Revealing Reliable Signatures by Learning Top-Rank Pairs

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Background – signature verification

- Signature verification
  - Writer-dependent
  - **Writer-independent**

?

?

?

Arsène Lupin

Arsène Lupin

Arsène Lupin

G Genuine signature

F Forgery signature

? Unknown signature

Reference G

?

Writer-independent classifier

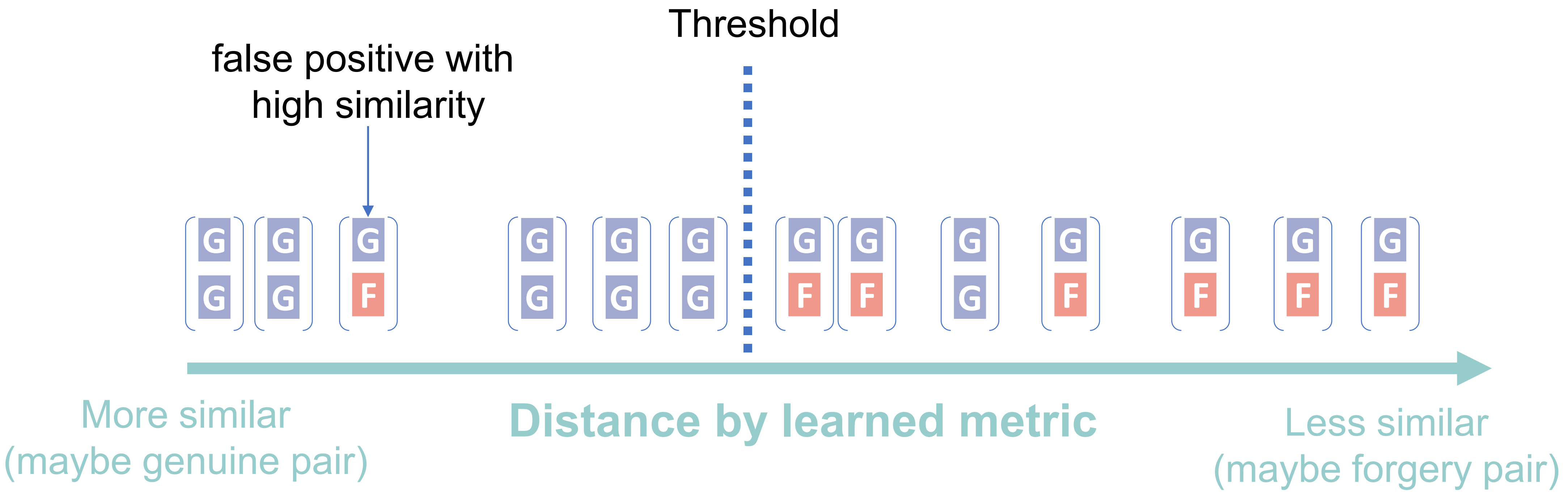
? is a G according to the Reference G

? is a F according to the Reference G

- **Higher reliability is needed**

However, typical metric learning methods can not always achieve the high reliability…

- Conventional methods aim at optimizing classification performance, while allowing **some mistakes** ← **they matter!**
  - **Metric learning** (optimizing the distance between samples)



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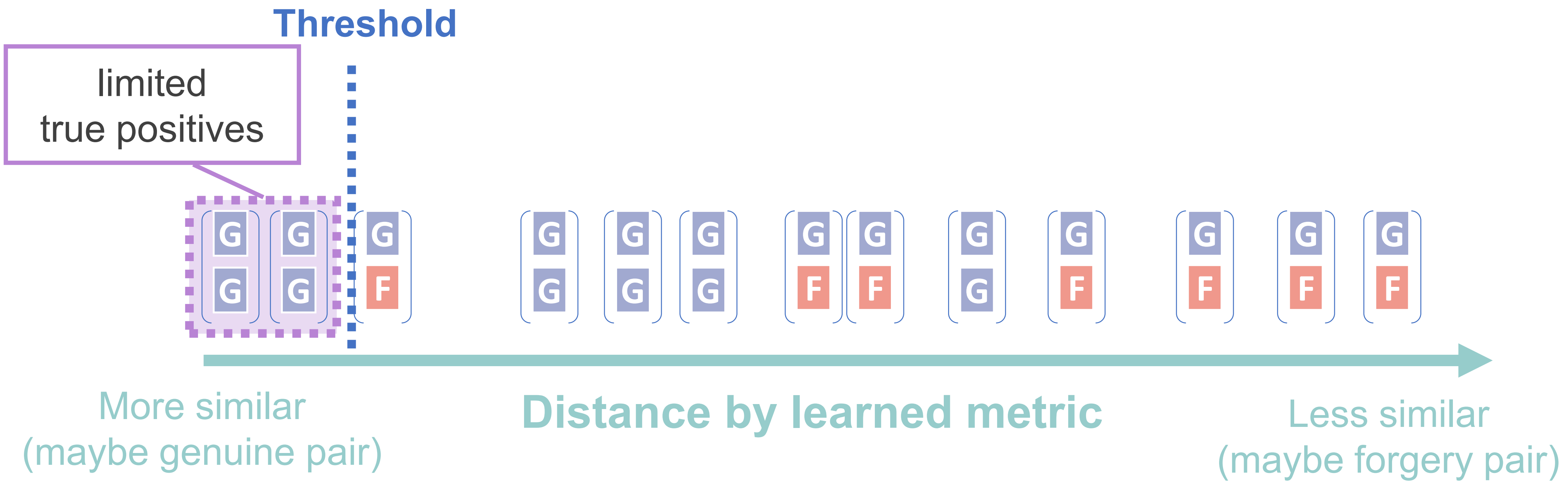
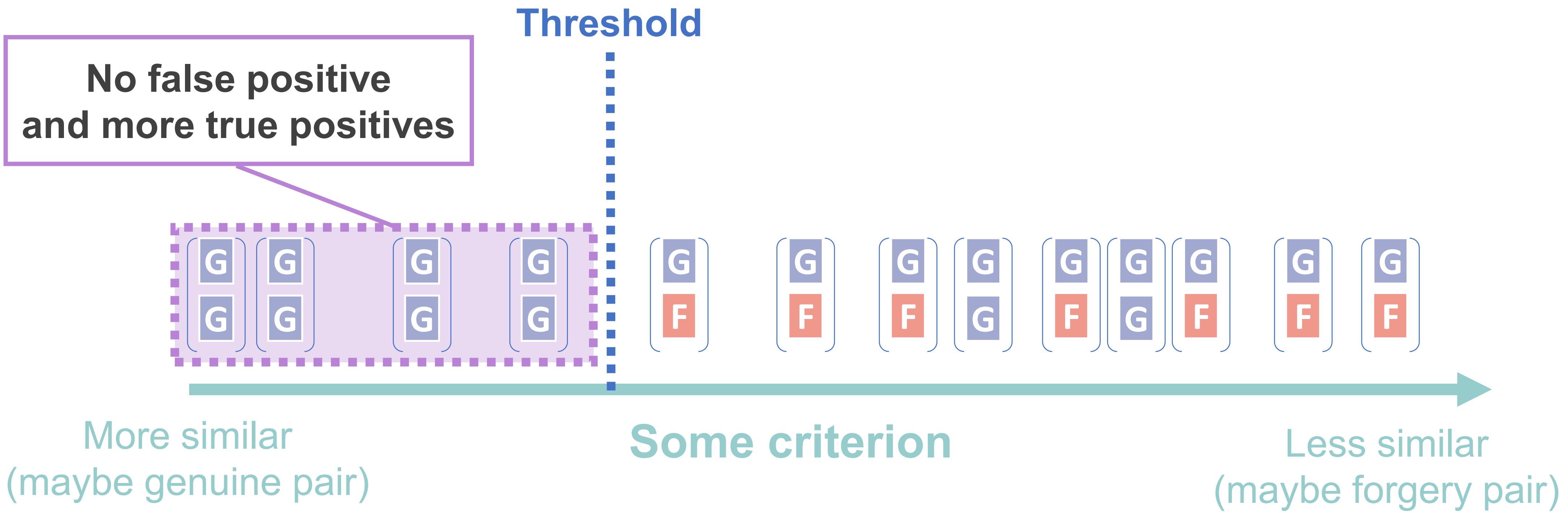


Purpose

- A new objective for more reliable “positives”
- **More reliable “positives” = Higher reliability**



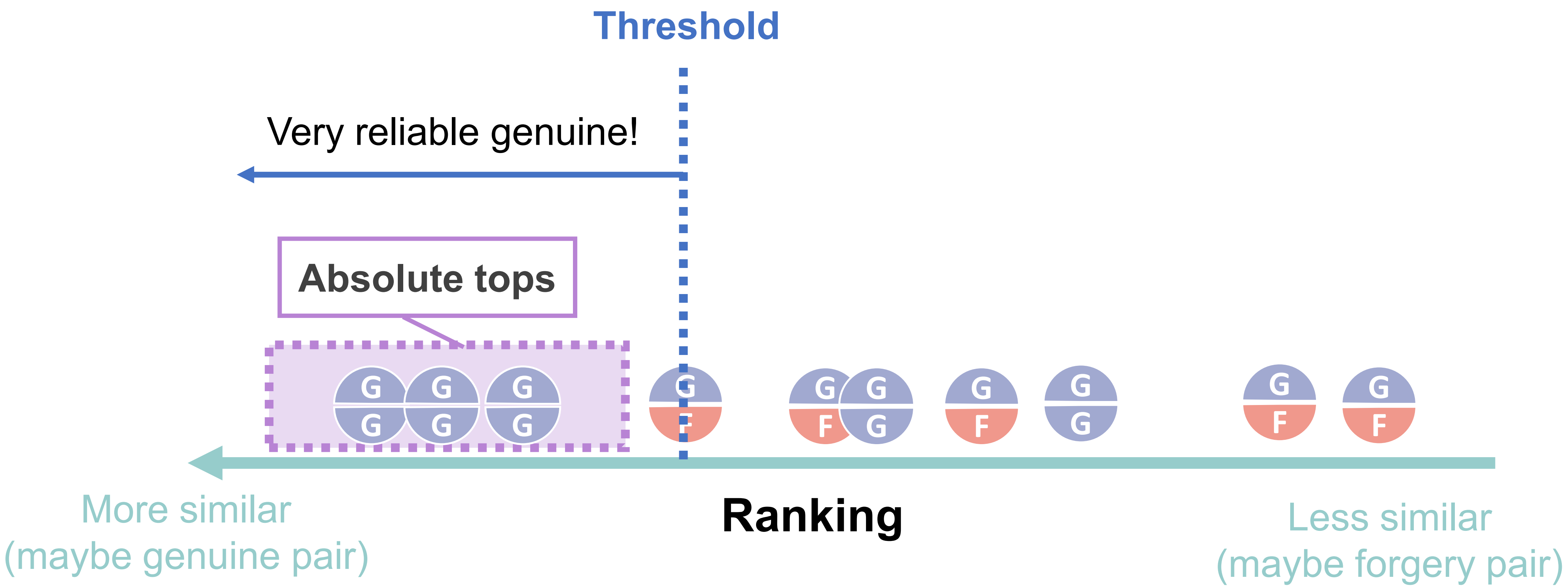
Idea 1: Ranking of paired samples

- **Not distance between samples, but ranking of each (paired) sample**

- **Typical ranking: More G-G samples should be ranked higher than G-F samples**

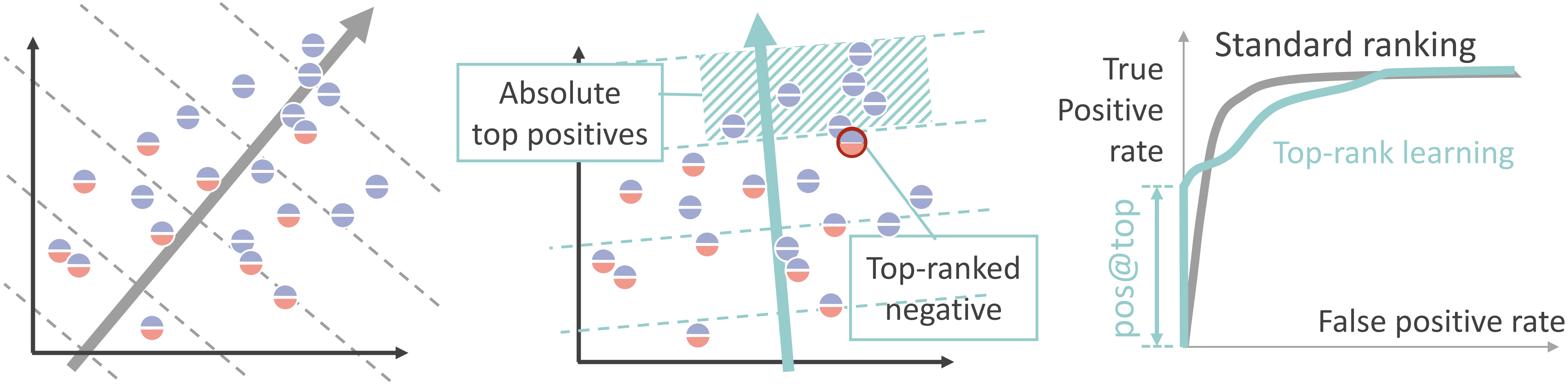
Idea 2: Top-rank learning

- "Push" more G-G samples to be top-ranked



Typical ranking vs top-rank: details

- Typical (Bipartite) Ranking = AUC maximization
- Top-rank learning = **pos@top** maximization



(a) Bipartite ranking[1]

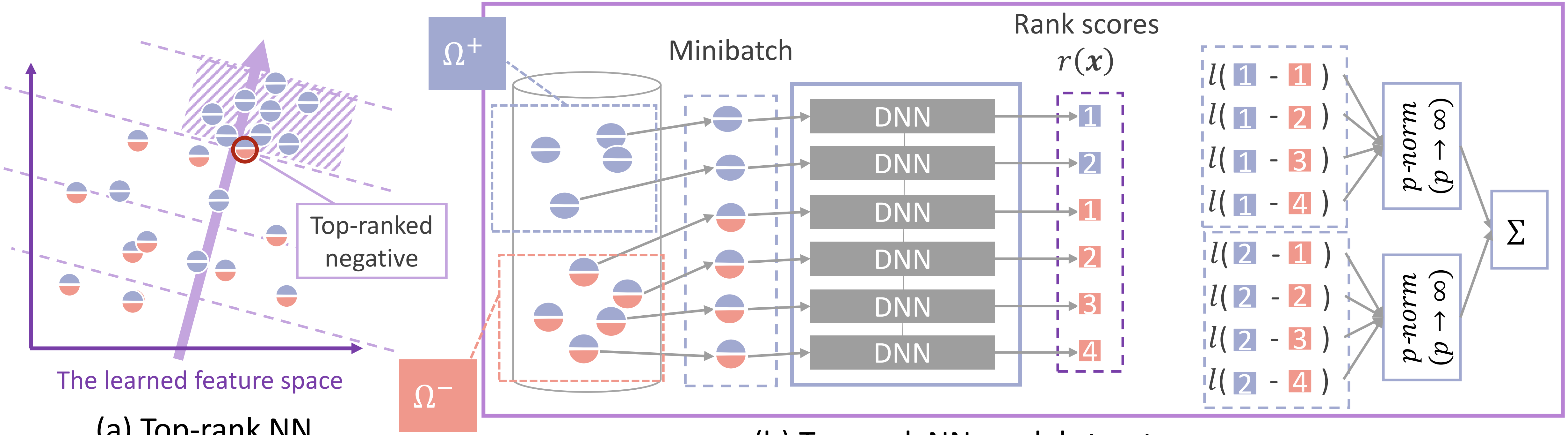
(b) Top-rank learning[2]

(c) Difference in ROCs

The objective function of (b): $pos@top = \frac{1}{m}\sum_{i=1}^{m} I\left(r(x_i^+) > \max_{1\le j\le n} r(x_j^-)\right)$

Learning top-rank pairs – top-rank NN[3]

- The learning objective and the structure of top-rank NN



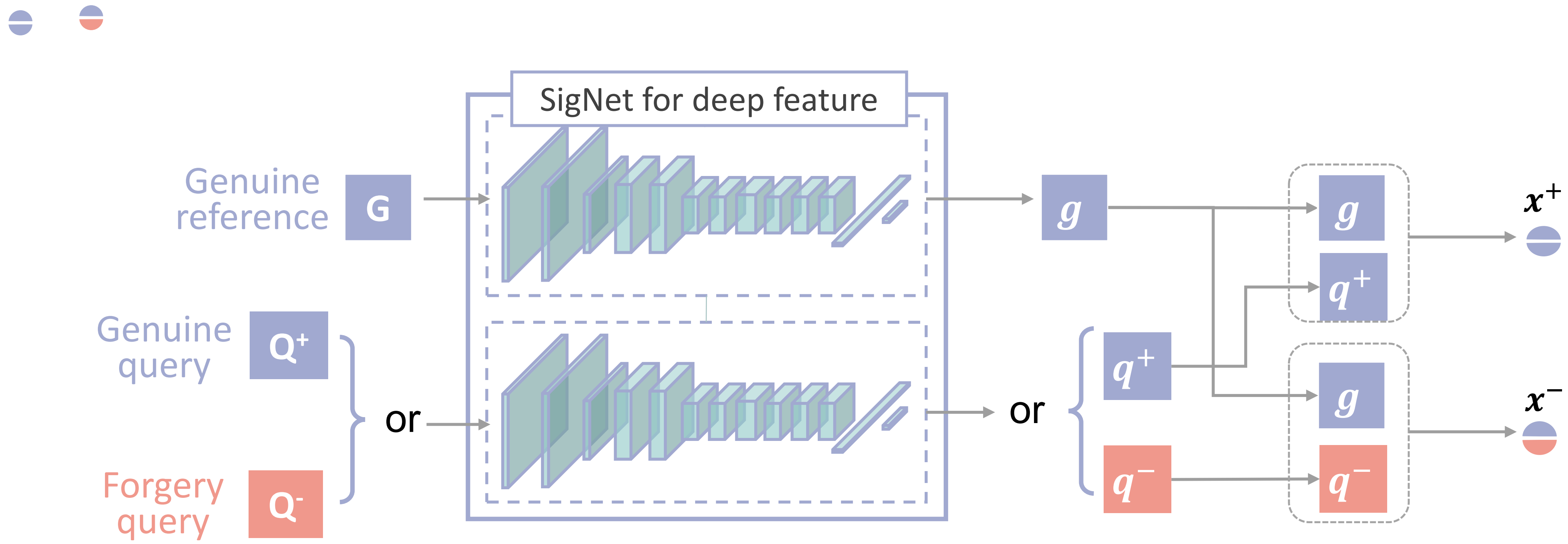
(a) Top-rank NN

(b) Top-rank NN model structure

$$L_{TopRank}(\Omega^+, \Omega^-) = \frac{1}{m}\sum_{i=1}^{m}\left(\sum_{j=1}^{n}\left(l\left(r(x_i^+) - r(x_j^-)\right)\right)^p\right)^{\frac{1}{p}}$$

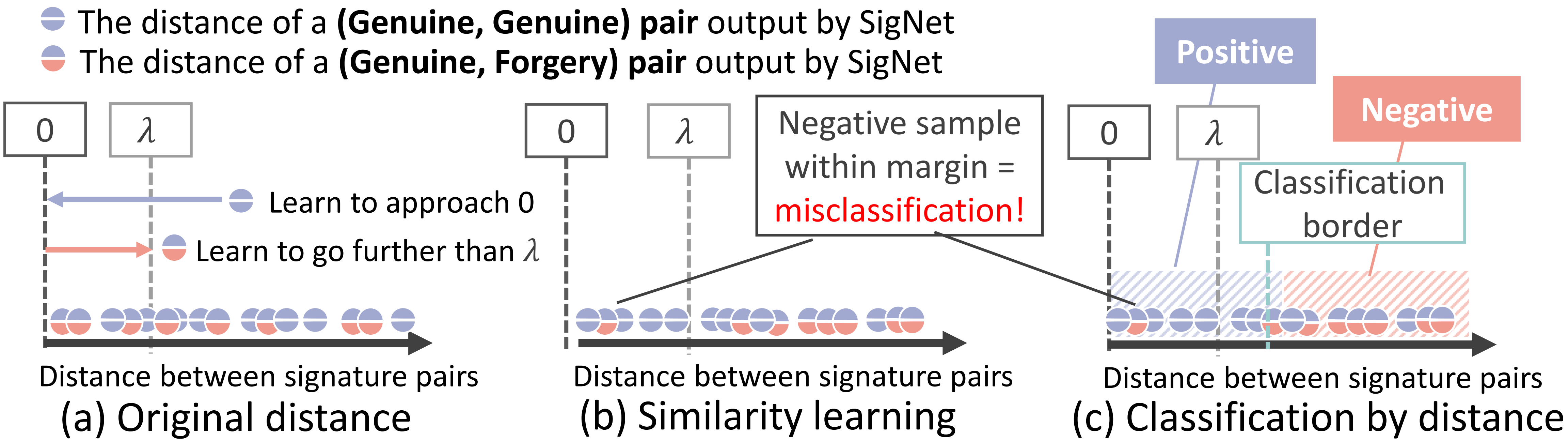
Learning top-rank pairs – pairing

- SigNet[4]
- Concatenate two feature vectors (g and q) into a single vector



Learning top-rank pairs – learning mechanism

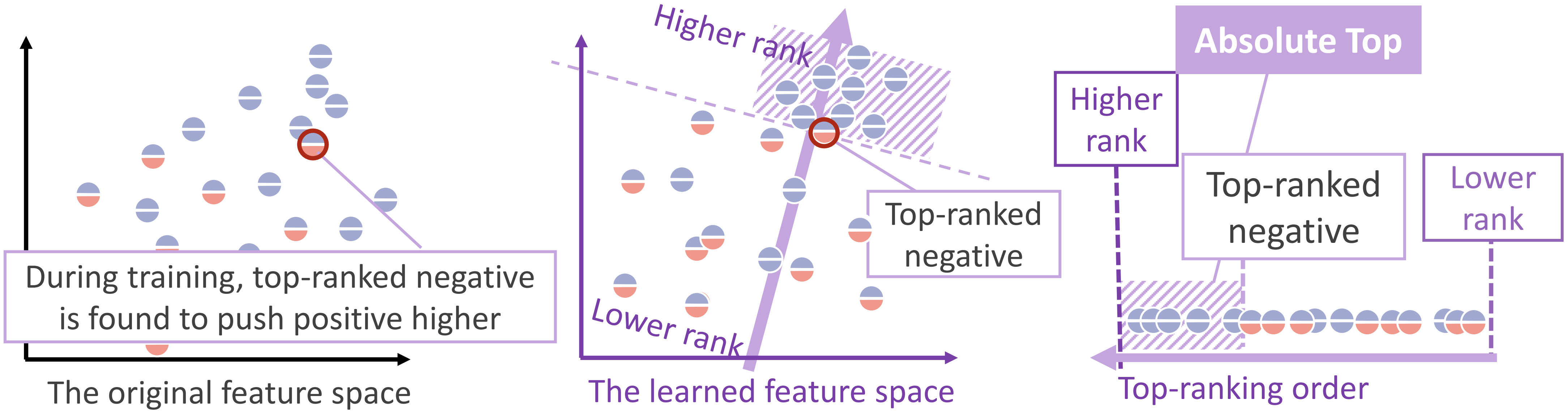
- Learning mechanism of SigNet



Learning top-rank pairs – learning mechanism

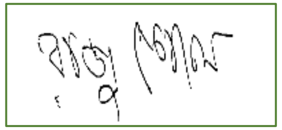
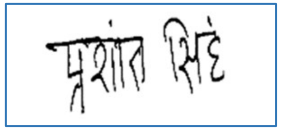
- Learning mechanism of learning top-rank pairs

The rank score of a **(Genuine, Genuine) pair** output by learning top-rank pairs
The rank score of a **(Genuine, Forgery) pair** output by learning top-rank pairs



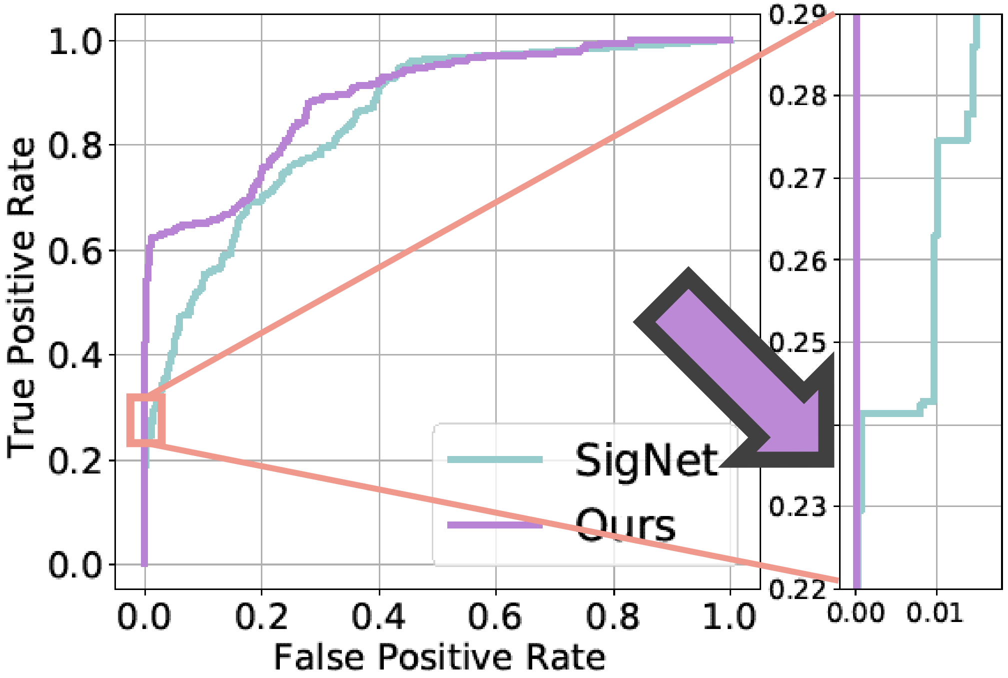
(a) Original distribution (b) Top-rank learning (c) Obtaining Absolute Top

Experimental setting – data and evaluation

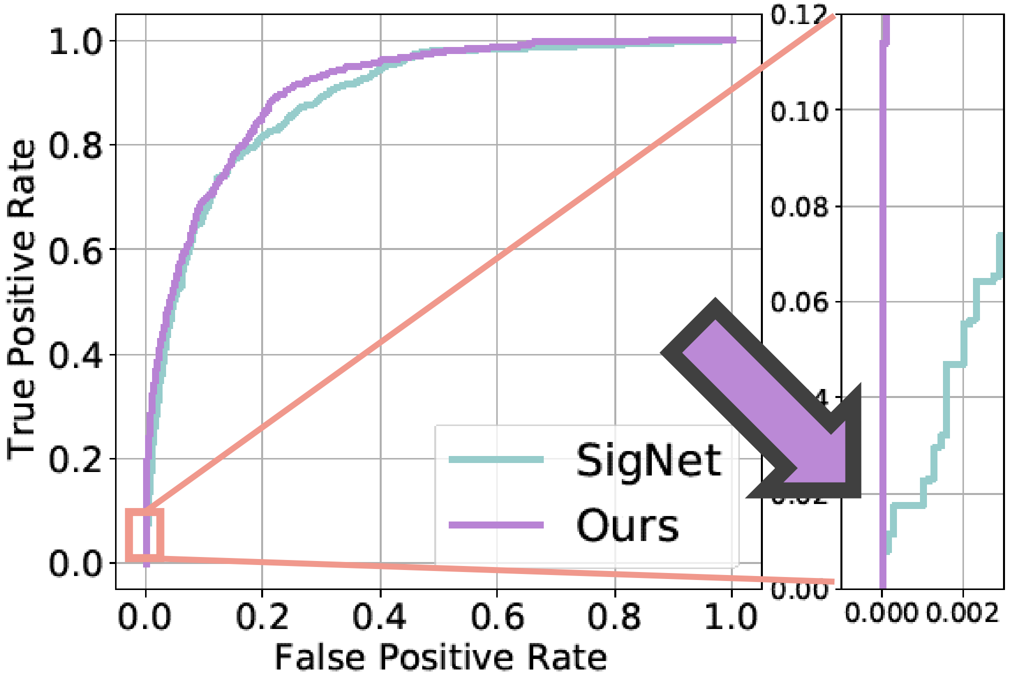
- Datasets used in this experiment
  - BHSig260 dataset[5]
    - **BHSig-B**   **BHSig-H**  
- Evaluation criteria
  - **pos@top**: (absolute positives)/(all true positives)
  - **Accuracy**: the maximum result of 0.5×(TPR+TNR)
  - **AUC**: Area under the curve
  - **FAR**: false acceptance rate
  - **FRR**: false rejection rate

Results and analysis – ROC curves

- The ROC curves show our method achieves better pos@top on both dataset BHSig-B and BHSig-H



(a) ROC curve of BHSig-B



(b) ROC curve of BHSig-H

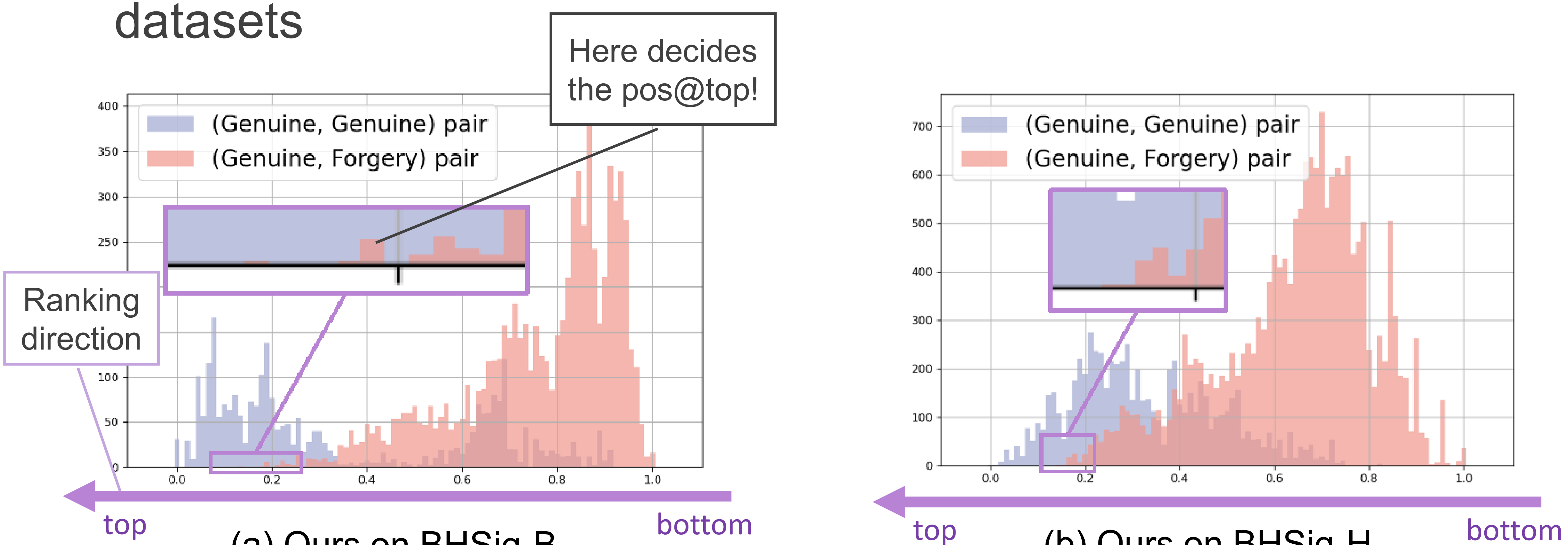
Results and analysis – quantitative evaluation

- On both dataset BHSig-B and BHSig-H, our method achieves better performance on each evaluation criteria
- SigNet has 0 pos@top on both datasets!?

Dataset	Approaches	pos@top(↑)	Accuracy(↑)	AUC(↑)	FAR(↓)	FRR(↓)
BHSig-B	**Ours**	**0.283**	**0.806**	**0.889**	**0.222**	**0.222**
	SigNet	0.000	0.756	0.847	0.246	0.247
BHSig-H	**Ours**	**0.114**	**0.836**	**0.908**	**0.179**	**0.178**
	SigNet	0.000	0.817	0.891	0.192	0.192

Results and analysis – histograms(**ours**)

- Rank scores of signature pairs show in histograms on both datasets

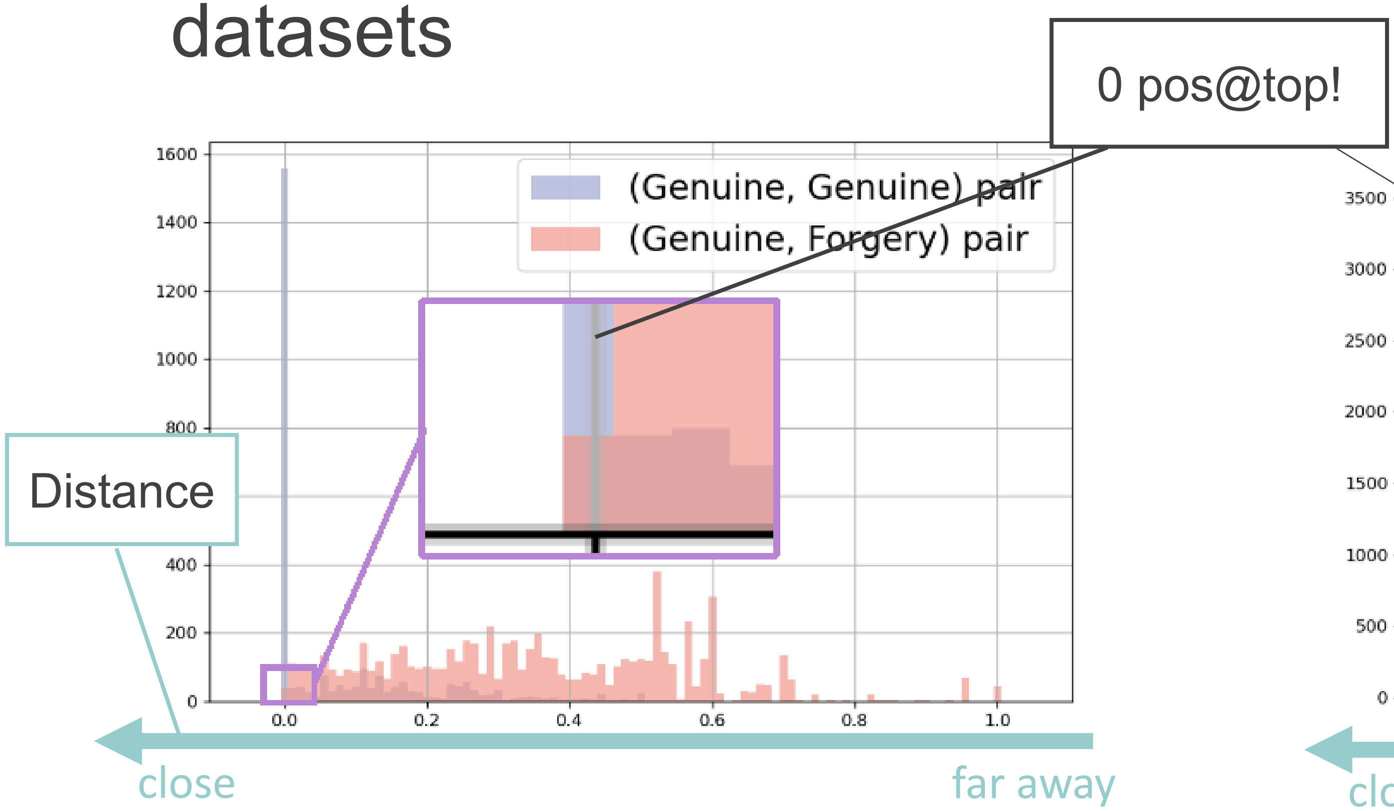


(a) Ours on BHSig-B

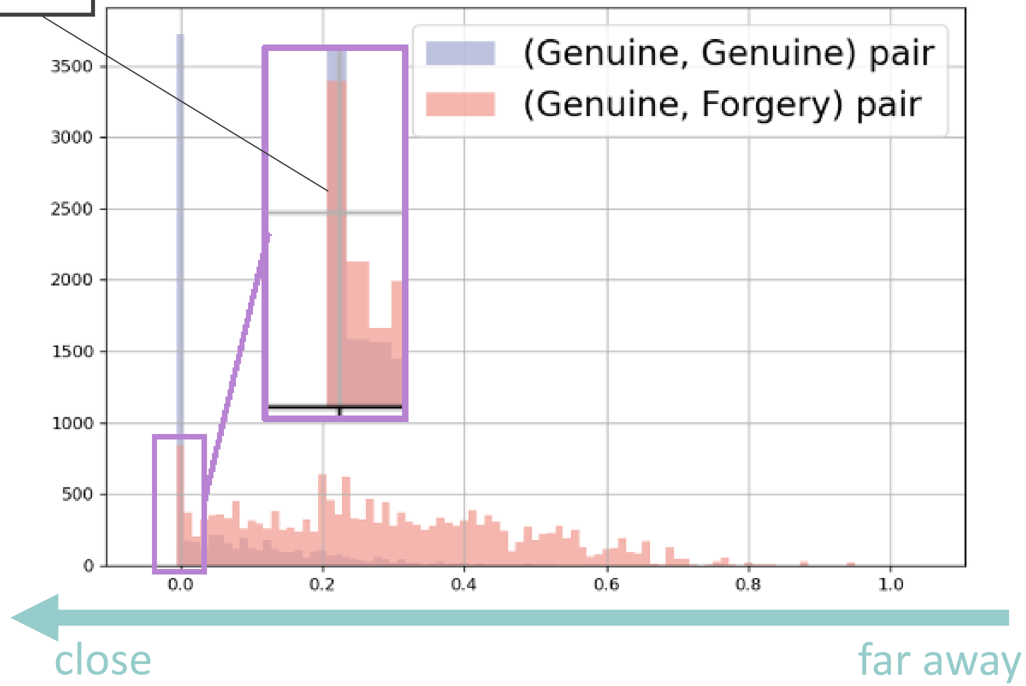
(b) Ours on BHSig-H

Results and analysis – histograms(SigNet)

- Distances of signature pairs show in histograms on both datasets



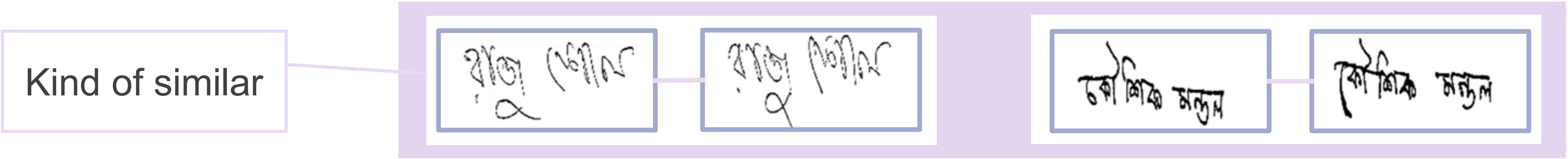
(a) Distances between pairs on BHSig-B



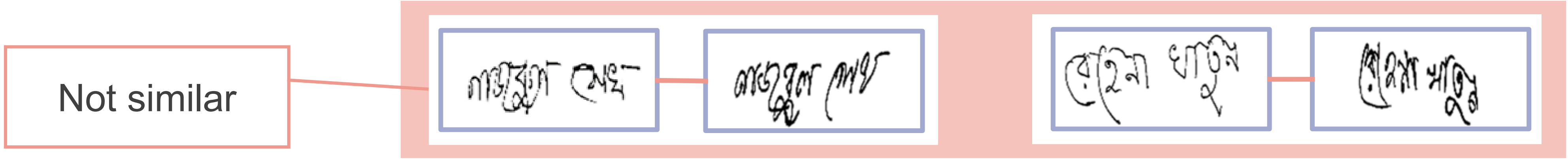
(b) Distances between pairs on BHSig-H

Results and analysis – some examples(BHSig-B)

(a) Absolute top (Genuine, Genuine) pairs of BHSig-B



(b) Non-absolute top (Genuine, Genuine) pairs of BHSig-B



(c) (Genuine, Forgery) pairs of BHSig-B

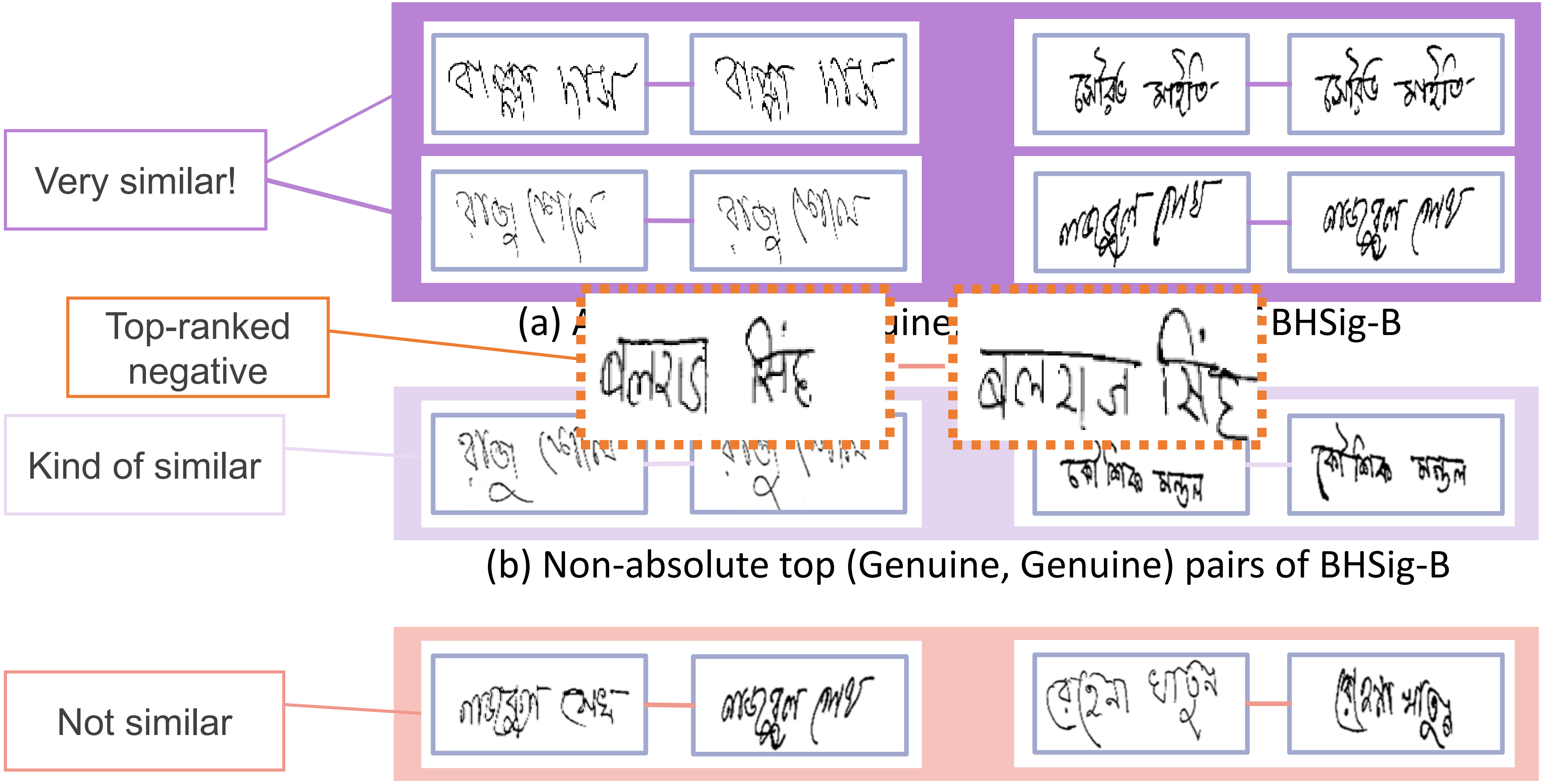
Conclusion

- A novel method: **learning top-rank pairs**
  - Pair-based top-rank learning
  - Increasing reliability of performance on signature verification
- Experiments on two signature proved the efficiency of our method
  - Achieved higher pos@top indeed
  - Convincing examples

[1] S. Agarwal, T. Graepel, R. Herbrich, S. Har-Peled, and D. Roth, “Generalization bounds for the area under the ROC curve,” J. Mach. Learn. Res., vol. 6, pp. 393–425, 2005.
[2] S. P. Boyd, C. Cortes, M. Mohri, and A. Radovanovic, “Accuracy at the top,” in Proceedings of the NIPS, 2012, pp. 962–970.
[3] Y. Zheng, Y. Zheng, D. Suehiro, and S. Uchida, “Top-rank convolutional neural network and its application to medical image-based diagnosis,” Pattern Recognit., vol. 120, p. 108138, 2021.
[4] S. Dey, A. Dutta, J. I. Toledo, S. K. Ghosh, J. Llad´os, and U. Pal, “Signet: Convolutional siamese network for writer independent offline signature verification,” CoRR, vol. abs/1707.02131, 2017.

THANK YOU !

Results and analysis – top-ranked negative



(b) Non-absolute top (Genuine, Genuine) pairs of BHSig-B

(c) (Genuine, Forgery) pairs of BHSig-B

Purpose – higher reliability

- **Ours: Learning top-rank pairs**
  - To maximize the number of absolute Genuine signature pairs
- Putting the rank scores on an axis
  - There are more absolute Genuine pairs than metric learning!
- **More absolute Genuine pairs = Higher reliability**