Unified Negative Pair Generation toward Well-Discriminative Feature Space for Face Recognition

Junuk Jung, Seonhoon Lee, Heung-Seon Oh*, Yongjun Park, Joochan Park, Sungbin Son
{rnans33, karma1002, ohhs, qkr2938, green669, sbson0621}@koreatech.ac.kr
Korea University of Technology and Education (KOREATECH)

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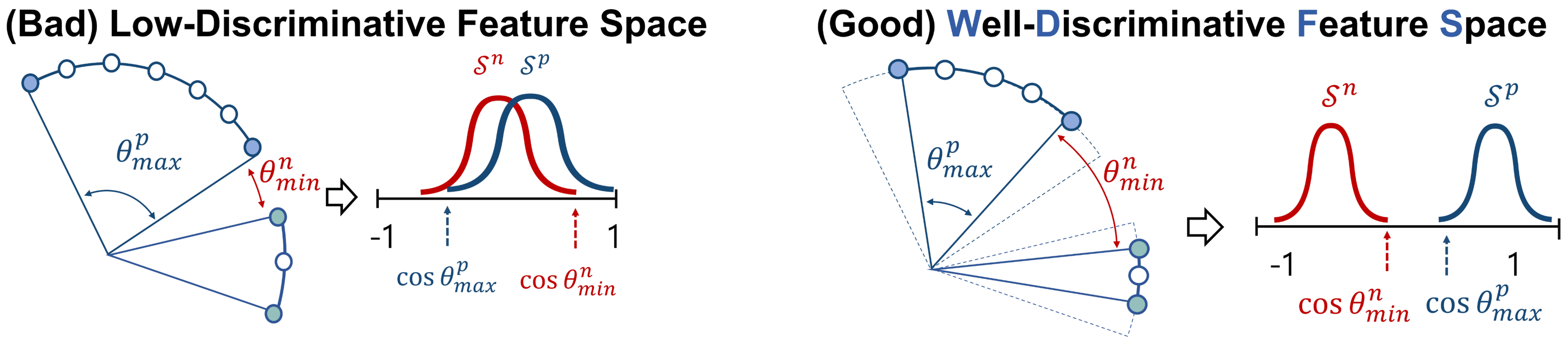
Definition

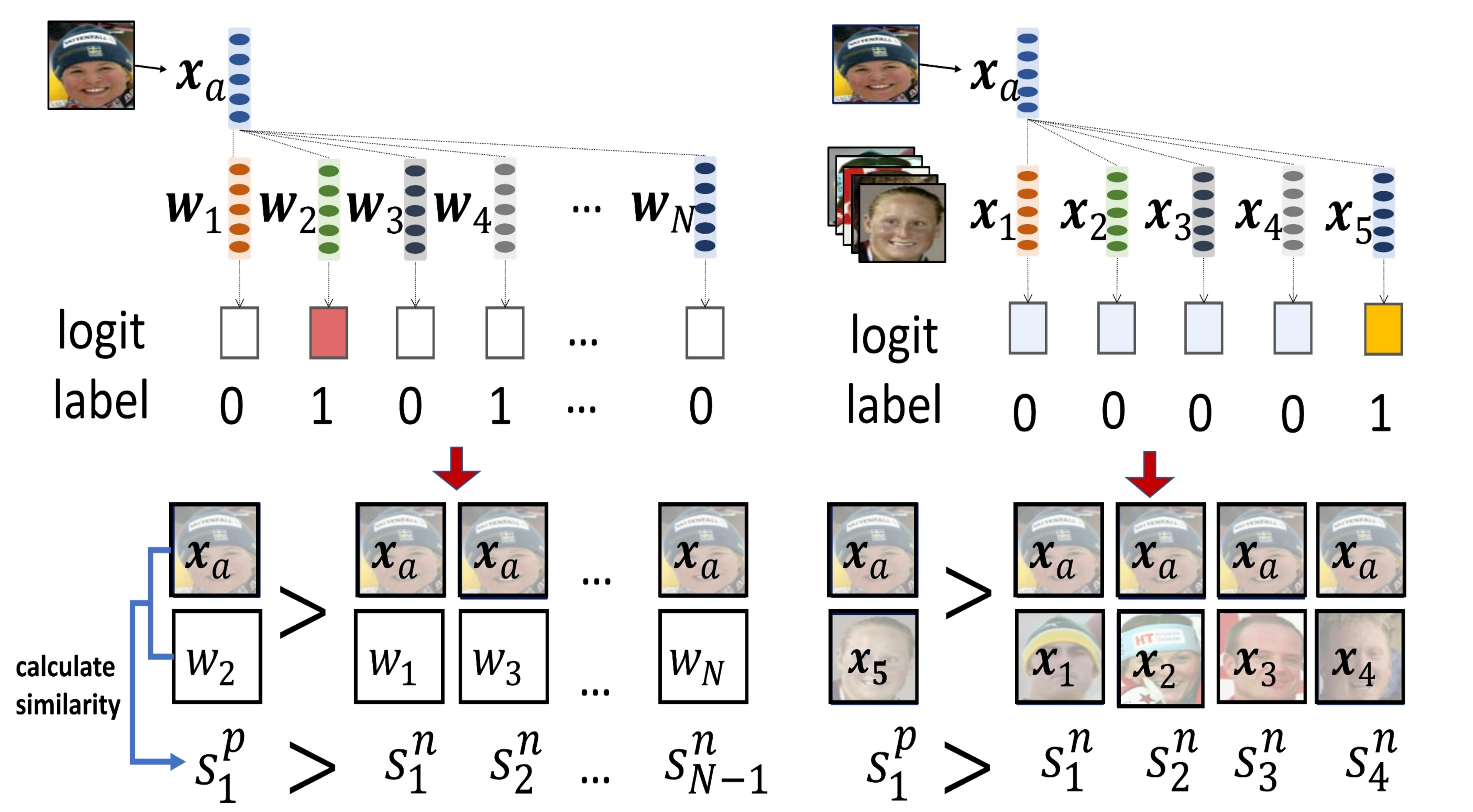
(Bad) Low-Discriminative Feature Space | (Good) Well-Discriminative Feature Space



Definition of WDFS: The space that for **all negative pair similarities,** s^n are lower than **any positive pair similarities,** s^p

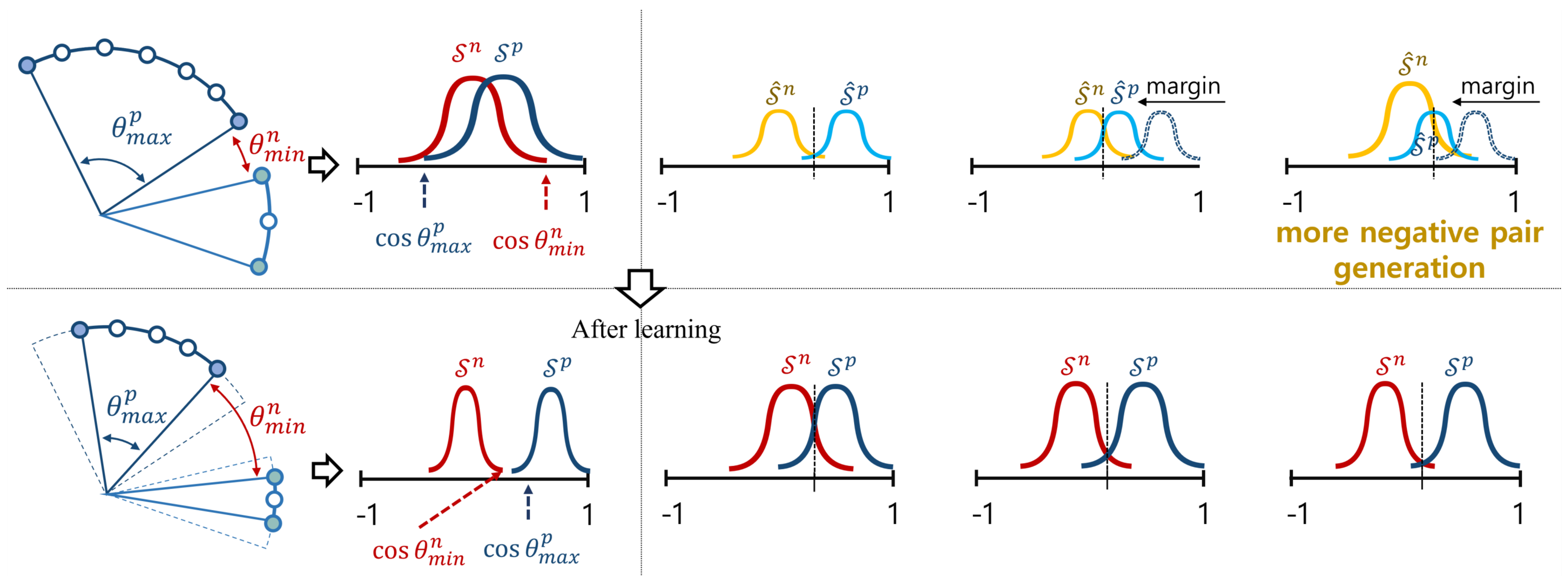
Motivation

Classification Loss with CLPG | Metric Loss with MLPG



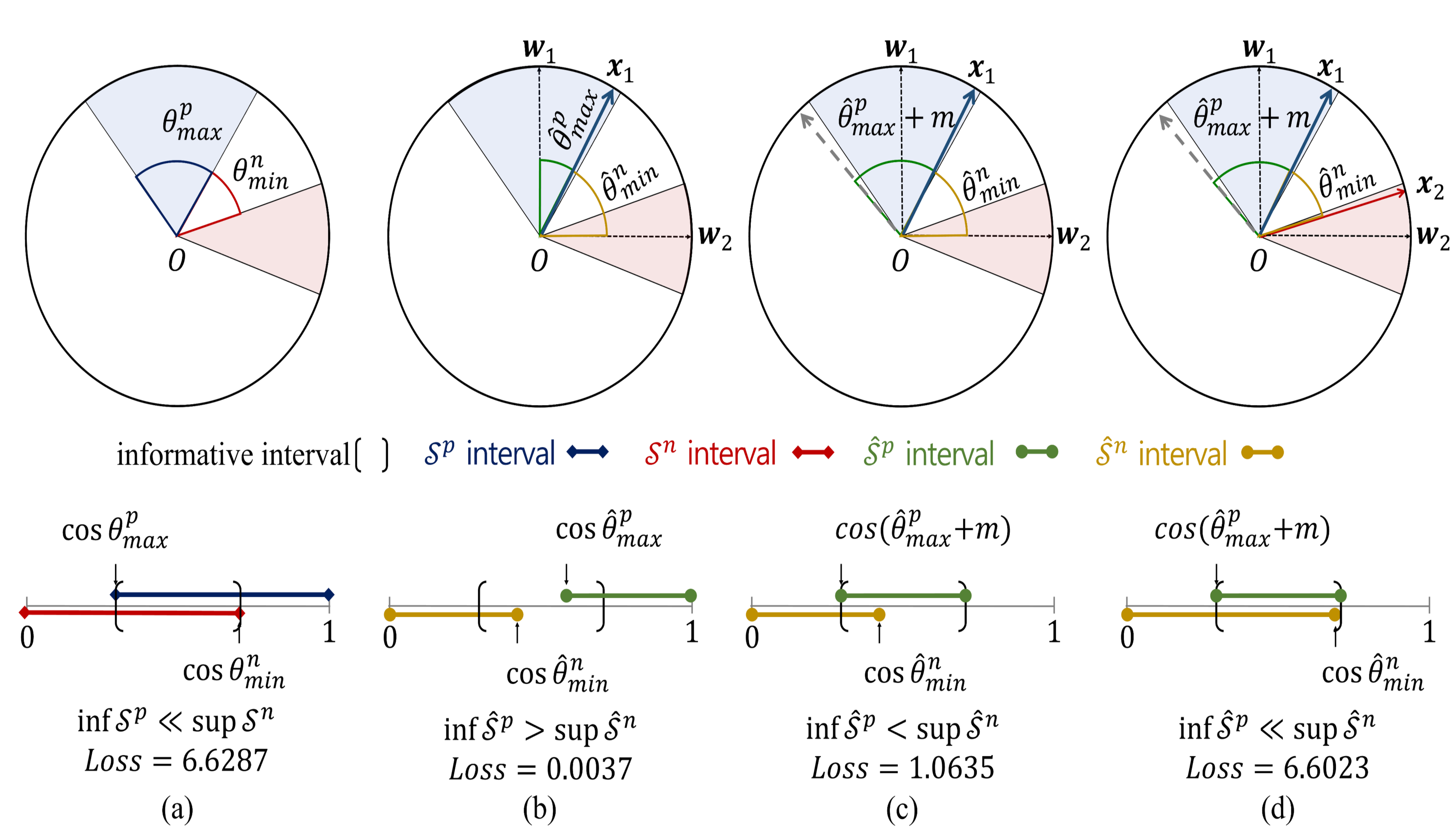
	Pros	Cons
CLPG	x_a can be matched with all weight vectors at once	x_a is only matched with weight vectors, **not real face features**
MLPG	x_a can be matched with **various real face features**	Making pairs can be **biased**

- CLPG and MLPG lack **the capability of balanced sampling** for WDFS.
- Both are complementary relations, so we unify two methods.

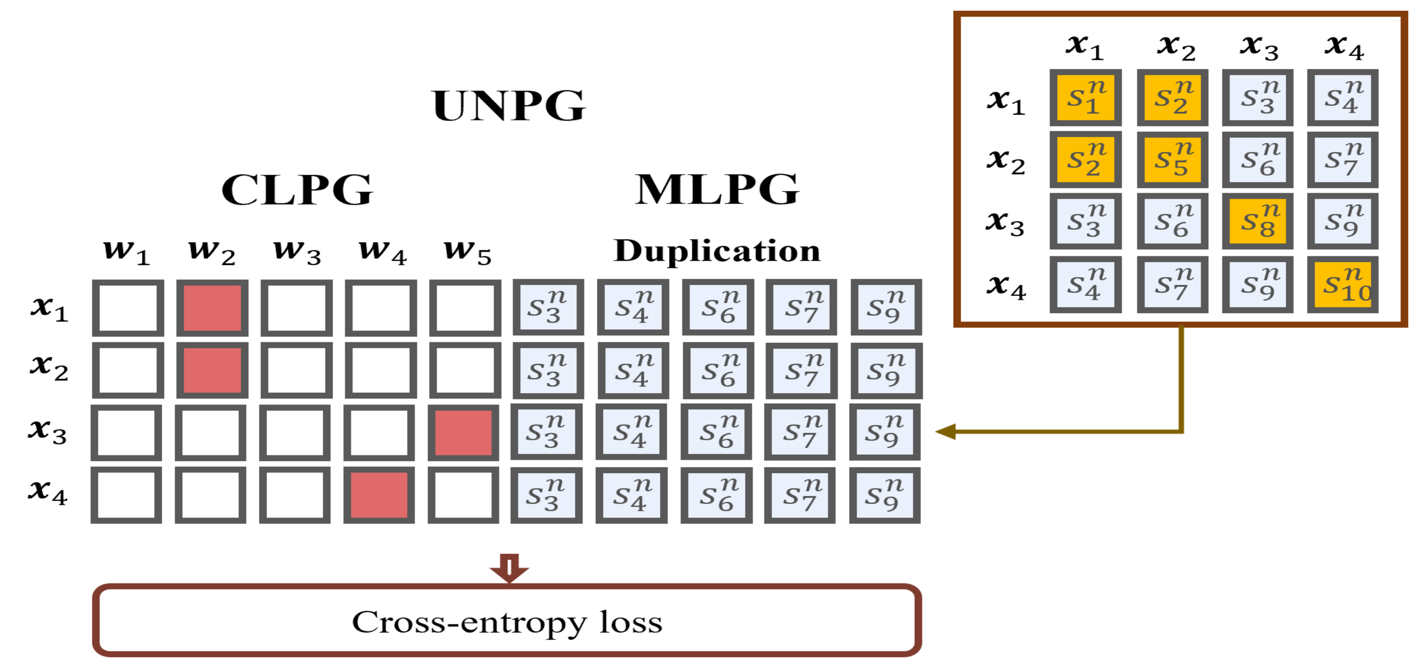


(a) Well-discriminative Feature Space (b) Softmax loss (c) Margin loss (d) Ours

- The **UNPG** can make up for **"biases"** in MLPG and **"only matched with weight vectors"** in CLPG under **the unified view.**
- It makes better chances for learning **various negative pairs**.

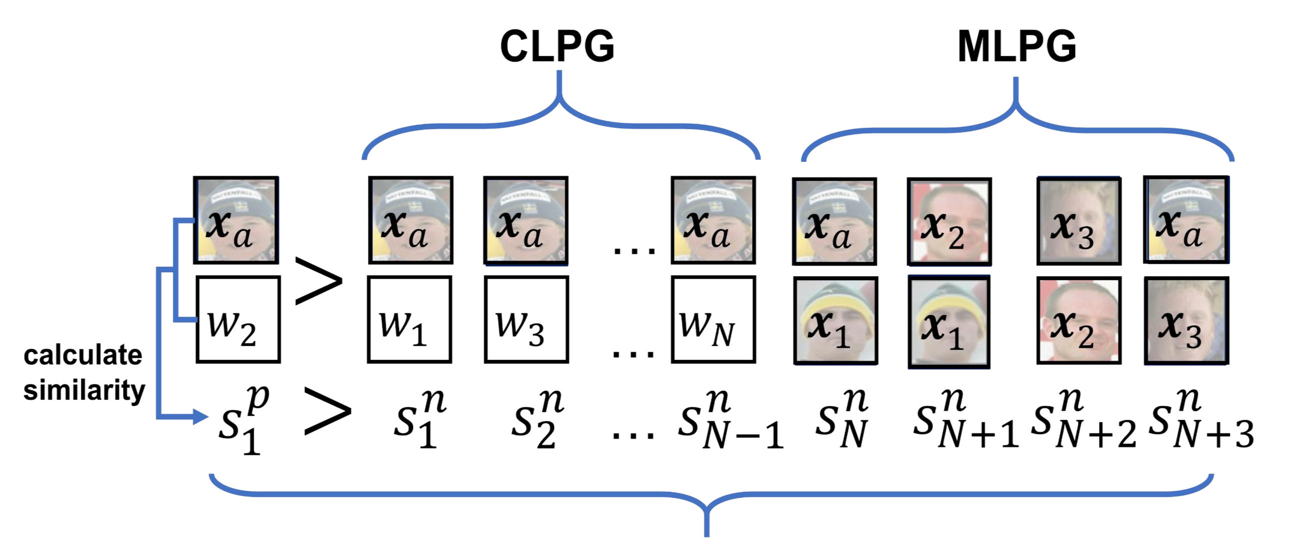


Proposed Methods



cosine similarity of positive pairs in $\mathcal{P}^{cl}$ or $\mathcal{P}^{ml}$

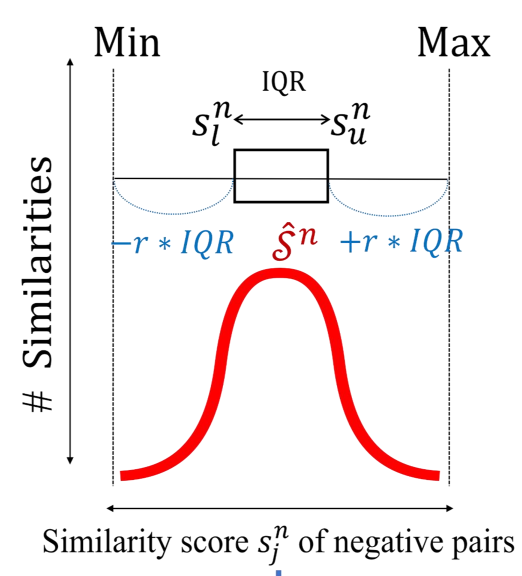
cosine similarity of negative pairs in $\mathcal{N}^{cl}$ or $\mathcal{N}^{ml}$



viewing and **integrating** CLPG and MLPG in UNPG

$$L_i^{uni} = -\log \frac{e^{\gamma s_i^p}}{e^{\gamma s_i^p} + \sum_{j=1}^{Lcl} e^{\gamma s_j^n} + \sum_{j=1}^{Lml} e^{\gamma s_k^n}}$$

IQR=Interquartile range



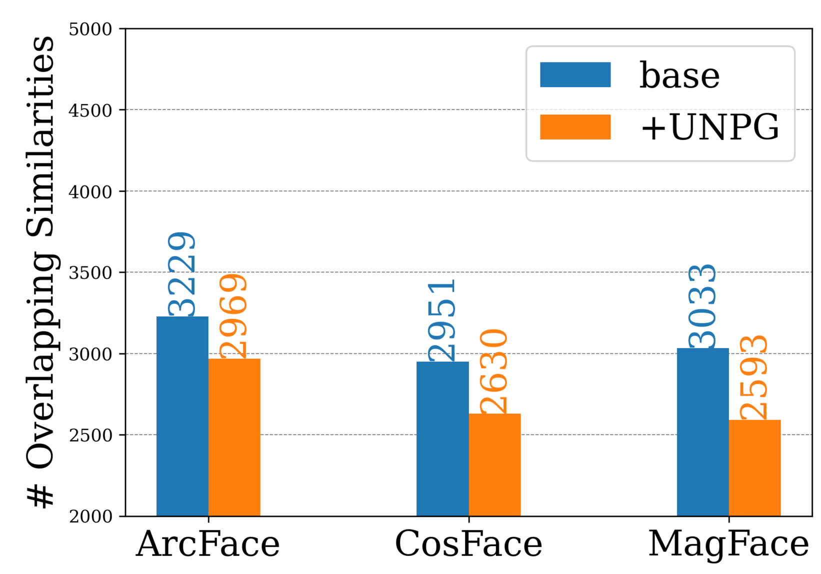
Filtering negative pairs

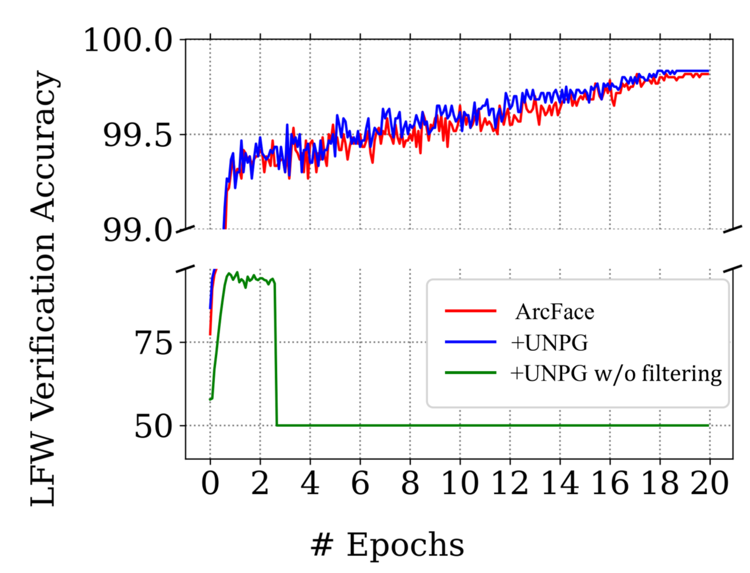
Experiments

Method	Backbone	IJB-B(TAR@FAR)					IJB-C(TAR@FAR)				
		1e-6	1e-5	1e-4	1e-3	1e-2	1e-6	1e-5	1e-4	1e-3	1e-2
VGGFace2*[2]	R50	-	67.10	80.00	-	-	-	74.70	84.00	-	-
Circle-loss*[30]	R34	-	-	-	-	-	-	86.78	93.44	96.04	-
Circle-loss*[30]	R100	-	-	-	-	-	-	89.60	93.95	**96.29**	-
ArcFace*[5]	R100	-	-	94.20	-	-	-	-	95.60	-	-
MagFace*[20]	R100	**42.32**	**90.36**	**94.51**	-	-	**90.24**	**94.08**	**95.97**	-	-
Triplet-loss	R34	4.42	12.57	32.65	61.33	88.78	4.04	15.32	36.86	66.46	90.77
contrastive-loss	R34	33.10	59.40	72.18	81.98	90.11	57.84	66.41	76.16	85.03	92.21
CosFace[36]	R34	39.70	87.47	93.55	95.71	97.05	85.95	92.57	95.23	96.81	97.94
Cos+UNPG	R34	**43.33**	87.51	93.58	**95.96**	97.24	87.84	92.49	**95.33**	**96.94**	**98.06**
ArcFace	R34	40.61	86.28	93.38	95.74	97.22	85.47	92.21	95.08	96.79	97.94
Arc+Triplet	R34	38.31	86.46	93.22	95.72	97.28	86.40	92.19	94.97	96.68	97.94
Arc+Contrastive	R34	38.07	86.54	93.03	95.61	**97.33**	85.21	92.54	94.86	96.60	98.01
Arc+UNPG	R34	40.27	**88.05**	**93.66**	**95.96**	97.17	**87.99**	**93.02**	**95.33**	96.88	97.92
CosFace	R100	42.27	89.38	94.39	96.17	97.35	86.56	94.42	96.35	**97.57**	98.26
Cos+UNPG	R100	**49.13**	90.61	94.99	96.50	97.36	86.95	94.48	**96.39**	**97.57**	98.24
ArcFace	R100	40.68	89.99	94.89	96.40	97.59	86.57	93.93	96.25	97.43	98.31
Arc+UNPG	R100	42.08	91.76	95.16	96.47	97.62	89.64	94.73	96.37	97.51	**98.32**
MagFace	R100	43.71	89.03	93.99	96.11	97.32	87.19	93.30	95.54	97.00	98.05
Mag+UNPG	R100	46.33	**90.93**	**95.21**	96.50	97.63	**90.01**	**94.70**	96.38	97.51	**98.32**

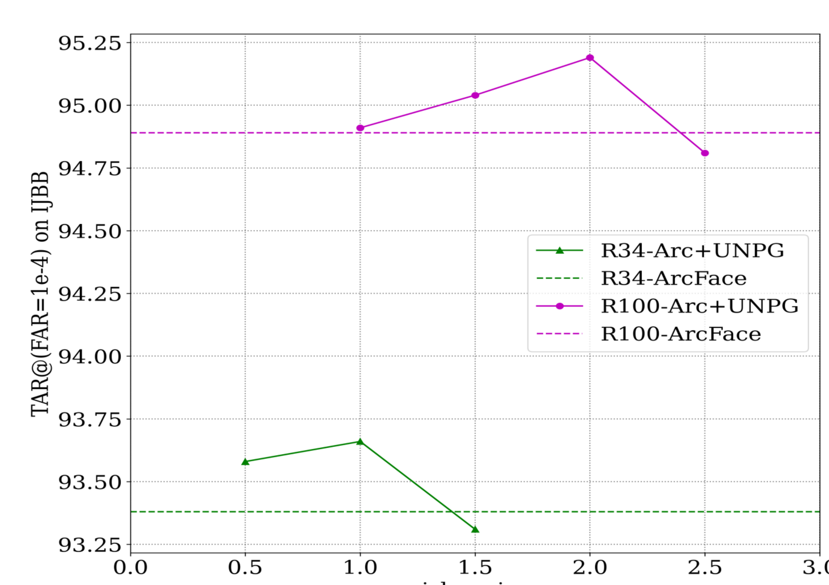
- Verification accuracy of TAR@FAR on IJB-B and IJB-C. "*" indicates results from the original paper

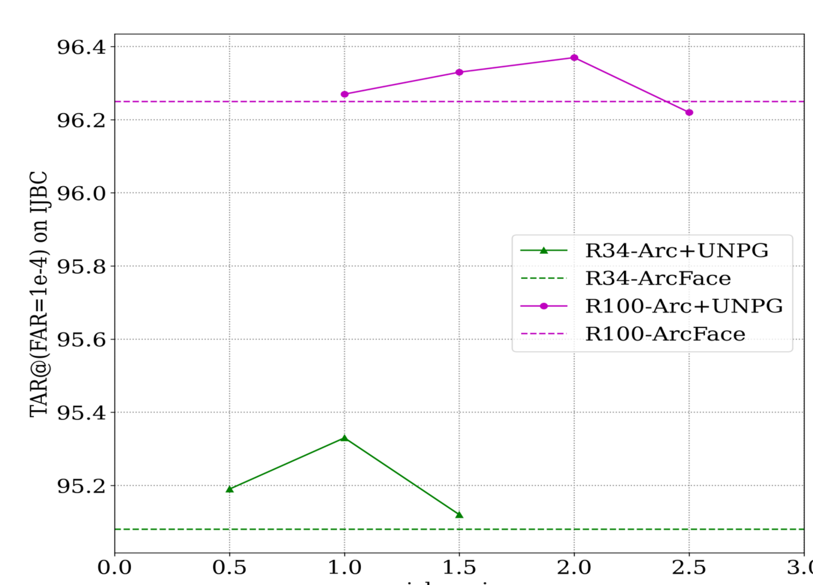
Analysis





- UNPG makes **less overlap** between negative and positive similarity sets.
- **Filtering negative pairs** stabilizes the learning process.





- **Analysis of scale factor** r over ResNet34 and ResNet100