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Exploring Multi-Task Learning in the Context of Masked AES Implementations

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Outline

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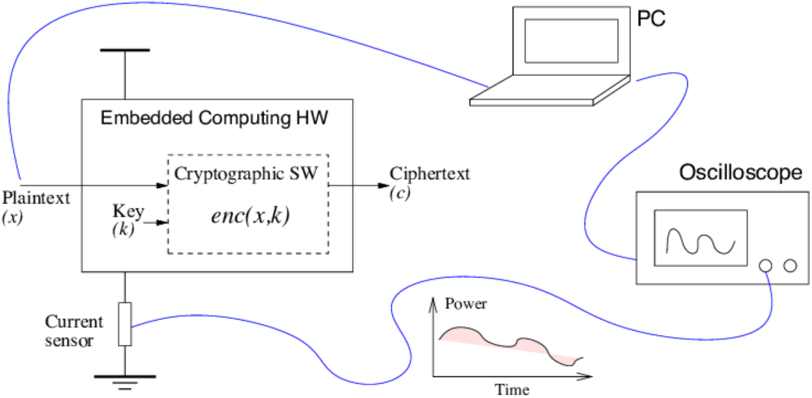


Figure: Power analysis classic setup [2]

Deep learning applied to side-channel attacks

Profiled attacks

- Require a clone of the target.
- Create a dataset with control of the inputs.
- Train deep networks on weak points (intermediates)
- Infer the key from the target.
- Straightforward in white-box

Challenges ?

Motivation

Plateau Effect

- Introduced in "Don't Learn What You Already Know", Masure et al. [3]
- Initial confusion due to the random values given as weights to the model
- Complexity of the attack => Passing the plateau

Plateau Effect

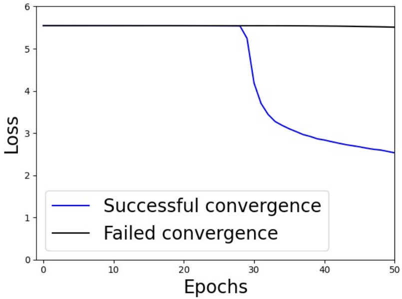


Figure: Example of the plateau effect on two training runs

How to build deep learning models that consistently break through the plateau?

Contributions

We discuss :

- The consistency of convergence of multi-task, and single-task models across seeds.
- Ways of sharing weights inside a deep learning model

We show that:

- Multi-task models are more consistent at breaking through the plateau
- Shared layers can introduce helpful constraints
- Multi-target strategies can be helpful even during training

Outline

Why does multi-task learning make sense?

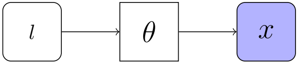
Introduced by Caruana in "Multitask Learning",[1]

Benefits

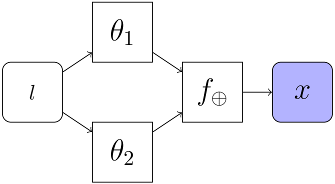
- Data amplification/augmentation.
- Input understanding.
- Eavesdropping between tasks.
- Representation bias.
- Better utilization of computing resources.

Drawbacks

- Competition of losses
- More expensive VRAM-wise



(a) Classic single-task model



(b) D-branch single-task model

Figure: Hard encoding of the masking scheme inside the network

Encoding the masking scheme in custom layers

Custom layers :

- $f_{\oplus}$: Xor
- $f_{\otimes}^{-1}$: Inverse multGF256

The calculation of $f_{\oplus}$, $f_{\otimes}^{-1}$ is a conditional probability:

$$\begin{cases} f_{\oplus}(x,y)[i] = \sum_{j=0}^{255} x[j] \times y[i \oplus j] \quad \forall\ i\ \in\ [0,255] & (1) \\ f_{\otimes}^{-1}(x,y)[i] = x[0] + \sum_{j=1}^{255} x[j] \times y[i \otimes j] \quad \forall\ i\ \in\ [0,255] & (2) \end{cases}$$

Outline

High-level parameter sharing

Classic design from Caruana [1] with shared layer $\theta_\forall$

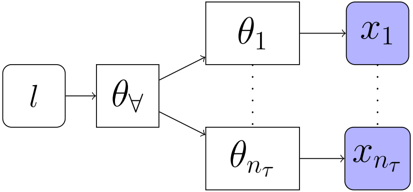


Figure: Multi-task design with high-level parameter sharing

Adapted design for two boolean shares with shared layer $\theta_\forall$

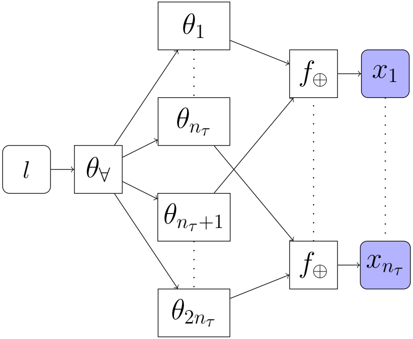


Figure: Multi-task design with high-level parameter sharing, d = 2

Layers $\theta_{n_{\tau+1}}$ to θ_{2n_τ} are collapsed into a single layer $\theta_{n_{\tau+1}}$

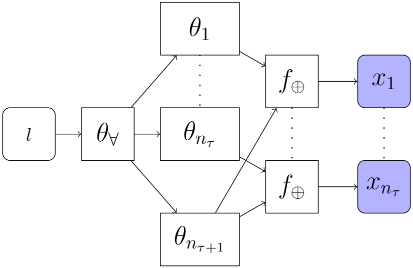


Figure: Multi-task design with high-level parameter sharing and shared randomness

Low-level parameter sharing
Not shared randomness

$\theta_{i*n_\tau+1}, \ \dots \ , \theta_{i*n_\tau+n_\tau}$ are fed to the respective prediction head $\theta_{d_{i+1}}$

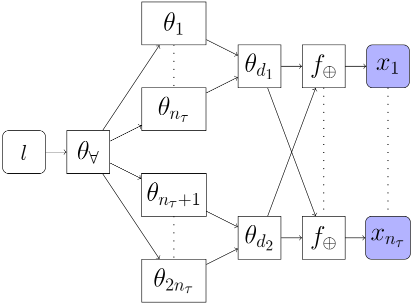


Figure: Multi-task design with high-level and low-level parameter sharing

Outline

Datasets and experiments

Datasets

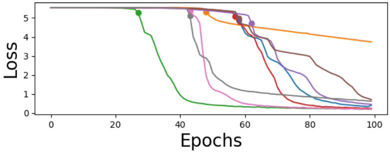
- ASCAD-r : raw traces with 250k samples
- ASCAD-v2 : extracted PoIs, permutations "disabled"
- Spartan-6 : extracted cycles of interest

Experiments

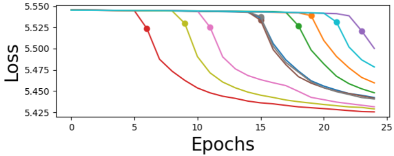
Collection of epoch of convergence with 10 different seeds

- Expert layer with shared mask (ASCADr, ASCADv2)
- Low-level parameter sharing (ASCADr, Spartan-6)
- Multi-target with shared mask (ASCADv2)

Collection of epoch of convergence



(a) ASCAD-r



(b) ASCAD-v2

Figure: Examples of the acquisition of the epoch of convergence for all seeds of one model type.

CHESCTF 2023, Spartan-6

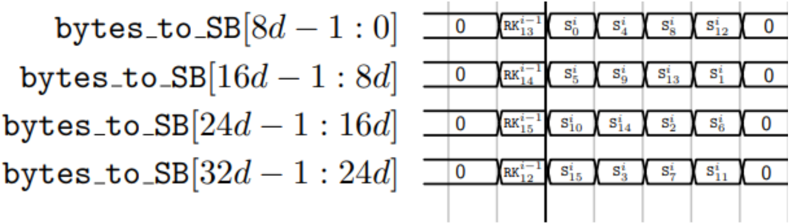


Figure: Dataflow on the Subbytes inputs wires

Leakage : Hamming distance

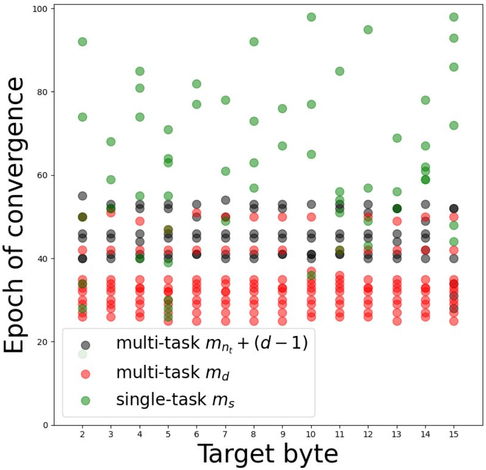
ASCAD-r : Expert layer with shared mask

Target : $t_i = (t_i \oplus r_i) \oplus r_i$

Models :

- Single-task: m_s
- Multi-task with expert layer: $m_{n_t+(d-1)}$
- Multi-task with expert layer, low-level parameter sharing: m_d

ASCAD-r : Expert layer with shared mask
Epoch of convergence



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ASCAD-r : Expert layer with shared mask
Performance metrics

Model type	f_r	$n_{\mathrm{win}}/n_{\mathrm{seeds}}$	$\overline{T_{\mathrm{win}}}$	*best* T_{win}
m_s	0.56	0.0	$>$100	$>$100
$m_{n_t+(d-1)}$	0.4	0.6	**4.33**	4
m_d	**0.0**	**1.0**	5.8	**2**

- f_r = failure rate of a training run across all bytes
- n_{win}/n_{seeds} = ratio of seeds leading to full key recovery
- T_{win} = Trace at which the full key is recovered

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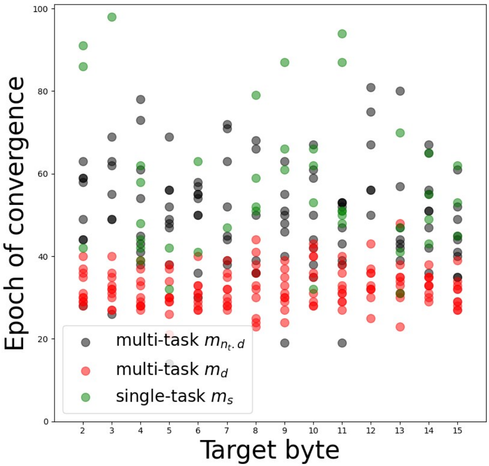
ASCAD-r : Low-level parameter sharing

Target : $s_i = (s_i \oplus r_i) \oplus r_i$

Models :

- Single-task : m_s
- Multi-task : $m_{n_t.d}$
- Multi-task with low-level parameter sharing : m_d

ASCAD-r : Low-level parameter sharing
Epoch of convergence



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	ASCAD-r			
Model type	f_r	$n_{\mathrm{win}}/n_{\mathrm{seeds}}$	$\overline{T}_{\mathrm{win}}$	*best* T_{win}
m_s	0.69	0.0	>100	>100
$m_{n_t.d}$	0.21	0.4	**6**	5
m_d	**0.0**	**1.0**	2.13	**2**

- f_r = failure rate of a training run across all bytes
- n_{win}/n_{seeds} = ratio of seeds leading to full key recovery
- T_{win} = Trace at which the full key is recovered

Spartan-6 : Low-level parameter sharing

Target : $t_i = (t_i \oplus r_i) \oplus r_i$

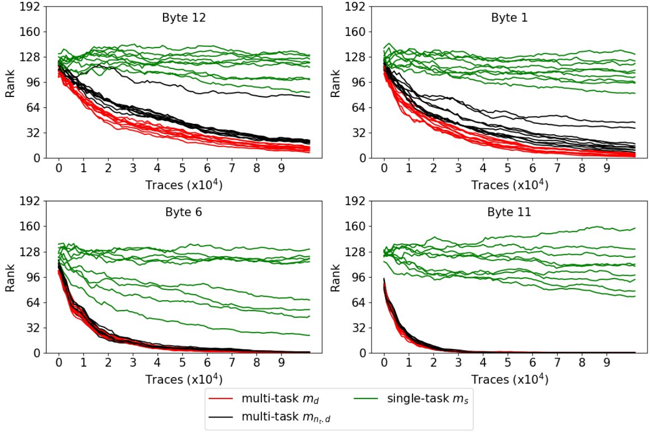

Figure: True rank evolution for all targeted bytes across all seeds and models

ASCAD-v2 : Multi-target with shared mask

Targets :

- $t_i = r_m \otimes^{-1} ((r_m \otimes t_i \oplus r_{in}) \oplus r_{in})$
- $s_i = r_m \otimes^{-1} ((r_m \otimes s_i \oplus r_{out}) \oplus r_{out})$

Models :

- Multi-task, single target trained only for t_i: m_{st-d}
- Multi-task, multi target: $m_{n_t+(d-1)}$
- Multi-task, multi target, and low-level parameter sharing : m_d

ASCAD-v2 : Multi-target with shared mask
Performance metrics

Model type	$n_{\mathrm{win}}/n_{\mathrm{seeds}}$	$\overline{T_{\mathrm{win}}}$	*best* T_{win}
m_{st-d}	0.0	>200	>200
$m_{n_t+(d-1)}$	0.0	>200	>200
m_d	**0.5**	**17.6**	**16**

- f_r = failure rate of a training run across all bytes
- n_{win}/n_{seeds} = ratio of seeds leading to full key recovery
- T_{win} = Trace at which the full key is recovered

Conclusion

What I am not saying

- Multi-task is always more performant than single-task
- Sharing layers is always beneficial

What can be concluded

- Multi-task needs less profiling traces to converge consistently
- Careful constraints are helpful to improve the latter point
- Multi-target strategies can be implemented even during training
- Multi-task make evaluations faster

Acknowledgments

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