UNIVERSITÄT ZÜRICH
UNIVERSIDADE FEDERAL DE MINAS GERAIS

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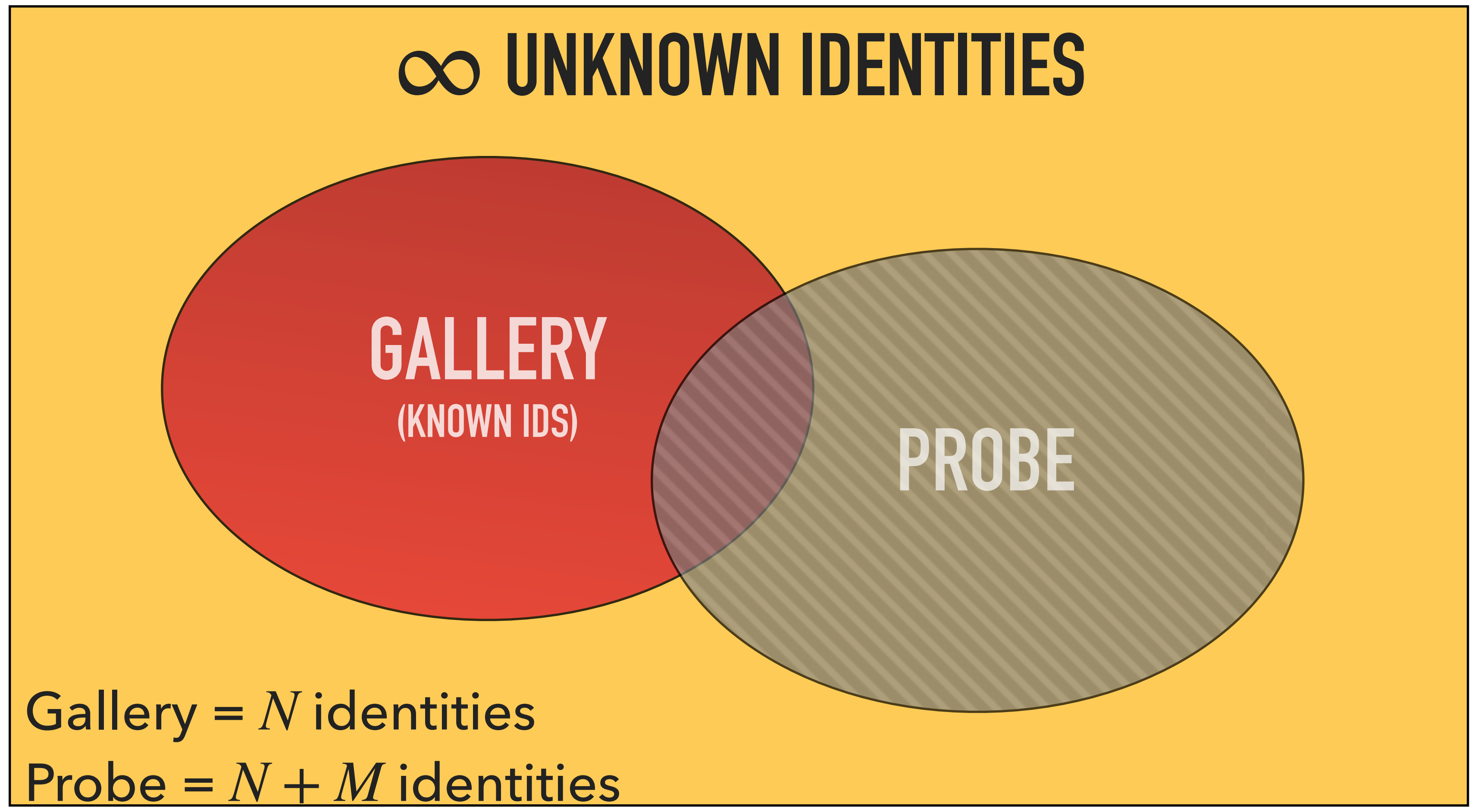
OPEN-SET FACE RECOGNITION WITH NEURAL ENSEMBLE, MAXIMAL ENTROPY LOSS AND FEATURE AUGMENTATION

OPEN-SET FACE RECOGNITION

Recognize faces of subjects that may have not been seen during training.



DOMINANT CHALLENGES

Face Recognition Task:

- Imbalanced datasets (bias)
- Classes and samples disparity (overfitting)
- Different face domains (pose, occlusion, quality)

Open Set Task:

- Neural networks do not know the unknown
- Unknown persons may resemble known subjects
- *Watchlists*: operate at low false-positive rate

RELATED WORKS

Towards Open-Set Face Recognition using Hashing Functions

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Reducing Network Agnostophobia

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Watchlist Adaptation: Protecting the Innocent

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Manifold Mixup: Better Representations by Interpolating Hidden States

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PROPOSED METHOD: MAXIMAL ENTROPY LOSS (MEL)

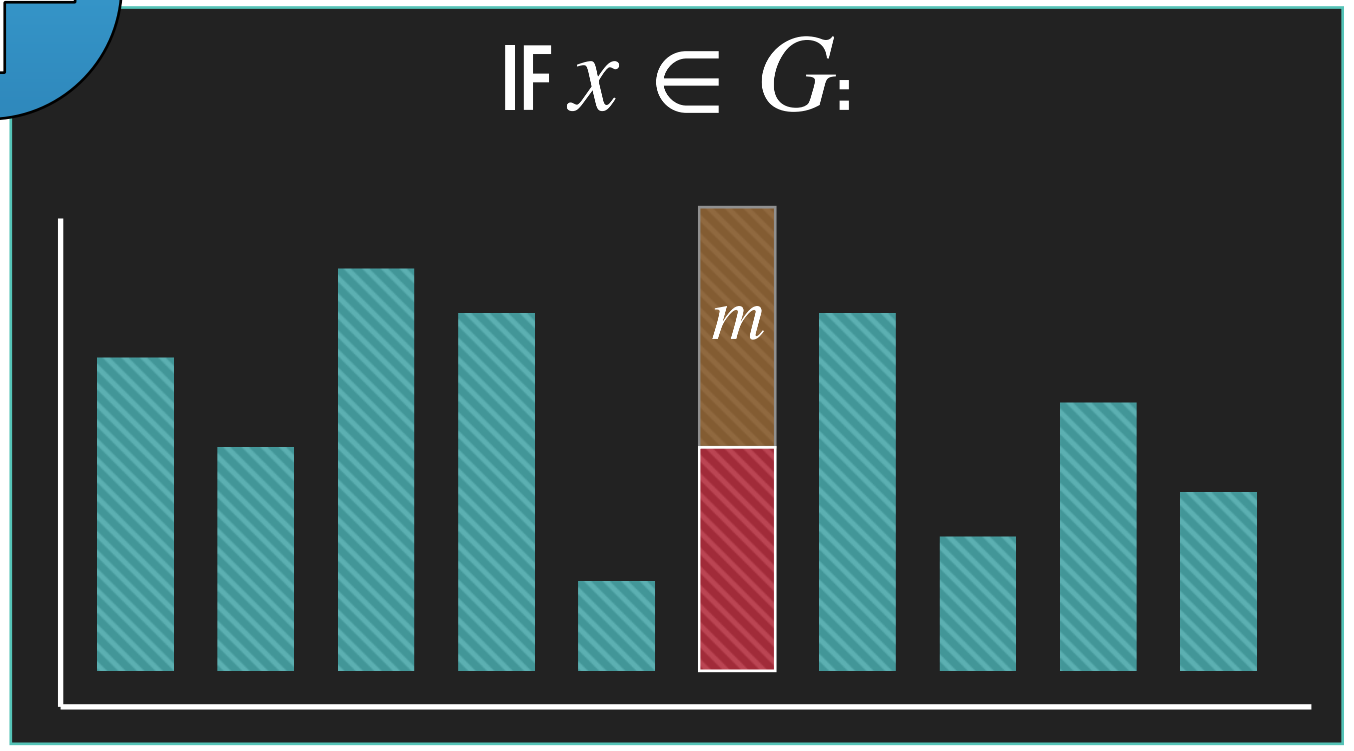
ISSUE: Stop network from returning high scores for unknown samples

$$J_M = \begin{cases} -\log A_{Sm}(x) & \text{if } x \in G \\ -\frac{1}{|G|} \sum_{g=1}^{|G|} \log A_S(x) & \text{if } x \notin G \end{cases}$$

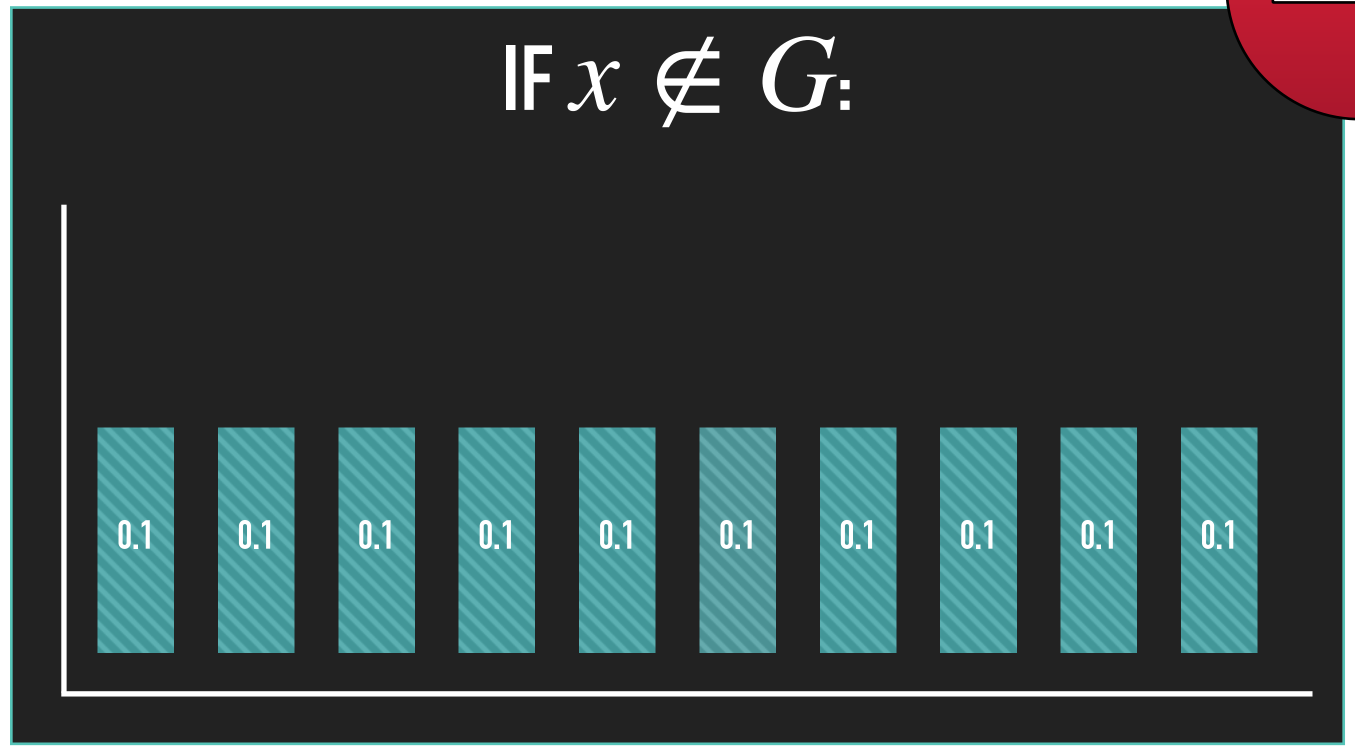
$$A_{Sm}(l_g) = \frac{e^{l_g(x)-m}}{e^{l_g(x)-m} + \sum_{\hat{g} \neq g}^{G} e^{l_{\hat{g}}(x)}}$$

$$A_S(l_g) = \frac{e^{l_g(x)}}{\sum_{\hat{g}}^{G} e^{l_{\hat{g}}(x)}}$$

Gallery/Positive Samples



Non-Gallery/Negative Samples



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PROPOSED METHOD: OPTIMIZED MIXUP AUGMENTATION (OMU)

ISSUE: Negative samples from different distributions do not cooperate

$$\bar{z} = \lambda \cdot z_i \; + \; (1 - \lambda) \cdot z_j$$

$$\text{s.t. } z_j = \text{argmax}_{(z_{i'}, g_{i'}) \in G} \; \cos(z_i, z_{i'}) \;\; \wedge \;\; g_i \neq g_{i'}$$

λ

0.3	0.7	0.2	0.9	0.5	0.6	0.8	0.5	0.3	0.4

$+(1 - \lambda)$

0.5	0.4	0.7	0.9	0.4	0.2	0.8	0.3	0.5	0.1

$\lambda = 0.5$

0.40	0.55	0.45	0.90	0.45	0.40	0.80	0.40	0.40	0.25

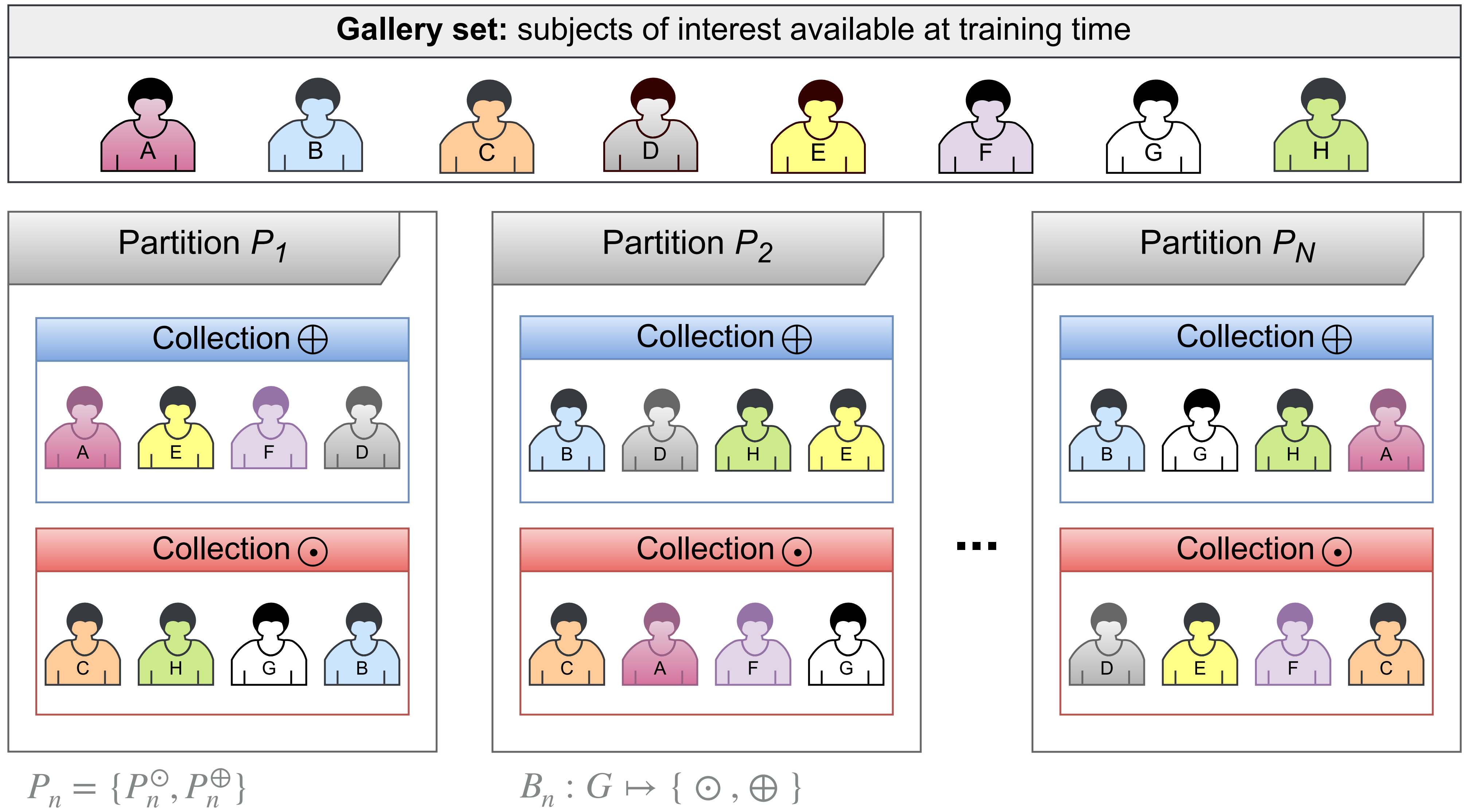
PROPOSED METHOD: NEURAL ADAPTER ENSEMBLE (NAE)

ISSUE: Imbalanced datasets bias neural networks toward majority classes

NAE data partitioning:

- Split the gallery set into N disjoint partitions $P_n = \{P_n^{\odot}, P_n^{\oplus}\}$
- Assign temporary new labels: $\oplus$ $\odot$
- Allocate identity $g \in G$ into $P_n^{\odot}$ or $P_n^{\oplus}$ following function $B_n : G \mapsto \{ \odot , \oplus \}$
- Fit classifier C_n to corresponding binary split P_n

Adapter from "Unconstrained face identification using ensembles trained on clustered data"



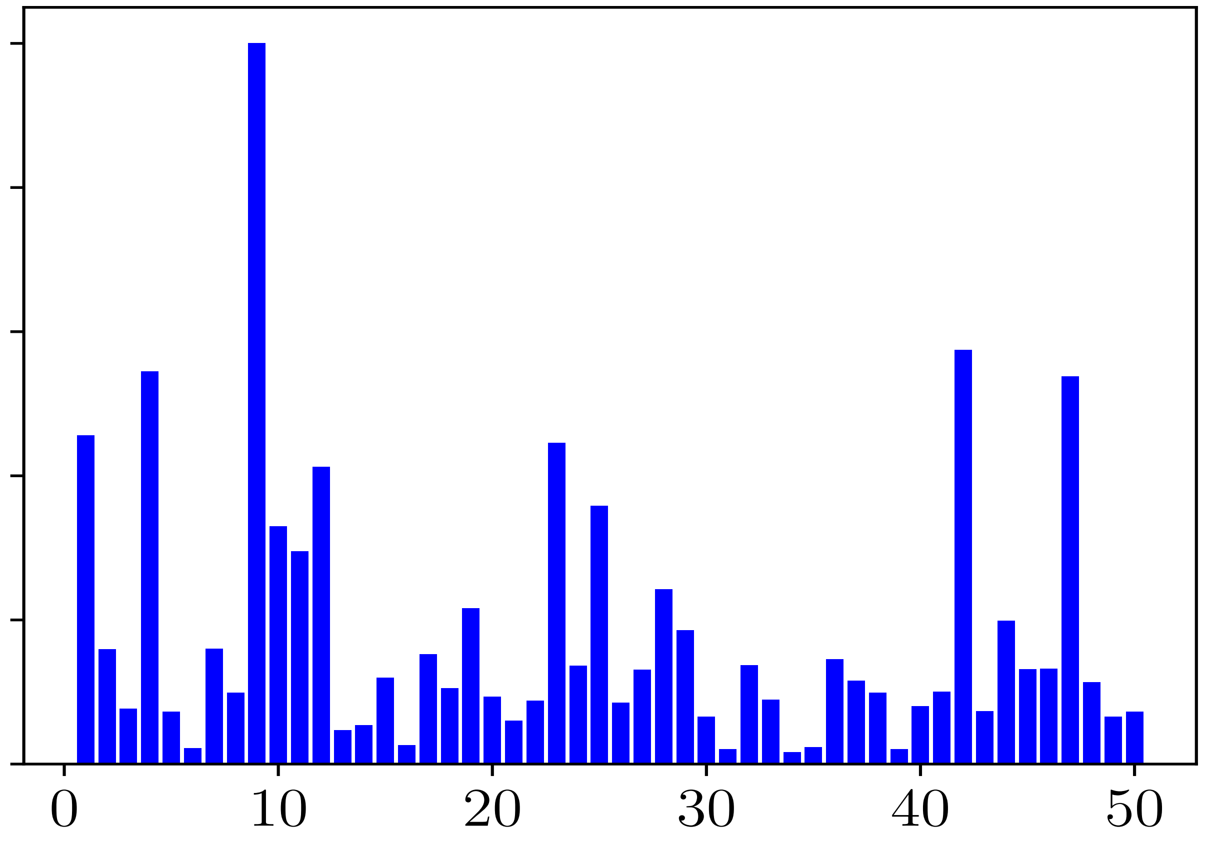
PROPOSED METHOD: NEURAL ADAPTER ENSEMBLE (NAE)

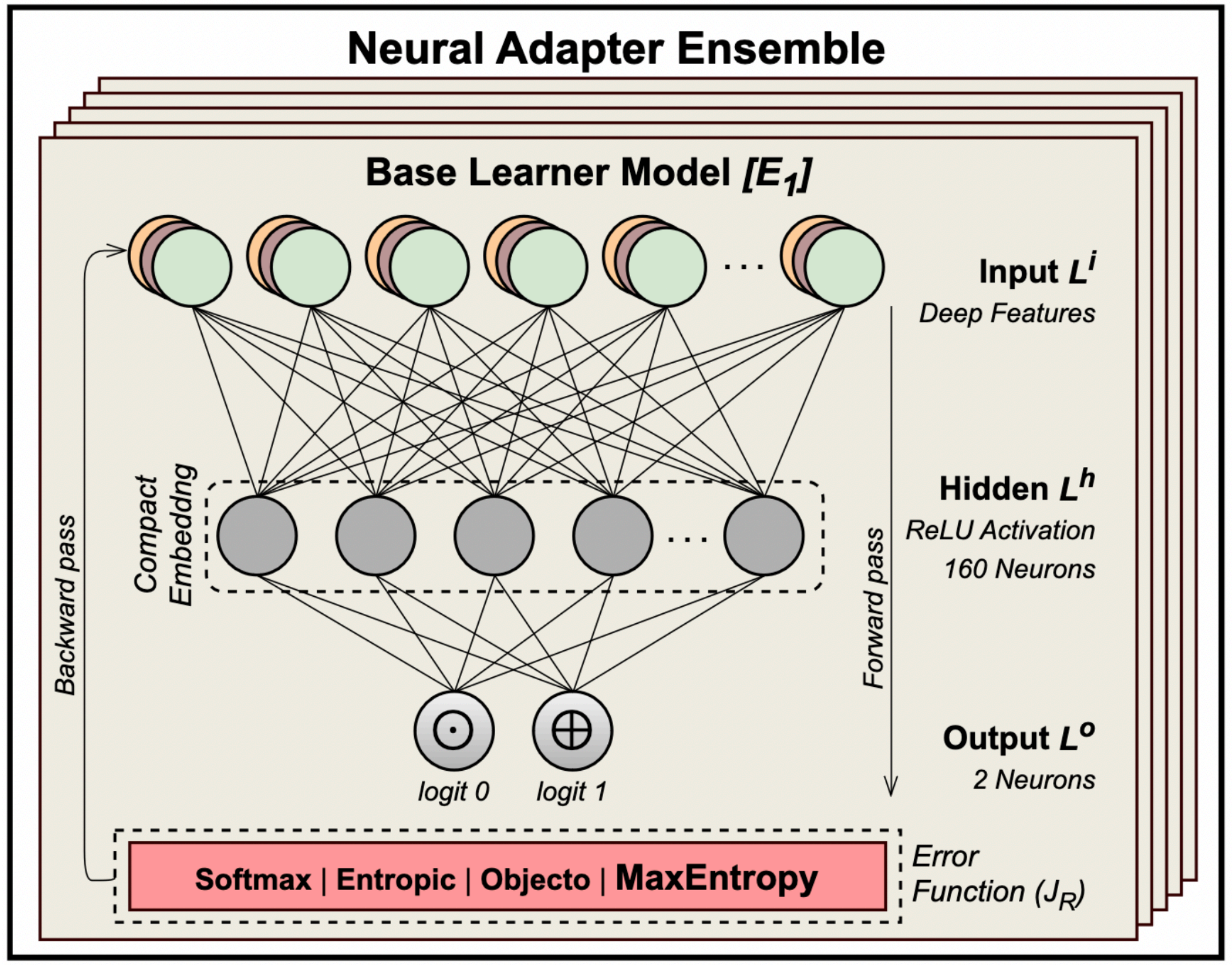
ISSUE: Map binary ids { ⊙ , ⊕ } back to original gallery ids

Rank of candidates:

$$\mathrm{sim}(z_p, g) = \sum_n [L_n^o]^{B_n(g)}(z_p),\ \forall\ g \in G$$

$P_n = \{P_n^{\odot}, P_n^{\oplus}\}$ $\quad$ $B_n : G \mapsto \{ \odot , \oplus \}$





DATASETS: LFW AND IJB-C

Labeled Faces in the Wild

- 13.233 near-frontal images from approximately six thousand persons
- Distinct poses, expressions, scenes and lighting

IARPA Janus Benchmark C

- Two gallery-sets (G1/G2) holding around 1.8K identities each
- Profile views, occlusion and low-resolution probe images

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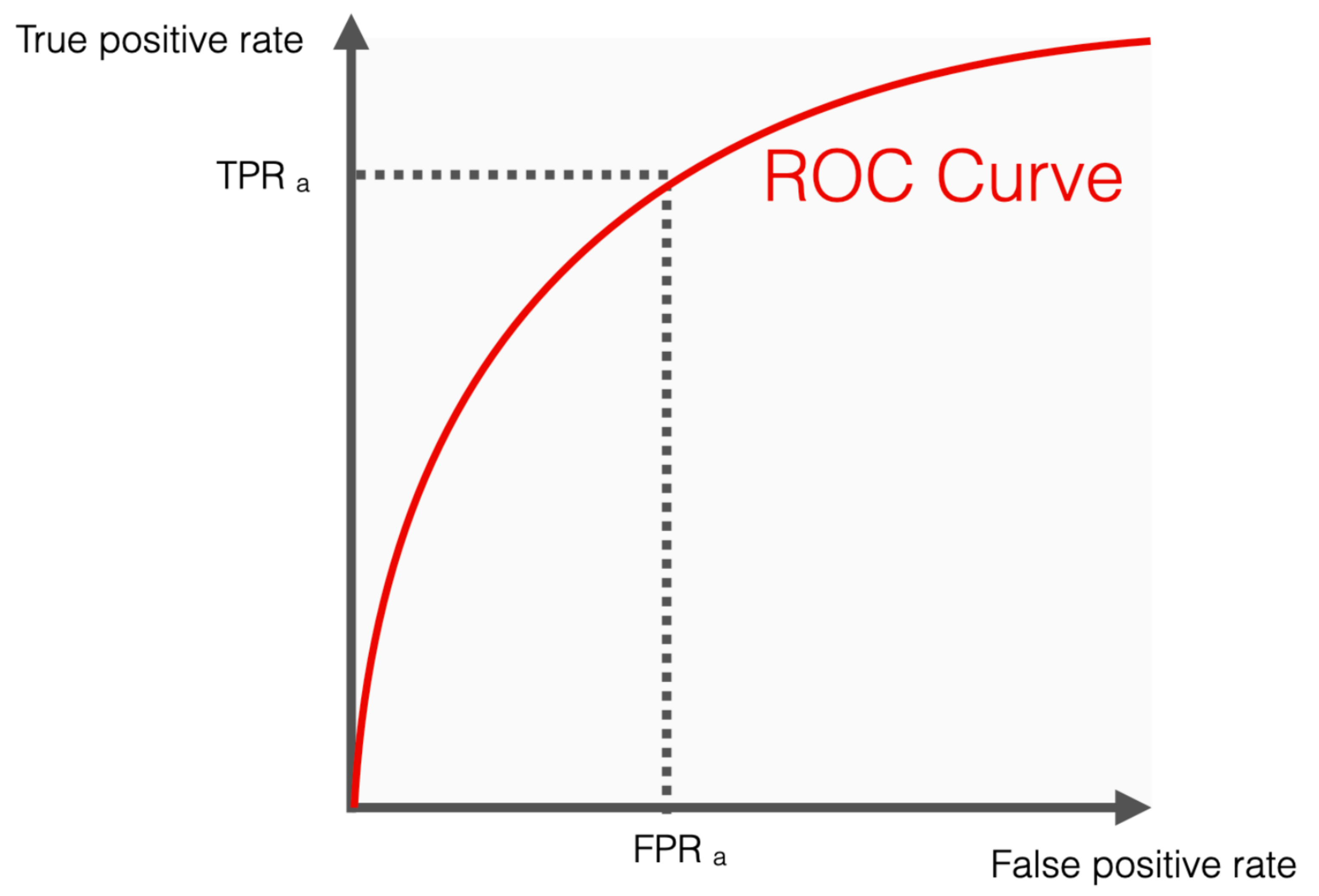
METRIC: OPEN–SET RECEIVER OPERATING CHARACTERISTIC

- Belongs to the gallery and retrieves correct ID
- Vertical and Horizontal axes:
  - True-positive Identification Rate
  - False-positive Identification Rate
- Hyper-parameters:
  - NAE size $|E|$, MEL margin m, OMU factor λ



LFW EVALUATION. OPEN-SET ASSESSMENT TO SELECT OPTIMAL VALUES FOR PARAMETERS λ, h AND $|E|$.

Parameters	$\|E\|$					m					λ				
DIR/VALUES	0.10	0.30	0.50	0.75	1.00	0.10	0.20	0.30	0.40	0.50	0.55	0.65	0.75	0.85	0.95
TPIR@FPIR = 1.00	0.82	0.92	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	0.93	0.94	0.94	0.94	**0.95**	0.94
TPIR@FPIR = 0.10	0.71	0.85	0.86	**0.88**	**0.88**	0.86	0.86	**0.87**	**0.87**	**0.87**	0.87	0.87	**0.89**	**0.89**	0.87
TPIR@FPIR = 0.01	0.57	0.72	0.73	**0.75**	**0.75**	0.73	0.74	**0.77**	0.76	0.74	**0.77**	**0.77**	**0.77**	0.74	0.75

EVALUATION: FEATURE AUGMENTATIONS STRATEGIES ON NAN

AUGMENTATION ANALYSIS. EVALUATION OF NAN TRAINED WITH CEL OR MEL ASSOCIATED WITH DIFFERENT AUGMENTATION SCHEMES ON IJB-C.

Method	Detection and Identification Rate (TPIR@) FPIR=1	FPIR=0.1	FPIR=0.01	FPIR=0.001
CEL	0.44	0.23	0.09	0.03
MEL+LFW	0.58	0.23	0.10	0.03
MEL+SFA	**0.68**	**0.53**	0.31	0.05
MEL+MMU	**0.68**	0.52	0.28	0.04
MEL+OMU	0.66	0.51	**0.33**	**0.10**

CEL: Cross-Entropy Loss
MEL: Maximal Entropy Loss

SFA: Stochastic Feature Augmentation
MMU: Manifold Mix-Up Augmentation
OMU: Optimized Mix-Up Augmentation

LFW: Labelled Faces in the Wild dataset

Watchlist Adaptation: Protecting the Innocent

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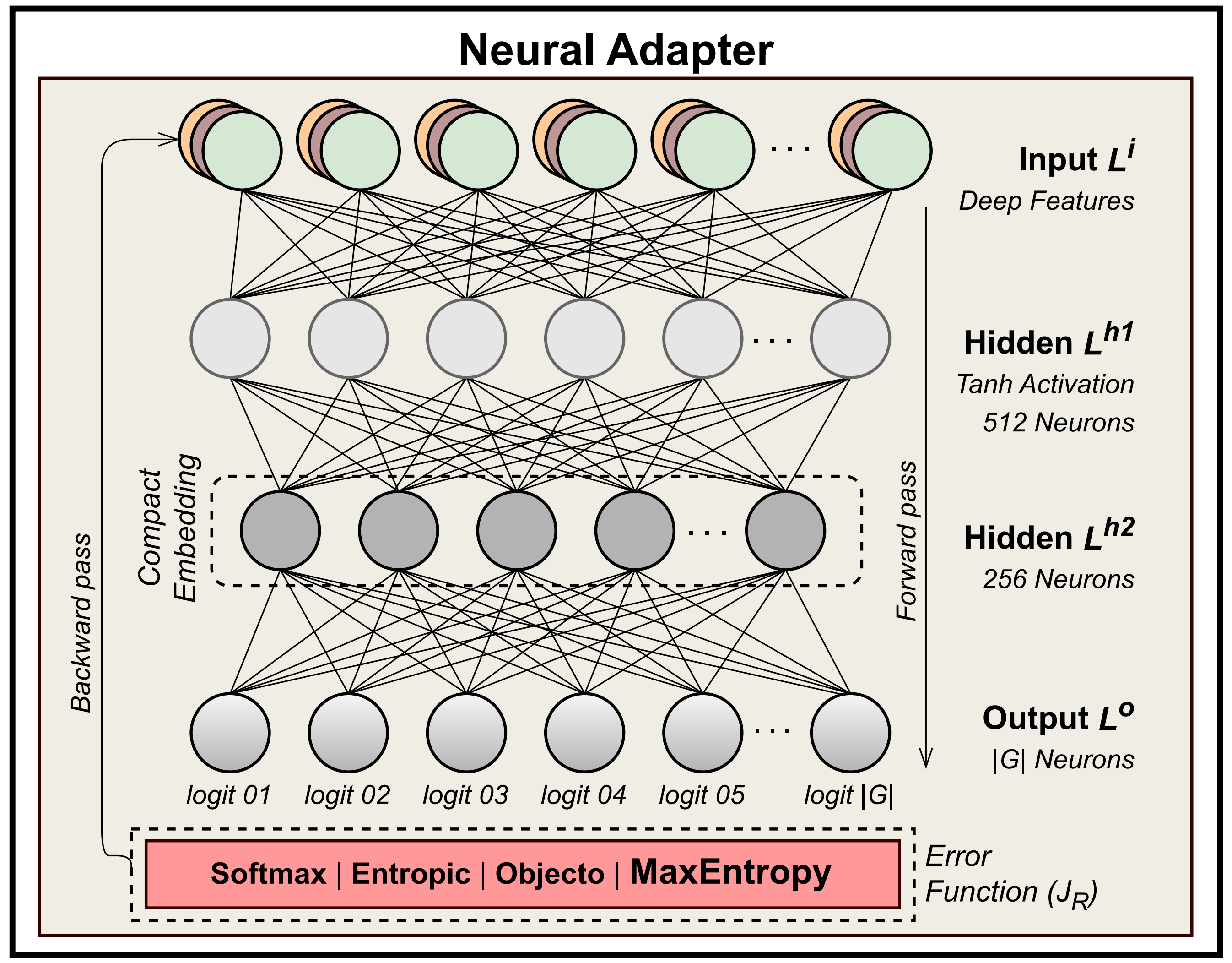

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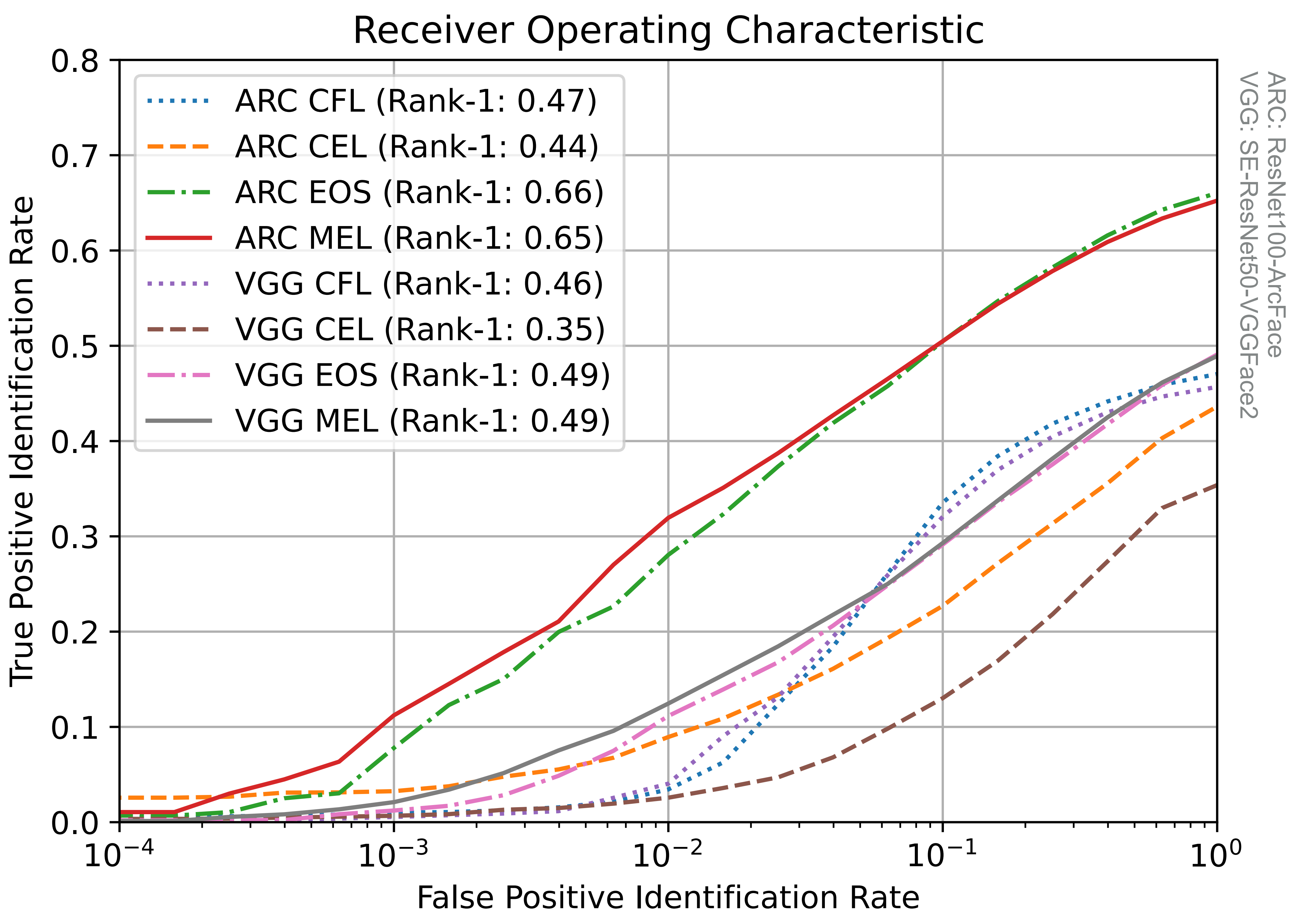
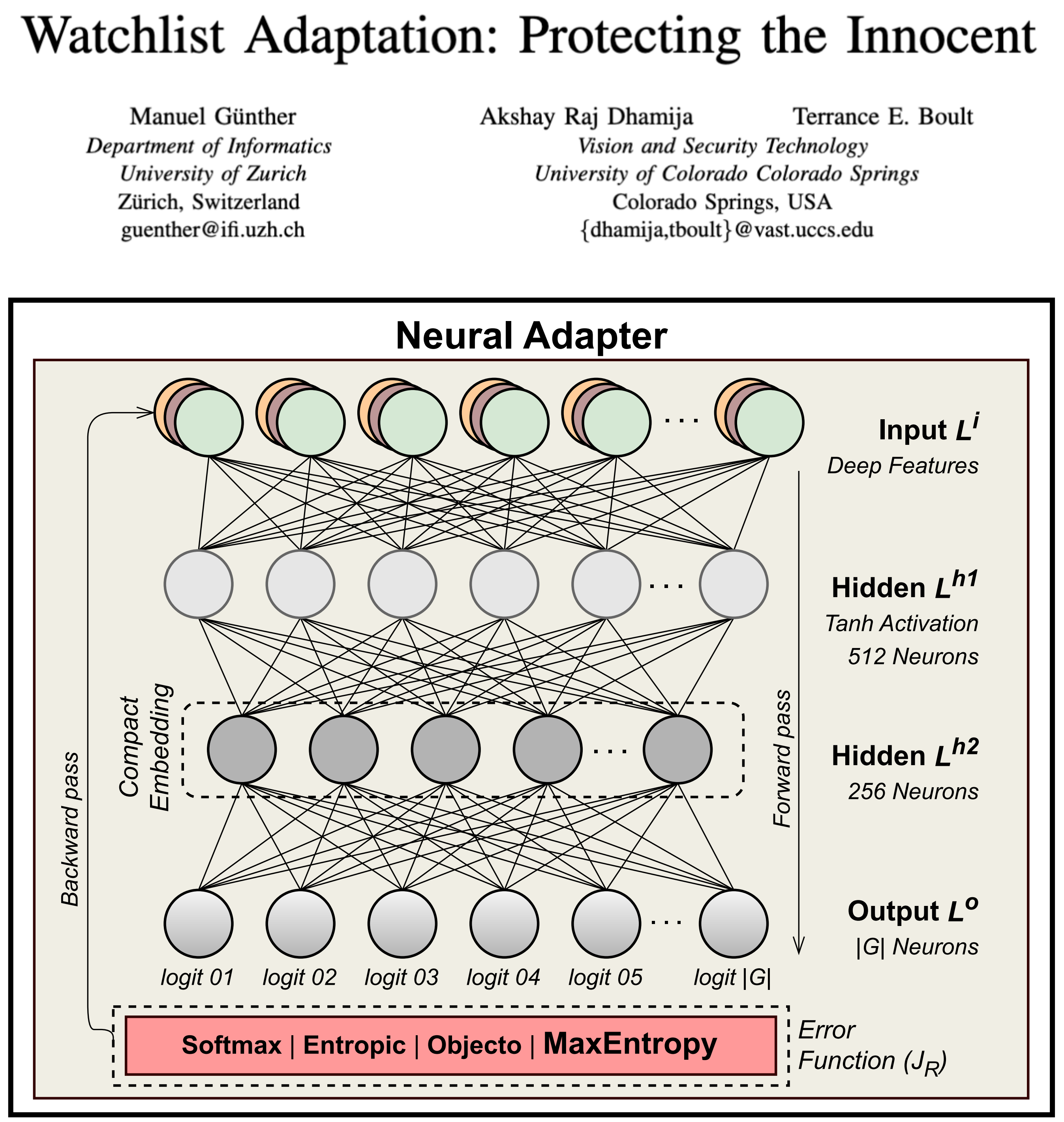
EVALUATION: CONTRASTING LOSS FUNCTIONS ON NAN





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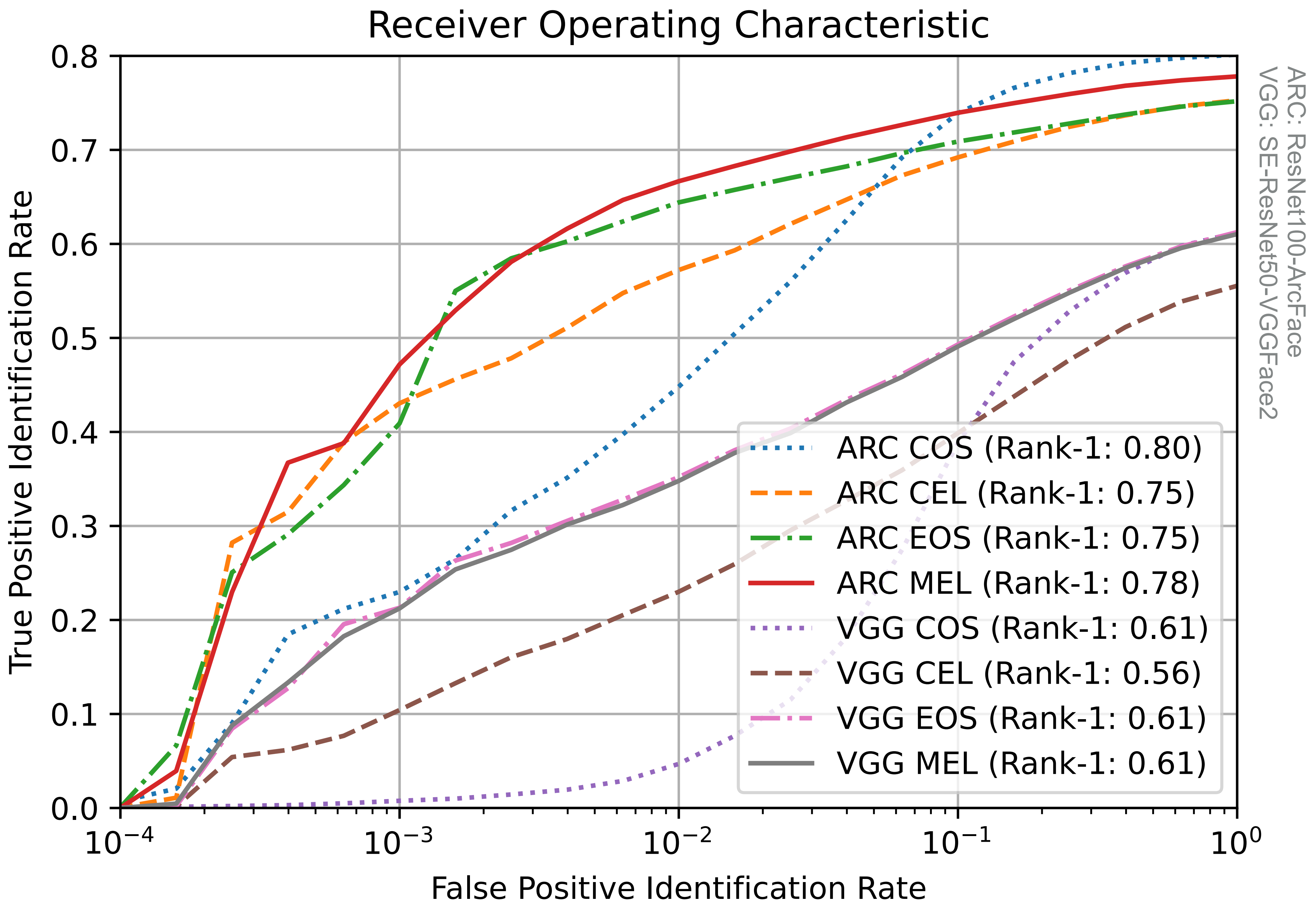
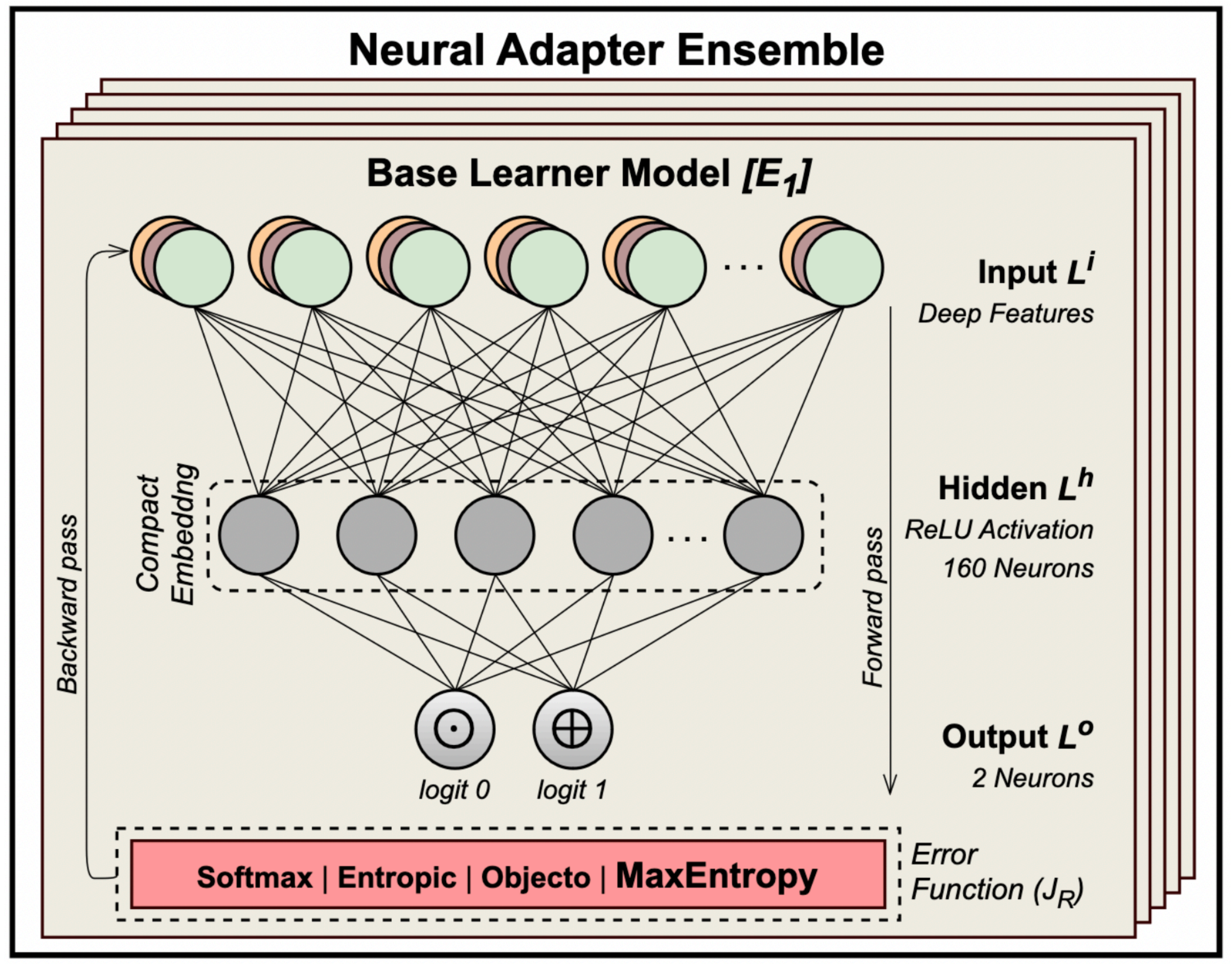
EVALUATION: CONTRASTING LOSS FUNCTIONS ON NAE





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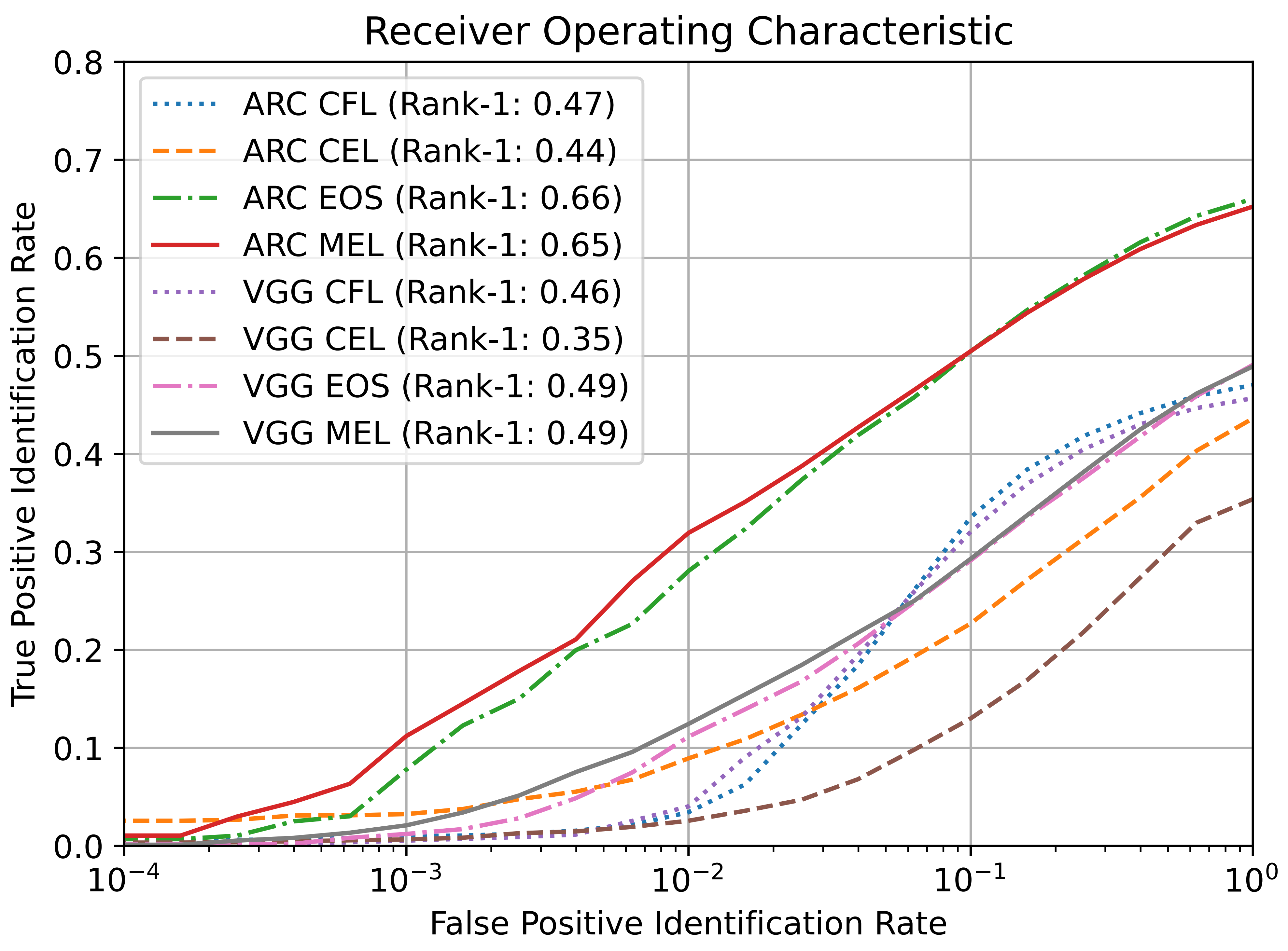
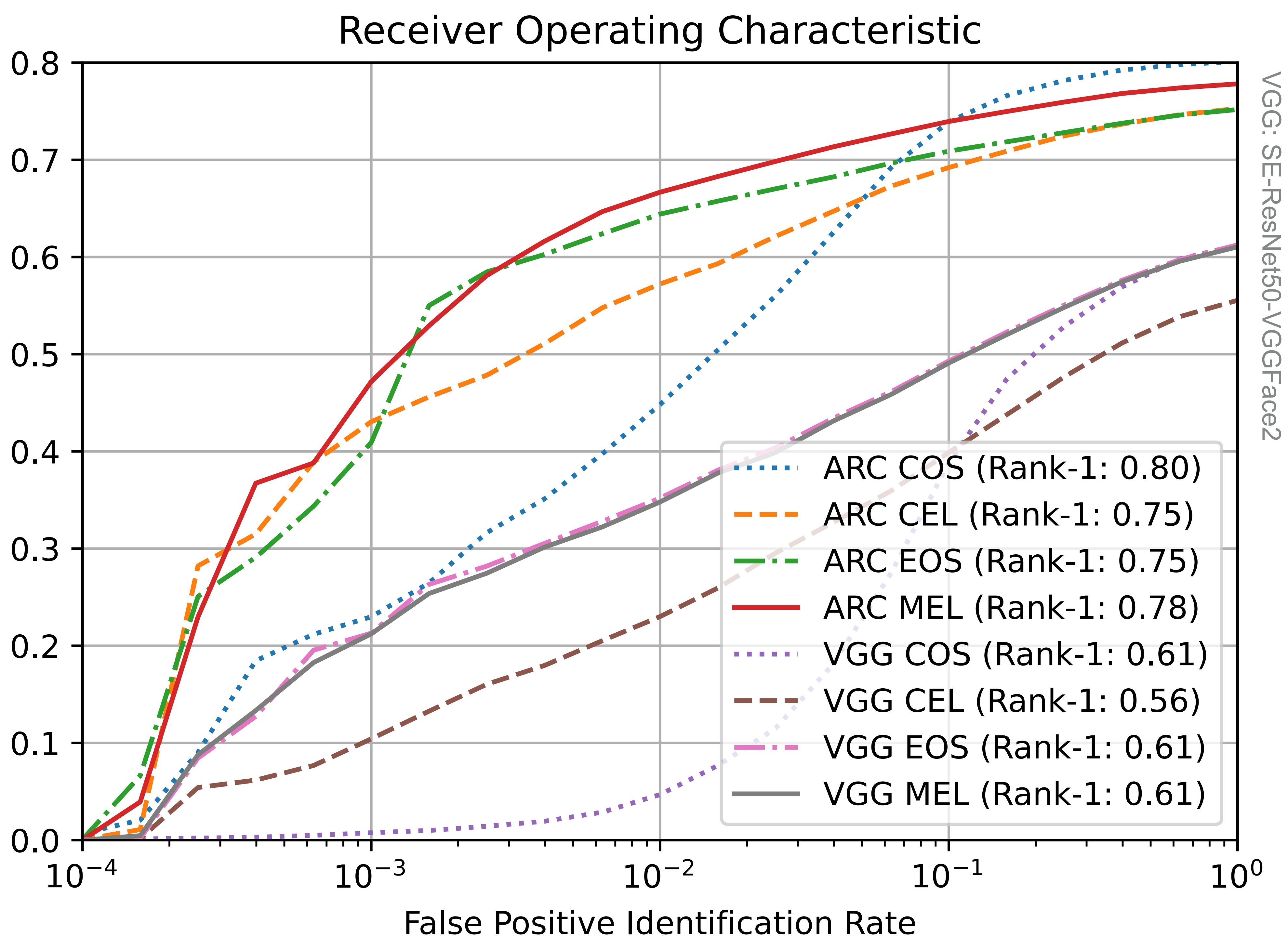
EVALUATION: CONTRASTING NEURAL ADAPTER APPROACHES

Neural Adapter Network (NAN)



Neural Adapter Ensemble (NAE)



ARC: ResNet100-ArcFace
VGG: SE-ResNet50-VGGFace2

CONCLUDING REMARKS

- Three different approaches:
  - Cost Function, Feature Augmentation and Ensemble
  - Parameters obtained in one domain and tested in another
  - Negative synthetic data boost performance when properly exploited by cost functions
- What from now?
  - Vision Transformers + MEL + OMU

IF YOU HAVE ANY PERSISTENT QUESTION, REACH US!

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