

# Revisiting the Expected Cost of Solving uSVP and Applications to LWE

Martin R. Albrecht<sup>1</sup>

Florian Göpfert<sup>2,3</sup>

Fernando Virdia<sup>1</sup>

Thomas Wunderer<sup>3</sup>

<sup>1</sup>Information Security Group, Royal Holloway, University of London,

<sup>2</sup>rockenstein AG,

<sup>3</sup>TU Darmstadt

4 December 2017

Asiacrypt 2017

# Overview

Lattice reduction cost models

Our experiments

Experimental and theoretical results

New security estimates

Conclusions

## Lattice reduction cost models

- >>> Lattice reduction algorithms are a fundamental tool for cryptanalysis of lattice-based cryptographic schemes
- >>> A common strategy is to use them to solve the Unique Shortest Vector Problem as part of 'primal lattice attacks'
- >>> Costing such algorithms is therefore a fundamental step for choosing secure parameters
- >>> Heads-up: cost models disagree on the asymptotic complexity

## Lattice reduction cost models

- >>> Lattice reduction algorithms are a fundamental tool for cryptanalysis of lattice-based cryptographic schemes
- >>> A common strategy is to use them to solve the Unique Shortest Vector Problem as part of 'primal lattice attacks'
- >>> Costing such algorithms is therefore a fundamental step for choosing secure parameters
- >>> Heads-up: cost models disagree on the asymptotic complexity

- >>> [GN08] is the first systematic study of lattice reduction strategies
- >>> The work looks at using BKZ for solving Unique-SVP, using a statistical approach for estimating its effectiveness
- >>> A necessary condition for successful recovery is obtained
- >>> This approach is later applied to LWE embedding lattices in [AFG14]

- >>> [GN08] is the first systematic study of lattice reduction strategies
- >>> The work looks at using BKZ for solving Unique-SVP, using a statistical approach for estimating its effectiveness
- >>> A necessary condition for successful recovery is obtained
- >>> This approach is later applied to LWE embedding lattices in [AFG14]

>>> Let  $\Lambda$  be our lattice of dimension  $d$  with a unique shortest vector  $\mathbf{v}$  (up to  $\pm$  sign), and let  $\lambda_i$  be the  $i^{\text{th}}$  minima

>>> Let  $\delta$  be the Hermite factor  $\iff$  BKZ recovers vectors long  $\approx \delta^d \text{Vol}(\Lambda)^{1/d}$

>>> If

$$\lambda_2(\Lambda)/\lambda_1(\Lambda) > \tau\delta^d, \quad \text{for } \tau \in (0,1) \quad (1)$$

the shortest vector is recovered

>>>  $\tau$  is estimated experimentally

>>> (1)  $\Rightarrow$  optimal number of LWE samples  $m_{2008}$  and BKZ block size  $\beta_{2008}$  to run the primal attack

>>> We refer to this work as *the 2008 model*

>>> Let  $\Lambda$  be our lattice of dimension  $d$  with a unique shortest vector  $\mathbf{v}$  (up to  $\pm$  sign), and let  $\lambda_i$  be the  $i^{\text{th}}$  minima

>>> Let  $\delta$  be the Hermite factor  $\iff$  BKZ recovers vectors long  $\approx \delta^d \text{Vol}(\Lambda)^{1/d}$

>>> If

$$\lambda_2(\Lambda)/\lambda_1(\Lambda) > \tau \delta^d, \quad \text{for } \tau \in (0,1) \quad (1)$$

the shortest vector is recovered

>>>  $\tau$  is estimated experimentally

>>> (1)  $\Rightarrow$  optimal number of LWE samples  $m_{2008}$  and BKZ block size  $\beta_{2008}$  to run the primal attack

>>> We refer to this work as *the 2008 model*

>>> Let  $\Lambda$  be our lattice of dimension  $d$  with a unique shortest vector  $\mathbf{v}$  (up to  $\pm$  sign), and let  $\lambda_i$  be the  $i^{\text{th}}$  minima

>>> Let  $\delta$  be the Hermite factor  $\iff$  BKZ recovers vectors long  $\approx \delta^d \text{Vol}(\Lambda)^{1/d}$

>>> If

$$\lambda_2(\Lambda)/\lambda_1(\Lambda) > \tau\delta^d, \quad \text{for } \tau \in (0, 1) \quad (1)$$

the shortest vector is recovered

>>>  $\tau$  is estimated experimentally

>>> (1)  $\Rightarrow$  optimal number of LWE samples  $m_{2008}$  and BKZ block size  $\beta_{2008}$  to run the primal attack

>>> We refer to this work as *the 2008 model*

>>> Let  $\Lambda$  be our lattice of dimension  $d$  with a unique shortest vector  $\mathbf{v}$  (up to  $\pm$  sign), and let  $\lambda_i$  be the  $i^{\text{th}}$  minima

>>> Let  $\delta$  be the Hermite factor  $\iff$  BKZ recovers vectors long  $\approx \delta^d \text{Vol}(\Lambda)^{1/d}$

>>> If

$$\lambda_2(\Lambda)/\lambda_1(\Lambda) > \tau\delta^d, \quad \text{for } \tau \in (0, 1) \quad (1)$$

the shortest vector is recovered

>>>  $\tau$  is estimated experimentally

>>> (1)  $\implies$  optimal number of LWE samples  $m_{2008}$  and BKZ block size  $\beta_{2008}$  to run the primal attack

>>> We refer to this work as *the 2008 model*

>>> [ADPS16] introduces a new success condition for solving Unique-SVP with BKZ when  $\|\mathbf{v}\|$  is known

>>> The strategy is based on the Geometric Series Assumption, and on the structure of the BKZ algorithm

>>> We refer to this work as *the 2016 model*

>>> To explain the condition we will first review how BKZ works

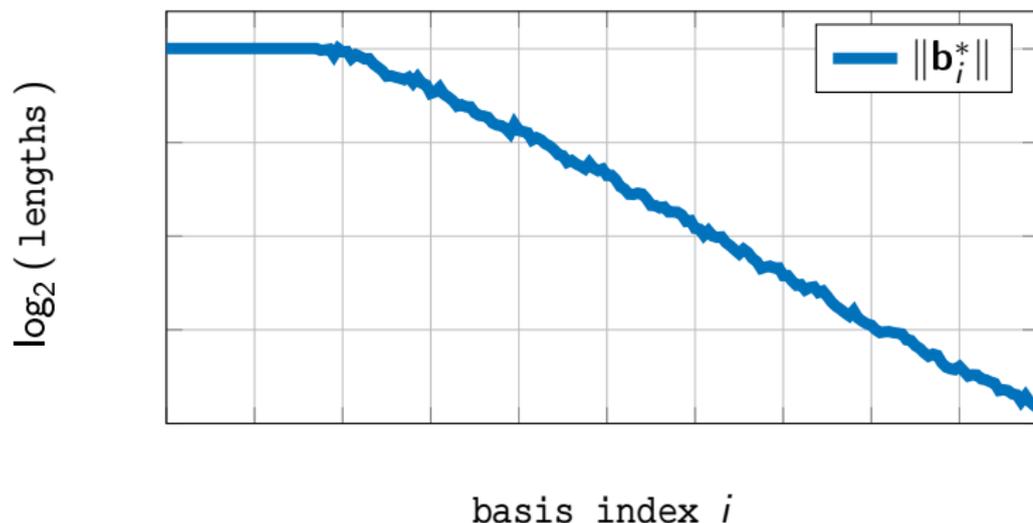
>>> [ADPS16] introduces a new success condition for solving Unique-SVP with BKZ when  $\|\mathbf{v}\|$  is known

>>> The strategy is based on the Geometric Series Assumption, and on the structure of the BKZ algorithm

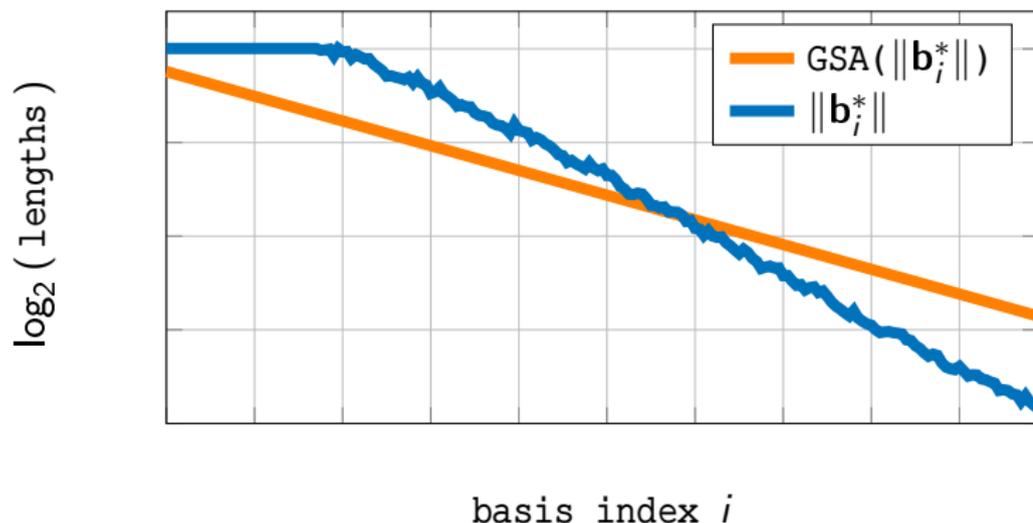
>>> We refer to this work as *the 2016 model*

>>> To explain the condition we will first review how BKZ works

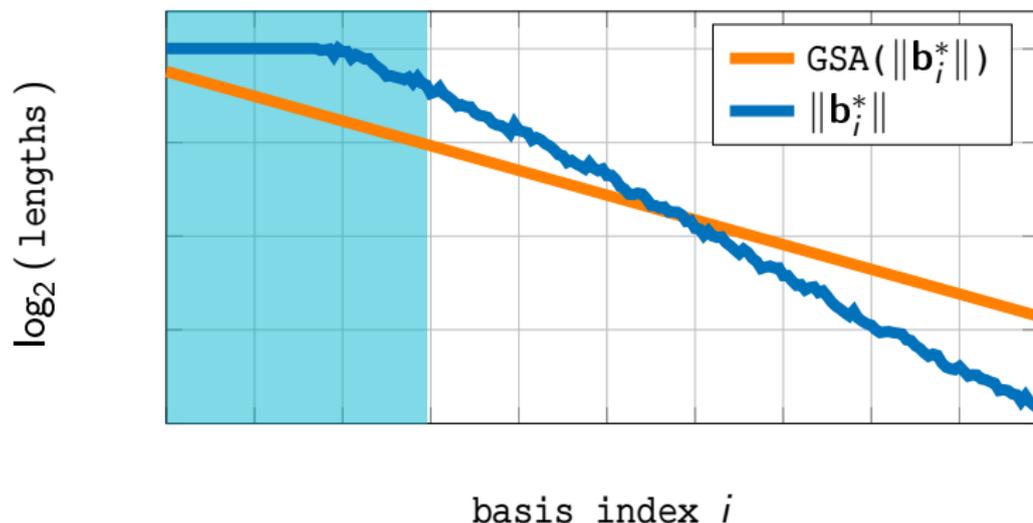
>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j^*\}_{j=1}^{i-1}$



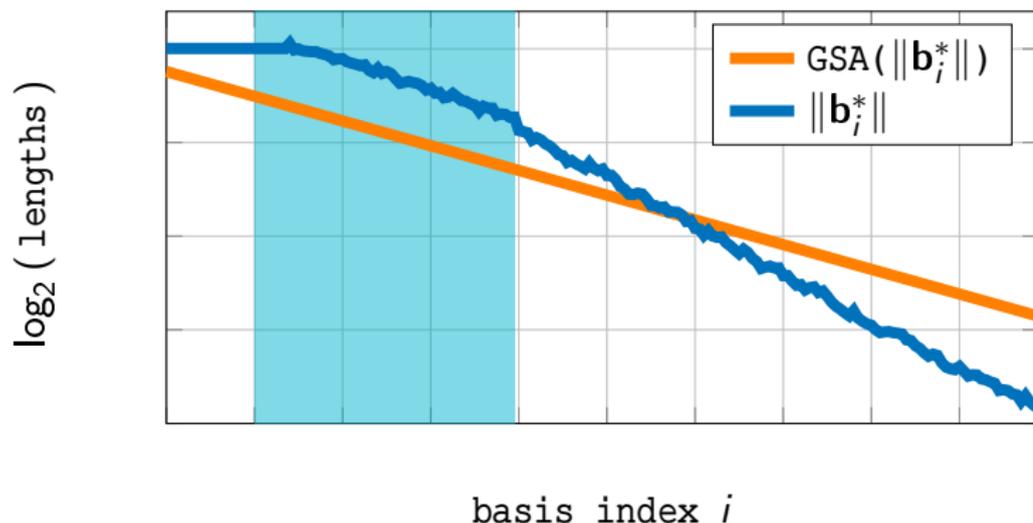
>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j^*\}_{j=1}^{i-1}$



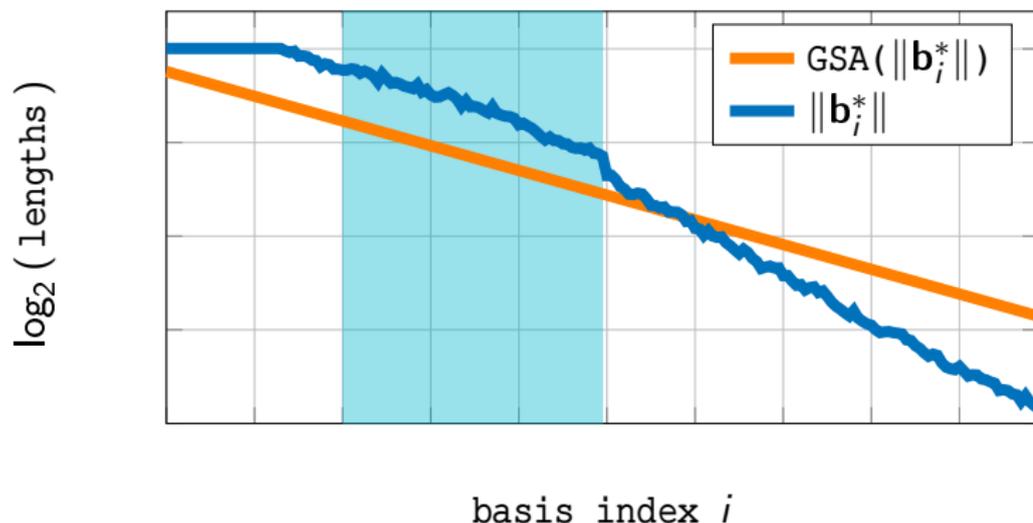
>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j^*\}_{j=1}^{i-1}$



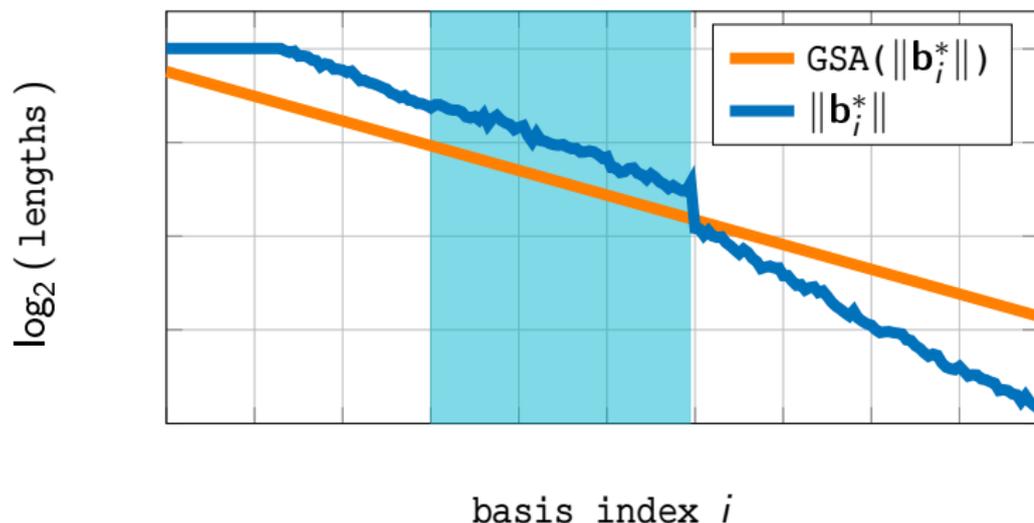
>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j^*\}_{j=1}^{i-1}$



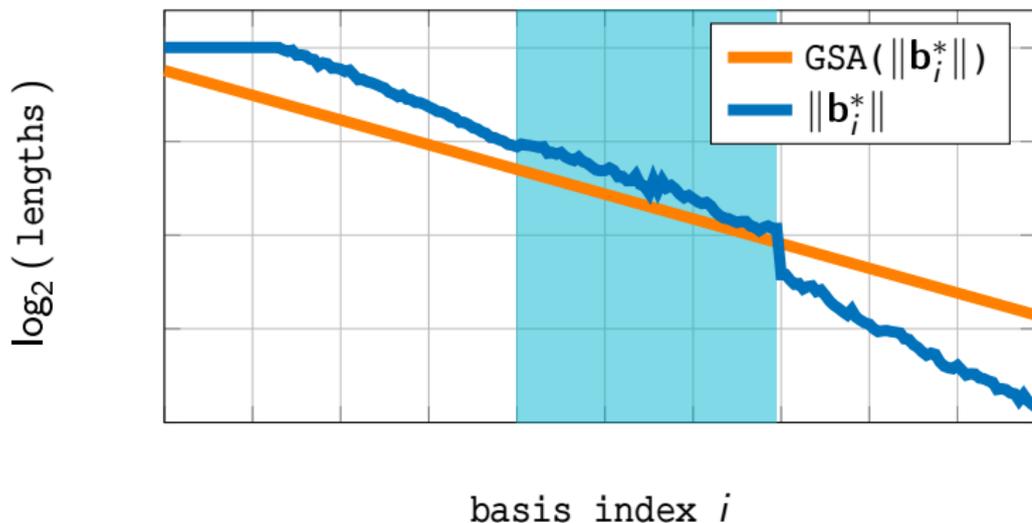
>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j^*\}_{j=1}^{i-1}$



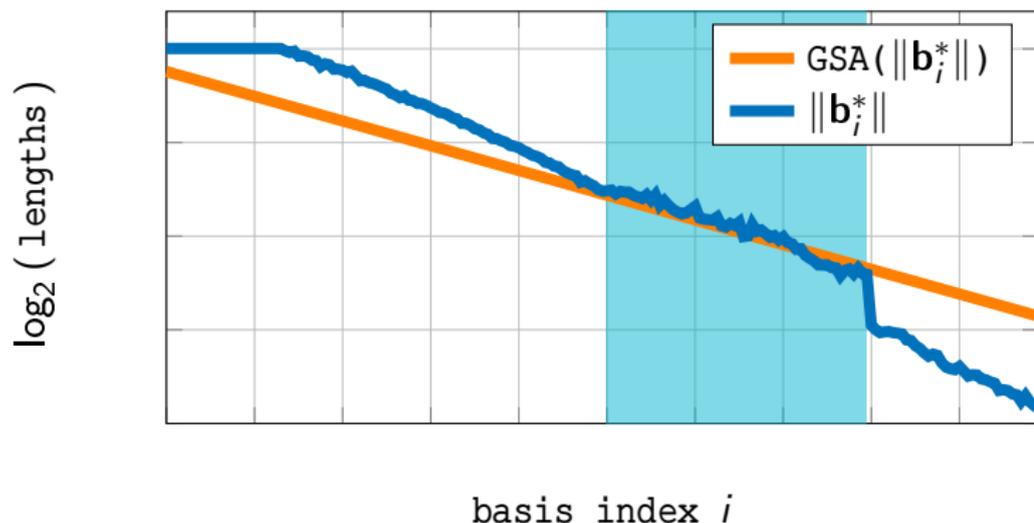
>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j^*\}_{j=1}^{i-1}$



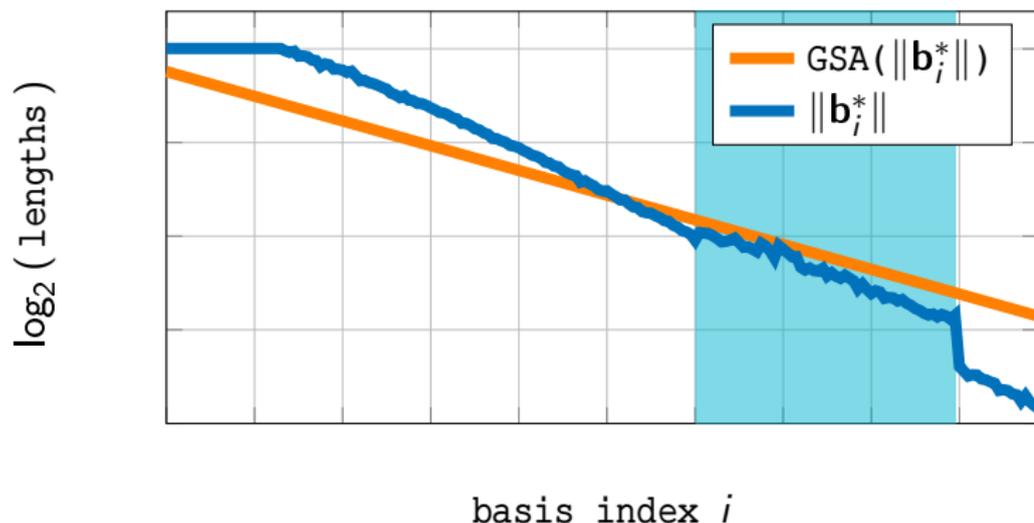
>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j^*\}_{j=1}^{i-1}$



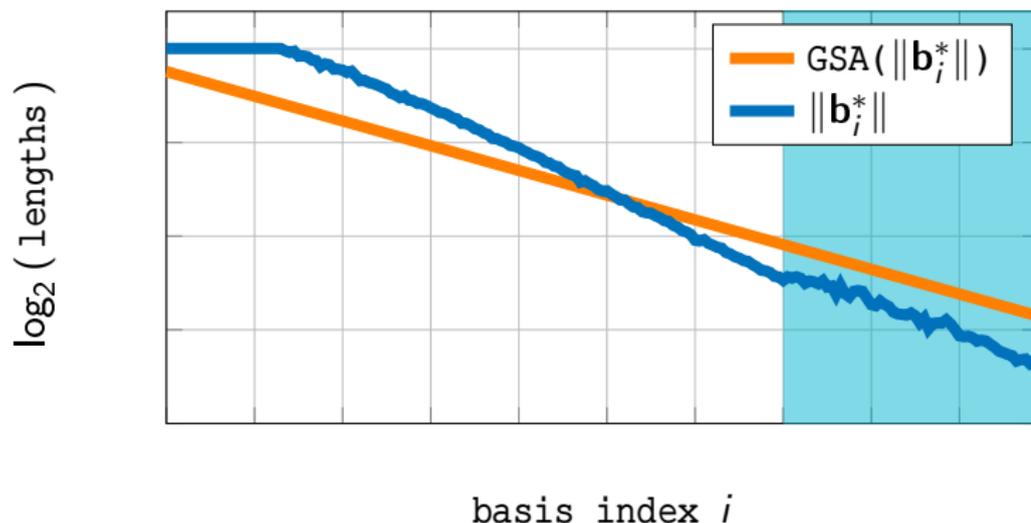
>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j^*\}_{j=1}^{i-1}$



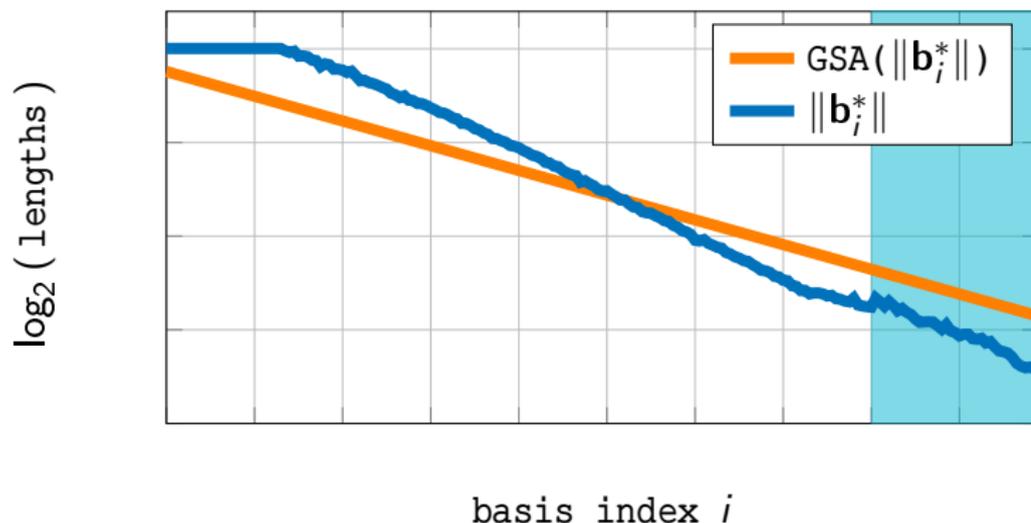
>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j^*\}_{j=1}^{i-1}$



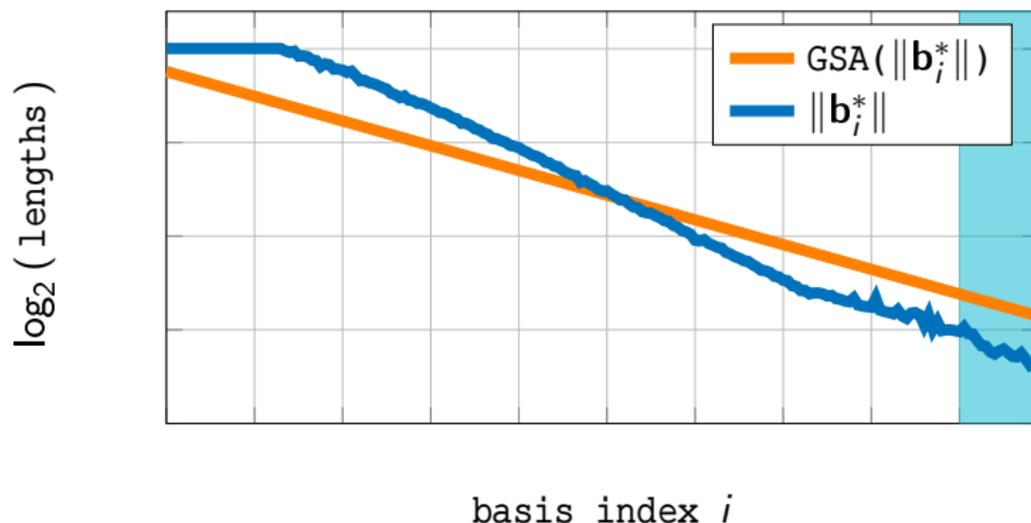
>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j\}_{j=1}^{i-1}$



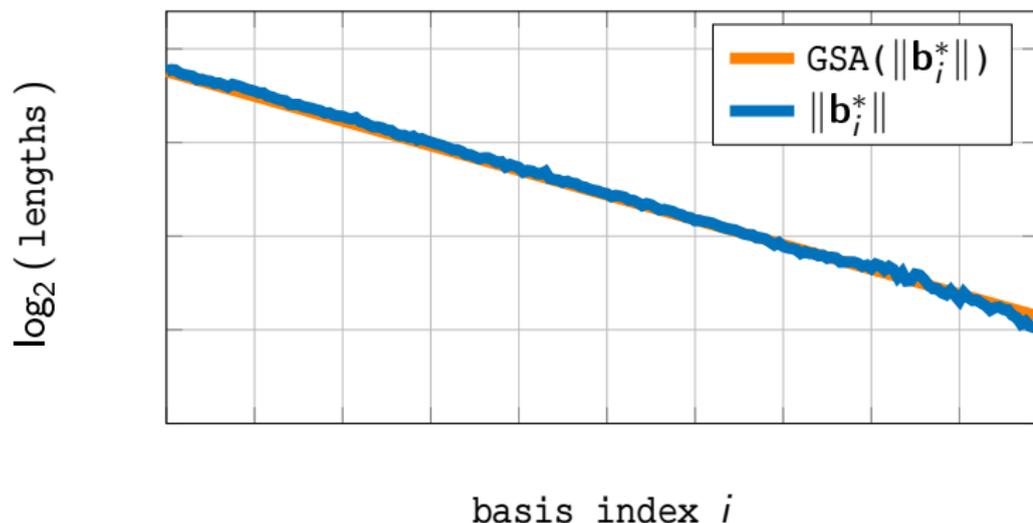
>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j^*\}_{j=1}^{i-1}$



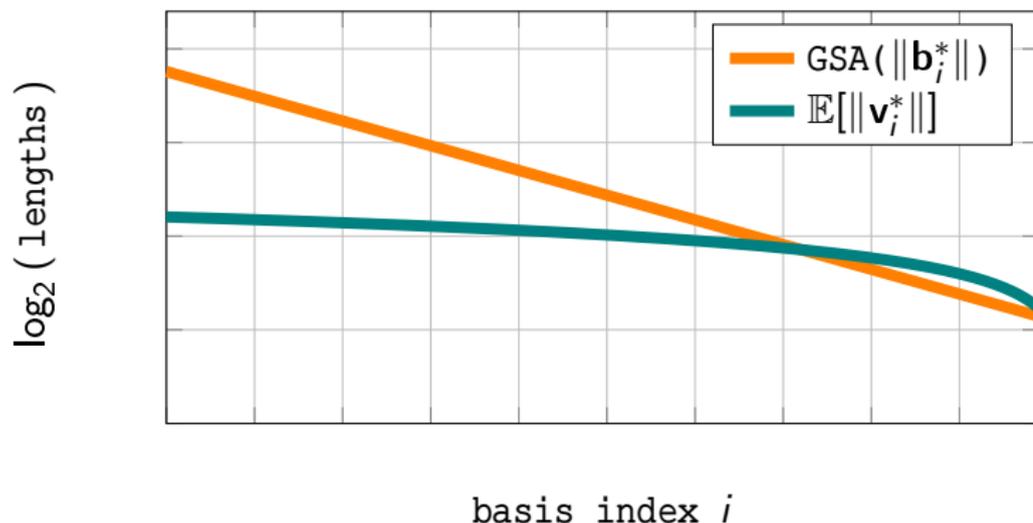
>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j^*\}_{j=1}^{i-1}$



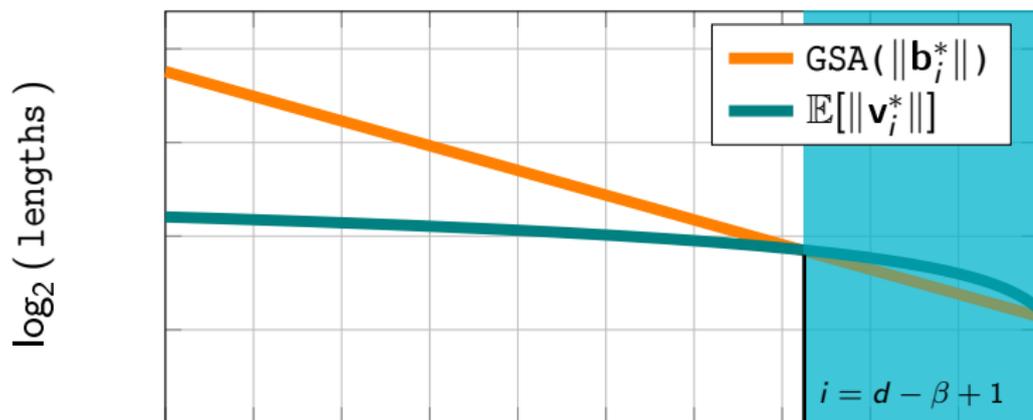
>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j^*\}_{j=1}^{i-1}$



>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j^*\}_{j=1}^{i-1}$



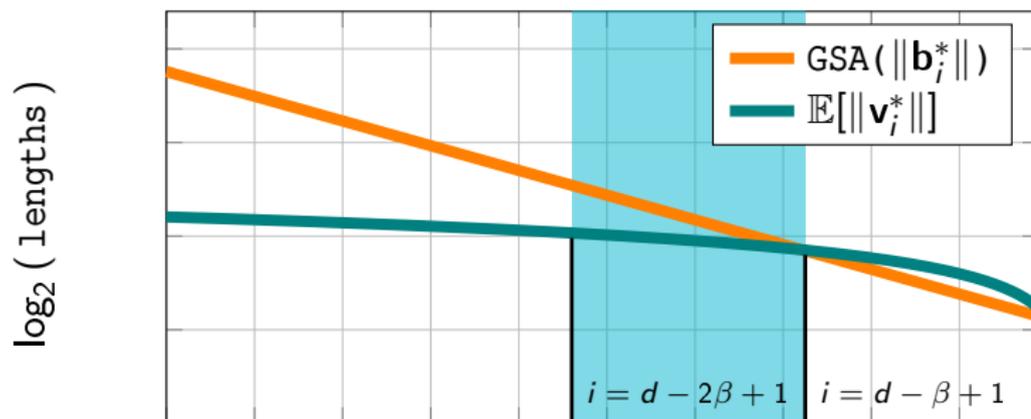
>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j^*\}_{j=1}^{i-1}$



>>> Choose  $\beta$  such that  $\|\mathbf{v}_{d-\beta+1}^*\| < \text{GSA}(\|\mathbf{b}_{d-\beta+1}^*\|)$

>>> Instantly solves Decision-LWE

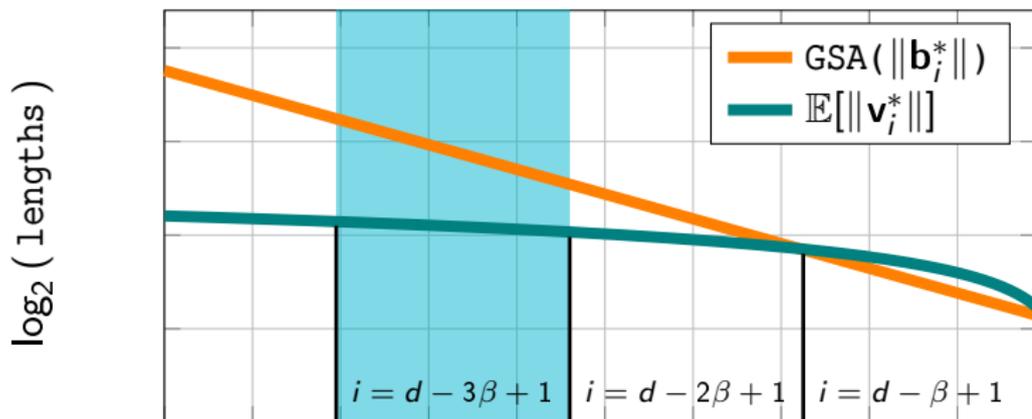
>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j^*\}_{j=1}^{i-1}$



>>> Choose  $\beta$  such that  $\|\mathbf{v}_{d-\beta+1}^*\| < GSA(\|\mathbf{b}_{d-\beta+1}^*\|)$

>>> Instantly solves Decision-LWE

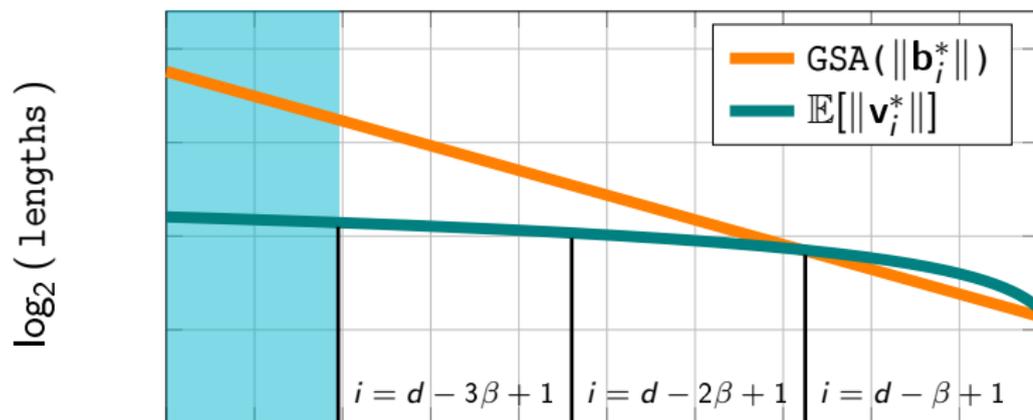
>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j^*\}_{j=1}^{i-1}$



>>> Choose  $\beta$  such that  $\|\mathbf{v}_{d-\beta+1}^*\| < GSA(\|\mathbf{b}_{d-\beta+1}^*\|)$

>>> Instantly solves Decision-LWE

>>> Let  $\{\mathbf{b}_i\}_i$  be  $\Lambda$ 's basis,  $\{\mathbf{b}_i^*\}_i$  their Gram-Schmidt vectors, and  $\mathbf{v}_i^*$  the projection of  $\mathbf{v} \perp \{\mathbf{b}_j^*\}_{j=1}^{i-1}$

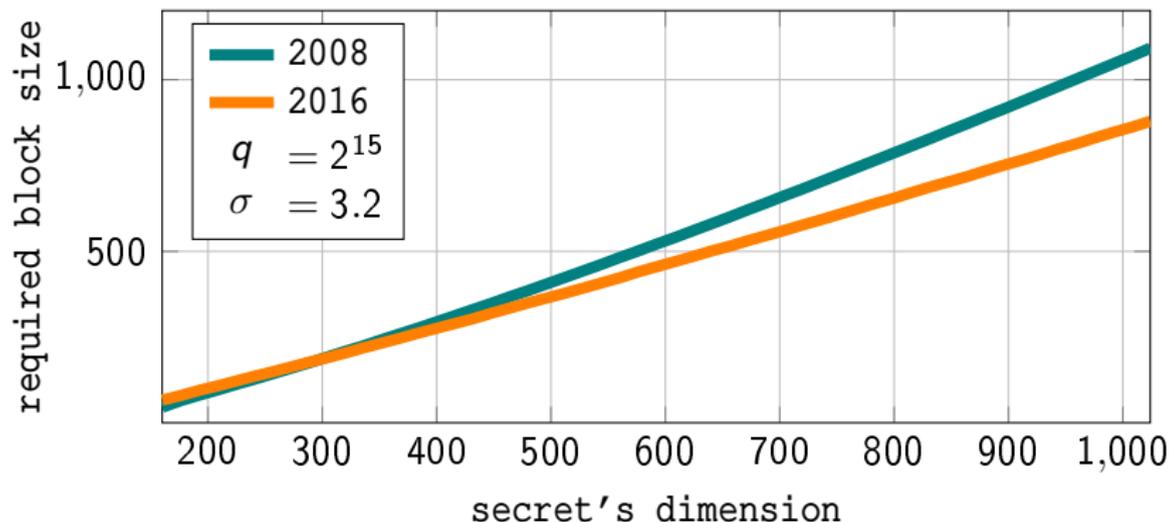


>>> Choose  $\beta$  such that  $\|\mathbf{v}_{d-\beta+1}^*\| < GSA(\|\mathbf{b}_{d-\beta+1}^*\|)$

>>> Instantly solves Decision-LWE

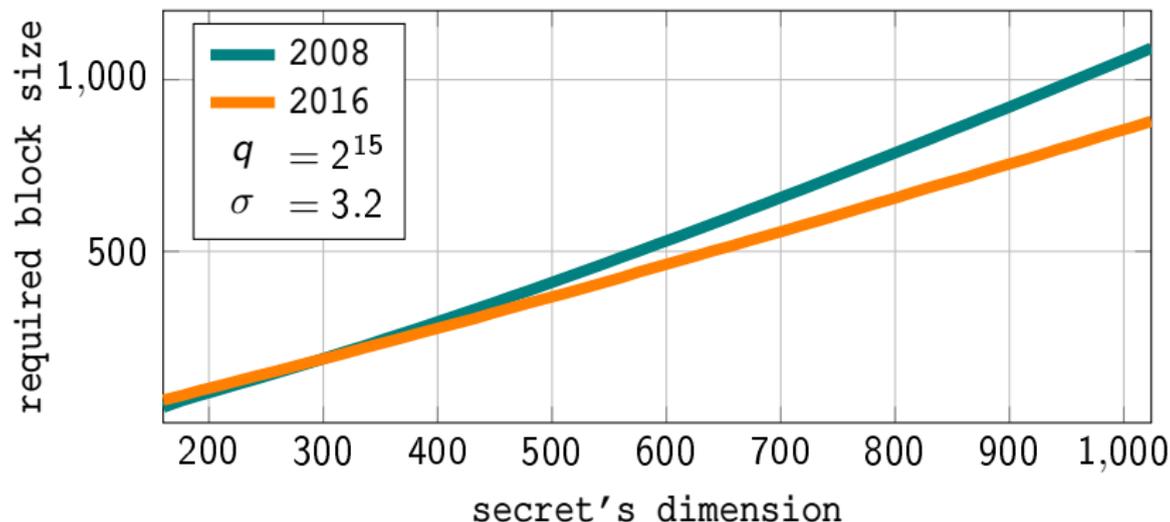
>>> Should solve Search-LWE with at most  $\lceil d/\beta \rceil - 1$  more SVP oracle calls

>>> The two models disagree on the primal attack's asymptotic complexity



>>> We decided to experimentally investigate the accuracy of the 2016 model's predictions

>>> The two models disagree on the primal attack's asymptotic complexity



>>> We decided to experimentally investigate the accuracy of the 2016 model's predictions

## Our experiments

- >>> Given  $(n, q, \sigma)$ , the 2008 model provides parameters  $(m_{2008}, \beta_{2008})$  for 10% recovery probability [AFG14]
- >>> We pick  $(m_{2016}, \beta_{2016})$  according to [ADPS16], run BKZ2 and measure the recovery rate
- >>> We instrument BKZ to take detailed statistics about the  $v_i^*$  length and moment of recovery
- >>> To simplify analysis we make some changes to subroutine calls to LLL
- >>> All our experiments were run using the FpyLLL lattice reduction library [FPL17, FPY17]

## Our experiments

- >>> Given  $(n, q, \sigma)$ , the 2008 model provides parameters  $(m_{2008}, \beta_{2008})$  for 10% recovery probability [AFG14]
- >>> We pick  $(m_{2016}, \beta_{2016})$  according to [ADPS16], run BKZ2 and measure the recovery rate
- >>> We instrument BKZ to take detailed statistics about the  $\mathbf{v}_i^*$  length and moment of recovery
- >>> To simplify analysis we make some changes to subroutine calls to LLL
- >>> All our experiments were run using the FpyLLL lattice reduction library [FPL17, FPY17]

## Our experiments

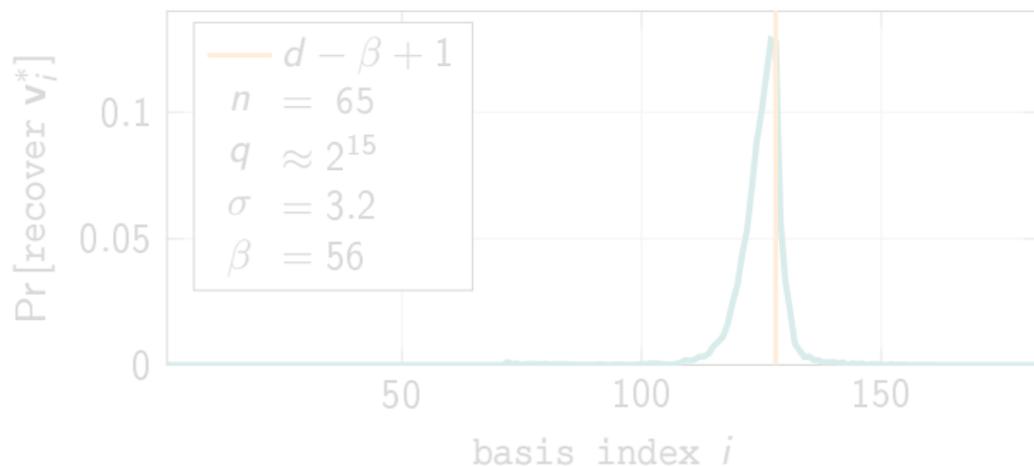
- >>> Given  $(n, q, \sigma)$ , the 2008 model provides parameters  $(m_{2008}, \beta_{2008})$  for 10% recovery probability [AFG14]
- >>> We pick  $(m_{2016}, \beta_{2016})$  according to [ADPS16], run BKZ2 and measure the recovery rate
- >>> We instrument BKZ to take detailed statistics about the  $\mathbf{v}_i^*$  length and moment of recovery
- >>> To simplify analysis we make some changes to subroutine calls to LLL
- >>> All our experiments were run using the FpyLLL lattice reduction library 🍷 [FPL17, FPY17]

# Results

LWE parameters			[ADPS16]		Experiments		
$n$	$q$	$\sigma$	$\beta_{2016}$	$m_{2016}$	$\beta$	#	recovery rate
65	521	3.2	56	182	56	10000	93.3%
					51		52.8%
					46		4.8%
80	1031	3.2	60	204	60	1000	94.2%
					55		60.6%
					50		8.9%
					45		0.2%
100	2053	3.2	67	243	67	500	88.8%
					62		39.6%
					57		5.8%
					52		0.2%
108	2053	3.2	77	261	77	5	100.0%
110	2053	3.2	78	272	78	5	100.0%

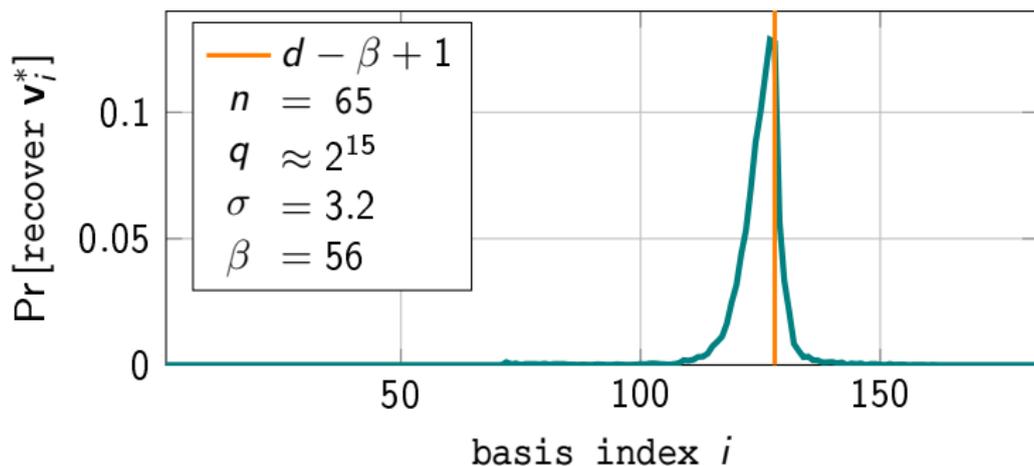
>>> Experiments agree with the 2016 model, but we noticed two unexpected behaviours

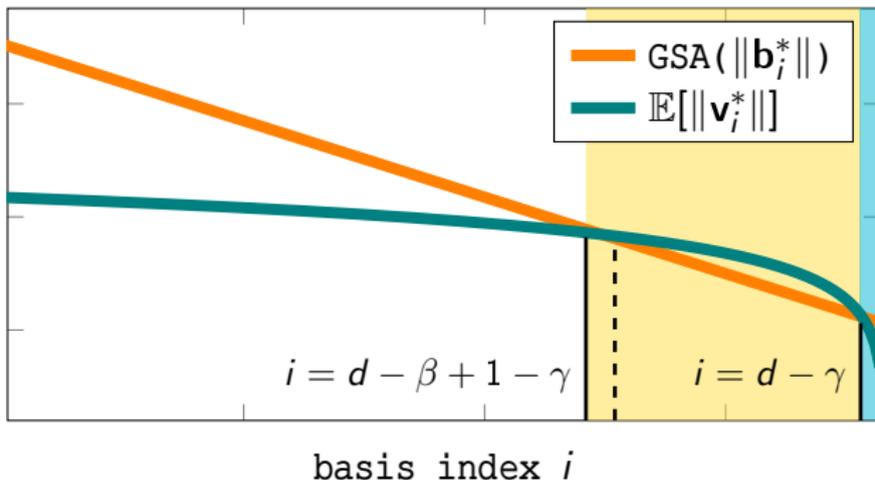
>>> First, while expecting BKZ to recover  $\mathbf{v}_{d-\beta+1}^*$ , for small experiments we observed



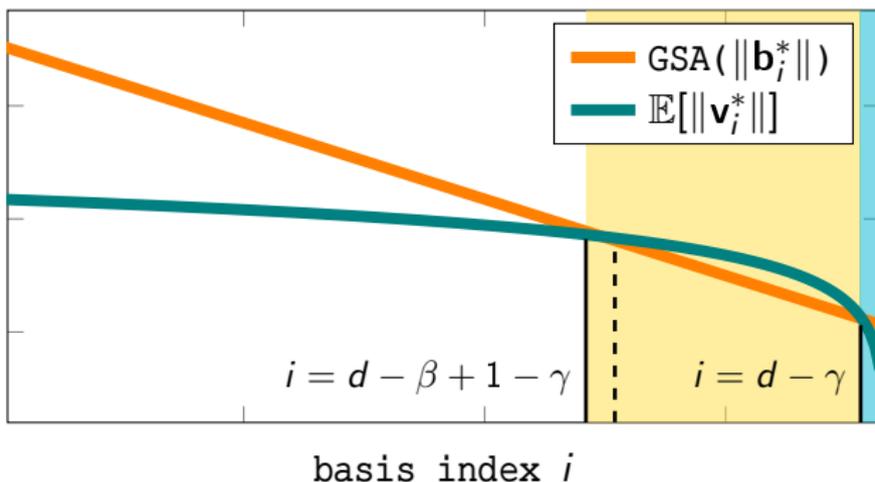
>>> Experiments agree with the 2016 model, but we noticed two unexpected behaviours

>>> First, while expecting BKZ to recover  $\mathbf{v}_{d-\beta+1}^*$ , for small experiments we observed





- >>>  $v_i^*$  is first recovered at the rightmost intersection at  $i = d - \gamma$
- >>> In the next tour this projection is extended at  $i = d - \beta + 1 - \gamma$
- >>> The double intersection is not common for cryptographically chosen parameters, and can be easily avoided



- >>>  $\mathbf{v}_i^*$  is first recovered at the rightmost intersection at  $i = d - \gamma$
- >>> In the next tour this projection is extended at  $i = d - \beta + 1 - \gamma$
- >>> The double intersection is not common for cryptographically chosen parameters, and can be easily avoided

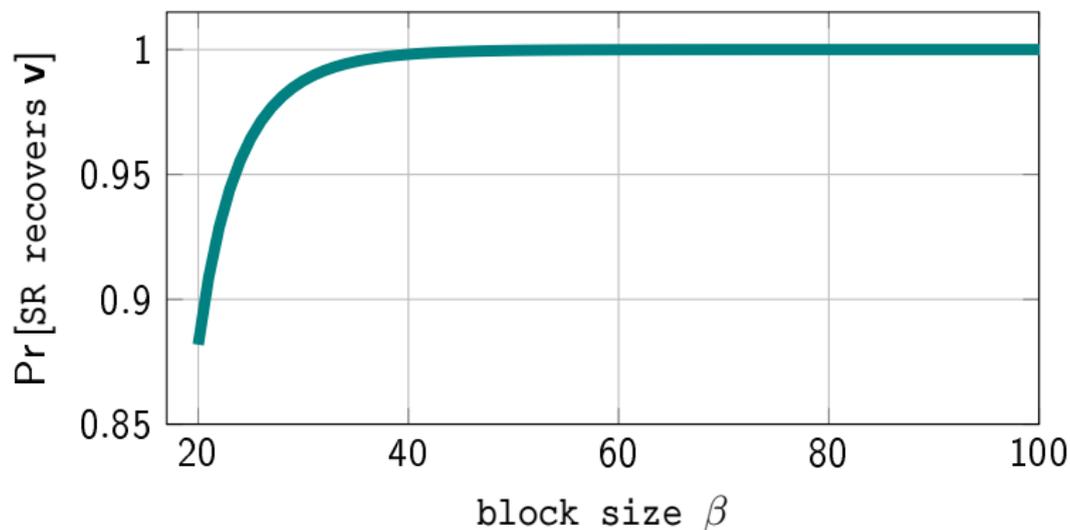
>>> Second, 99.7%+ of the time  $\mathbf{v}$  is recovered immediately after the SVP oracle finds its projection

>>> We model the state of the bases after first finding  $\mathbf{v}_{d-\beta+1}^*$

>>> Second, 99.7%+ of the time  $\mathbf{v}$  is recovered immediately after the SVP oracle finds its projection

>>> We model the state of the bases after first finding  $\mathbf{v}_{d-\beta+1}^*$

>>> Lemma For  $\beta > 40$ , Size Reduction recovers  $\mathbf{v}$  from  $\mathbf{v}_{d-\beta+1}^*$  with overwhelming probability □



## New security estimates

>>> We added the 2016 model to the LWE estimator from [APS15], and used it to recast the primal attack against proposed schemes (as of May 2017)

>>> For each scheme we used their proposed cost strategy

## New security estimates

>>> We added the 2016 model to the LWE estimator from [APS15], and used it to recast the primal attack against proposed schemes (as of May 2017)

>>> For each scheme we used their proposed cost strategy

Scheme	Estimate as of May 17	Our estimate
Lizard [CKLS16a, CKLS16b]	129.7--131.6	85.9--88.7
TESLA [BG14, ABBD15]	71.0--142.0	61.5--122.4
SEAL v2.1 [CLP17]	97.6--130.5	99.6--129.5

- >>> Security estimates for Lizard (PKE), TESLA (Signatures) and SEAL 2.1 (FHE) under the 2016 model, as of May 2017; more in the paper
- >>> Some schemes were parametrised against the dual attack from [Alb17], which is still (often) cheaper against sparse and small secrets. Nonetheless, in those cases the gap between primal and dual attack narrows

# Conclusions

>>> We confirmed the validity of the 2016 model [ADPS16]

>>> Some existing lattice based schemes may need reparametrisation to resist cryptanalysis via lattice reduction

>>> The double intersection observation and the difference in success probability between models tell a cautionary tale about extrapolating asymptotics from small dimensional experiments

# Conclusions

- >>> We confirmed the validity of the 2016 model [ADPS16]
- >>> Some existing lattice based schemes may need reparametrisation to resist cryptanalysis via lattice reduction
- >>> The double intersection observation and the difference in success probability between models tell a cautionary tale about extrapolating asymptotics from small dimensional experiments

## Conclusions

- >>> We confirmed the validity of the 2016 model [ADPS16]
- >>> Some existing lattice based schemes may need reparametrisation to resist cryptanalysis via lattice reduction
- >>> The double intersection observation and the difference in success probability between models tell a cautionary tale about extrapolating asymptotics from small dimensional experiments

# Thank you



- >>> Paper @ <https://ia.cr/2017/815>
- >>> Experiments (code && data) @ <https://github.com/fvirdia/agvw17-code-data>
- >>> Estimator [APS15] @ <https://bitbucket.org/malb/lwe-estimator>

- [ABBD15] Erdem Alkim, Nina Bindel, Johannes Buchmann, and Özgür Dagdelen.  
TESLA: Tightly-secure efficient signatures from standard lattices.  
  
Cryptography ePrint Archive, Report 2015/755, 2015.  
<http://eprint.iacr.org/2015/755>.
- [ADPS16] 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*, pages 327--343. USENIX Association, 2016.
- [AFG14] Martin R. Albrecht, Robert Fitzpatrick, and Florian Göpfert.  
On the efficacy of solving LWE by reduction to unique-SVP.  
In Hyang-Sook Lee and Dong-Guk Han, editors, *ICISC 13*, volume 8565 of *LNCS*, pages 293--310. Springer, Heidelberg, November 2014.
- [Alb17] Martin R. Albrecht.  
On dual lattice attacks against small-secret LWE and parameter choices in HELib and SEAL.  
In Jean-Sébastien Coron and Jesper Buus Nielsen, editors, *EUROCRYPT 2017, Part II*, volume 10211 of *LNCS*, pages 103--129. Springer, Heidelberg, April / May 2017.
- [APS15] Martin R. Albrecht, Rachel Player, and Sam Scott.  
On the concrete hardness of Learning with Errors.

*Journal of Mathematical Cryptology*, 9(3):169--203, 2015.

- [BG14] Shi Bai and Steven D. Galbraith.  
An improved compression technique for signatures based on learning with errors.  
In Josh Benaloh, editor, *CT-RSA 2014*, volume 8366 of *LNCS*, pages 28--47. Springer, Heidelberg, February 2014.
- [CKLS16a] Jung Hee Cheon, Duhyeong Kim, Joohee Lee, and Yongsoo Song.  
Lizard: Cut off the tail! Practical post-quantum public-key encryption from *LWE* and *LWR*.  
Cryptology ePrint Archive, Report 2016/1126 (20161222:071525), 2016.  
<http://eprint.iacr.org/2016/1126/20161222:071525>.
- [CKLS16b] Jung Hee Cheon, Duhyeong Kim, Joohee Lee, and Yongsoo Song.  
Lizard: Cut off the tail! Practical post-quantum public-key encryption from *LWE* and *LWR*.  
Cryptology ePrint Archive, Report 2016/1126, 2016.  
<http://eprint.iacr.org/2016/1126>.
- [CLP17] Hao Chen, Kim Laine, and Rachel Player.  
Simple encrypted arithmetic library - SEAL v2.1.  
Cryptology ePrint Archive, Report 2017/224, 2017.  
<http://eprint.iacr.org/2017/224>.
- [FPLL17] The FPLLL development team.

fp111, a lattice reduction library.

Available at <https://github.com/fp111/fp111>, 2017.

[FPY17]

The FPYLLL development team.

fpy111, a Python (2 and 3) wrapper for fp111.

Available at <https://github.com/fp111/fpy111>, 2017.

[GN08]

Nicolas Gama and Phong Q. Nguyen.

Predicting lattice reduction.

In Nigel P. Smart, editor, *EUROCRYPT 2008*, volume 4965 of *LNCS*, pages 31--51. Springer, Heidelberg, April 2008.