Focus is Key to Success

A Focal Loss Function for Deep Learning-Based Side-Channel Analysis

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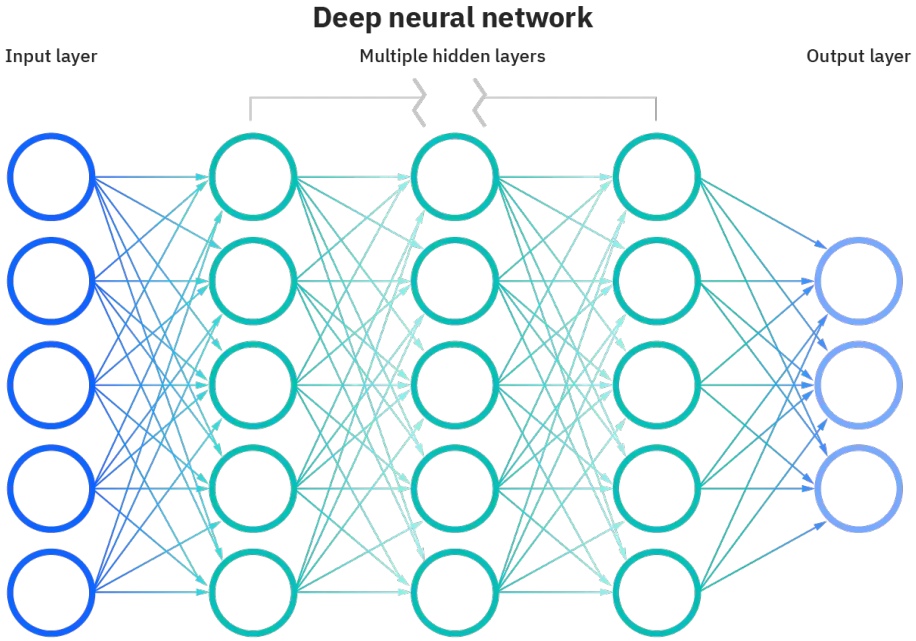
Introduction

- Loss functions
  - Estimate the prediction error
  - Derivatives are used to update weights
  - Key role in learning process

- Example: mean absolute error (MAE)

$$\boldsymbol{y} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \ \hat{\boldsymbol{y}} = \begin{bmatrix} 0.3 \\ 0.5 \\ 0.2 \end{bmatrix}$$

$$\frac{|0-0.3|+|1-0.5|+|0-0.2|}{3} = 0.33$$



Introduction

- Mean absolute error
  - $MAE(\boldsymbol{y}, \hat{\boldsymbol{y}}) = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$
- Mean squared error
  - $MSE(\boldsymbol{y}, \hat{\boldsymbol{y}}) = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$
- Categorical cross-entropy
  - $CCE(\boldsymbol{y}, \hat{\boldsymbol{y}}) = -\sum_{i=1}^{n} y_i \log \hat{y}_i$

Loss Functions in SCA

- Zhang et al. (2020), Cross Entropy Ratio (CER)
  - Maximize the loss with incorrect predictions

$$cer(\mathbf{y}, \hat{\mathbf{y}}) = \frac{CE(\mathbf{y}, \hat{\mathbf{y}})}{\frac{1}{n}\sum_{i=1}^{N} CE(\mathbf{y}_{r_i}, \hat{\mathbf{y}})}$$

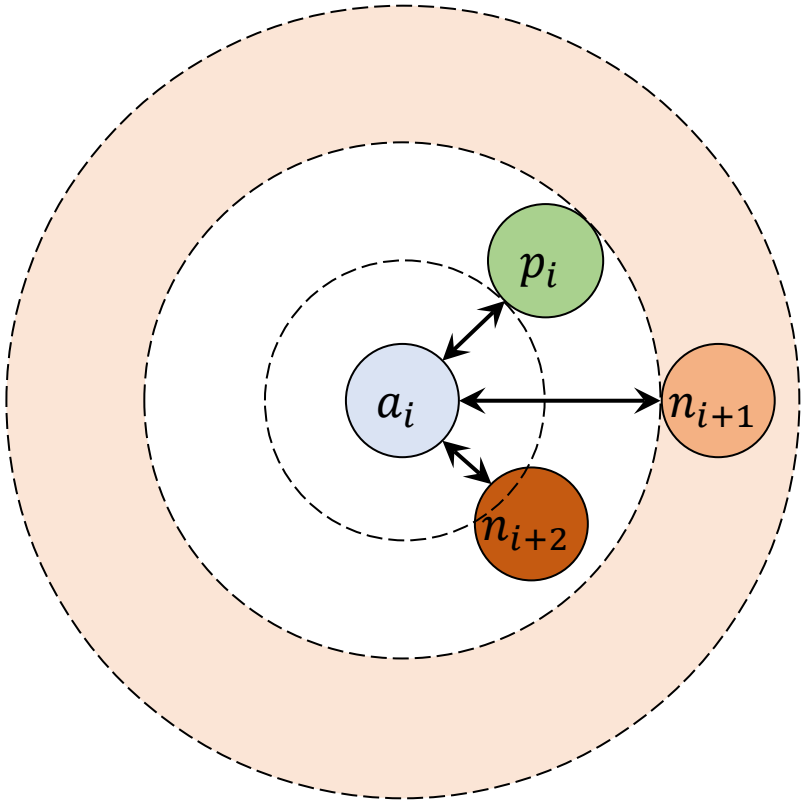
- Zaid et al. (2020), Ranking loss (RKL)
  - Maximize the rank difference of the correct key and the other key bytes

- Kerkhof et al. (2021)
  - Broad analysis of loss function performance
  - Multiple architectures, datasets, leakage models
  - CER performs well in many settings

$$rkl(\mathbf{s}) = \sum_{\substack{k \in \mathcal{K} \\ k \neq k^*}} \left(\log_2\left(1 + e^{-\alpha(s(k^*) - s(k))}\right)\right)$$

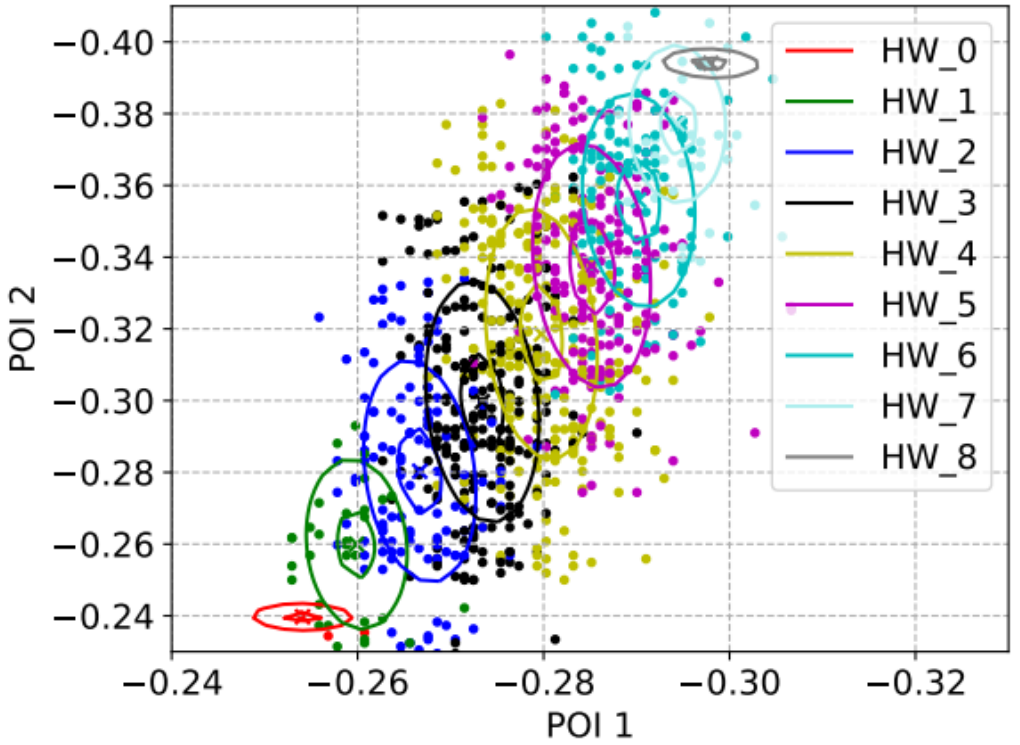
Motivation: learn from the hard samples

- Easy positives/negatives (n_{i+1}):
  - samples classified as positive/negative examples.
  - The bias introduced by easy samples makes it difficult for a network to learn rich semantic relationships from samples
- Hard positives/negatives (n_{i+2}):
  - samples misclassified as negative/positive examples.



Motivation: fight with the imbalanced data

- Middle classes (i.e., HW=4) is over-represented compared to the other classes



Focal Loss Ratio

- Focal Loss Ratio (FLR)
  - Combines both objectives into a loss single function

$$FLR(\boldsymbol{y}, \hat{\boldsymbol{y}}) = \frac{-\boldsymbol{\alpha}(1-\hat{\boldsymbol{y}})^{\gamma} CCE(\boldsymbol{y}, \hat{\boldsymbol{y}})}{\sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} -\boldsymbol{\alpha}(1-\hat{\boldsymbol{y}})^{\gamma} CCE(\boldsymbol{y_s}, \hat{\boldsymbol{y}})}$$

  - $\boldsymbol{\alpha}$: weight vector for each classes
  - $\boldsymbol{\gamma}$: attention level on hard examples

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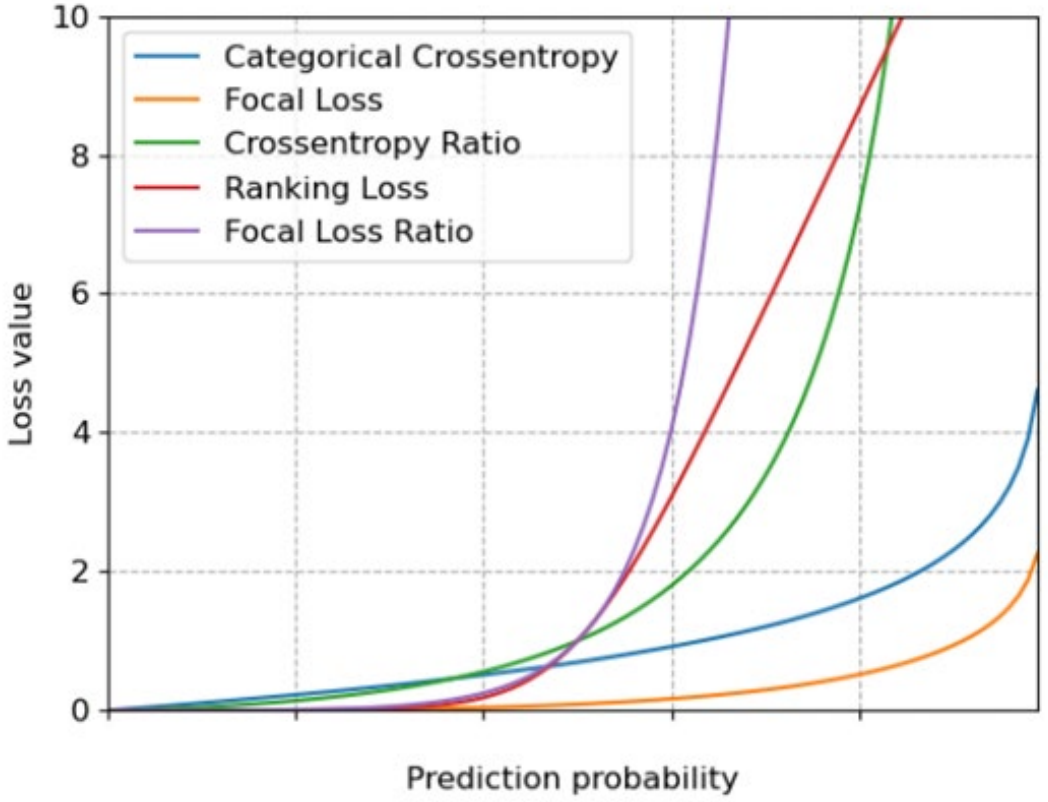

Performance Evaluation Strategy

1: Generate, train, and test 100 models sampled from range *S* with loss function *L*.

2: Select the best performing model T_b.

3: Train and test the model T_b 10 times.

4: Select the median performing model T_{bm}.

5: Evaluate T_{bm} with evaluation metrics: GE and SR.

Experimental Setup

- Focal Loss Ratio (FLR) tuning strategy
  - FLR: fixed value: $\alpha = 0.25$ and $\gamma = 2.0$;
  - FLR_optimized: optimized via random search;
  - FLR_balanced: determined by the sample number of each class

- Searching range for MLP and CNN:

Hyperparameter	**Options**
Dense layers	2 to 8 in a step of 1
Neurons per layer	100 to 1 000 in a step of 100
Learning rate	1e-6 to 1e-3 in a step of 1e-5
Batch size	100 to 1 000 in a step of 100
Activation function (all layers)	ReLU, Tanh, ELU, or SeLU
Loss function	RMSprop, Adam

Hyperparameter	Options
Convolution layers	1 to 2 in a step of 1
Convolution filters	8 to 32 in a step of 4
Kernel size	10 to 20 in a step of 2
Pooling type	Max pooling, Average pooling
Pooling size	2 to 5 in a step of 1
Pooling stride	2 to 10 in a step of 1
Dense layers	2 to 3 in a step of 1
Neurons per layer	100 to 1 000 in a step of 100
Learning rate	1e-6 to 1e-3 in a step of 1e-5
Batch size	100 to 1 000 in a step of 100
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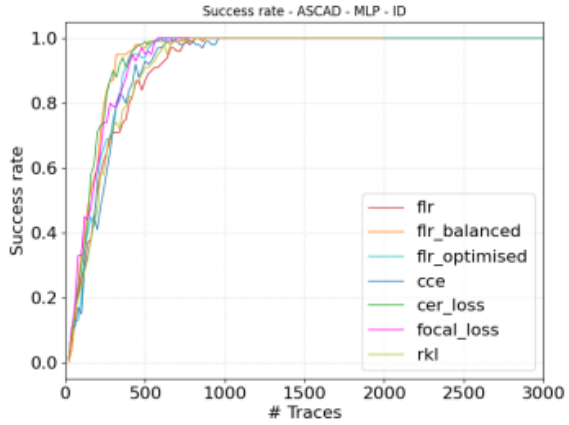
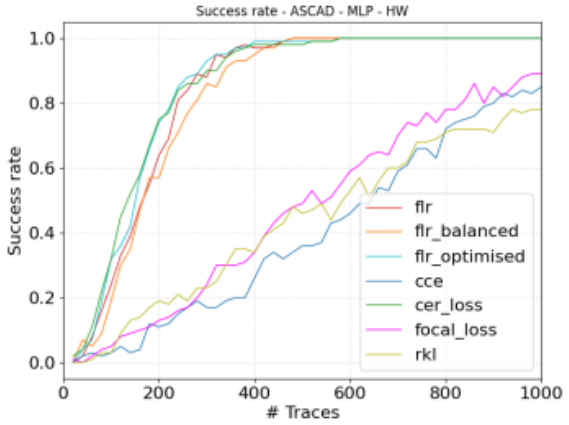
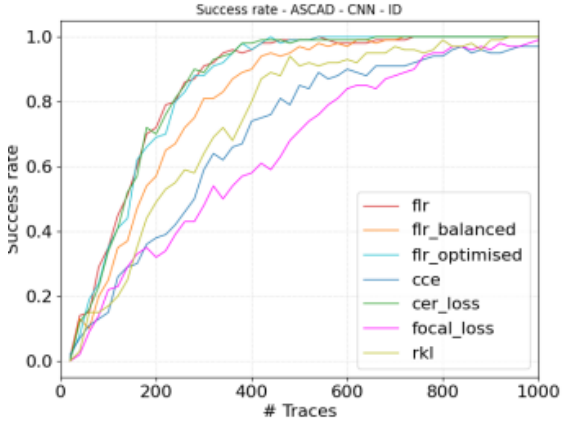
Experimental Results (ASCADf)



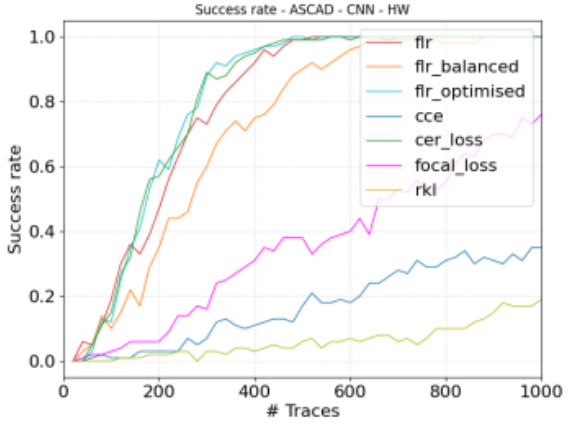
(a) MLP models, ID leakage model.



(b) MLP models, HW leakage model.



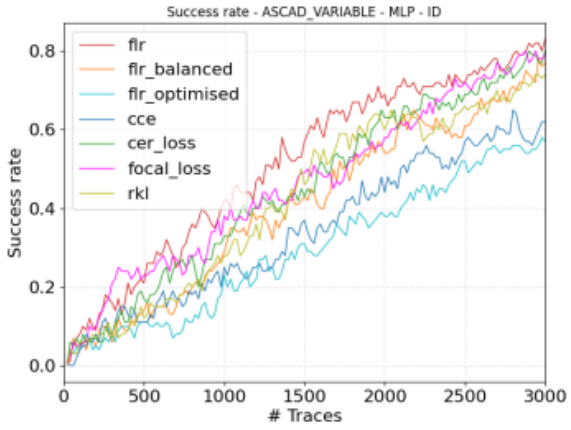
(c) CNN models, ID leakage model.



(d) CNN models, HW leakage model.

	L_{focal}	CCE	CER loss	FLR
MLP ID	580	860	570	640
MLP HW	1480	1560	560	490
CNN ID	1250	1360	600	520
CNN HW	1840	>2000	540	500

Experimental Results (ASCADr)



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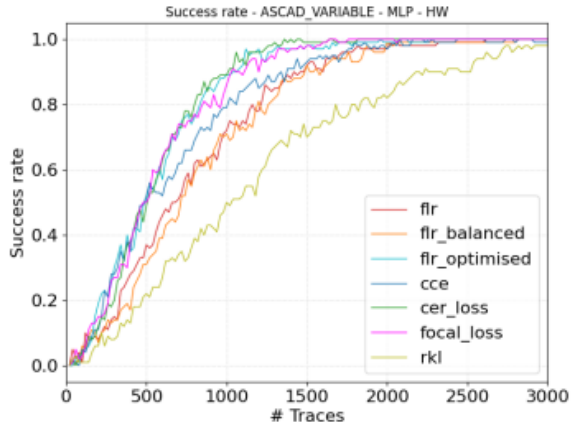
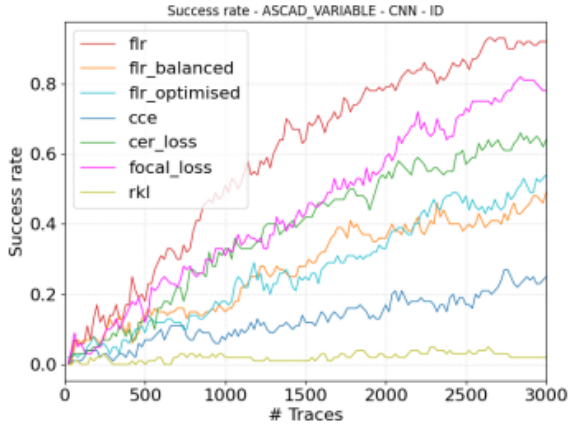


(b) MLP models, HW leakage model.



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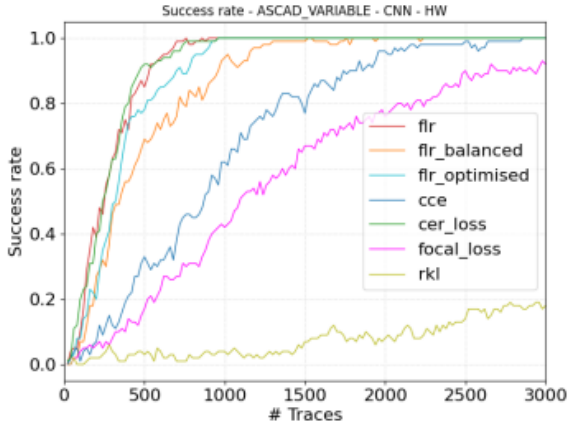
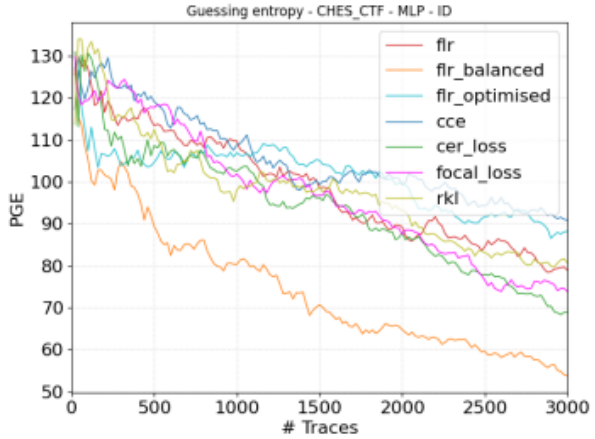


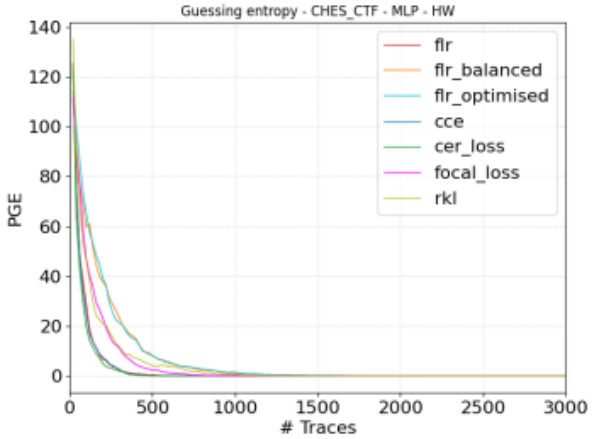
(d) CNN models, HW leakage model.

	L_{focal}	CCE	CER loss	FLR
MLP ID	>3000	>3000	>3000	>3000
MLP HW	1940	2600	1340	1340
CNN ID	>3000	>3000	>3000	>3000
CNN HW	>3000	2840	950	800

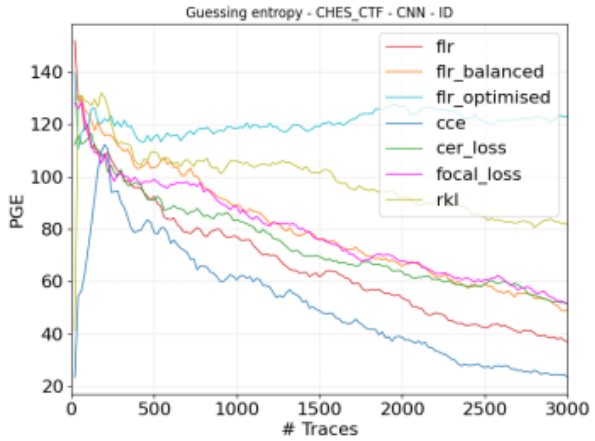
Experimental Results (CHES CTF)



(a) MLP models, ID leakage model.



(b) MLP models, HW leakage model.



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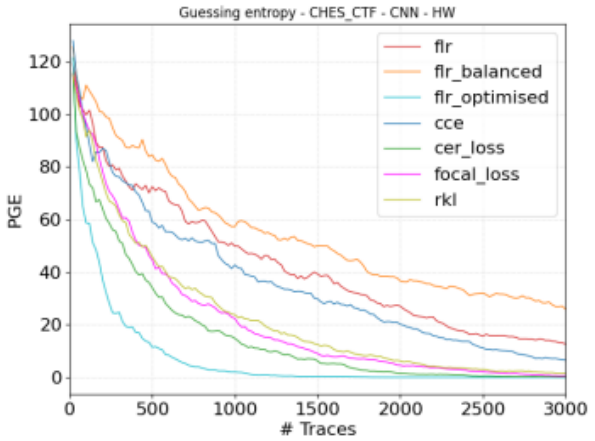
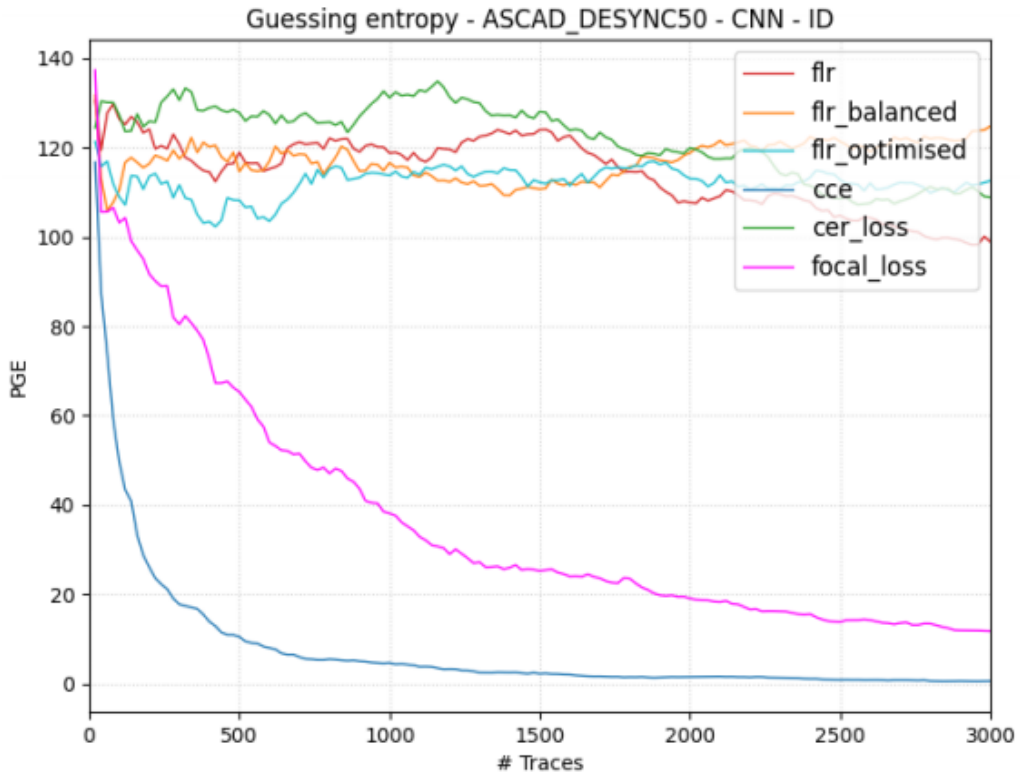
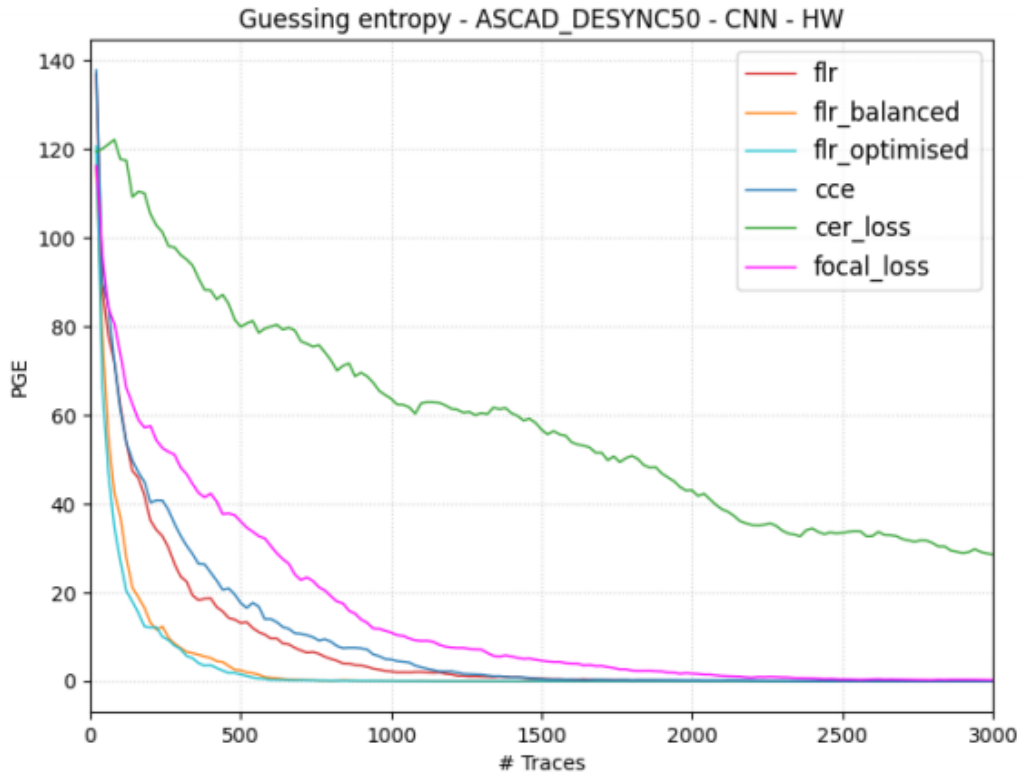


(d) CNN models, HW leakage model.

	L_{focal}	CCE	CER loss	FLR
MLP ID	>3000	>3000	>3000	>3000
MLP HW	1220	630	480	1080
CNN ID	>3000	>3000	>3000	>3000
CNN HW	>3000	>3000	>3000	2070

Experimental Results with Misalignment





Conclusion

- FLR is able to learn from the hard samples and deal with the class imbalance
- FLR loss performs well in various test scenarios, while it still requires hyperparameter tuning
- When using FLR loss, it is a good option to start with fixed hyperparameter (i.e., one used in the paper), then start tuning

- For future work, it would be interesting to explore other optimization strategies
- Develop loss functions based on SCA metrics

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