CR-FIQA: Face Image Quality Assessment by Learning Sample Relative Classifiability

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CR-FIQA: Face Image Quality Assessment by Learning Sample Relative Classifiability

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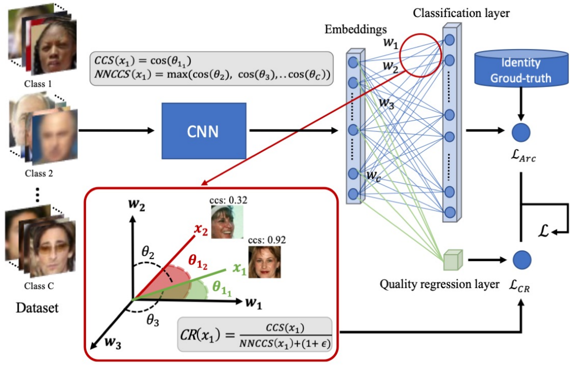
Overview: This work proposes a novel face image quality assessment (FIQA) method, **CR-FIQA**, that **estimates the face image quality** of a sample by learning to predict its **relative classifiability**. This classifiability is measured based on the allocation of the training sample feature representation in angular space with respect to **its class center and the nearest negative class center**. We experimentally illustrate the correlation between the face image quality and the sample relative classifiability. As such property is only observable for the training dataset, we propose to **learn** this property by **probing internal network observations** during the training process and utilizing it to **predict the quality of unseen samples**.

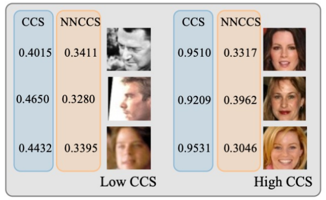
CR-FIQA:

if a given sample was hypothetically part of the FR model training (which it is not), how relatively close would it be to its class center?



$$CR(x_1) = \frac{CCS(x_1)}{NNCCS(x_1)+(1+\epsilon)}$$

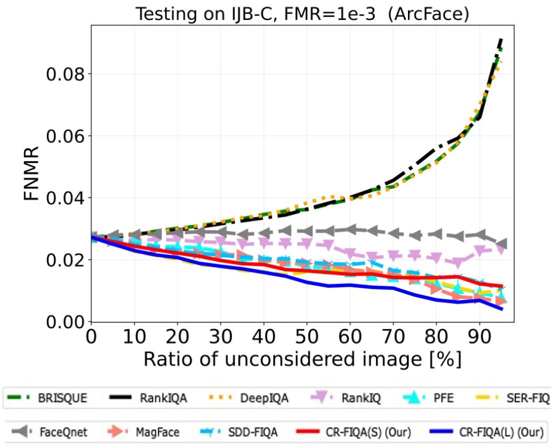
- CCS: a proximity between sample x and its class center
- NNCCD: a proximity between sample x and the nearest negative class center
- Certainty Ratio (CR): a relative proximity of sample x to its class center and negative class center



Comparison with SOTA: Quality scores as an embedding weighting term

FIQ		IJB-C 1:1 mixed Verification: TAR (%) at FAR					
		ArcFace			ElasticFace		
		1e-6	1e-5	1e-4	1e-6	1e-5	1e-4
	-	89.85	94.47	96.28	89.15	94.54	96.49
FIQA	RankIQ	88.78	94.42	96.20	88.88	94.64	96.45
	PFE	89.50	94.51	96.31	89.10	94.67	96.51
	SER-FIQ	89.74	94.65	96.32	90.05	94.79	96.57
	FaceQNet	87.87	94.04	96.12	86.26	94.09	96.25
	MagFace	89.49	94.41	96.22	89.37	94.69	96.46
	SDD-FIQA	89.39	94.61	96.34	88.07	94.82	96.49
	CR-FIQA(S)	89.59	**94.78**	96.35	**90.30**	**94.97**	**96.63**
	CR-FIQA(L)	**90.16**	94.75	**96.36**	90.00	94.92	96.58

Comparison with SOTA FIQA methods



Take home messages:

- Propose CR-FIQA approach to estimate FIQ
- CR-FIQA training paradigm simultaneously learns to optimize the class center while learning to predict sample relative classifiability
- CR-FIQA outperformed SOTA FIQ approaches

https://github.com/fdbtrs/CR-FIQA

What is Face image quality (FIQ)?

- Face image utility indicates the utility (value) of an image to face recognition (FR) algorithms
- What face quality estimator should answer?

How usable (utility*) is the sample for automatic face recognition systems?

*Utility: the observed or predicted positive or negative contribution of an individual sample to the overall performance of a biometric system.

Why do we need FIQ?

- The performance of biometric recognition is driven by the quality of its samples

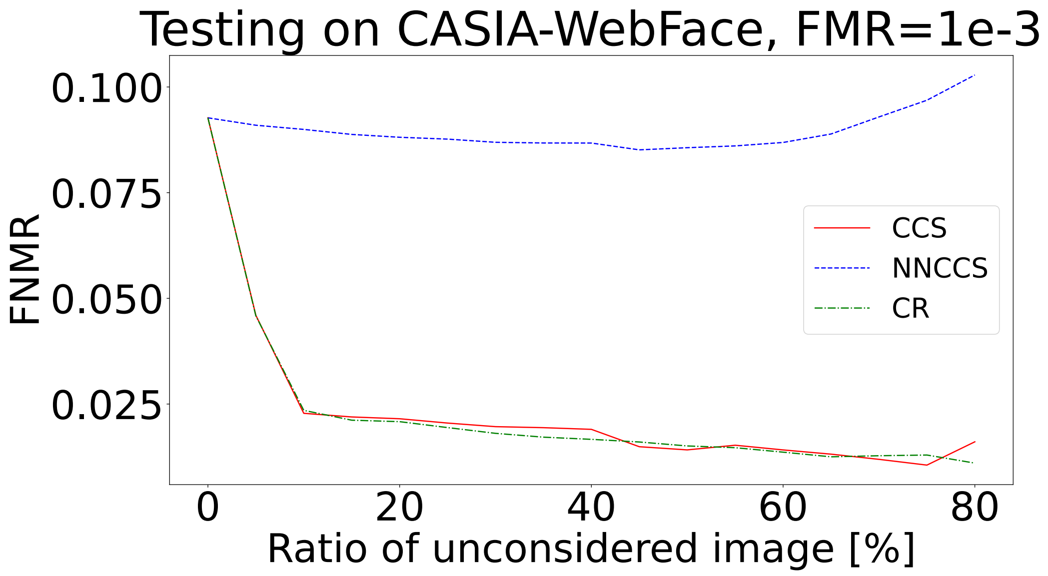
Biometric sample quality: estimate the suitability of a sample for recognition

- Some advantages of sample quality

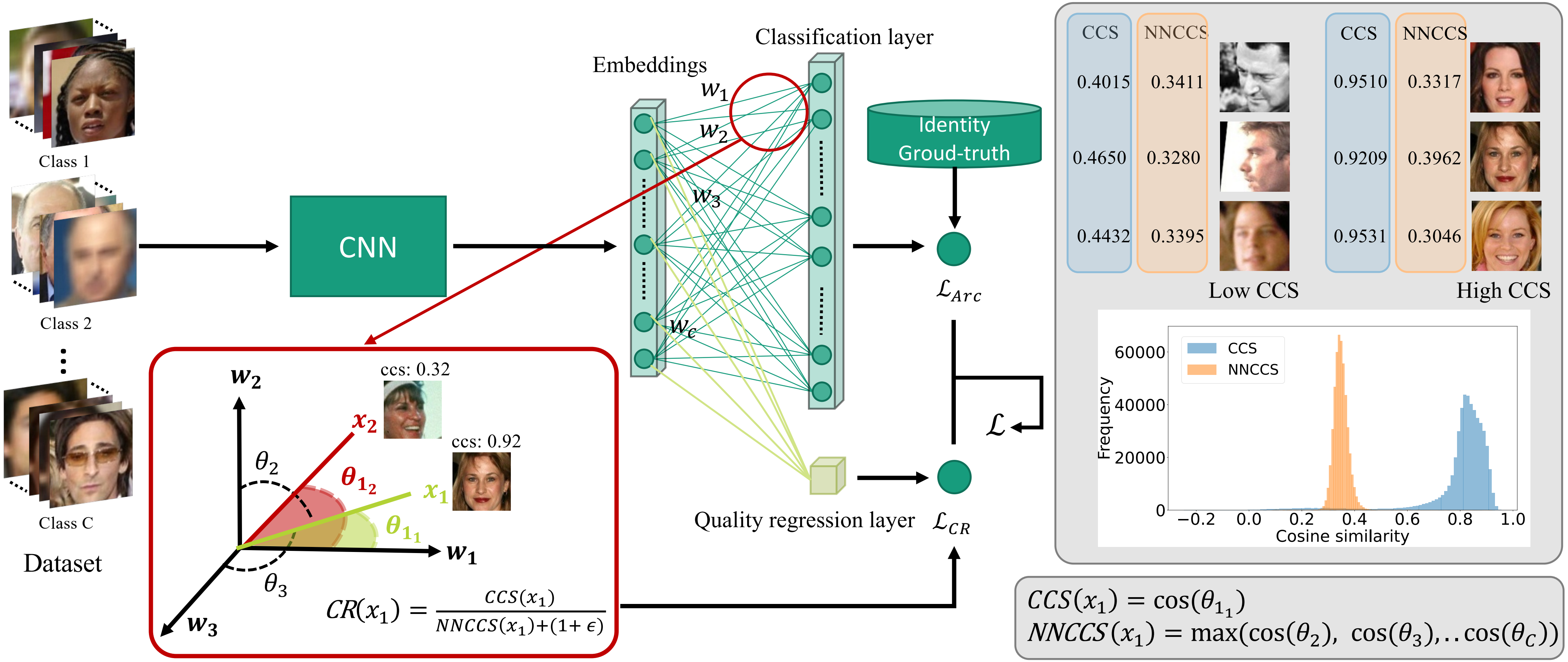
✓ More robust enrolment
✓ More secure negative identification systems
✓ Enables quality-based fusion approaches

How can we evaluate face image quality estimator?

- If we removed the worse data (according to our quality estimation), do the face verification/identification performance on the rest of the data (higher quality) enhance?
- Error vs. Reject Curves (ERC): ERC plots the percentage of the neglected data (of the worst estimated quality) vs. a biometric verification/identification error rate.
- Area under the Curve (AUC) of the ERC: provide a quantitative aggregate measure of verification performance across all rejection ratios.



CR-FIQA: Face Image Quality Assessment by Learning Sample Relative Classifiability

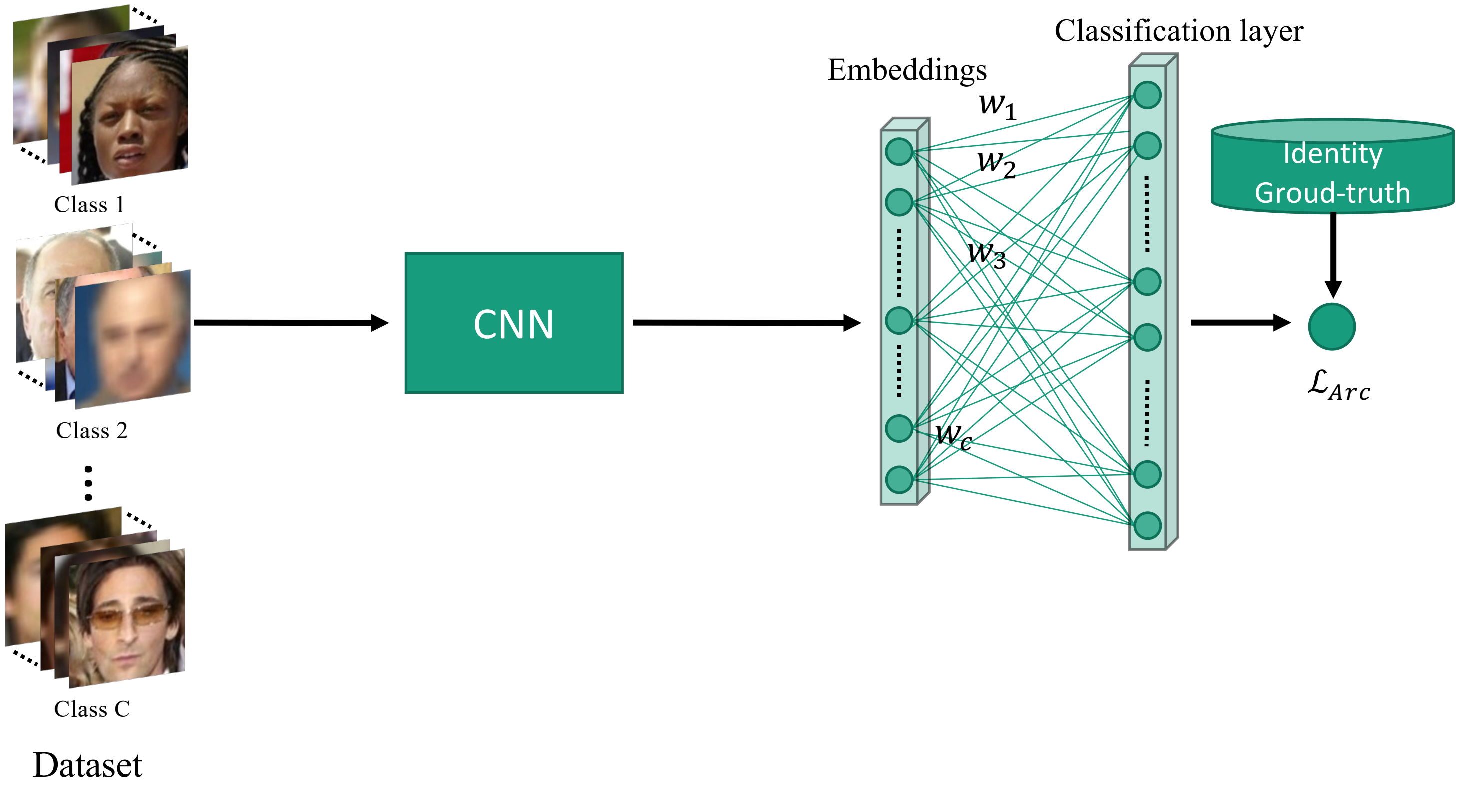


$CCS(x_1) = \cos(\theta_{1_1})$

$NNCCS(x_1) = \max(\cos(\theta_2),\ \cos(\theta_3), .. \cos(\theta_C))$

CR-FIQA: Face Image Quality Assessment by Learning Sample Relative Classifiability

Face recognition training under multi-class classification



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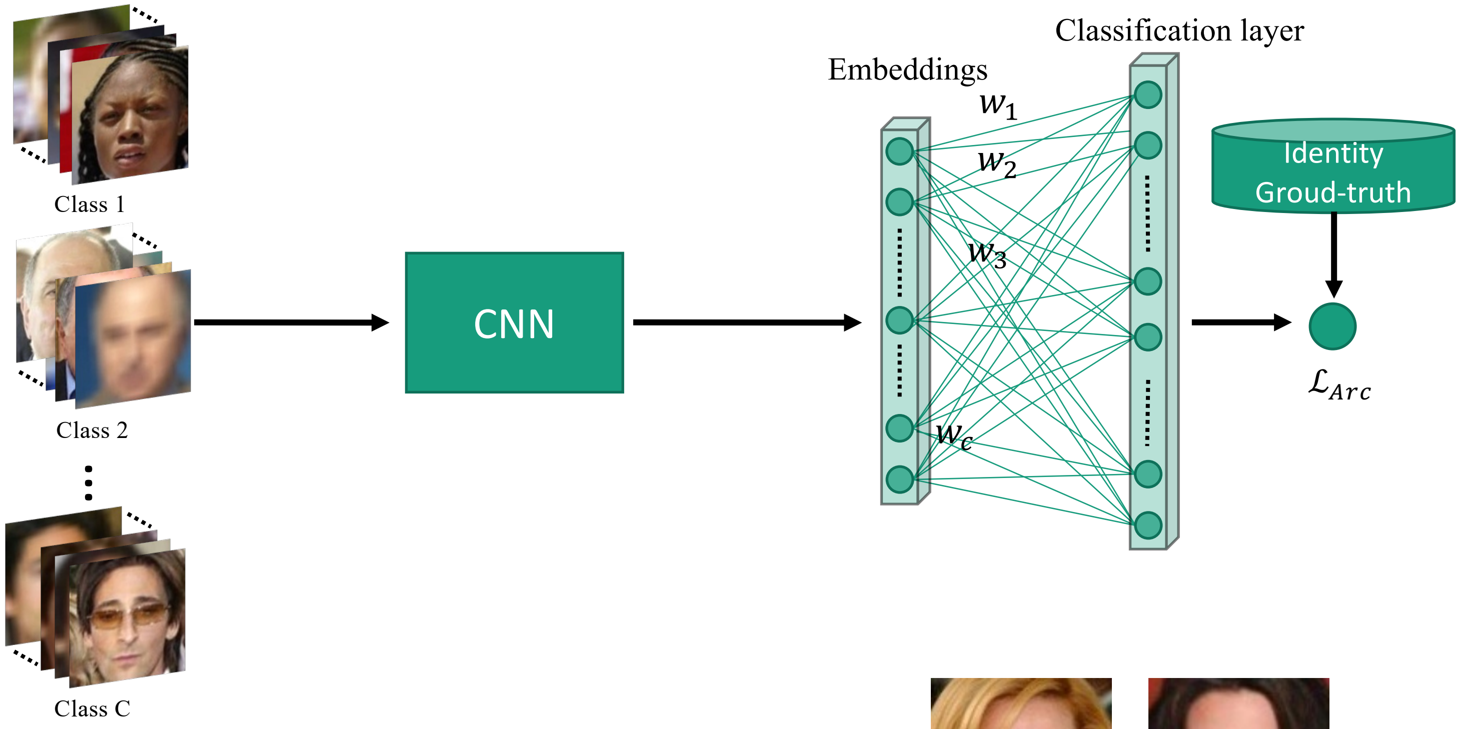

High quality

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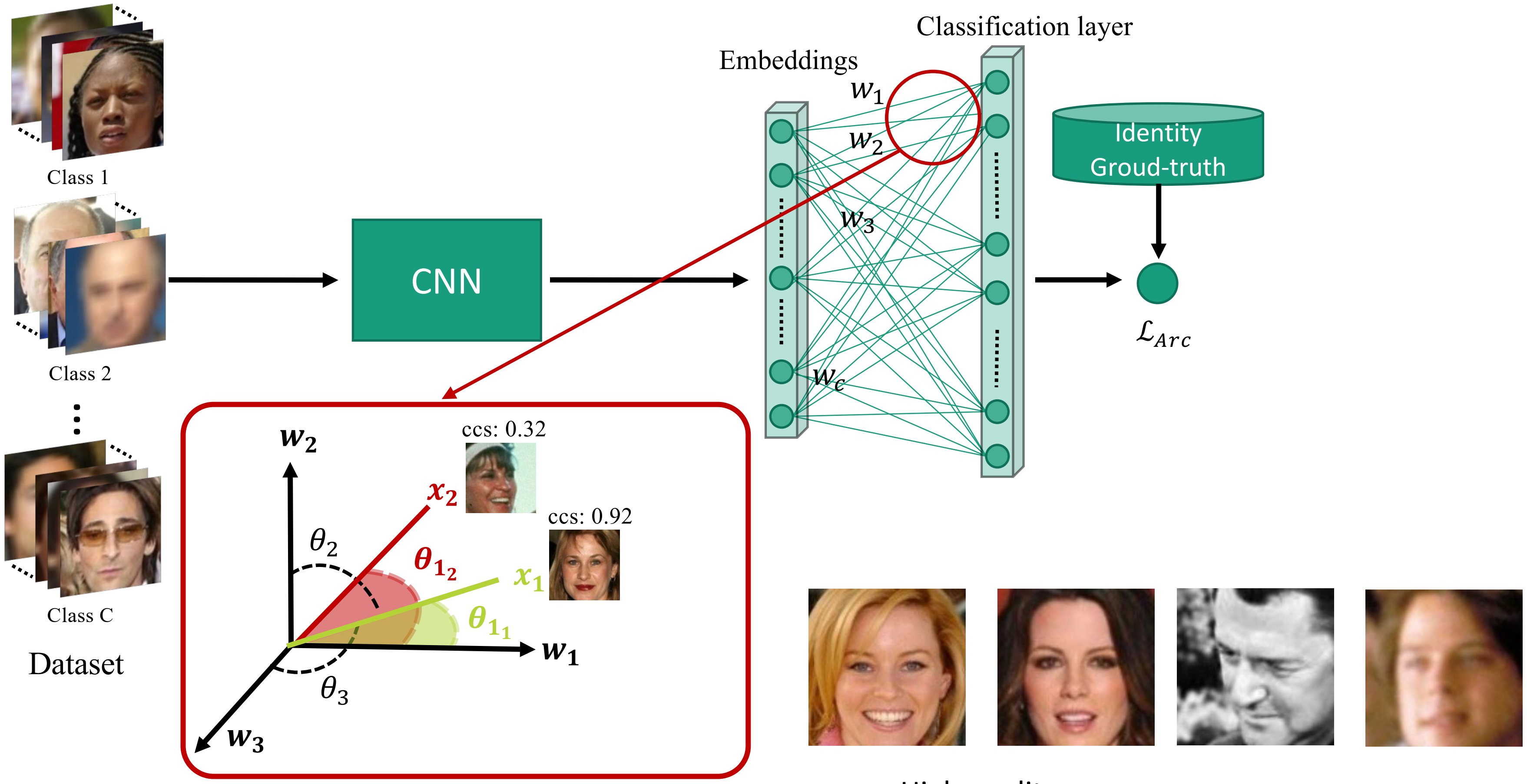

High quality Low quality

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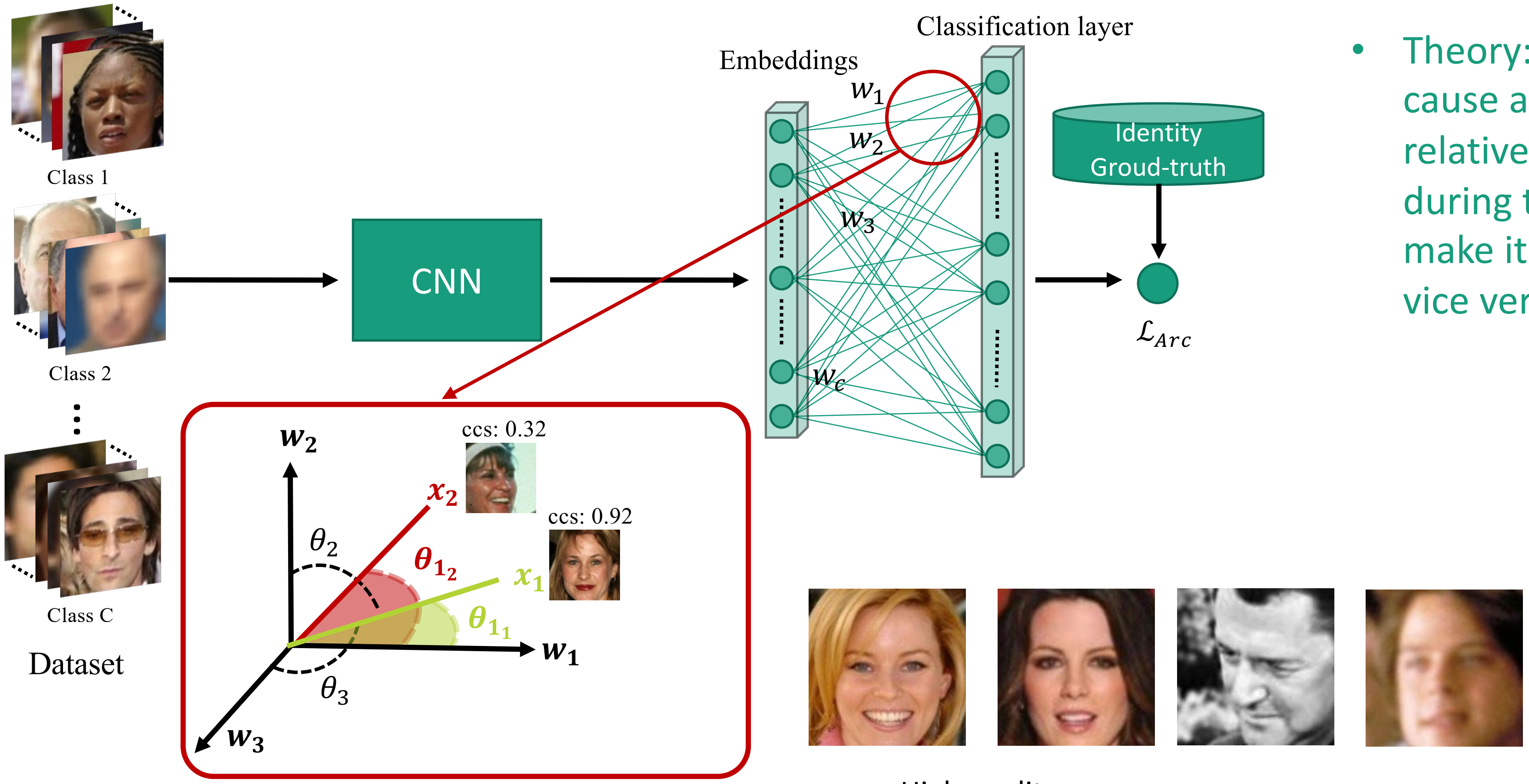
Face recognition training under multi-class classification

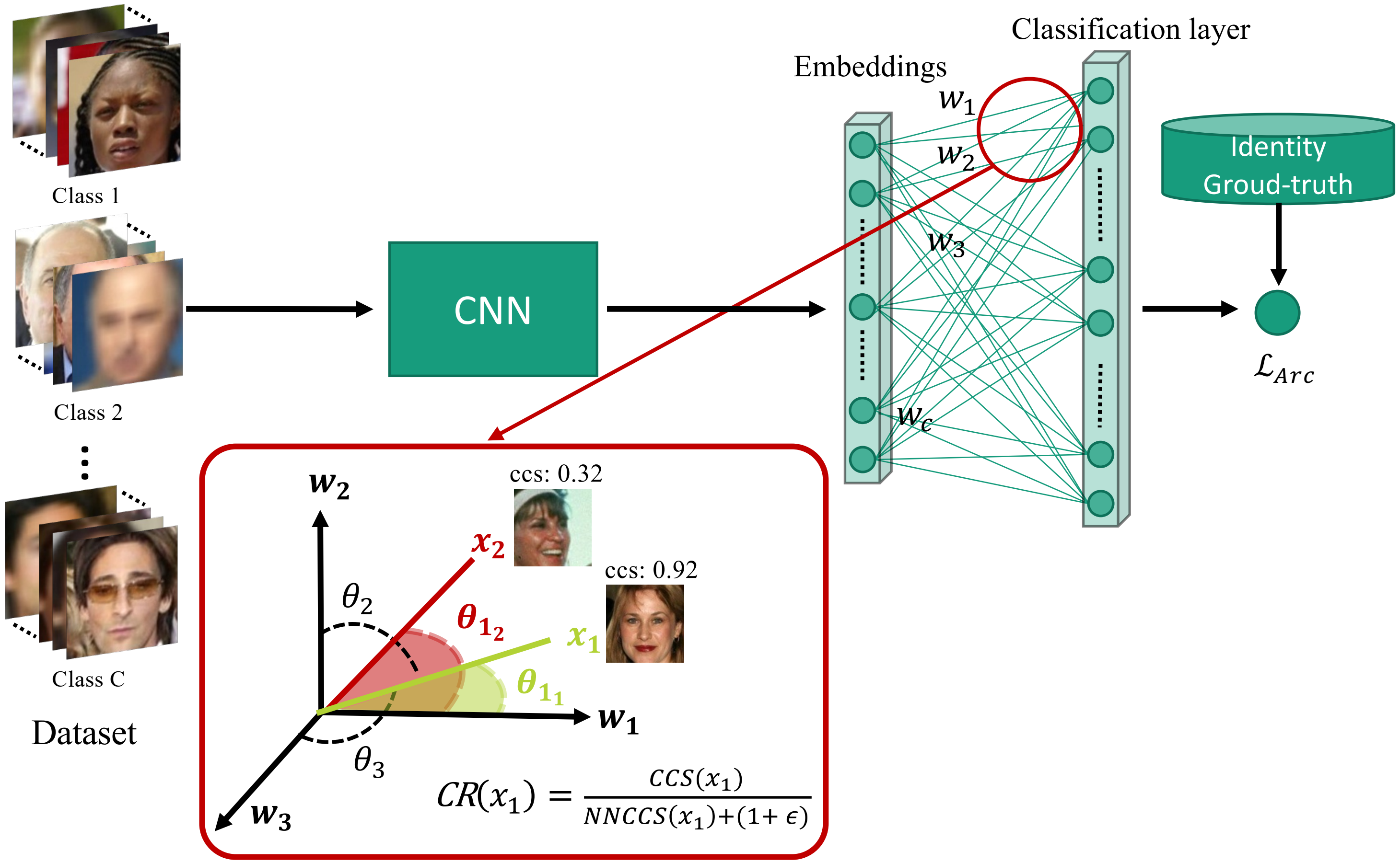


- Theory: "the properties that cause a face sample to lay relatively closer to its class center during training are the ones that make it a high-quality sample, and vice versa"

High quality Low quality

CR-FIQA: Face Image Quality Assessment by Learning Sample Relative Classifiability

Certainty Ratio



- **CCS** (Class Center Angular Similarity): a proximity between sample x and its class center
  $CCS(x_1) = \cos(\theta_{1_1})$

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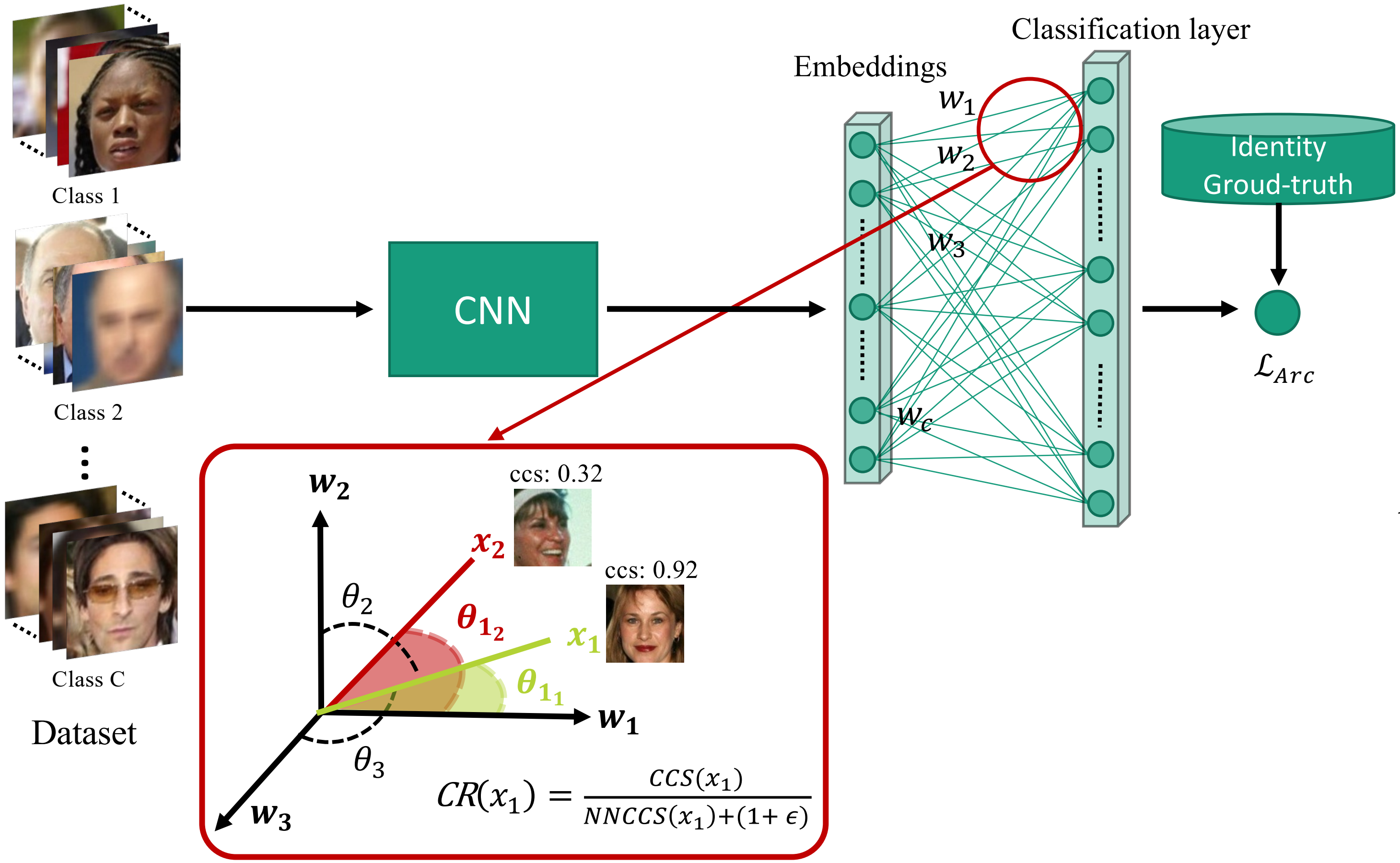
Certainty Ratio



- **CCS** (Class Center Angular Similarity): a proximity between sample x and its class center
  $$CCS(x_1) = \cos(\theta_{1_1})$$
- **NNCCD** (Closest Nearest Negative Class Center Angular Similarity): a proximity between sample x and the nearest negative class center

$$NNCCS(x_1) = \max(\cos(\theta_2),\ \cos(\theta_3), .. \cos(\theta_C))$$

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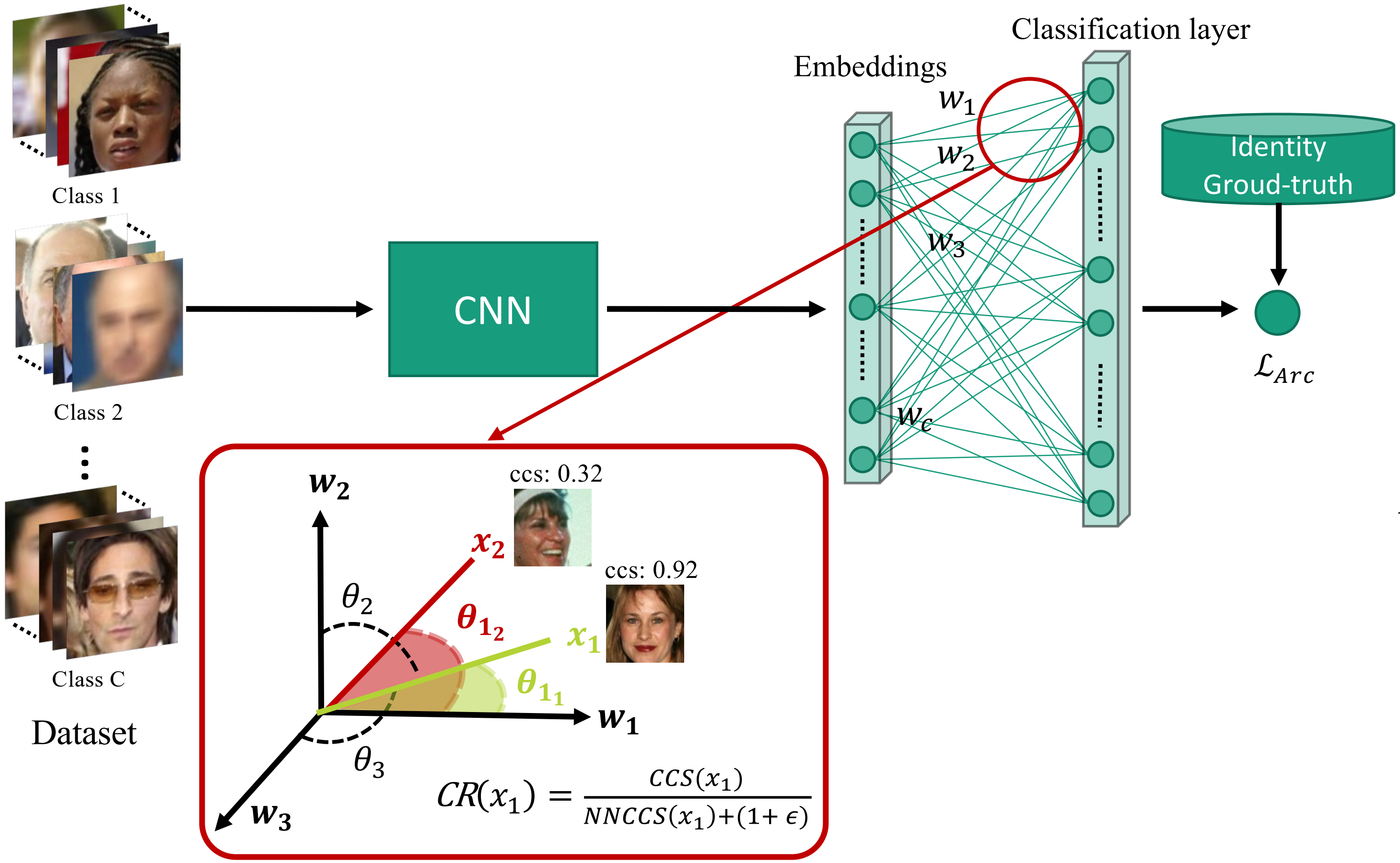
Certainty Ratio



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$$NNCCS(x_1) = \max(\cos(\theta_2),\ \cos(\theta_3), ..\cos(\theta_C))$$

- **Certainty Ratio (CR)**: a relative proximity of sample x to its class center and negative class center

$$CR(x_1) = \frac{CCS(x_1)}{NNCCS(x_1)+(1+\epsilon)}$$

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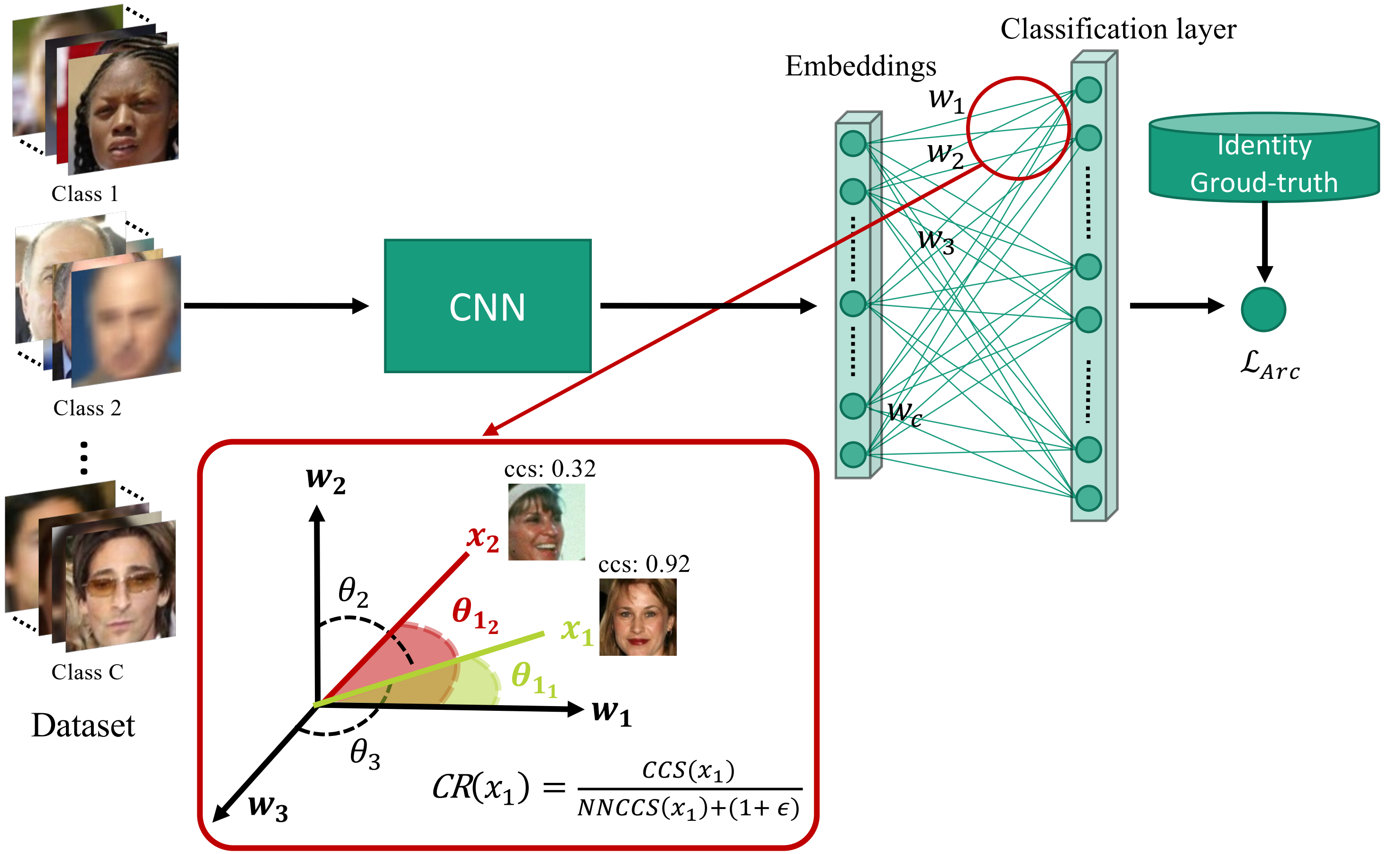
Relation between the CR and FIQ



- If the **CR values** achieved by training samples of an FR model were used as FIQ, would they **behave as expected** from an optimal **FIQ**?

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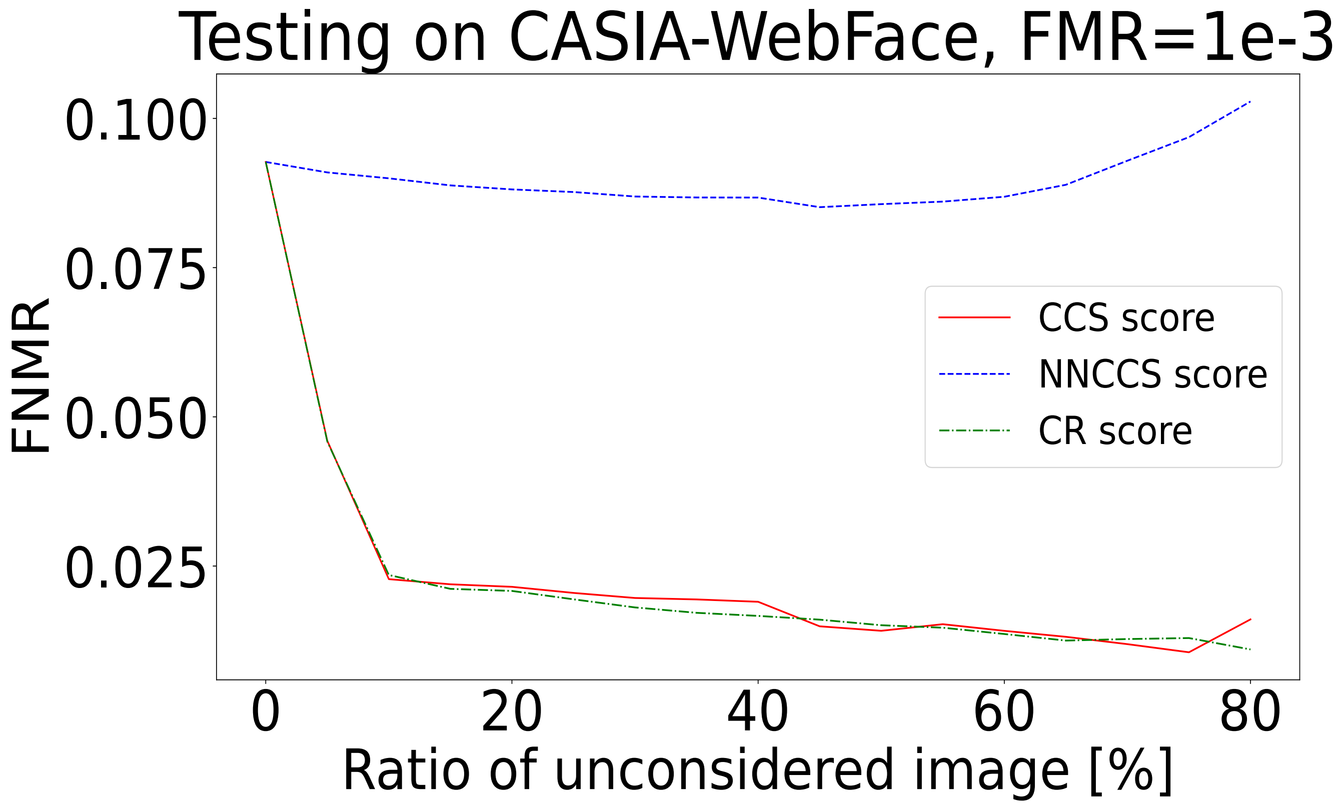
Relation between the CR and FIQ



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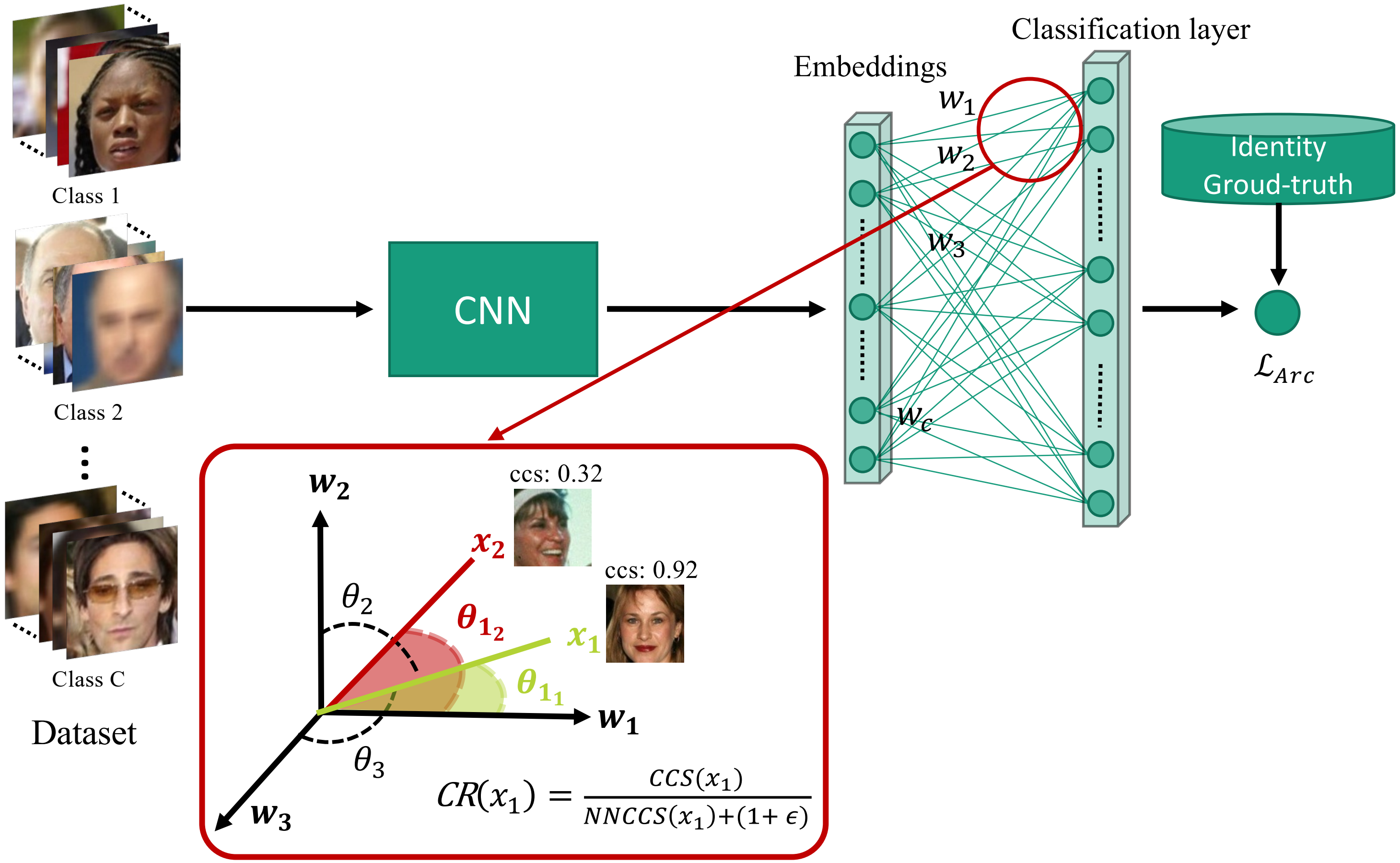

- If a given **sample** was hypothetically **part** of the **FR** model **training** (which it is not), how relatively close would it be to its class center?

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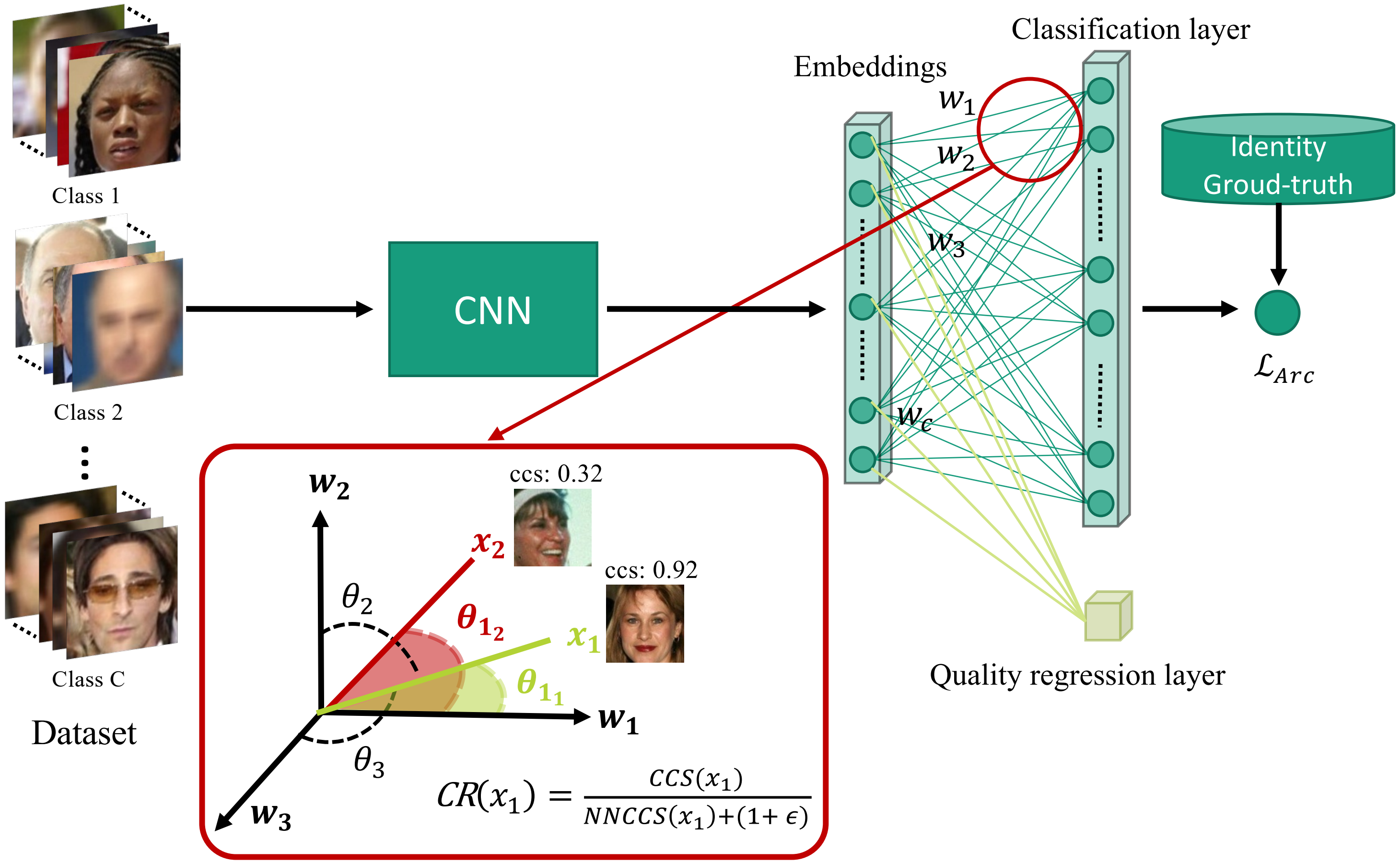
Simultaneously learning



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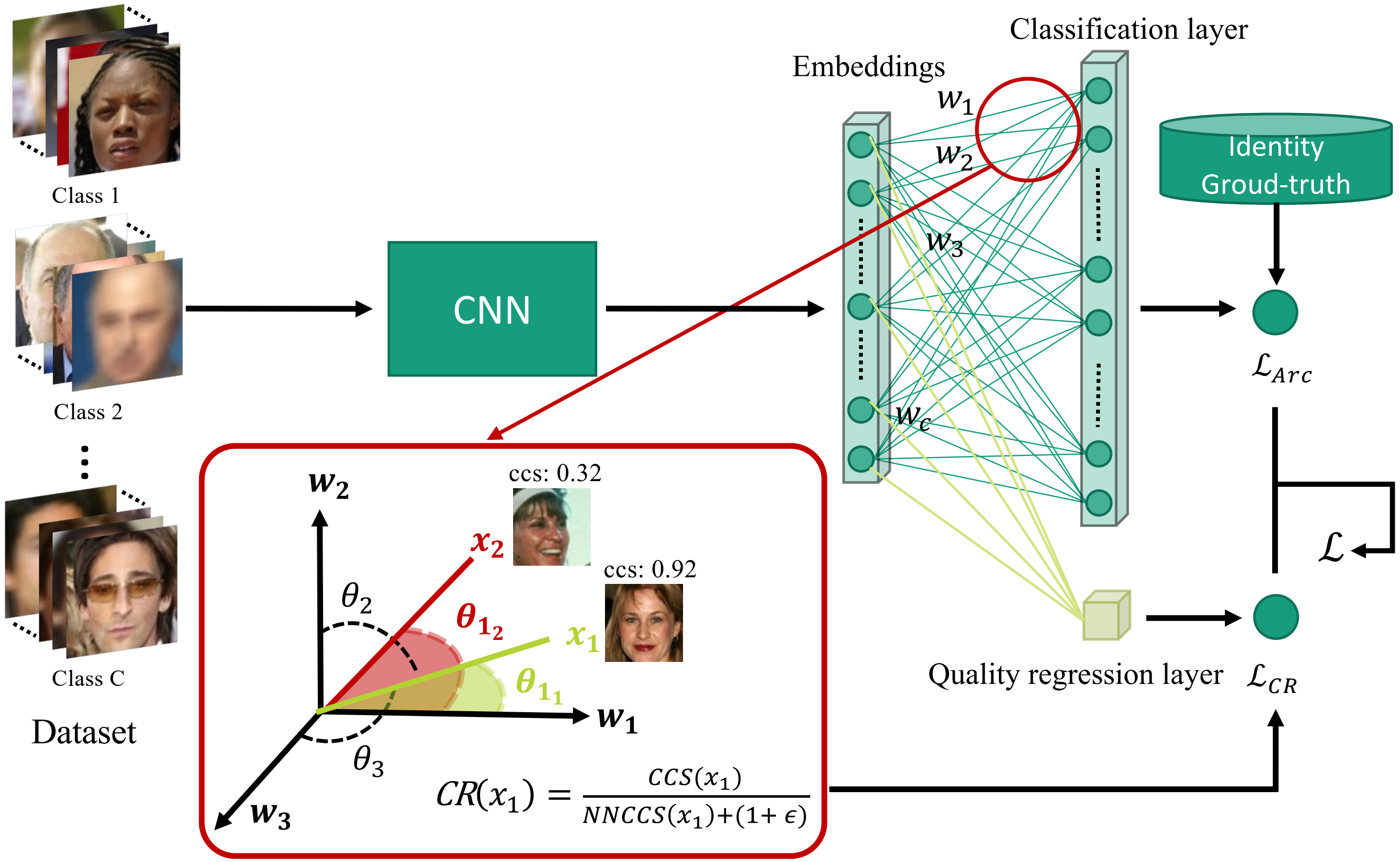
Simultaneously learning



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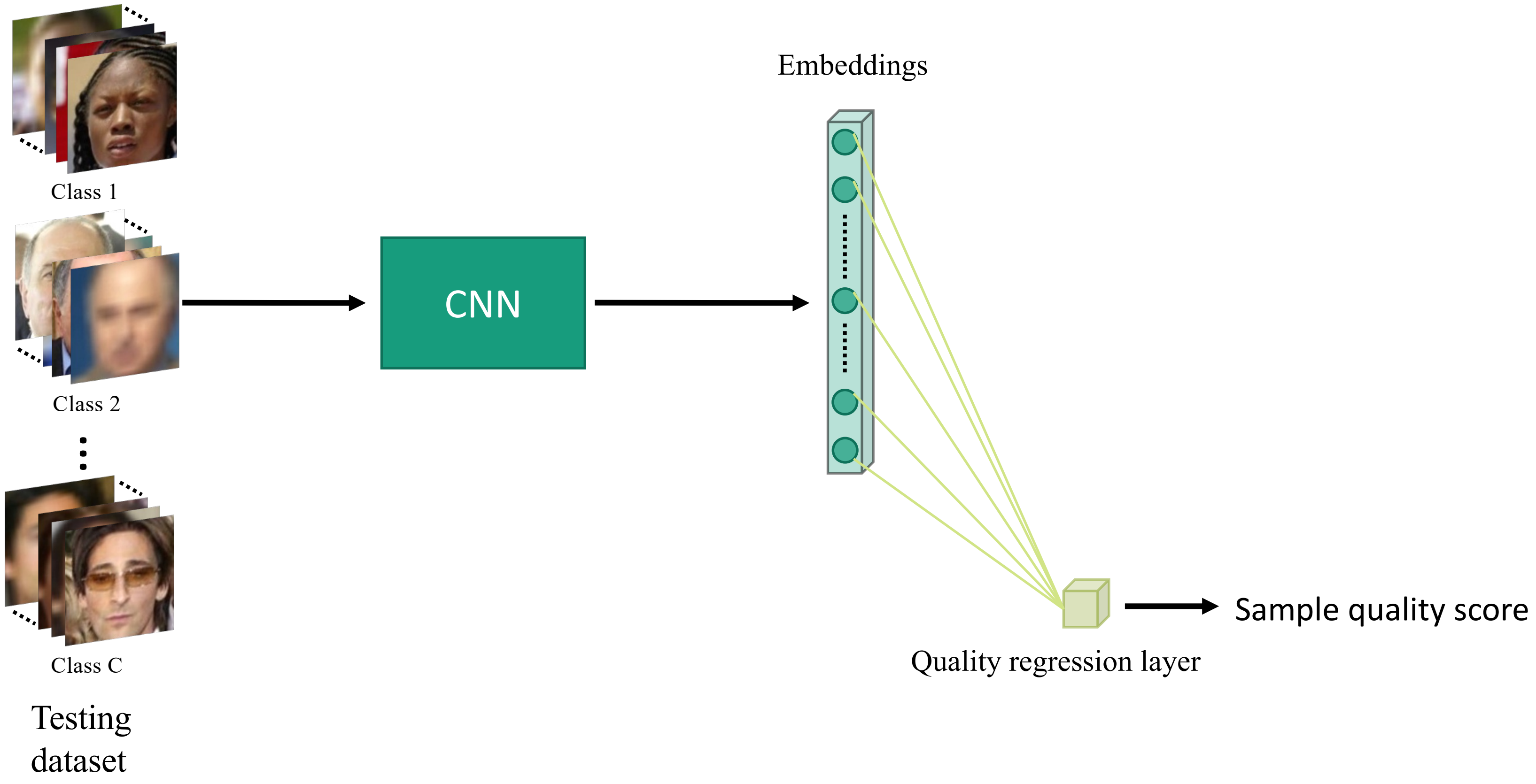
Quality estimation



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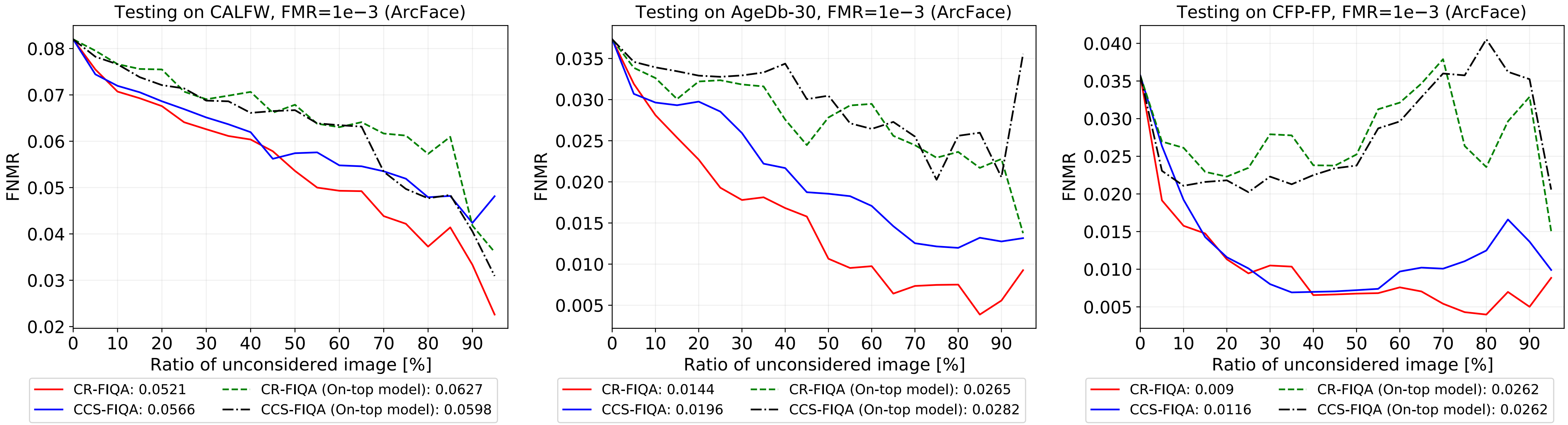
Evaluation setups

- CR-FIQA (S)
  - Training dataset: CASIA-WebFace
  - Network architecture: ResNet-50
- CR-FIQA (L)
  - Training dataset: MS1MV2
  - Network architecture: ResNet-100

- Face recognition models
  - ElasticFace
  - ArcFace
  - MagFace
  - CurricularFace

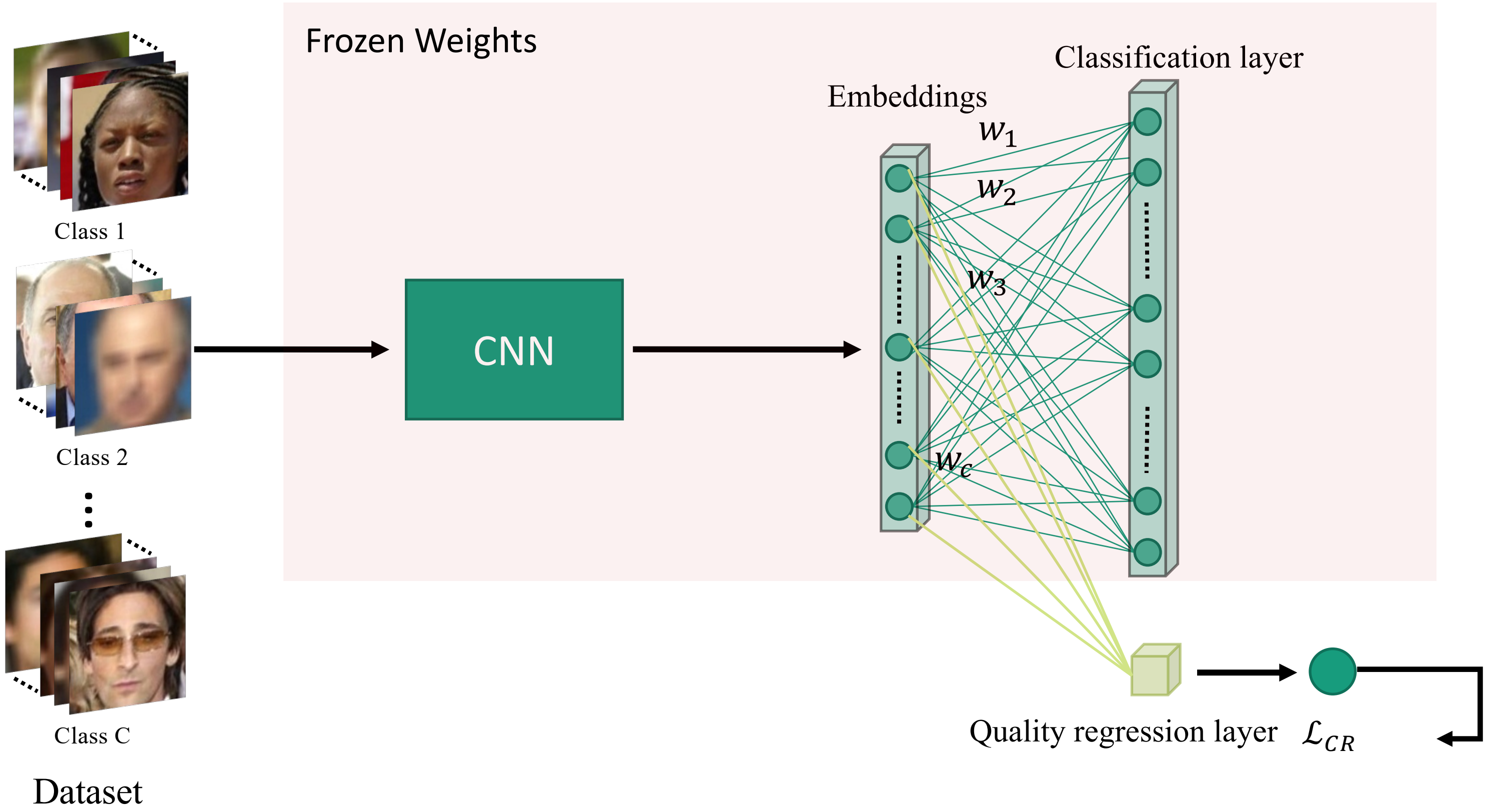
- Evaluation benchmarks:
  - LFW
  - AgeDB-30
  - CFP-FP
  - CALFW
  - Adience
  - CPLFW
  - XQLFW
  - IJB-C

Ablation study
Does CR-FIQA benefit from the NNCCS scaling term?



Ablation study

Dose the simultaneous learning lead to better performance in comparison to on-the-top learning?



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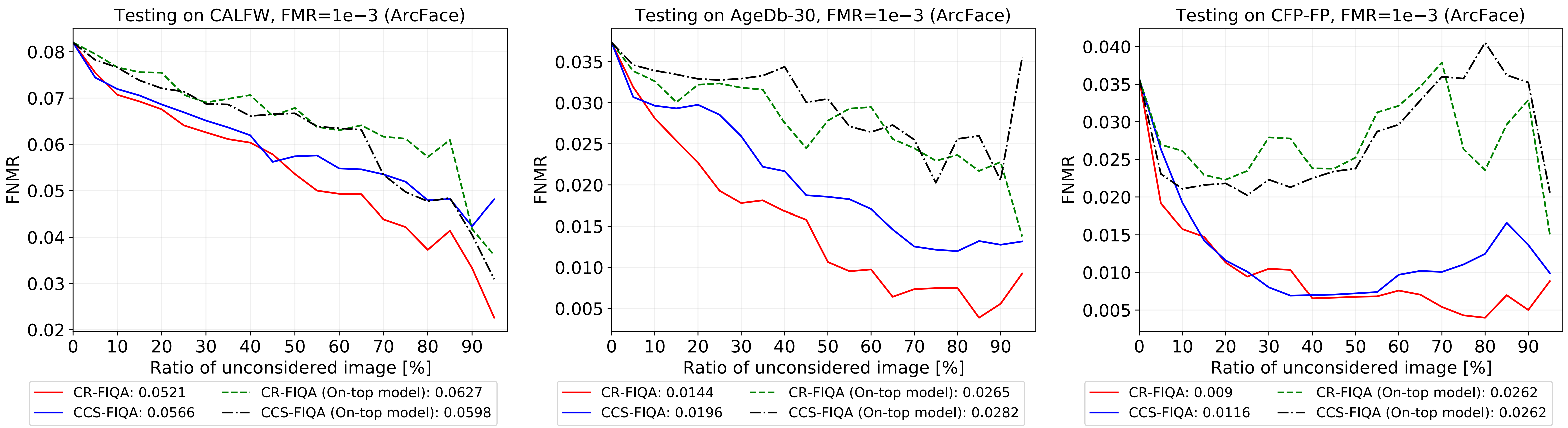
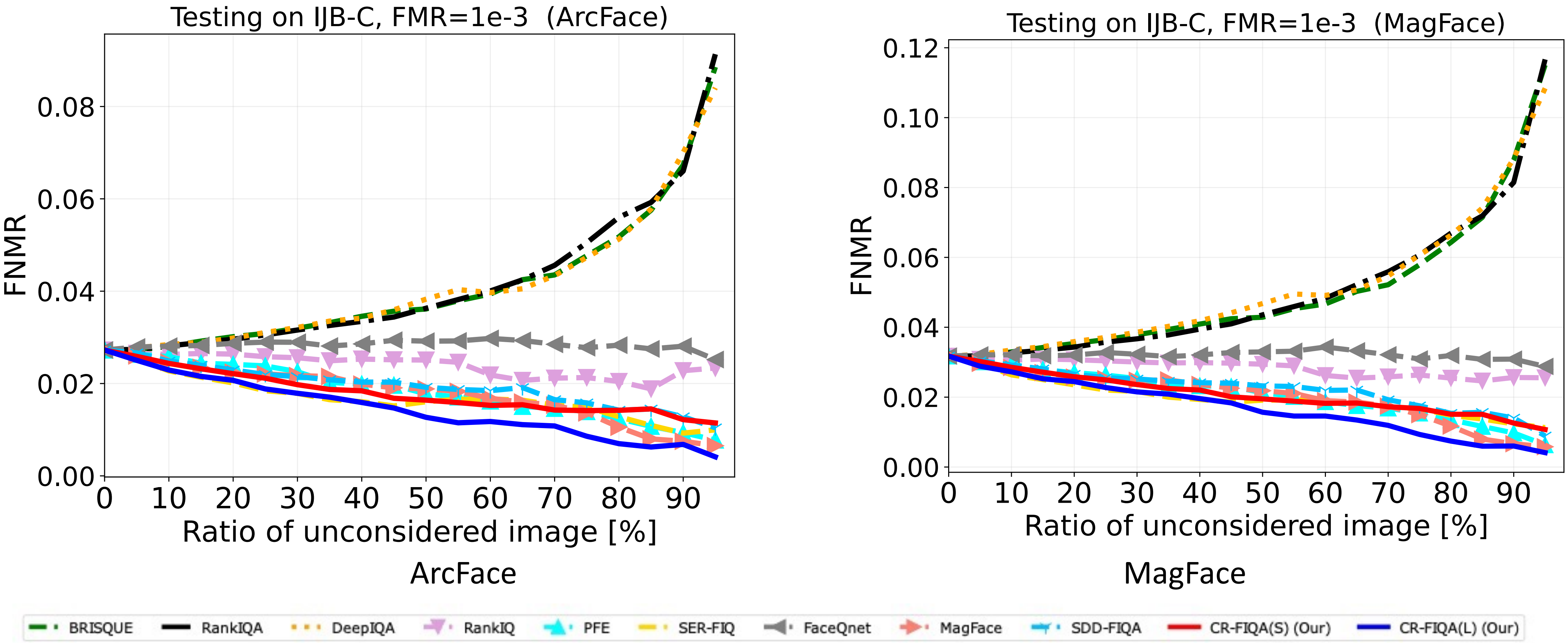


CR-FIQA: What did we achieve?

Comparisons with SOTA FIQ methods



ArcFace

MagFace

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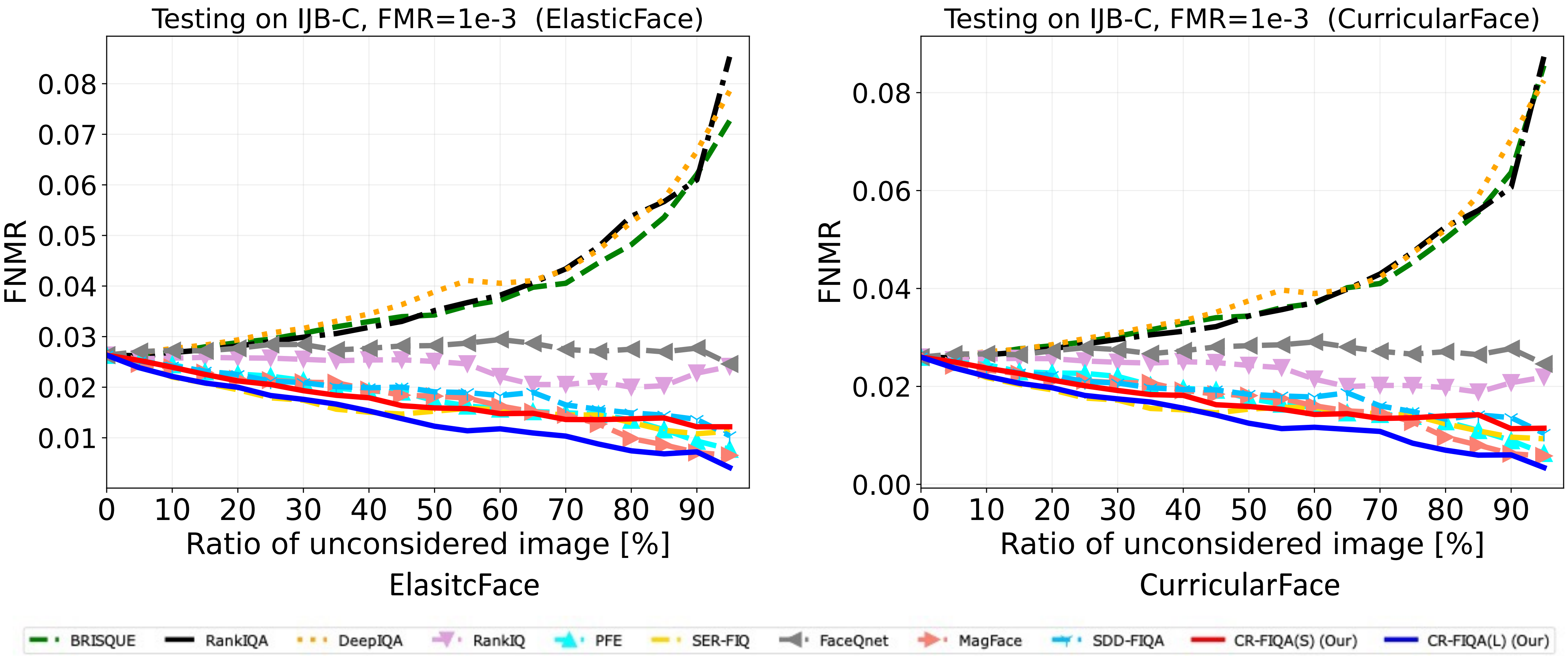

CR-FIQA: What did we achieve?

Comparisons with SOTA FIQ methods

FR		Method	Adience [6]		AgeDB-30 [31]		CFP-FP [33]		LFW [16]		CALFW [41]		CPLFW [40]		XQLFW [23]		IJB-C [27]	
			1e−3	1e−4	1e−3	1e−4	1e−3	1e−4	1e−3	1e−4	1e−3	1e−4	$1e^{-3}$	1e−4	1e−3	1e−4	1e−3	1e−4
ArcFace [5]	IQA	BRISQUE [29]	0.0565	0.1285	0.0400	0.0585	0.0343	0.0433	0.0043	0.0049	0.0755	0.0813	0.2558	0.3037	0.6680	0.7122	0.0381	0.0656
		RankIQA [26]	0.0400	0.0933	0.0372	0.0523	0.0301	0.0384	0.0039	0.0045	0.0846	0.0915	0.2437	0.2969	0.6584	0.7039	0.0385	0.0640
		DeepIQA [2]	0.0568	0.1372	0.0403	0.0523	0.0238	0.0292	0.0049	0.0056	0.0793	0.0850	0.2309	0.2856	0.5958	0.6458	0.0383	0.0640
	FIQA	RankIQ [4]	0.0353	0.0873	0.0322	0.0420	0.0152	0.0260	*0.0018*	*0.0024*	0.0608	0.0672	0.0633	0.0848	0.2789	0.3332	0.0227	0.0342
		PFE [34]	0.0212	0.0428	0.0172	0.0226	0.0092	0.0129	0.0023	0.0028	0.0647	0.0681	0.0450	0.0638	0.2302	0.2710	0.0176	0.0248
		SER-FIQ [36]	0.0223	0.0434	0.0167	0.0223	*0.0065*	*0.0103*	0.0023	0.0028	0.0595	0.0627	*0.0389*	0.0584	**0.1812***	**0.2295***	*0.0161*	*0.0241*
		FaceQnet [14, 15]	0.0346	0.0734	0.0197	0.0245	0.0240	0.0273	0.0022	0.0027	0.0774	0.0822	0.1504	0.1751	0.5829	0.6136	0.0270	0.0376
		MagFace [28]	*0.0207*	*0.0425*	*0.0156*	0.0198	0.0073	0.0105	**0.0016**	**0.0021**	*0.0568*	*0.0602*	0.0492	0.0642	0.4022	0.4636	0.0171	0.0254
		SDD-FIQA [32]	0.0248	0.0562	0.0186	0.0206	0.0122	0.0193	0.0021	0.0027	0.0641	0.0698	0.0517	0.0670	0.3090	0.3561	0.0186	0.0270
		CR-FIQA(S)(Our)	0.0241	0.0517	**0.0144**	**0.0187**	0.0090	0.0145	0.0020	0.0025	**0.0521**	**0.0554**	0.0391	*0.0567*	0.2377	0.2740	0.0171	0.0250
		CR-FIQA(L)(Our)	**0.0204**	**0.0353**	0.0159	*0.0189*	**0.0050**	**0.0082**	0.0023	0.0029	0.0616	0.0632	**0.0360**	**0.0515**	*0.2084*	*0.2441*	**0.0138**	**0.0207**
ElasticFace [3]	IQA	BRISQUE [29]	0.0644	0.1184	0.0375	0.0403	0.0281	0.0372	0.0034	0.0047	0.0726	0.0747	0.2641	0.4688	0.6343	0.6964	0.0357	0.0621
		RankIQA [26]	0.0433	0.0862	0.0374	0.0436	0.0269	0.0318	0.0033	0.0045	0.0810	0.0835	0.2325	0.4306	0.6189	0.6856	0.0366	0.0599
		DeepIQA [2]	0.0645	0.1203	0.0384	0.0411	0.0191	0.0256	0.0043	0.0056	0.0756	0.0772	0.2401	0.4541	0.5400	0.5832	0.0379	0.0590
	FIQA	RankIQ [4]	0.0400	0.0777	0.0309	0.0337	0.0149	0.0180	**0.0013**	**0.0020**	0.0598	0.0614	0.0581	0.0727	0.2468	0.2776	0.0226	0.0334
		PFE [34]	*0.0222*	*0.0381*	0.0163	0.0172	0.0088	0.0113	0.0018	0.0025	0.0628	0.0643	0.0419	0.0895	0.2112	0.2436	0.0171	0.0247
		SER-FIQ [36]	0.0240	0.0417	0.0163	0.0179	*0.0061*	*0.0085*	0.0021	0.0028	0.0574	0.0590	0.0387	0.0513	**0.1576***	**0.1868***	*0.0156*	*0.0235*
		FaceQnet [14, 15]	0.0369	0.0667	0.0194	0.0207	0.0227	0.0247	0.0021	0.0026	0.0763	0.0777	0.1420	0.2880	0.5549	0.5844	0.0263	0.0370
		MagFace [28]	0.0225	0.0385	0.0150	**0.0158**	0.0069	0.0095	*0.0014*	*0.0021*	*0.0553*	*0.0563*	0.0474	0.0597	0.3973	0.4282	0.0166	0.0243
		SDD-FIQA [32]	0.0277	0.0512	0.0187	0.0200	0.0098	0.0118	0.0019	0.0027	0.0624	0.0638	0.0493	0.0634	0.3052	0.3562	0.0183	0.0266
		CR-FIQA(S)(Our)	0.0257	0.0465	**0.0146**	0.0160	0.0070	0.0096	0.0015	0.0022	**0.0509**	**0.0522**	*0.0383*	*0.0502*	0.2093	0.2835	0.0167	0.0244
		CR-FIQA(L)(Our)	**0.0214**	**0.0357**	*0.0149*	*0.0159*	**0.0045**	**0.0065**	0.0018	0.0025	0.0594	0.0608	**0.0350**	**0.0462**	*0.1798*	*0.2060*	**0.0135**	**0.0203**

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			1e−3	1e−4	1e−3	1e−4	1e−3	1e−4	1e−3	1e−4	1e−3	1e−4	1e−3	1e−4	1e−3	1e−4	1e−3	1e−4
MagFace [28]	IQA	BRISQUE [29]	0.0594	0.1308	0.0442	0.0799	0.0422	0.0589	0.0043	0.0058	0.0758	0.0788	0.4649	0.6809	0.6911	0.7229	0.0462	0.0787
		RankIQA [26]	0.0407	0.0889	0.0370	0.0681	0.0369	0.0543	0.0041	0.0056	0.0829	0.0857	0.3251	0.6475	0.6706	0.7046	0.0461	0.0750
		DeepIQA [2]	0.0571	0.1302	0.0417	0.0721	0.0322	0.0545	0.0048	0.0059	0.0787	0.0809	0.3672	0.6632	0.6162	0.6519	0.0474	0.0765
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		SER-FIQ [36]	0.0233	0.0451	0.0185	0.0293	*0.0080*	0.0139	0.0025	0.0033	0.0590	0.0607	*0.0397*	*0.0821*	**0.2139***	**0.2562***	*0.0189*	*0.0270*
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		MagFace [28]	*0.0212*	*0.0417*	**0.0159**	0.0247	0.0085	0.0129	**0.0017**	**0.0022**	*0.0562*	*0.0578*	0.0506	0.0887	0.4478	0.4900	0.0195	0.0279
		SDD-FIQA [32]	0.0253	0.0562	0.0216	0.0305	0.0146	0.0201	0.0021	*0.0027*	0.0643	0.0657	0.0525	0.1188	0.3404	0.3928	0.0215	0.0307
		CR-FIQA(S)(Our)	0.0244	0.0507	*0.0165*	**0.0234**	0.0102	*0.0121*	0.0020	0.0028	**0.0516**	**0.0528**	0.0409	0.0840	0.2670	0.3336	0.0198	0.0284
		CR-FIQA(L)(Our)	**0.0211**	**0.0372**	0.0174	*0.0235*	**0.0062**	**0.0080**	0.0023	0.0028	0.0614	0.0628	**0.0374**	**0.0679**	*0.2369*	*0.2839*	**0.0162**	**0.0236**
CurricularFace [17]	IQA	BRISQUE [29]	0.0502	0.1095	0.0433	0.0491	0.0323	0.0357	0.0041	0.0047	0.0755	0.0784	0.2709	0.5057	0.6146	0.6336	0.0362	0.0589
		RankIQA [26]	0.0359	0.0752	0.0394	0.0510	0.0298	0.0356	0.0039	0.0045	0.0806	0.0865	0.2346	0.4654	0.5900	0.6212	0.0361	0.0556
		DeepIQA [2]	0.0492	0.1070	0.0407	0.0476	0.0227	0.0278	0.0050	0.0056	0.0764	0.0786	0.2488	0.4961	0.5165	0.5526	0.0376	0.0571
	FIQA	RankIQ [4]	0.0314	0.0715	0.0365	0.0417	0.0186	0.0249	*0.0018*	*0.0024*	0.0590	0.0640	0.0541	0.0730	0.2449	0.2880	0.0220	0.0320
		PFE [34]	**0.0198**	0.0365	0.0197	0.0227	0.0100	0.0134	0.0024	0.0028	0.0630	0.0657	0.0402	0.0983	0.1982	0.2220	0.0170	0.0238
		SER-FIQ [36]	0.0211	0.0381	0.0167	**0.0193**	*0.0074*	*0.0111*	0.0025	0.0030	0.0587	0.0610	0.0356	0.0520	**0.1558***	**0.1866***	*0.0153*	*0.0228*
		FaceQNet [14, 15]	0.0326	0.0626	0.0221	0.0267	0.0226	0.0274	0.0022	0.0027	0.0767	0.0799	0.1384	0.3229	0.5035	0.5411	0.0259	0.0354
		MagFace [28]	*0.0200*	*0.0364*	0.0167	0.0195	0.0078	0.0111	**0.0016**	**0.0021**	*0.0563*	*0.0590*	0.0449	0.0607	0.3758	0.4178	0.0163	0.0232
		SDD-FIQA [32]	0.0230	0.0462	0.0219	0.0254	0.0138	0.0185	0.0021	0.0027	0.0637	0.0675	0.0465	0.0671	0.2649	0.3053	0.0178	0.0254
		CR-FIQA(S)(Our)	0.0227	0.0446	**0.0156**	*0.0198*	0.0097	0.0148	0.0020	0.0025	**0.0513**	**0.0534**	*0.0340*	*0.0501*	0.2101	0.2470	0.0165	0.0234
		CR-FIQA(L)(Our)	**0.0198**	**0.0336**	*0.0162*	0.0200	**0.0054**	**0.0080**	0.0023	0.0029	0.0605	0.0618	**0.0324**	**0.0462**	*0.1716*	*0.2318*	**0.0134**	**0.0194**

CR-FIQA: What did we achieve?

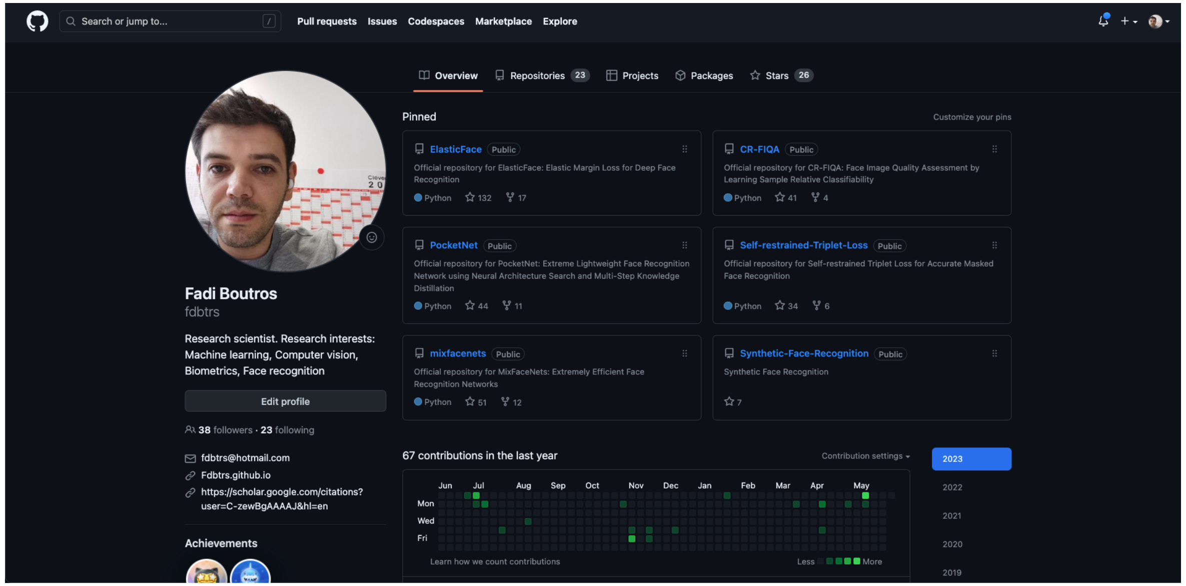
Evaluation: quality scores as an embedding weighting term

Quality Estimation		1:1 mixed Verification: TAR (%) at											
		ArcFace [5]			ElasticFace [3]			MagFace [28]			CurricularFace [17]		
		FAR=1e-6	FAR=1e-5	FAR=1e-4	FAR=1e-6	FAR=1e-5	FAR=1e-4	FAR=1e-6	FAR=1e-5	FAR=1e-4	FAR=1e-6	FAR=1e-5	FAR=1e-4
	-	*89.85*	94.47	96.28	89.15	94.54	96.49	85.67	93.08	96.65	90.46	94.89	96.58
IQA	BRISQUE [29]	86.65	93.62	95.98	85.68	93.51	95.65	81.11	90.64	94.82	88.16	93.98	96.29
	RankIQA [26]	86.37	93.61	95.83	86.71	93.46	96.00	80.78	90.75	94.86	88.16	94.11	96.22
	DeepIQA [2]	81.97	91.64	94.67	78.93	91.59	94.81	73.53	86.34	92.90	82.65	92.04	95.00
FIQA	RankIQ [4]	88.78	94.42	96.20	88.88	94.64	96.45	85.63	92.66	95.70	90.00	94.93	96.53
	PFE [35]	89.50	94.51	96.31	89.10	94.67	96.51	84.93	92.44	95.60	90.36	95.04	96.54
	SER-FIQ [36]	89.74	94.65	96.32	*90.05*	94.79	96.57	86.02	93.35	95.80	90.66	95.11	96.58
	FaceQNet [14, 15]	87.87	94.04	96.12	86.26	94.09	96.25	82.91	90.56	95.03	89.61	94.65	96.36
	MagFace [28]	89.49	94.41	96.22	89.37	94.69	96.46	85.75	92.71	95.54	90.34	95.02	96.50
	SDD-FIQA [32]	89.39	94.61	96.34	88.07	94.82	96.49	84.69	92.83	95.73	89.91	*95.12*	*96.63*
	CR-FIQA(S)(Our)	89.59	**94.78**	*96.35*	**90.30**	**94.97**	**96.63**	*86.45*	*93.48*	**95.95**	**90.82**	**95.13**	**96.64**
	CR-FIQA(L)(Our)	**90.16**	*94.75*	**96.36**	90.00	*94.92*	*96.58*	**87.12**	**93.67**	*95.90*	*90.79*	*95.12*	96.58

The verification performances of CR-FIQA (L) as feature extraction model

Model	LFW Acc (%)	AgeDB-30 Acc (%)	CFP-FP Acc (%)	CALFW Acc (%)	CPLFW Acc (%)	IJB-C TAR at FAR1e-4
ArcFace [5]	99.82	98.15	98.27	95.45	92.08	96.28
ElasticFace [3]	99.80	98.35	98.67	96.17	93.27	96.49
MagFace [16]	99.83	98.17	98.46	96.15	92.87	96.65
CurricularFace [11]	99.80	98.32	98.37	96.20	93.13	96.58
CR-FIQA (L) (Ours)	99.80	98.17	98.49	96.15	92.90	96.23

Code and pretrained models



https://github.com/fdbtrs/CR-FIQA

Fadi Boutros, Meiling Fang, Marcel Klemt, Biying Fu, Naser Damer:
CR-FIQA: Face Image Quality Assessment by Learning Sample Relative Classifiability. CVPR 2023: 5836-5845

Take home messages:

- CR-FIQA training paradigm **simultaneously** learns to **optimize** the **class center** while **learning** to predict **sample relative classifiability**

- Demonstrate the effectiveness of our CR-FIQA under two protocols (small and large) based on the training dataset and the training model architecture

  - ResNet50 (43.6m parameters) trained on CASIA-WebFace (0.5m images)
  - ResNet100 (65.2 parameters) trained on MS1MV2 (5.8m images)

- Provide one of the most extensive evaluation experiments, outperforming SOTA FIQ methods

  - 8 benchmarks
  - Comparisons with 9 SOTA approaches
- Open-source implementation

CR-FIQA: Face Image Quality Assessment by Learning Sample Relative Classifiability

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European Association for Biometrics / Face Image Quality Workshop

07-09.11.2023

Virtual Event