

# Tighter Security for Efficient Lattice Cryptography via the Rényi Divergence of Optimized Orders

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# Background

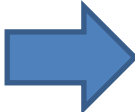
# Lattice Cryptography

- Lattice cryptography has novel properties.
  - Resist quantum attacks
  - Worst-case/Average-case reduction
  - Faster computation and parallelizable

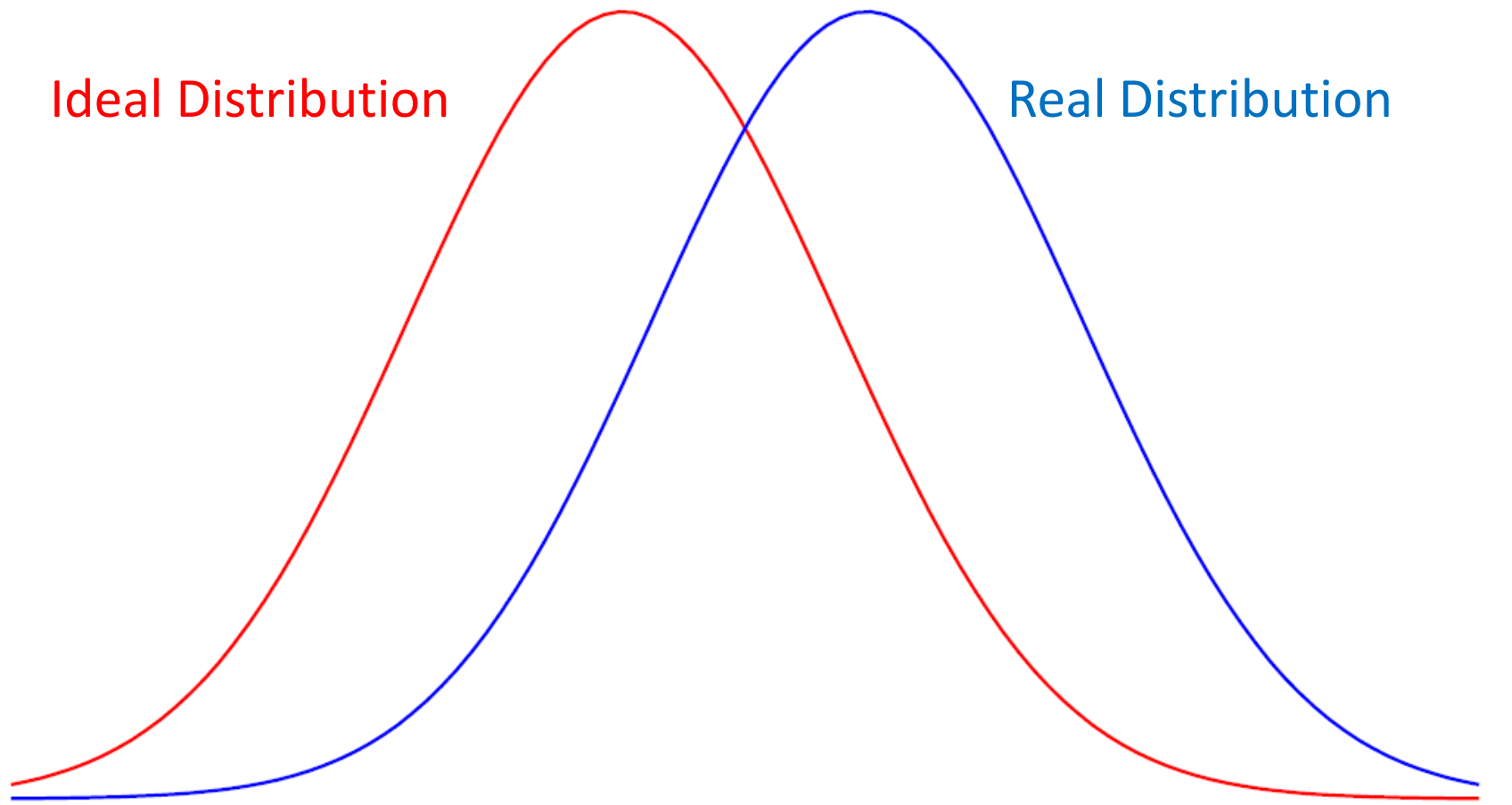
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e.g., zero centered and non-zero centered discrete Gaussian distributions.

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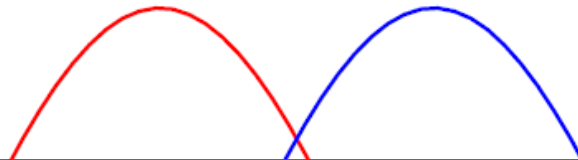
- Lattice cryptography has novel properties.
    - Resist quantum attacks
    - Worst-case/Average-case reduction
    - Faster computation and parallelizable
  - In the security reduction, there are *statistical* steps; to measure the closeness of two probability distributions.  
e.g., zero centered and non-zero centered discrete Gaussian distributions.
-  The security reduction follows through when the distributions are statistically close.

# Statistical Analysis



# Statistical Analysis

Ideal Distribution



Real Distribution

Ideal distributions and real distributions are statistically close



Simulated cryptographic scheme and real scheme are statistically indistinguishable.

# Statistical Analysis

- The larger parameters (e.g. Gaussian deviations),
- two distributions become statistically close e.g. the real schemes become secure,
  - the scheme becomes less efficient.
- ✓ We want to analyze the appropriate trade-off.

The analyses owe to statistical measures.

Which measure should be used?

Statistical Distance vs Rényi Divergence



# Statistical Measure

## Statistical Distance (SD)


- SD is widely used in security reduction.
- SD should be much smaller than the advantage for the reduction.

 inefficient parameters

- Small SD offers **tight reduction**.

## Rényi Divergence (RD)

- RD is recently used in security reduction for lattice crypto. [LPR13,LSS14,LPSS14,BLL+15].
- RD can be independent of the advantage.

 **smaller parameters**

- Even if RD is small, reductions always **lose the tightness**.

# Statistical Measure

## Statistical Distance (SD)

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Can we prove the security with *both* **small parameters** and **tight reduction**?

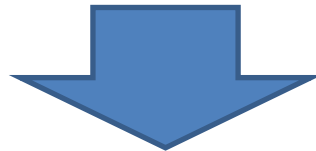
- Small SD offers **tight reduction**.
- Even if RD is small, reductions always **lose the tightness**.

# Our Solution

- In the previous RD based analyses, the order is fixed to  $\alpha = 2$ .
- In this work, we use the optimized order.  
The optimization offers tighter reduction even if we use the RD.

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Our approach offers

- tighter reduction than the previous RD based analyses,
- with smaller parameters than the SD based analyses.

# Precomputed Table Size for BLISS Signature

statistical measure	table bit-size	reduction loss $\varepsilon/\varepsilon'$
SD [DDLL13]	6003	$\leq 2$
KLD [PDG14]	4872	$\leq 2$
RD, $\alpha = +\infty$ [BLL+15]	2291	$\leq 2$
RD, $\alpha = 2$ [BLL+15]	1160	$\approx 2^{128}$
RD, <b>optimized order</b> Ours	1276	$\leq 2$

# Our Approach

# Overview of the Security Reduction

- Problem  $P$ : given  $X = \{x_i: x_i \leftarrow \Phi\}_{i=1,\dots,k}$  and compute  $f(X)$
- Problem  $P'$ : given  $X' = \{x'_i: x'_i \leftarrow \Phi'\}_{i=1,\dots,k}$  and compute  $f(X')$
- ✓ When two probability distributions  $\Phi$  and  $\Phi'$  are statistically close, the adversary for the problem  $P$  is also the adversary for the problem  $P'$ .

# SD Based Analysis

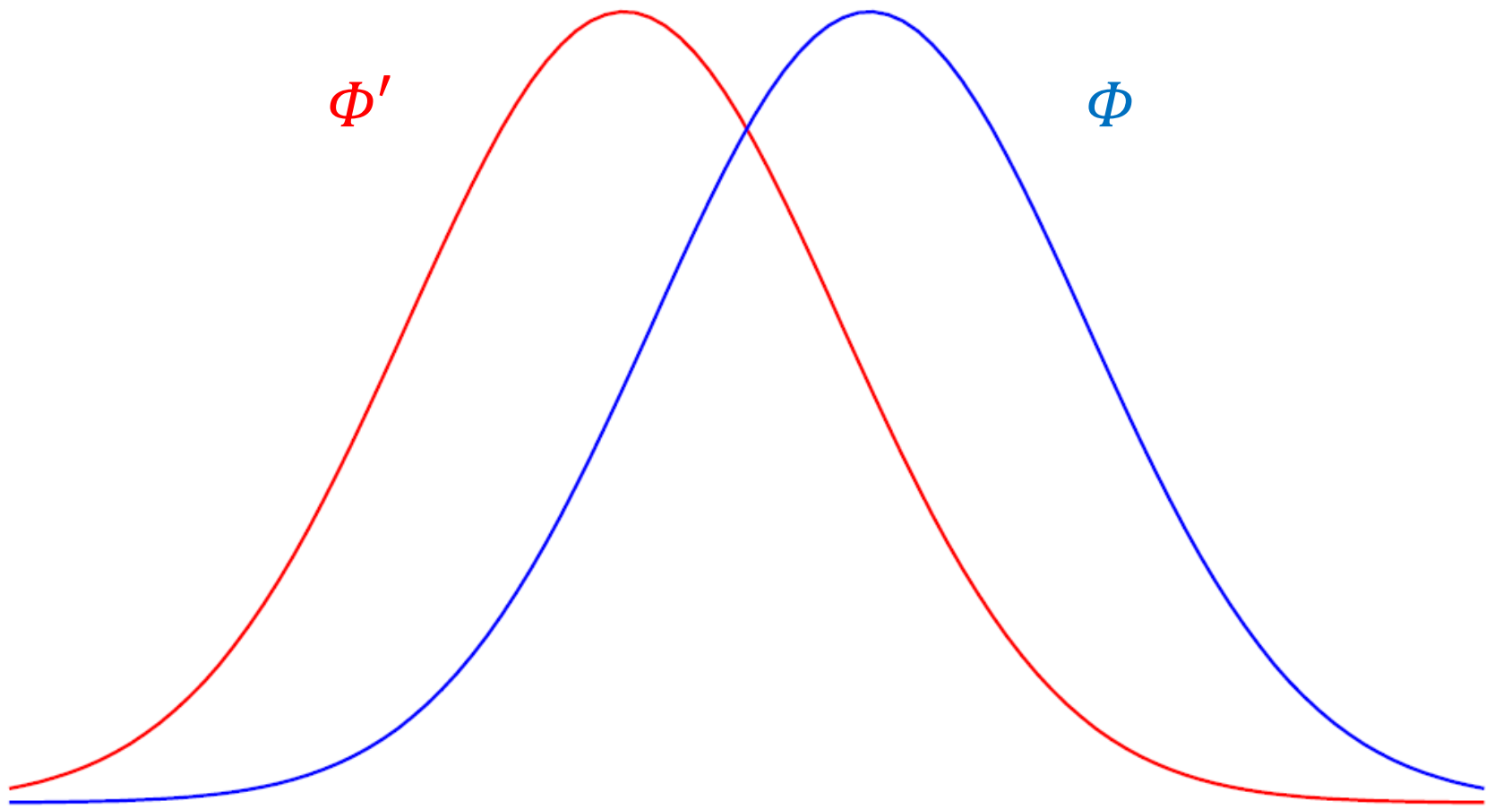
- $\varepsilon$ : the advantage for the adversary to solve  $P$
- $\varepsilon'$ : the advantage for the adversary to solve  $P'$

The SD between  $\Phi$  and  $\Phi'$ :

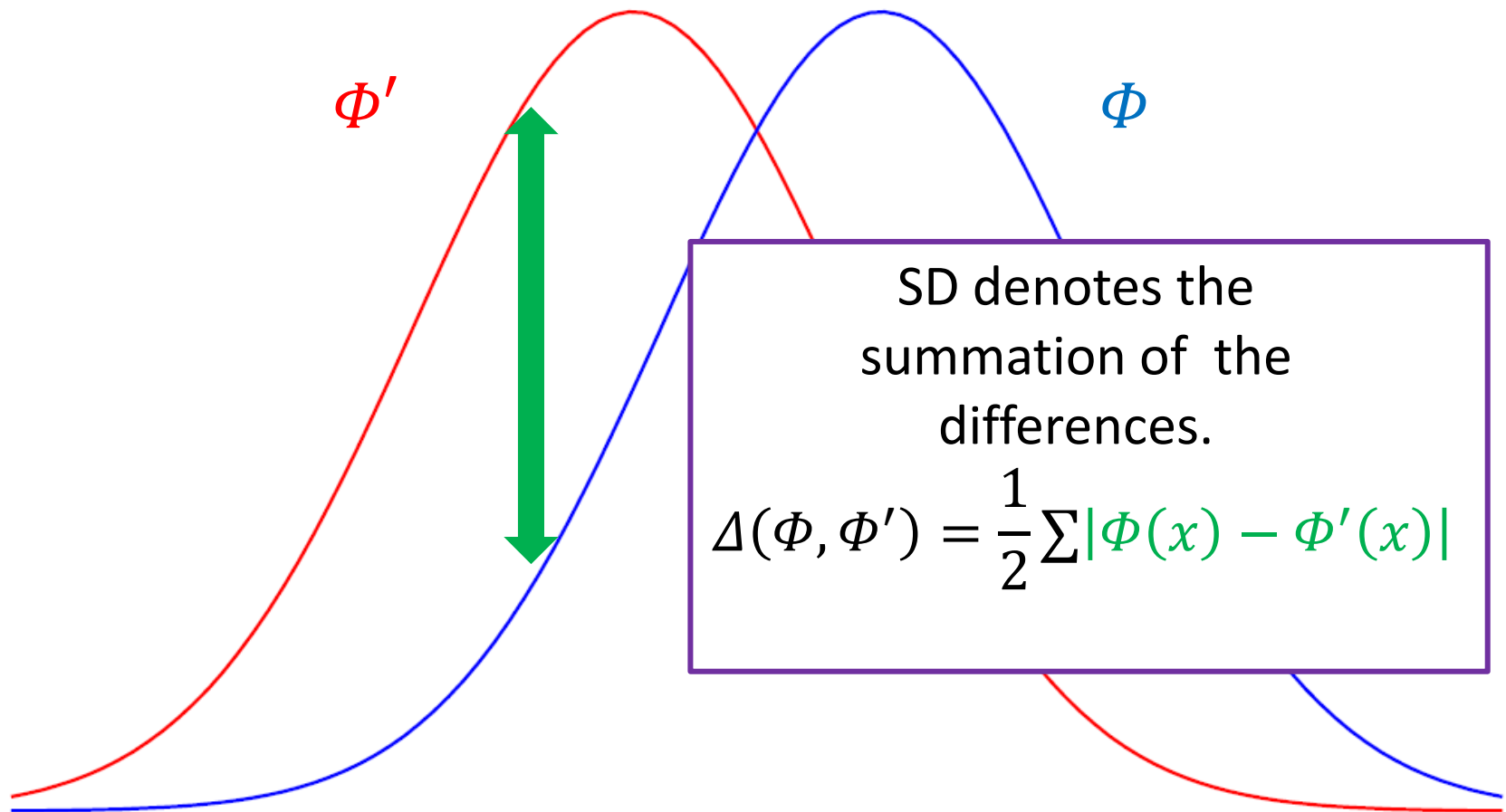
$$\Delta(\Phi, \Phi') = \frac{1}{2} \sum |\Phi(x) - \Phi'(x)|$$



# SD Based Analysis



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SD denotes the summation of the differences.

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$$\varepsilon \leq \varepsilon' + k \Delta(\Phi, \Phi')$$

SD should be *much smaller than  $\varepsilon/k$*

The *strong requirement* leads to **inefficient parameters**.

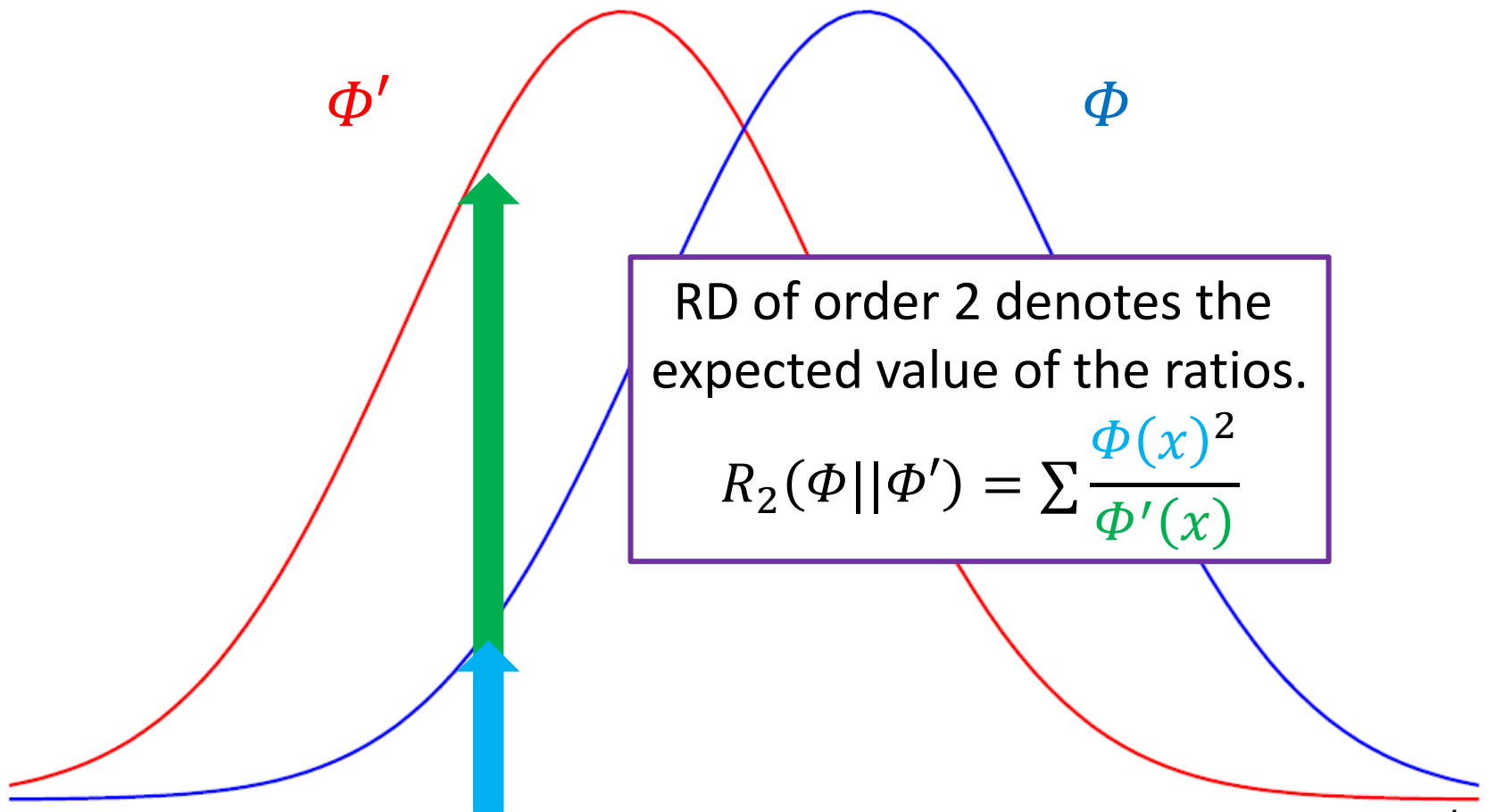
# Previous RD Based Analysis

- $\varepsilon$ : the advantage for the adversary to solve  $P$
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The RD (of order 2) between  $\Phi$  and  $\Phi'$ :

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➔ Significant **parameter savings!**

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- RD are allowed to be larger bounds (small constant).

➔ Significant **parameter savings!**

- Even if RD is extremely small (almost 1), the RHS is always larger than  $\varepsilon'^{1/2}$ .

➔ The reduction always **loses the tightness.**



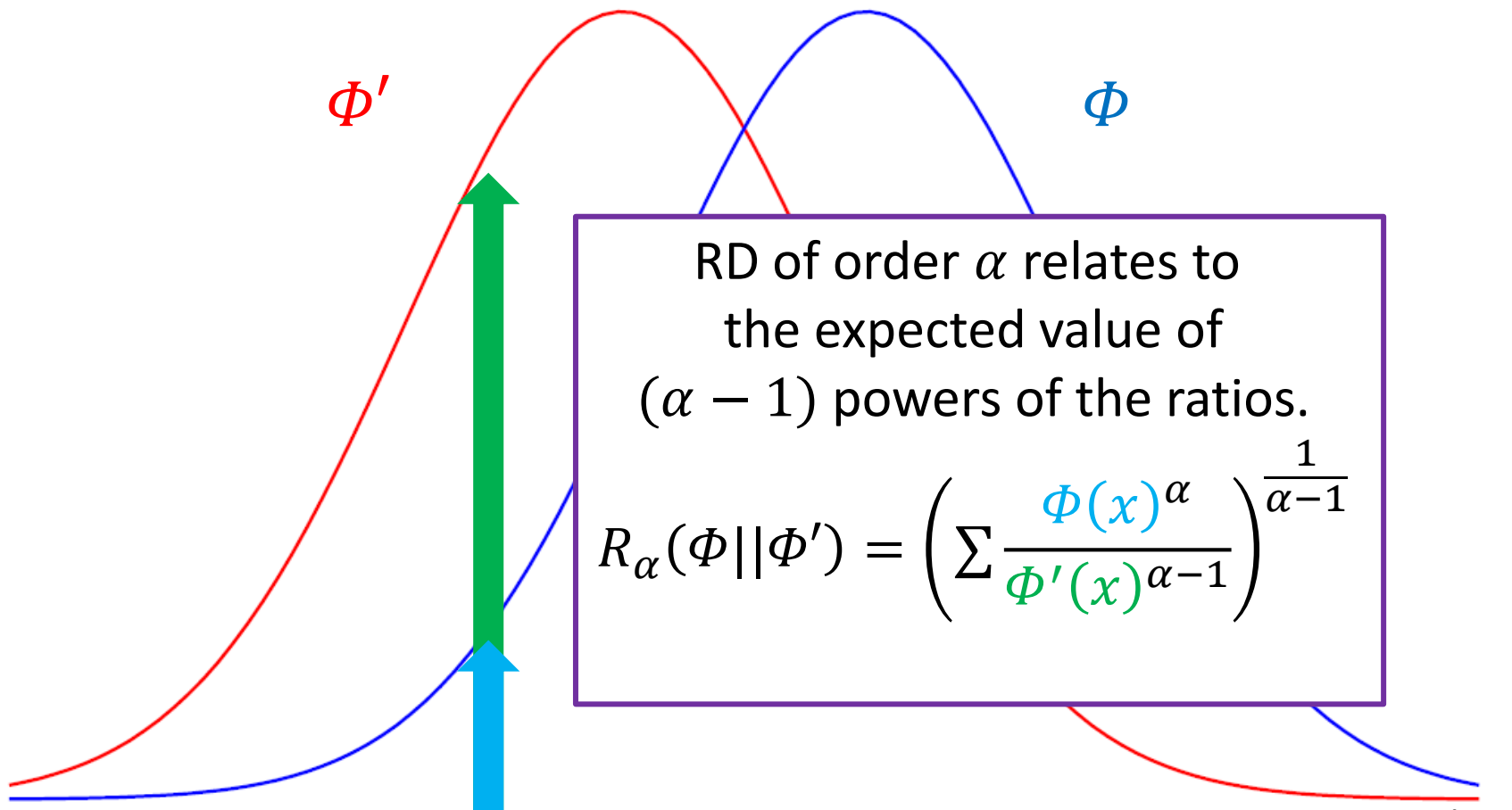
# Our RD Based Analysis

- $\varepsilon$ : the advantage for the adversary to solve  $P$
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The RD between  $\Phi$  and  $\Phi'$ :

$$R_\alpha(\Phi || \Phi') = \left( \sum \frac{\Phi(x)^\alpha}{\Phi'(x)^{\alpha-1}} \right)^{\frac{1}{\alpha-1}}$$

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When the larger  $\alpha$  is used, the exponent of  $\underline{\varepsilon}'$  becomes close to 1.



**Tighter reduction!**

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We adaptively optimize the order  $\alpha$  for the reduction to become as tight as possible.

- ✓ Since RD becomes exponential of  $\alpha$ ,  $\alpha$  cannot be infinitely large.

# Adaptive Optimization of the Order

Assume  $R_\alpha(\Phi||\Phi') \leq \exp(\alpha \cdot \gamma)$ ,

$$\begin{aligned} \varepsilon &\leq \left( \varepsilon' \cdot R_\alpha(\Phi||\Phi')^k \right)^{\frac{\alpha-1}{\alpha}} \\ &\leq \exp\left( \frac{\alpha-1}{\alpha} \cdot \ln(\varepsilon') + (\alpha-1) \cdot k\gamma \right). \end{aligned}$$

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The RHS is lower bounded as

$$= \exp \left( \ln(\varepsilon') - k\gamma + \left( \frac{-\ln(\varepsilon')}{\alpha} + \alpha \cdot k\gamma \right) \right)$$



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The RHS is lower bounded as

$$\begin{aligned} &= \exp \left( \ln(\varepsilon') - k\gamma + \left( \frac{-\ln(\varepsilon')}{\alpha} + \alpha \cdot k\gamma \right) \right) \\ &\geq \exp \left( \ln(\varepsilon') - k\gamma + 2\sqrt{-\ln(\varepsilon') \cdot k\gamma} \right) \end{aligned}$$

by the inequality of arithmetic mean and geometric mean.

# Adaptive Optimization of the Order

The equality holds iff

$$\frac{-\ln(\varepsilon')}{\alpha} = \alpha \cdot k\gamma \quad \Rightarrow \quad \alpha = \sqrt{\frac{-\ln(\varepsilon')}{k\gamma}}.$$

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$$\frac{-\ln(\varepsilon')}{\alpha} = \alpha \cdot k\gamma \quad \longrightarrow \quad \alpha = \sqrt{\frac{-\ln(\varepsilon')}{k\gamma}}.$$

We use the order and the inequality becomes

$$\begin{aligned} \varepsilon &\leq \exp\left(\ln(\varepsilon') - k\gamma + 2\sqrt{-\ln(\varepsilon') \cdot k\gamma}\right) \\ &= \exp\left(-\left(\sqrt{-\ln(\varepsilon')} - \sqrt{k\gamma}\right)^2\right). \end{aligned}$$

When RD is small ( $\gamma \approx 0$ ), the RHS of the inequality becomes  $\approx \varepsilon'$ .

# Summary of Our Results

- Our approach offers security reduction where
  - $\approx \varepsilon' \leftarrow \approx \varepsilon'^{1/2}$  for computing problems and
  - $\approx \varepsilon'^{1/2} \leftarrow \approx \varepsilon'^{1/3}$  for distinguishing problems.
- Applications of our approaches are
  - Sampling discrete Gaussian over the integers with **smaller precomputed tables** for BLISS signatures.
  - **Tighter** LWE to  $k$ -LWE reduction.
  - **Tighter** SIS to  $k$ -SIS reduction.

# Sampling Discrete Gaussian over the Integers

# Bimodal Lattice Signature Scheme

BLISS signatures [DDLL13]

- are secure under the worst case ideal lattice problem (SIS).
- are comparably efficient as RSA and ECDSA
- requires to sample several hundreds of independent samples from one-dimensional *discrete Gaussian distributions over the integers* for a signing.

# Sampling Discrete Gaussian over the Integers [DDLL13]

Discrete Gaussian distributions  $D_{\mathbb{Z},s}$  can be sampled by using *Bernoulli random variables* with probabilities

$$c_i = \exp\left(-\frac{\pi 2^i}{s^2}\right) \text{ for } i = 0, \dots, l - 1.$$

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Storing the truncated probabilities  $\tilde{c}_i$  with bit precisions  $p$ , Bernoulli random variables can be sampled efficiently.

Larger  $p$  with security  
vs  
Smaller  $p$  with efficiency

✓ An appropriate trade-off should be analyzed.

# Statistical Analyses

The trade-off can be analyzed by estimating the statistical closeness between the *real distributions* (with probabilities  $\tilde{c}_i$ ) and the *ideal distributions* (with probabilities  $c_i$ ).

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Several statistical measures have been used

- SD [DDLL13]
- Kullback-Leibler divergence [PDG14]
- RD of order  $\alpha = 2$  and  $+\infty$  [BLL+15]
- ✓ We use the RD of *optimized orders*.

# Comparison

statistical measure	table bit-size	reduction loss $\varepsilon/\varepsilon'$
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# Our Results

- In the security reduction of lattice cryptography, the closeness of two probability distributions should be measured. To bound the closeness via the *Rényi divergence*, we **adaptively optimize the order**.
- Applications of our approach are
  - Sampling discrete Gaussian over the integers with **smaller precomputed tables**
  - **Tighter** LWE to  $k$ -LWE reduction
  - **Tighter** SIS to  $k$ -SIS reduction