On Adaptive Bandwidth Selection for Efficient MIA

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COSADE
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Laboratoire d'Informatique de Robotique et de Microélectronique de Montpellier

Outline

- Context
- Kernel Density Estimation (KDE)
- How to set the tuning parameters of Kernel-MIA?
- Experimental results
- Conclusion

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- Leakage models

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Kernel density estimation (KDE) overview

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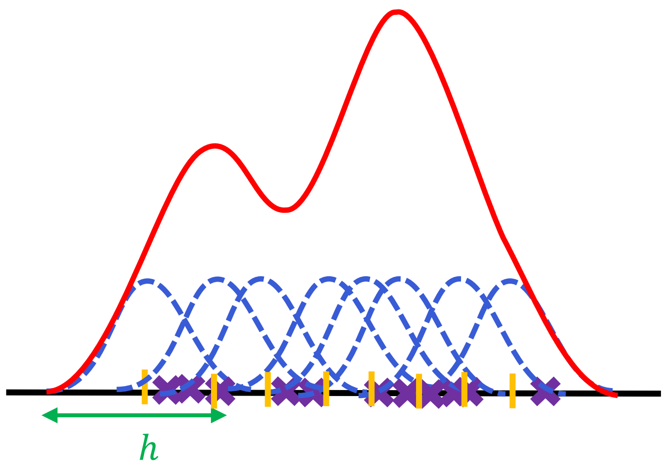
$$\hat{f}(q_b) = \frac{1}{Nh}\sum_{n=1}^{N} K\left(\frac{q_b - Y_n}{h}\right), \; 1 \leq b \leq B$$



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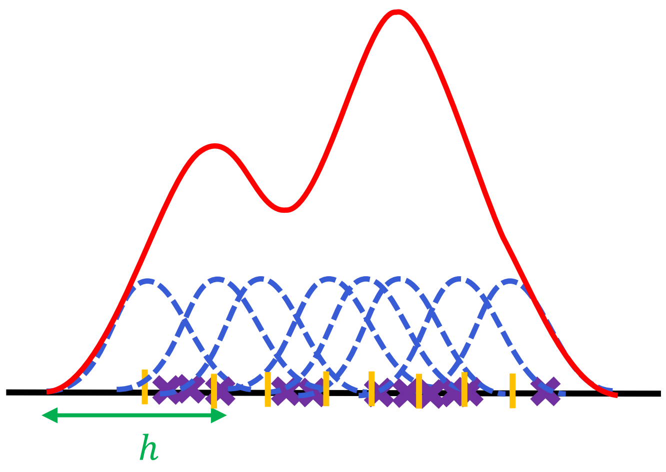

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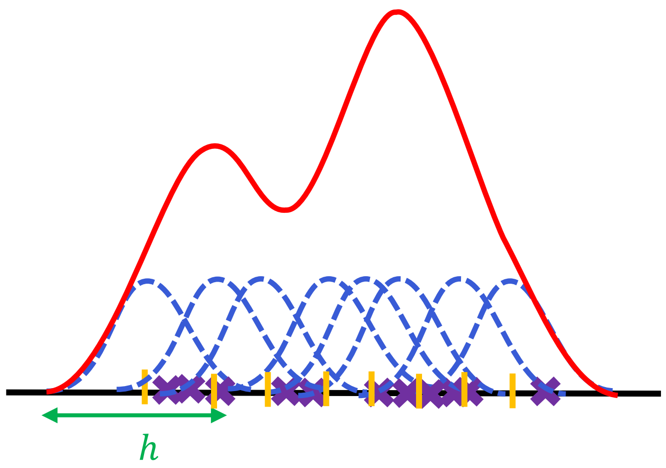

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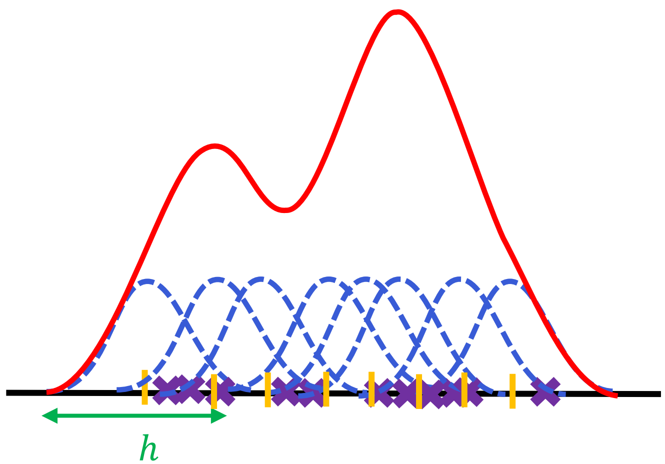

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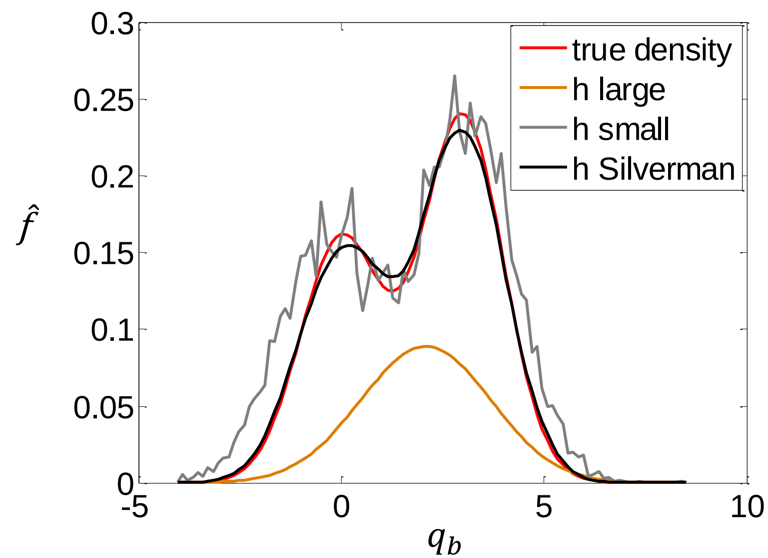
  - Bandwidth (h)
    - Trade-off bias /variance ⇨ big impact in KDE.
    - Silverman's rule commonly used



Tuning parameters of Kernel-MIA

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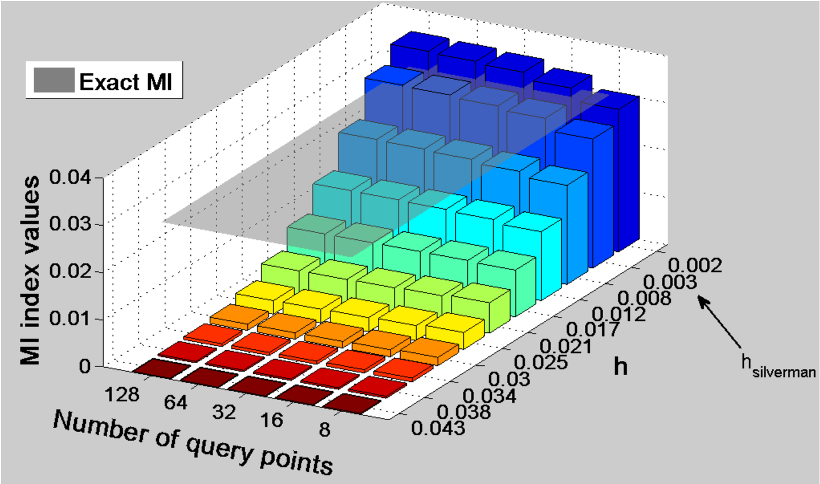
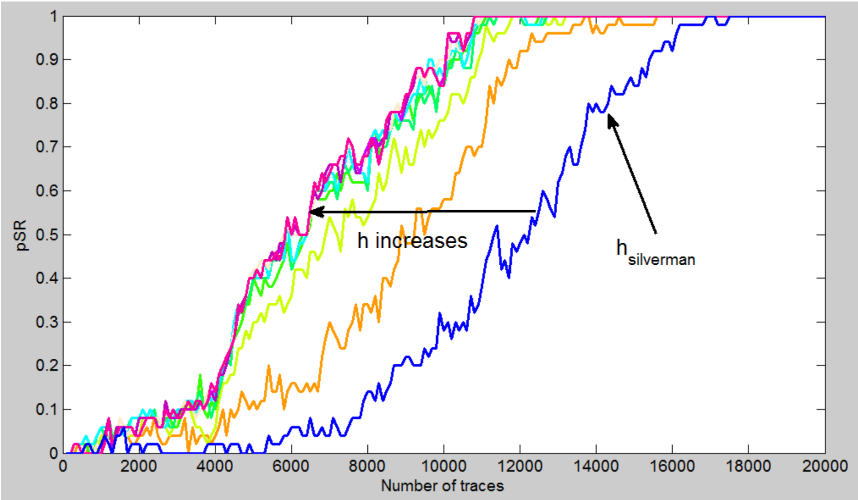


- Partial Success Rate on 1^{st} Sbox at the last round using HD function at the word level (DPA Contest v2).



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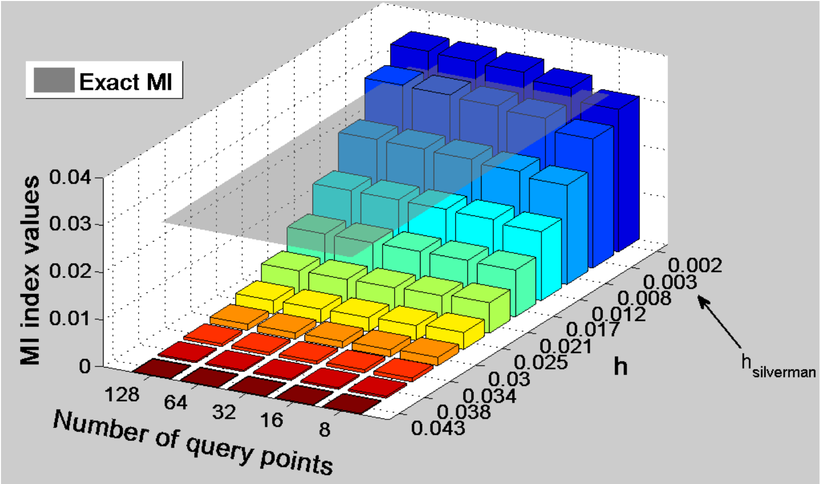

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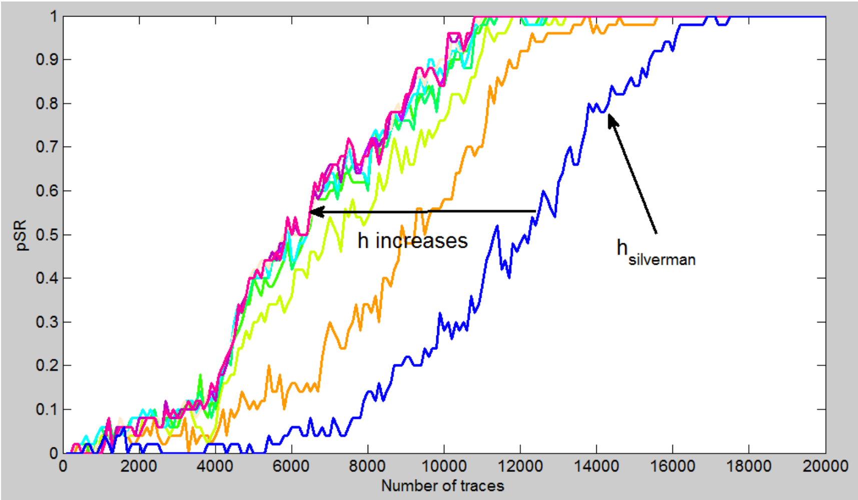

Accurate PDF estimation $\neq$ Efficient MIA !

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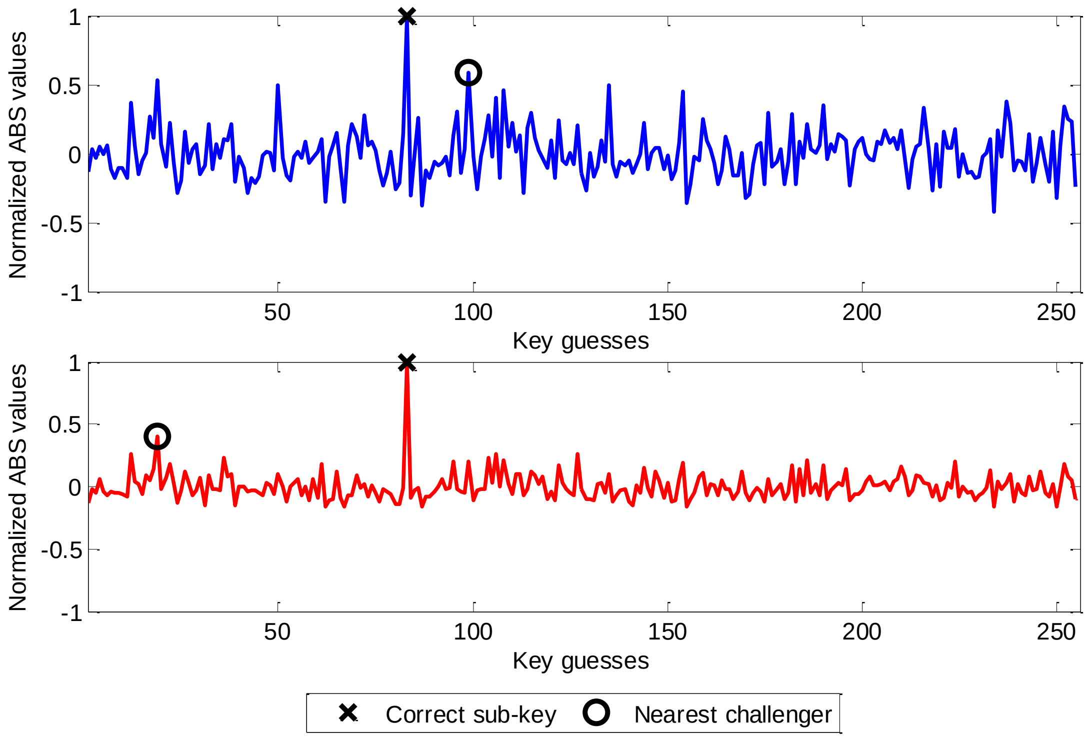

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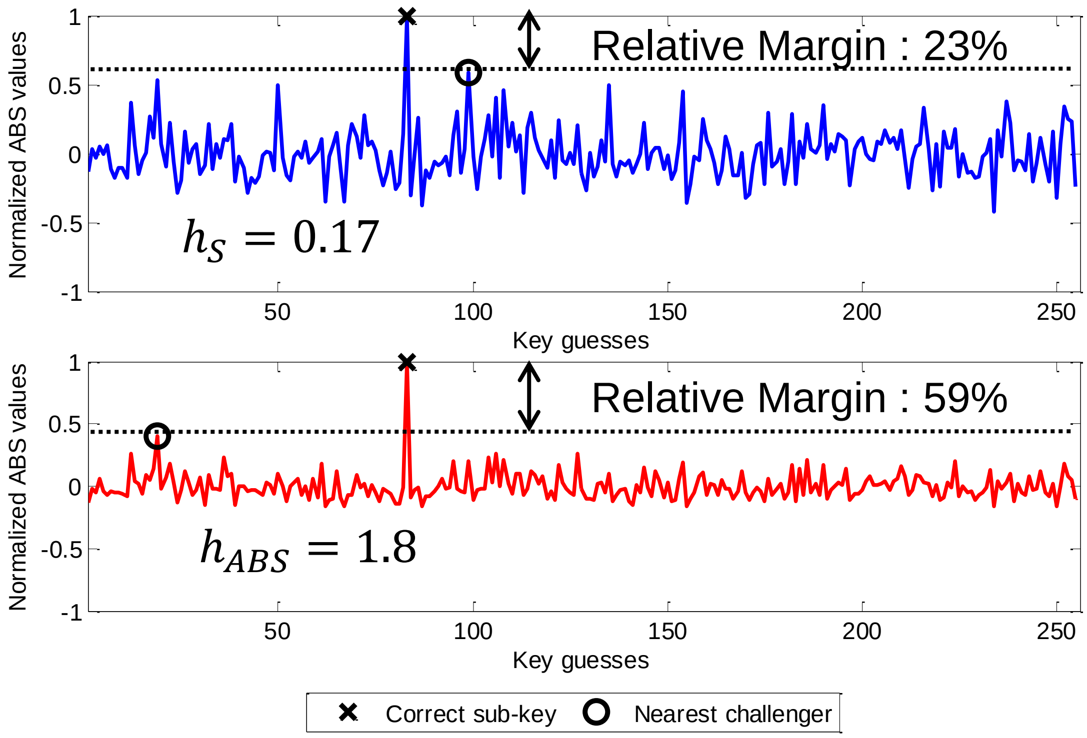

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Experimental Results

- 3 attacks were considered: ABS-MIA, S-MIA and CPA (as a benchmark)
- Success Rate metric (Standaert '08) used to measure the attack efficiency.
- Comparisons were conducted according to 2 scenarii at the
  - Bit level (Multi-bit, 'mb').
  - Word level ('wd').
- Evaluations were performed across 2 different data sets
  - DpaContestV2.
  - EM traces provided from an hardware FPGA implementing AES.

Experimental Results : Efficiency

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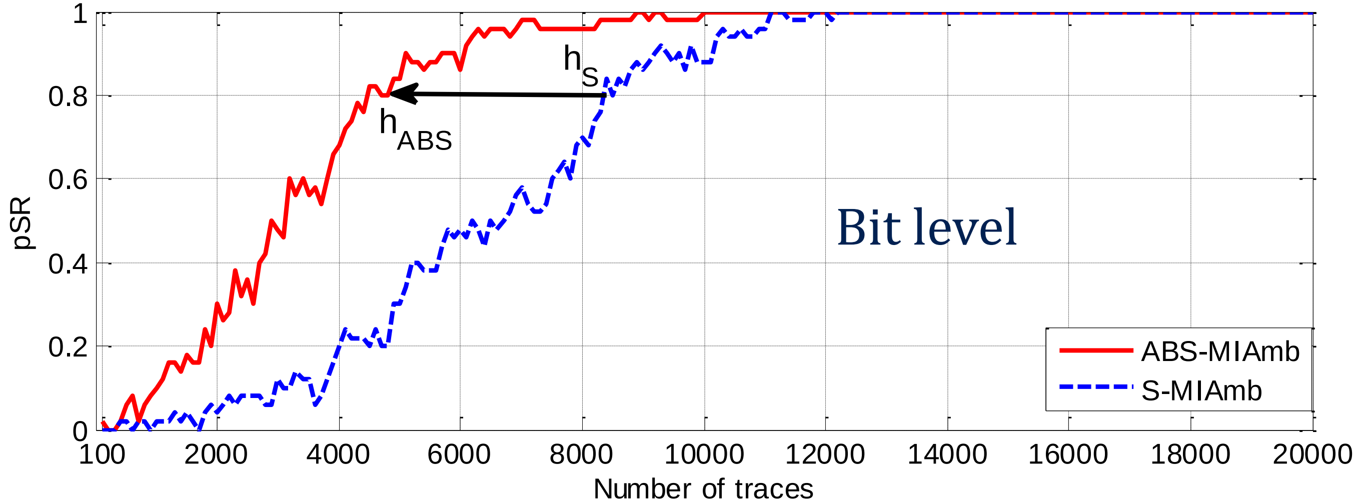
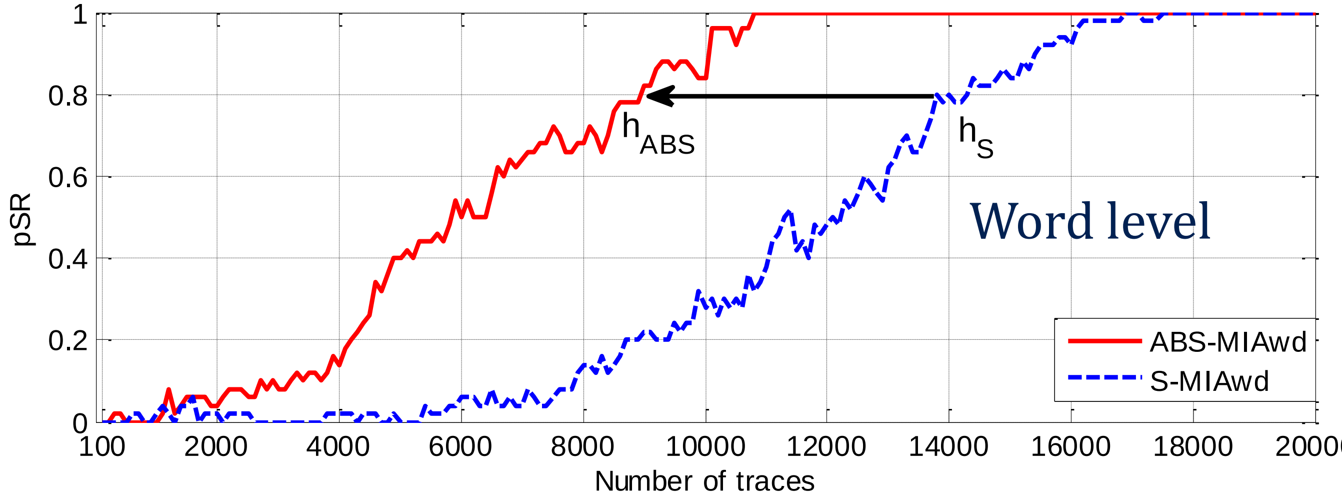
DPAcontestV2 (AES, 10^{th} round , Sbox1, HD).





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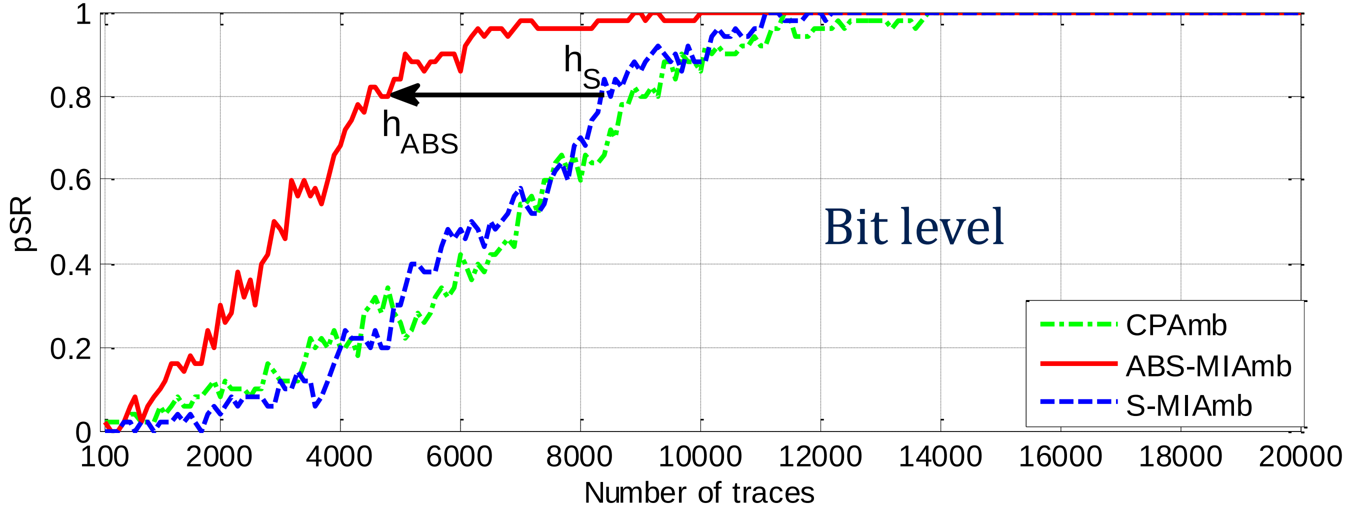

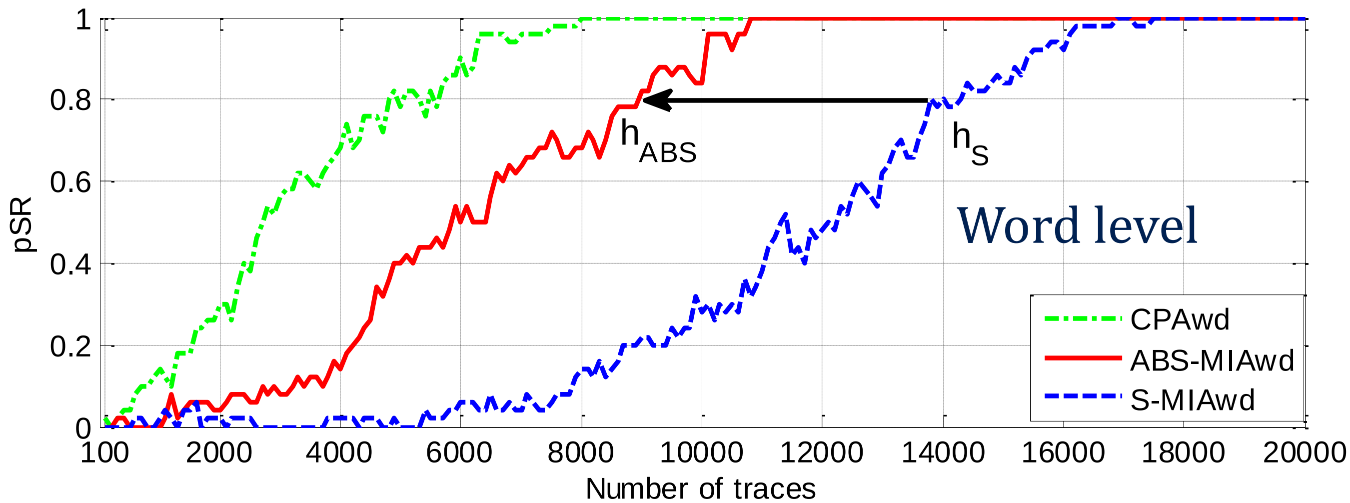

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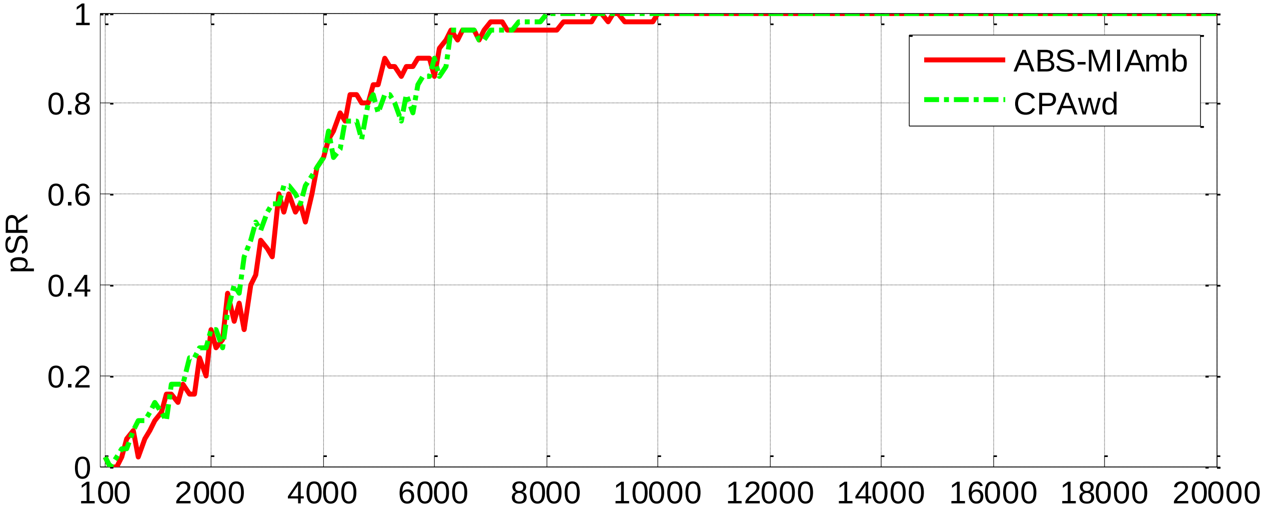

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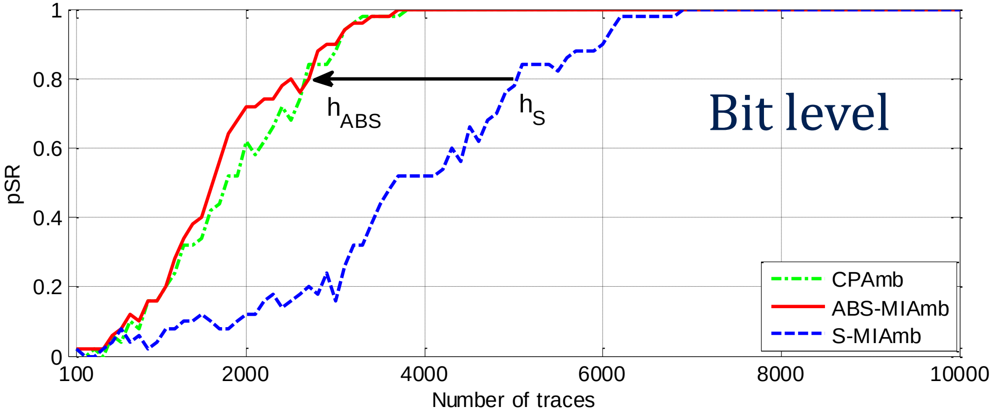
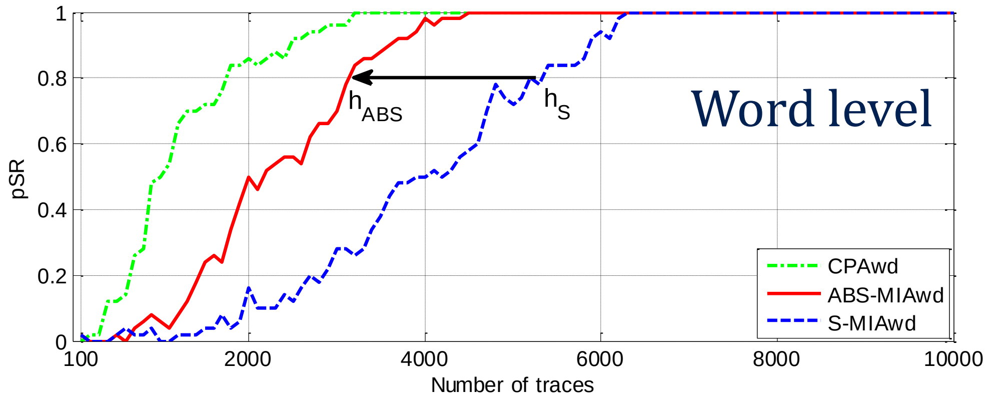
EM traces (AES, 10^{th}round, Sbox4, HD)





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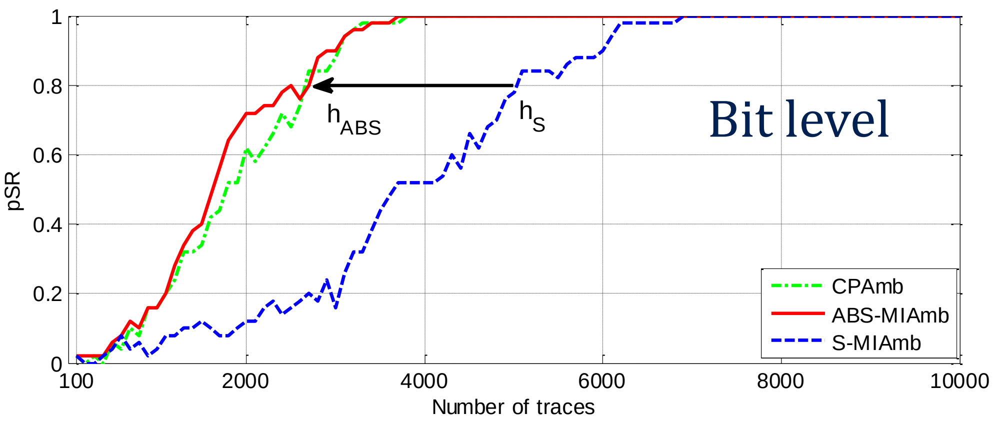
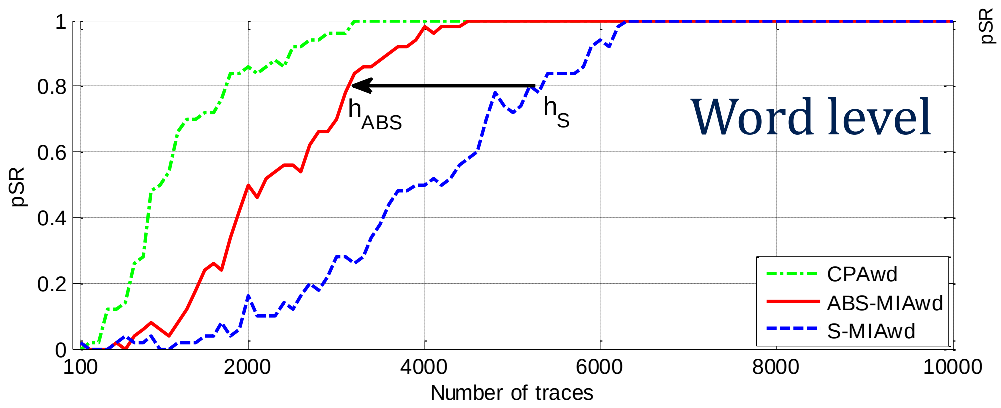
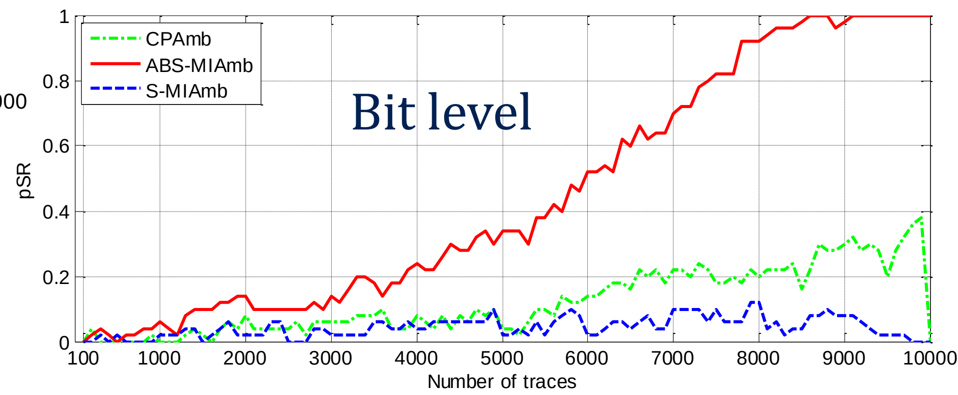




EM traces (AES, 10^{th}round, Sbox4, HW)



Conclusion

- Accurately estimating PDF $\neq$ Efficiently performing MIA.
- Our proposal increases efficiency and genericity.
- Other tuning parameters could be evaluated by our approach.

Thank you for your attention !

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