

Writer Identification and Verification Using GMM Supervectors

Pattern Recognition Lab (CS 5)

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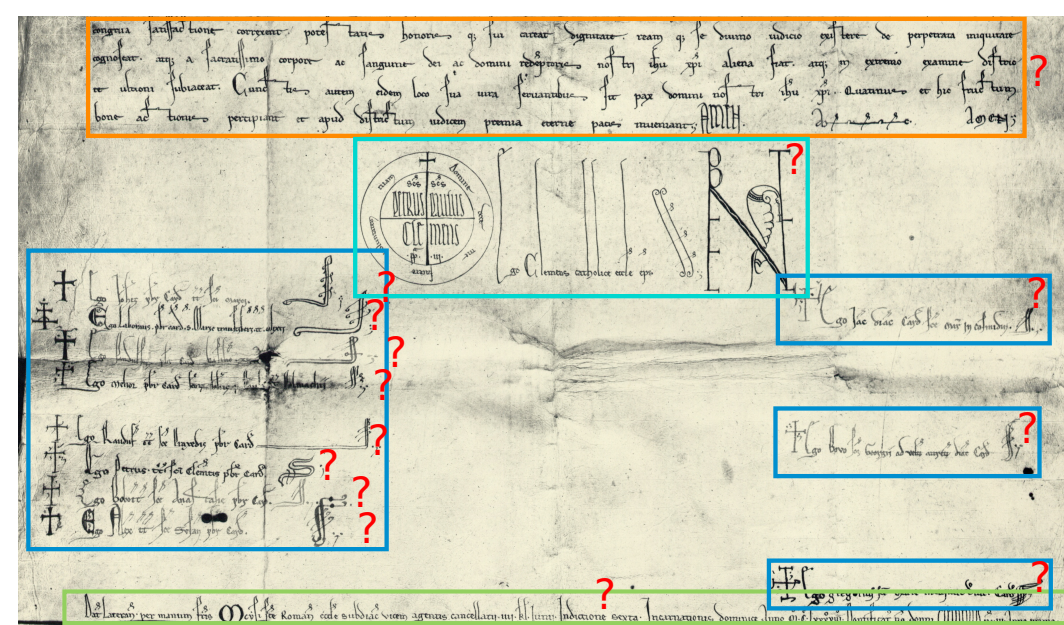


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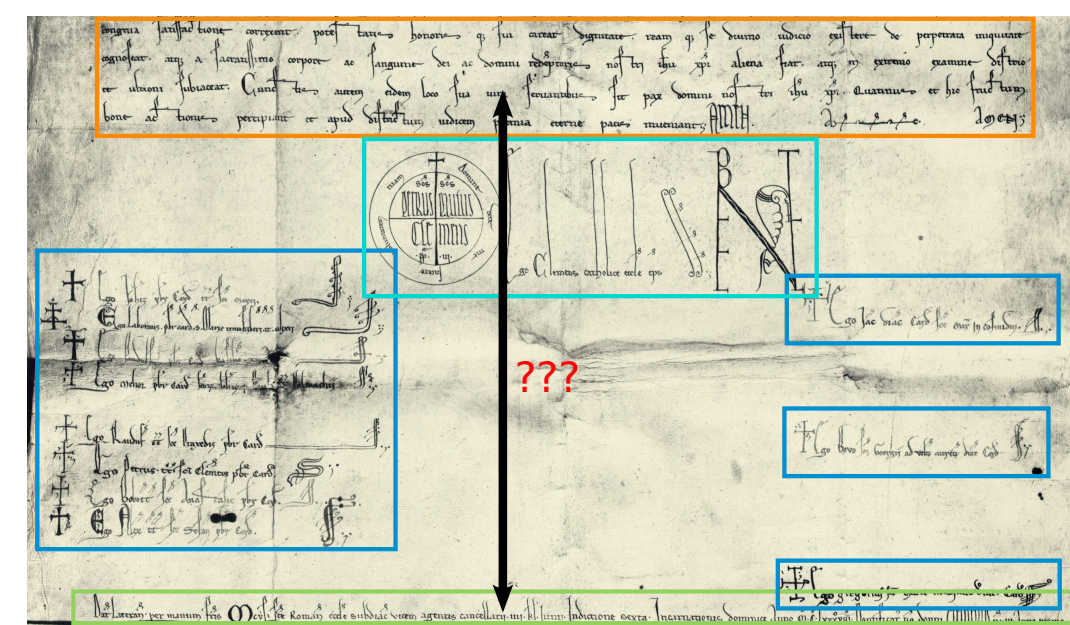
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Motivation

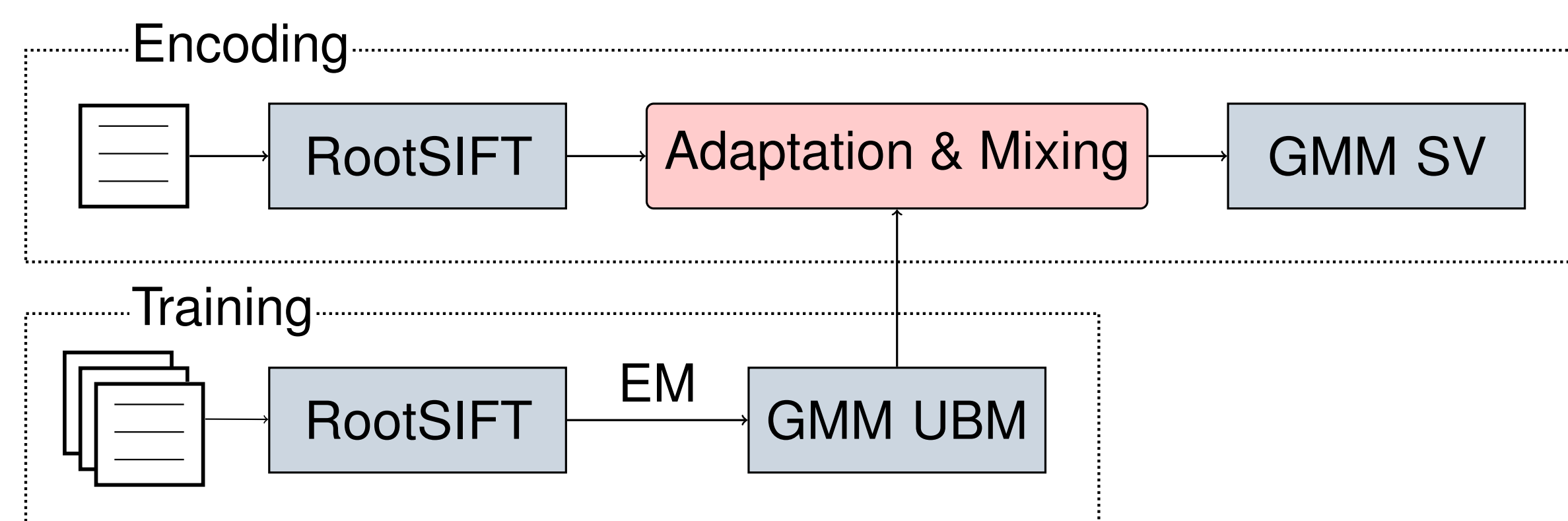
Writer Identification



Writer Verification

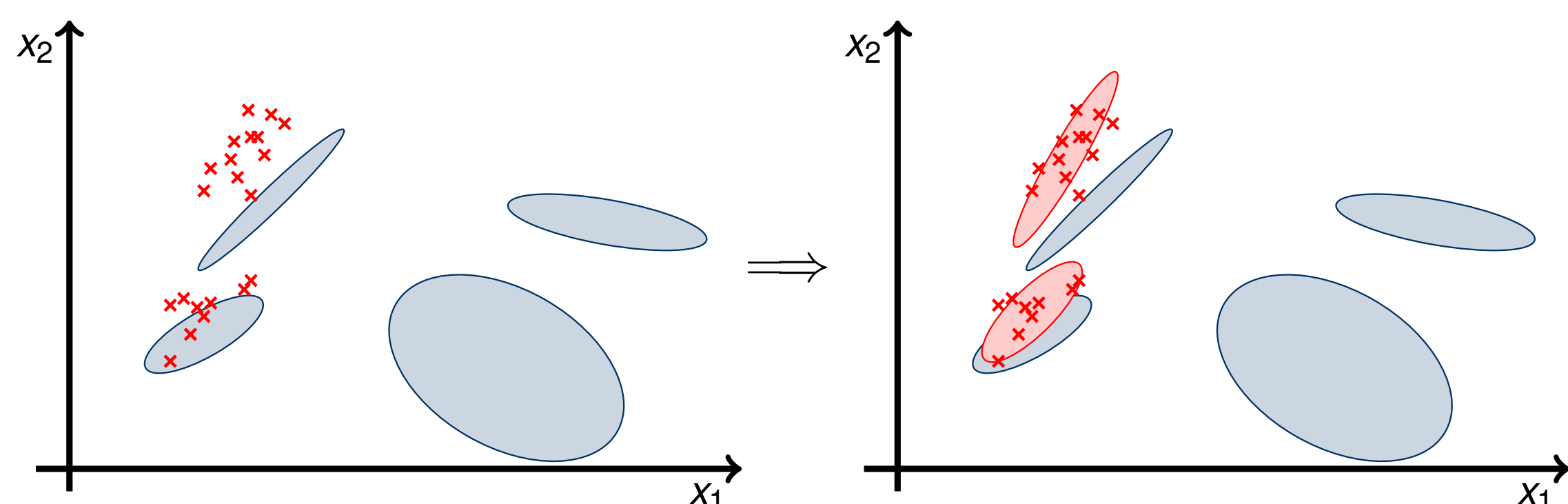


Method Overview



GMM Adaptation

A universal background model (UBM) using a Gaussian Mixture Model is created from the training data. New data is represented as an adaptation to the UBM.



Adaptation and Mixing:

$$\hat{w}_i = \alpha_i(r) \frac{1}{M} \sum_{j=1}^M \pi_j(i) + (1 - \alpha_i(r)) w_i$$

$$\hat{\mu}_i = \alpha_i(r) \frac{\sum_{j=1}^M \pi_j(i) \mathbf{x}_j}{\sum_{j=1}^M \pi_j(i)} + (1 - \alpha_i(r)) \mu_i$$

$$\hat{\sigma}_i = \alpha_i(r) \frac{\sum_{j=1}^M \pi_j(i) \mathbf{x}_j \odot \mathbf{x}_j}{\sum_{j=1}^M \pi_j(i)} + (1 - \alpha_i(r)) (\sigma_i \odot \sigma_i + \mu_i \odot \mu_i) - \hat{\mu}_i \odot \hat{\mu}_i$$

\odot element-wise vector multiplication r relevance factor
 $\pi(i)$ posterior probability for mixture i $\alpha_i(r)$ mixing function
 M number of descriptors per document

GMM Supervector

Supervector (SV): Stacking of the adapted GMM parameters:

$$\mathbf{s} = (\hat{w}_1, \dots, \hat{w}_N, \hat{\mu}_1^T, \dots, \hat{\mu}_N^T, \hat{\sigma}_1^T, \dots, \hat{\sigma}_N^T)^T$$

Other Encoding Methods:

- Fisher Vectors (FV) [5]
- Vector of Locally Aggregated Descriptors (VLAD) [4]

Datasets

CVL

- 309 writers
- 5 forms (1 German, 4 English)

ICDAR

- Training: 100, test-set: 250
- 4 forms (2 English / 2 Greek)

*Sann magst du mich in Tüscheln ablegen,
 Dann will ich gern zu Grunde gehn!
 Sann mag die Toddingeloch stellen,
 Dann bist du deins Drencks frey,
 Die Uhr mag stehen, dir Segen fallen,
 Es sey die Zeit für mich vrbey!*

*Πότε μιν αναμνηστέας τα στυγα του ανείναι! Να στας τα στυγα!
 Να σπείρασ ότι σπείρασ τα πλάνα σου. Να ηδαιεύσ και να κες:
 Εύατος σε υπέσθ! Τι θα νεί ευτυχία; Να ηείσ όλης ευτυχίας.*

SIFT vs. RootSIFT

*Πότε μιν αναμνηστέας τα στυγα του ανείναι! Να στας τα στυγα!
 Να σπείρασ ότι σπείρασ τα πλάνα σου. Να ηδαιεύσ και να κες:
 Εύατος σε υπέσθ! Τι θα νεί ευτυχία; Να ηείσ όλης ευτυχίας.*

[Top-1]	SV	FV	VLAD
SIFT	0.943	0.828	0.861
RootSIFT [1]	0.972	0.945	0.931

RootSIFT: hellinger normalized version of SIFT

References

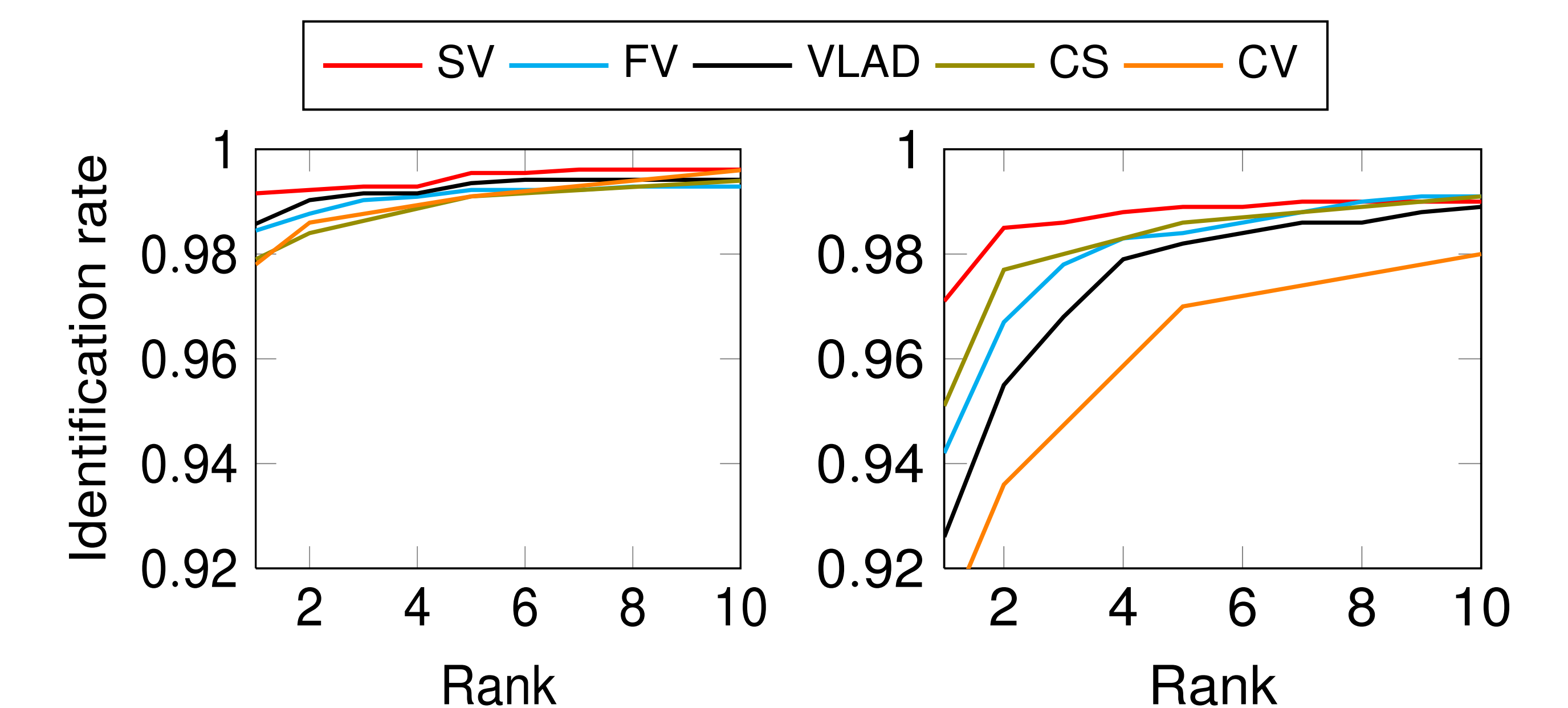
- [1] R. Arandjelovic and A. Zisserman. Three things everyone should know to improve object retrieval. In *CVPR*, 2012.
- [2] S. Fiel and R. Sablatnig. Writer Identification and Writer Retrieval using the Fisher Vector on Visual Vocabularies. In *ICDAR*, 2013.
- [3] R. Jain and D. Doermann. Writer Identification Using an Alphabet of Contour Gradient Descriptors. In *ICDAR*, 2013.
- [4] H. Jégou and M. Douze. Aggregating local descriptors into a compact image representation. In *CVPR*, 2010.
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Evaluation

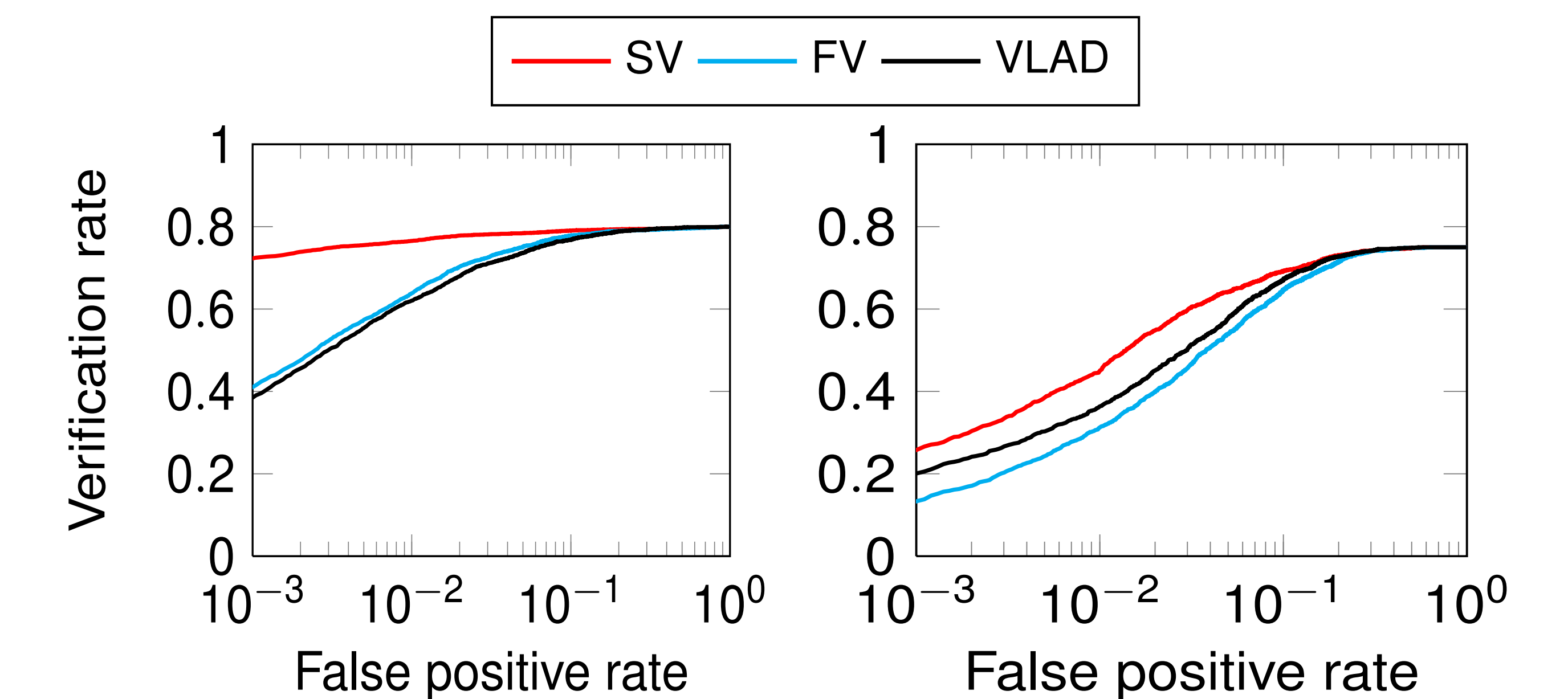
Writer Identification (Hard Criterion):

	CVL			ICDAR		
	Top-1	Top-4	mAP	Top-1	Top-3	mAP
CV [2]	0.978	0.758	–	0.909	0.245	–
CS [3]	0.979	0.483	–	0.951	0.071	–
VLAD	0.986	0.720	0.936	0.926	0.248	0.651
FV	0.984	0.756	0.940	0.942	0.25	0.677
SV	0.992	0.887	0.971	0.971	0.238	0.671

Writer Identification (Soft Criterion):



Writer Verification:



Conclusion

- RootSIFT improves encoding methods over SIFT
- GMM Supervectors outperform the current state of the art in writer identification / verification
- Overall, GMM Supervectors outperform other adaptation methods