1 (See Lemma 2)**.** *For each M and a fixed $\alpha > 1$, let $A_M \in \Omega$ be a random variable and let $P_M \in \mathbb{R}$ be a fixed number. For each $\varepsilon, \beta > 0$, let $T_{\varepsilon,\alpha,\beta} \subset \Omega$ satisfy*

$$\forall M \qquad \Big(P_M = \varepsilon \implies \mathbb{P}\big[A_M \in T_{\varepsilon,\alpha,\beta}\big] \leq \beta\Big). \tag{1}$$

Further suppose that, if $\varepsilon_1 \leq \varepsilon_2$, then $T_{\varepsilon_1,\alpha,\beta} \supset T_{\varepsilon_2,\alpha,\beta}$. Then, for all M and all $\beta > 0$,

$$\Pr\{\, P_M \geq \sup\{\varepsilon > 0 : A_M \in T_{\varepsilon,\alpha,\beta}\}\} \geq 1 - \beta. \tag{2}$$

The proof can be interpreted as the following: A_M is the auditing procedures output when applied to mechanism M that we are auditing, P_M is the true epsilon, ε_{true} that the mechanism satisfies. For Eq 8, if the null hypothesis is true, that is M is (α, ε)-RDP the probability we reject it is at most β. We estimate the true privacy parameter by taking the largest ε for which the null hypothesis can still be rejected. By properties of RDP, we can make the monotonicity assumption that was used in the proof, that if we can reject ε_2 and $\varepsilon_1 \leq \varepsilon_2$, we can also reject ε_1.

2.4 Black-Box Auditing Algorithm

In the black-box setting an adversary does not have intermediate access to a mechanism, and only can view/choose inputs and outputs. More on choosing specific model parameters and inputs can be found in our discussion. For our black-box auditing algorithm, we follow the standard algorithms shown in (Nasr et al., 2023; Muthu Selva Annamalai & De Cristofaro, 2024). In these works, one trains the model under DP-SGD both with and without the canary input. Lastly, we measure the Rényi divergence of the output losses either using a variational or numerical approach. The process is depicted in Algorithm 3.

3 Theoretical Results

In this section we present the main theoretical contributions of the paper.

3.1 Hypothesis Testing

Our test statistic for our auditing procedure is the empirical ε_α estimate, $\widehat{R}_\alpha$ obtained by running algorithm M. We define our null hypothesis as for an $\varepsilon_0 > 0$, $\alpha_0 > 1$ $D_{\alpha_0}\big(M(D) \,\|\, M(D')\big) \leq \varepsilon_0$,

Args: training dataset D, loss function ℓ, canary input (x', y'), number of observations T
Observations: $O \leftarrow \{\}$,
$O' \leftarrow \{\}$ **for** $t = 1$ *to* T **do**
  $\theta \leftarrow$ DP-SGD on dataset D
  $\theta' \leftarrow$ DP-SGD on dataset $D \cup \{(x', y')\}$
  $O[t] \leftarrow \ell(\theta, (x', y'))$
  $O'[t] \leftarrow \ell(\theta', (x', y'))$
end
Using each entry from 1 to T in O, O' and `Renyi` loss;
Estimate for ε_α: $\widehat{R}_\alpha = \max\{R_\alpha(O, O'), R_\alpha(O', O)\}$;
Return $\widehat{R}_\alpha, \alpha$

Algorithm 3: Black-box auditing for DP-SGD with Renyi divergence

$\forall \varepsilon_\alpha \geq \varepsilon_0, \alpha \leq \alpha_0$. To put it concretely, the null hypothesis is that the Rényi divergence at order α_0 satisfies $(\alpha_0, \varepsilon_0)$-RDP. Consequently, is also satisfies $(\alpha, \varepsilon_\alpha)$-RDP, $\forall \varepsilon_\alpha \geq \varepsilon_0, \alpha \leq \alpha_0$. This means our alternative hypothesis is for an $\varepsilon_1 > 0$, $\alpha_1 > 1$ $D_{\alpha_0}\big(M(D) \,\|\, M(D')\big) > \varepsilon_1$, The alternative hypothesis is that the Rényi divergence at order α_0 does not satisfy $(\alpha_0, \varepsilon_0)$-RDP. Consequently, it also does not hold for $(\alpha, \varepsilon_\alpha)$-RDP, for all $\varepsilon_\alpha \leq \varepsilon_0, \alpha \geq \alpha_0$. (See Lemma 1.)

3.2 Rényi-DP Lower Bound Analysis

In this section, we provide high-probability lower confidence bounds for the true Rényi divergence $D_\alpha(P\|Q)$ based on the empirical estimator computed by our auditing procedure. In Section B.1, we also discuss upper bounds.

Let $X_1, \ldots, X_n \sim Q$ denote the independent loss evaluations drawn under the canary-absent dataset, and write $L(x) = \log\left(\frac{p(x)}{q(x)}\right)$, $\quad Z_i = e^{\alpha L(X_i)}, \widehat{Z} = \frac{1}{n}\sum_{i=1}^n Z_i$, so that the empirical Rényi estimate returned by the auditor is $\widehat{D}_\alpha(P\|Q) = \frac{1}{\alpha-1}\log \widehat{Z}$. Recall that $\mu := \mathbb{E}_Q[Z_i] = \exp\big((\alpha-1)D_\alpha(P\|Q)\big)$, where $\mathbb{E}_Q[Z_i]$ is with respect to Q.

We now state finite-sample guarantees for estimating $D_\alpha(P\|Q)$. The lower bound (Theorem 1) follows from a direct application of Markov's inequality. In contrast, an *upper* confidence bound requires additional structural assumptions on the privacy-loss random variable; without such assumptions, no nontrivial distribution-free upper bound is possible for general nonnegative random variables. See Section B.1 for a discussion on upper bounds.

Lower confidence bound. We first recall the standard lower-tail guarantee for the empirical Rényi estimator.

Theorem 1 (Lower bound for Rényi-DP estimate)**.** *For any $\beta \in (0, 1)$, with probability at least $1 - \beta$, $D_\alpha(P\|Q) \geq \widehat{D}_\alpha(P\|Q) - \frac{1}{\alpha-1}\log\left(\frac{1}{\beta}\right)$.*

Proof. By Markov's inequality applied to $\widehat{Z}$ and the identity $\mu = \exp\big((\alpha-1)D_\alpha(P\|Q)\big)$, one obtains $\Pr[\widehat{Z} > \mu/\beta] \leq \beta$ so that with probability $\geq 1 - \beta$, $\mu \geq \beta\widehat{Z}$. Taking logarithms, we obtain $D_\alpha(P\|Q) = \frac{1}{\alpha-1}\log\mu \geq \frac{1}{\alpha-1}\log\widehat{Z} + \frac{1}{\alpha-1}\log\beta = \widehat{D}_\alpha(P\|Q) - \frac{1}{\alpha-1}\log\frac{1}{\beta}$. □

We can use the result we just solved for in the following way: Say we run our audit with output $\widehat{R_\alpha}$, Following Lemma 1, choose a desired confidence level $0 \leq 1 - \beta < 1$, and add $\frac{1}{\alpha-1}\log\beta$ to $\widehat{R_\alpha}$. Since if $\varepsilon_1 \leq \varepsilon_2$, $T_{\varepsilon_1,\alpha,\beta} \supset T_{\varepsilon_2,\alpha,\beta}$, choose $\varepsilon = \widehat{R}_\alpha + \frac{1}{\alpha-1}\log\beta$ for the lower bound.

3.3 DV Rényi Analysis

In this section, we solve for a non-asymptotic/finite-sample confidence bound for the DV Rényi representation and show that the bound is tight (up to polylogarithmic factors). As a corollary of

the finite-sample bound, we obtain that the DV Rényi representation estimator is consistent. That is, the estimation error for our DV Rényi representation converges to 0 when using neural networks to approximate the measure.

Theorem 2 (Consistency and finite-sample confidence interval for DV Rényi estimators (see Theorem 7))**.** *Let $\alpha \in \mathbb{R}_{>0} \setminus \{1\}$. Let P, Q be probability distributions on a measurable space Ω. Let $\{X_i\}_{i=1}^n \sim Q$ and $\{Y_i\}_{i=1}^n \sim P$ be independent samples.*

*Let $\Theta \subset \mathbb{R}^d$ be a parameter set with $\|\theta\| \le K$. Assume the critic family $\{T_\theta : \Omega \to \mathbb{R}\}_{\theta\in\Theta}$ satisfies: (i) (*Uniform boundedness*) $\sup_{\theta,z} |T_\theta(z)| \le M$. (ii) (*Lipschitz parameterization*) For all $z \in \Omega$, $|T_\theta(z) - T_{\theta'}(z)| \le L\|\theta - \theta'\|$. Define the population DV Rényi functional $V(\theta) := \frac{1}{\alpha-1} \log \mathbb{E}_Q\left[e^{(\alpha-1)T_\theta(X)}\right] - \frac{1}{\alpha} \log \mathbb{E}_P\left[e^{\alpha T_\theta(Y)}\right]$, and its empirical estimator $\widehat{V}_n(\theta) := \frac{1}{\alpha-1} \log\left(\frac{1}{n}\sum_{i=1}^n e^{(\alpha-1)T_\theta(X_i)}\right) - \frac{1}{\alpha} \log\left(\frac{1}{n}\sum_{i=1}^n e^{\alpha T_\theta(Y_i)}\right)$.*

Define $R_\alpha^\Theta(Q\|P) := \sup_{\theta\in\Theta} V(\theta)$, $\quad \widehat{R}_{\alpha,n}^\Theta(Q\|P) := \sup_{\theta\in\Theta} \widehat{V}_n(\theta)$.

Then for any $\delta \in (0,1)$, with probability at least $1-\delta$, $\left|\widehat{R}_{\alpha,n}^\Theta(Q\|P) - R_\alpha^\Theta(Q\|P)\right| \le \varepsilon_n(\delta)$, where $\varepsilon_n(\delta) = C_{\alpha,M}\left(\sqrt{\frac{d\log\left(\frac{K}{\eta}\right)+\log(1/\delta)}{n}} + \eta\right)$, for any $\eta > 0$, and $C_{\alpha,M} = O\left(e^{2|\alpha|M}\max\left\{\frac{1}{|\alpha-1|}, \frac{1}{|\alpha|}\right\}\right)$.

In particular, choosing $\eta = O(n^{-1/2})$ yields a valid $(1-\delta)$ finite-sample confidence interval $\left[\widehat{R}_{\alpha,n}^\Theta(Q\|P) - \varepsilon_n(\delta),\ \widehat{R}_{\alpha,n}^\Theta(Q\|P) + \varepsilon_n(\delta)\right]$. Moreover, the estimator $\widehat{R}_{\alpha,n}^\Theta(Q\|P)$ is consistent in the sense: $\left|\widehat{R}_{\alpha,n}^\Theta(Q\|P) - R_\alpha^\Theta(Q\|P)\right| \to 0$ as $n \to \infty$.

Theorem 2 establishes that the class-restricted DV Rényi estimator converges at a rate scaling as $O(d/\varepsilon^2)$ (up to logarithmic factors). We now show that this dependence is unavoidable in general. Specifically, we prove an information-theoretic lower bound demonstrating that, under the same boundedness and Lipschitz assumptions on the critic class, no estimator can uniformly estimate the population DV objective $\theta \mapsto V(\theta)$ with accuracy ε and constant success probability unless the sample size scales as $\Omega(d/\varepsilon^2)$. This result matches Theorem 2 in its leading dependence on the critic dimension and accuracy, establishing minimax-optimality up to logarithmic factors.

Theorem 3 (Lower bound matching Theorem 2 up to log factors (see Theorem 8))**.** *Fix $\alpha \in \mathbb{R}_{>0}\setminus\{1\}$. There exist constants $c, c_0, c_1 > 0$, depending only on α, such that the following holds. For every sufficiently large d, there exist a measurable space Ω, a parameter set $\Theta \subset \mathbb{R}^d$, a critic class $\{T_\theta : \Omega \to \mathbb{R}\}_{\theta\in\Theta}$, and a family of distribution pairs $\mathcal{P}_d = \{(P, Q_u) : u \in \mathcal{U}_d\}$ such that: $\|\theta\|_2 \le 1, \quad |T_\theta(z)| \le 1, \quad |T_\theta(z) - T_{\theta'}(z)| \le c_0\|\theta - \theta'\|_2$ for all $\theta, \theta' \in \Theta$ and all $z \in \Omega$, and the following minimax lower bound holds. Let*

$$V_{P,Q}(\theta) = \frac{1}{\alpha-1}\log \mathbb{E}_Q\left[e^{(\alpha-1)T_\theta(X)}\right] - \frac{1}{\alpha}\log \mathbb{E}_P\left[e^{\alpha T_\theta(Y)}\right].$$

For any estimator $\widehat{V}_n : \Theta \to \mathbb{R}$ based on n i.i.d. samples from Q and n i.i.d. samples from P,

$$\inf_{\widehat{V}_n} \sup_{(P,Q)\in\mathcal{P}_d} \Pr_{P,Q}\left[\sup_{\theta\in\Theta}\left|\widehat{V}_n(\theta) - V_{P,Q}(\theta)\right| \ge \varepsilon\right] \ge \frac{1}{4}$$

whenever $n \le c\,\frac{d}{\varepsilon^2}$, for all $0 < \varepsilon \le c_1$. Consequently, any distribution-free confidence band that controls $\sup_{\theta\in\Theta}|\widehat{V}_n(\theta) - V_{P,Q}(\theta)|$ must have sample complexity at least $\Omega(d/\varepsilon^2)$ in general.

Our theoretical results isolate the statistical estimation error of the class-restricted Donsker–Varadhan objective. Although Algorithm 1 introduces optimization errors, our theorem represents an estimation-theoretic guarantee for the variational objective. Since optimization error can only reduce the value attained by the learned critic relative to the empirical supremum, the resulting lower bound becomes more conservative. The optimization error can be observed in our experiments, Section 4.

4 Experimental Results

As discussed in Section 2.1, in our reported audits, we convert the variational objective to the standard Rényi divergence normalization. Thus, whenever Algorithm 1 returns $R_\alpha^\Theta(Q\|P)$, the certified RDP

lower bound is $\alpha R_\alpha^\Theta(Q\|P)$. For simplicity, all experimental results report values in the standard RDP scale.

In this section we evaluate our auditing procedure using image datasets commonly used to benchmark differentially private machine learning models. (Additional experimental results can be found in Section C.) We include results for audited privacy level $\widehat{\varepsilon}_{emp}$ from our neural estimation model We collect 500 loss observations for each canary in (O) and canary out (O') at a privacy level for each experiment. To estimate the Rényi divergence which doubles as a $\widehat{\varepsilon}_{emp}$, we use the DV Rényi model. We compare our black-box RDP results to (Muthu Selva Annamalai & De Cristofaro, 2024), performing the appropriate conversions between $\mu-$GDP (Dong et al., 2019), (ε, δ)-DP, and $(\alpha, \varepsilon_\alpha)$-RDP. Specifically, we start with $(\varepsilon, 10^{-5})$-DP, convert to $\mu-$GDP, and then to $(1.25, \varepsilon_\alpha)$ and $(2, \varepsilon_\alpha)$-RDP.

4.1 Datasets and Models

For our datasets $(\mathcal{D})$, we use the MNIST (LeCun, 1998) and CIFAR-10 (Krizhevsky et al., 2009) datasets. MNIST is composed of 28×28 grayscale images with 60,000 training samples and 10,000 testing samples. There are 10 separate classes for digits 0–9. CIFAR-10 has 50,000 training and 10,000 testing samples on 32×32 RGB images and also consists of 10 classes. The model that we are most interested in auditing is the convolutional neural networks (CNNs). Batch sizes are set to n to ease auditing. We assume adversaries have the option to choose the canary. Previous works have experimented with both blank samples (Nasr et al., 2023) and ClipBKD (Jagielski et al., 2020). The blank canary just has all values of 0, and the ClipBKD canary is calculated by taking the training set, performing a principal component analysis, and using the last principal component. For our experiments we use blank canaries for our CNN models.

4.2 Crafting Worst-Case Initial Parameters

DP-SGD's privacy holds for both randomly initialized models as well as models with fixed parameters (Nasr et al., 2023; Jagielski et al., 2020). We follow the method in (Muthu Selva Annamalai & De Cristofaro, 2024) of crafting worst-case initial parameters. We pre-train the CNN models when analyzing the MNIST dataset on half of the full dataset for 5 epochs with a batch size of 32 and learning rate of $1e^{-2}$. For analyzing the CNN on CIFAR-10, we pre-train the model on the CIFAR-100 dataset for 300 epochs with batch size 128 and a learning rate of 0.1. Then, we (non-privately) fine-tune the model on half of the full dataset for 100 epochs, with a batch size of 256 and a learning rate of 0.1.

4.3 Results

When privately training the model we set the batch size to the dataset size and the clipping threshold to $C = 1.0$. We privately train the model for 100 epochs on the other half of the dataset not used for pretraining. We privately train our models calibrating the noise σ to satisfy $\mu-$GDP with $\mu = [0.5, 1, \sqrt{2}, 2, \sqrt{10}]$, which can then be converted to $(2, \varepsilon_\alpha)$-RDP with $\varepsilon_\alpha = [0.25, 1.0, 2.0, 4.0, 10.0]$ and $(1.25, \varepsilon_\alpha)$-RDP with $\varepsilon_\alpha = [0.15625, 0.625, 1.25, 2.5, 6.25]$. Note that these conversions also satisfy $(\varepsilon, 10e^{-5})$-DP, where ε is $[2.0, 4.38, 6.57, 10.0, 17.85]$. For all of our results, we include the results from the auditing method of Muthu Selva Annamalai & De Cristofaro (2024) (yellow on graphs), which is the current state of the art for black-box auditing. We showcase experimental efficiency here with additional experiments in the appendix.

The results for $\alpha = 1.25$ are shown in Table 1, and the results for $\alpha = 2.0$ are shown in Table 2. We show an overall improvement on the current state of the art.

4.4 Discussion

Our experiments show that the proposed auditing framework yields an overall improvement on black-box RDP audits than prior state-of-the-art methods across datasets, models, and privacy regimes. In particular, our DV-based estimator recovers larger empirical Rényi divergence values, with the most pronounced gains at low and moderate privacy parameters, where accurate auditing is typically most difficult. These improvements stem from directly auditing *Rényi divergence itself*, rather than relying

Table 1: Empirical RDP audits at $\alpha = 1.25$.

Dataset	Target ε_α	SOTA black-box	DV-Rényi
MNIST	0.15625	0.056 ± 0.025	$\mathbf{0.115} \pm 0.080$
	0.625	0.272 ± 0.020	$\mathbf{0.469} \pm 0.197$
	1.25	0.588 ± 0.016	$\mathbf{0.995} \pm 0.289$
	2.5	1.256 ± 0.091	$\mathbf{2.239} \pm 0.473$
	6.25	3.325 ± 0.218	$\mathbf{3.884} \pm 0.327$
CIFAR-10	0.15625	0.031 ± 0.004	$\mathbf{0.118} \pm 0.025$
	0.625	0.289 ± 0.050	$\mathbf{0.551} \pm 0.056$
	1.25	0.693 ± 0.082	$\mathbf{1.095} \pm 0.120$
	2.5	1.539 ± 0.234	$\mathbf{2.248} \pm 0.344$
	6.25	4.128 ± 0.336	$\mathbf{4.577} \pm 0.430$

Table 2: Empirical RDP lower-bound audits at $\alpha = 2.0$.

Dataset	Target ε_α	SOTA black-box	DV-Rényi
MNIST	0.25	0.089 ± 0.040	$\mathbf{0.202} \pm 0.142$
	1.0	0.436 ± 0.032	$\mathbf{0.867} \pm 0.339$
	2.0	0.940 ± 0.025	$\mathbf{1.527} \pm 0.325$
CIFAR-10	0.25	0.050 ± 0.007	$\mathbf{0.206} \pm 0.041$
	1.0	0.463 ± 0.080	$\mathbf{0.953} \pm 0.213$
	2.0	1.109 ± 0.131	$\mathbf{1.624} \pm 0.178$

on indirect privacy conversions or attack-specific heuristics. By framing RDP auditing as a statistical estimation problem with explicit confidence guarantees, our approach cleanly separates estimation error from true privacy leakage, avoiding premature saturation observed in earlier methods. The use of worst-case initialization further increases statistical power by amplifying the canary's influence on training dynamics, while preserving the validity of DP-SGD's privacy guarantees. The observed experimental trends align closely with our theoretical analysis. Smaller datasets increase the relative impact of the canary and lead to tighter audits, while larger clipping norms inject more noise and reduce detectability; both effects predicted by our finite-sample bounds. We note specifically that the DV-based estimator is flexible and provides sample-valid confidence intervals, ensuring statistical soundness. The strong empirical performance of our method is consistent with the minimax lower bounds proved in Section 3, suggesting that further improvements are fundamentally limited by information-theoretic constraints.

5 Conclusion

This work establishes a principled foundation for auditing machine learning systems that claim Rényi differential privacy. By formulating RDP auditing as a statistical estimation problem, we derived explicit, non-asymptotic confidence guarantees for black-box audits based on variational Rényi divergence estimators. Our analysis provides both finite-sample lower confidence bounds and matching minimax lower bounds, thereby characterizing the fundamental statistical limits of estimating the class-restricted DV Rényi auditing objective. Beyond theory, our empirical results demonstrate that the proposed methods yield substantial overall improvements: our black-box audits of DP-SGD outperform previous work, especially at small and moderate Rényi orders, across a range of datasets and model architectures. Several directions remain open: An important avenue for future work is extending optimal Rényi auditing guarantees to interactive and distributed settings. Another is exploring alternative variational formulas (Birrell et al., 2023) that exhibit lower variance for larger values of $\alpha > 1$.

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AI USE STATEMENT

In this work, we used generative AI tools for generating the code to run the experiments.

We have reviewed all AI-assisted work. We take full responsibility for the final content of this work.

A NOTIONS OF DP AND THEIR CONVERSIONS

In our experiments, we convert our results from traditional (ε, δ)-DP to Gaussian DP ($\mu-$GDP) (Dong et al., 2019) to $(\alpha, \varepsilon_\alpha)$-RDP. We convert with Corollary 2.13 and B6 in (Dong et al., 2019).

Corollary 1. *(2.13): A mechanism is μ-GDP if and only if it is $(\varepsilon, \delta(\varepsilon))$-DP for all $\varepsilon \geq 0$, where:*

$$\delta(\varepsilon) = \Phi\left(-\frac{\varepsilon}{\mu} + \frac{\mu}{2}\right) - e^{\varepsilon}\,\Phi\left(-\frac{\varepsilon}{\mu} - \frac{\mu}{2}\right). \tag{3}$$

Corollary 2. *(B6): If a mechanism is μ-GDP, then it is $(\alpha, \frac{1}{2}\mu^2\alpha)$-RDP for any $\alpha > 1$.*

B ADDITIONAL THEORETICAL RESULTS AND OMITTED PROOFS (FROM MAIN BODY)

This appendix provides supporting theoretical results that complement and strengthen the main guarantees in the main body. While the main body of the paper focuses on just stating lower confidence bounds and minimax-optimal estimation of Rényi divergence via variational (DV-based) methods, we provide proofs we could not include in the main body (due to space restrictions).

In this appendix, our results clarify three important aspects:

1. **What can and cannot be estimated from finite samples.** We show that lower confidence bounds on Rényi divergence are available under no assumptions, whereas meaningful upper confidence bounds are impossible without additional structural constraints on the privacy-loss random variable. This delineates a sharp boundary between what empirical privacy auditing can guarantee in a distribution-free manner and what requires stronger modeling assumptions.
2. **How bounded privacy loss enables two-sided confidence intervals.** By imposing a bounded privacy-loss assumption (exact for pure DP and a reasonable high-probability surrogate for many RDP mechanisms) we derive finite-sample upper and lower confidence bounds using classical concentration inequalities. These results justify when empirical audits can certify both privacy violations and near-tight compliance.
3. **Why the DV-based estimator is statistically sound for auditing.** We provide a full non-asymptotic analysis of the DV variational estimator over restricted critic classes, showing uniform convergence, explicit rates, and consistency. This formally validates the use of neural divergence estimators as statistically principled auditing tools, rather than heuristic approximations.

Our results complete the theoretical foundation of our auditing framework by characterizing both its guarantees and its fundamental limitations.

B.1 RÉNYI-DP UPPER BOUND ANALYSIS

We adopt a natural bounded privacy-loss assumption, which holds exactly for $(\varepsilon, 0)$-DP mechanisms and serves as an effective high-probability surrogate for many RDP mechanisms in practice.

Upper confidence bound under bounded privacy loss. In contrast to the lower bound, an upper bound on $D_\alpha(P\|Q)$ from samples cannot be obtained without further assumptions: there exist distributions with arbitrarily large means that nevertheless produce finitely many small observations with high probability. We therefore impose the following assumption, natural for many DP mechanisms:

Assumption 4 (Bounded privacy loss)**.** *There exists $B \in \mathbb{R}$ such that $L(x) \le B$ for all x in the support of Q. Equivalently, $\frac{p(x)}{q(x)} \le e^B$ for all x. Under this assumption,*

$$0 \;\le\; Z_i = e^{\alpha L(X_i)} \;\le\; e^{\alpha B} \;=:\; M \qquad \textit{for all } i.$$

This is exact for $(\varepsilon, 0)$-DP mechanisms, where $B = \varepsilon$, and serves as a practical high-probability truncation model for Gaussian or other mechanisms.

Theorem 5 (Upper bound for Rényi-DP estimate under bounded privacy loss)**.** *Suppose Assumption 4 holds. Then for any $\beta \in (0,1)$, with probability at least $1-\beta$,*

$$D_\alpha(P\|Q) \;\le\; \frac{1}{\alpha-1}\log\left(\widehat{Z} \;+\; e^{\alpha B}\sqrt{\frac{\log(2/\beta)}{2n}}\right).$$

Equivalently, defining

$$\widehat{\varepsilon}_\alpha^{\,\mathrm{upper}} := \frac{1}{\alpha-1}\log\left(\widehat{Z} \;+\; e^{\alpha B}\sqrt{\tfrac{\log(2/\beta)}{2n}}\right),$$

we have $\Pr[\, D_\alpha(P\|Q) \le \widehat{\varepsilon}_\alpha^{\,\mathrm{upper}}\,] \ge 1-\beta$.

Proof. Under Assumption 4, $Z_i \in [0, M]$ almost surely. Hoeffding's inequality yields

$$\Pr\Big[\big|\widehat{Z} - \mu\big| \ge t\Big] \;\le\; 2\exp\left(-\frac{2nt^2}{M^2}\right) \qquad \text{for all } t > 0.$$

Setting $t = M\sqrt{\log(2/\beta)/(2n)}$ gives a deviation probability at most β, hence with probability at least $1-\beta$,

$$\mu \;\le\; \widehat{Z} + M\sqrt{\tfrac{\log(2/\beta)}{2n}} = \widehat{Z} + e^{\alpha B}\sqrt{\tfrac{\log(2/\beta)}{2n}}.$$

Since $\mu = \exp\big((\alpha-1)D_\alpha(P\|Q)\big)$, taking logarithms and dividing by $(\alpha-1)$ gives the stated upper bound. □

Unlike lower confidence bounds, which follow directly from Markov-type arguments and hold for arbitrary nonnegative random variables, upper confidence bounds on Rényi divergence cannot be obtained in a fully distribution-free manner. So, a random variable may have arbitrarily large expectation while producing small empirical averages with high probability, making any finite-sample upper bound vacuous without further structure.

For privacy auditing, this means that while violations of claimed RDP guarantees can always be certified from data, certifying near-tight compliance necessarily requires assumptions about the privacy-loss distribution. The bounded privacy-loss assumption introduced below captures exactly the setting of pure differential privacy and serves as a realistic approximation for many RDP mechanisms used in practice.

B.2 Tighter lower bound with Hoeffding's Inequality

We can prove a tighter lower bound for the Rényi divergence using similar assumptions to Theorem 5.

Theorem 6 (Lower confidence bound under bounded privacy loss (Hoeffding))**.** *Fix $\alpha > 1$. Assume Assumption 4 holds. Then for any $\beta \in (0,1)$, with probability at least $1-\beta$,*

$$D_\alpha(P\|Q) \;\ge\; \frac{1}{\alpha-1}\log\left(\max\left\{1,\; \widehat{Z} - M\sqrt{\frac{\log(1/\beta)}{2n}}\right\}\right).$$

Proof. Under the bounded privacy-loss assumption, we have $0 \le Z_i \le M$ almost surely. Hence $\widehat{Z} = \frac{1}{n}\sum_{i=1}^n Z_i$ is an average of i.i.d. bounded random variables. By Hoeffding's inequality (one-sided lower tail), for all $t > 0$,

$$\Pr\Big(\widehat{Z} - \mu \le -t\Big) \;\le\; \exp\left(-\frac{2nt^2}{M^2}\right). \tag{4}$$

Set

$$t := M\sqrt{\frac{\log(1/\beta)}{2n}}.$$

Then $\exp\left(-\frac{2nt^2}{M^2}\right) = \beta$, and (4) becomes

$$\Pr\left(\widehat{Z} - \mu \le -t\right) \le \beta,$$

which is equivalent to: with probability at least $1-\beta$,

$$\mu \;\ge\; \widehat{Z} - t. \tag{5}$$

Also, for $\alpha > 1$, Rényi divergence is nonnegative, hence $\mu \ge 1$. Combining this deterministic fact with (5), we obtain on the same event

$$\mu \;\ge\; \max\{1, \widehat{Z} - t\}.$$

We know that $D_\alpha(P\|Q) = \frac{1}{\alpha-1}\log\mu$, which yields

$$D_\alpha(P\|Q) = \frac{1}{\alpha-1}\log\mu \;\ge\; \frac{1}{\alpha-1}\log\Big(\max\{1, \widehat{Z} - t\}\Big).$$

Substituting $t = M\sqrt{\frac{\log(1/\beta)}{2n}}$ and $M = e^{\alpha B}$ completes the proof. □

B.3 Finite-sample Confidence Intervals for DV Rényi estimators

Why Uniform Convergence of the DV Estimator Matters The DV variational representation is central to our auditing methodology, as it allows Rényi divergence to be estimated via optimization over a parameterized function class. However, for auditing purposes, pointwise convergence for a fixed critic is insufficient: the estimator must converge *uniformly* over the entire class to justify taking a supremum.

Theorem 7 establishes this uniform convergence under mild boundedness and Lipschitz assumptions, yielding explicit finite-sample confidence intervals and consistency guarantees. This result bridges modern neural divergence estimation techniques with classical statistical learning theory, and ensures that the resulting privacy audits admit rigorous, sample-valid interpretation.

Theorem 7 (Consistency and finite-sample confidence interval for DV Rényi estimators)**.** *Let $\alpha \in \mathbb{R}_{>0} \setminus \{1\}$. Let P, Q be probability distributions on a measurable space Ω. Let $\{X_i\}_{i=1}^n \sim Q$ and $\{Y_i\}_{i=1}^n \sim P$ be independent samples.*

Let $\Theta \subset \mathbb{R}^d$ be a parameter set with $\|\theta\| \le K$. Assume the critic family $\{T_\theta : \Omega \to \mathbb{R}\}_{\theta\in\Theta}$ satisfies:

1. *(**Uniform boundedness**)* $\sup_{\theta,z} |T_\theta(z)| \le M$.
2. *(**Lipschitz parameterization**) For all $z \in \Omega$,*

$$|T_\theta(z) - T_{\theta'}(z)| \le L\|\theta - \theta'\|.$$

Define the population DV Rényi functional

$$V(\theta) := \frac{1}{\alpha-1}\log\mathbb{E}_Q\left[e^{(\alpha-1)T_\theta(X)}\right] - \frac{1}{\alpha}\log\mathbb{E}_P\left[e^{\alpha T_\theta(Y)}\right],$$

and its empirical estimator

$$\widehat{V}_n(\theta) := \frac{1}{\alpha-1}\log\left(\frac{1}{n}\sum_{i=1}^n e^{(\alpha-1)T_\theta(X_i)}\right) - \frac{1}{\alpha}\log\left(\frac{1}{n}\sum_{i=1}^n e^{\alpha T_\theta(Y_i)}\right).$$

Define

$$R_\alpha^\Theta(Q\|P) := \sup_{\theta\in\Theta} V(\theta), \qquad \widehat{R}_{\alpha,n}^\Theta(Q\|P) := \sup_{\theta\in\Theta} \widehat{V}_n(\theta).$$

Then for any $\delta \in (0,1)$, with probability at least $1-\delta$,

$$\left|\widehat{R}^{\Theta}_{\alpha,n}(Q\|P) - R^{\Theta}_{\alpha}(Q\|P)\right| \;\le\; \varepsilon_n(\delta),$$

where

$$\varepsilon_n(\delta) = C_{\alpha,M}\left(\sqrt{\frac{d\log\left(\frac{K}{\eta}\right)+\log(1/\delta)}{n}}+\eta\right),$$

for any $\eta > 0$, and

$$C_{\alpha,M} = O\Big(e^{2|\alpha|M}\max\Big\{\tfrac{1}{|\alpha-1|},\tfrac{1}{|\alpha|}\Big\}\Big).$$

In particular, choosing $\eta = O(n^{-1/2})$ yields a valid $(1-\delta)$ finite-sample confidence interval

$$\Big[\widehat{R}^{\Theta}_{\alpha,n}(Q\|P) - \varepsilon_n(\delta),\ \widehat{R}^{\Theta}_{\alpha,n}(Q\|P) + \varepsilon_n(\delta)\Big].$$

In addition, the estimator $\widehat{R}^{\Theta}_{\alpha,n}(Q\|P)$ is consistent in the following sense: $\left|\widehat{R}^{\Theta}_{\alpha,n}(Q\|P) - R^{\Theta}_{\alpha}(Q\|P)\right| \to 0$ as $n \to \infty$.

Proof. The proof for the finite-sample bound proceeds in four steps.

Step 1: Concentration for fixed θ. Define

$$A_\theta := \mathbb{E}_Q[e^{(\alpha-1)T_\theta(X)}], \qquad \widehat{A}_\theta := \frac{1}{n}\sum_{i=1}^{n} e^{(\alpha-1)T_\theta(X_i)}.$$

Since $|T_\theta| \le M$,

$$e^{-|\alpha-1|M} \le e^{(\alpha-1)T_\theta(X)} \le e^{|\alpha-1|M}.$$

Thus $\widehat{A}_\theta$ is an average of i.i.d. bounded random variables. Hoeffding's inequality implies that for all $t > 0$,

$$\mathbb{P}\left(|\widehat{A}_\theta - A_\theta| \ge t\right) \le 2\exp\left(-\frac{nt^2}{2e^{2|\alpha-1|M}}\right).$$

Similarly, define

$$B_\theta := \mathbb{E}_P[e^{\alpha T_\theta(Y)}], \qquad \widehat{B}_\theta := \frac{1}{n}\sum_{i=1}^{n} e^{\alpha T_\theta(Y_i)},$$

and obtain

$$\mathbb{P}\left(|\widehat{B}_\theta - B_\theta| \ge t\right) \le 2\exp\left(-\frac{nt^2}{2e^{2|\alpha|M}}\right).$$

Step 2: From moment errors to log errors. Since $A_\theta, \widehat{A}_\theta \ge e^{-|\alpha-1|M}$, the logarithm is Lipschitz on this interval with constant $e^{|\alpha-1|M}$. Thus

$$|\log \widehat{A}_\theta - \log A_\theta| \le e^{|\alpha-1|M}|\widehat{A}_\theta - A_\theta|.$$

An analogous bound holds for $\log \widehat{B}_\theta$.

Combining both terms,

$$|\widehat{V}_n(\theta) - V(\theta)| \le \frac{e^{|\alpha-1|M}}{|\alpha-1|}|\widehat{A}_\theta - A_\theta| + \frac{e^{|\alpha|M}}{|\alpha|}|\widehat{B}_\theta - B_\theta|.$$

Therefore there exists a constant $c > 0$ such that

$$\mathbb{P}\left(|\widehat{V}_n(\theta) - V(\theta)| \ge u\right) \le 4\exp\left(-c\,n\,u^2 e^{-4|\alpha|M}\right).$$

Step 3: Uniformization over Θ via covering numbers. Let $\mathcal{N}_\eta$ be an η-net of Θ in Euclidean norm. Since $\Theta \subseteq B(0,K) \subset \mathbb{R}^d$,

$$|\mathcal{N}_\eta| \le \left(\frac{3K}{\eta}\right)^d.$$

Applying a union bound,

$$\mathbb{P}\left(\max_{\vartheta\in\mathcal{N}_\eta} |\widehat{V}_n(\vartheta) - V(\vartheta)| \ge u\right) \le |\mathcal{N}_\eta| \cdot 4\exp\left(-c\,n\,u^2 e^{-4|\alpha|M}\right).$$

Choosing

$$u = C_{\alpha,M}\sqrt{\frac{d\log(K/\eta) + \log(1/\delta)}{n}}$$

ensures the above probability is at most $\delta/2$.

Step 4: Extension from the net to all parameters. The Lipschitz assumption implies that both $V(\theta)$ and $\widehat{V}_n(\theta)$ are Lipschitz in θ with constant $O(|\alpha|Le^{2|\alpha|M})$. Hence for any $\theta \in \Theta$ and nearest net point $\vartheta \in \mathcal{N}_\eta$,

$$|\widehat{V}_n(\theta) - V(\theta)| \le |\widehat{V}_n(\vartheta) - V(\vartheta)| + O(\eta).$$

Taking the supremum over θ yields

$$\sup_{\theta\in\Theta} |\widehat{V}_n(\theta) - V(\theta)| \le \max_{\vartheta\in\mathcal{N}_\eta} |\widehat{V}_n(\vartheta) - V(\vartheta)| + O(\eta).$$

Step 5: Confidence interval for the supremum. Finally, for any functions f, g,

$$|\sup f - \sup g| \le \sup|f - g|.$$

Applying this inequality completes the proof of the finite-sample bound.

The consistency statement follows from the finite-sample bound.

□

Corollary 3 (DP-auditing via finite-sample DV Rényi certificates)**.** *Fix $\alpha \in (1,\infty)$ and let $\delta_{\mathrm{CI}} \in (0,1)$. Consider neighboring datasets D, D' and let $P := \mathsf{M}(D)$ and $Q := \mathsf{M}(D')$ denote the output distributions of a (possibly randomized) mechanism M. Let $\Theta \subset \mathbb{R}^d$ and $\{T_\theta\}_{\theta\in\Theta}$ satisfy the assumptions of Theorem 2 (boundedness and Lipschitz parameterization).*

Suppose we can draw independent samples $\{Y_i\}_{i=1}^n \overset{iid}{\sim} P$ and $\{X_i\}_{i=1}^n \overset{iid}{\sim} Q$, and compute the empirical DV Rényi estimator

$$\widehat{R}^{\Theta}_{\alpha,n}(Q\|P) := \sup_{\theta\in\Theta} \widehat{V}_n(\theta) \quad \textit{as defined in Theorem 2.}$$

Let $\varepsilon_n(\delta_{\mathrm{CI}})$ be the corresponding confidence radius from Theorem 2. Define the one-sided lower confidence bound (LCB)

$$\mathrm{LCB}_{\alpha,n} \;:=\; \widehat{R}^{\Theta}_{\alpha,n}(Q\|P) - \varepsilon_n(\delta_{\mathrm{CI}}).$$

Then with probability at least $1-\delta_{\mathrm{CI}}$ over the samples,

$$R^{\Theta}_{\alpha}(Q\|P) \;\ge\; \mathrm{LCB}_{\alpha,n}.$$

Consequently, for any claimed Rényi-DP level $\rho \ge 0$ (at order α), the following auditing test *is valid:*

$$\textit{Reject the null } H_0 :\; R^{\Theta}_{\alpha}(Q\|P) \le \rho \quad \textit{if } \mathrm{LCB}_{\alpha,n} > \rho.$$

This test has Type-I error at most δ_{CI}:

$$\sup_{(P,Q):\, R^{\Theta}_{\alpha}(Q\|P)\le\rho} \mathbb{P}\big(\mathrm{LCB}_{\alpha,n} > \rho\big) \;\le\; \delta_{\mathrm{CI}}.$$

Moreover, this yields a conservative (ε,δ)-DP violation certificate*: for any target $\delta \in (0,1)$, define*

$$\varepsilon_{\mathrm{LCB}}(\delta) := \frac{\alpha-1}{\alpha}\,\mathrm{LCB}_{\alpha,n} + \frac{1}{\alpha}\log\Big(\frac{1}{\delta}\Big).$$

Then, with probability at least $1-\delta_{\mathrm{CI}}$, the mechanism M cannot satisfy (ε,δ)-DP for any $\varepsilon < \varepsilon_{\mathrm{LCB}}(\delta)$; equivalently,

$$\textit{if } \varepsilon < \varepsilon_{\mathrm{LCB}}(\delta), \;\; \textit{then } \; \mathsf{M} \textit{ violates } (\varepsilon,\delta)\textit{-DP}.$$

Proof. The first claim is immediate from Theorem 2: with probability at least $1 - \delta_{\mathrm{CI}}$,

$$\left|\widehat{R}^{\Theta}_{\alpha,n}(Q\|P) - R^{\Theta}_{\alpha}(Q\|P)\right| \le \varepsilon_n(\delta_{\mathrm{CI}}),$$

which rearranges to $R^{\Theta}_{\alpha}(Q\|P) \ge \widehat{R}^{\Theta}_{\alpha,n}(Q\|P) - \varepsilon_n(\delta_{\mathrm{CI}}) = \mathrm{LCB}_{\alpha,n}$.

For the hypothesis test, under the null H_0 we have $R^{\Theta}_{\alpha}(Q\|P) \le \rho$. On the event $\{R^{\Theta}_{\alpha}(Q\|P) \ge \mathrm{LCB}_{\alpha,n}\}$ (which holds with probability at least $1 - \delta_{\mathrm{CI}}$), the inequality $\mathrm{LCB}_{\alpha,n} > \rho$ cannot occur. Hence

$$\mathbb{P}_{H_0}\big(\mathrm{LCB}_{\alpha,n} > \rho\big) \le \mathbb{P}\big(R^{\Theta}_{\alpha}(Q\|P) < \mathrm{LCB}_{\alpha,n}\big) \le \delta_{\mathrm{CI}}.$$

For the (ε, δ)-DP violation certificate, recall the standard implication: if a mechanism is ρ-RDP at order $\alpha > 1$, i.e. $R_\alpha(Q\|P) \le \rho$ for all neighboring pairs, then it is also (ε, δ)-DP with

$$\varepsilon = \rho + \frac{\log(1/\delta)}{\alpha - 1}.$$

Equivalently (contrapositive), if for some neighboring (P, Q) we have

$$R_\alpha(Q\|P) > \varepsilon - \frac{\log(1/\delta)}{\alpha - 1},$$

then the mechanism violates (ε, δ)-DP. Applying this contrapositive with the class-restricted divergence and the lower bound $R^{\Theta}_{\alpha}(Q\|P) \ge \mathrm{LCB}_{\alpha,n}$ shows that on the same high-probability event, whenever

$$\mathrm{LCB}_{\alpha,n} > \varepsilon - \frac{\log(1/\delta)}{\alpha - 1},$$

the mechanism cannot satisfy (ε, δ)-DP. Rearranging gives the stated threshold

$$\varepsilon < \mathrm{LCB}_{\alpha,n} + \frac{\log(1/\delta)}{\alpha - 1}.$$

□

Theorem 8 (Lower bound matching Theorem 7 up to log factors)**.** *Fix $\alpha \in \mathbb{R}_{>0} \setminus \{1\}$. There exist constants $c, c_0, c_1 > 0$, depending only on α, such that the following holds. For every sufficiently large d, there exist a measurable space Ω, a parameter set $\Theta \subset \mathbb{R}^d$, a critic class $\{T_\theta : \Omega \to \mathbb{R}\}_{\theta\in\Theta}$, and a family of distribution pairs*

$$\mathcal{P}_d = \{(P, Q_u) : u \in \mathcal{U}_d\}$$

such that:

$$\|\theta\|_2 \le 1, \qquad |T_\theta(z)| \le 1, \qquad |T_\theta(z) - T_{\theta'}(z)| \le c_0\|\theta - \theta'\|_2$$

for all $\theta, \theta' \in \Theta$ and all $z \in \Omega$, and the following minimax lower bound holds. Let

$$V_{P,Q}(\theta) = \frac{1}{\alpha - 1}\log \mathbb{E}_Q\left[e^{(\alpha-1)T_\theta(X)}\right] - \frac{1}{\alpha}\log \mathbb{E}_P\left[e^{\alpha T_\theta(Y)}\right].$$

For any estimator $\widehat{V}_n : \Theta \to \mathbb{R}$ based on n i.i.d. samples from Q and n i.i.d. samples from P,

$$\inf_{\widehat{V}_n} \sup_{(P,Q)\in\mathcal{P}_d} \Pr_{P,Q}\left[\sup_{\theta\in\Theta}\left|\widehat{V}_n(\theta) - V_{P,Q}(\theta)\right| \ge \varepsilon\right] \ge \frac{1}{4}$$

whenever

$$n \le c\,\frac{d}{\varepsilon^2},$$

for all $0 < \varepsilon \le c_1$. Consequently, any distribution-free confidence band that controls $\sup_{\theta\in\Theta}|\widehat{V}_n(\theta) - V_{P,Q}(\theta)|$ must have sample complexity at least $\Omega(d/\varepsilon^2)$ in general.

Proof. We prove the result by a Fano reduction from multi-way hypothesis testing (Cover & Thomas, 2006). The construction is chosen so that the population DV objective $\theta \mapsto V_{P,Q}(\theta)$ encodes a hidden d-bit vector, while the KL divergence between the corresponding sample distributions remains of order $n\varepsilon^2$ (Alabi, 2026). This yields the desired d/ε^2 lower bound.

Step 1: A balanced packing. Let d be even. (For odd d, apply the construction in dimension $d-1$ and embed it into $\mathbb{R}^d$ by adding one unused coordinate; this changes constants only.) By the Gilbert–Varshamov bound restricted to the middle slice of the hypercube (MacWilliams & Sloane, 1978), there exists a set

$$\mathcal{U}_d \subseteq \{-1,+1\}^d$$

such that every $u \in \mathcal{U}_d$ is balanced,

$$\sum_{i=1}^{d} u_i = 0,$$

and

$$|\mathcal{U}_d| \geq \exp(c_{\mathrm{VG}} d),$$

for a universal constant $c_{\mathrm{VG}} > 0$, and for every distinct $u, v \in \mathcal{U}_d$,

$$\frac{d}{4} \leq d_H(u,v) \leq \frac{3d}{4}.$$

Equivalently, writing

$$\rho(u,v) := \frac{1}{d}\sum_{i=1}^{d} u_i v_i,$$

we have

$$\rho(u,u) = 1, \qquad \rho(u,v) \leq \frac{1}{2} \quad \text{for all } u \neq v.$$

Indeed, since

$$\rho(u,v) = 1 - \frac{2d_H(u,v)}{d},$$

the lower bound $d_H(u,v) \geq d/4$ gives $\rho(u,v) \leq 1/2$.

Step 2: Parameter set and critic class. Let

$$\Theta := \left\{ \theta^u := \frac{u}{\sqrt{d}} : u \in \mathcal{U}_d \right\} \subset \mathbb{R}^d.$$

Then $\|\theta^u\|_2 = 1$ for every $u \in \mathcal{U}_d$. Let the sample space be

$$\Omega := \{1, 2, \ldots, d\}.$$

Fix a constant $\tau \in (0,1]$, to be chosen sufficiently small depending only on α. For $\theta^u \in \Theta$, define

$$T_{\theta^u}(i) := \tau u_i, \qquad i \in \Omega.$$

Then $|T_{\theta^u}(i)| \leq \tau \leq 1$.

We next verify Lipschitzness. For distinct $u, v \in \mathcal{U}_d$,

$$|T_{\theta^u}(i) - T_{\theta^v}(i)| = \tau |u_i - v_i| \leq 2\tau.$$

On the other hand,

$$\|\theta^u - \theta^v\|_2 = \frac{1}{\sqrt{d}}\|u - v\|_2 = \frac{2}{\sqrt{d}}\sqrt{d_H(u,v)} \geq 1,$$

because $d_H(u,v) \geq d/4$. Therefore

$$|T_{\theta^u}(i) - T_{\theta^v}(i)| \leq 2\tau \|\theta^u - \theta^v\|_2.$$

Thus the critic class is Lipschitz on Θ with constant $L = 2\tau$, and has $K = 1$, $M = \tau$, all absolute constants. Since the theorem only needs a critic class indexed by Θ, no extension outside Θ is required. If one wants Θ to be a full subset with an extension to all of $\mathbb{R}^d$, one may apply the McShane extension theorem (McShane, 1934; Whitney, 1934) pointwise in i, preserving the same Lipschitz constant and boundedness after clipping.

Step 3: A family of distributions. Let P be the uniform distribution on Ω:

$$P(i) = \frac{1}{d}, \qquad i = 1, \dots, d.$$

For each hidden vector $u \in \mathcal{U}_d$, define Q_u by

$$Q_u(i) := \frac{1 + \delta u_i}{d}, \qquad i = 1, \dots, d,$$

where $0 < \delta \leq 1/2$. Since u is balanced,

$$\sum_{i=1}^{d} Q_u(i) = \frac{1}{d} \sum_{i=1}^{d} (1 + \delta u_i) = 1 + \frac{\delta}{d} \sum_{i=1}^{d} u_i = 1.$$

Moreover, $Q_u(i) > 0$ for all i, so Q_u is a valid probability distribution.

The statistical experiment associated with u consists of n i.i.d. samples from Q_u and n i.i.d. samples from the fixed distribution P. The samples from P carry no information about u, but they are included to match the DV estimation setting.

Step 4: Compute the DV functional. Fix $u, v \in \mathcal{U}_d$. We evaluate the DV objective under the pair (P, Q_u) at the critic θ^v. Write

$$a := (\alpha - 1)\tau.$$

First,

$$\mathbb{E}_{Q_u}\left[e^{(\alpha-1)T_{\theta^v}(X)}\right] = \sum_{i=1}^{d} \frac{1 + \delta u_i}{d} e^{a v_i}.$$

Because v is balanced,

$$\frac{1}{d} \sum_{i=1}^{d} e^{a v_i} = \frac{e^a + e^{-a}}{2} = \cosh(a).$$

Also,

$$\frac{1}{d} \sum_{i=1}^{d} u_i e^{a v_i} = \frac{1}{d} \sum_{i=1}^{d} u_i \big(\cosh(a) + v_i \sinh(a)\big).$$

Since u is balanced, $\sum_i u_i = 0$, so

$$\frac{1}{d} \sum_{i=1}^{d} u_i e^{a v_i} = \sinh(a) \frac{1}{d} \sum_{i=1}^{d} u_i v_i = \sinh(a) \rho(u, v).$$

Therefore

$$\mathbb{E}_{Q_u}\left[e^{(\alpha-1)T_{\theta^v}(X)}\right] = \cosh(a) + \delta \sinh(a) \rho(u, v).$$

Similarly, with

$$b := \alpha\tau,$$

we have

$$\mathbb{E}_{P}\left[e^{\alpha T_{\theta^v}(Y)}\right] = \frac{1}{d} \sum_{i=1}^{d} e^{b v_i} = \cosh(b),$$

again because v is balanced. Hence

$$V_u(\theta^v) := V_{P,Q_u}(\theta^v) = \frac{1}{\alpha - 1} \log(\cosh(a) + \delta \sinh(a) \rho(u, v)) - \frac{1}{\alpha} \log \cosh(b).$$

The second term is independent of both u and v. Thus separation of the DV objective is controlled by the first term.

Step 5: Separation of the correct critic. Define

$$F(r) := \frac{1}{\alpha - 1} \log(\cosh(a) + \delta \sinh(a) r), \qquad r \in [-1, 1].$$

For $\delta \leq 1/2$, the argument of the logarithm is strictly positive, provided τ is fixed. Differentiating gives

$$F'(r) = \frac{\delta \sinh(a)}{(\alpha - 1)(\cosh(a) + \delta \sinh(a) r)}.$$

Since $a = (\alpha - 1)\tau$, the quantity

$$\frac{\sinh(a)}{\alpha - 1}$$

is positive for every $\alpha \neq 1$. Therefore F is increasing in r. Moreover, because τ is a fixed constant depending only on α, and $\delta \leq 1/2$, there exists a constant $c_\alpha > 0$, depending only on α and τ, such that

$$F'(r) \geq c_\alpha \delta \qquad \text{for all } r \in [-1, 1].$$

Indeed, the denominator is bounded above and below by positive constants depending only on α and τ.

For the true index u, we have $\rho(u, u) = 1$. For any distinct $v \in \mathcal{U}_d$, we have $\rho(u, v) \leq 1/2$. Therefore

$$V_u(\theta^u) - V_u(\theta^v) = F(1) - F(\rho(u, v)) \geq F(1) - F(1/2) \geq \frac{c_\alpha}{2} \delta.$$

Let

$$\Delta := \frac{c_\alpha}{2} \delta.$$

Then, for every $u \in \mathcal{U}_d$,

$$V_u(\theta^u) \geq \max_{v \neq u} V_u(\theta^v) + \Delta.$$

Step 6: Uniform estimation implies decoding. Suppose an estimator $\widehat{V}_n : \Theta \to \mathbb{R}$ satisfies

$$\sup_{\theta \in \Theta} |\widehat{V}_n(\theta) - V_u(\theta)| < \frac{\Delta}{4}.$$

Define the decoder

$$\widehat{u} \in \arg\max_{v \in \mathcal{U}_d} \widehat{V}_n(\theta^v).$$

Then $\widehat{u} = u$. To see this, for every $v \neq u$,

$$\widehat{V}_n(\theta^u) \geq V_u(\theta^u) - \frac{\Delta}{4} \geq V_u(\theta^v) + \Delta - \frac{\Delta}{4} = V_u(\theta^v) + \frac{3\Delta}{4} \geq \widehat{V}_n(\theta^v) + \frac{\Delta}{2}.$$

Thus θ^u is the unique maximizer of $\widehat{V}_n$ over the packing points. Consequently,

$$\Pr_u(\widehat{u} \neq u) \leq \Pr_u \left[\sup_{\theta \in \Theta} |\widehat{V}_n(\theta) - V_u(\theta)| \geq \frac{\Delta}{4} \right].$$

Step 7: KL control. We next bound the KL divergence between two hypotheses. For $u, v \in \mathcal{U}_d$,

$$D_{\mathrm{KL}}(Q_u \| Q_v) = \sum_{i=1}^{d} \frac{1 + \delta u_i}{d} \log \frac{1 + \delta u_i}{1 + \delta v_i}.$$

Since both u and v are balanced, the number of coordinates with $(u_i, v_i) = (1, -1)$ equals the number of coordinates with $(u_i, v_i) = (-1, 1)$. Let this number be m. Then $d_H(u, v) = 2m$. Hence

$$D_{\mathrm{KL}}(Q_u \| Q_v) = \frac{m}{d}(1 + \delta) \log \frac{1 + \delta}{1 - \delta} + \frac{m}{d}(1 - \delta) \log \frac{1 - \delta}{1 + \delta}.$$

Therefore

$$D_{\mathrm{KL}}(Q_u \| Q_v) = \frac{2m\delta}{d} \log \frac{1 + \delta}{1 - \delta}.$$

For $0 < \delta \le 1/2$,

$$\log \frac{1+\delta}{1-\delta} \le C\delta,$$

so

$$D_{\mathrm{KL}}(Q_u \| Q_v) \le C\delta^2 \frac{m}{d} \le C\delta^2.$$

Applying this coordinatewise gives

$$D_{\mathrm{KL}}(Q_u \| Q_v) \le C\delta^2 \frac{d_H(u,v)}{d} \le C\delta^2.$$

The full observation law under u is

$$\mathbb{P}_u = Q_u^{\otimes n} \otimes P^{\otimes n}.$$

Since P is the same under all hypotheses,

$$D_{\mathrm{KL}}(\mathbb{P}_u \| \mathbb{P}_v) = n D_{\mathrm{KL}}(Q_u \| Q_v) \le Cn\delta^2.$$

Step 8: Fano's inequality. Let U be uniformly distributed on $\mathcal{U}_d$, and let the samples be drawn according to $\mathbb{P}_U$. By the KL bound above,

$$I(U; \text{samples}) \le \frac{1}{|\mathcal{U}_d|^2} \sum_{u,v \in \mathcal{U}_d} D_{\mathrm{KL}}(\mathbb{P}_u \| \mathbb{P}_v) \le Cn\delta^2.$$

Fano's inequality (Cover & Thomas, 2006) gives, for every decoder $\widehat{U}$,

$$\Pr(\widehat{U} \ne U) \ge 1 - \frac{I(U; \text{samples}) + \log 2}{\log |\mathcal{U}_d|}.$$

Since $\log |\mathcal{U}_d| \ge c_{\mathrm{VG}} d$, if

$$Cn\delta^2 + \log 2 \le \frac{1}{2} c_{\mathrm{VG}} d,$$

then

$$\Pr(\widehat{U} \ne U) \ge \frac{1}{2}.$$

In particular, there exists a universal constant $c' > 0$ such that if

$$n \le c' \frac{d}{\delta^2},$$

then every decoder has error probability at least $1/2$.

Step 9: Convert testing hardness into estimation hardness. Set

$$\delta := \frac{8\varepsilon}{c_\alpha}.$$

For $\varepsilon \le c_1$, with $c_1 > 0$ sufficiently small depending only on α, this choice satisfies $\delta \le 1/2$. With this choice,

$$\frac{\Delta}{4} = \frac{1}{4} \cdot \frac{c_\alpha}{2} \delta = \frac{c_\alpha \delta}{8} = \varepsilon.$$

Suppose, for contradiction, that there exists an estimator $\widehat{V}_n$ such that

$$\sup_{u \in \mathcal{U}_d} \Pr_u \left[\sup_{\theta \in \Theta} |\widehat{V}_n(\theta) - V_u(\theta)| \ge \varepsilon \right] < \frac{1}{4}.$$

Then the decoder

$$\widehat{u} \in \arg\max_{v \in \mathcal{U}_d} \widehat{V}_n(\theta^v)$$

would satisfy

$$\sup_{u \in \mathcal{U}_d} \Pr_u(\widehat{u} \ne u) < \frac{1}{4},$$

contradicting Fano's inequality whenever

$$n \le c' \frac{d}{\delta^2} = c' \frac{c_\alpha^2}{64} \frac{d}{\varepsilon^2}.$$

Absorbing constants into $c > 0$, we obtain

$$n \le c \frac{d}{\varepsilon^2} \quad \Longrightarrow \quad \inf_{\widehat{V}_n} \sup_{u \in \mathcal{U}_d} \Pr_u \left[\sup_{\theta \in \Theta} |\widehat{V}_n(\theta) - V_u(\theta)| \ge \varepsilon \right] \ge \frac{1}{4}.$$

This is the desired lower bound. □

Remark 1 (Tightness of Theorem 7)**.** *Theorem 7 shows that the leading d/ε^2 sample complexity in Theorem 2 is minimax-optimal for class-restricted DV Rényi estimation, up to logarithmic factors coming from covering/metric entropy.*

B.4 Group Privacy and Multiple Canaries

One can have multiple canaries in our auditing set up such that the datasets we input into the mechanism have a distance greater than one. In this case, we follow the group privacy result from (Mironov, 2017):

Proposition 1 (Proposition 2 in (Mironov, 2017))**.** *If $f : \mathcal{D} \to \mathcal{R}$ is (α, ε)-RDP; $g : \mathcal{D}' \to \mathcal{D}$ is 2^c-stable and $\alpha \ge 2^{c+1}$, then $f \circ g$ is $(\alpha/2^c, 3^c\varepsilon)$-RDP.*

Lemma 2. *For each M and a fixed $\alpha > 1$, let $A_M \in \Omega$ be a random variable and let $P_M \in \mathbb{R}$ be a fixed number. For each $\varepsilon, \beta > 0$, let $T_{\varepsilon,\alpha,\beta} \subset \Omega$ satisfy*

$$\forall M \qquad \Big(P_M = \varepsilon \implies \mathbb{P}\big[A_M \in T_{\varepsilon,\alpha,\beta}\big] \le \beta \Big). \tag{6}$$

Further suppose that, if $\varepsilon_1 \le \varepsilon_2$, then $T_{\varepsilon_1,\alpha,\beta} \supset T_{\varepsilon_2,\alpha,\beta}$. Then, for all M and all $\beta > 0$,

$$\Pr\{\, P_M \ge \sup\{\varepsilon > 0 : A_M \in T_{\varepsilon,\alpha,\beta}\}\} \ge 1 - \beta. \tag{7}$$

Proof. We follow a very similar proof as outlined in Lemma 4.7 of Steinke et al. (2023), just using the monotonicity of RDP and subsequently the null hypothesis's rejection region. Fix an output of A_M and let $P_M < \sup\{\varepsilon > 0 : A_M \in T_{\varepsilon,\alpha,\beta}\}$. Then there is a $\varepsilon \ge P_M$ with $A_M \in T_{\varepsilon,\alpha,\beta}$, and therefore

$$A_M \in \bigcup_{\varepsilon \ge P_M} T_{\varepsilon,\alpha,\beta} = T_{P_M,\alpha,\beta}. \tag{8}$$

By monotonicity of the rejection region. Thus,

$$\Pr[P_M < \sup\{\varepsilon > 0 : A_M \in T_{\varepsilon,\alpha,\beta}\}] \le \Pr\big[A_M \in T_{P_M,\alpha,\beta}\big] \le \beta. \tag{9}$$

For the above to hold, we assume that $\alpha > 1$ is fixed. □

C Additional Experimental Results

This section in the appendix provides additional interpretation of the experimental results reported in Section 4 (in main body) and the accompanying figures. The primary purpose of these experiments is not to propose a new attack on DP-SGD, but rather to validate the theoretical auditing guarantees developed in Section 3 and 4 under realistic machine learning workloads. In particular, the experiments are designed to answer the following questions:

- Do DV-based Rényi divergence estimators produce empirically meaningful lower bounds on privacy loss (Alabi, 2026)?
- How closely do empirical audits track the theoretically claimed RDP guarantees?
- How does estimator choice affect auditing accuracy, especially at small privacy budgets?

Across all datasets and models, the experimental findings are consistent with the predictions of our theory. It took around 100 GPU hours on A100 to audit an model trained on MNIST data and 500 GPU hours for a model trained on CIFAR-10 data. For the SOTA black-box in each of the following tables we refer to Muthu Selva Annamalai & De Cristofaro (2024).

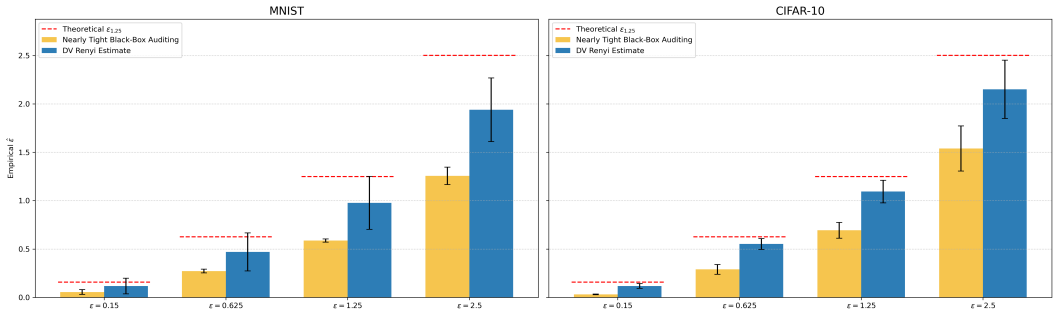

Figure 2: Graph for auditing at $\alpha = 1.25$ for CIFAR-10 and MNIST datasets on a CNN

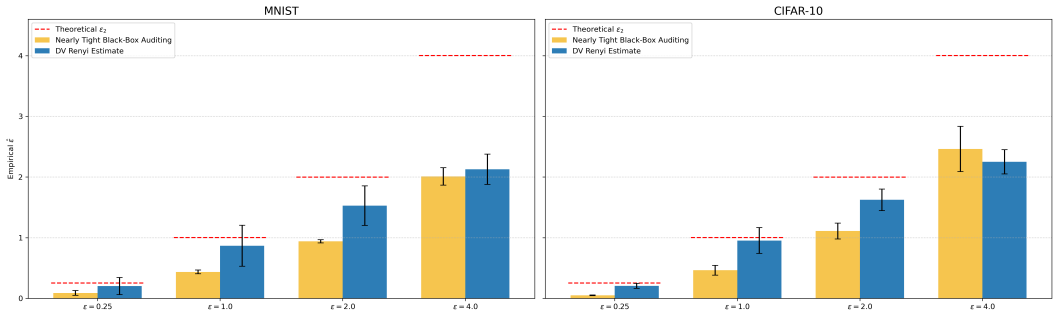

Figure 3: Graph for auditing at $\alpha = 2.0$ for CIFAR-10 and MNIST datasets on a CNN

Worst-case initializations. A recurring theme in prior work is that DP-SGD privacy guarantees must hold even for adversarially chosen initial parameters. To stress-test our auditing framework, we therefore follow the experimental protocol of Annamalai et al. (2024); Muthu Selva Annamalai & De Cristofaro (2024) and evaluate models initialized using worst-case pretraining strategies. All of our experiments occur in this setting. Despite the adversarial initialization, the DV-based Rényi estimator consistently produces nontrivial lower bounds that closely track the claimed theoretical privacy levels. This behavior is particularly notable at smaller values of ε, where auditing is statistically most challenging. These results empirically corroborate the distribution-free lower confidence bounds established in our theory and demonstrate that our estimator remains stable even under worst-case conditions.

Comparison of estimators. We compare the following approaches to estimating Rényi divergence from observed losses: (i) our DV-based variational estimator, (ii) nearly tight black-box auditing results from prior work.

Across all experiments, the DV-based estimator achieves a favorable balance between bias and variance. While prior black-box methods can be overly conservative at small ε, the DV estimator yields tighter empirical lower bounds that remain statistically valid for low ε. This behavior is especially pronounced in the low-ε regime, where small estimation errors translate into large relative differences in privacy guarantees.

These trends are consistent with our finite-sample analysis, which predicts that the DV estimator can achieve near-optimal accuracy given a sufficiently expressive critic class.

C.1 DV Rényi Model

In our auditing procedure we use a DV Rényi model to calculate a divergence estimate that serves as an empirical RDP estimate. For this model, consider a dataset (consisting of final model losses trained with DP-SGD) with size n. Our neural networks use two intermediate layers of 100 nodes.

Table 3: Empirical RDP audits at $\alpha = 1.25$. Same as in Section 4

Dataset	Target ε_α	SOTA black-box	DV-Rényi
MNIST	0.15625	0.056 ± 0.025	$\mathbf{0.115} \pm 0.080$
	0.625	0.272 ± 0.020	$\mathbf{0.469} \pm 0.197$
	1.25	0.588 ± 0.016	$\mathbf{0.995} \pm 0.289$
	2.5	1.256 ± 0.091	$\mathbf{2.239} \pm 0.473$
	6.25	3.325 ± 0.218	$\mathbf{3.884} \pm 0.327$
CIFAR-10	0.15625	0.031 ± 0.004	$\mathbf{0.118} \pm 0.025$
	0.625	0.289 ± 0.050	$\mathbf{0.551} \pm 0.056$
	1.25	0.693 ± 0.082	$\mathbf{1.095} \pm 0.120$
	2.5	1.539 ± 0.234	$\mathbf{2.248} \pm 0.344$
	6.25	4.128 ± 0.336	$\mathbf{4.577} \pm 0.430$

Table 4: Empirical RDP audits at $\alpha = 1.25$, with Dataset size: 100 samples.

Dataset	Target ε_α	SOTA black-box	DV-Rényi
MNIST	0.15625	0.086 ± 0.042	$\mathbf{0.152} \pm 0.061$
	0.625	$\mathbf{0.506} \pm 0.124$	0.184 ± 0.029
	1.25	$\mathbf{0.875} \pm 0.075$	0.172 ± 0.014
	2.5	$\mathbf{1.921} \pm 0.249$	0.176 ± 0.011
	6.25	$\mathbf{4.685} \pm 0.370$	0.177 ± 0.006
CIFAR-10	0.15625	0.036 ± 0.010	$\mathbf{0.147} \pm 0.034$
	0.625	0.323 ± 0.039	$\mathbf{0.486} \pm 0.053$
	1.25	$\mathbf{0.730} \pm 0.085$	0.649 ± 0.052
	2.5	$\mathbf{1.631} \pm 0.179$	0.767 ± 0.045
	6.25	$\mathbf{4.341} \pm 0.368$	0.848 ± 0.045

At $\alpha = 1.25$, we use 750 epochs and lr = 7e-5 for CIFAR-10 and 500 epochs with lr = 2e-4 for MNIST, and a batch size of 400. We use an EMA rate of 0.99 and our neural network is structured with two intermediate layers of 100 nodes with a ReLU activation function. 400 (80%) of the loss samples are used in the training set and the last 100 (20%) of the loss samples are used in the validation set. We scale our DV estimate R_α by α so $D_\alpha = \alpha R_\alpha$. At $\alpha = 2$, all the parameters are the same besides a slight decrease of the iterative learning, setting lr = 1.25e-4 for MNIST and 350 training epochs for CIFAR-10. As α increases, the model becomes increasingly sensitive and overall learning of the model needs to be decreased to avoid high MSE due to the divergence's exponential nature. To apply our theorems to our experimental settings and results, consistency results for our neural networks satisfying Theorem 2, Theorem 8 can be found in (Birrell et al., 2021).

C.2 Tightness lost in GDP to RDP conversions

A concern when comparing RDP audits to prior black-box auditing methods is that converting an audit through intermediate privacy notions can introduce unnecessary slack. In particular, Muthu Selva Annamalai & De Cristofaro (2024) produces a binary classifier that distinguishes whether a model was trained on dataset D or its neighboring dataset D'. This classifier is summarized by its true-positive rate TPR and false-positive rate FPR, which can then be used to estimate a μ-GDP lower bound. However, converting this estimate to GDP and then to RDP may lose tightness. Therefore, we evaluate a direct RDP baseline from the binary attack itself. The binary distinguisher induces two Bernoulli distributions: one corresponding to the attack output under D, with success probability TPR, and one corresponding to the attack output under D', with success probability FPR. Therefore, instead of passing through an intermediate GDP estimate, we directly compute the order-α Rényi divergence

$$\hat{\varepsilon} = D_\alpha \left(\mathrm{Bern}(\mathrm{TPR}) \,\|\, \mathrm{Bern}(\mathrm{FPR}) \right).$$

Although this provides a more direct RDP lower bound, the Bernoulli distributions from TPR and FPR are not robust to Rényi divergence estimation, shown in Table 11.

Table 5: Empirical RDP audits at $\alpha = 1.25$, with Dataset size: 1000 samples.

Dataset	Target ε_α	SOTA black-box	DV-Rényi
MNIST	0.15625	0.095 ± 0.057	$\mathbf{0.155} \pm 0.068$
	0.625	$\mathbf{0.493} \pm 0.104$	0.185 ± 0.034
	1.25	$\mathbf{0.863} \pm 0.104$	0.167 ± 0.015
	2.5	$\mathbf{1.844} \pm 0.154$	0.172 ± 0.009
	6.25	$\mathbf{4.478} \pm 0.310$	0.174 ± 0.007
CIFAR-10	0.15625	0.031 ± 0.004	$\mathbf{0.118} \pm 0.025$
	0.625	0.289 ± 0.050	$\mathbf{0.551} \pm 0.056$
	1.25	0.693 ± 0.082	$\mathbf{1.095} \pm 0.120$
	2.5	1.539 ± 0.234	$\mathbf{2.248} \pm 0.344$
	6.25	4.128 ± 0.336	$\mathbf{4.577} \pm 0.430$

Table 6: Empirical RDP audits at $\alpha = 1.25$, with Max grad norm: 10.0.

Dataset	Target ε_α	SOTA black-box	DV-Rényi
MNIST	0.15625	0.001 ± 0.001	$\mathbf{0.006} \pm 0.007$
	0.625	0.033 ± 0.026	$\mathbf{0.098} \pm 0.112$
	1.25	0.035 ± 0.022	$\mathbf{0.070} \pm 0.086$
	2.5	0.035 ± 0.016	$\mathbf{0.118} \pm 0.074$
	6.25	0.059 ± 0.028	$\mathbf{4.764} \pm 9.191$
CIFAR-10	0.15625	0.002 ± 0.001	$\mathbf{0.005} \pm 0.009$
	0.625	0.065 ± 0.030	$\mathbf{0.166} \pm 0.092$
	1.25	0.191 ± 0.012	$\mathbf{0.456} \pm 0.118$
	2.5	0.652 ± 0.035	$\mathbf{1.657} \pm 0.275$
	6.25	2.445 ± 0.130	$\mathbf{5.577} \pm 2.545$

Table 7: Empirical RDP audits at $\alpha = 2$, same as in Section 4.

Dataset	Target ε_α	SOTA black-box	DV-Rényi
MNIST	0.25	0.089 ± 0.040	$\mathbf{0.202} \pm 0.142$
	1.0	0.436 ± 0.032	$\mathbf{0.867} \pm 0.339$
	2.0	0.940 ± 0.025	$\mathbf{1.527} \pm 0.325$
	4.0	2.010 ± 0.145	$\mathbf{2.127} \pm 0.250$
	10.0	$\mathbf{5.320} \pm 0.349$	2.650 ± 0.159
CIFAR-10	0.25	0.050 ± 0.007	$\mathbf{0.206} \pm 0.041$
	1.0	0.463 ± 0.080	$\mathbf{0.953} \pm 0.213$
	2.0	1.109 ± 0.131	$\mathbf{1.624} \pm 0.178$
	4.0	$\mathbf{2.463} \pm 0.374$	2.250 ± 0.200
	10.0	$\mathbf{6.605} \pm 0.538$	2.751 ± 0.170

Table 8: Empirical RDP audits at $\alpha = 2$, with Dataset size: 100 samples.

Dataset	Target ε_α	SOTA black-box	DV-Rényi
MNIST	0.25	0.138 ± 0.067	$\mathbf{0.407} \pm 0.335$
	1.0	0.810 ± 0.198	$\mathbf{1.512} \pm 0.662$
	2.0	1.399 ± 0.120	$\mathbf{1.910} \pm 0.390$
	4.0	$\mathbf{3.074} \pm 0.398$	2.360 ± 0.294
	10.0	$\mathbf{7.496} \pm 0.592$	2.796 ± 0.150
CIFAR-10	0.25	0.058 ± 0.015	$\mathbf{0.257} \pm 0.048$
	1.0	0.517 ± 0.063	$\mathbf{1.138} \pm 0.128$
	2.0	1.169 ± 0.136	$\mathbf{1.829} \pm 0.098$
	4.0	$\mathbf{2.609} \pm 0.286$	2.322 ± 0.146
	10.0	$\mathbf{6.945} \pm 0.589$	2.845 ± 0.185

Table 9: Empirical RDP audits at $\alpha = 2$, with Dataset size: 1000 samples.

Dataset	Target ε_α	SOTA black-box	DV-Rényi
MNIST	0.25	0.151 ± 0.091	$\mathbf{0.381} \pm 0.262$
	1.0	0.789 ± 0.166	$\mathbf{1.272} \pm 0.427$
	2.0	1.380 ± 0.166	$\mathbf{1.822} \pm 0.338$
	4.0	$\mathbf{2.950} \pm 0.246$	2.218 ± 0.242
	10.0	$\mathbf{7.165} \pm 0.495$	2.618 ± 0.171
CIFAR-10	0.25	0.050 ± 0.007	$\mathbf{0.206} \pm 0.041$
	1.0	0.463 ± 0.080	$\mathbf{0.953} \pm 0.213$
	2.0	1.109 ± 0.131	$\mathbf{1.624} \pm 0.178$
	4.0	$\mathbf{2.463} \pm 0.374$	2.250 ± 0.200
	10.0	$\mathbf{6.605} \pm 0.538$	2.751 ± 0.170

Table 10: Empirical RDP audits at $\alpha = 2$, with Max grad norm: 10.0.

Dataset	Target ε_α	SOTA black-box	DV-Rényi
MNIST	0.25	0.001 ± 0.002	$\mathbf{0.014} \pm 0.011$
	1.0	0.052 ± 0.042	$\mathbf{0.164} \pm 0.184$
	2.0	0.056 ± 0.035	$\mathbf{0.131} \pm 0.148$
	4.0	0.056 ± 0.025	$\mathbf{0.210} \pm 0.175$
CIFAR-10	0.25	0.004 ± 0.002	$\mathbf{0.012} \pm 0.019$
	1.0	0.104 ± 0.049	$\mathbf{0.324} \pm 0.192$
	2.0	0.306 ± 0.019	$\mathbf{2.200} \pm 2.979$
	4.0	1.044 ± 0.056	$\mathbf{6.983} \pm 3.233$

Table 11: Comparison of empirical RDP lower bounds at $\alpha = 2$, with a direct $\hat{\varepsilon} = D_\alpha(\mathrm{Bern}(\mathrm{TPR}) \| \mathrm{Bern}(\mathrm{FPR}))$ estimate for previous SOTA.

Dataset	Theor. ε at $\alpha = 2$	$\hat{\varepsilon} = D_\alpha(\mathrm{Bern}(\mathrm{TPR}) \| \mathrm{Bern}(\mathrm{FPR}))$	$\hat{\varepsilon}$-RDP DV
CIFAR-10	0.25	0.097 ± 0.059	$\mathbf{0.206} \pm 0.041$
	1.0	0.375 ± 0.11	$\mathbf{0.953} \pm 0.213$
	2.0	0.685 ± 0.124	$\mathbf{1.624} \pm 0.178$
	4.0	1.097 ± 0.134	$\mathbf{2.25} \pm 0.2$
	10.0	1.446 ± 0.239	$\mathbf{2.751} \pm 0.17$
MNIST	0.25	0.115 ± 0.064	$\mathbf{0.202} \pm 0.142$
	1.0	0.35 ± 0.115	$\mathbf{0.867} \pm 0.339$
	2.0	0.618 ± 0.135	$\mathbf{1.527} \pm 0.325$
	4.0	1.022 ± 0.14	$\mathbf{2.127} \pm 0.25$
	10.0	1.444 ± 0.186	$\mathbf{2.65} \pm 0.159$