

The Rényi Divergence and Security Proofs

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THALES

Introduction

1 Introduction

2 Theory

- 1 The Rényi Divergence
- 2 Three useful lemmas
- 3 Framework for proving stuff

3 Practice

- 1 Application 1: Security of a Sampler from [MW17]
- 2 Application 2: Revisiting the Table Approach
- 3 Application 4: Standard Deviation of Trapdoor Samplers
- 4 Application 5: Precision of Trapdoor Samplers

4 Conclusion

- 1 Quick Summary
- 2 Open Questions

What is the Rényi divergence and why use it?

Security proofs involving distributions:

- **The standard approach:** use the statistical distance Δ .
 - Take a hard problem relying on some ideal distribution \mathcal{Q} ,
 - Replace \mathcal{Q} by a “real-life” distribution \mathcal{P} ,
 - If $\Delta(\mathcal{P}, \mathcal{Q})$ is small enough, we win: the problem is still hard.
- **Lattice-based cryptography:** often relevant to replace SD by Rényi divergence.
 - Sharper parameters [LSS14, LPSS14, BLL⁺15, BGM⁺16, Pre17, HLS17]
 - KEMs distributions [ADPS16, BCD⁺16]
 - Reduction between LWE problems [AD17]

This presentation:

- 1 Formalize and optimize the use of the Rényi divergence in security proofs \Rightarrow Section 2.
- 2 More applications of the Rényi divergence to lattice-based cryptography \Rightarrow Section 3.
- 3 A brief discussion on open problems \Rightarrow Section 4.

Based on [Pre17].

Theory

- ① Introduction
- ② Theory**
 - ① The Rényi Divergence
 - ② Three useful lemmas
 - ③ Framework for proving stuff
- ③ Practice
- ④ Conclusion

The Rényi Divergence

Definition. For $\alpha \in (1, +\infty)$, the Rényi divergence between two distributions \mathcal{P}, \mathcal{Q} is

$$R_\alpha(\mathcal{P} \parallel \mathcal{Q}) = \left(\sum_{x \in \text{Supp}(\mathcal{P})} \frac{\mathcal{P}(x)^\alpha}{\mathcal{Q}(x)^{\alpha-1}} \right)^{\frac{1}{\alpha-1}}$$

Motivation. We consider a cryptographic scheme doing q queries to a distribution \mathcal{D}_i ($i \in \{0, 1\}$), we note ε_i the probability of an event breaking the scheme.

➤ With the statistical distance:

$$\varepsilon_0 \geq \varepsilon_1 - q\Delta(\mathcal{D}_1, \mathcal{D}_0)$$

$$\Delta \leq 2^{-\lambda} \Rightarrow \text{we win}$$

➤ With the Rényi divergence:

$$\varepsilon_0 \geq \varepsilon_1^{\frac{\alpha}{\alpha-1}} / R_\alpha(\mathcal{D}_1 \parallel \mathcal{D}_0)^q$$

$$(\alpha \geq \lambda) \ \& \ (\log R_\alpha \leq 1/q) \Rightarrow \text{we win}$$

Observation. For “equal” values ($\log R_\alpha \approx \Delta$), Rényi divergence is more interesting when $q \ll 2^\lambda$ [BLL⁺15]. And typically:

➤ $128 \leq \lambda \leq 256$

➤ $1 \leq q \leq 2^{64}$

The first and second lemmas

1 **Tailcut.** Let $\delta > 0$ such that $\frac{D_\delta}{D} \leq 1 + \delta$. For $\alpha \in (1, \infty]$:

$$\Rightarrow R_\alpha(D_\delta \| D) \leq (1 + \delta)^{\alpha/\alpha-1}$$

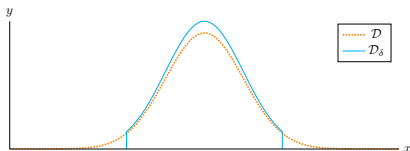
Example: D_δ is a tailcut of D (discard a set S such that $D(S) \leq \delta$).

2 **Relative error.** Suppose $\text{Supp}(D_\delta) = \text{Supp}(D)$.

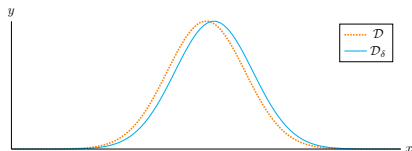
Let $\delta > 0$ such that $1 - \delta \leq \frac{D_\delta}{D} \leq 1 + \delta$. For $\alpha \in (1, \infty)$:

$$\Rightarrow R_\alpha(D_\delta \| D) \leq \left(1 + \frac{\alpha(\alpha-1)\delta^2}{2(1-\delta)^{\alpha+1}}\right)^{\frac{1}{\alpha-1}} \underset{\delta \rightarrow 0}{\sim} 1 + \frac{\alpha\delta^2}{2}$$

Example: D_δ implements D with finite precision (relative error δ).



Tailcut lemma usecase



Relative error lemma usecase

The third lemma

The max-log distance. Introduced in [MW17].¹

For two distributions \mathcal{P} and \mathcal{Q} over the same support S :

$$\Delta_{\text{ML}}(\mathcal{P}, \mathcal{Q}) = \max_{x \in S} |\log \mathcal{P}(x) - \log \mathcal{Q}(x)|$$

Unlike the Rényi divergence, it is a distance, so it verifies the:

- Triangle inequality: $\Delta_{\text{ML}}(\mathcal{P}, \mathcal{R}) \leq \Delta_{\text{ML}}(\mathcal{P}, \mathcal{Q}) + \Delta_{\text{ML}}(\mathcal{Q}, \mathcal{R})$
- Symmetry: $\Delta_{\text{ML}}(\mathcal{P}, \mathcal{Q}) = \Delta_{\text{ML}}(\mathcal{Q}, \mathcal{P})$

[MW17] essentially states that $\Delta_{\text{ML}} \leq 2^{-\lambda/2} \Rightarrow$ we win.

¹Actually similar to the differential privacy.

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[MW17] essentially states that $\Delta_{\text{ML}} \leq 2^{-\lambda/2} \Rightarrow$ we win.

- ③ **A reverse Pinsker inequality.** For two distributions \mathcal{P}, \mathcal{Q} of common support, we have:

$$R_\alpha(\mathcal{P} \parallel \mathcal{Q}) \leq \left(1 + \frac{\alpha(\alpha-1)(e^{\Delta_{\text{ML}}(\mathcal{P}, \mathcal{Q})} - 1)^2}{2(2 - e^{\Delta_{\text{ML}}(\mathcal{P}, \mathcal{Q})})^{\alpha+1}} \right)^{\frac{1}{\alpha-1}} \underset{\Delta_{\text{ML}} \rightarrow 0}{\sim} 1 + \frac{\alpha \Delta_{\text{ML}}(\mathcal{P}, \mathcal{Q})^2}{2}$$

Consequence: Instead of $\Delta_{\text{ML}} \leq 2^{-\lambda/2}$, we only need $\Delta_{\text{ML}} \leq \frac{1}{\sqrt{\lambda q}}$.

¹Actually similar to the differential privacy.

Framework for using the Rényi Divergence

- 1 Take your favourite scheme
- 2 Set more aggressive parameters:
 - 1 First, try to apply the relative error lemma (the most powerful)
 - 2 Wherever it doesn't work, apply either the tailcut lemma or the reverse Pinsker's inequality
- 1 Taking $R_\alpha \leq 1 + \frac{1}{q}$ is sufficient.
- 1 Taking $\alpha \geq \lambda$ gives tight, efficient proofs.
- 3 Goto step 1



- 1 *These arguments are only valid for search problems!
For decision problems, achieving the same efficiency is still open.*
- 1 *In the rest of this presentation, we assume $q \leq 2^{64}$.*

Practice

1 Introduction

2 Theory

3 Practice

- ① Application 1: Security of a Sampler from [MW17]
- ② Application 2: Revisiting the Table Approach
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- ④ Application 5: Precision of Trapdoor Samplers

4 Conclusion

Application 1: Security of a Sampler from [MW17]

Context. A new sampler over \mathbb{Z} was introduced in [MW17].

Previous works. [MW17] perform a max-log distance-based analysis of the sampler. They find that

64 bits of precision $\Rightarrow \Delta_{\text{ML}} \leq 2^{-50} \Rightarrow$ About 100 bits of security

This work. We use the reverse Pinsker's inequality:

64 bits of precision $\Rightarrow \Delta_{\text{ML}} \leq 2^{-50}$
 $\Rightarrow R_\alpha \leq 1 + 2^{-96}$
 \Rightarrow 256 bits of security, even with up to 2^{94} queries

We gain this much security *for free*.

No knowledge about the sampler is required.

Application 2: Revisiting the Table Approach

Context. We study the use of precomputed tables for sampling discrete distributions – typically, (pseudo)Gaussians.

Previous works. Existing approaches [Pei10, PDG14, DG14] require high precision ($\geq \lambda/2$) and/or floating-point arithmetic.

This work. We propose a simple approach which requires less than 64 bits of *fixed* precision in practice.

The classical CDF-table approach

Let \mathcal{D} be a distribution over \mathbb{N} that we want to sample from.
We suppose we have a precomputed table of $\text{CDF}_{\mathcal{D}}$ defined over \mathbb{N} by:

$$\text{CDF}_{\mathcal{D}}(z) = \sum_{i \leq z} \mathcal{D}(i)$$

Algorithm 1 CDF sampler

Require: A precomputed table of $\text{CDF}_{\mathcal{D}}$

- 1: $z \leftarrow 0$
 - 2: $u \leftarrow [0, 1]$ uniformly
 - 3: **while** $u \geq \text{CDF}_{\mathcal{D}}(z)$ **do**
 - 4: $z \leftarrow z + 1$
 - 5: **Return** z
-

Suppose we want to sample a half-Gaussian D_{σ}^{+} .

- ⇒ *Statistical distance-based analysis.* We need to store about:
 - ⇒ $\sigma \cdot \sqrt{2\lambda}$ values,
 - ⇒ With a precision λ .
- ⇒ *Rényi Divergence-based analysis.* We need to store about:
 - ⇒ $\sigma \cdot \sqrt{2q}$ values,
 - ⇒ With a precision λ . **But we prefer/expect $\log_2(q)$ or $\log_2(q)/2!$**

The CoDF sampler

Our solution. We use a “Rényi divergence-friendly” table. This requires a different algorithm. We define the conditional density function of \mathcal{D} by:

$$\text{CoDF}_{\mathcal{D}}(z) = \mathcal{D}(z) / \sum_{i \geq z} \mathcal{D}(i)$$

Algorithm 2 CoDF sampler

Require: A precomputed table of $\text{CoDF}_{\mathcal{D}}$

Ensure: $z \leftarrow \mathcal{D}$

$z \leftarrow 0$

$u \leftarrow [0, 1]$ uniformly

while $u \geq \text{CoDF}_{\mathcal{D}}(z)$ **do**

$z \leftarrow z + 1$

$u \leftarrow [0, 1]$ uniformly

Return z

Suppose we want to sample a half-Gaussian D_{σ}^{+} .

⇒ Rényi Divergence-based analysis. We need to store about:

⇒ $\sigma \cdot \sqrt{2q}$ values,

⇒ With a precision $\log_2(q)/2!$

Example and Conclusion

Gain in theory:

- CDF+SD approach: $\sigma \cdot \sqrt{2\lambda}$ values with precision λ
- CoDF+RD approach: $\sigma \cdot \sqrt{2q}$ values with precision $\log_2(q)/2$

A practical example: the distribution $D_{\mathbb{Z},0.85\dots}^+$ from [DDLL13].

- CDF+SD approach: 20 elements of 266 bits each $\Rightarrow \approx 5\,300$ bits.
- CoDF+RD approach: 11 elements of 53 bits each $\Rightarrow \approx 600$ bits.

Conclusion:

- Both in theory and practice, we gain an order of magnitude.
- Requires only standard (64 bits) fixed-point arithmetic.
- Highly composable with other table-based techniques.

Application 4: Standard Deviation of Trapdoor Samplers

Context. Trapdoor sampling allows to sample a discrete Gaussian $D_{\Lambda(\mathbf{B}),\sigma,\mathbf{c}}$.

- Allows hash-and-sign, IBE [GPV08], standard model signatures [CHKP10, Boy10], hierarchical IBE [CHKP10, ABB10a, ABB10b], attribute-based encryption [Boy13, BGG⁺14] and so on.
- Current algorithms [Kle00, GPV08, Pei10, MP12, DP16] heavily rely on floating-point arithmetic.

This work. Two axes of improvement for trapdoor samplers:

- 1 Squeezing the standard deviation
- 2 Reducing the required precision

These had critical impacts for the signature scheme Falcon [PFH⁺17].

Our test subject: Klein's sampler

Algorithm 3 $\text{Klein}_{\mathbf{L},\sigma}(\mathbf{t})$

Require: $\sigma \geq \eta_\epsilon(\mathbb{Z}^n) \cdot \|\mathbf{B}\|_{\text{GS}}$, the GSO $\mathbf{B} = \mathbf{L} \cdot \tilde{\mathbf{B}}$, values $\sigma_j = \sigma / \|\tilde{\mathbf{b}}_j\|$, a target \mathbf{t}

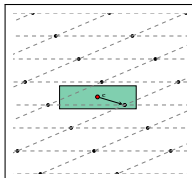
Ensure: A vector \mathbf{z} such that $\mathbf{z}\mathbf{B} \leftarrow D_{\Lambda(\mathbf{B}),\sigma,\mathbf{t}\mathbf{B}}$

for $j = n, \dots, 1$ **do**

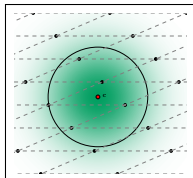
$c_j \leftarrow t_j + \sum_{i>j} (t_j - z_j) L_{ij}$

$z_j \leftarrow D_{\mathbb{Z},\sigma_j,c_j}$

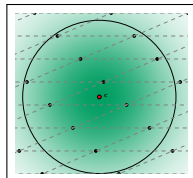
return \mathbf{z}



σ too small



The "right" σ

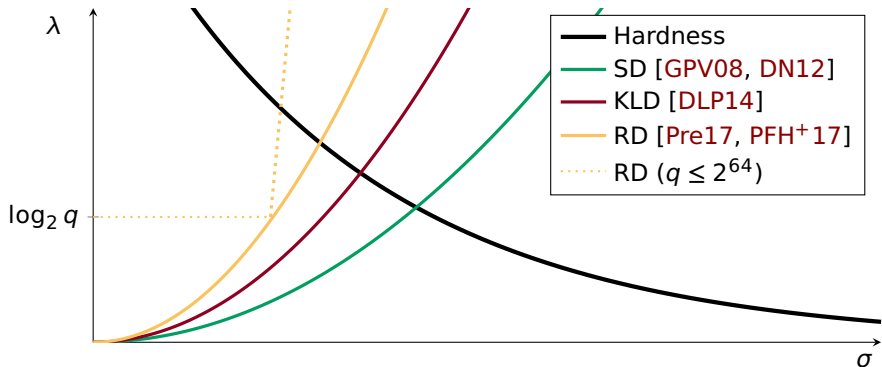


σ too large

- σ too large \Rightarrow $\text{Klein}_{\mathbf{L},\sigma}$ is useless in a cryptographic context.
- σ too small \Rightarrow $\text{Klein}_{\mathbf{L},\sigma}$ does not behave like a perfect Gaussian.

So σ must be small but the output of $\text{Klein}_{\mathbf{L},\sigma}$ must still look like a Gaussian.

Trapdoor Sampling



The adequate value for σ is at the intersection of the hardness curve (constraint ①) and the SD/KLD/RD curve (constraint ②).

➤ A Rényi divergence-based analysis proves to be much more efficient than an SD/KLD-based one.

➤ Interesting fact: in practice, σ is not conditioned by λ but by q .

In practice, we gain about 30 bits of security (compared to the SD).

Application 5: What about the precision?

- ⇒ **With the SD:** λ bits of precision
- ⇒ **With the KLD [LP15]:** $\lambda/2$ bits of precision
- ⇒ **With the RD [Pre17]:** $\log_2 q/2$ bits of precision

Conclusion

① Introduction

② Theory

③ Practice

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① Quick Summary

② Open Questions

The current state of affairs.

- Rényi divergence is a powerful tool, but not easy to use.
- With the reverse Pinsker's inequality, the fact that the Rényi divergence is not a distance is no longer a problem.
- We can have much better parameters if these conditions are met:
 - Limited number of queries
 - Search problems
 - A bit of luck
- These results are generic (not limited to lattice-based cryptography).

Interesting questions IMHO.

- When is the Rényi divergence *worse* than the statistical distance?
- Applications outside lattice-based cryptography?
- Application to theoretical LBC rather than “production line” LBC?
- Achieve a similar efficiency for decision problems?






Interesting questions IMHO.

- When is the Rényi divergence *worse* than the statistical distance?
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- Achieve a similar efficiency for decision problems?



Thanks!



-  Shweta Agrawal, Dan Boneh, and Xavier Boyen.
Efficient lattice (H)IBE in the standard model.
In Gilbert [[Gil10](#)], pages 553–572.
-  Shweta Agrawal, Dan Boneh, and Xavier Boyen.
Lattice basis delegation in fixed dimension and shorter-ciphertext hierarchical IBE.
In Rabin [[Rab10](#)], pages 98–115.
-  Martin R. Albrecht and Amit Deo.
Large modulus ring-LWE \geq module-LWE.
In Takagi and Peyrin [[TP17](#)], pages 267–296.
-  Erdem Alkim, Léo Ducas, Thomas Pöppelmann, and Peter Schwabe.
Post-quantum key exchange - A new hope.
In Thorsten Holz and Stefan Savage, editors, *25th USENIX Security Symposium, USENIX Security 16, Austin, TX, USA, August 10-12, 2016.*, pages 327–343. USENIX Association, 2016.
-  Joppe W. Bos, Craig Costello, Léo Ducas, Ilya Mironov, Michael Naehrig, Valeria Nikolaenko, Ananth Raghunathan, and Douglas Stebila.
Frodo: Take off the ring! Practical, quantum-secure key exchange from LWE.

In Edgar R. Weippl, Stefan Katzenbeisser, Christopher Kruegel, Andrew C. Myers, and Shai Halevi, editors, *ACM CCS 16*, pages 1006–1018. ACM Press, October 2016.



Dan Boneh, Craig Gentry, Sergey Gorbunov, Shai Halevi, Valeria Nikolaenko, Gil Segev, Vinod Vaikuntanathan, and Dhinakaran Vinayagamurthy.

Fully key-homomorphic encryption, arithmetic circuit ABE and compact garbled circuits.

In Nguyen and Oswald [**NO14**], pages 533–556.



Andrej Bogdanov, Siyao Guo, Daniel Masny, Silas Richelson, and Alon Rosen.

On the hardness of learning with rounding over small modulus.

In Eyal Kushilevitz and Tal Malkin, editors, *TCC 2016-A, Part I*, volume 9562 of *LNCS*, pages 209–224. Springer, Heidelberg, January 2016.



Shi Bai, Adeline Langlois, Tancredè Lepoint, Damien Stehlé, and Ron Steinfeld.

Improved security proofs in lattice-based cryptography: Using the Rényi divergence rather than the statistical distance.

In Tetsu Iwata and Jung Hee Cheon, editors, *ASIACRYPT 2015, Part I*, volume 9452 of *LNCS*, pages 3–24. Springer, Heidelberg, November / December 2015.



Xavier Boyen.

Lattice mixing and vanishing trapdoors: A framework for fully secure short signatures and more.

In Phong Q. Nguyen and David Pointcheval, editors, *PKC 2010*, volume 6056 of *LNCS*, pages 499–517. Springer, Heidelberg, May 2010.



Xavier Boyen.

Attribute-based functional encryption on lattices.

In Amit Sahai, editor, *TCC 2013*, volume 7785 of *LNCS*, pages 122–142. Springer, Heidelberg, March 2013.



David Cash, Dennis Hofheinz, Eike Kiltz, and Chris Peikert.

Bonsai trees, or how to delegate a lattice basis.

In Gilbert [[Gil10](#)], pages 523–552.



Léo Ducas, Alain Durmus, Tancrede Lepoint, and Vadim Lyubashevsky.

Lattice signatures and bimodal Gaussians.

In Ran Canetti and Juan A. Garay, editors, *CRYPTO 2013, Part I*, volume 8042 of *LNCS*, pages 40–56. Springer, Heidelberg, August 2013.



Nagarjun C. Dwarakanath and Steven D. Galbraith.

Sampling from discrete gaussians for lattice-based cryptography on a constrained device.

Appl. Algebra Eng. Commun. Comput., 25(3):159–180, 2014.



Léo Ducas, Vadim Lyubashevsky, and Thomas Prest.

Efficient identity-based encryption over NTRU lattices.

In Palash Sarkar and Tetsu Iwata, editors, *ASIACRYPT 2014, Part II*, volume 8874 of *LNCS*, pages 22–41. Springer, Heidelberg, December 2014.



Léo Ducas and Phong Q. Nguyen.

Faster Gaussian lattice sampling using lazy floating-point arithmetic.

In Xiaoyun Wang and Kazue Sako, editors, *ASIACRYPT 2012*, volume 7658 of *LNCS*, pages 415–432. Springer, Heidelberg, December 2012.



Léo Ducas and Thomas Prest.

Fast fourier orthogonalization.

In Sergei A. Abramov, Eugene V. Zima, and Xiao-Shan Gao, editors, *Proceedings of the ACM on International Symposium on Symbolic and Algebraic Computation, ISSAC 2016, Waterloo, ON, Canada, July 19-22, 2016*, pages 191–198. ACM, 2016.



Henri Gilbert, editor.

EUROCRYPT 2010, volume 6110 of *LNCS*. Springer, Heidelberg, May 2010.



Craig Gentry, Chris Peikert, and Vinod Vaikuntanathan.

Trapdoors for hard lattices and new cryptographic constructions. In Richard E. Ladner and Cynthia Dwork, editors, *40th ACM STOC*, pages 197–206. ACM Press, May 2008.



Andreas Hülsing, Tanja Lange, and Kit Smeets.

Rounded gaussians – fast and secure constant-time sampling for lattice-based crypto.

Cryptology ePrint Archive, Report 2017/1025, 2017.

<https://eprint.iacr.org/2017/1025>.



Philip N. Klein.

Finding the closest lattice vector when it's unusually close.

In *SODA*, 2000.




Vadim Lyubashevsky and Thomas Prest.


Quadratic time, linear space algorithms for Gram-Schmidt orthogonalization and Gaussian sampling in structured lattices.


In Elisabeth Oswald and Marc Fischlin, editors, *EUROCRYPT 2015, Part I*, volume 9056 of *LNCS*, pages 789–815. Springer, Heidelberg, April 2015.

 San Ling, Duong Hieu Phan, Damien Stehlé, and Ron Steinfeld.
Hardness of k-LWE and applications in traitor tracing.

In Juan A. Garay and Rosario Gennaro, editors, *CRYPTO 2014, Part I*, volume 8616 of *LNCS*, pages 315–334. Springer, Heidelberg, August 2014.

 Adeline Langlois, Damien Stehlé, and Ron Steinfeld.
GGHLite: More efficient multilinear maps from ideal lattices.
In Nguyen and Oswald [NO14], pages 239–256.


 Daniele Micciancio and Chris Peikert.
Trapdoors for lattices: Simpler, tighter, faster, smaller.
In David Pointcheval and Thomas Johansson, editors, *EUROCRYPT 2012*, volume 7237 of *LNCS*, pages 700–718. Springer, Heidelberg, April 2012.

 Daniele Micciancio and Michael Walter.
Gaussian sampling over the integers: Efficient, generic, constant-time.


In Jonathan Katz and Hovav Shacham, editors, *CRYPTO 2017, Part II*, volume 10402 of *LNCS*, pages 455–485. Springer, Heidelberg, August 2017.


-  Phong Q. Nguyen and Elisabeth Oswald, editors. *EUROCRYPT 2014*, volume 8441 of *LNCS*. Springer, Heidelberg, May 2014.
-  Thomas Pöppelmann, Léo Ducas, and Tim Güneysu. Enhanced lattice-based signatures on reconfigurable hardware. In Lejla Batina and Matthew Robshaw, editors, *CHES 2014*, volume 8731 of *LNCS*, pages 353–370. Springer, Heidelberg, September 2014.
-  Chris Peikert. An efficient and parallel Gaussian sampler for lattices. In Rabin [[Rab10](#)], pages 80–97.
-  Thomas Prest, Pierre-Alain Fouque, Jeffrey Hoffstein, Paul Kirchner, Vadim Lyubashevsky, Thomas Pornin, Thomas Ricosset, Gregor Seiler, William Whyte, and Zhenfei Zhang. **Falcon**. Technical report, National Institute of Standards and Technology, 2017.

available at <https://csrc.nist.gov/projects/post-quantum-cryptography/round-1-submissions>.

 [Thomas Prest](#).
Sharper bounds in lattice-based cryptography using the Rényi divergence.

In Takagi and Peyrin [TP17], pages 347–374.

 [Tal Rabin, editor](#).
CRYPTO 2010, volume 6223 of LNCS. Springer, Heidelberg, August 2010.

 [Tsuyoshi Takagi and Thomas Peyrin, editors](#).
ASIACRYPT 2017, Part I, volume 10624 of LNCS. Springer, Heidelberg, December 2017.