Template Attacks on Different Devices

COSADE 2014

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Outline

- Template Attacks [Chari et al., CHES ’02]

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- Problems when using different devices

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- Extensive evaluation of TA on different devices
  - 4 devices and 5 acquisition campaigns
  - several compression methods
  - several methods to improve attack

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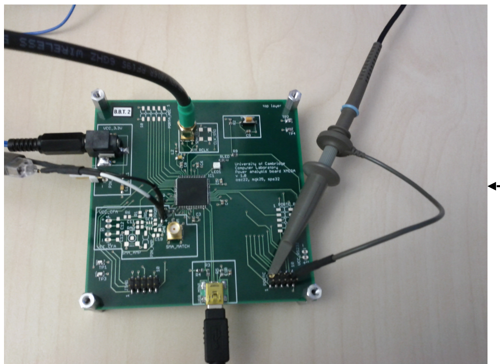
- Template Attacks [Chari et al., CHES ’02]
- Problems when using different devices
- Extensive evaluation of TA on different devices
  - 4 devices and 5 acquisition campaigns
  - several compression methods
  - several methods to improve attack
- PCA and LDA
  - Guideline for PCA/LDA to make it efficient
  - Method for improving PCA

Template Attacks on DPA contest v4

Participant	Submission date	Key found	Max PGE < 10	Key found (stable)	Max PGE stable < 10	Time/Trace (ms)	Attack type
Liran Lerman Université Libre de Bruxelles, Belgium	19/09/2013	22	13	22	13	24 ms	Profiling
Amir Moradi RUB, Germany	02/10/2013	174	148	174	148	305 ms	Non Profiling
Tang Ming Wuhan University, China	03/11/2013	763	465	990	482	271 ms	Non Profiling
Frank Schuhmacher Segrids, Germany	26/02/2014	1	1	1	1	5 ms	Profiling
Hideo Shimizu Toshiba Corporation Corporate Research & Development Center, Japan	28/02/2014	1	1	1	1	30 ms	Profiling
Xavier Bodart, Liran Lerman Université Libre de Bruxelles, Belgique	06/03/2014	21	17	21	17	400 ms	Profiling

- **Key found**: Number of traces needed to find the correct key
- **Max PGE < 10**: Number of traces for the maximum Partial Guessing Entropy to be below 10
- **Key found (stable)**: Number of traces needed to find the correct key for good
- **Max PGE stable < 10**: Number of traces for the maximum Partial Guessing Entropy to be stable below 10
- **Time/Trace**: Mean time per trace

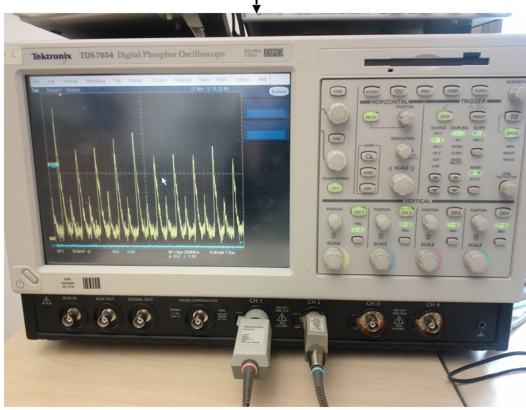
Template Attacks – Setup

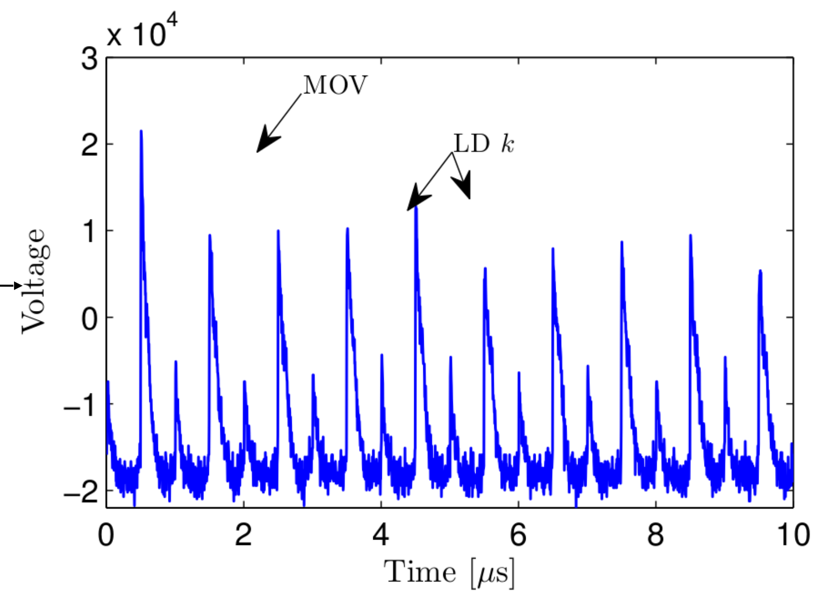


k

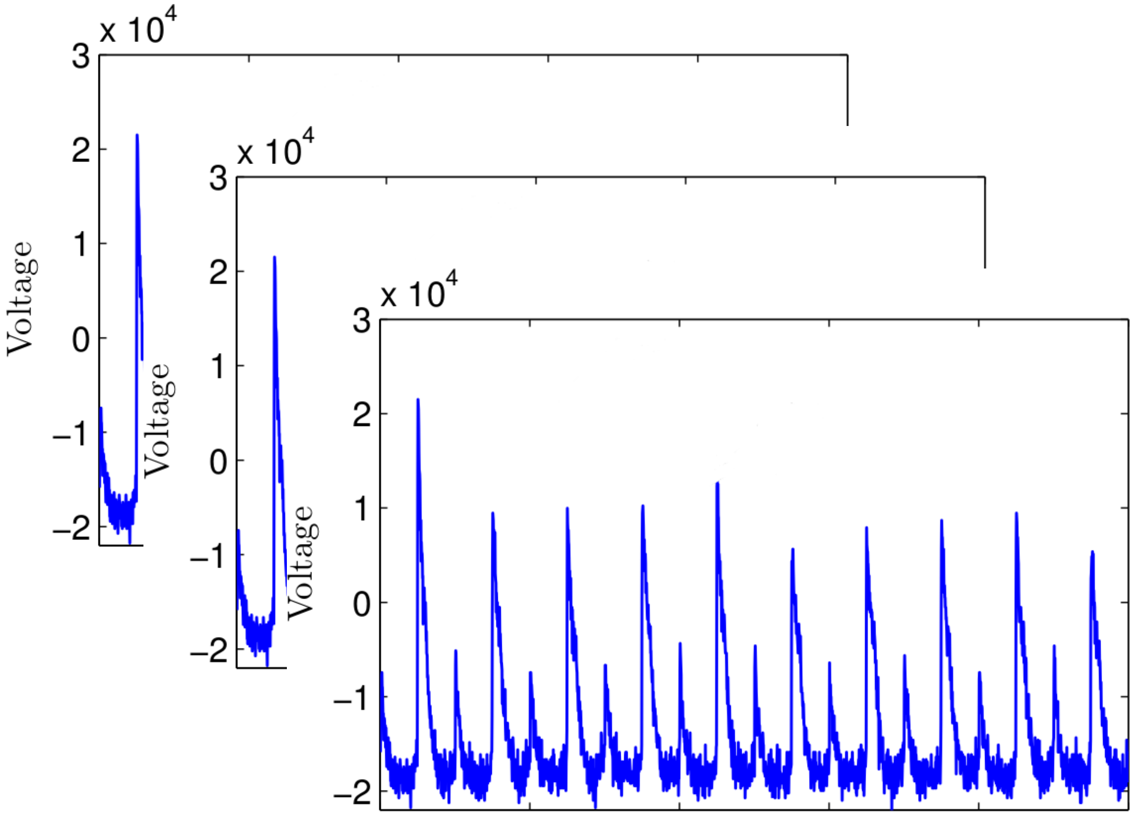
CODE

```
...
movw r30, r24
ld r8, Z+
ld r9, Z+        <-  target
ld r10, Z+
ld r11, Z+
...
```





Template Attacks – Profiling

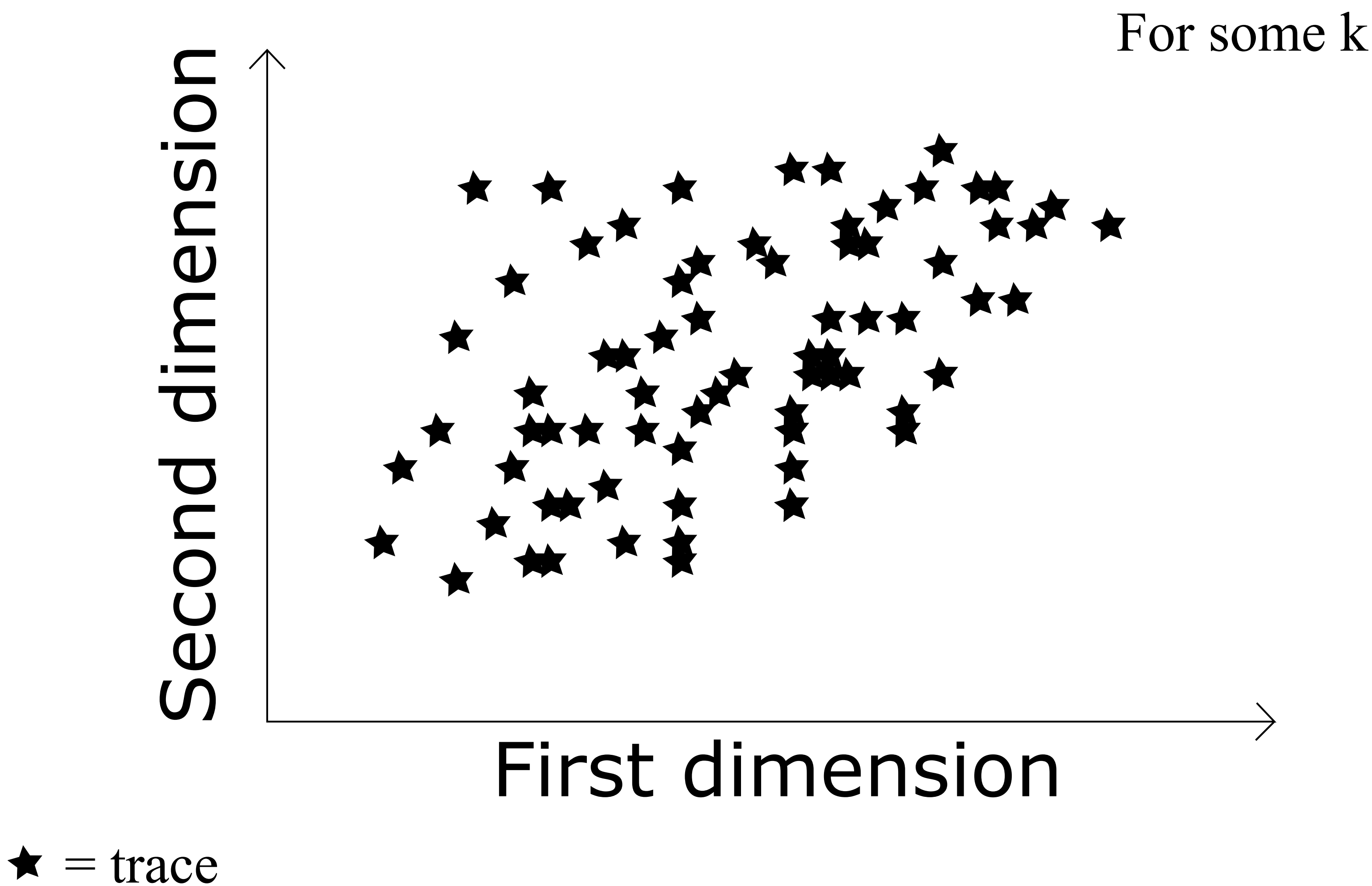


k = 0, 1, 2, ..., 255

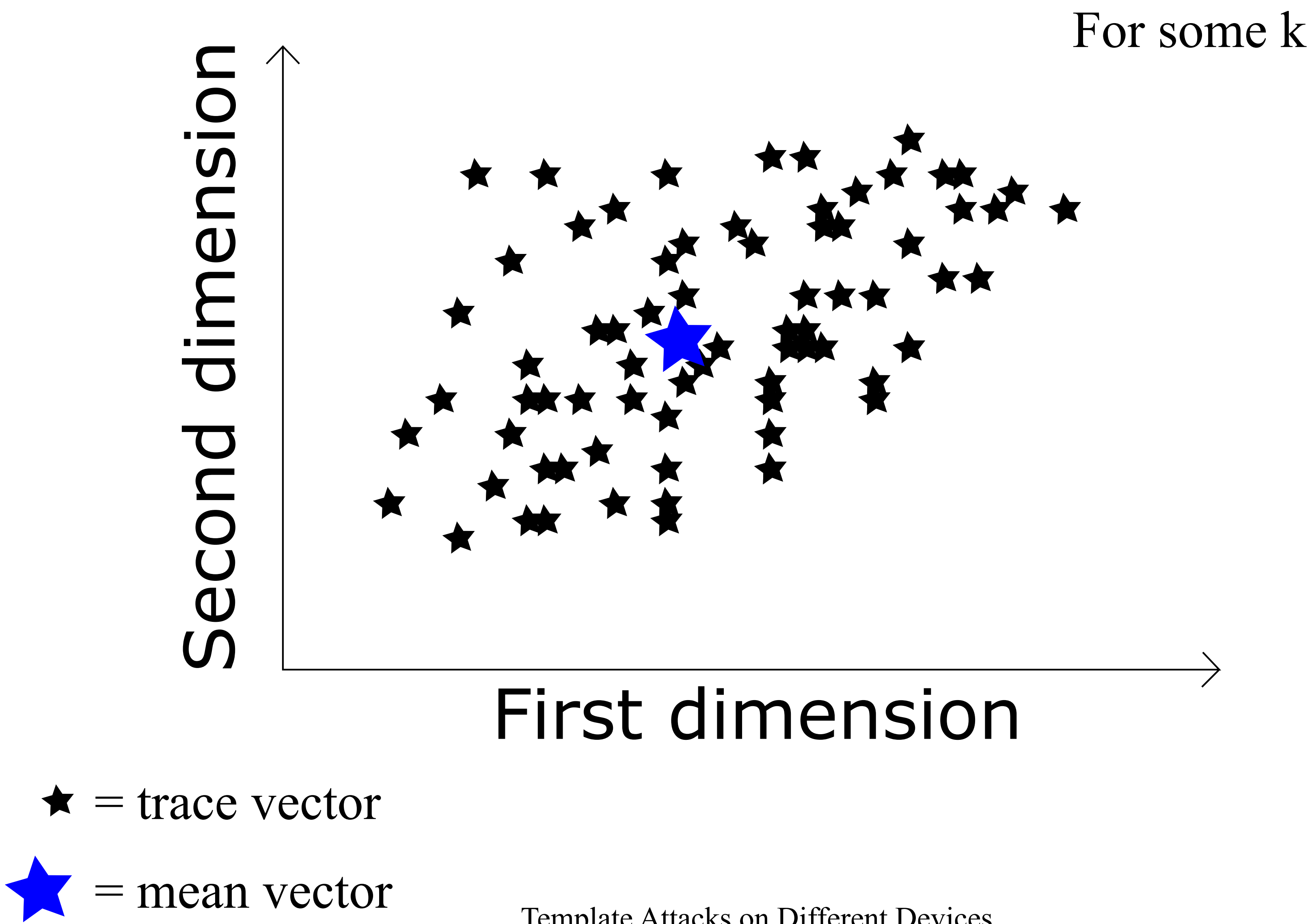
$n_\mathrm{p} = 1000$ profiling traces per k

$m = 2500$ samples per trace

Data space

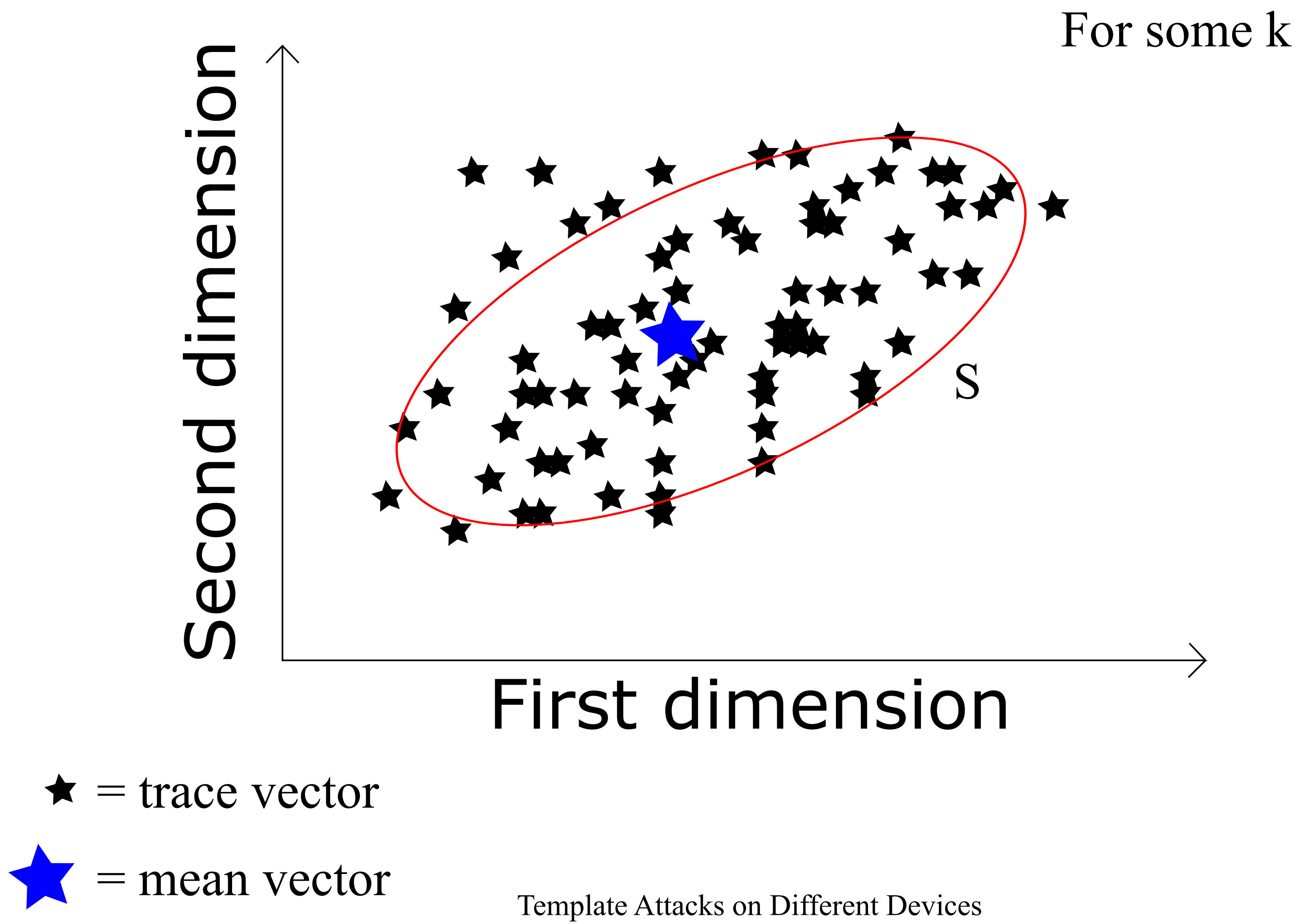


Data space



For some k
Second dimension
First dimension
= trace vector
= mean vector

Data space



For some k
Second dimension
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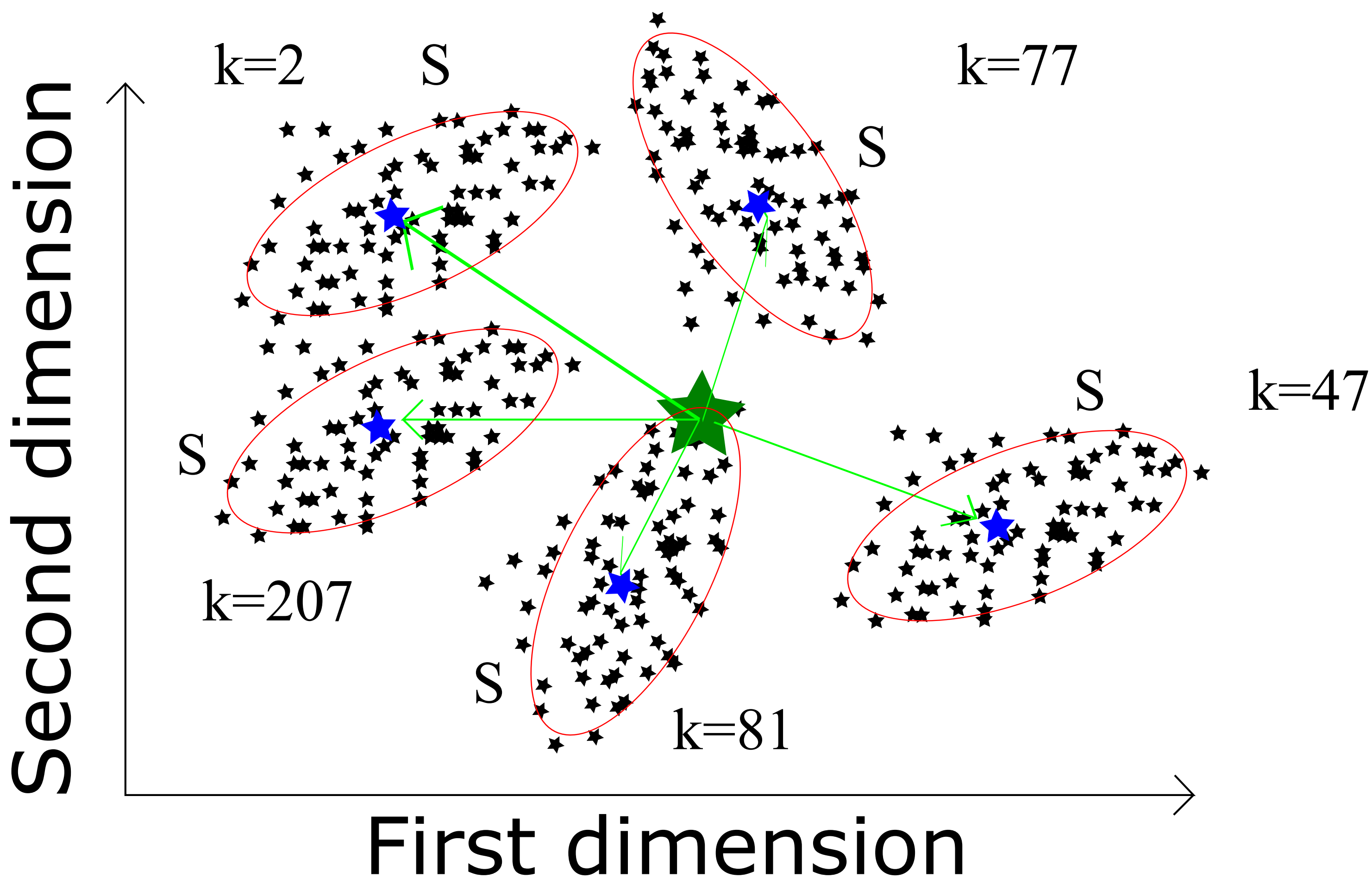
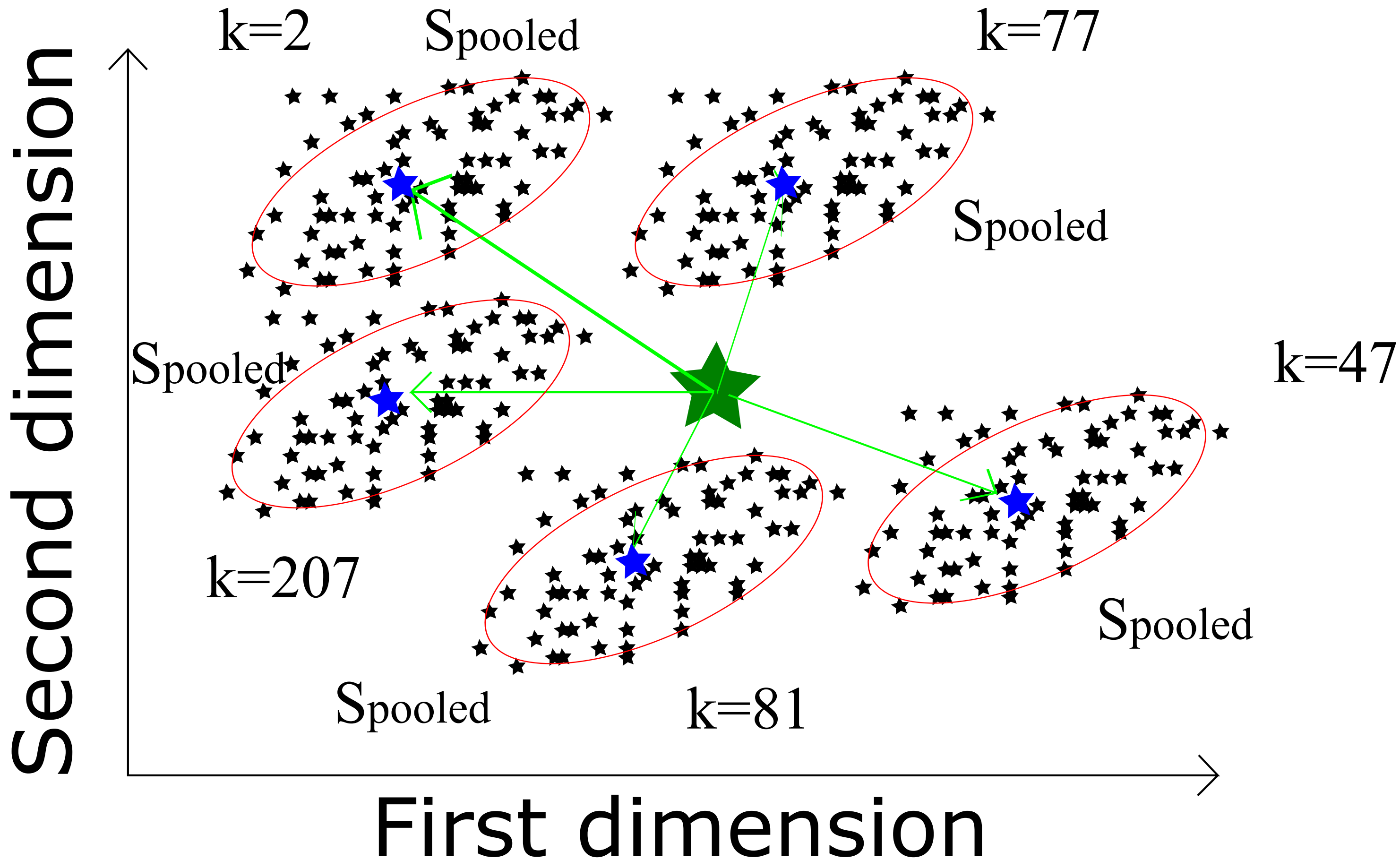
First dimension
= trace vector
= mean vector

Data space

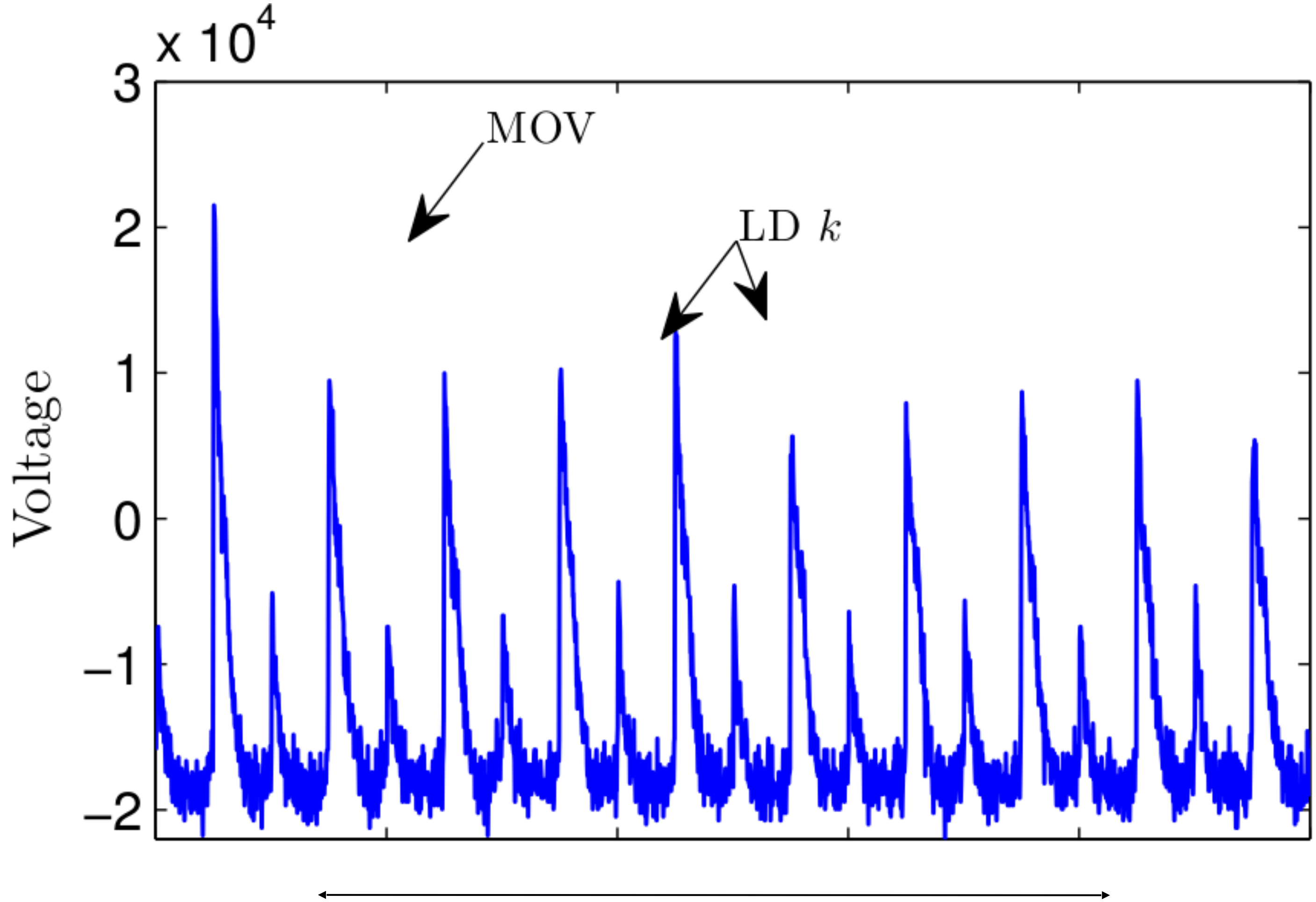


Data space



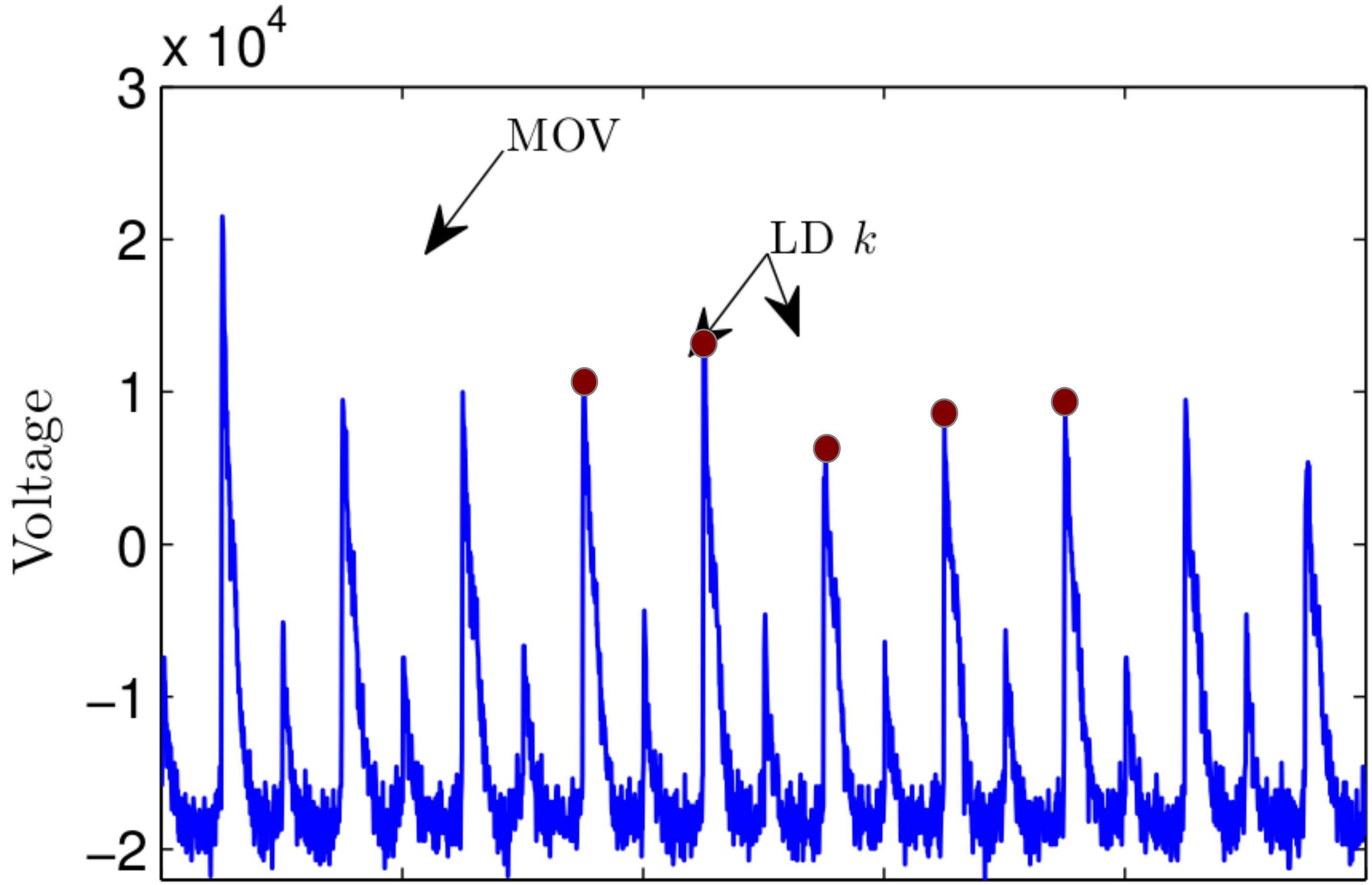
k=2
Spooled
k=77
Spooled
Spooled
k=47
k=207
Spooled
Spooled
k=81
Second dimension
First dimension

Template Attacks – Compression



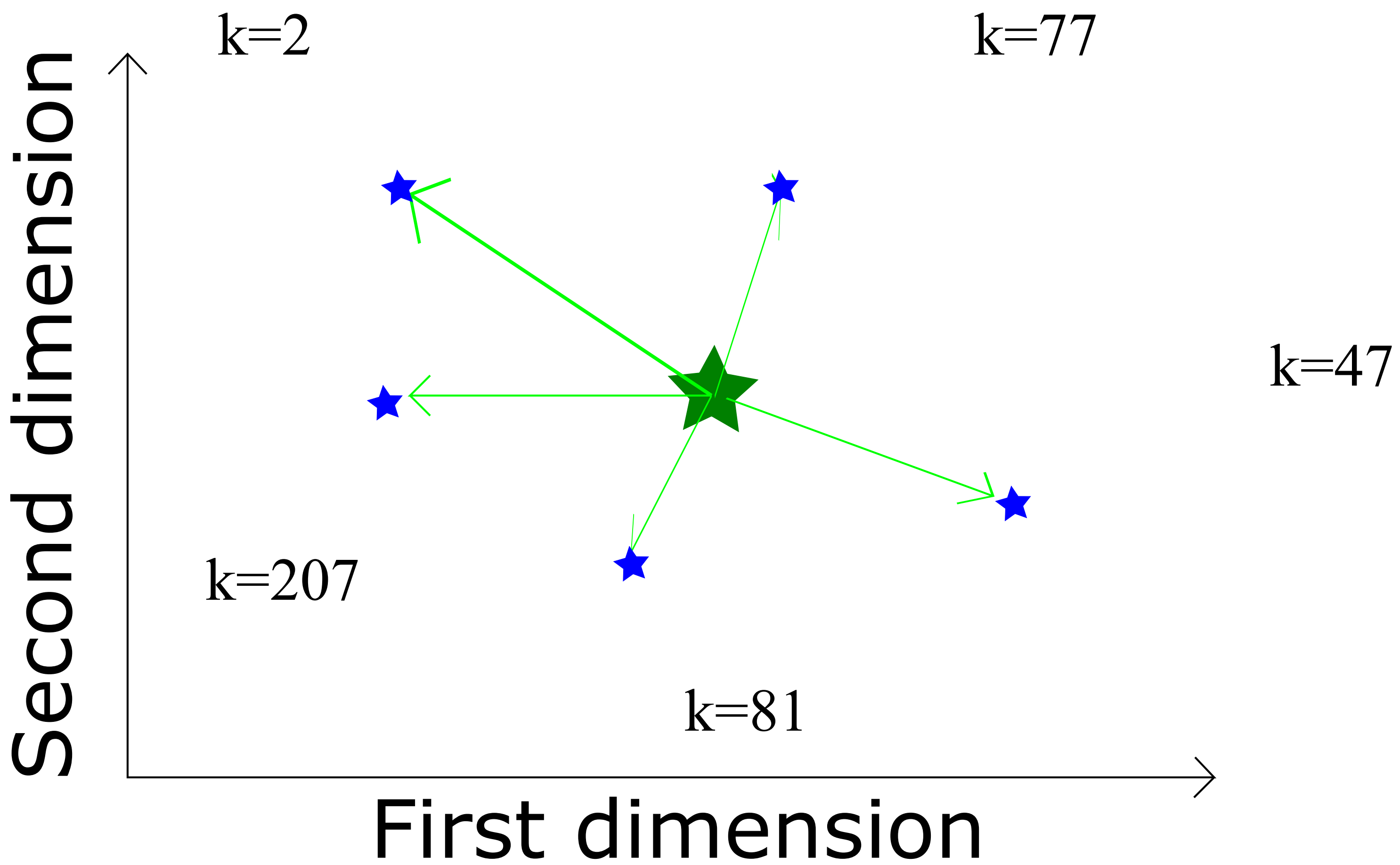
m = 2500 samples (points)

Select samples



$m = 5$

Principal Component Analysis (PCA)



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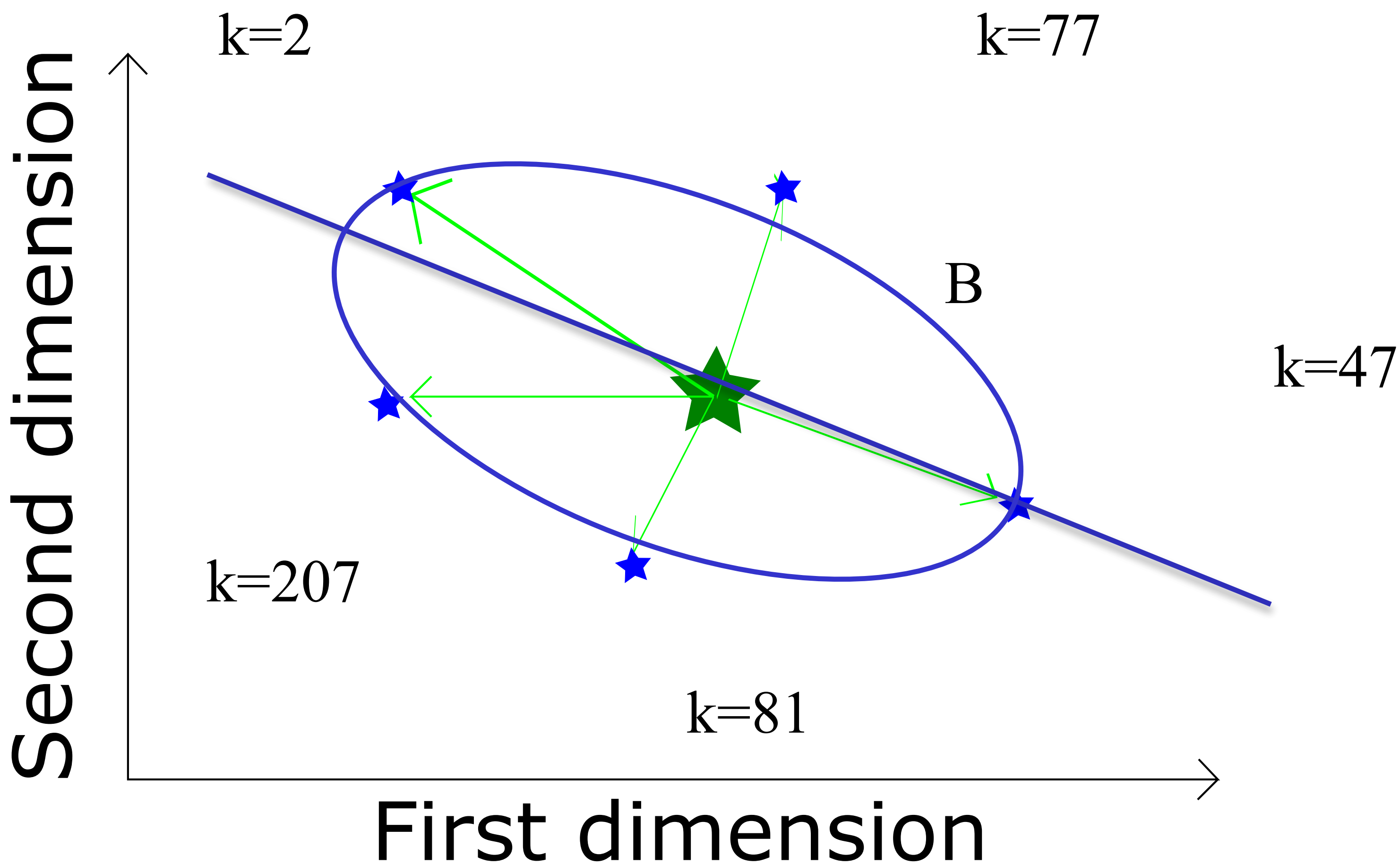

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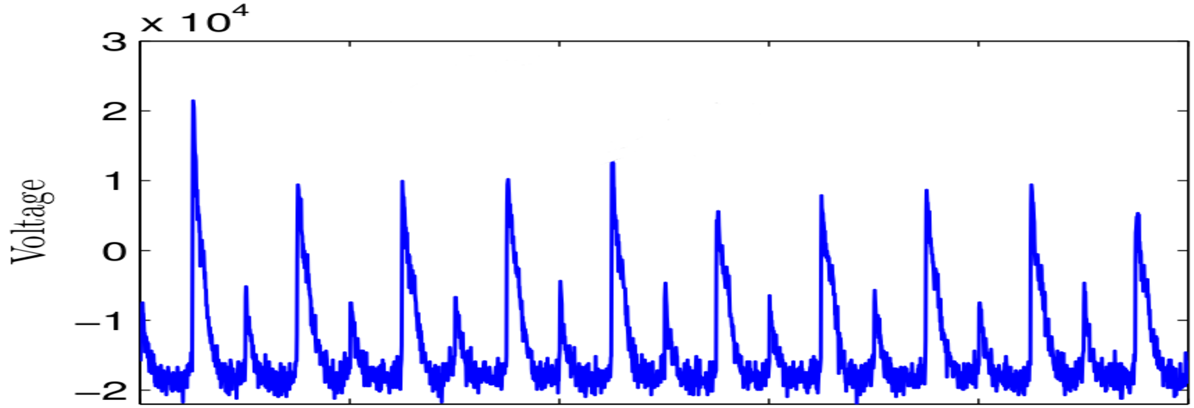
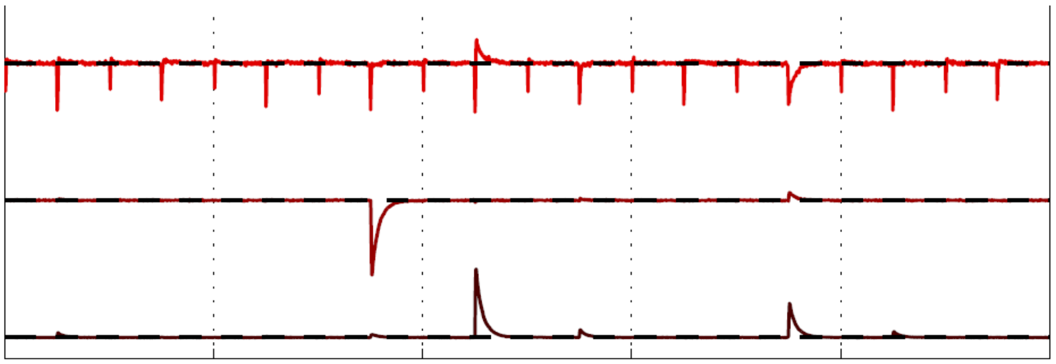
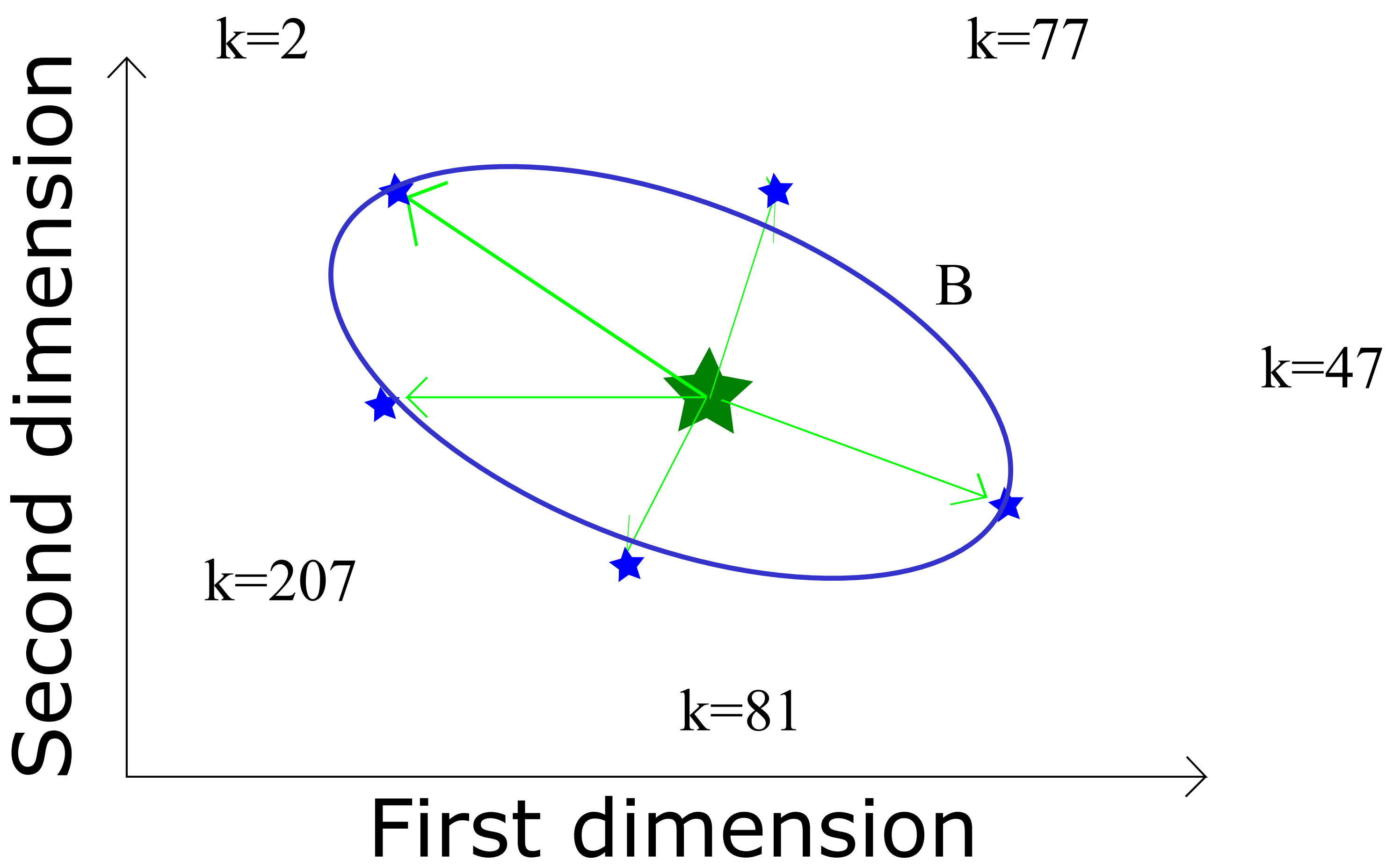


$m = 3$



U=SVD(B)

Linear Discriminant Analysis (LDA)



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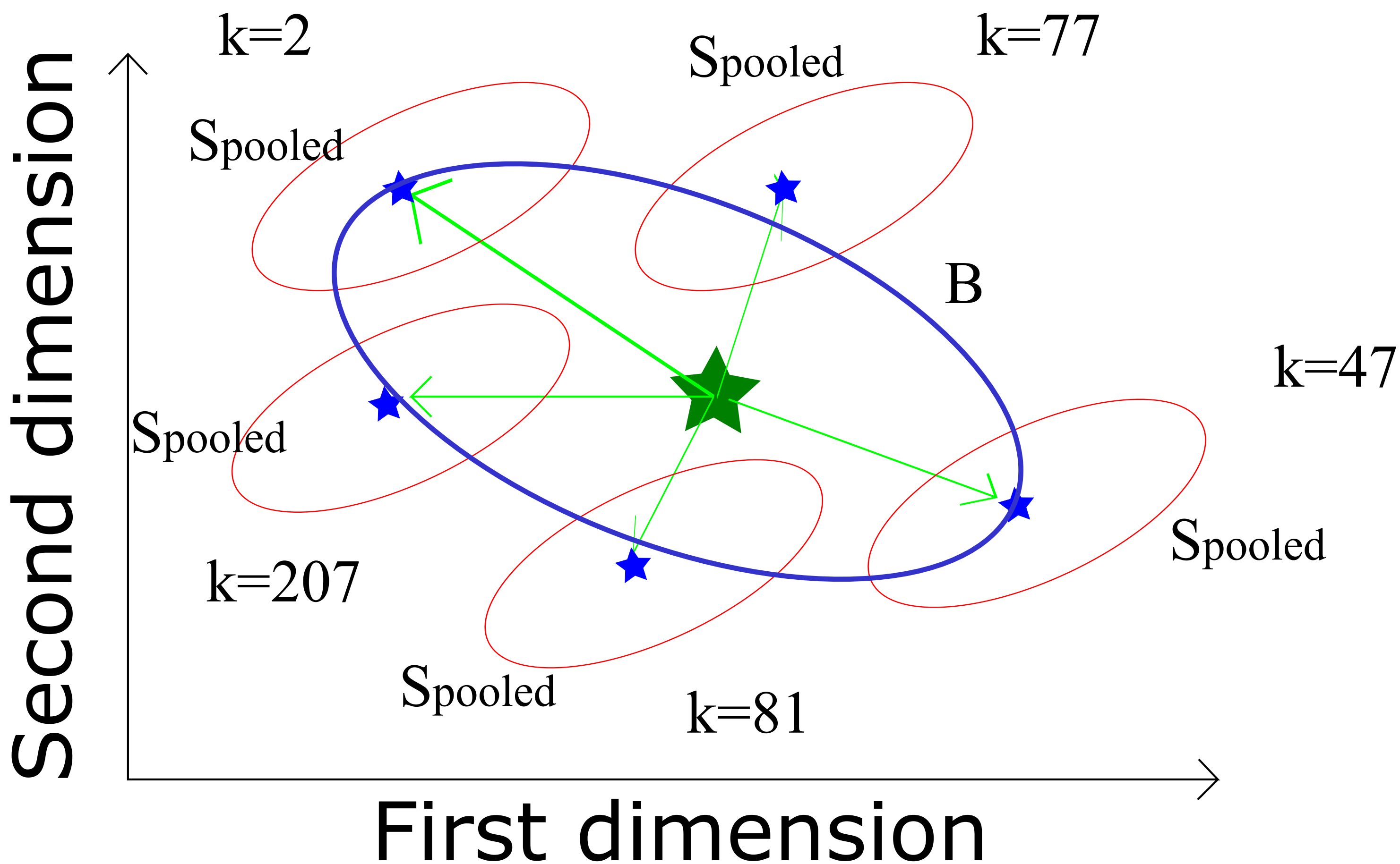

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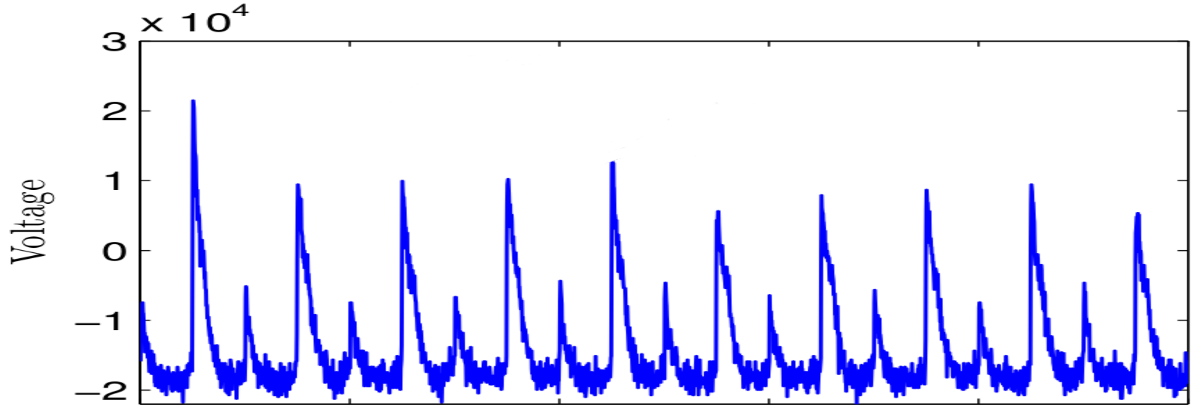
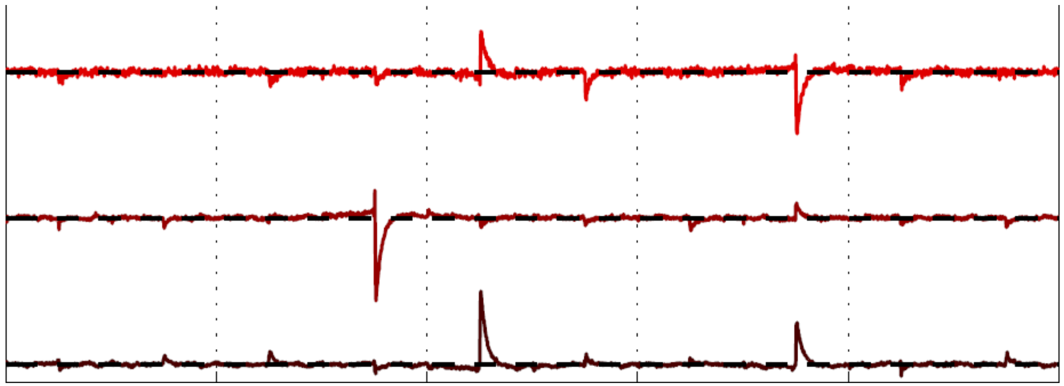


$m = 3$

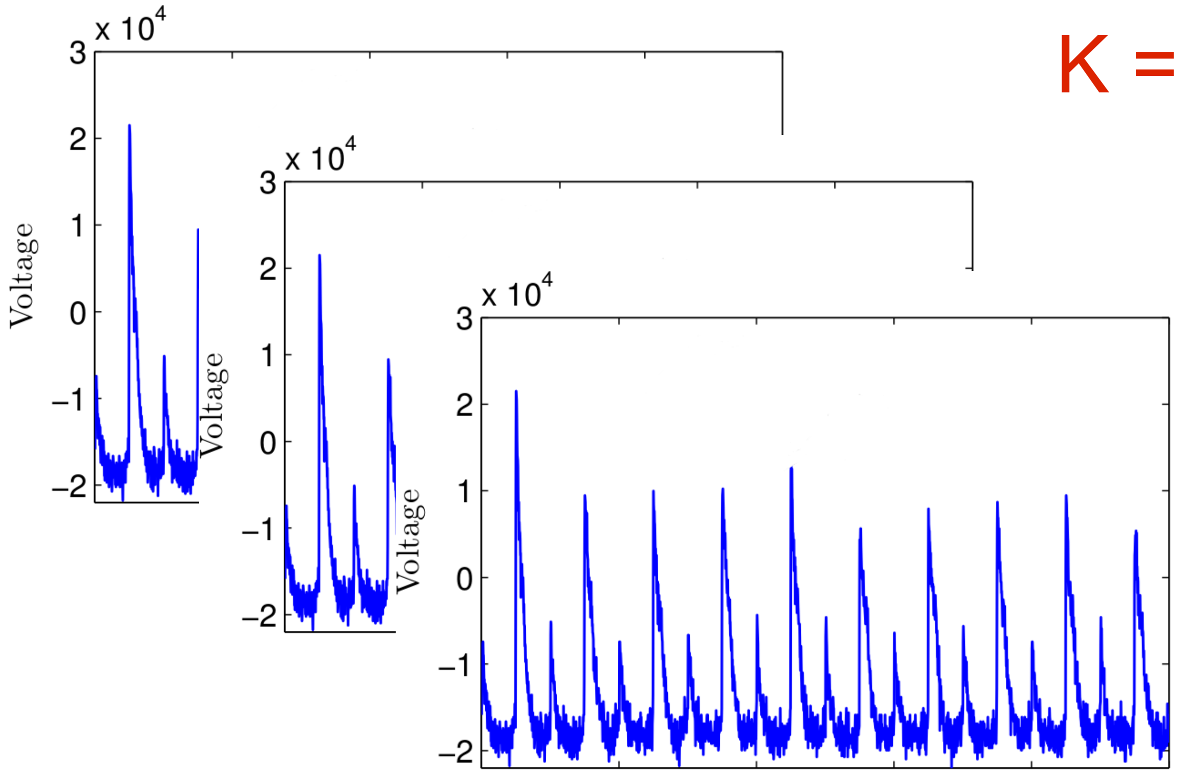
.



U=SVD(B/S)

Template Attacks on Different Devices

Template Attacks - Attack



K = ???

$1 \leqslant n_a \leqslant 1000$

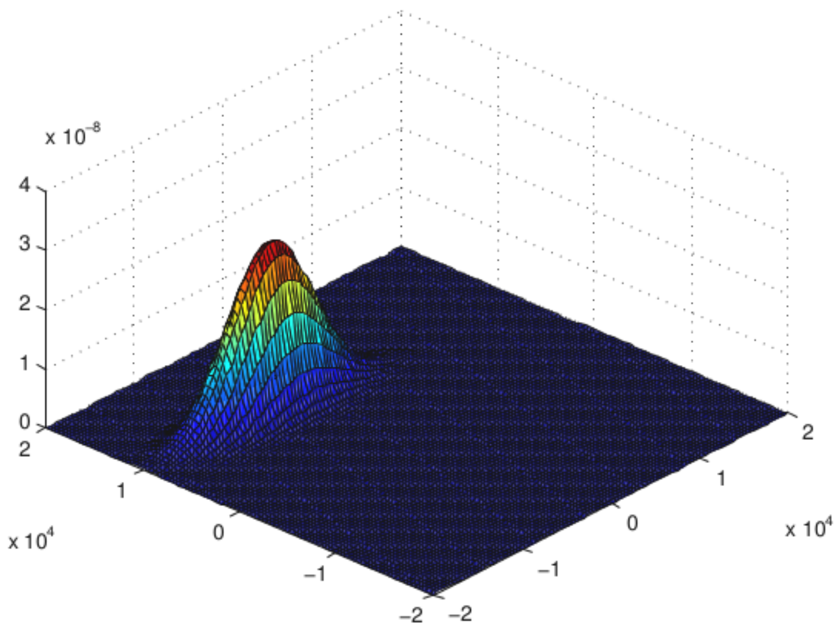
Template Attacks - Attack

K = 0, 1, 2, …, 255

Option 1: Multivariate Gaussian Distribution
[Chari et al., CHES '02]

$$\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_{n_\mathrm{a}}\}$$

$$\mathrm{d}(k \mid \mathbf{X}) = \prod_{\mathbf{x}\in\mathbf{X}} \frac{1}{\sqrt{(2\pi)^m |\mathbf{S}|}} \exp\left(-\frac{1}{2}(\mathbf{x}-\bar{\mathbf{x}}_k)'\mathbf{S}^{-1}(\mathbf{x}-\bar{\mathbf{x}}_k)\right)$$



$$k^\star = \arg\max_k \mathrm{d}(k \mid \mathbf{X})$$

Template Attacks - Attack

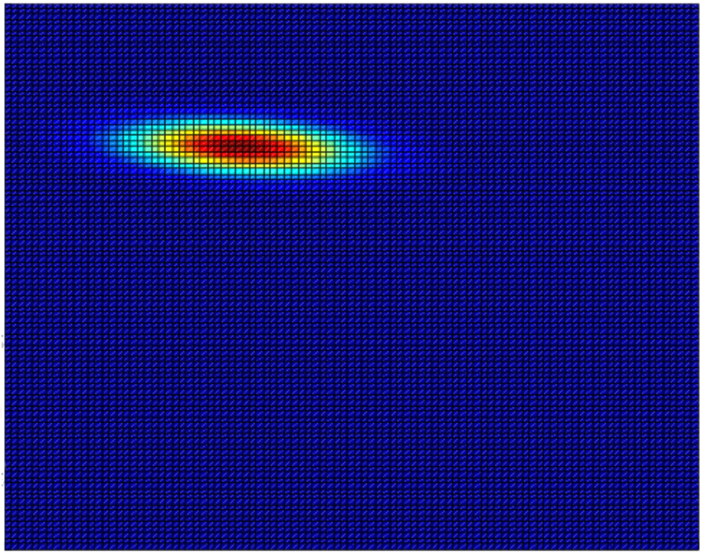
K = 0, 1, 2, ..., 255

Option 2: Mahalanobis Distance or Linear Discriminant [Choudary and Kuhn, CARDIS '13]

$$\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_{n_\mathrm{a}}\}$$

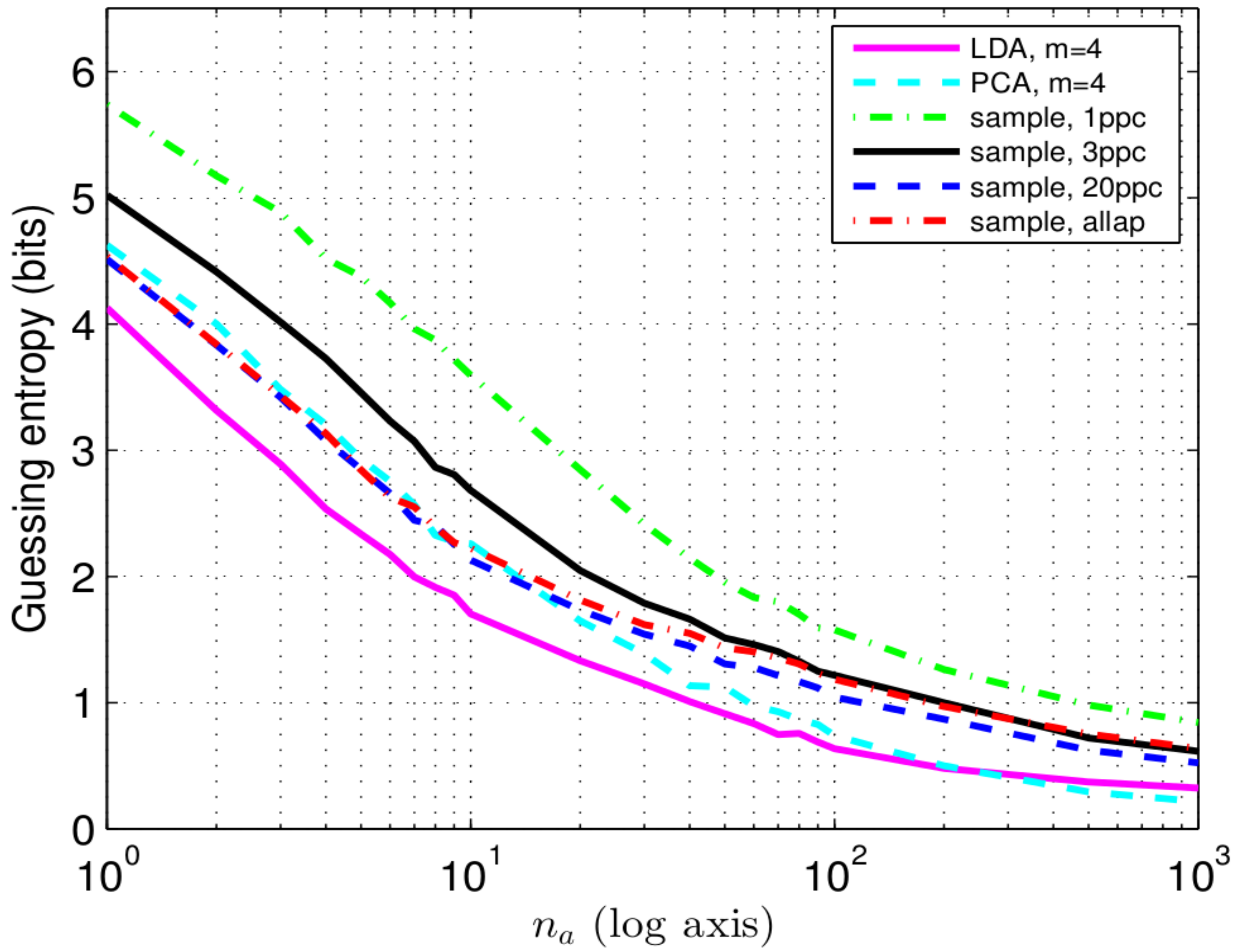
$$\mathrm{d}_{\mathrm{MD}}(k \mid \mathbf{X}) = -\frac{1}{2} \sum_{\mathbf{x} \in \mathbf{X}} (\mathbf{x} - \bar{\mathbf{x}}_k)' \mathbf{S}^{-1} (\mathbf{x} - \bar{\mathbf{x}}_k)$$

$$\mathrm{d}_{\mathrm{Linear}}(k \mid \mathbf{X}) = \bar{\mathbf{x}}_k' \mathbf{S}^{-1} \left(\sum_{\mathbf{x} \in \mathbf{X}_{k\star}} \mathbf{x} \right) - \frac{n_\mathrm{a}}{2} \bar{\mathbf{x}}_k' \mathbf{S}^{-1} \bar{\mathbf{x}}_k$$



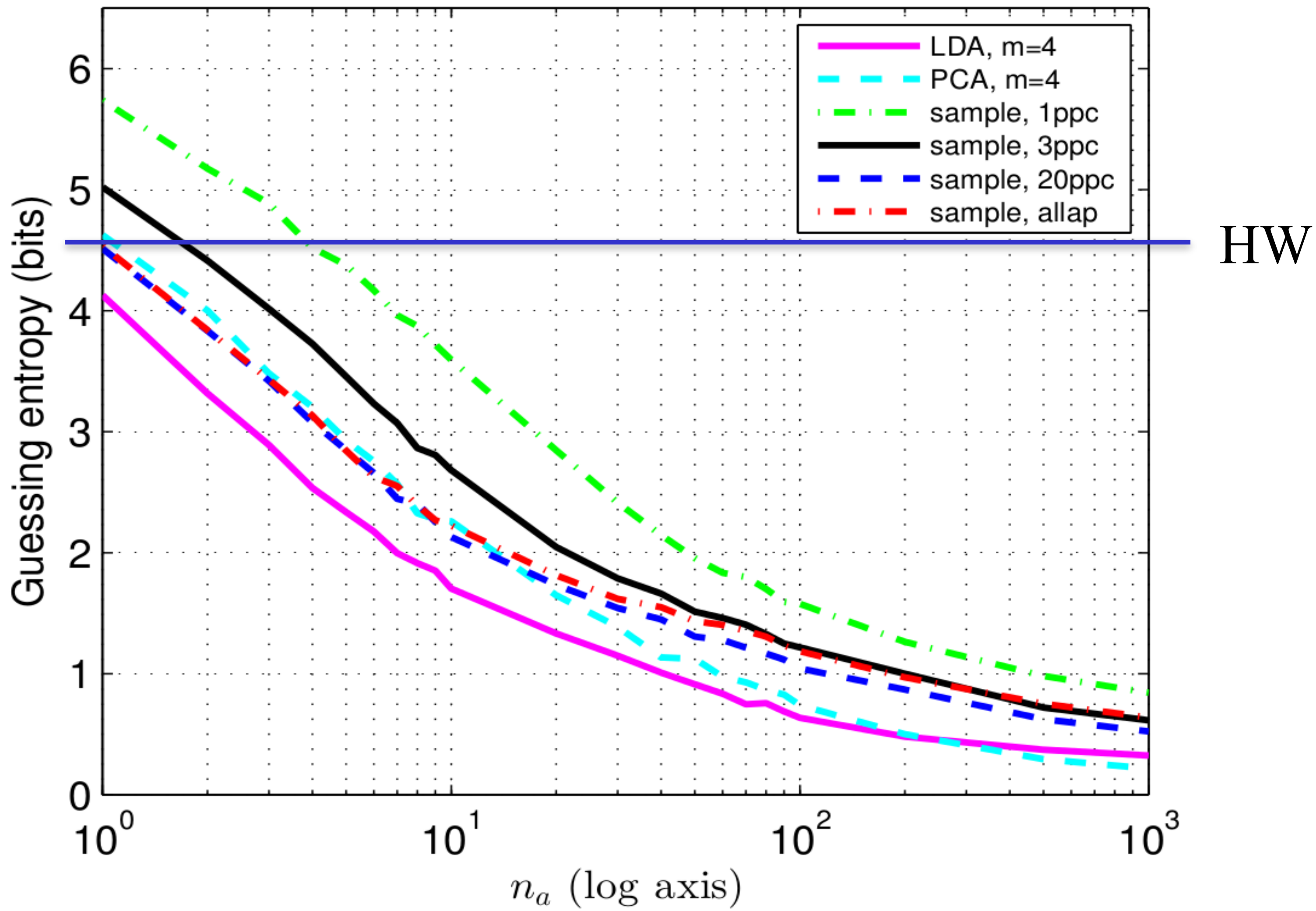
$$k^\star = \arg\max_k \mathrm{d}(k \mid \mathbf{X})$$

TA on same campaign [CARDIS '13]



Template Attacks on Different Devices

TA on same campaign [CARDIS '13]



TA on different devices

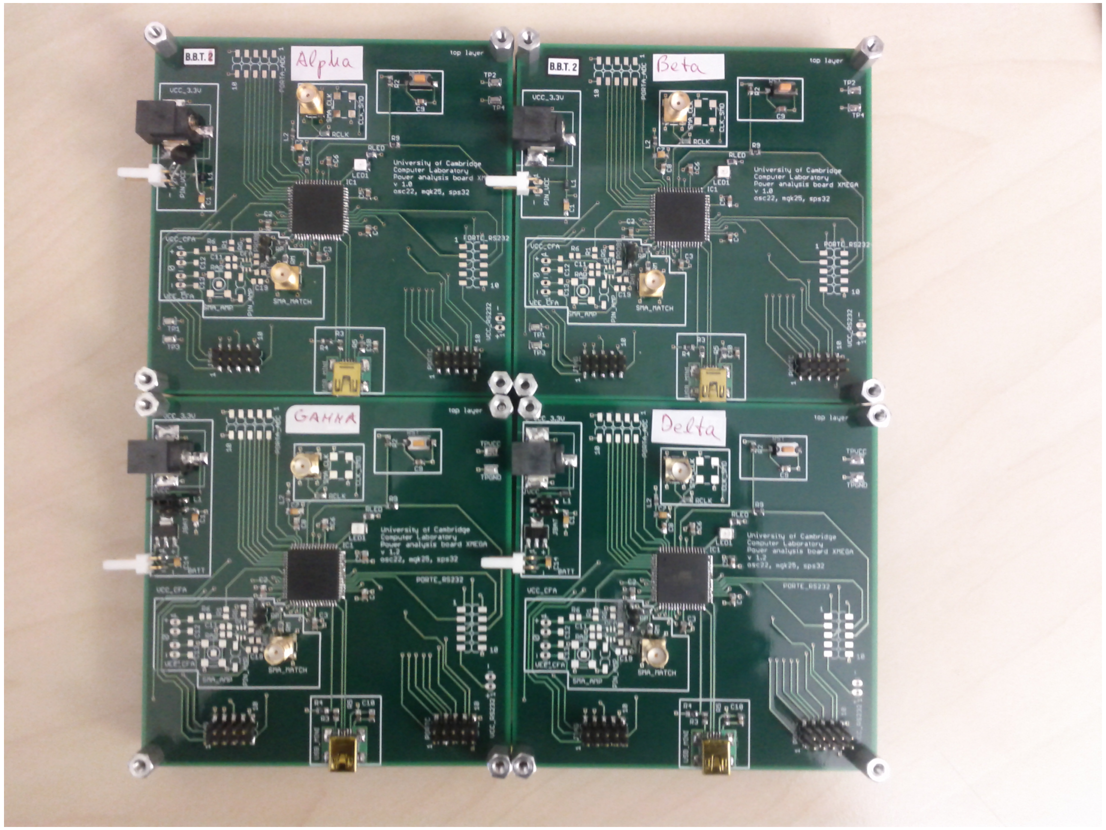
- [Renauld et al., Eurocrypt ’11]
  - Bad results across different ASIC devices
  - Used 20 different devices
  - Sample selection with 1 to 3 samples
- [Elaabid et al., Journal Crypto Engineering ’12]
  - Bad results on same device but different campaigns
  - PCA with 1 principal component

Our evaluation

- 4 different devices (Atmel XMEGA 8-bit uC)

Alpha

Beta



Gamma

Delta

Our evaluation

- 4 different devices (Atmel XMEGA 8-bit uC)
- Same CARDIS'13 scenario

CODE

```
...
movw r30, r24
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ld r9, Z+        <-  target
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```

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- 4 different devices (Atmel XMEGA 8-bit uC)
- Same CARDIS'13 scenario
- 5 acquisition campaigns
  - 1 per device
  - 1 additional campaign on one device

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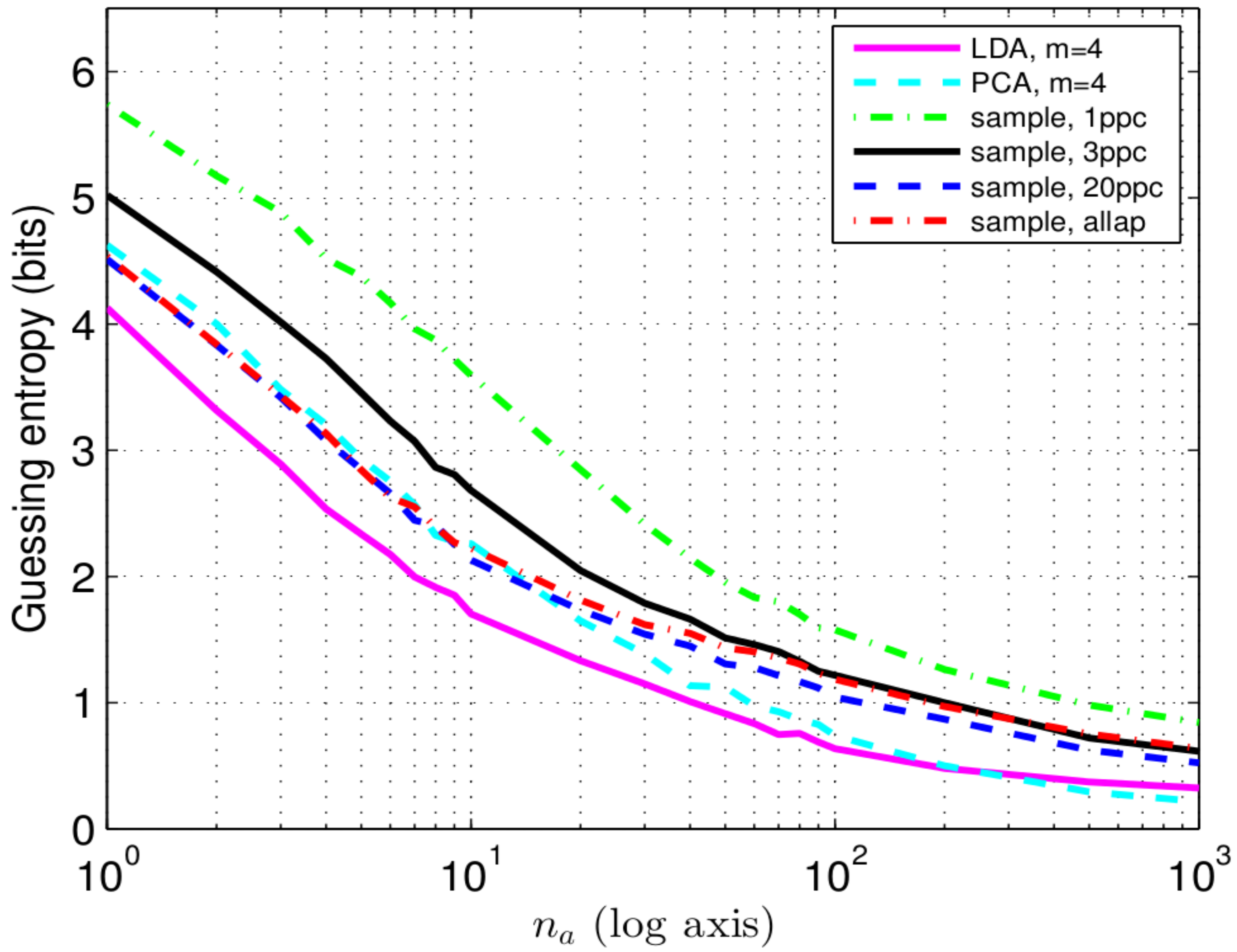
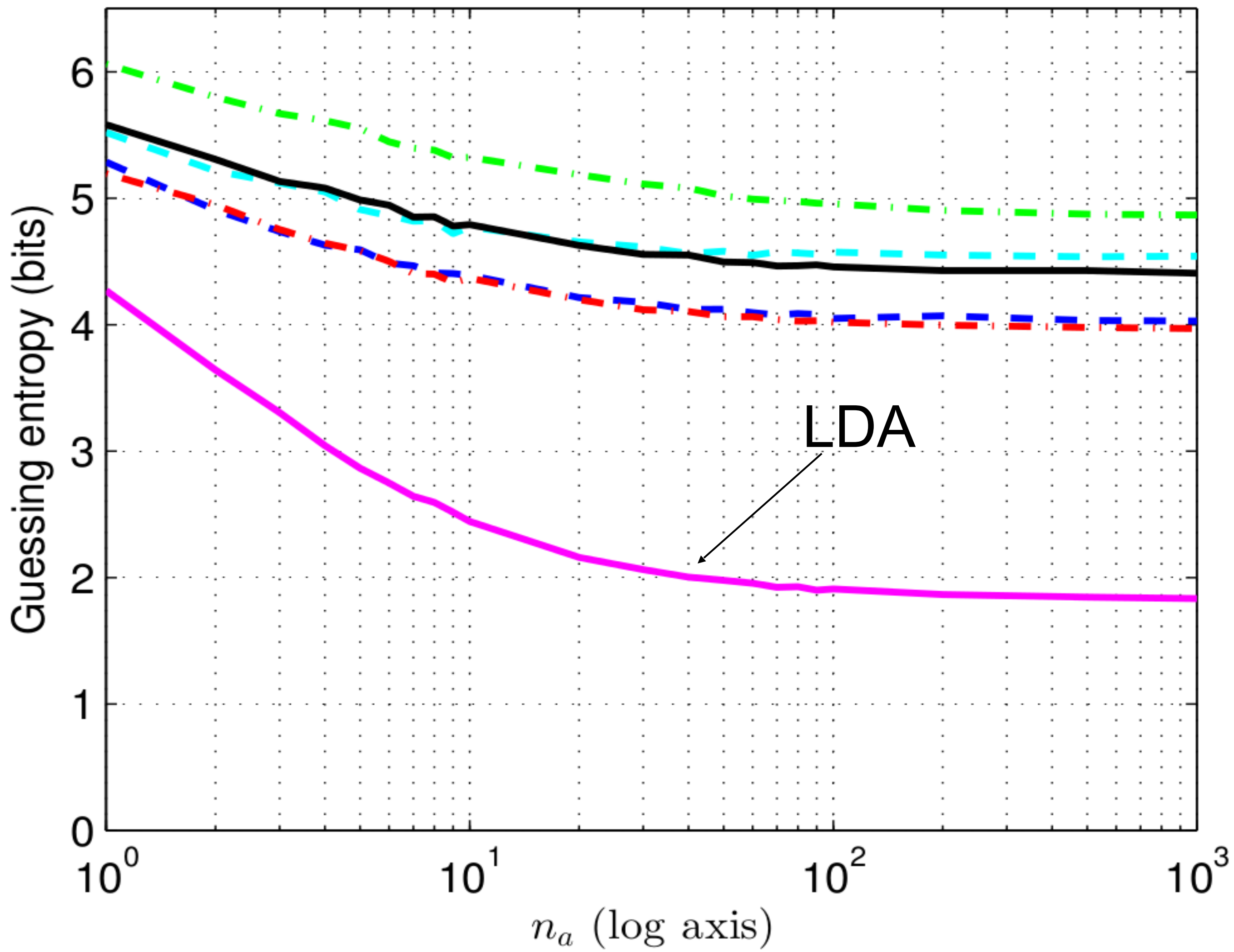
- Several compressions with different params
- Several methods to improve TA

Standard TA (Met. 1) same device

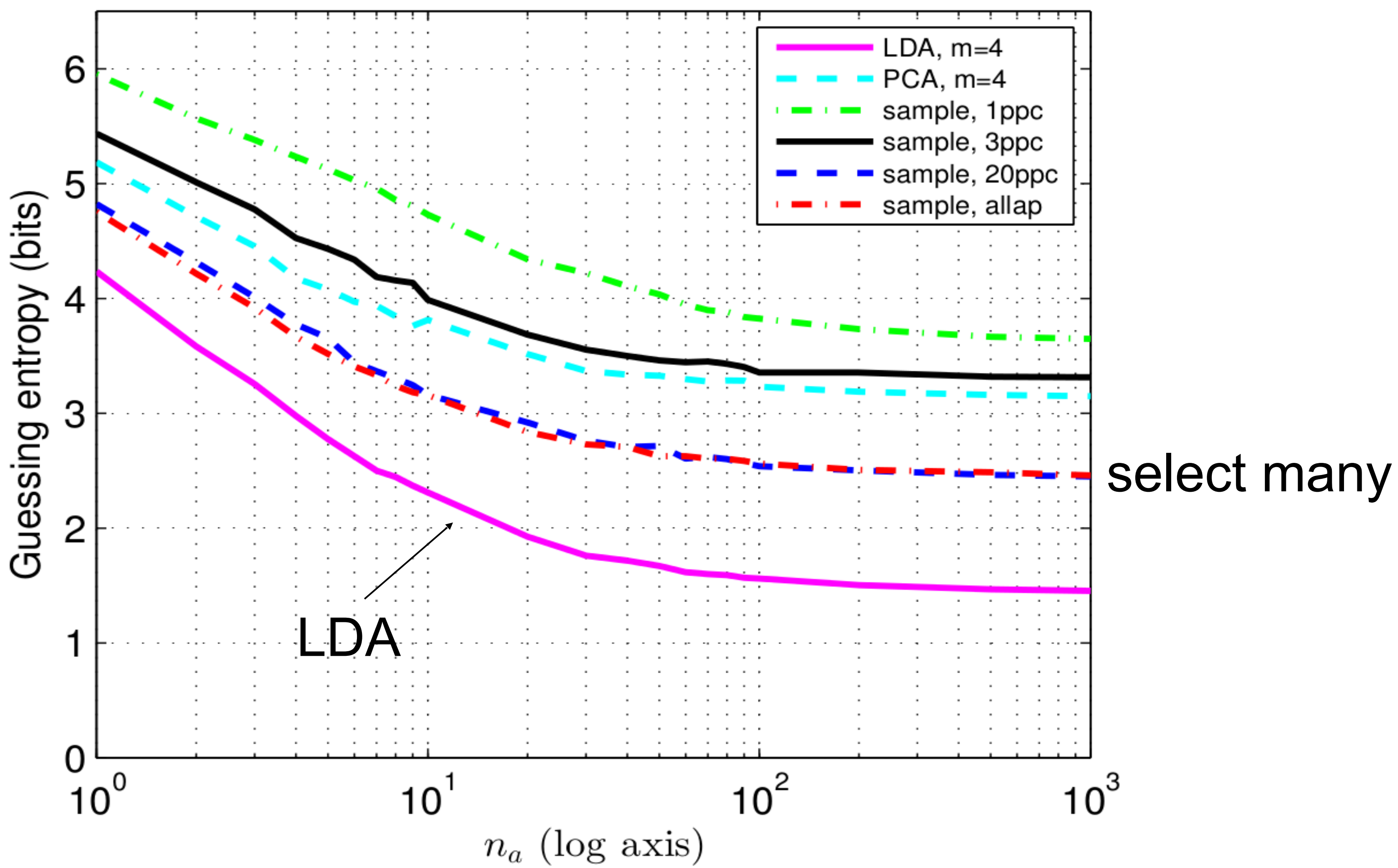


Standard TA (Met. 1) different devices

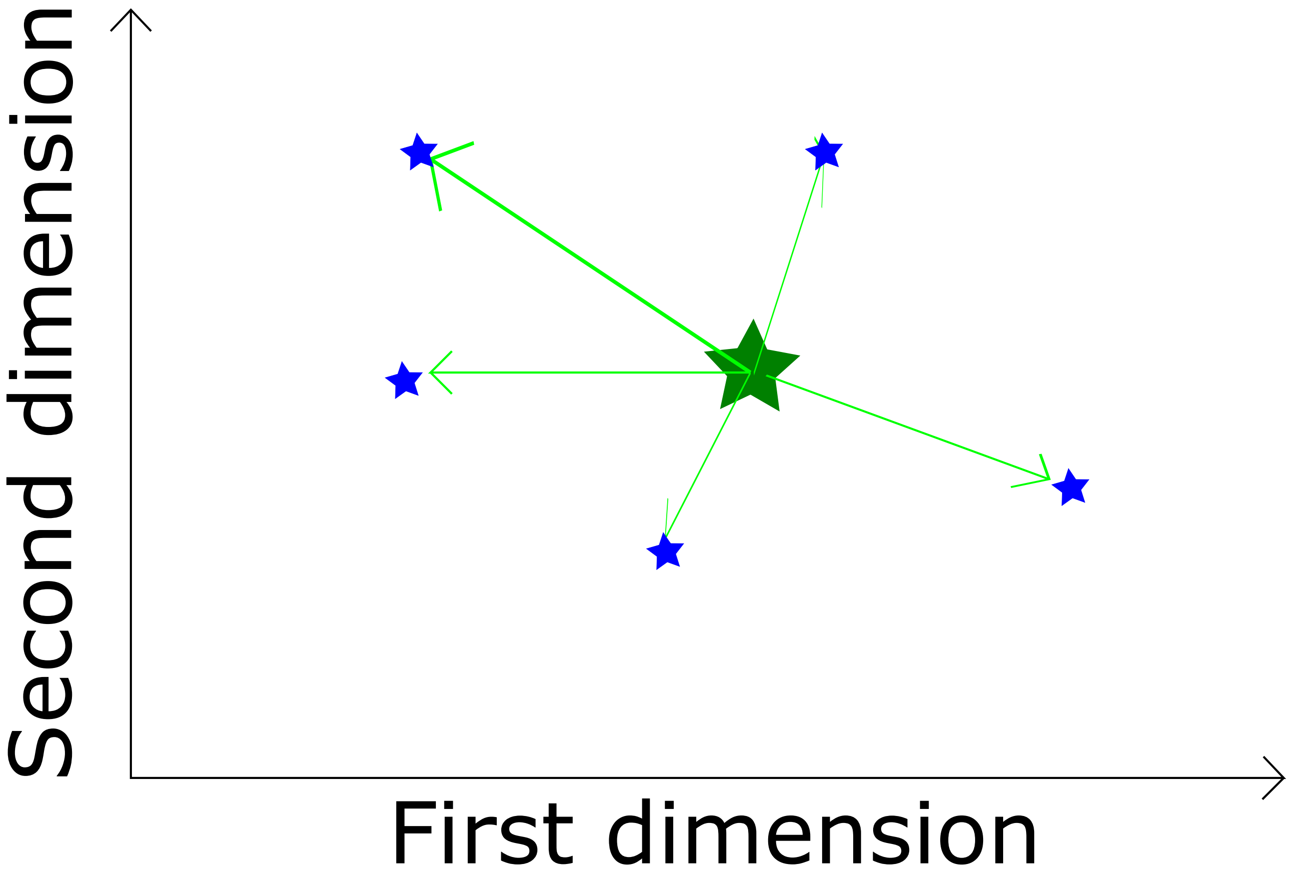


Template Attacks on Different Devices

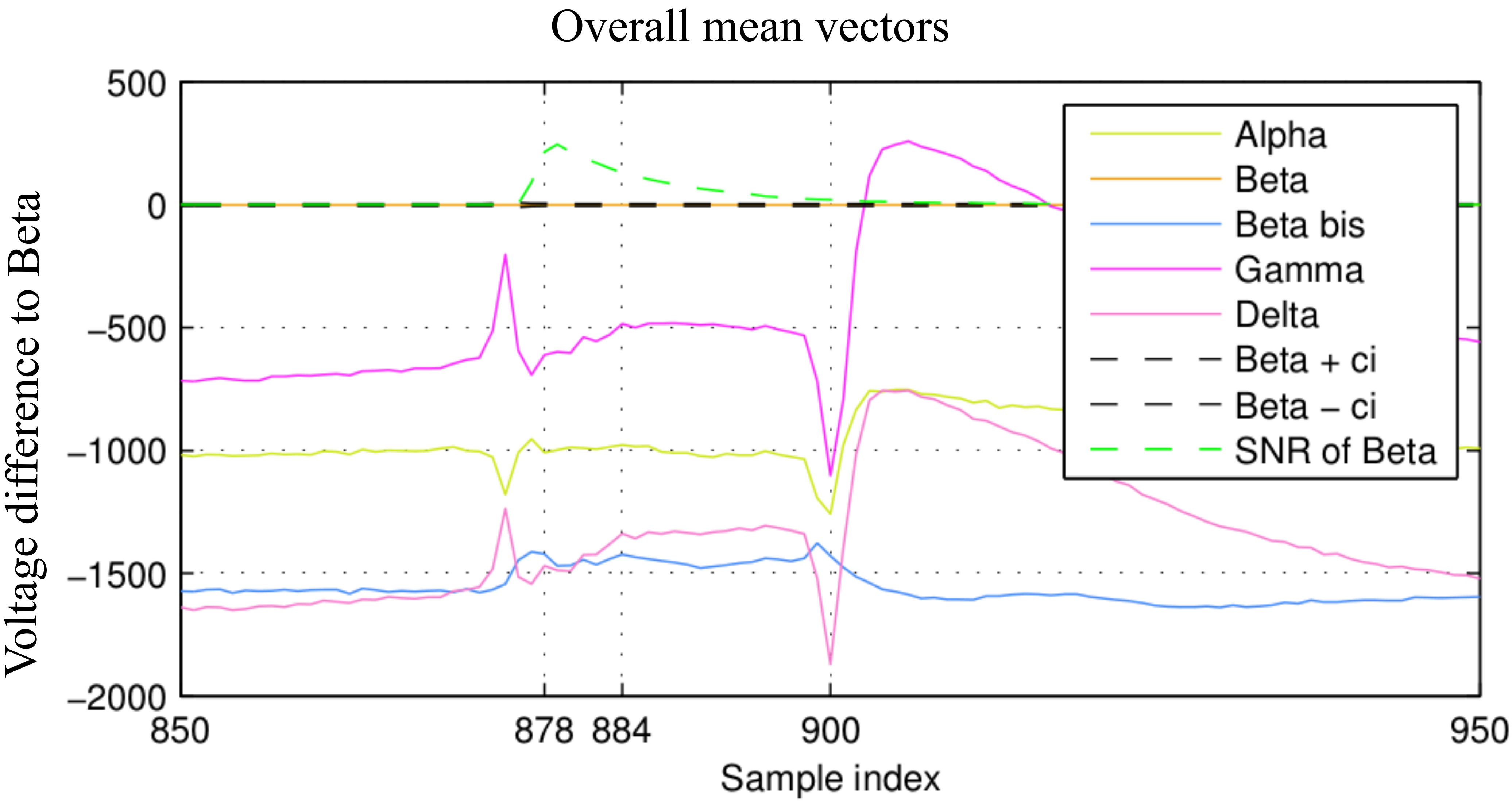
Profiling on 3 devices (Met. 2)



Analysis of overall mean vectors



Major problem: low-frequency offset



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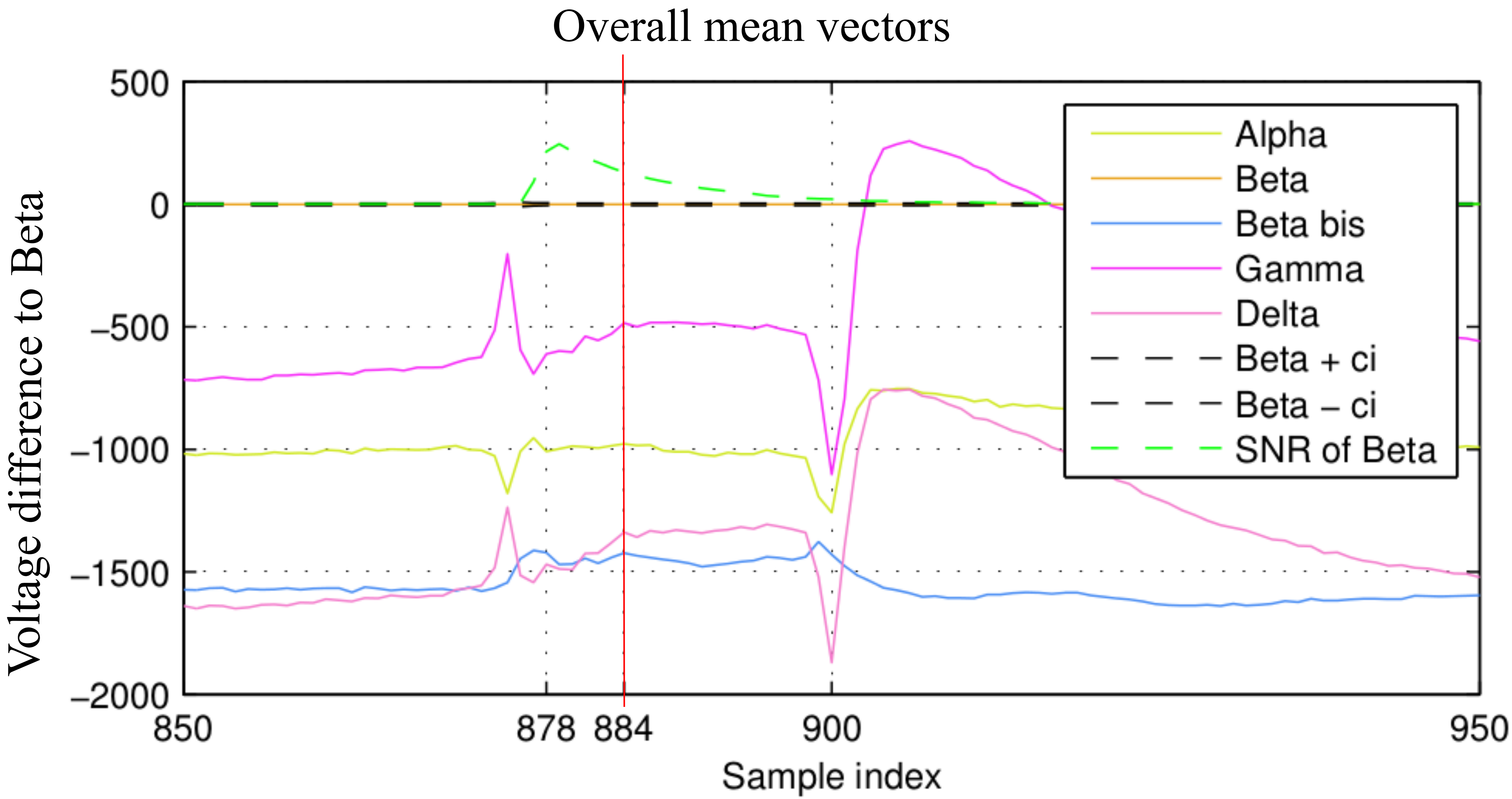
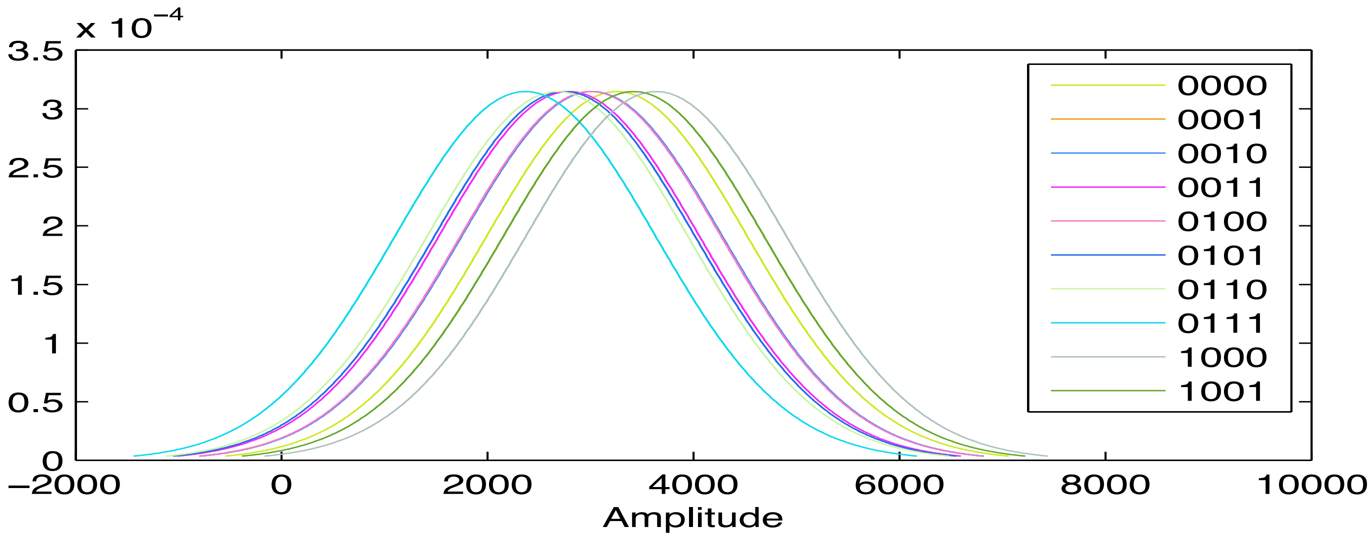


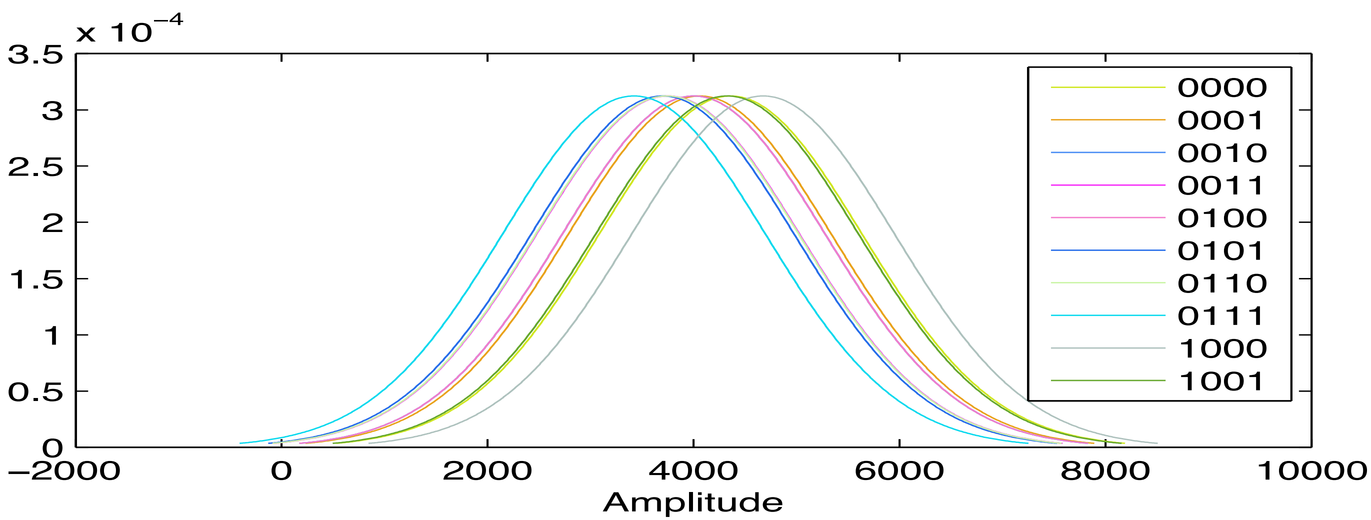
Major problem: low-frequency offset

k = 0, 1, …, 9



Alpha

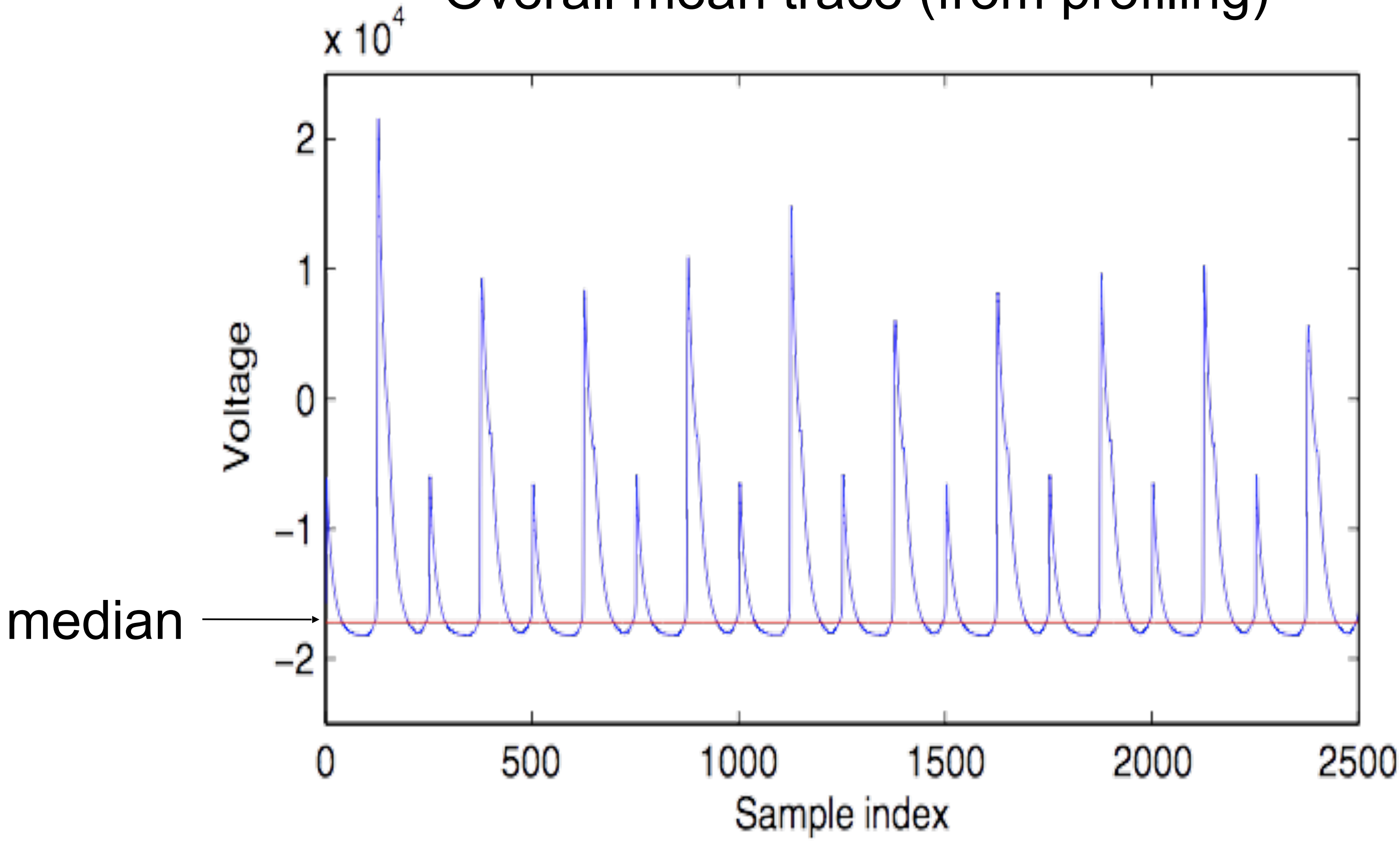
Sample j=884



Beta

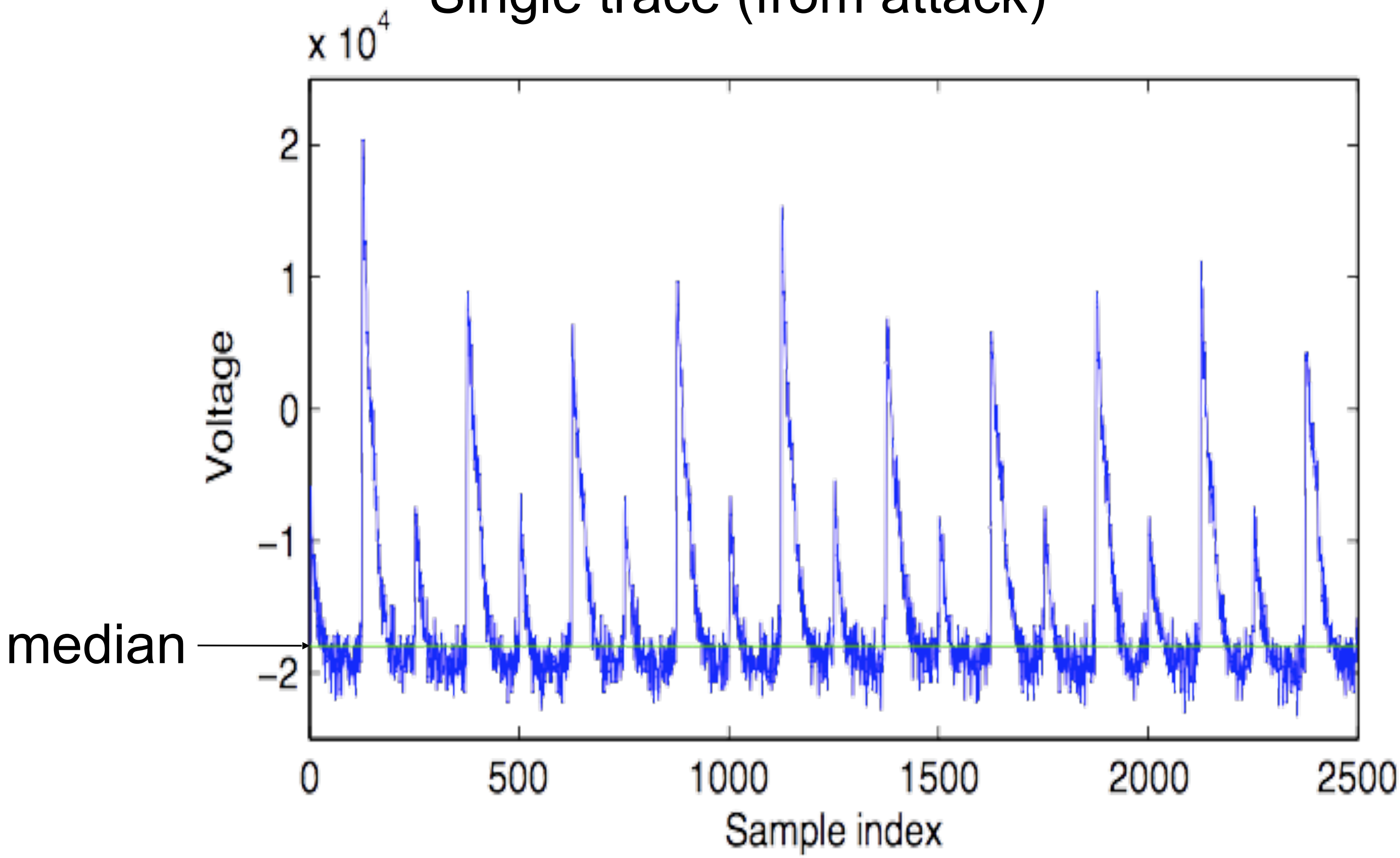
Adapt for the offset (Met. 3)

Overall mean trace (from profiling)

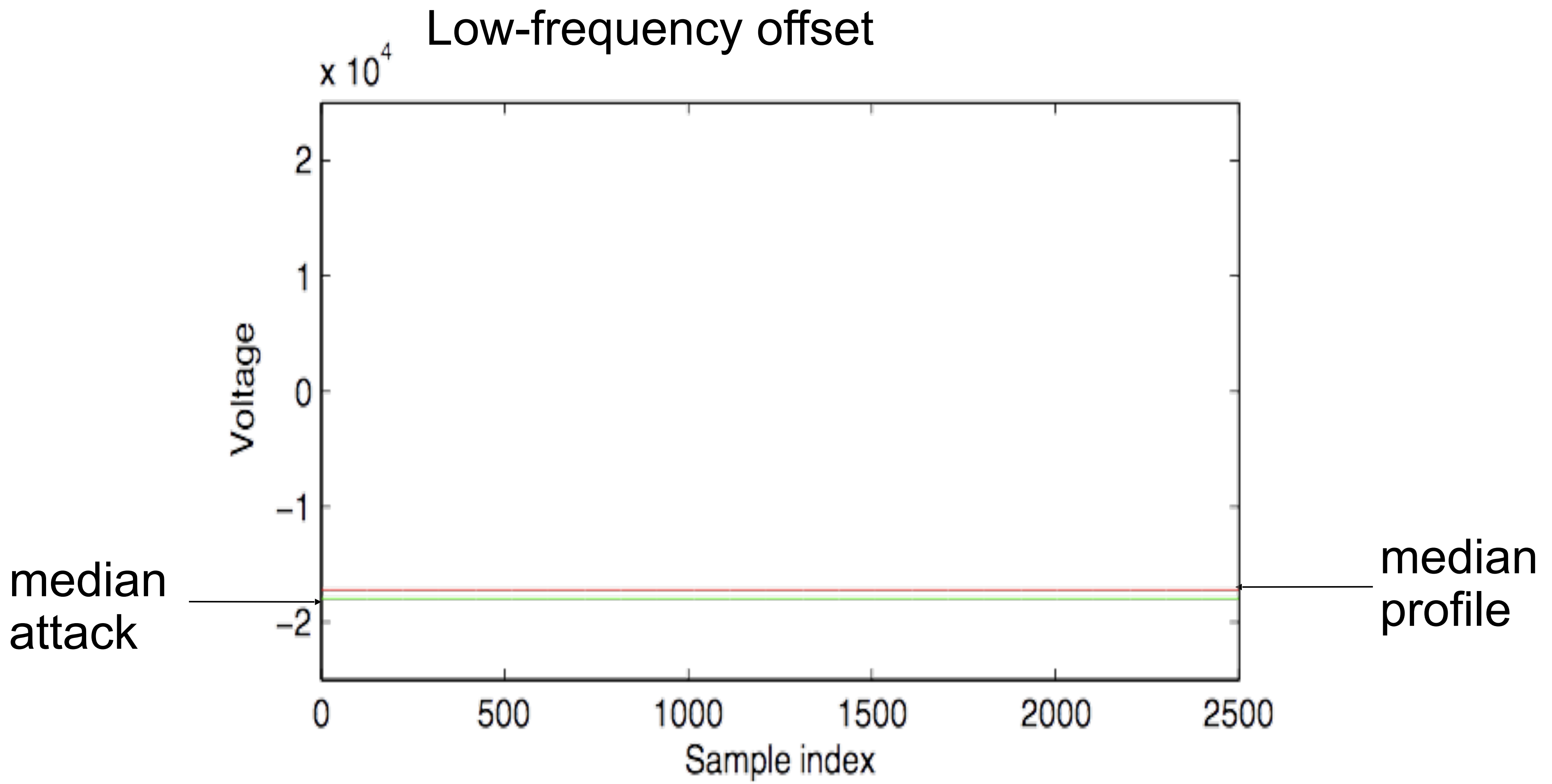


Adapt for the offset (Met. 3)

Single trace (from attack)

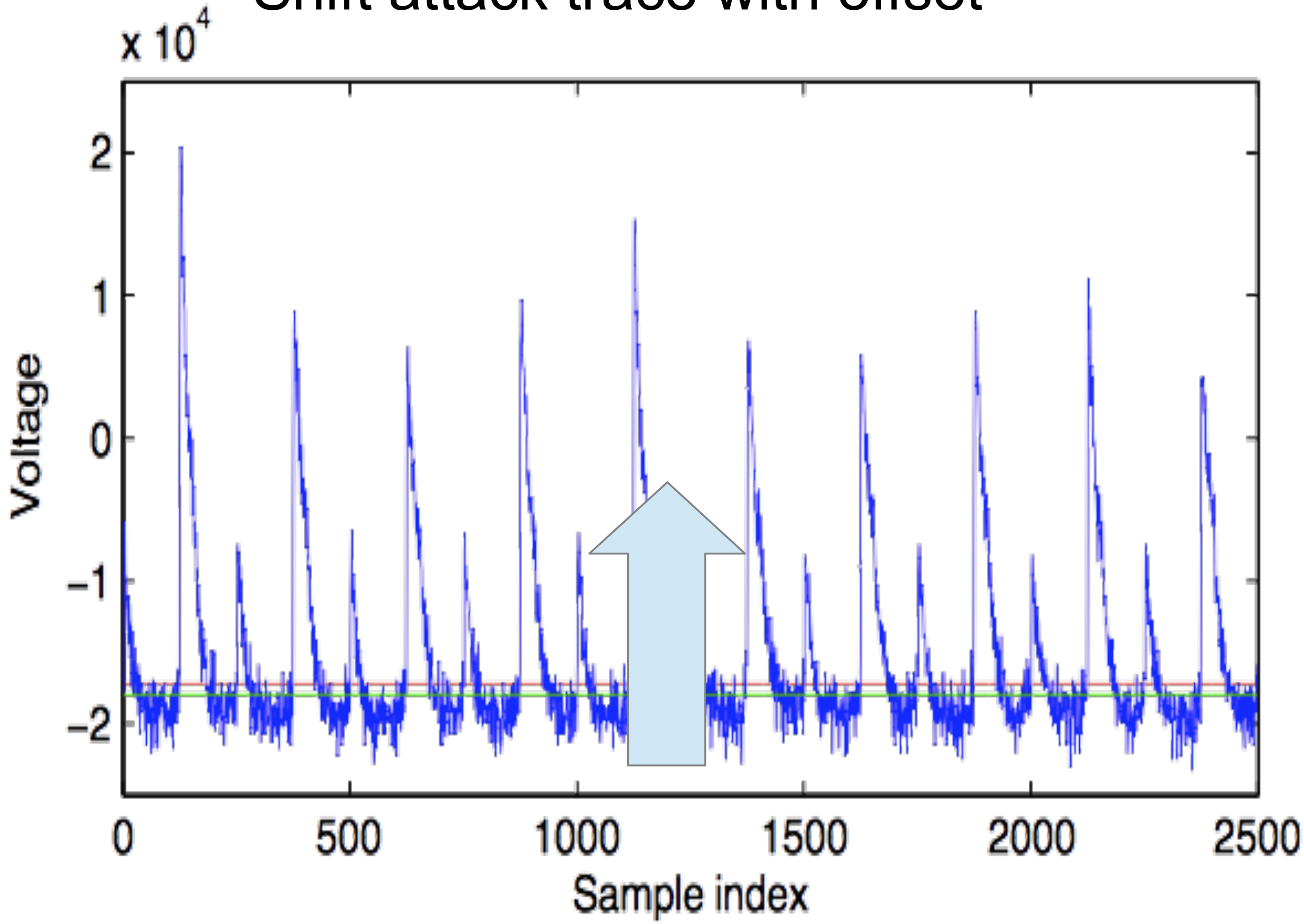


Adapt for the offset (Met. 3)

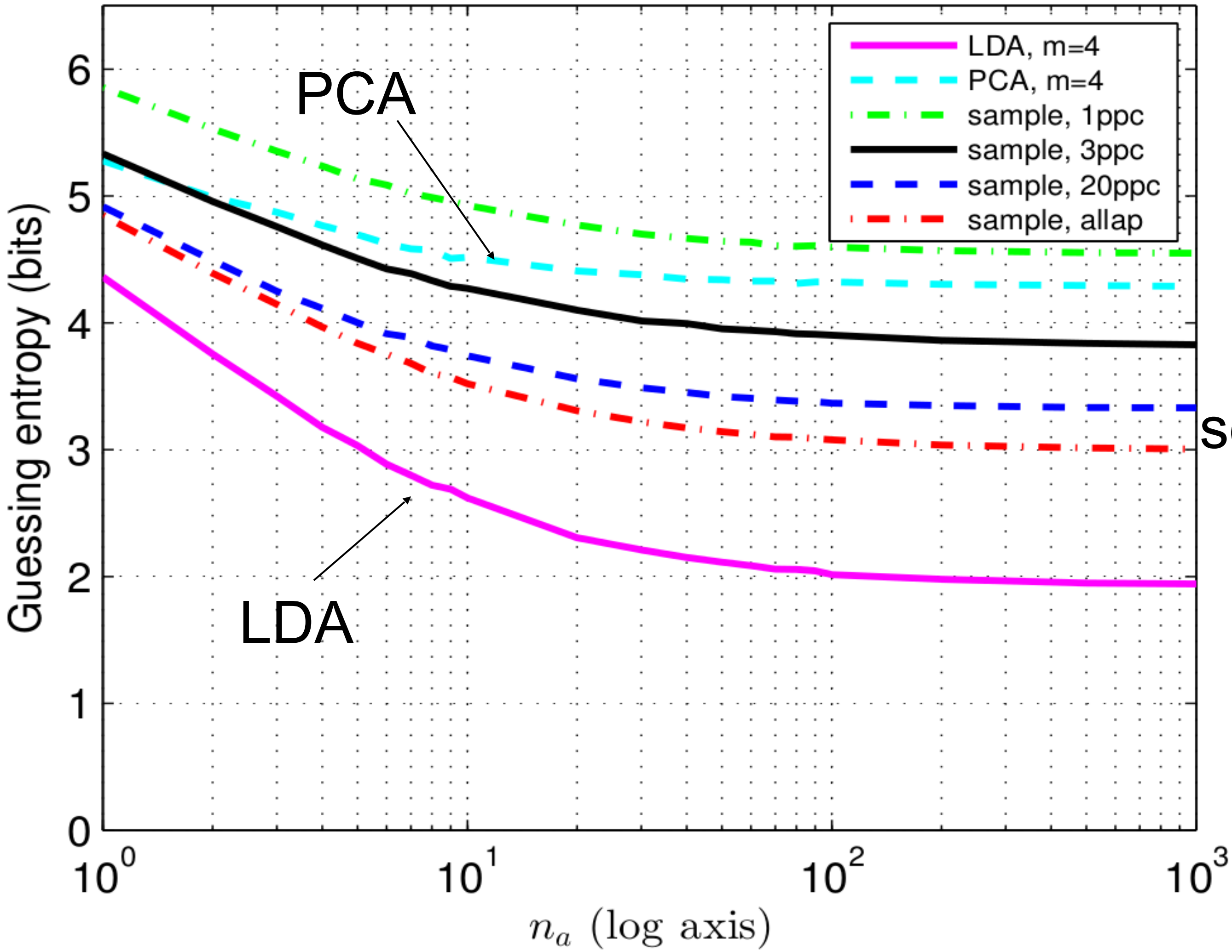


Adapt for the offset (Met. 3)

Shift attack trace with offset

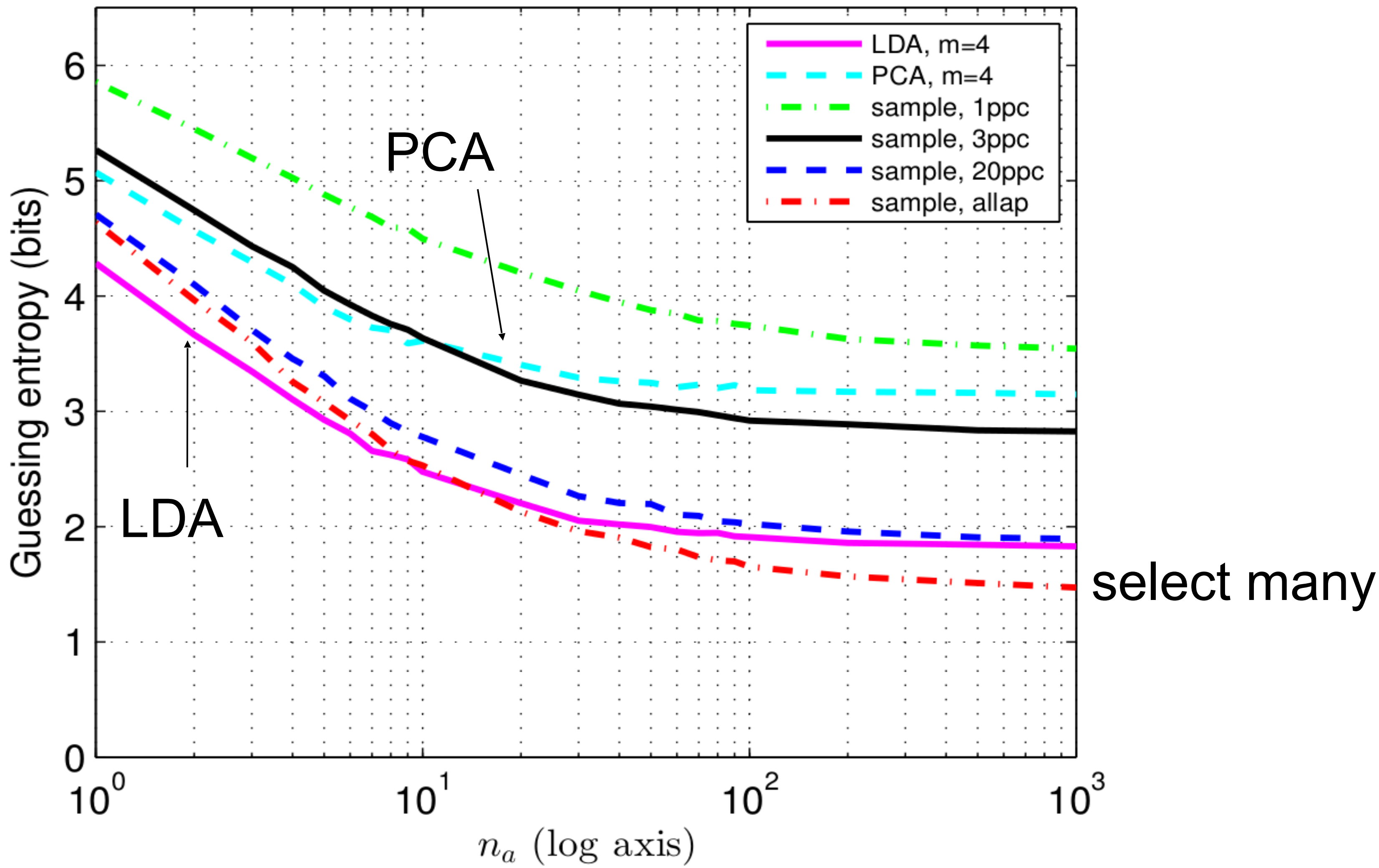


Adapt for the offset (Met. 3)

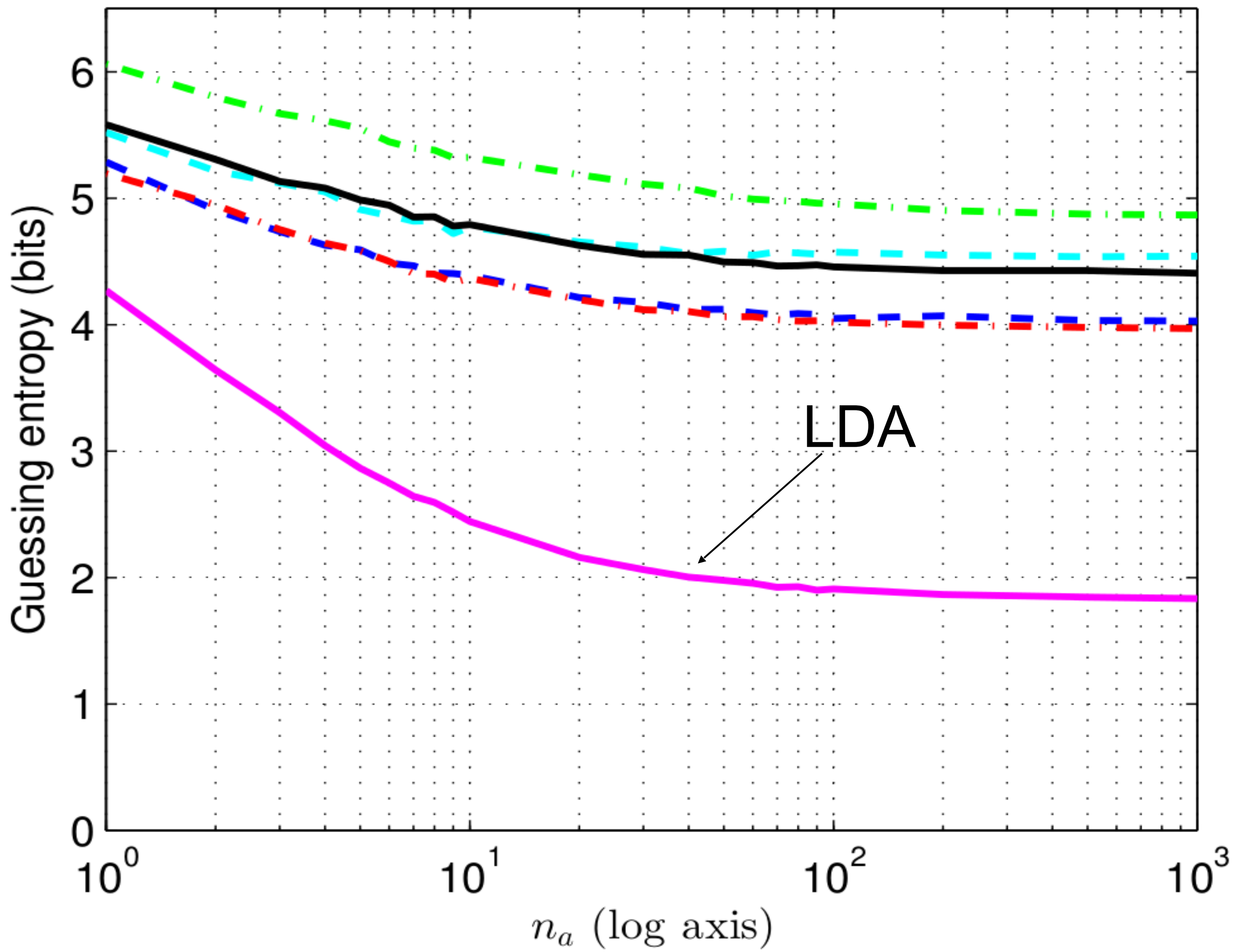


select many

Profile on 3 devices & adapt offset (Met. 4)



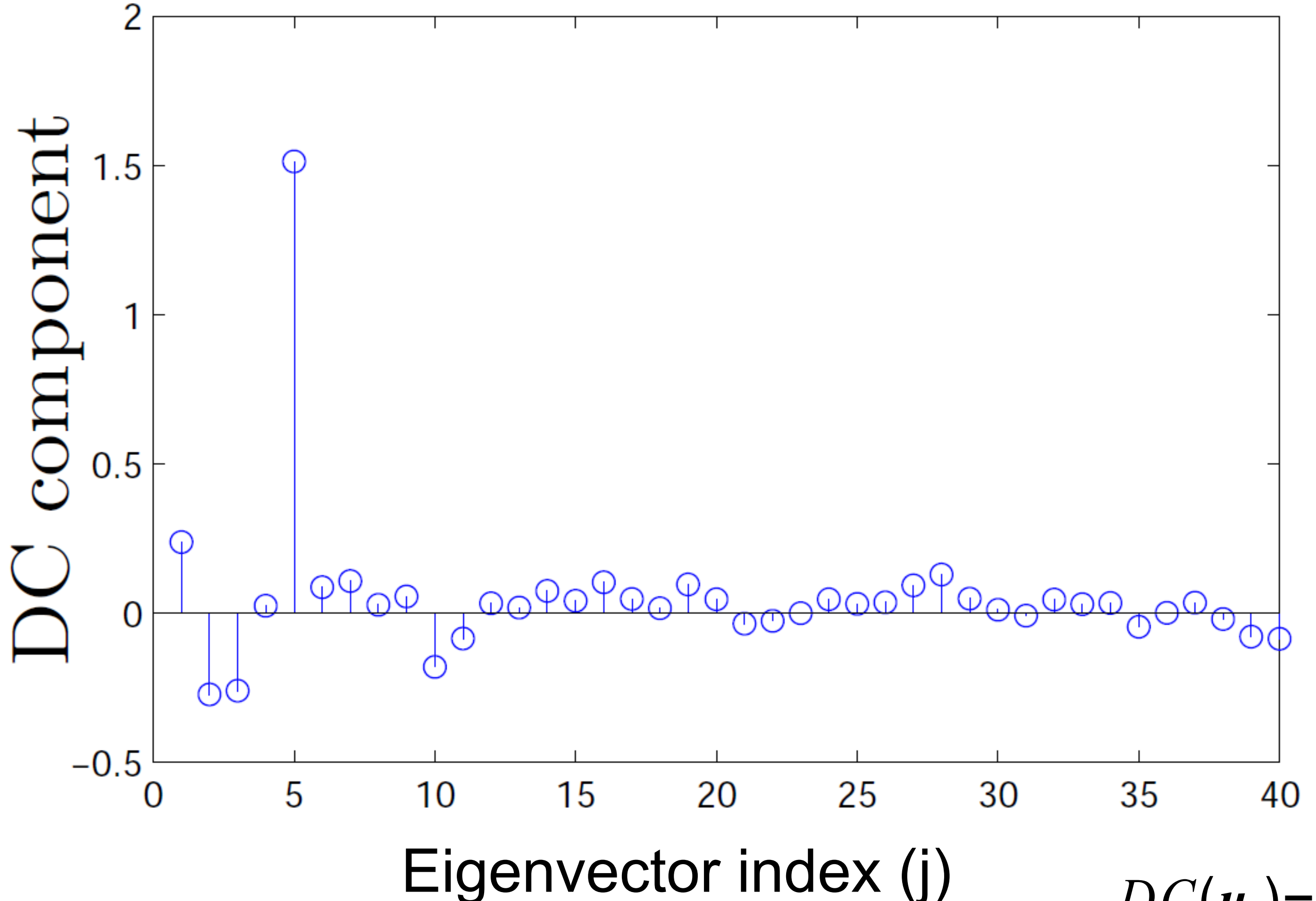
Standard TA work well with LDA



Standard TA work well with LDA

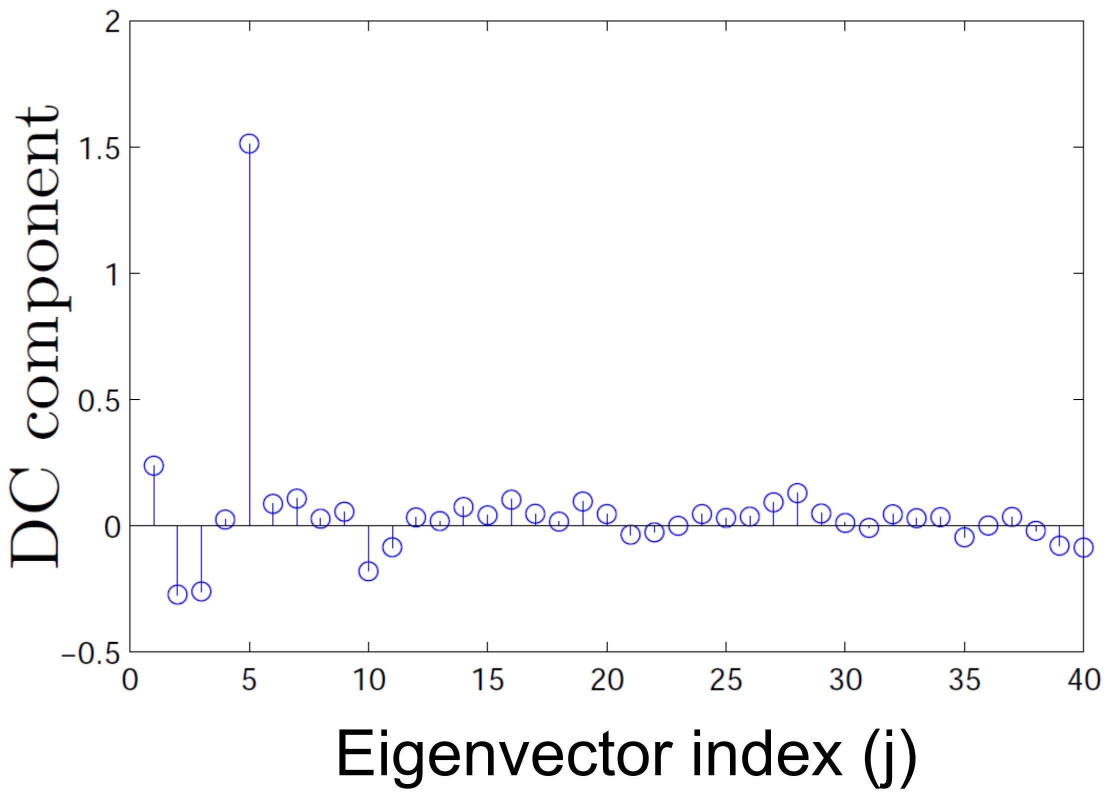
- LDA uses common covariance matrix $\mathrm{S}_{\mathrm{pooled}}$ in computation of eigenvectors
- $\mathrm{S}_{\mathrm{pooled}}$ captures noise factors, such as temperature variations
  - Our acquisition campaigns took several hours to complete
- If variation due to noise is similar across campaigns then LDA can be useful

How to select LDA eigenvectors (1)



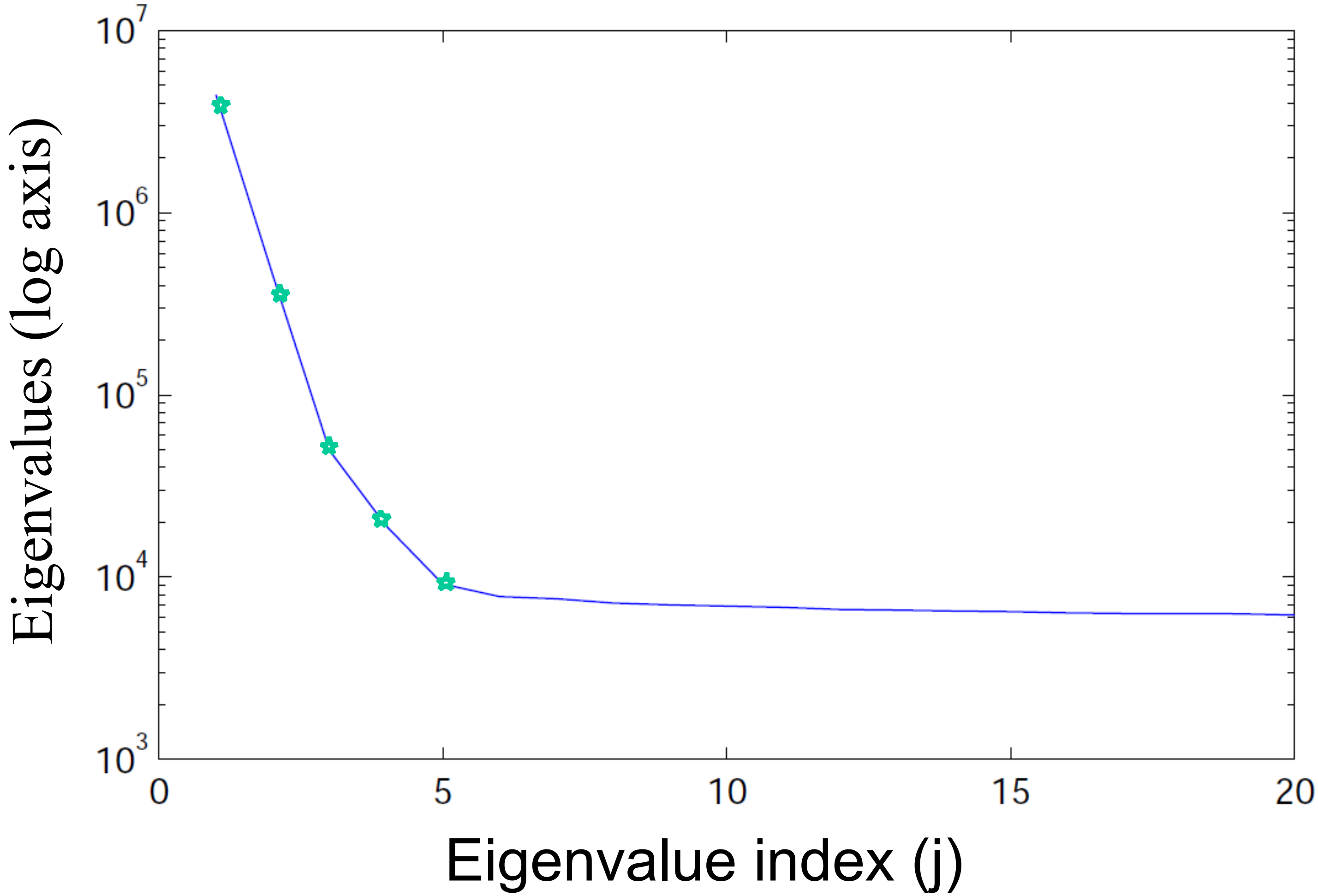
$$DC(\boldsymbol{u}_j) = u_j^1 + \ldots + u_j^m$$

How to select LDA eigenvectors (1)



$m = 4$

How to select LDA eigenvectors (2)



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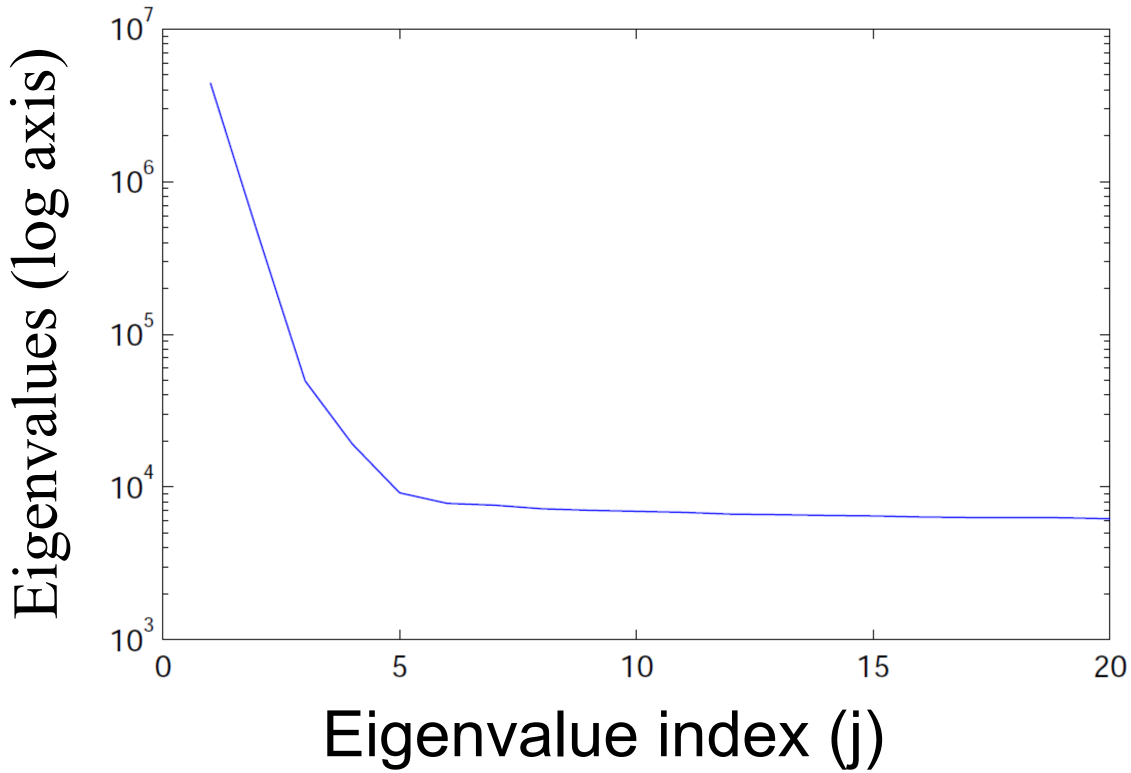

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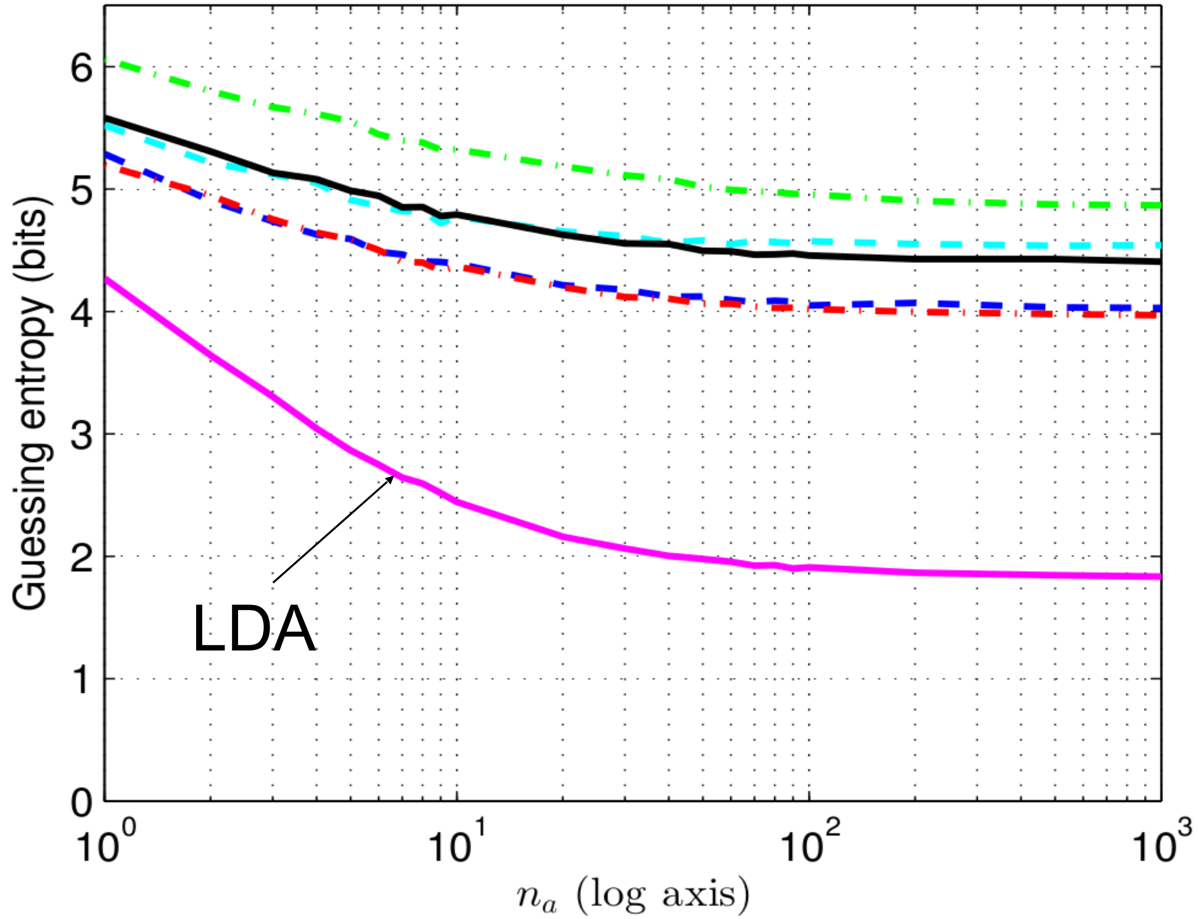
How to select LDA eigenvectors

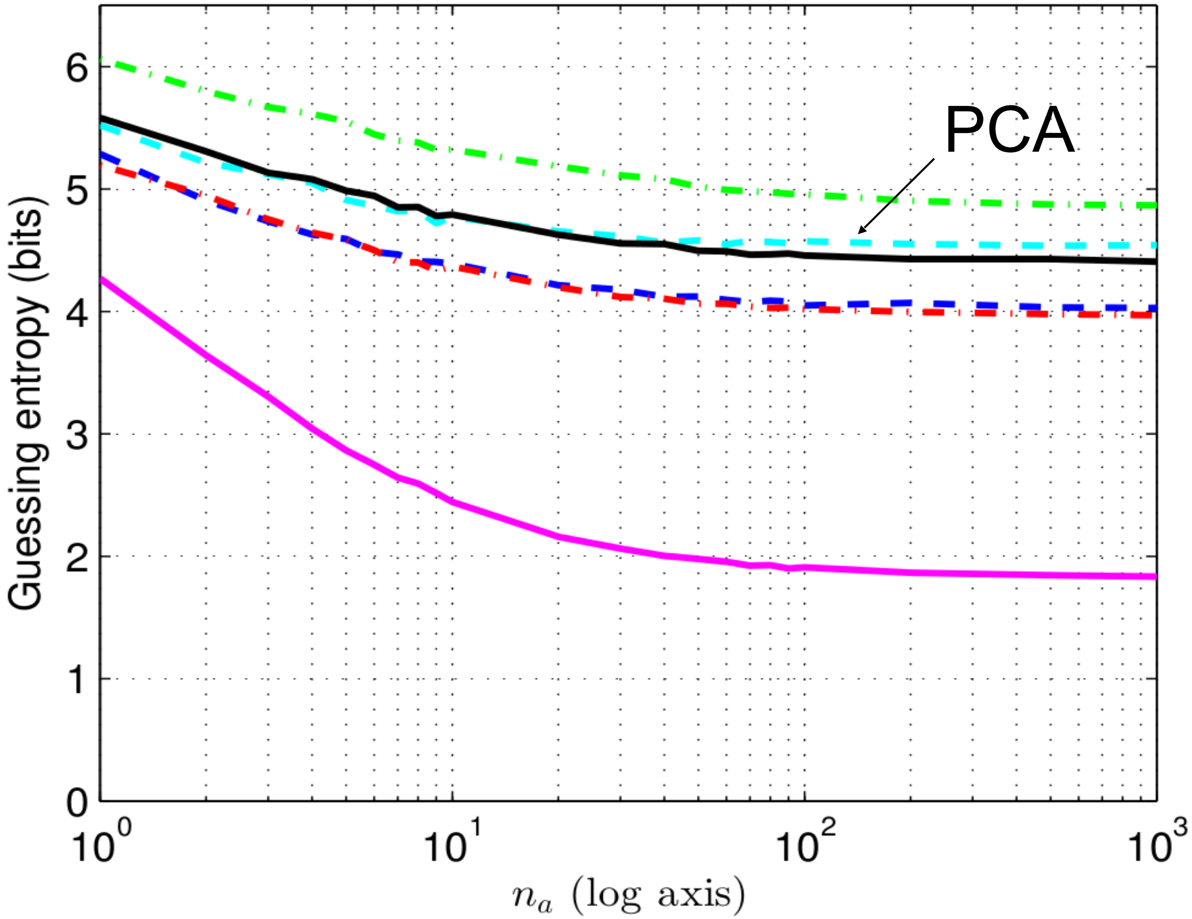


$m = 4$

Good selection of m was only by chance!

We should look at DC component of eigenvectors

Can we improve PCA?



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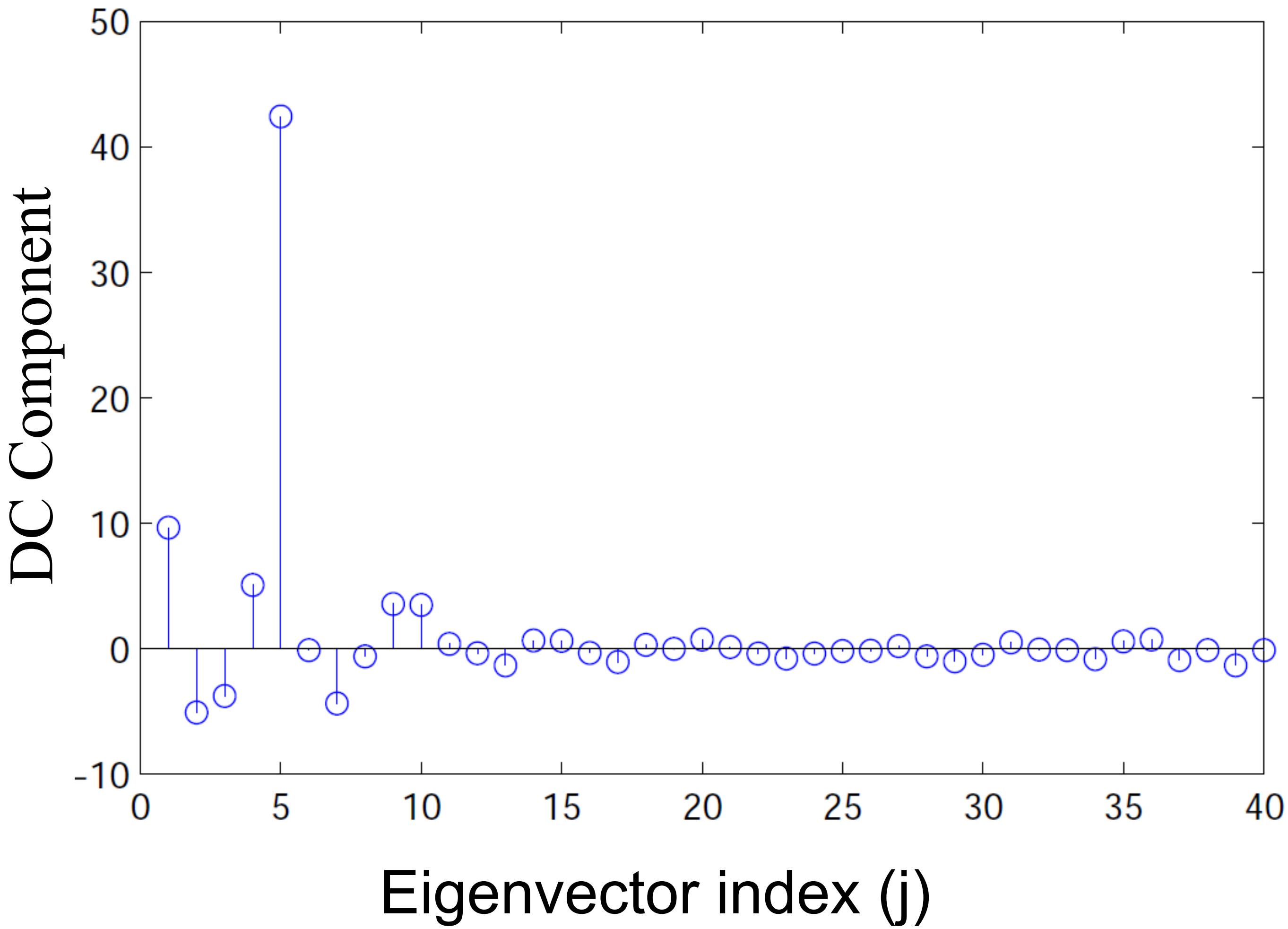

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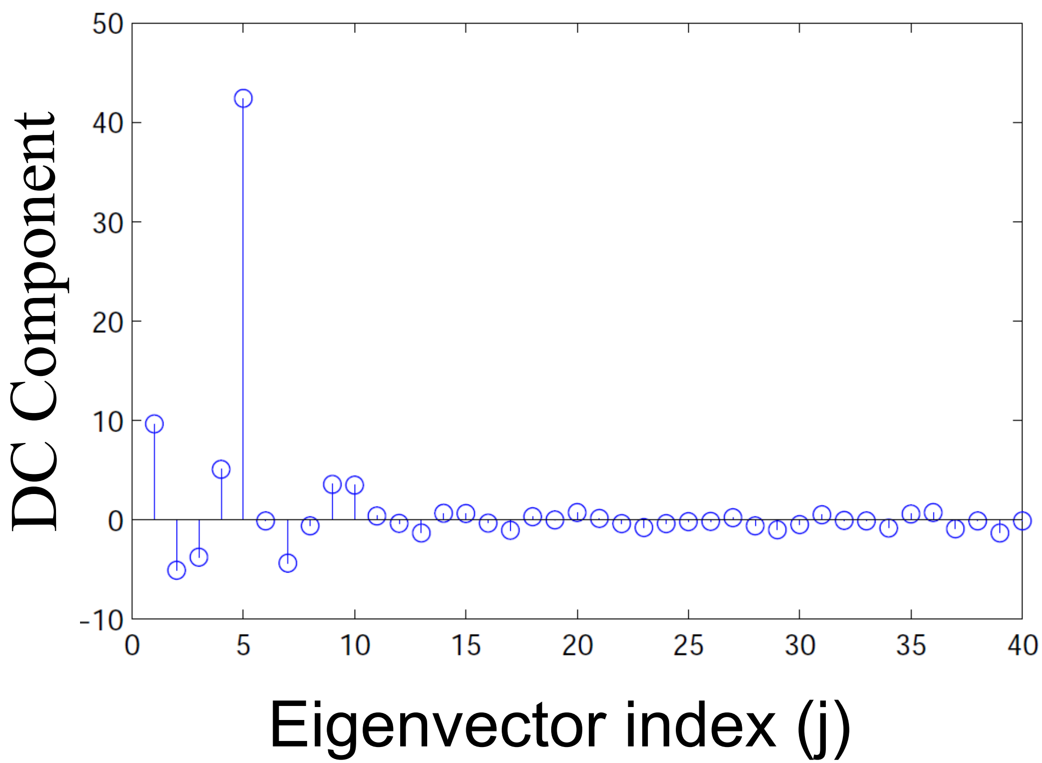
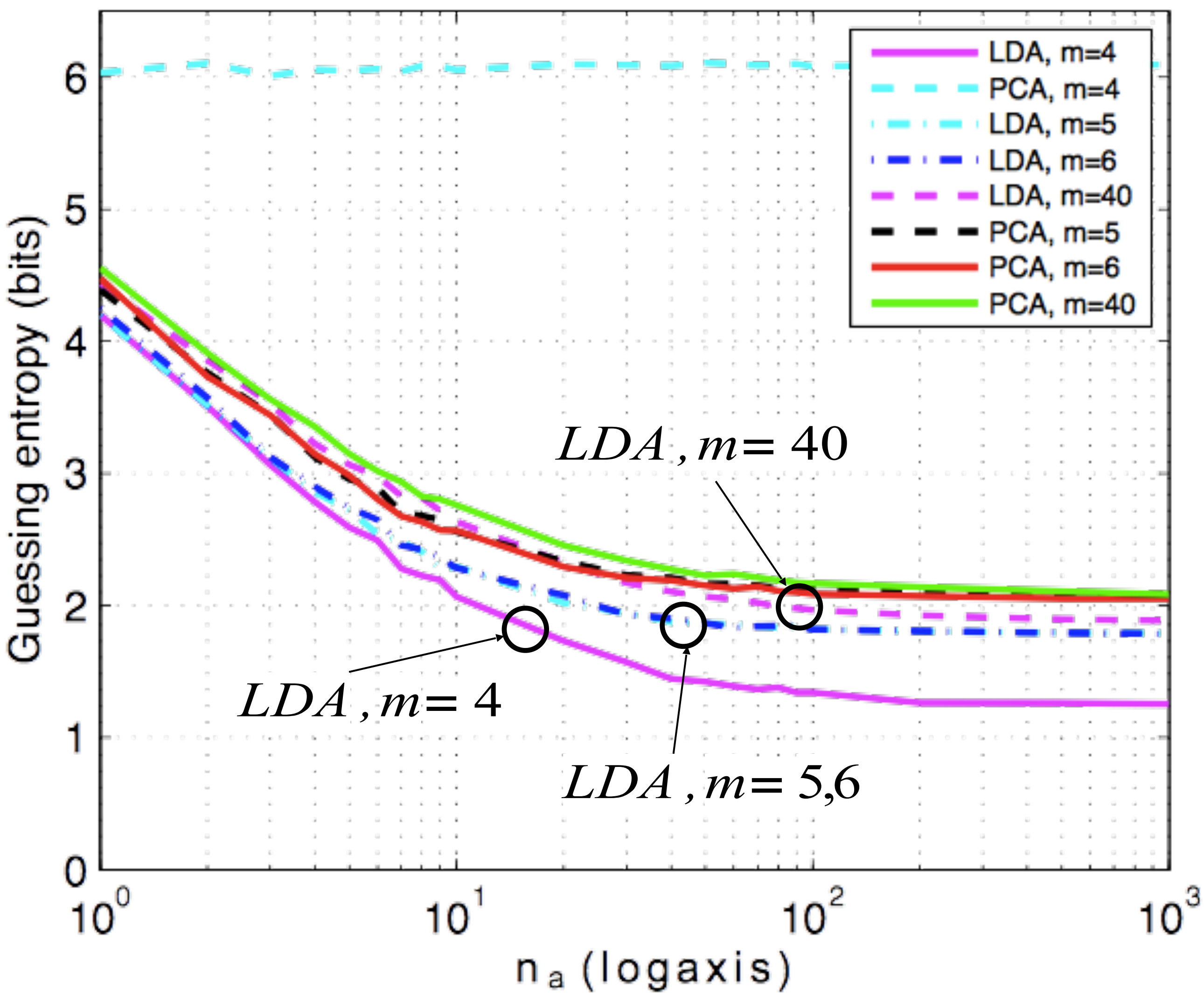


$m \geqslant 5$

Standard TA with PCA and LDA



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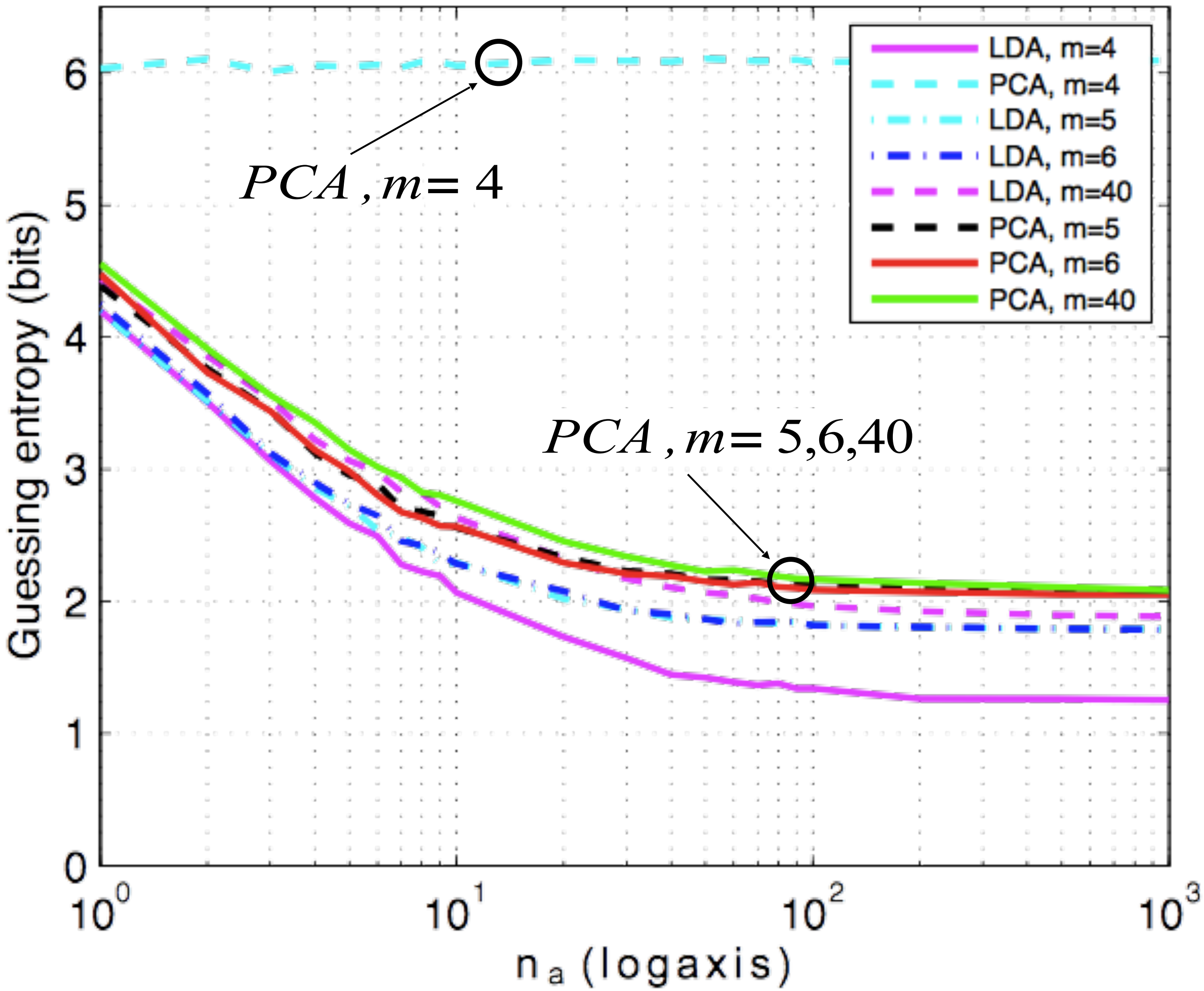
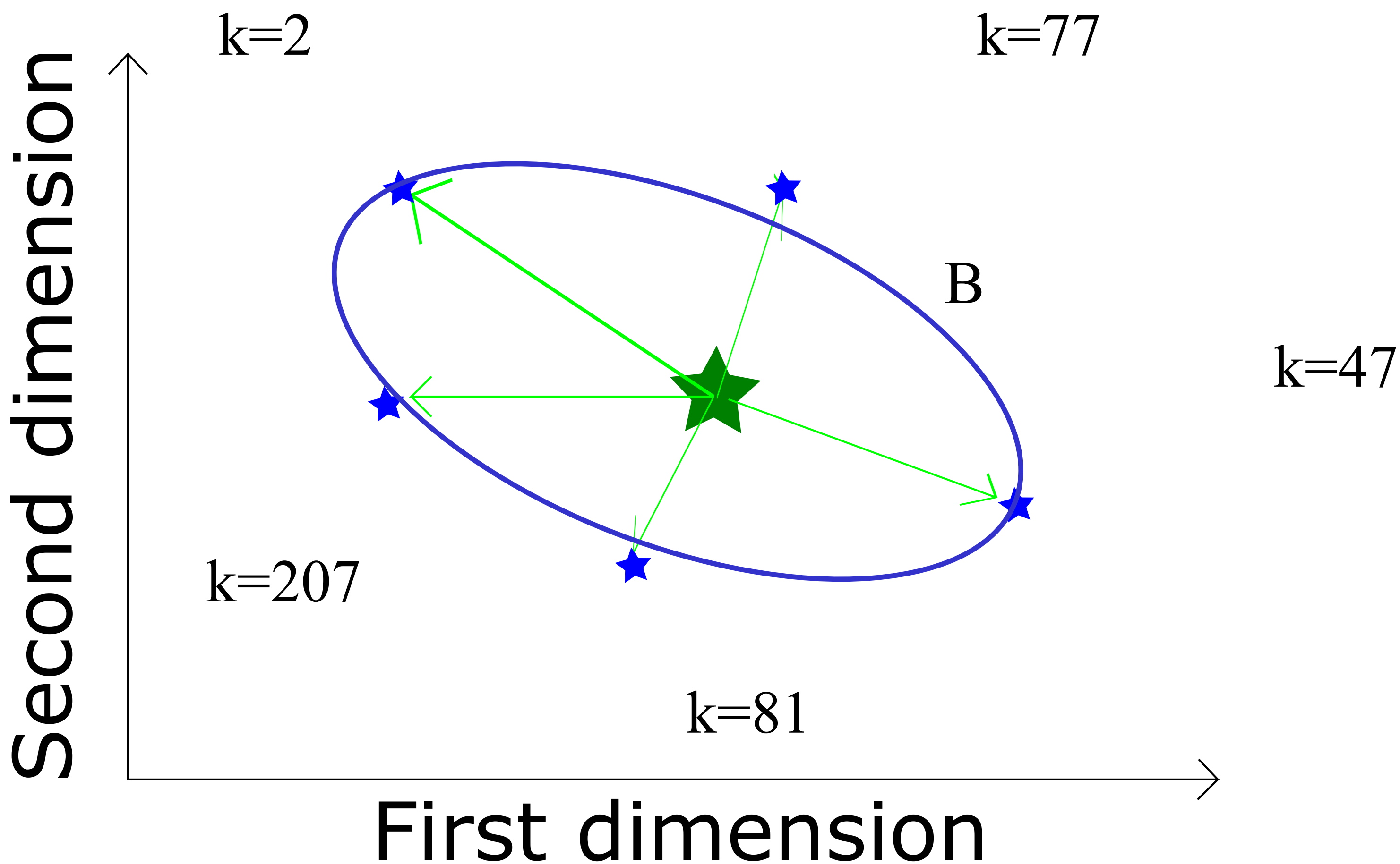
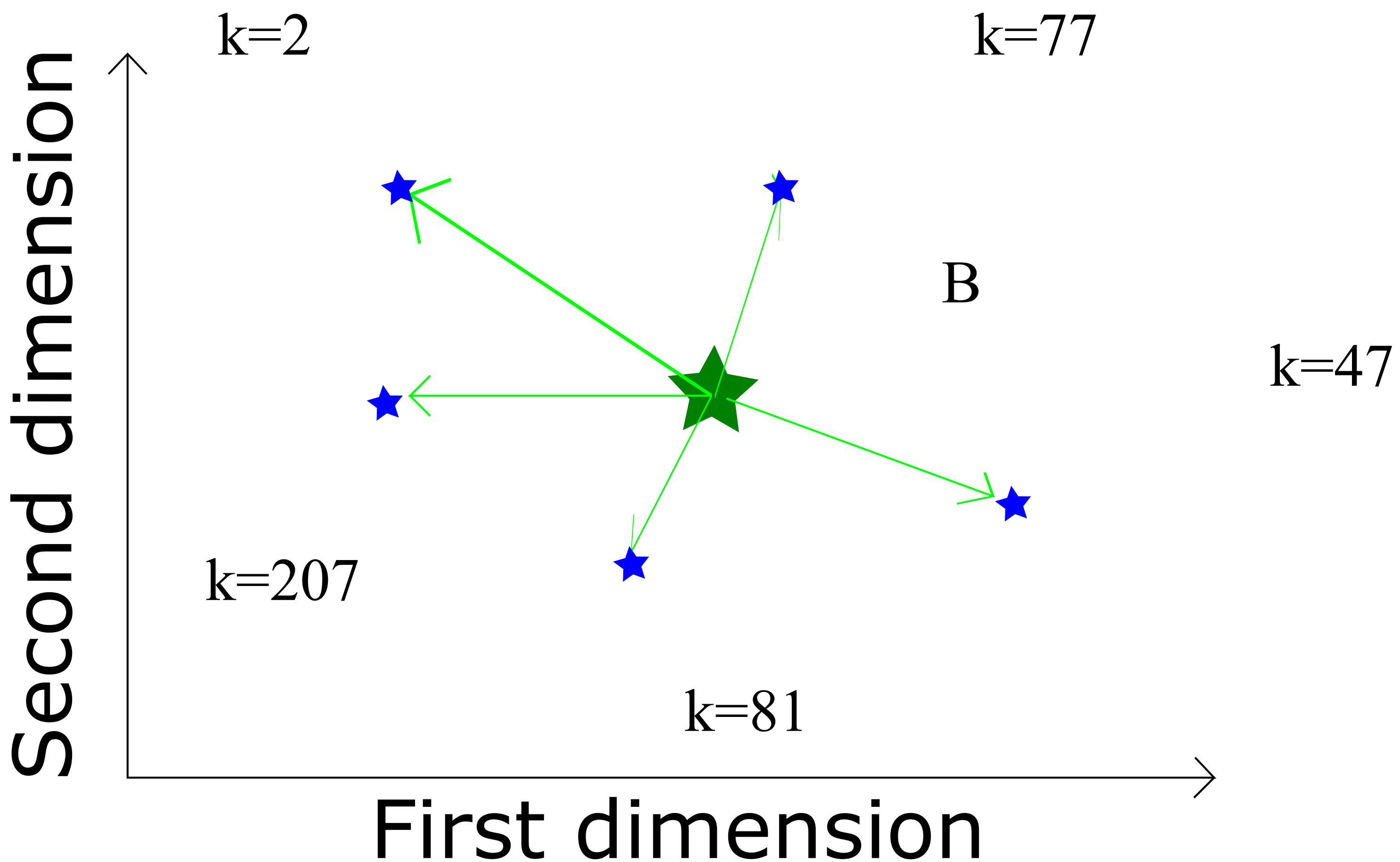


Template Attacks on Different Devices

Method 5: improving PCA



Method 5: improving PCA



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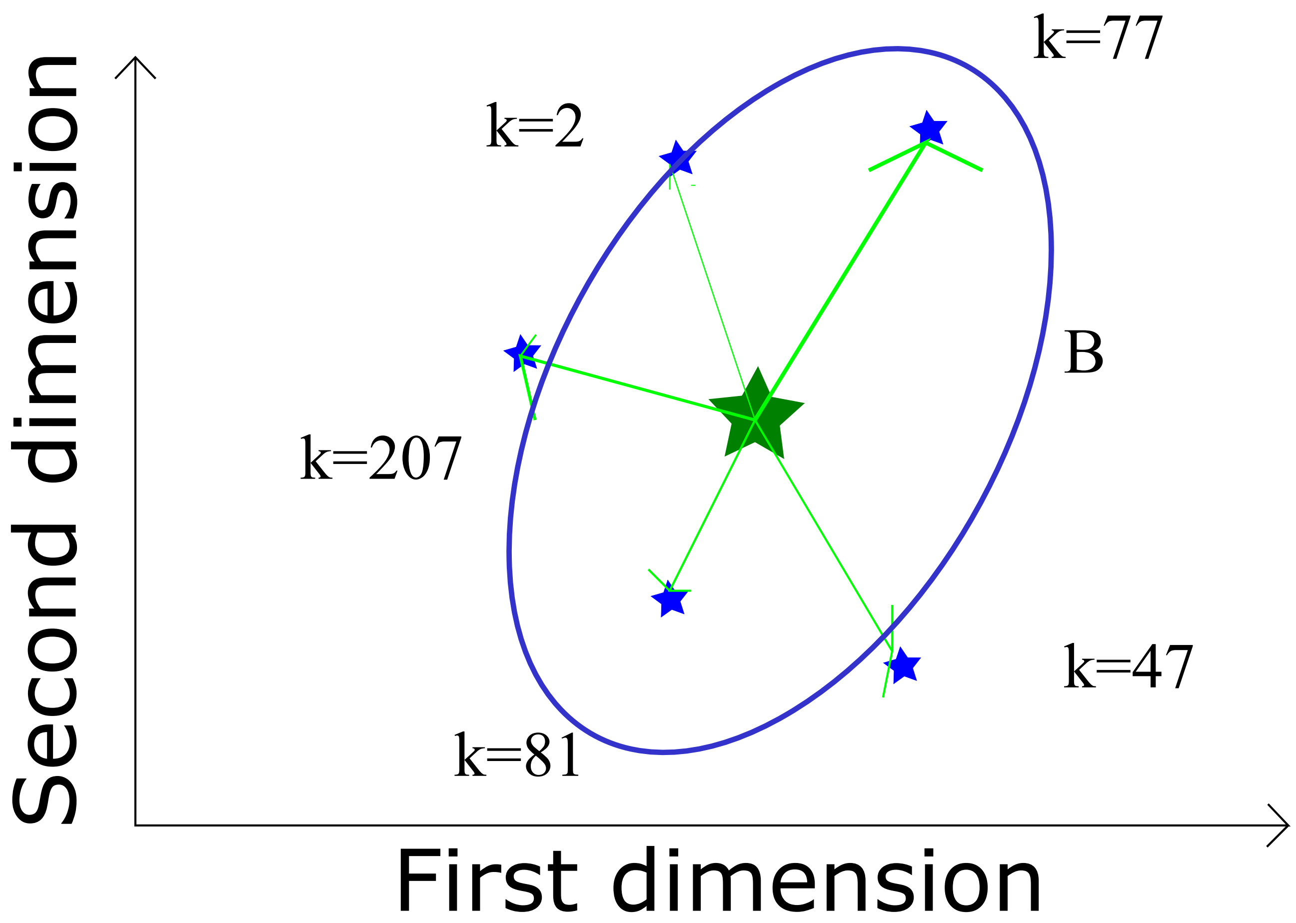

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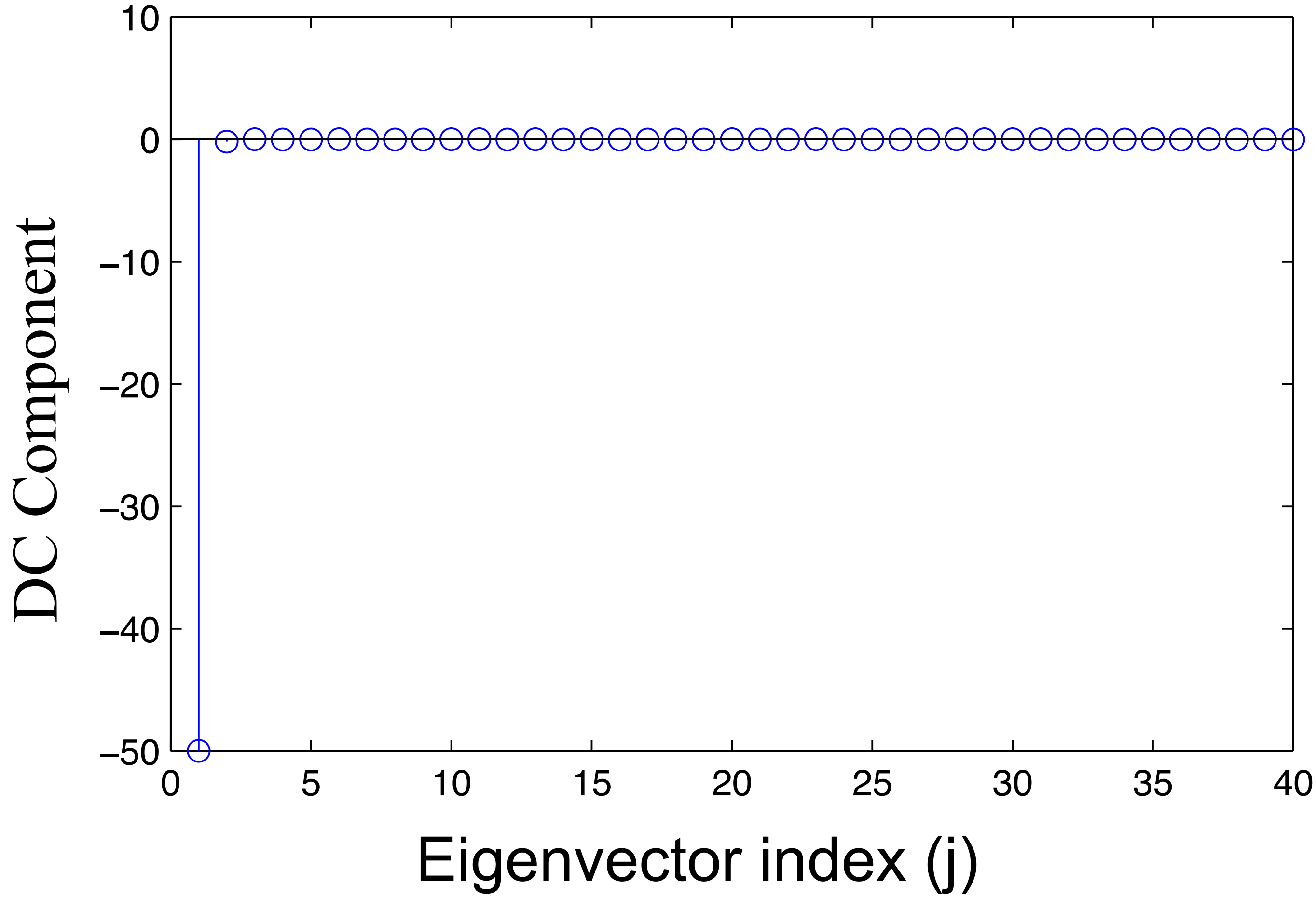

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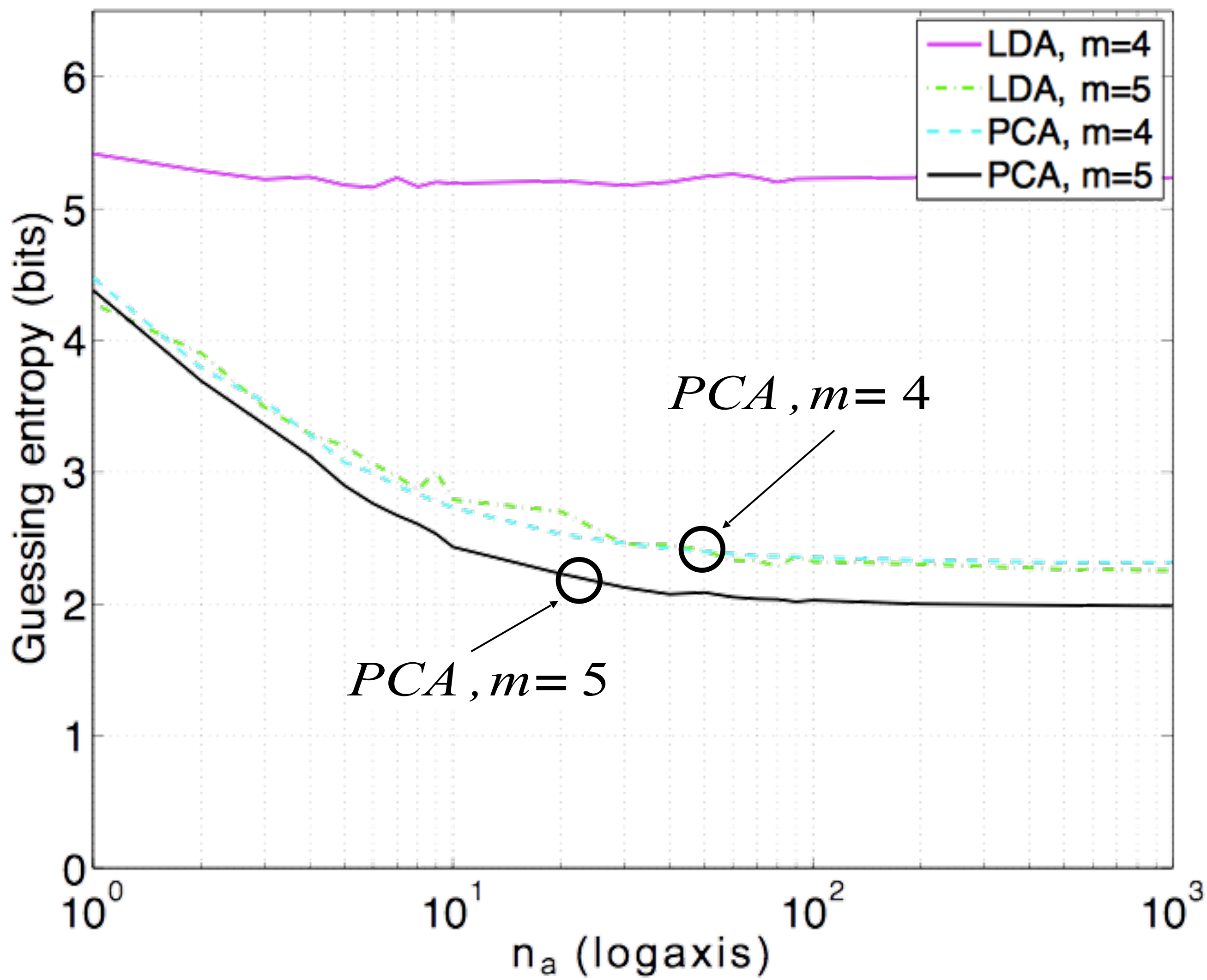
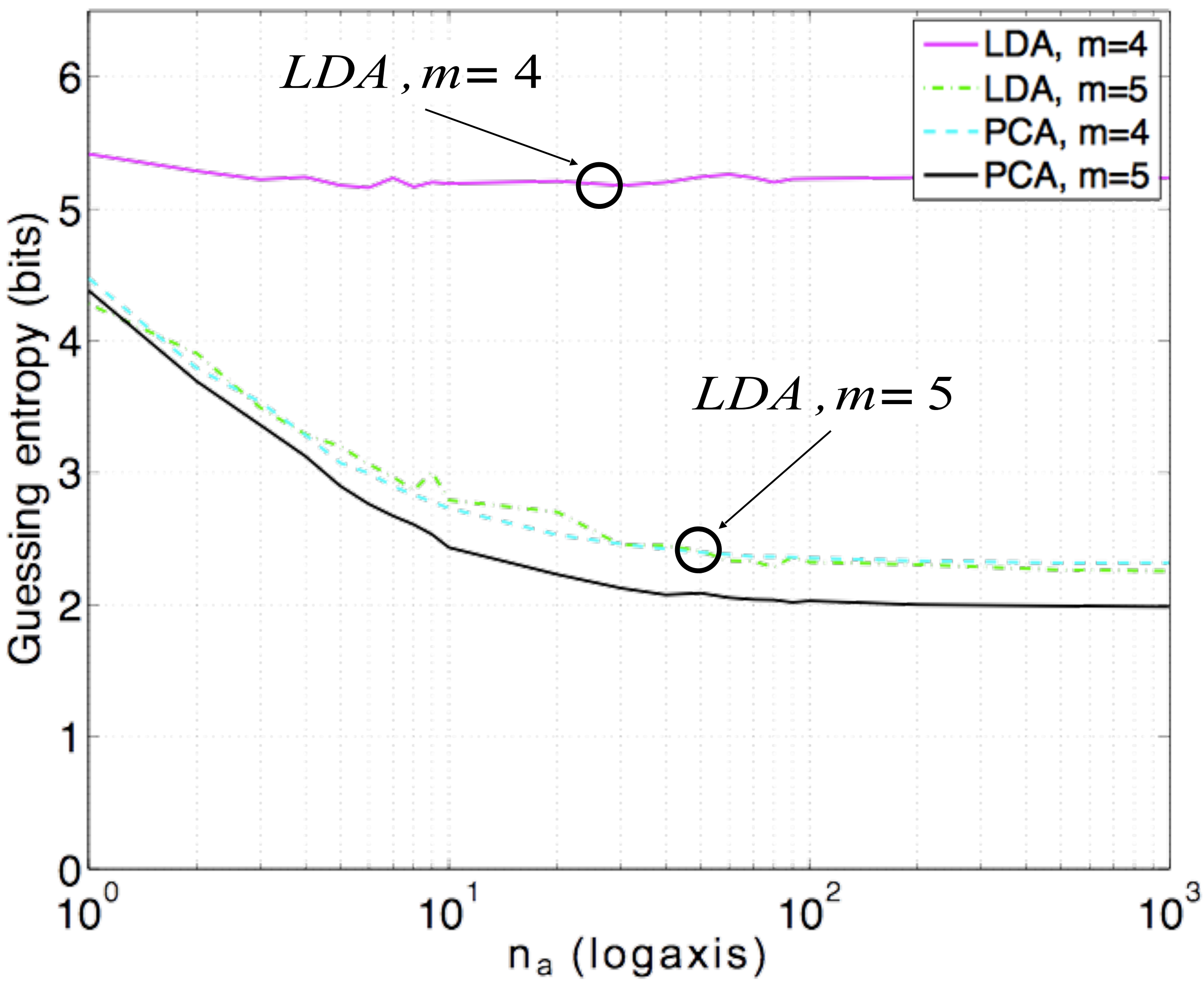


Template Attacks on Different Devices

Method 5: improving PCA



Conclusions

- Extensive evaluation of TA on different devices
  - 4 devices, 5 campaigns
  - Tested compression methods: LDA, PCA, 1/3/20/5%-ile sample selection
  - 5 methods to improve TA
- Inter-device differences similar to inter-campaign differences
- Mostly low frequency offset
- Profiling on multiple devices and manipulation of DC offset can help
- But PCA and LDA can work with standard TA
  - Need to look at DC component
- Improved PCA by forcing in a DC eigenvector
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Questions

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