QCFace: Image Quality Control for Boosting Face Representation & Recognition

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ĐẠI HỌC QUỐC GIA THÀNH PHỐ HỒ CHÍ MINH
TRƯỜNG ĐẠI HỌC BÁCH KHOA

Overview

1. Face Recognition Introduction
2. Previous Approaches
3. Problem Statement
4. Proposal
5. Experimental Results
6. Discussion
7. Conclusion

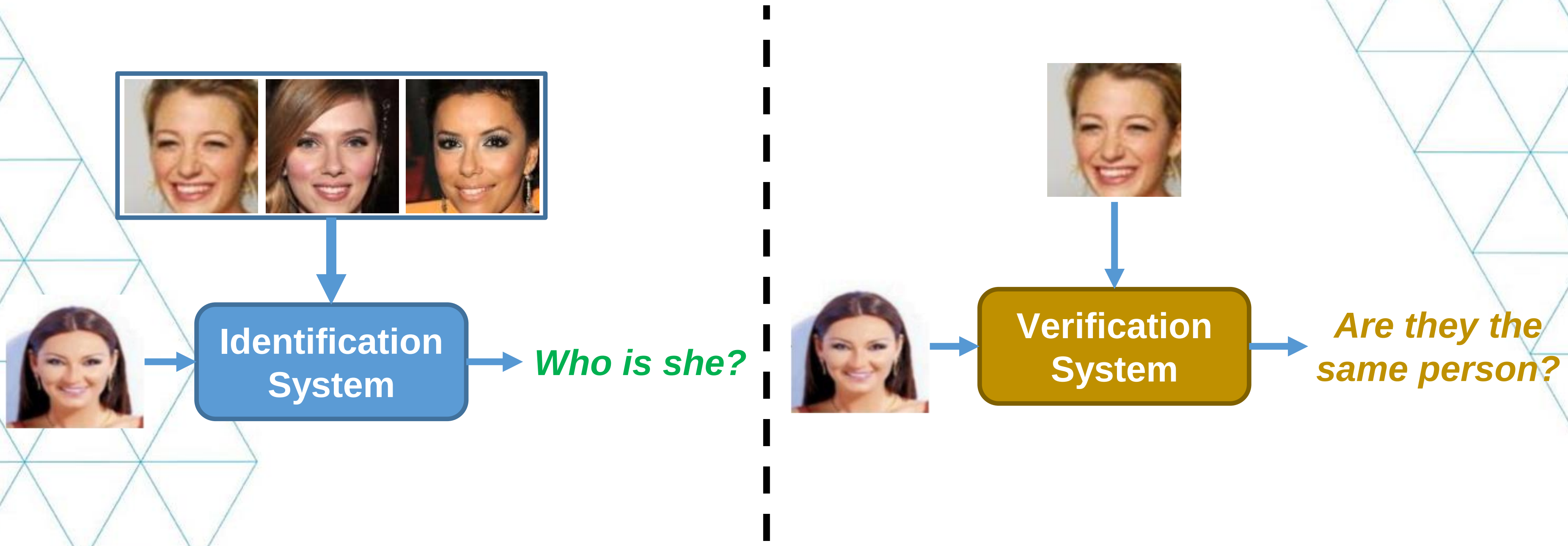
Advanced Institute of Interdisciplinary Science and Technology

1. Face Recognition Introduction

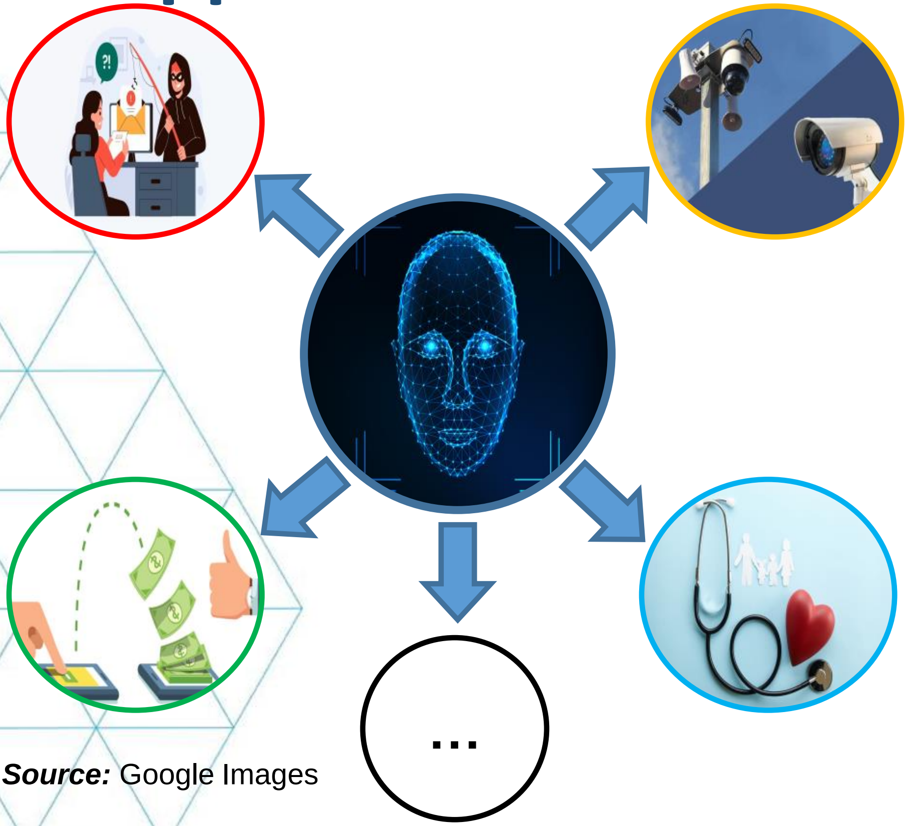
1.1 What is face recognition?

1.2 Application

What is face recognition?



Application



The efficiency of FR in the system integration:

- Non-requirement for personal cooperation
- User-friendly
- High confidence

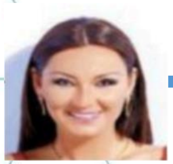
Source: Google Images

2. Face Recognition Approach

2.1 Traditional Image Processing

2.2 Deep Learning

Traditional Image Processing

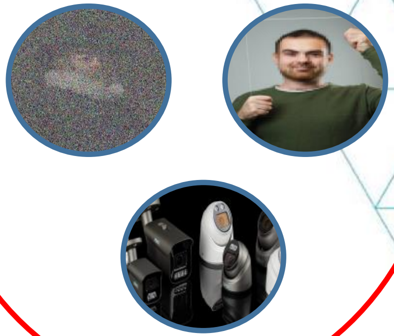


FR System

Feature Extractor (FE) → Decision Making (DM)

Who is she?
Are they a match?

→ **Limitations:**

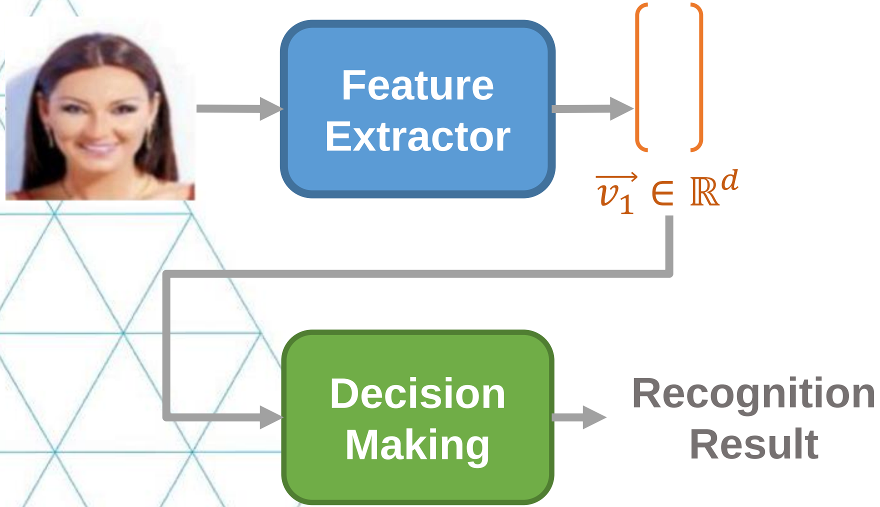


Handcrafted feature extraction techniques

- LBP
- HOG
- SIFT
- SURF
- Landmark Base
- …

Source: Google Images

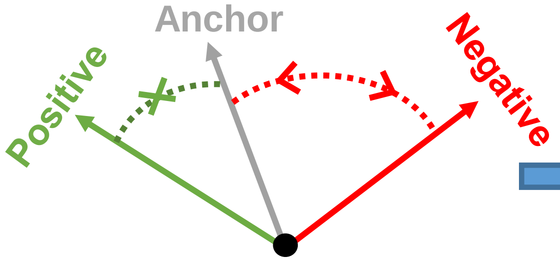
Deep Learning



Deep Learning

Feature Extractor

$\overrightarrow{v_1} \in \mathbb{R}^d$



Sample-to-Sample base

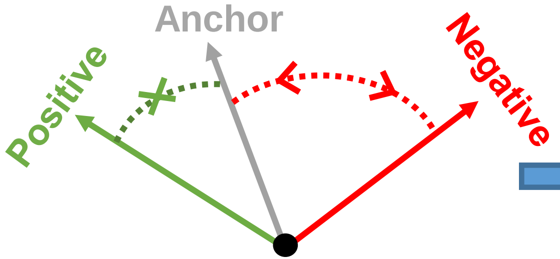
Decision Making

Recognition Result

Deep Learning

Feature Extractor

$\overrightarrow{v_1} \in \mathbb{R}^d$



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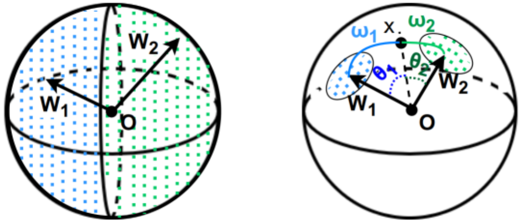


Class center base

Decision Making

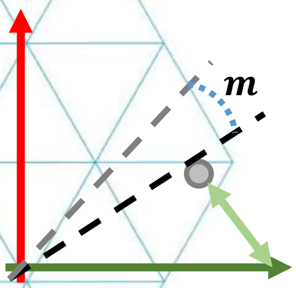
Recognition Result

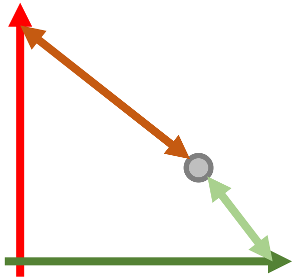
Source: Liu, W., Wen, Y., Yu, Z., Li, M., Raj, B., & Song, L. (2017). SphereFace: Deep hypersphere embedding for face recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 212-220).

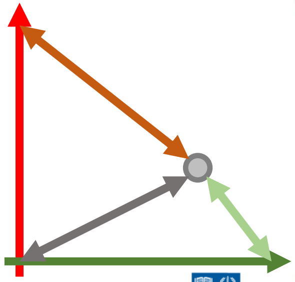
Class Center Loss - Literature

Face
Class Center Loss

- Margin-based Softmax Loss
- Misclassified Softmax Loss
- Magnitude-base Softmax Loss





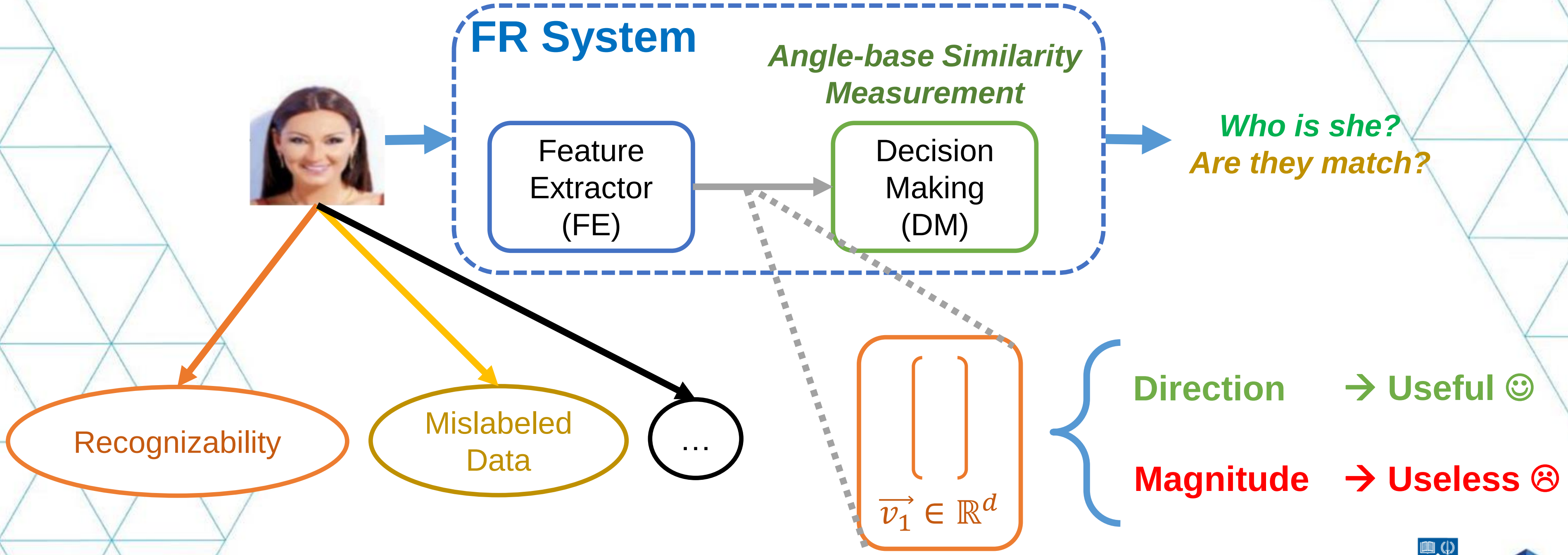


3. Problem Statement

3.1 Inefficient exploitation of feature magnitude

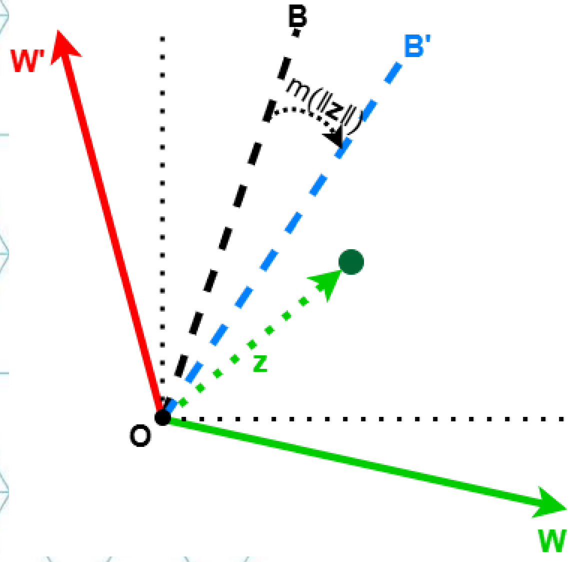
3.2 Mutual overlapping effect

Inefficient exploitation of feature magnitude



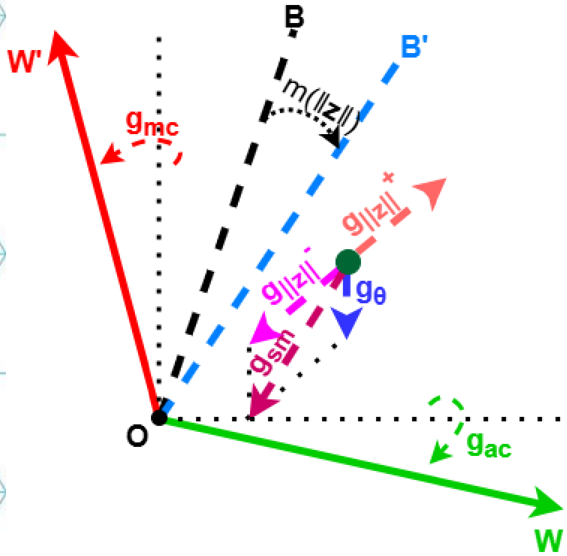
Mutual overlapping effect (MagFace(*))

$$\mathcal{L}_{total} = \mathcal{L}_{sm} + \lambda.\mathcal{L}_{reg}$$



(*) Meng, Q., Zhao, S., Huang, Z., & Zhou, F. (2021). MagFace: A universal representation for face recognition and quality assessment. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (pp. 14225-14234).

Mutual overlapping effect (MagFace)

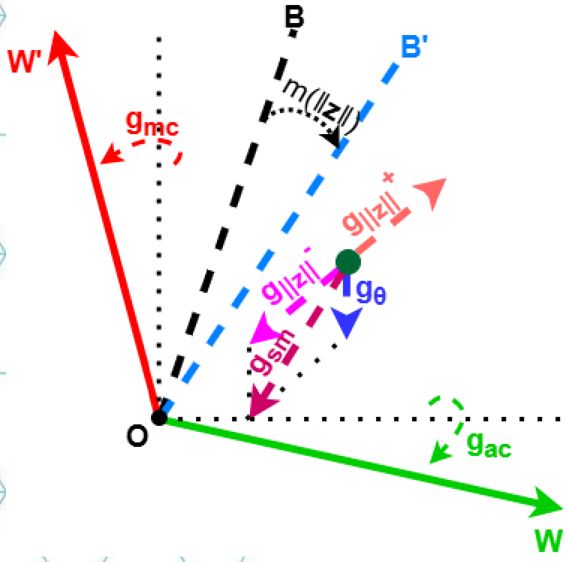


$$\mathcal{L}_{total} = \mathcal{L}_{sm} + \lambda.\mathcal{L}_{reg}$$

$$\mathcal{L}_{sm} \begin{cases} g_{ac},\ g_{mc} \\ g_{sm} = g_{\|z\|^-} + g_\theta \end{cases}$$

$$\mathcal{L}_{reg} \rightarrow g_{\|z\|^+}$$

Mutual overlapping effect (MagFace)



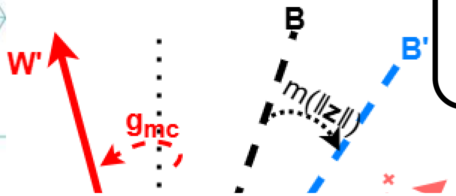
$$\mathcal{L}_{total} = \mathcal{L}_{sm} + \lambda . \mathcal{L}_{reg}$$

$$\mathcal{L}_{sm} \begin{cases} g_{ac}, g_{mc} \\ g_{sm} = g_{\|z\|^-} + g_{\theta} \end{cases}$$

$$\mathcal{L}_{reg} \rightarrow g_{\|z\|^+}$$

$$\left. \begin{array}{l} g_{\theta} \coloneqq g_{\theta}(\theta, \|z\|) \\ g_{\|z\|^-} \coloneqq g_{\|z\|^-}(\theta, \|z\|) \end{array} \right\} \rightarrow$$ ***Mutual overlapping effect!***

Mutual overlapping effect (MagFace)



$$\mathcal{L}_{sm} = -\log \frac{e^{s.F\left(\mathbb{M},\theta_{w_{y_i},z_i}\right)}}{e^{s.F\left(\mathbb{M},\theta_{w_{y_i},z_i}\right)} + \sum_{j \neq y_i}^{n} e^{s.N\left(t,\theta_{w_j,z_i}\right)}} \quad (A.0.1)$$

$\mathcal{L}_{sm}$

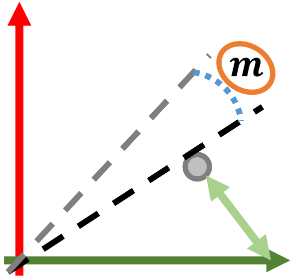
$\mathcal{L}_{reg} \rightarrow g_{\|z\|}+$

Property 1

In Eq. (A.0.1), if m_2 is a strictly increasing convex function of $\|z_i\|$ (i.e., $m_2(\|z_i\|)$), then the norm $\|z_i\|$ influences the gradient with respect to θ (i.e., g_θ), while θ in turn affects the gradient with respect to $\|z_i\|$ (i.e., $g_{\|z_i\|}$). This manifests as a mutual overlapping gradient.

Research Questions

- ***RQ1:*** *Do margin value adjustment strategies influence the effectiveness of face representation learning?*



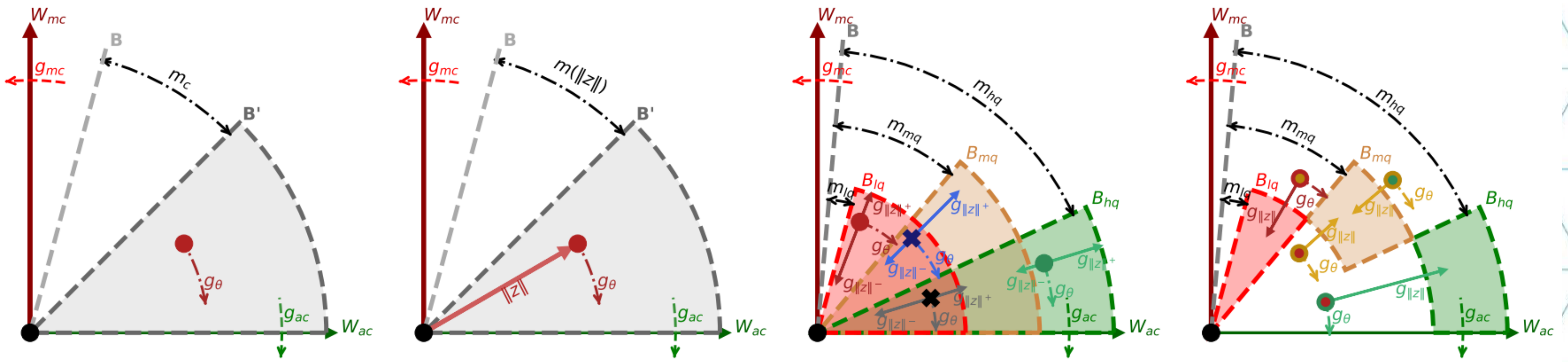
- ***RQ2:*** *How to design a new margin strategy with explicit enforcement mechanisms that correlate recognizability levels with magnitude value during face representation learning?*

4. Proposal

4.1 Hard margin strategy

4.2 QCFace

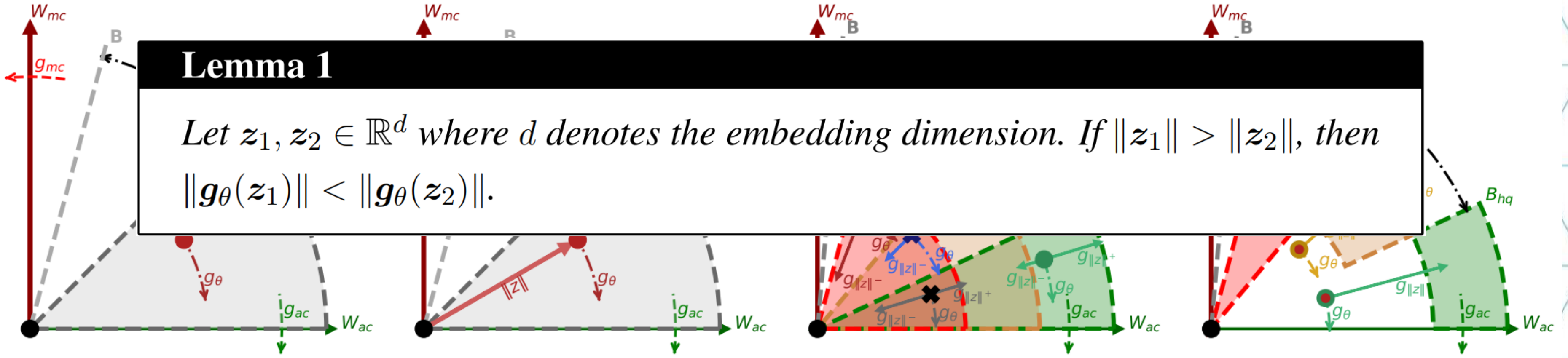
Margin strategy → RQ1



(a) Constant Margin (b) Soft Margin w/o MVP (c) Soft Margin with MVP **(d) Hard Margin (Ours)**

Small representation!

Margin strategy → RQ1



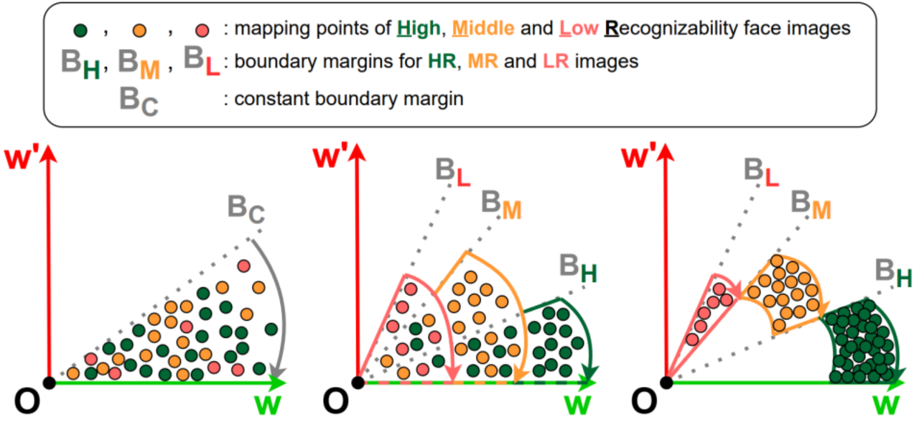
Lemma 1

Let $z_1, z_2 \in \mathbb{R}^d$ where d denotes the embedding dimension. If $\|z_1\| > \|z_2\|$, then $\|g_\theta(z_1)\| < \|g_\theta(z_2)\|$.

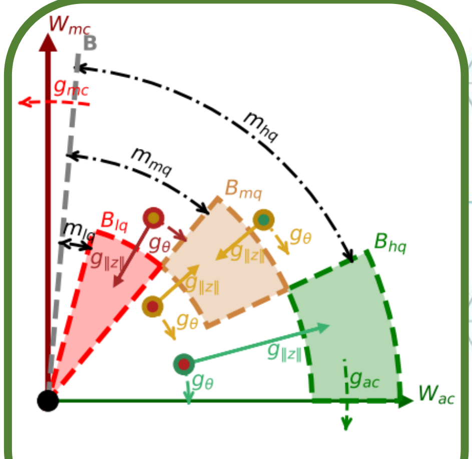
(a) Constant Margin (b) Soft Margin w/o MVP (c) Soft Margin with MVP (d) **Hard Margin (Ours)**

Small representation!

Hard margin strategy → RQ2



(a) Constant margin (b) Soft margin (c) *Hard margin*



(d) Hard Margin (Ours)

$$\mathcal{L}_{total} = \mathcal{L}_{sm} + \lambda . \mathcal{L}_{reg}$$

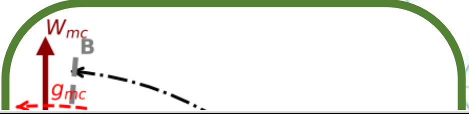
Finding optimal θ

Finding optimal $\|z\|$

Hard margin strategy → RQ2

● , ● , ● : mapping points of **H**igh, **M**iddle and **L**ow **R**ecognizability face images

B_H, B_M, B_L : boundary margins for HR, MR and LR images



Lemma 2

Suppose that $a_1, a_2 \in \mathbb{R}$ are two independent variables, and a function $f(a_1, a_2) : \mathbb{R}^2 \rightarrow \mathbb{R}$. If f can be described as a form of $f(a_1, a_2) = f_1(a_1) + f_2(a_2)$ where $f_1, f_2 : \mathbb{R} \rightarrow \mathbb{R}$, then the mutual overlapping gradient calculated from the derivative of f does not exist.

$$\mathcal{L}_{total} = \mathcal{L}_{sm} + \lambda.\mathcal{L}_{reg}$$

Finding optimal θ

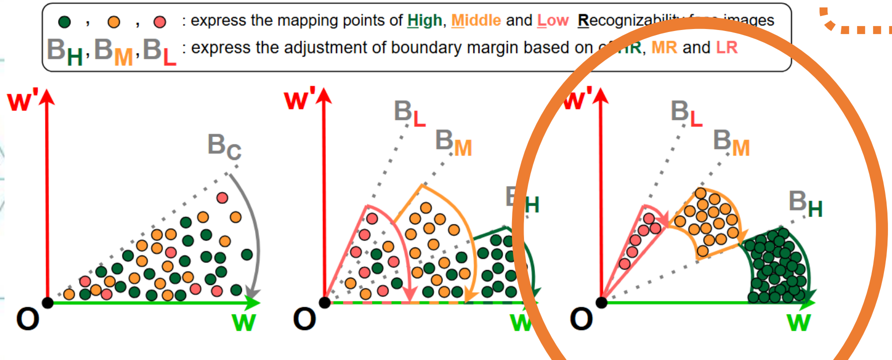
Finding optimal $\|z\|$

QCFace

Reuse
ArcFace

$$\mathcal{L}_{total} = \mathcal{L}_{sm} + \lambda.\,\mathcal{L}_{reg}$$

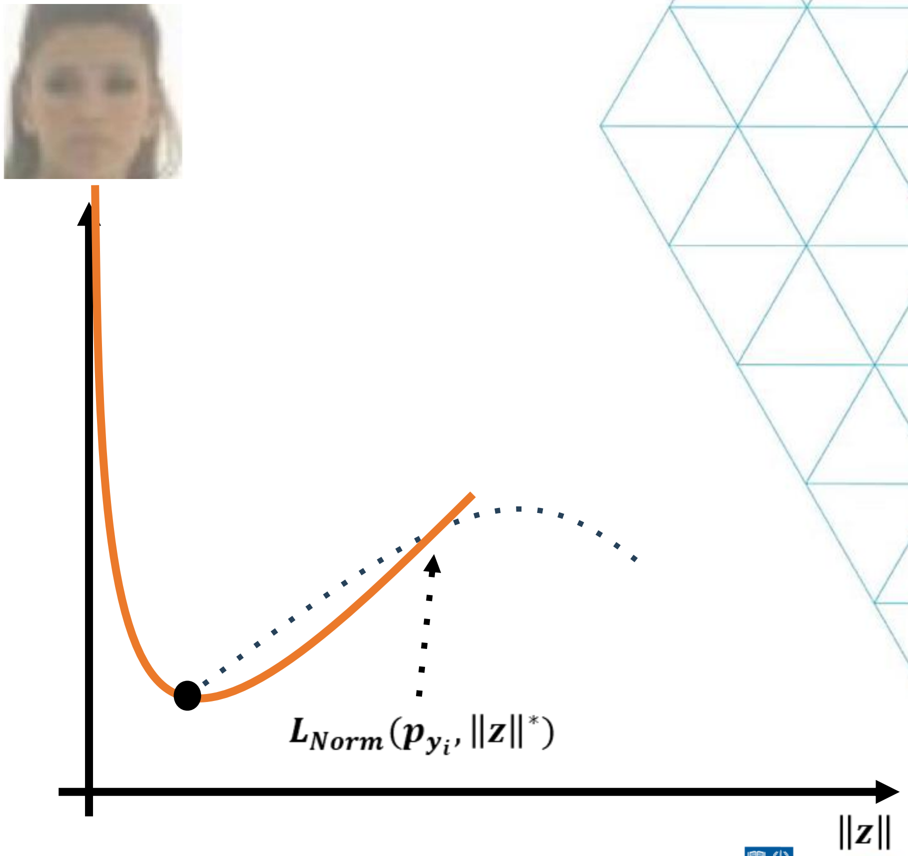
$$\mathcal{L}_{reg} = k \times p_d \times \left(\frac{1}{\|z\|} + \frac{\|z\|}{u_a^2}\right) + (1 - p_d) \times \left(\frac{1}{\|z\|} + \frac{\|z\|}{l_a^2}\right) - b$$



(a) Constant (b) Soft (c) ***Hard***

How it works

$$\mathcal{L}_{reg} = k \times p_d \times \left(\frac{1}{\|z\|} + \frac{\|z\|}{u_a^2}\right) + (1 - p_d) \times \left(\frac{1}{\|z\|} + \frac{\|z\|}{l_a^2}\right) - b$$



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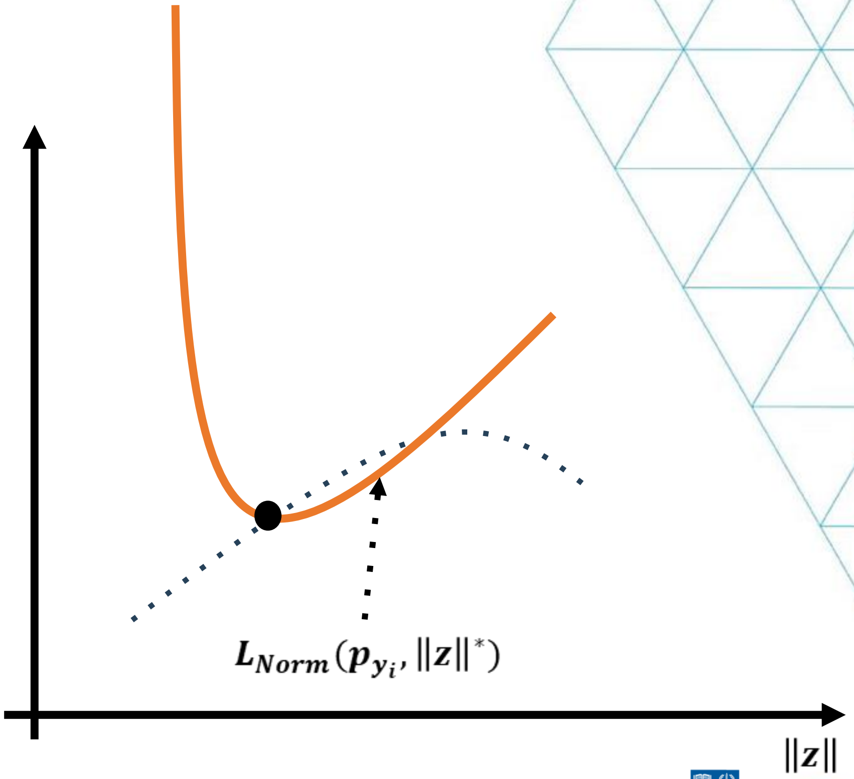

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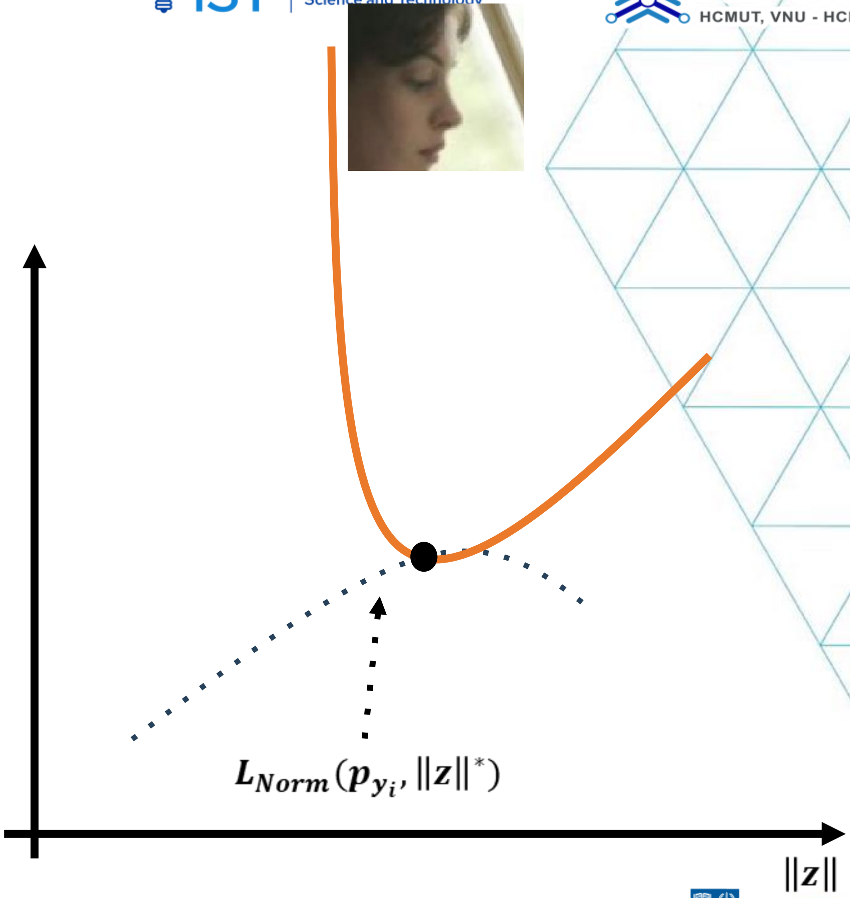

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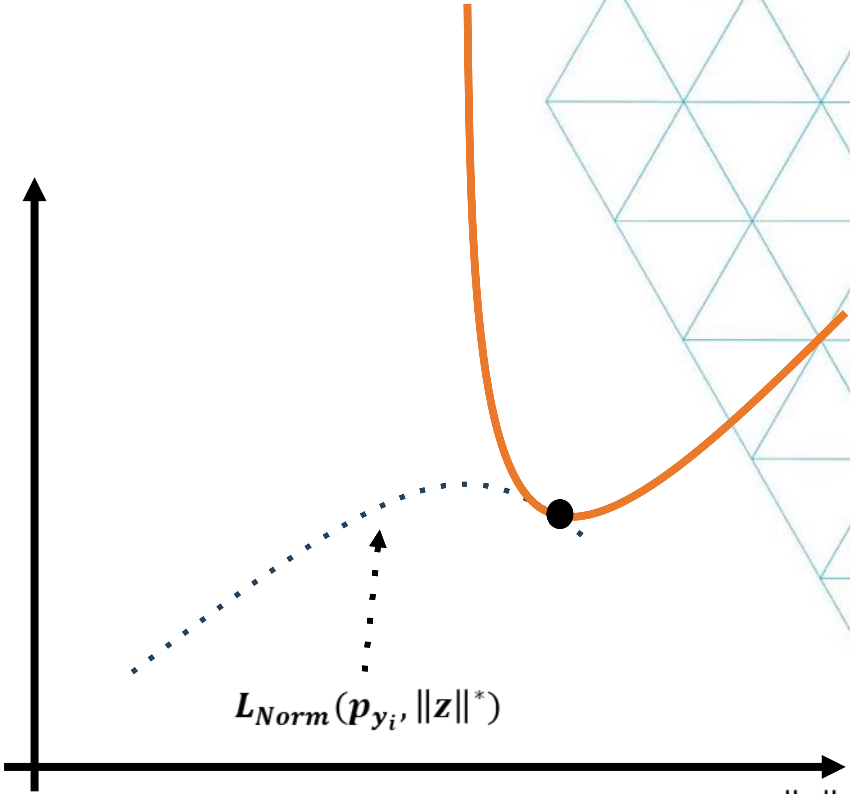

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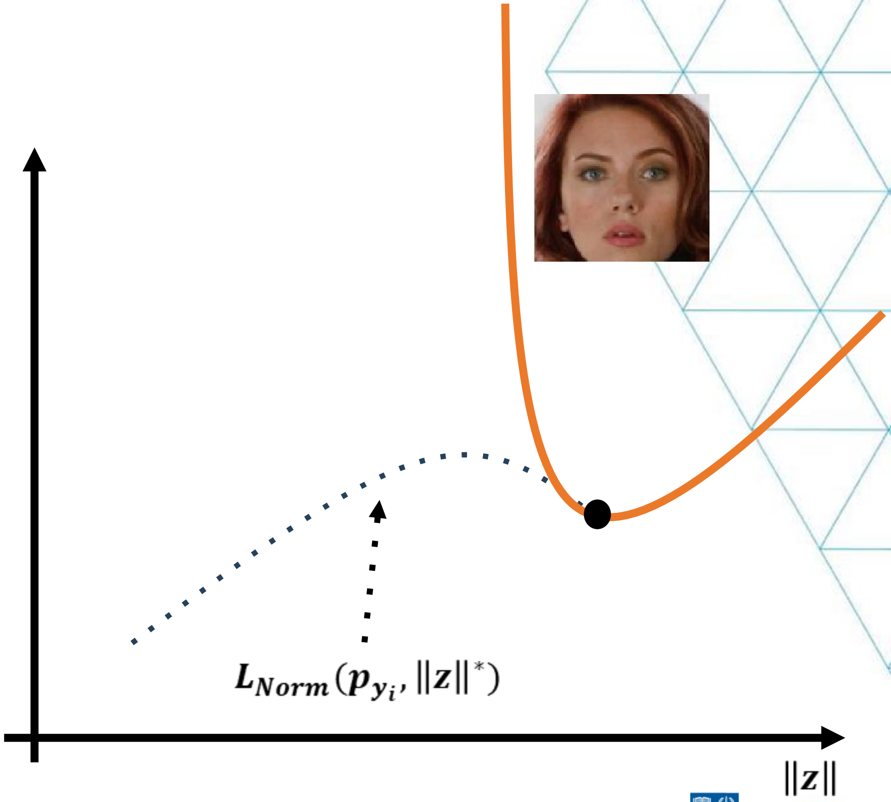

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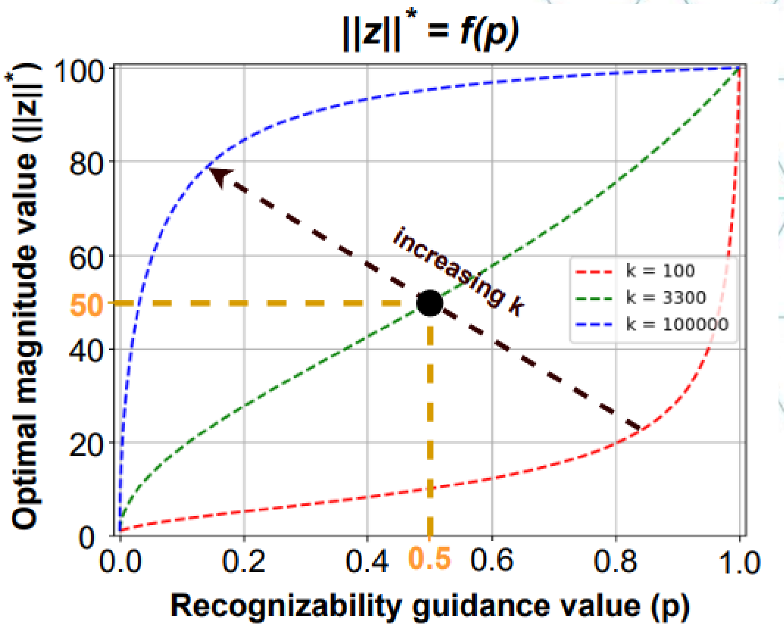

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How it works

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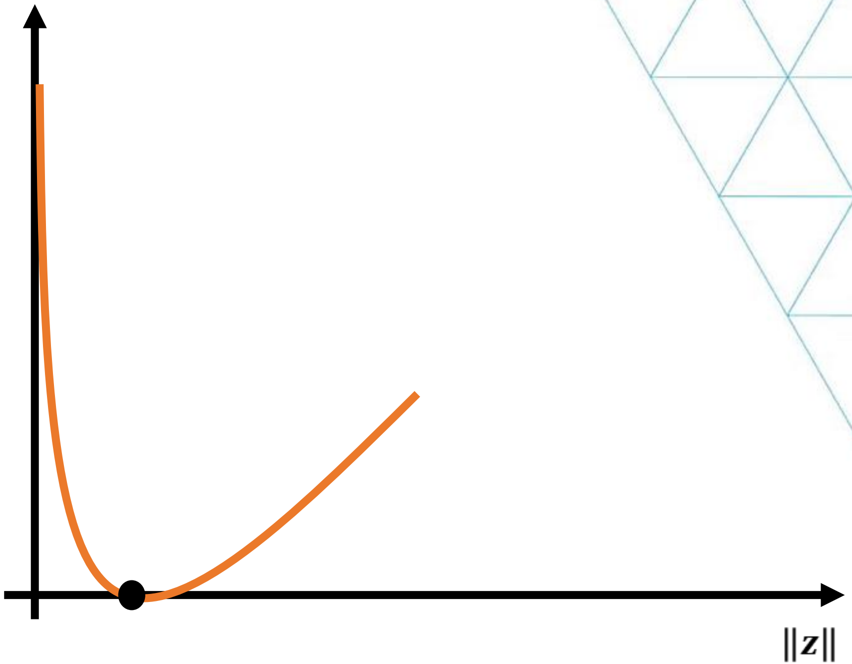

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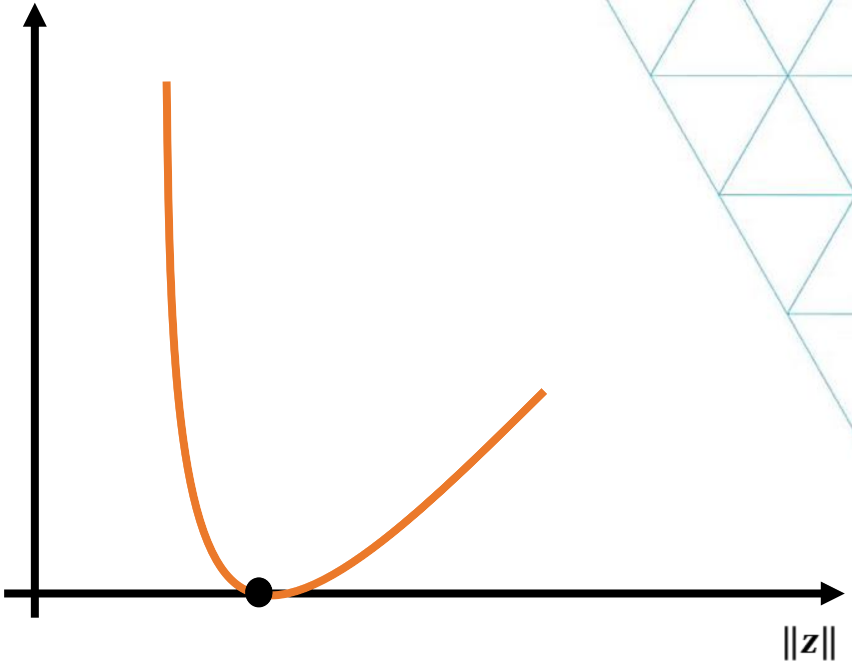

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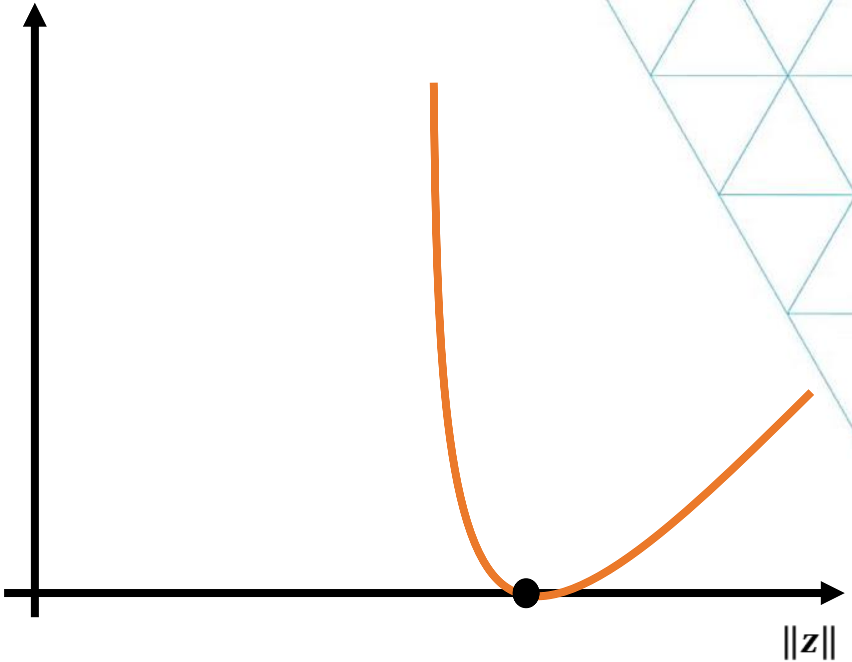

QCFace

Reuse *ArcFace*

$$\mathcal{L}_{total} = \mathcal{L}_{sm} + \lambda.\mathcal{L}_{reg}$$

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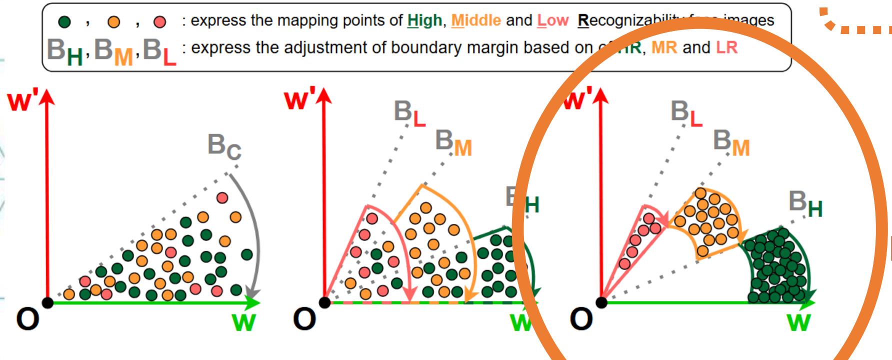

(a) Constant (b) Soft (c) *Hard*

- Each image has its expected magnitude $\|z\|^*$.
- $\|z\|^* = \mathcal{F}(p_d)$ where p_d is ***guidance value***.
- $\mathcal{L}_{rc}$ must satisfy:

p_d has positive corelation with recognizability level.

p_d must **detached** from computational graph.

Probability at actual class from **converged model** trained with **class-center loss** is chosen as p_d value.

Training process divide into **two phases**: **warm-up** and **hypersphere planning phases**.

QCFace

Reuse ***ArcFace***

$$\mathcal{L}_{total} = \mathcal{L}_{sm} + \lambda . \mathcal{L}_{reg}$$

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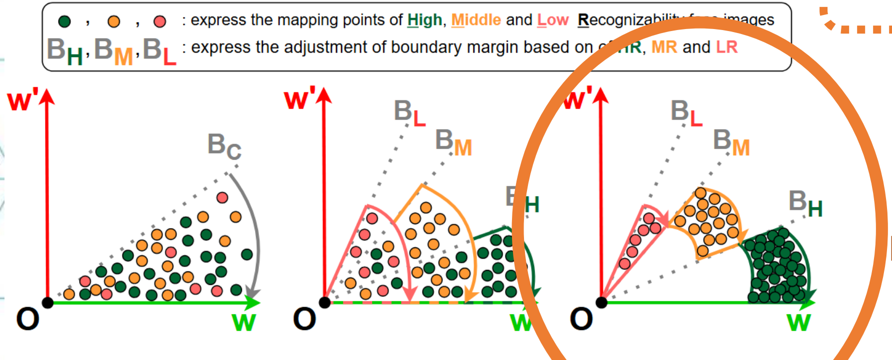

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QCFace

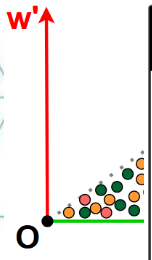
Reuse ArcFace

$$\mathcal{L}_{total} = \mathcal{L}_{sm} + \lambda.\mathcal{L}_{reg}$$

$$p_d = \frac{e^{s.\cos\left(\theta_{w_{y_i},z_i}\right)}}{e^{s.\cos\left(\theta_{w_{y_i},z_i}\right)} + \sum_{j\neq y_i}^{n} e^{s.\cos\left(\theta_{w_j,z_i}\right)}} \quad (C.0.13)$$

$$(1 - p_d) \times \left(\frac{1}{\|z\|} + \frac{\|z\|}{l_a^2}\right) - b$$

●, ●, ● : express the mapping points of High, Middle and Low Recognizability face images
B_H, B_M, B_L : express the adjustment of boundary margin based on HR, MR and LR



(a) Co

Property 3

Suppose that $z_1, z_2 \in \mathbb{R}^d$ where d denotes the embedding dimension, and let their corresponding guidance values (i.e., $p_{d1}, p_{d2} \in [0, 1]$) be computed by Eq. (C.0.13). If $p_{d1} > p_{d2}$, then $\|g_\theta(z_1)\| < \|g_\theta(z_2)\| \; \forall z_1, z_2$.

e $\|z\|^*$.
value.
zability
graph.

➡ Probability at actual class from **converged model** trained with **class-center loss** is chosen as p_d value.

➡ Training process divide into **two phases**: **warm-up** and **hypersphere planning phases**.

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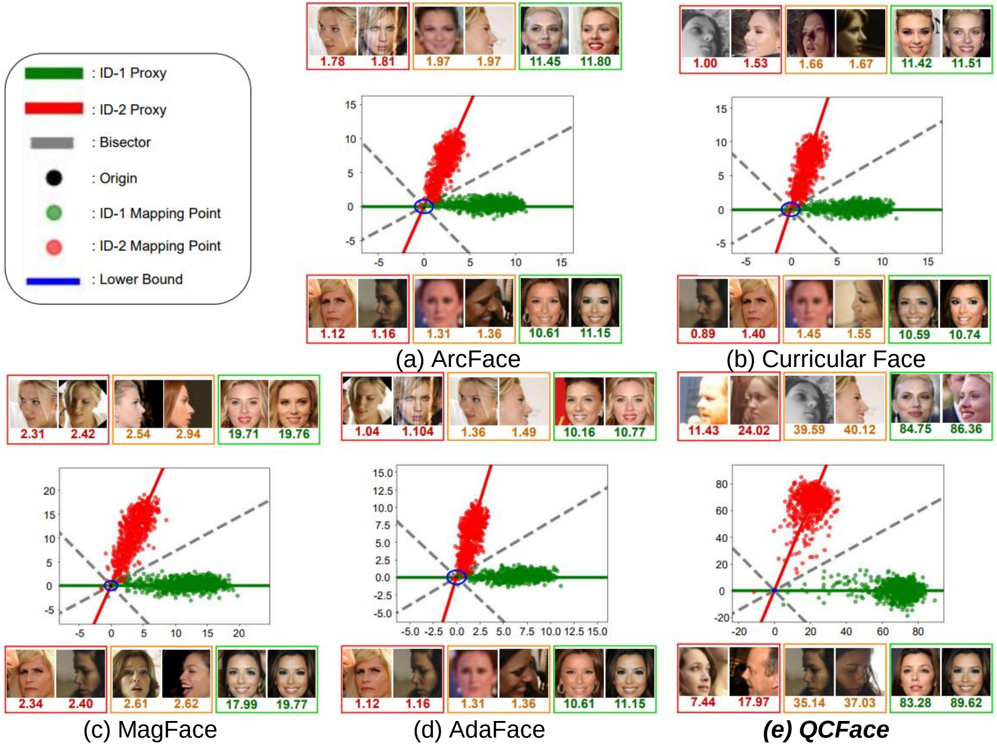
5. Experimental Results

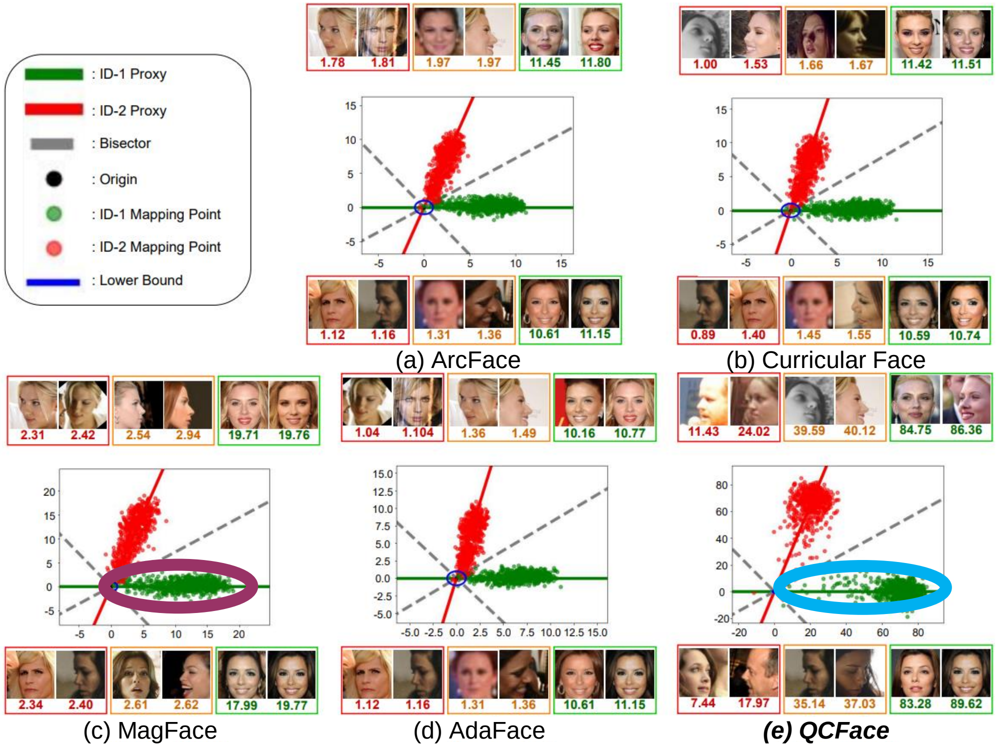
5.1 Representation Results

5.2 Recognition Performance

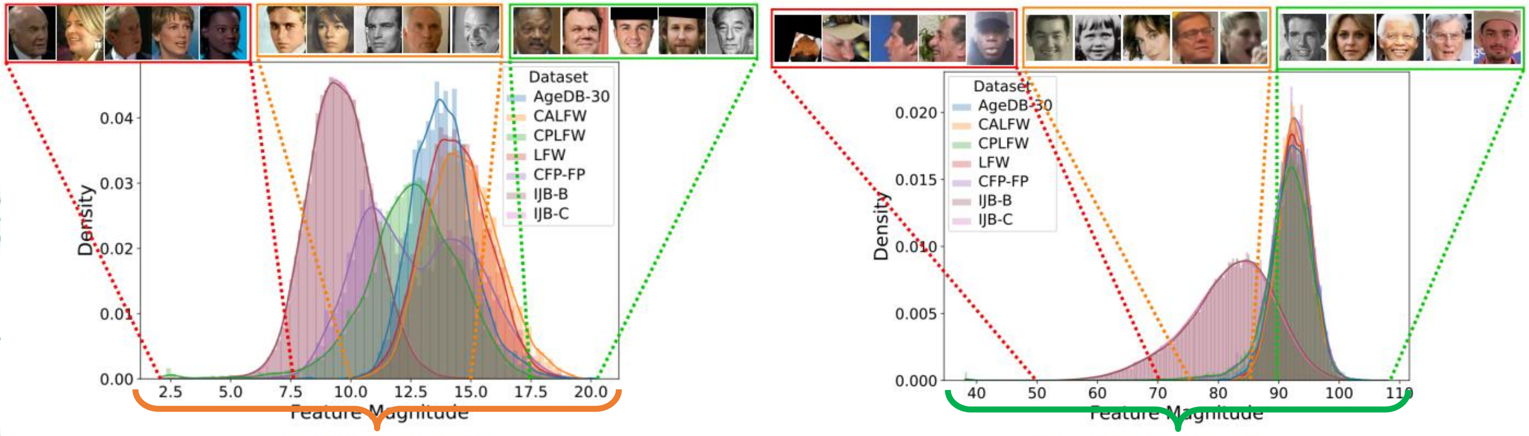
Representation Results–Magnitude Encoding



Representation Results–Magnitude Encoding



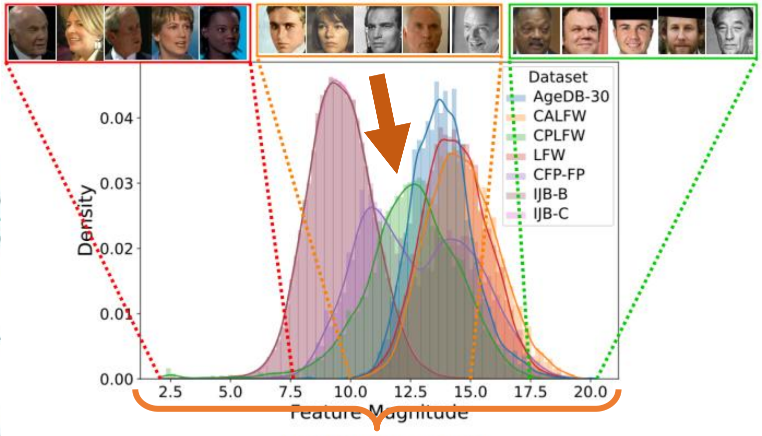
Representation Results–Magnitude Histogram



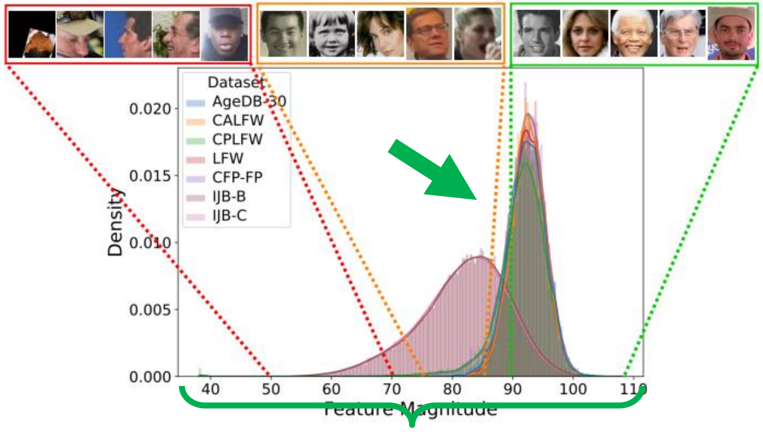
(a) MagFace

(b) QCFace

Representation Results–Magnitude Histogram



(a) MagFace



(b) QCFace

Recognition Performance–Verification Accuracy (HQ)

Table 1: Comparison in verification accuracy and AUC-ROC on high-quality datasets. The **bold**, underlined and *italic* numbers correspondingly express **top-1**, top-2 and *top-3* accuracy. In notation (Q)QCFace-X, (Q) expresses the use of [65] as a similarity score calculation instead of cosine similarity in decision making, X expresses the name of softmax loss (i.e., Arc - ArcFace, Cur - CurricularFace, MVS - MVSoftmax). Green and red backgrounds express the use of margin-based and misclassified softmax losses.

Year	Method	AgeDB-30		CFP-FP		LFW		CALFW		CPLFW		XQLFW	
		Ver	*AUC*	*Ver*	*AUC*	*Ver*	*AUC*	*Ver*	*AUC*	*Ver*	*AUC*	Ver	AUC
2018	CosFace [68]	97.033	98.866	95.743	98.497	99.750	99.862	95.467	97.866	90.317	94.635	81.783	90.128
2019	ArcFace [17]	97.133	98.917	95.100	98.521	99.633	99.878	95.517	97.921	90.217	94.707	81.833	90.087
2020	MV-Arc-Softmax [72]	97.100	98.972	95.757	98.541	99.700	99.826	95.617	97.918	90.233	94.414	83.150	90.814
2020	CurricularFace [27]	97.100	98.962	94.686	98.418	99.550	99.846	95.700	97.929	90.083	94.607	82.650	90.265
2021	MagFace [44]	96.867	98.797	95.357	98.593	99.600	*99.889*	95.517	97.797	89.583	94.105	81.233	89.090
2021	VPLFace [19]	97.183	98.984	94.257	98.163	99.700	99.865	95.683	97.858	89.617	94.483	83.117	90.677
2022	SphereFace2 [73]	96.000	98.777	94.029	98.210	99.583	99.878	95.283	97.949	90.100	94.677	83.933	91.551
2022	Elastic-Arc [8]	97.283	98.930	94.329	98.004	99.467	99.851	95.500	97.799	89.800	94.156	82.467	89.896
2022	Elastic-Cos [8]	97.417	98.979	95.357	98.432	99.700	*99.890*	95.733	97.837	89.400	94.395	82.350	89.729
2022	AdaFace [32]	96.817	98.924	95.614	98.723	99.717	99.866	95.733	97.790	90.917	94.957	82.017	89.839
2023	QAFace [52]	96.783	98.942	95.243	98.469	99.733	99.887	95.400	97.877	89.817	94.430	83.550	90.946
2023	QMagFace [65]	97.250	98.895	96.014	99.119	99.700	99.916	95.617	97.801	90.683	96.042	81.483	88.922
2023	UniFace [87]	97.083	98.903	95.686	98.749	99.617	99.829	95.667	97.856	90.683	95.029	82.700	90.755
2023	UniTSFace [29]	97.217	99.008	95.371	98.550	99.667	99.889	95.717	97.936	90.450	94.835	83.517	91.171
2024	TopoFR [16]	97.500	*99.021*	95.871	99.015	99.750	99.876	95.650	97.913	90.383	95.490	83.583	91.070
Now	***QCFace-Arc (Proposal)***	98.100	99.129	*98.200*	99.372	**99.800**	99.872	*95.950*	*98.031*	92.483	95.624	86.067	93.327
Now	***QQCFace-Arc (Proposal)***	**98.183**	**99.175**	**98.457**	99.524	**99.800**	99.879	*95.950*	**98.087**	**92.833**	*96.403*	**86.267**	**93.634**
Now	***QCFace-Cur (Proposal)***	97.700	98.979	*98.200*	*99.515*	99.783	99.895	**96.083**	*98.031*	92.383	96.404	83.283	91.060
Now	***QQCFace-Cur (Proposal)***	*97.917*	99.013	98.271	**99.528**	*99.767*	**99.900**	96.067	98.032	*92.467*	**96.718**	83.283	91.466

Recognition Performance–Verification Accuracy (MQ)

Table 2: Benchmarking results on IJB dataset based on TAR@FAR.

Year	Method	IJB-B (TAR@FAR) 10^{-6}	10^{-5}	10^{-4}	10^{-3}	AUC	IJB-C (TAR@FAR) 10^{-6}	10^{-5}	10^{-4}	10^{-3}	AUC
2018	CosFace [68]	37.81	84.36	91.82	95.27	99.44	82.44	90.02	94.07	96.45	99.57
2019	ArcFace [17]	36.71	85.15	91.61	95.09	99.47	82.85	89.40	93.66	96.22	99.59
2020	MV-Arc-Softmax [72]	*39.02*	80.41	90.87	94.73	99.44	79.61	87.82	93.26	96.05	99.59
2020	CurricularFace [27]	37.63	84.99	92.27	95.22	99.40	*85.12*	*90.79*	94.20	96.35	99.53
2021	MagFace [44]	38.10	83.59	91.47	95.16	99.32	81.64	88.81	93.38	96.17	99.51
2021	VPLFace [19]	36.90	*85.55*	91.64	95.19	99.42	86.52	90.26	93.79	96.29	99.55
2022	SphereFace2 [73]	36.79	80.86	90.10	94.50	99.50	78.70	86.67	92.34	95.73	*99.63*
2022	Elastic-Arc [8]	36.48	83.97	91.79	95.01	99.45	80.43	89.95	*94.33*	96.18	99.56
2022	Elastic-Cos [8]	34.37	83.72	91.67	95.03	99.50	82.48	89.65	93.80	96.19	99.61
2022	AdaFace [32]	35.01	85.07	*92.44*	*95.31*	99.38	80.43	89.95	*94.33*	*96.49*	99.56
2023	QAFace [52]	40.00	80.19	89.49	93.99	**99.54**	79.02	87.17	92.27	95.63	*99.63*
2023	QMagFace [65]	36.80	83.42	88.25	93.17	99.38	81.24	87.28	91.23	95.16	99.61
2023	UniFace [87]	37.16	85.46	92.16	95.30	99.41	82.62	90.35	94.21	96.47	99.57
2023	UniTSFace [29]	34.35	82.71	91.64	95.20	99.47	79.78	88.66	93.64	96.42	99.64
2024	TopoFR [16]	**40.25**	82.88	91.25	95.25	*99.49*	77.94	88.28	93.30	96.42	*99.63*
Now	***QCFace-Arc (Proposal)***	34.42	**89.39**	**94.30**	**96.23**	99.44	**88.85**	**93.82**	**95.84**	**97.37**	99.62
Now	***QQCFace-Arc (Proposal)***	37.89	88.80	93.93	95.90	*99.48*	80.57	91.70	95.48	97.01	**99.66**

Recognition Performance–Identification Accuracy (LQ)

Table 3: Benchmarking results of identification performance on IJB, TinyFace and MegaFace datasets. In the MegaFace benchmark, Iden refers Rank-1 identification accuracy and Veri expresses verification performance based on TAR@FAR= 10^{-6}. The notation “-" denotes lack of support for similarity score calculation of “*qmf*” by MegaFace devkit.

Year	Method	IJB-B		IJB-C		TinyFace		MegaFace	
		Rank-1	*Rank-5*	*Rank-1*	*Rank-5*	*Rank-1*	*Rank-5*	*Iden*	Veri
2018	CosFace [68]	*93.554*	95.891	94.789	96.392	60.381	64.941	95.617	96.260
2019	ArcFace [17]	93.204	95.852	94.314	96.193	57.672	62.607	95.242	95.895
2020	MV-Arc-Softmax [72]	92.882	95.813	94.233	96.172	59.120	64.297	94.188	94.944
2020	CurricularFace [27]	93.476	95.794	94.794	96.366	60.649	64.941	95.637	96.316
2021	MagFace [44]	92.911	95.803	94.187	96.045	57.833	62.527	94.965	96.052
2021	VPLFace [19]	93.427	*96.076*	94.666	96.448	57.913	62.446	94.937	95.978
2022	SphereFace2 [73]	92.162	95.170	93.610	95.743	57.994	63.251	92.595	94.224
2022	Elastic-Arc [8]	92.911	95.813	94.391	96.203	57.779	62.607	95.674	96.429
2022	Elastic-Cos [8]	93.262	96.008	94.473	96.315	60.086	64.565	94.989	95.602
2022	AdaFace [32]	93.525	96.018	94.814	*96.524*	*60.837*	64.995	95.888	96.694
2023	QAFace [52]	92.687	95.764	94.018	96.320	57.967	62.983	93.510	94.738
2023	QMagFace [65]	91.870	95.560	93.707	96.213	57.833	62.527	-	-
2023	UniFace [87]	93.350	95.979	*94.886*	96.402	60.327	64.887	95.961	96.350
2023	UniTSFace [29]	93.155	95.891	94.442	96.366	60.408	*65.236*	94.409	95.737
2024	TopoFR [16]	93.019	95.813	94.243	96.289	59.871	64.029	*95.913*	*96.636*
Now	***QCFace-Arc (Proposal)***	94.761	96.884	96.157	97.468	62.634	**66.738**	**98.347**	**98.500**
Now	***QQCFace-Arc (Proposal)***	**94.898**	**96.923**	**96.172**	**97.484**	**64.941**	68.160	-	-

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Magnitude Assignment – Performance Impact (1)

!?

$$\mathcal{L}_{total} = \mathcal{L}_{sm} + \lambda.\mathcal{L}_{reg}$$

$$\mathcal{L}_{reg} = k \times p_d \times \left(\frac{1}{\|z\|} + \frac{\|z\|}{u_a^2}\right) + (1 - p_d) \times \left(\frac{1}{\|z\|} + \frac{\|z\|}{l_a^2}\right) - b$$

Small representation:

Lemma 1

Let $z_1, z_2 \in \mathbb{R}^d$ *where* d *denotes the embedding dimension. If* $\|z_1\| > \|z_2\|$, *then* $\|g_\theta(z_1)\| < \|g_\theta(z_2)\|$.

Magnitude Assignment – Performance Impact (2)

$$\mathcal{L}_{reg} = k \times p_d \times \left(\frac{1}{\|z\|} + \frac{\|z\|}{u_a^2}\right) + (1 - p_d) \times \left(\frac{1}{\|z\|} + \frac{\|z\|}{l_a^2}\right) - b$$

Lemma 1

Let $z_1, z_2 \in \mathbb{R}^d$ where d denotes the embedding dimension. If $\|z_1\| > \|z_2\|$, then $\|g_\theta(z_1)\| < \|g_\theta(z_2)\|$.

Assigned with small gradient

Assigned with large gradient

Magnitude Assignment – Performance Impact (2)

$$\mathcal{L}_{reg} = k \times p_d \times \left(\frac{1}{\|z\|} + \frac{\|z\|}{u_a^2}\right) + (1 - p_d) \times \left(\frac{1}{\|z\|} + \frac{\|z\|}{l_a^2}\right) - b$$

Lemma 1

Let $z_1, z_2 \in \mathbb{R}^d$ where d denotes the embedding dimension. If $\|z_1\| > \|z_2\|$, then $\|g_\theta(z_1)\| < \|g_\theta(z_2)\|$.

$$\mathcal{L}_{total} = \mathcal{L}_{sm} + \lambda.\mathcal{L}_{rc}$$

Assigned with small gradient

Assigned with large gradient

7. Conclusion (1)

- Proposing ***hard margin strategy*** in hypersphere planning to avoid mutual overlapping effects in recognizability representation.
- Modeling ***hard margin strategy*** by ***QCFace loss function*** with ***guidance value*** to orientate magnitude encoding.
- Experimental results show the superiority of ***QCFace*** over the SoTAs in face recognition, on ***recognizability representation and recognition ability***.

7. Conclusion (2)

Table 4: Comparison between class center loss variants

Method	BMAP	BMMcP	MS	RRL	MC
SphereFace	Angular	✗	*Constant margin*	✗	Low
CosFace	Additive	✗	*Constant margin*	✗	Low
ArcFace	Additive angular	✗	*Constant margin*	✗	Low
MV-Softmax	Additive angular	Constant	*Constant margin*	✗	Low
CurricularFace	Additive angular	Adaptive	*Constant margin*	✗	Low
MagFace	Additive angular	✗	*Soft margin*	Middle	Low
VPLFace	Additive angular	Adaptive	*Constant margin*	✗	Middle
AdaFace	AAa	✗	*Soft margin*	Low	Low
QAFace	Additive angular	Adaptive	*Constant margin*	✗	High
UniFace	AAa	Constant	*Constant margin*	✗	Low
UniTSFace	AAa	Constant	*Constant margin*	✗	Middle
TopoFR	Additive angular	✗	*Constant margin*	✗	High
QCFace (Proposal)	Additive angular	*n/a*	***Hard margin***	***High***	***Low***

Note:

- **BMAP: B**oundary **M**argin for **A**ctual **P**roxies
- **BMMcP: B**oundary **M**argin **M**is**c**lassified **P**roxies
- **Aa: A**dditive **a**ngular margin
- **AAa: A**nguar & **A**dditive **a**ngular margin
- **MS: M**argin **S**trategy
- **RRL: R**ecognizability **R**epresentation **L**evel
- **MC: M**emory **C**ost

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