Unraveling Scribal Authorship: New Frontiers in Writer Retrieval

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Thank you!

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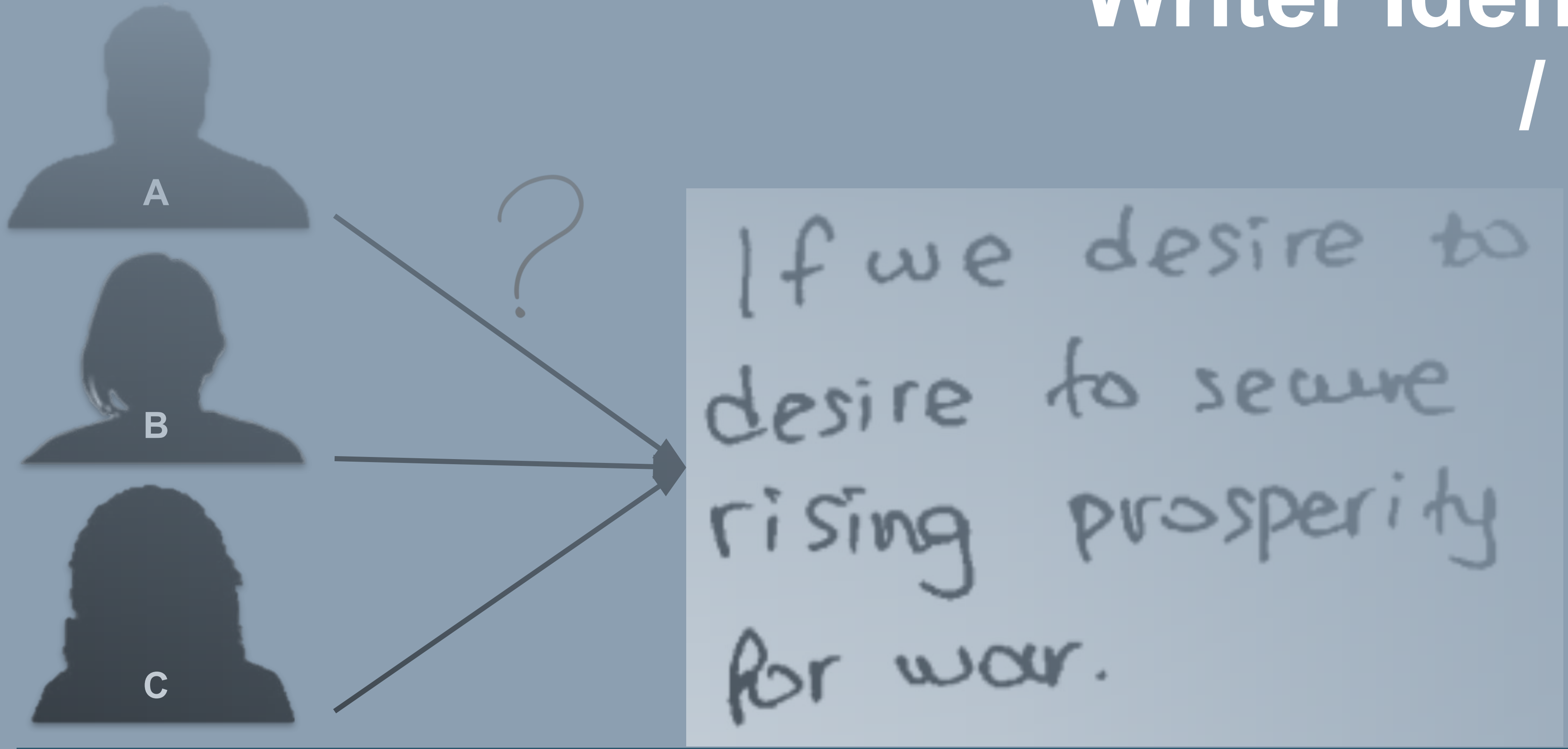
Alexander Mattick
Benjamin Schuster
Richin Sukesh
Johan Zenk
…

All collaborators and the amazing DAR community!

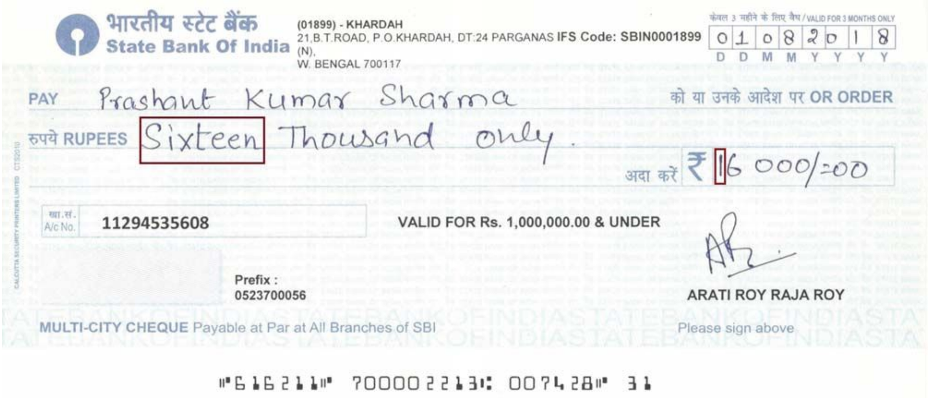
Writer Identification / Retrieval



Motivation

Forensics

- Assessing authenticity
- Examples:
  - Bank cheques
  - Threat letters
  - Testaments

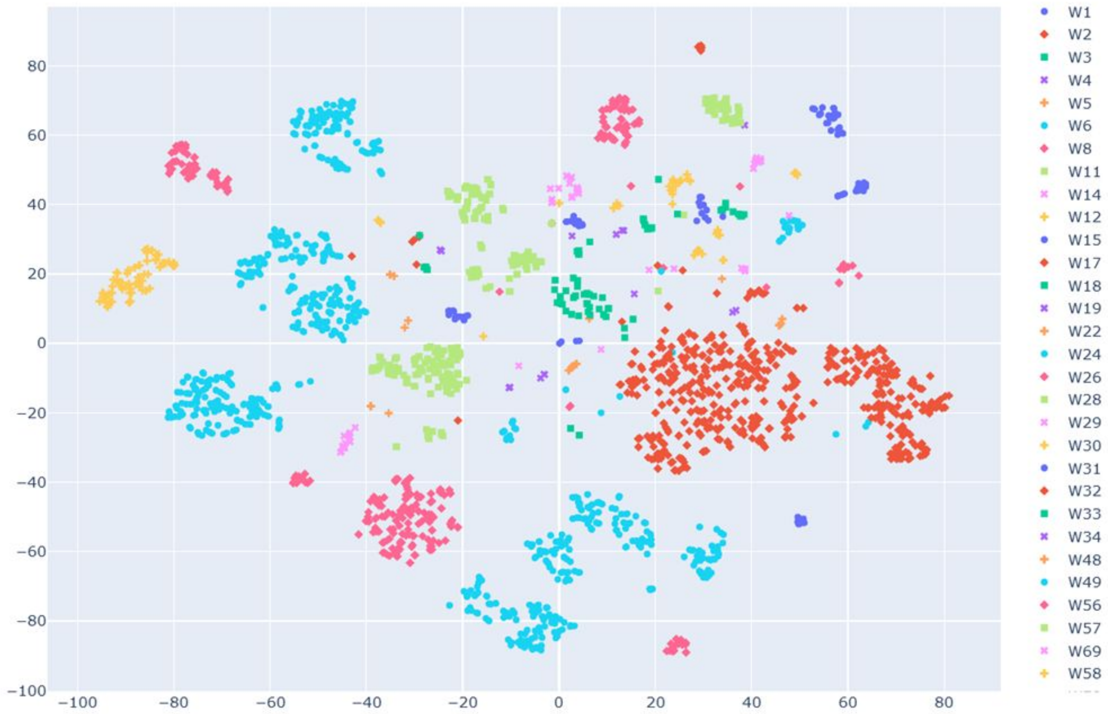


Source: P Roy, S Bag, "Forensic performance on handwriting to identify forgery owing to word alteration", ISBA 2019

Motivation

Paleography

- Analysis of historical writing
  - Date writings
  - Assign writings to known (or unknown) scribes



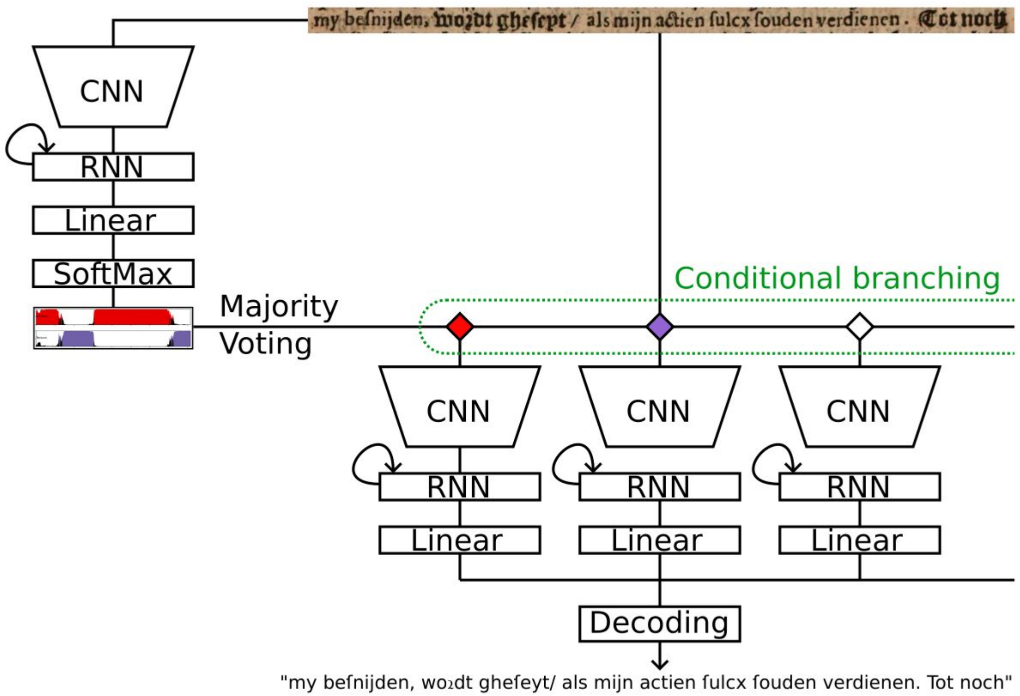
Registers of the French royal chancery (Paris, Arch. Nat., JJ37-JJ50)
Writer id. data: J. Guérout, in R. Fawtier, ed., Registres du trésor des chartes: inventaire analytique, 1958
T-SNE based on V. Christlein et al., “Unsupervised Feature Learning for Writer Identification and Writer Retrieval”, *ICDAR 2017*

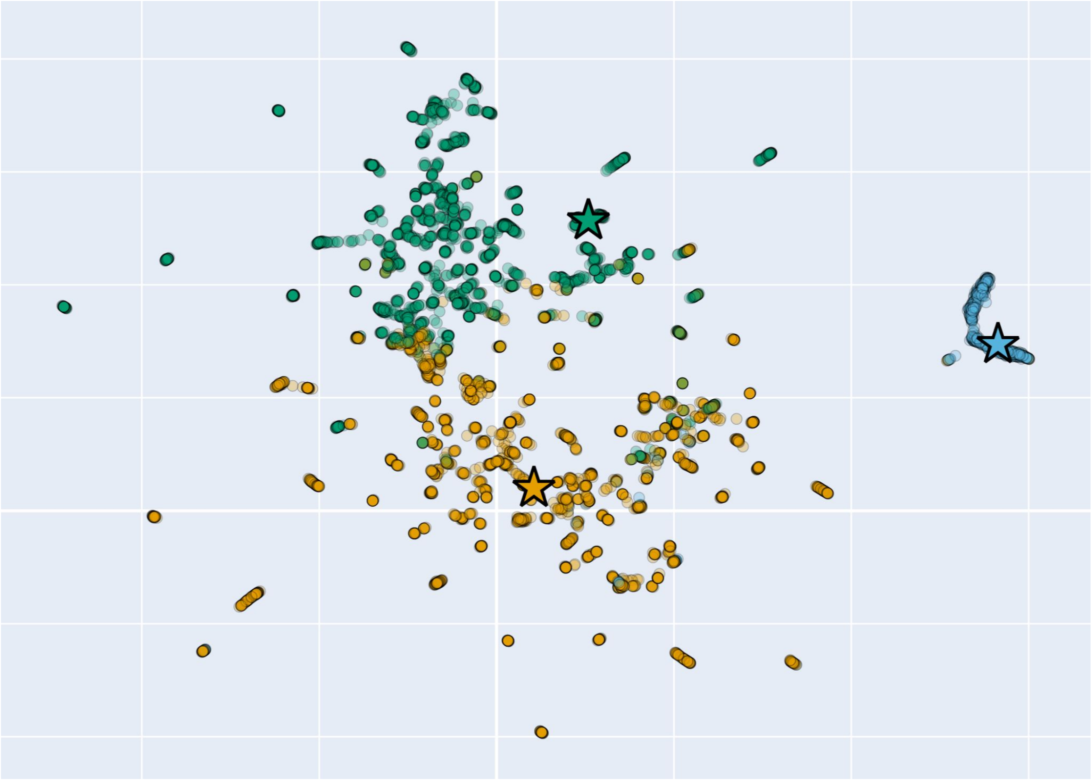
Stutzmann, Dominique. “Les livres de chartes et leur écriture : registres et cartulaires dans l’espace français (1250-1500).” In *Twenty-second Colloquium of the Comité international de paléographie latine: Encounters in written culture: influence, interchange, transfer, reception? / XXIIe colloque du Comité international de paléographie latine. Rencontres et culture écrite : influence, échange, transfert, réception ?* Praha, Czech Republic, 2022. https://hal.science/hal-03916938.

Motivation

Text Recognition

- Writer-individual HTR models



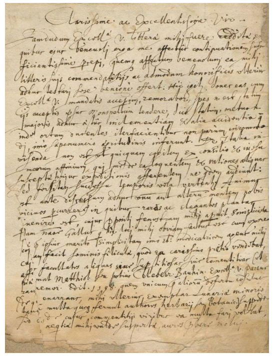


M. Seuret, J. van der Loop, N. Weichselbaumer, M. Mayr, J. Molnar, T. Hass & V. Christlein, “Combining OCR Models for Reading Early Modern Books”, ICDAR 2023

Modalities

Online

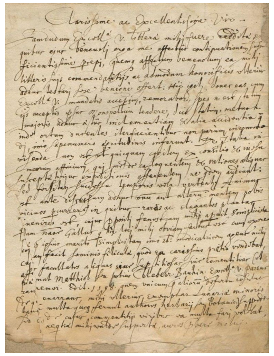
Offline



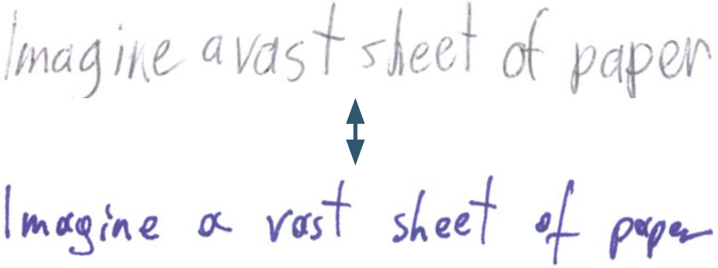
Modalities

Online

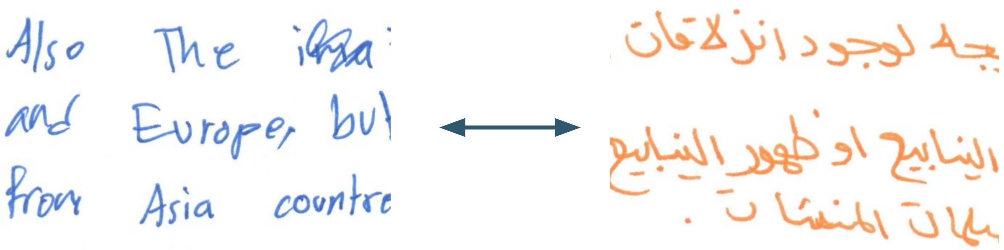
Offline



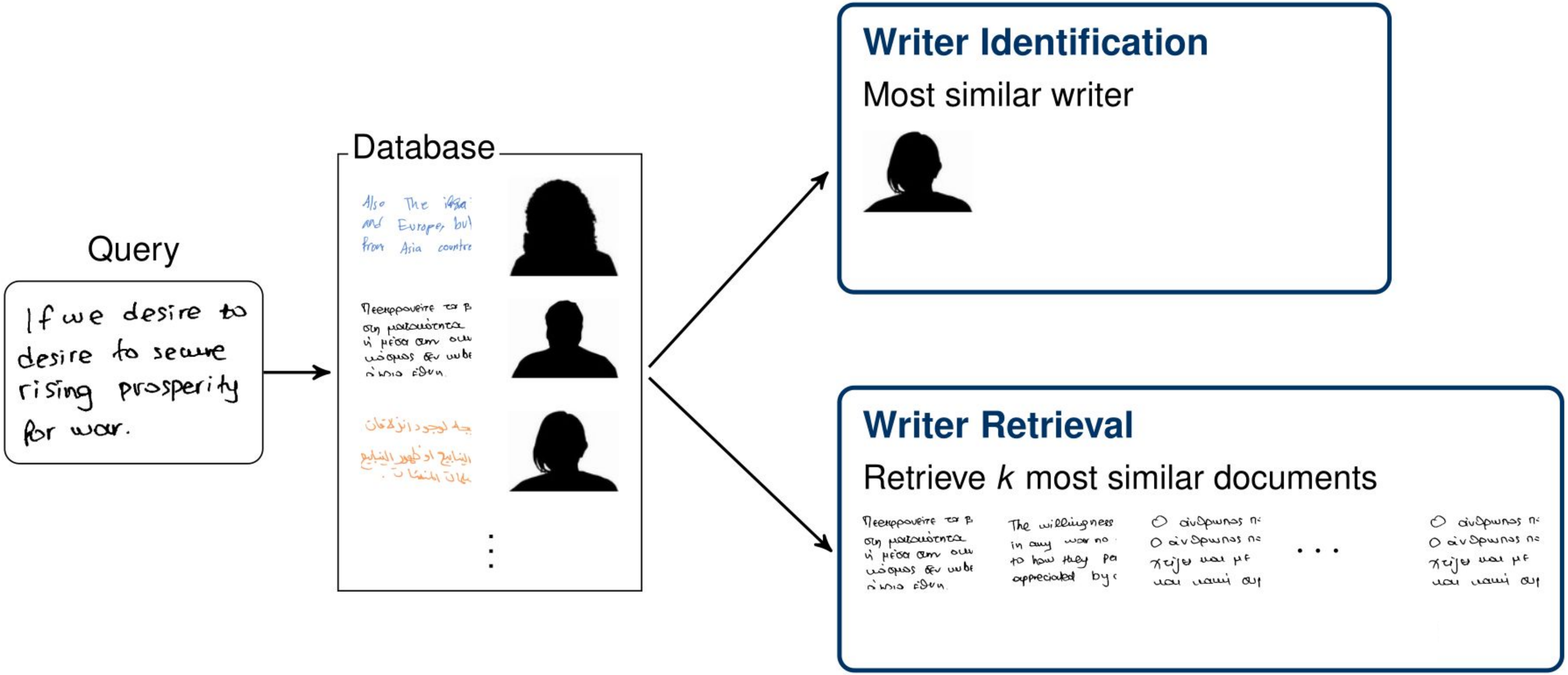
Text-dependent



Text-independent



Writer Identification/Retrieval



Source: ICDAR13 dataset, QUWI15 dataset, freepik.com

Evaluation Protocols Matter

Writer Identification

Most similar writer

Protocol A

- Each writer appears in Train + Test splits

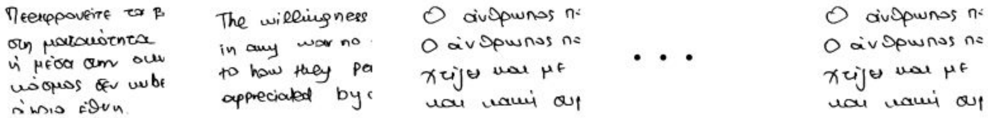
  → End-to-end training possible

  → Focus: **Classification**

- Metric: Accuracy/AUC/etc

Writer Retrieval / Writer Identification

Retrieve *k* most similar documents



Protocol B

- Typically writer-independent test set
- Leave-one-document-out cross-validation of the test set

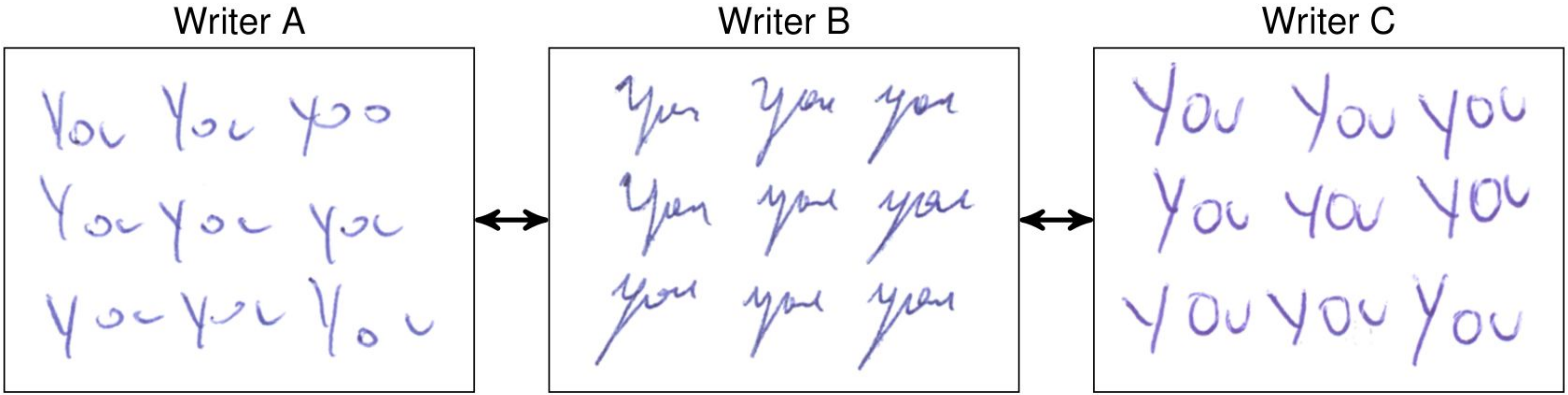
  → Focus: **Image retrieval, zero/one-shot learning**

- Metric: Top-1/mAP

Many papers compare results of different evaluation protocols or different test sets 😑

Challenges

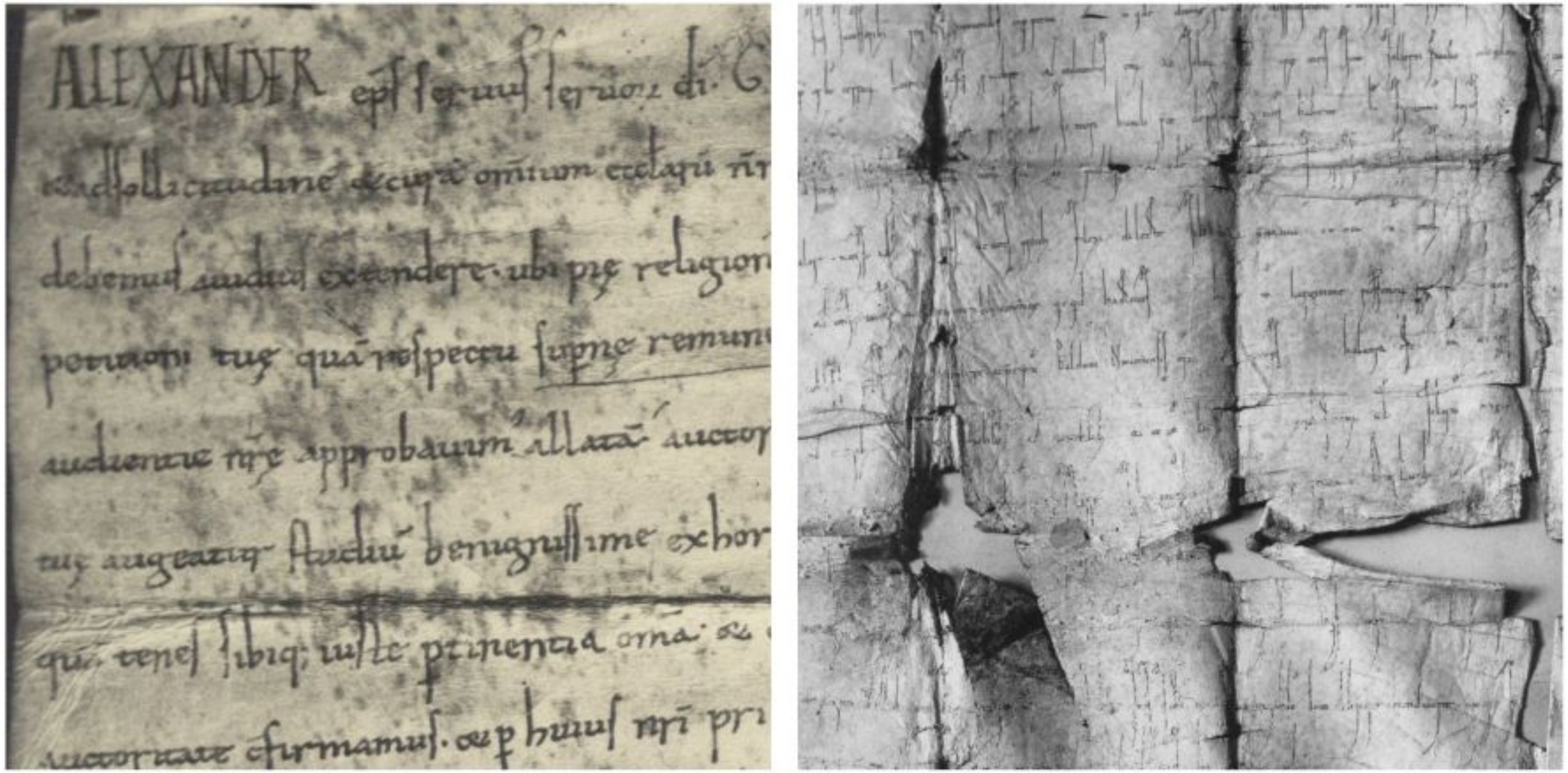
Internal Factors



- Within-writer variability
- Between-writer variability

Challenges

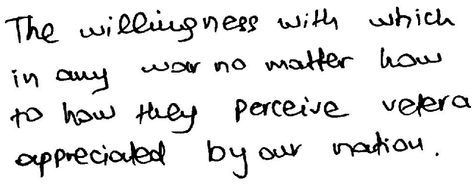
External Factors

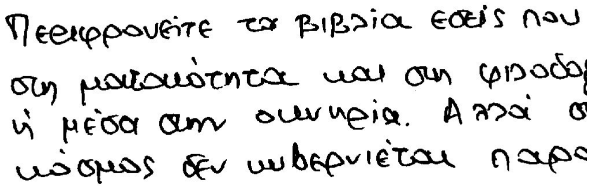


Source: Göttingen Academy of Sciences and Humanities, JL 4490, 4671

- Pen
- Document Material
- Artifacts

Datasets

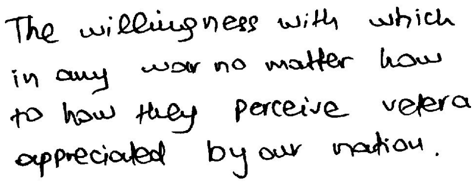


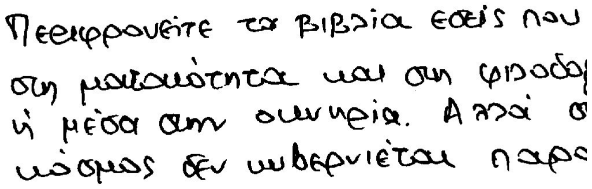


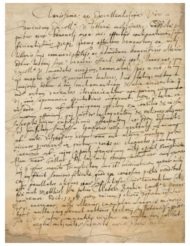
Contemporary

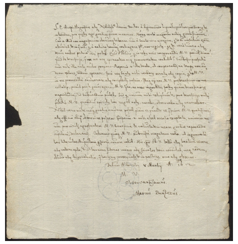
- ICDAR’13
  - Test-set: 4 samples of 250 writers
  - Multi-lingual
- CVL’13
  - Test-set: 5 samples of 283 writers
- Others: IAM, CERUG, Firemaker, QUWI, KHATT, ..
- Typically too small & too clean
- Saturated performances > 97% Top-1

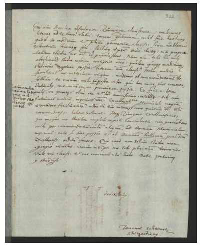
Datasets











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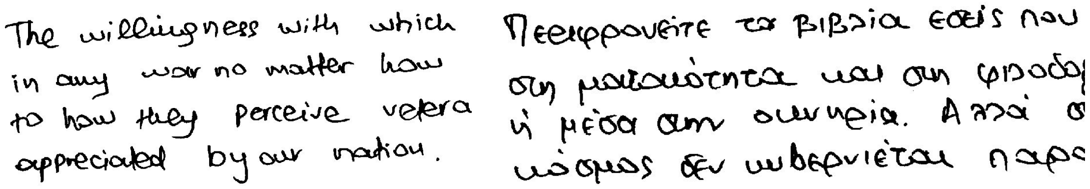
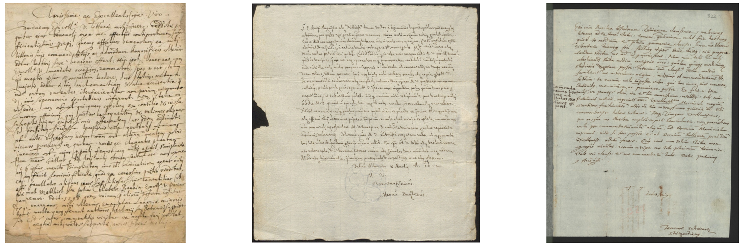
Historical

- ICDAR'17
  - Test-set: 5 samples of 720 writers
  - historical letters
  - binarized version available
- ICDAR'19
  - Test-set: 20k images from ~10k writers
  - very heterogeneous (manuscripts, letters, charters)
- Challenging but some mistakes due to wrong annotations
- Several other datasets (typically lower number of writers)

Datasets





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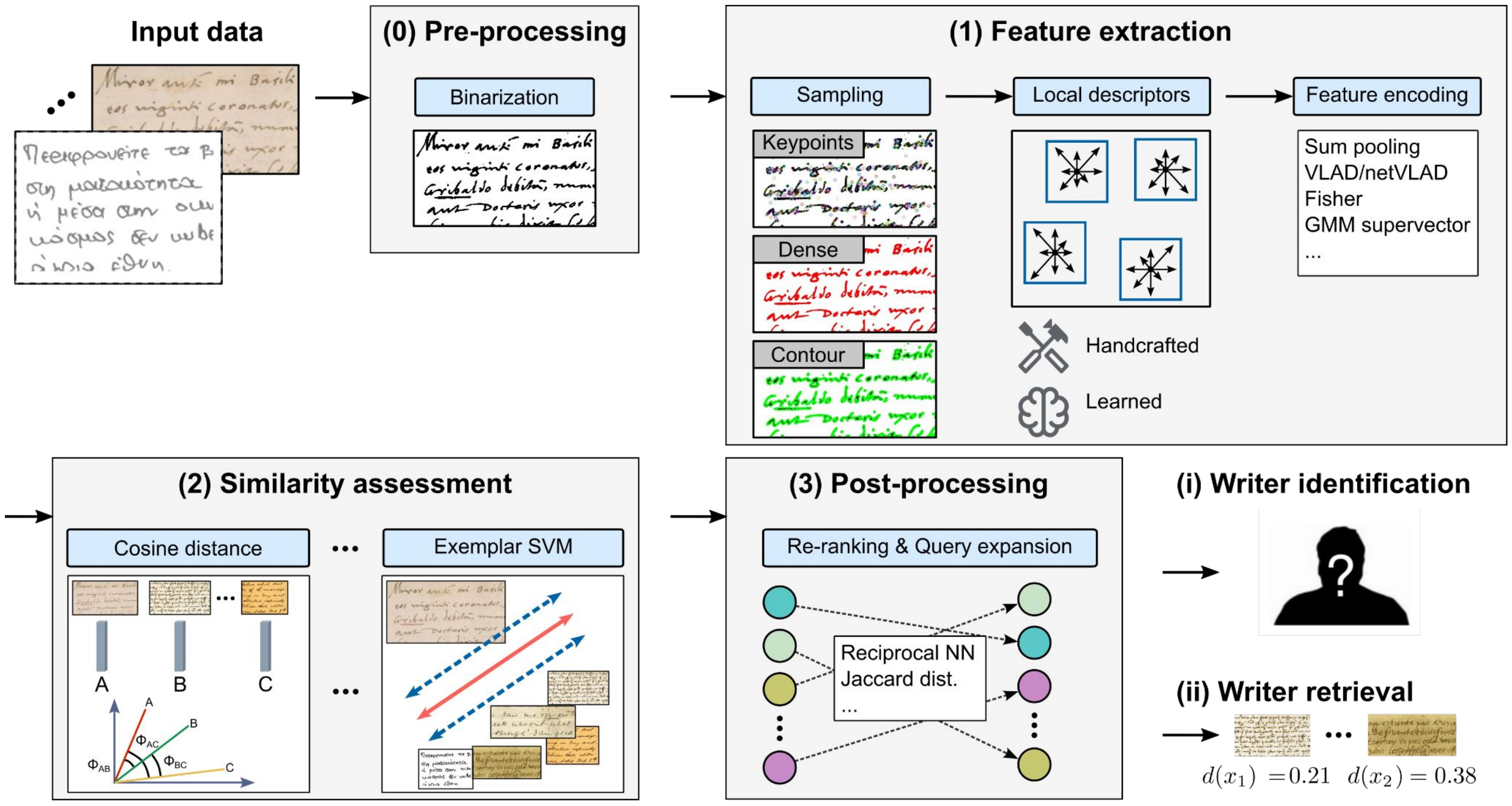
- Challenging but some mistakes due to wrong annotations
- Several other datasets (typically lower number of writers)

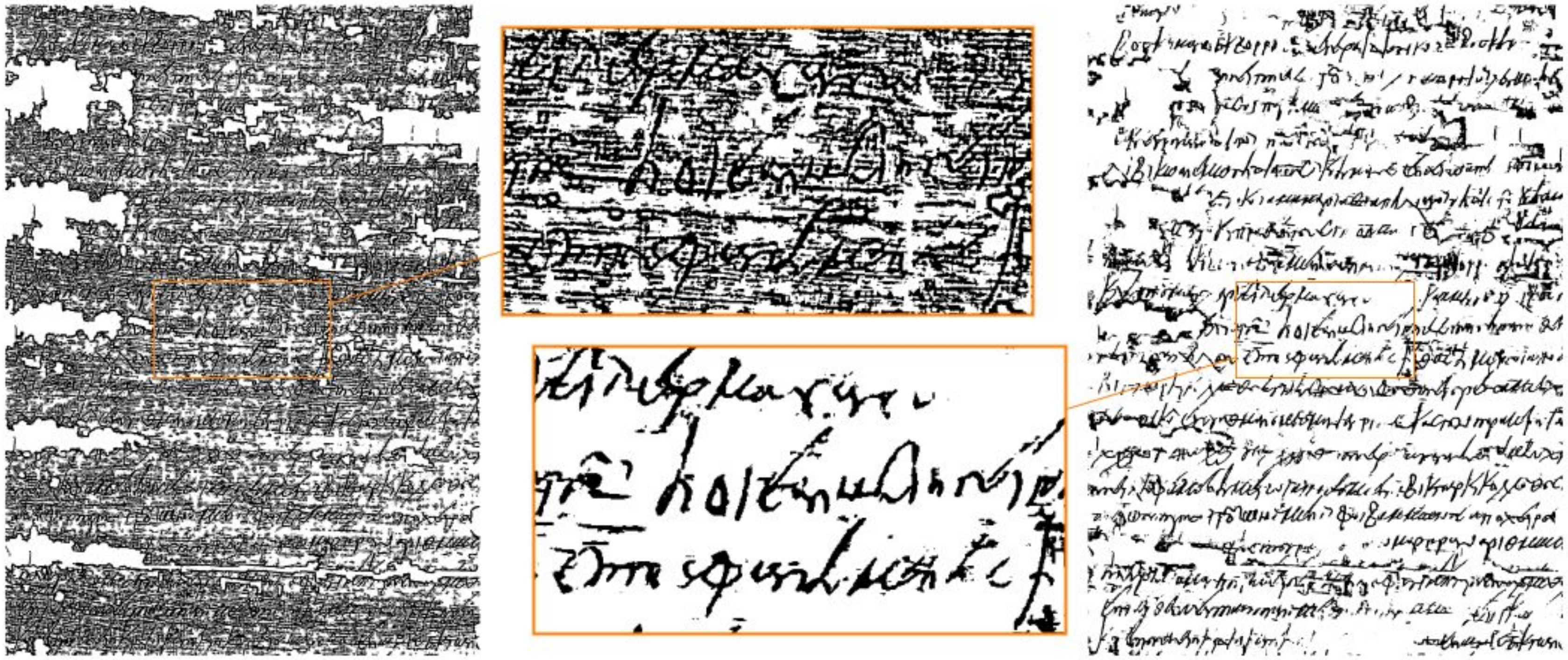
→ Larger (dirty) datasets would be great

Writer Identification/Retrieval



Binarization is not dead

… at least for Writer Retrieval/Identification

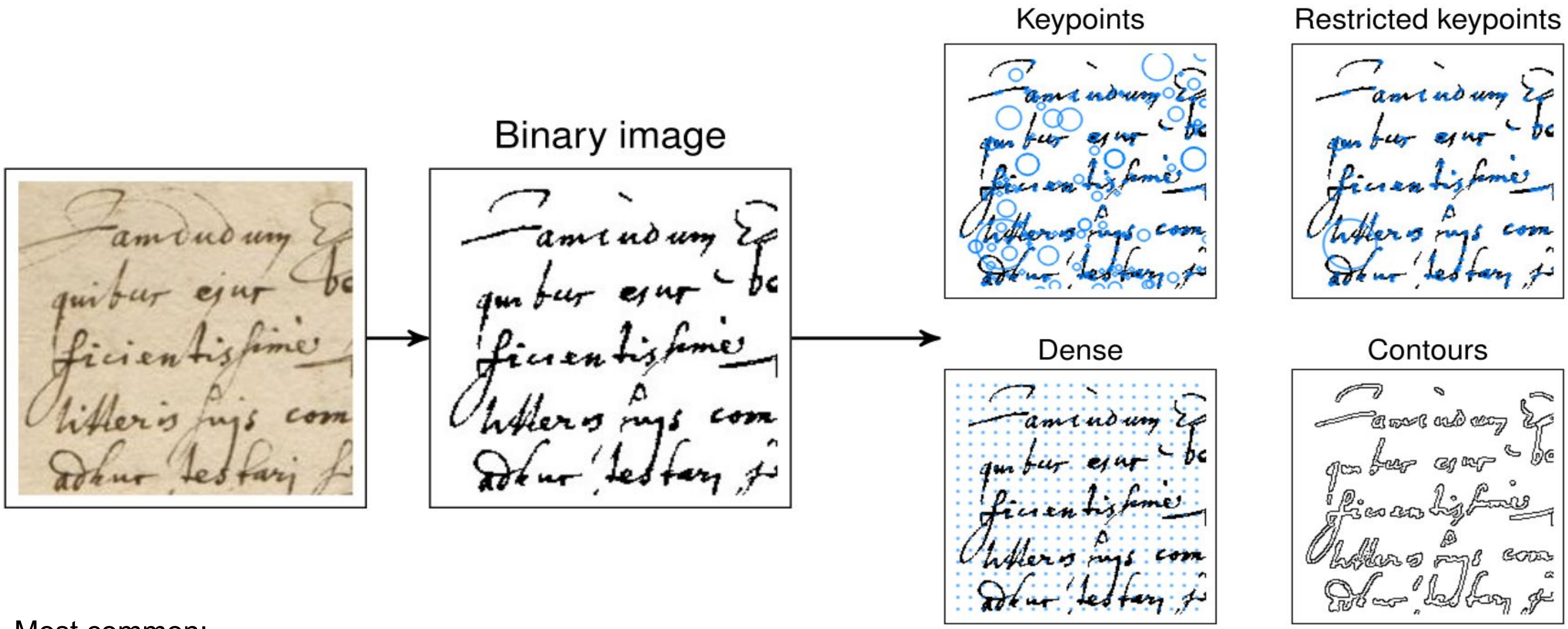


Source: GRK-Papyri, ID: Abraamios_4

- Needed or not?
- Depends on material and scenario → Especially important for papyri data
- → So far: No systematic study available

V. Christlein, I. Marthot-Santaniello, M. Mayr, A. Nicolaou, M. Seuret "Writer Retrieval and Writer Identification in Greek Papyri", IGS 2022.

Sampling

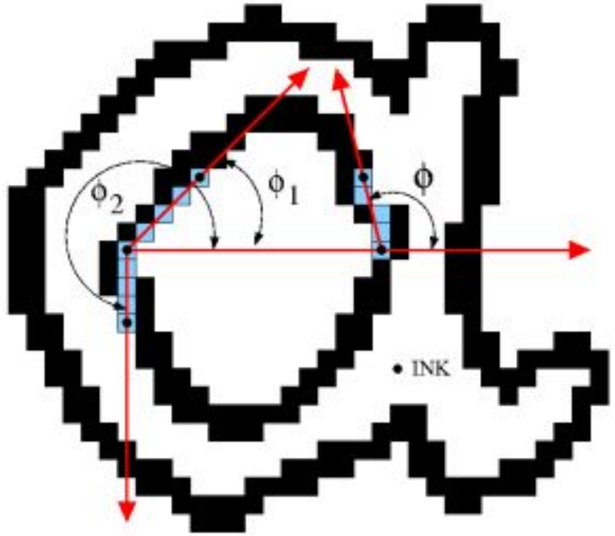


Most common:

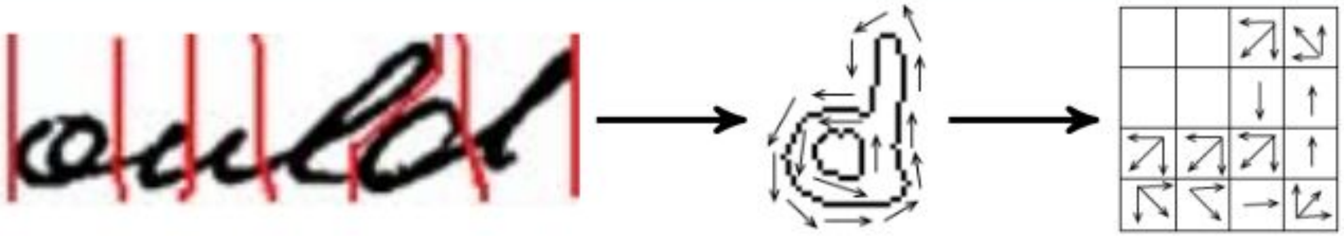
- Patches at keypoints (if you have enough text)
- Alternatively: dense with filtering

Feature Extraction

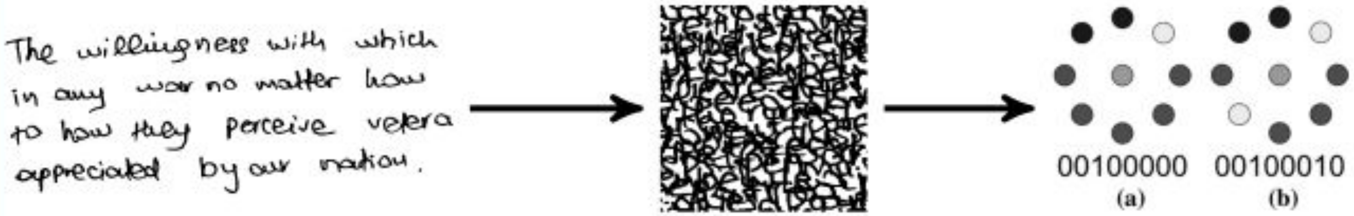
Handcrafted



Hinge Feature[2]



SIFT-like descriptors of vertical cuts[3]

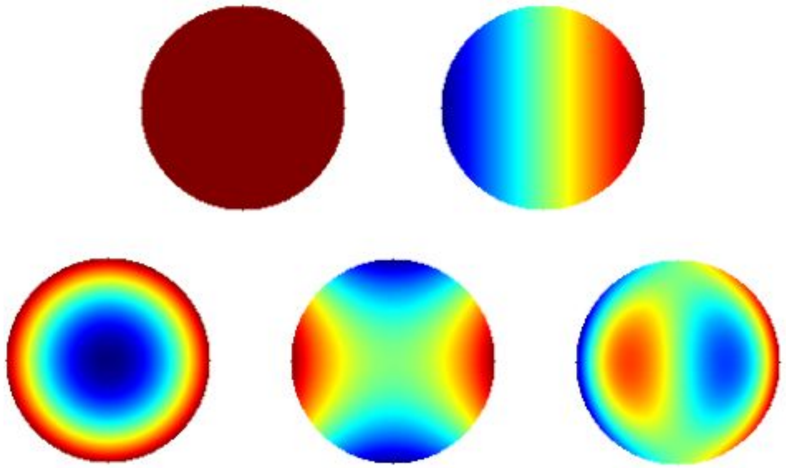


Texture descriptors of compressed sample[4]

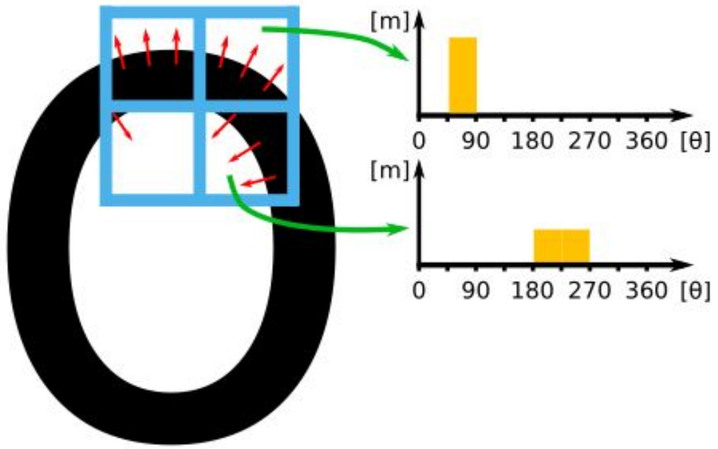
[2]A. Brink, J. Smit, M. Bulacu, and L. Schomaker, “Writer Identification Using Directional Ink-Trace Width Measurements”, Pattern Recognition 2012
[3]R. Jain and D. Doermann, “Writer Identification Using an Alphabet of Contour Gradient Descriptors”, ICDAR 2013
[4]D. Bertolini, L. Oliveira, E. Justino, and R. Sabourin, “Texture-based Descriptors for Writer Identification and Verification”, Expert Systems with Applications 2013
A. Nicolaou, A.D. Bagdanov, M. Liwicki, D. Karatzas, “Sparse radial sampling LBP for writer identification”, ICDAR 2015

Feature Extraction

Handcrafted



Zernike Moments



SIFT

Important Tweaks:

- Remove angle (= Upright)
- Power-normalization (RootSIFT)
- Decorrelation (PCA whitening)

V. Christlein, D. Bernecker and E. Angelopoulou, "Writer identification using VLAD encoded contour-Zernike moments," *ICDAR, 2015*
V. Christlein, D. Bernecker, F. Hönig and E. Angelopoulou, "Writer identification and verification using GMM supervectors," WACV 2014
V. Christlein, D. Bernecker, F. Hönig, A. Maier, and E. Angelopoulou, "Writer identification using GMM supervectors and exemplar-SVMs," Pattern Recognition 2017

Feature Extraction

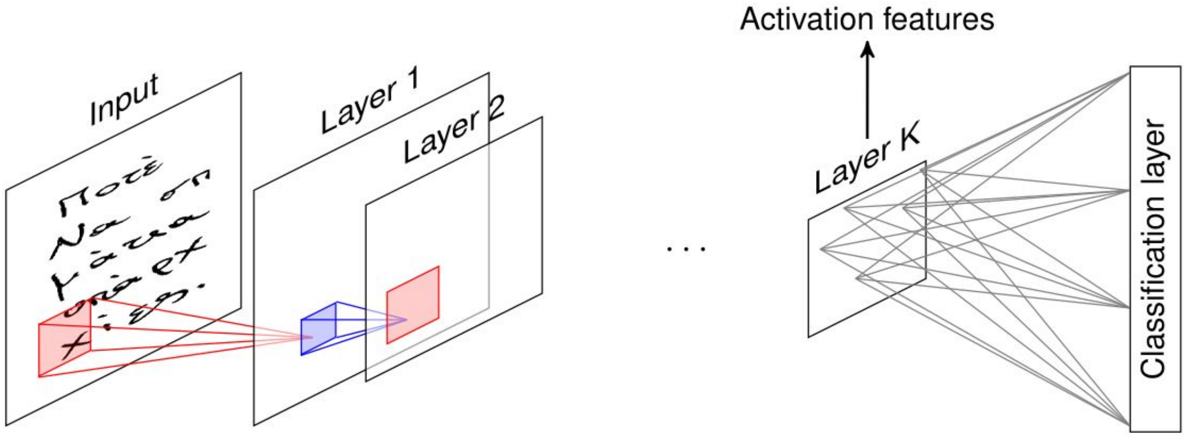
Learning-based

CNN Activation Features

- Recall: no end-to-end training possible
  ⇒ Surrogate task: classify writers of the training set

- Use CNN[1,2] or CNN + Transformer[3] as feature extractor
  - Cross-entropy loss
  - Triplet-loss

→ Drawback: training set with known identities necessary



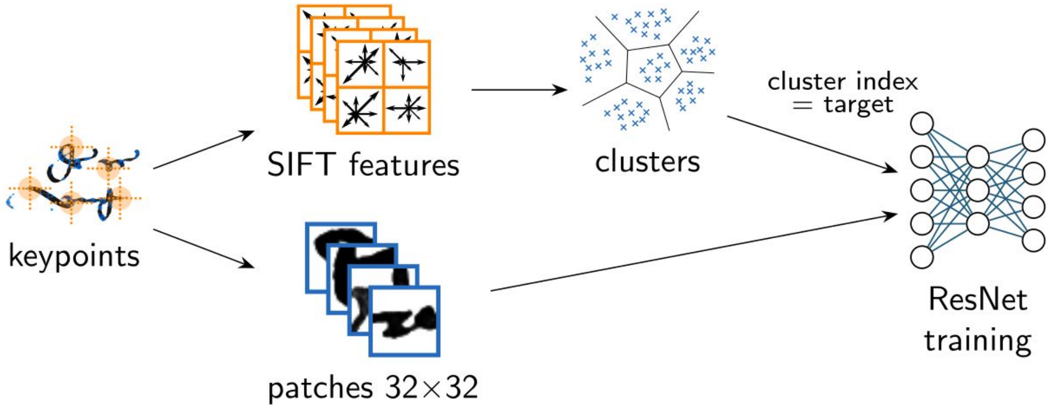
[1] V. Christlein, D. Bernecker, A. Maier, A., E. Angelopoulou, "Offline Writer Identification Using Convolutional Neural Network Activation Features", GCPR 2015
[2] S. Fiel,, and R. Sablatnig, "Writer identification and retrieval using a convolutional neural network", CAIP 2015
[3] M. Peer, F. Kleber, and R. Sablatnig, "Self-supervised Vision Transformers with Data Augmentation Strategies Using Morphological Operations for Writer Retrieval", ICFHR 2022

Feature Extraction

Learning-based

Self-supervised Features

- Clustering-based:[1]
    - New surrogate classes: cluster indices of SIFT descriptors → Map similar patches to each other



[1]V. Christlein, M. Gropp, S. Fiel and A. Maier, "Unsupervised Feature Learning for Writer Identification and Writer Retrieval," ICDAR 2017

Feature Extraction

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Self-supervised Features

- Clustering-based:[1]
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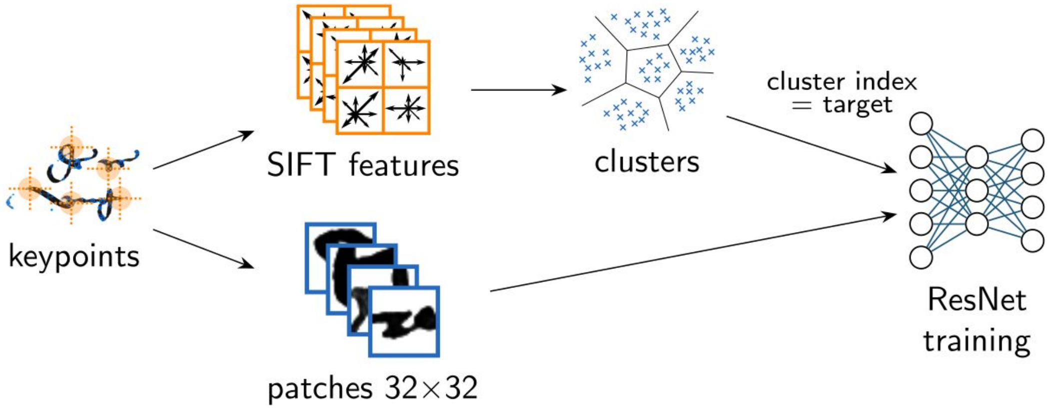
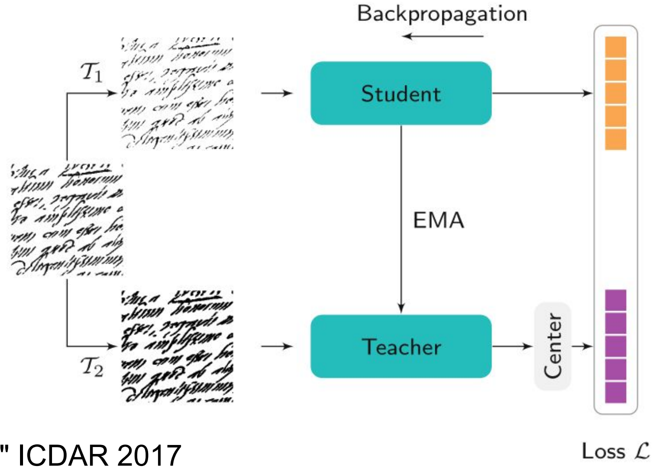
    → Map similar patches to each other
- Contrastive-learning-based:
  - Siamese-Network[2]
  - DINO[3]
  - AttMask[4] (Extension of DINO w. masking patches)
  - VICReg[5]
- Masked AutoEncoder[6]





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[3]M. Peer, F. Kleber, and R. Sablatnig, “Self-supervised Vision Transformers with Data Augmentation Strategies Using Morphological Operations for Writer Retrieval,” ICFHR 2022
[4]T. Raven, F. Gernot “Self-Supervised Vision Transformers for Writer Retrieval”, ICDAR 2024
[5]A Mattick, M Mayr, M Seuret, F Kordon, F Wu, V. Christlein, “Evaluating learned feature aggregators for writer retrieval”, IJDAR 2024
[6]Peer, M. Kleber, F., Sablatnig R.“SAGHOG: Self-Supervised Autoencoder for Generating HOG Features for Writer Retrieval”, ICDAR 2024

Feature Extraction

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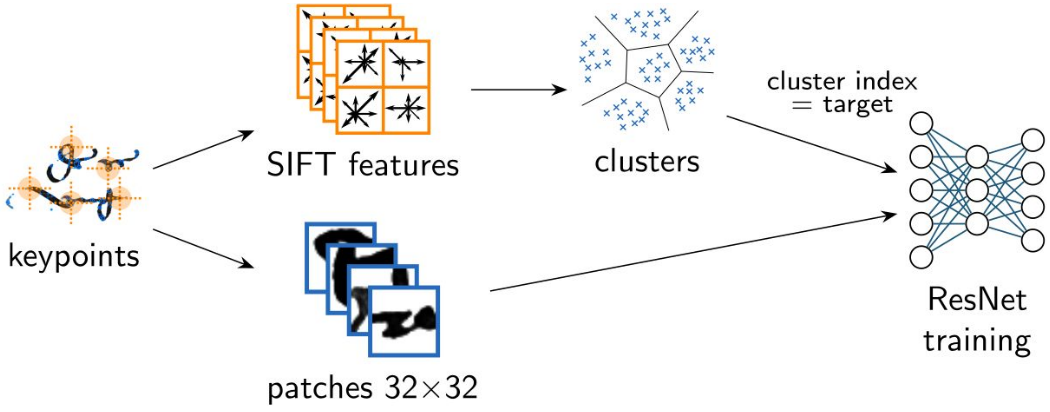
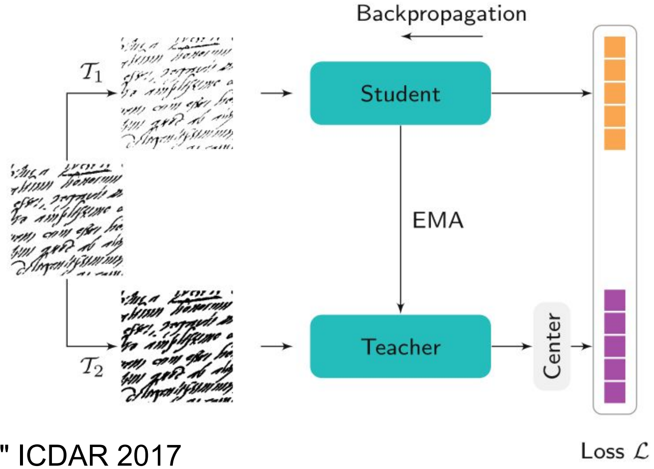
  - AttMask[4] (Extension of DINO w. masking patches)
  - VICReg[5]
- Masked AutoEncoder[6]
- → So far: no systematic study of SSL-based methods
  & learned keypoint-based features (SuperPoint, ALIKE, etc.)





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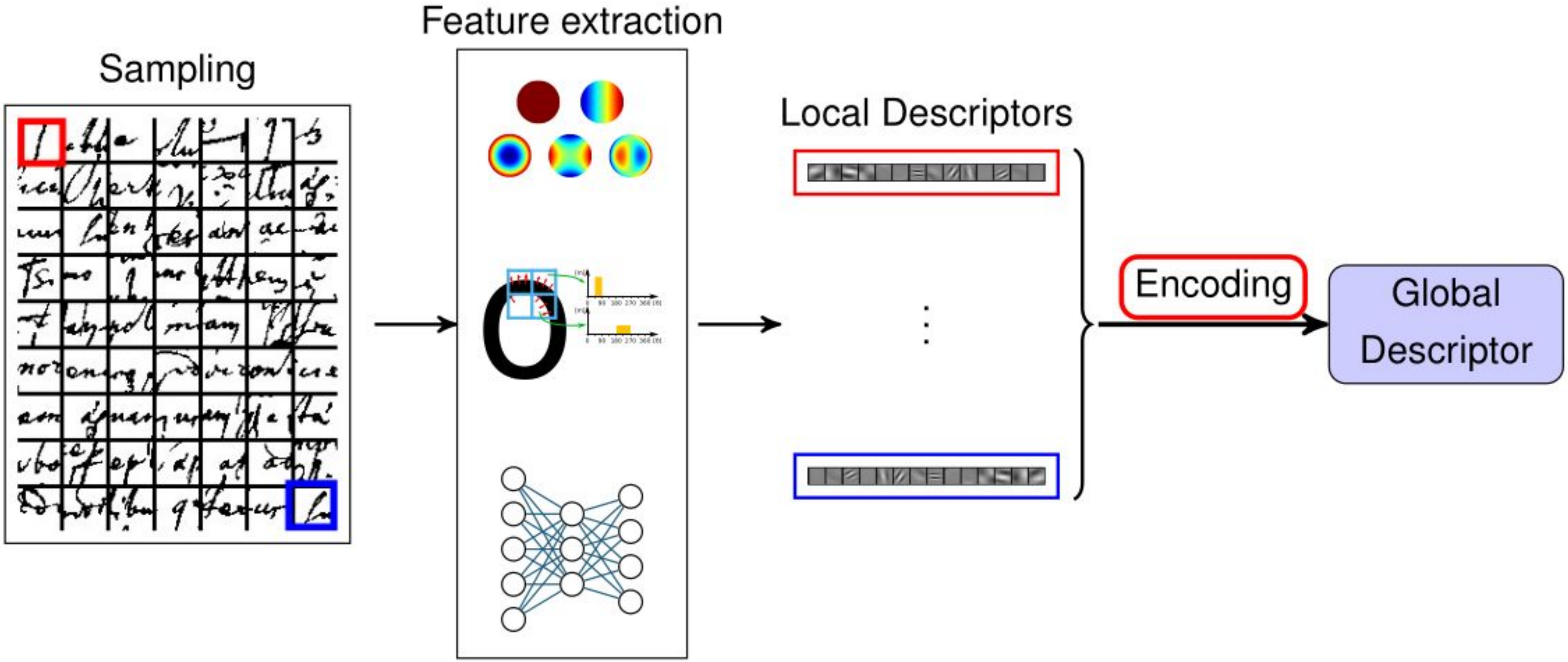
Writer Identification/Retrieval

Pipeline



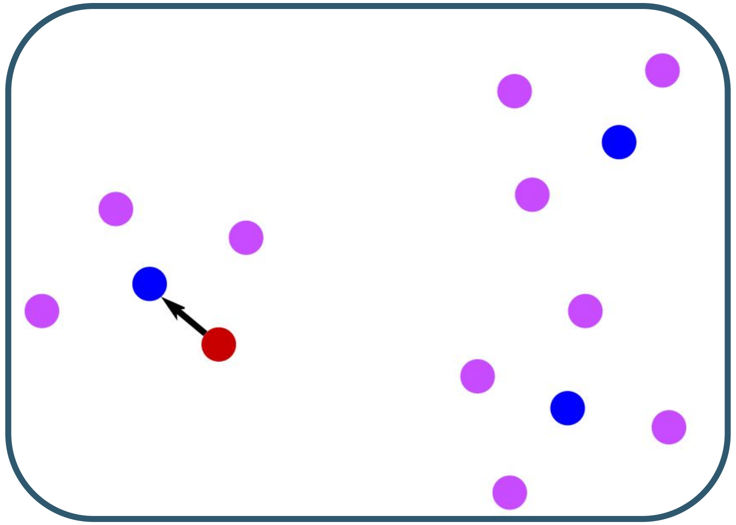
Global Embedding

Traditional:

- Sum-pooling
- Bag-of-words (0th order stats), Fisher Vectors (1st + 2nd order stats)[1]
- VLAD encoding (1st order stats)[2]

$$V_k = \sum_{i=1}^{N} \alpha_k(\boldsymbol{x} - i)(\boldsymbol{x}_i - \boldsymbol{c}_k)$$

$$\alpha_k(\boldsymbol{x}) = \begin{cases} 1 & \text{if} k = \text{argmin}_{j=1,\ldots,K} \|\boldsymbol{x} - \boldsymbol{c}_j\|_2 \\ 0 & \text{else} \end{cases}$$



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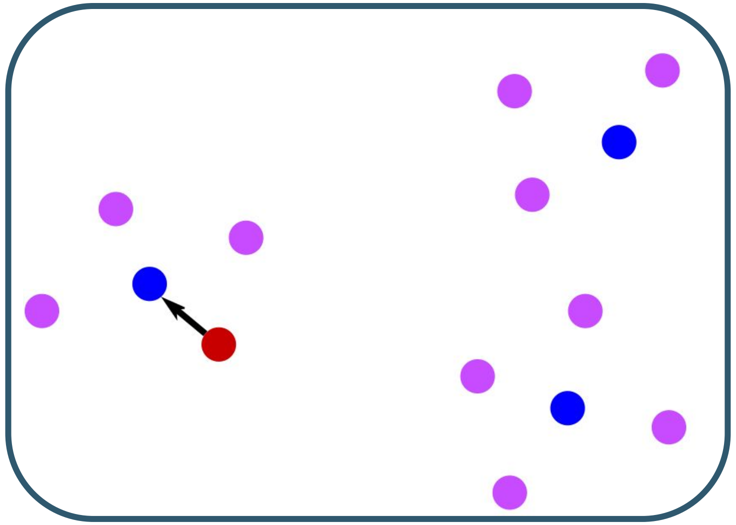
  - M-VLAD: use-multiple vocabularies, fuse outputs (PCA whitening)
  - bagged VLAD[3]
- Others:[4] GMM Supervectors, T-Emb, GVR, …

  → Takeaway: most of the time VLAD just works nicely



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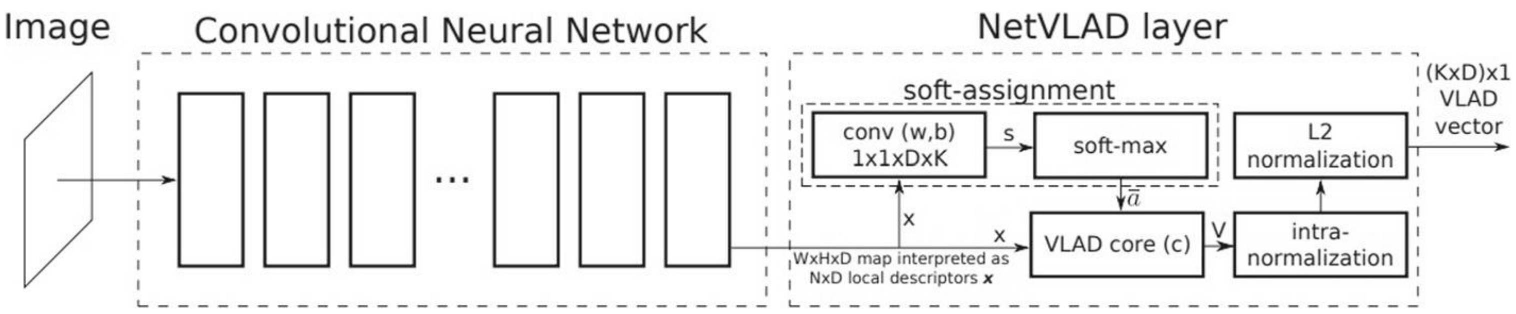
[2]V. Christlein, D. Bernecker and E. Angelopoulou, "Writer identification using VLAD encoded contour-Zernike moments", ICDAR 2015
[3]S. Lai, Y. Zhu and L. Jin, "Encoding Pathlet and SIFT Features With Bagged VLAD for Historical Writer Identification", TIFS 2020
[4]V. Christlein and A. Maier, "Encoding CNN Activations for Writer Recognition", DAS *2018*
V. Christlein "Handwriting Analysis with Focus on Writer Identification and Writer Retrieval", Doctoral Thesis 2019

Global Embedding

Deep-learning:

- NetVLAD[1]



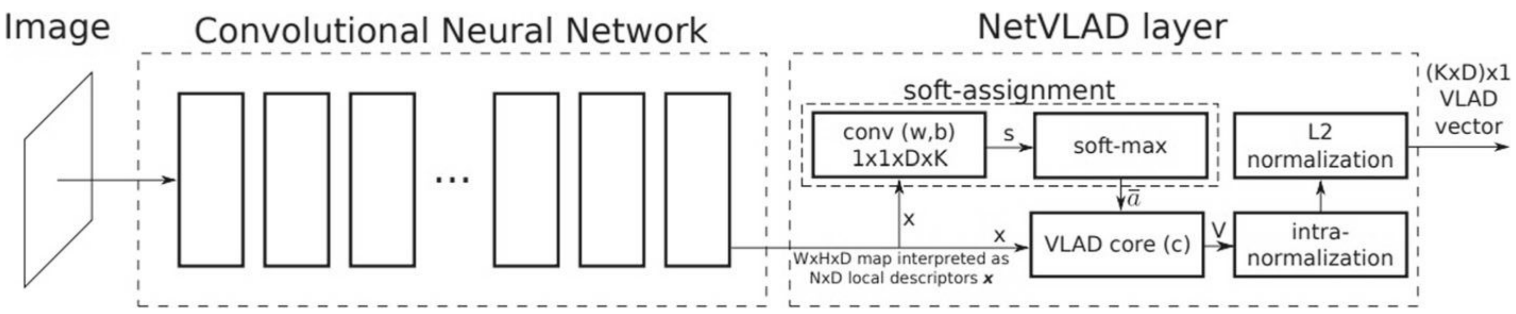
Source: Arandjelovic et al. “NetVLAD: CNN architecture for weakly supervised place recognition”, CVPR’16

[1] S. Rasoulzadeh & B. BabaAli, “Writer identification and writer retrieval based on NetVLAD with Re-ranking”, *IET Biometrics* 2021

Global Embedding

Deep-learning:

- NetVLAD[1]
    - A-VLAD[2]
        - Addeded attention weight
    - NetMVLAD[3]
        - Multiple vocabularies
    - NetRVLAD[4]
        - Different normalization
    - DeepTEN[5]



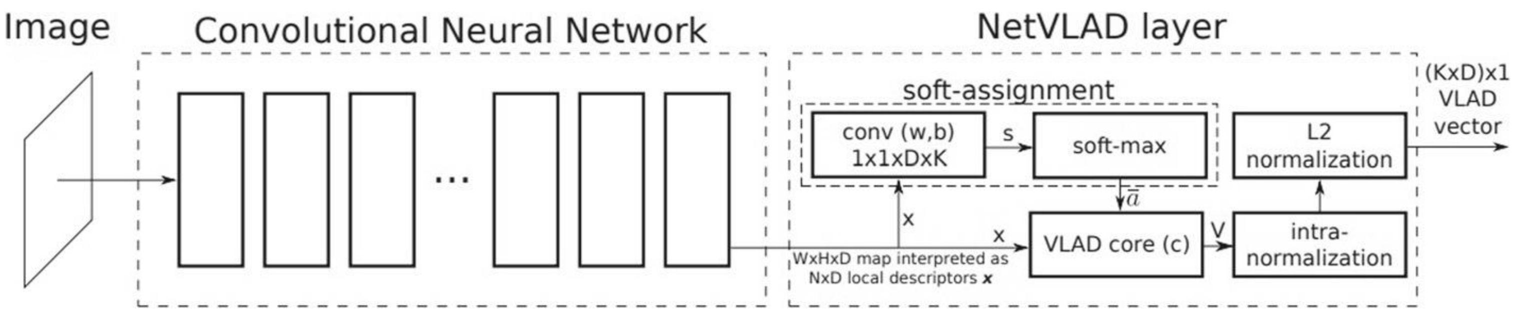
Source: Arandjelovic et al. "NetVLAD: CNN architecture for weakly supervised place recognition", CVPR'16

[1]S. Rasoulzadeh & B. BabaAli, "Writer identification and writer retrieval based on NetVLAD with Re-ranking", *IET Biometrics* 2021
[2]T.T. Ngo, H.T., Nguyen, M. Nakagawa, "A-VLAD: An End-to-End Attention-Based Neural Network for Writer Identification in Historical Document", *ICDAR* 2021
[3]M. Peer, F. Kleber and R. Sablatnig, "Writer Retrieval using Compact Convolutional Transformers and NetMVLAD", ICPR 2022
[4]M. Peer, F. Kleber, and R. Sablatnig, "Towards Writer Retrieval for Historical Datasets", *ICDAR 2023*
[5]Z. Wang, A. Maier, V. Christlein, "Towards End-to-End Deep Learning-based Writer Identification", INFORMATIK 2020

Global Embedding

Deep-learning:

- NetVLAD[1]
  - A-VLAD[2]
    - Addeded attention weight
  - NetMVLAD[3]
    - Multiple vocabularies
  - NetRVLAD[4]
    - Different normalization
  - DeepTEN[5]
- (Deep) Generalized Max-pooling[6]



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[5]Z. Wang, A. Maier, V. Christlein, "Towards End-to-End Deep Learning-based Writer Identification", INFORMATIK 2020
[6]V. Christlein, L. Spranger, M. Seuret, A. Nicolaou, P. Král and A. Maier, "Deep Generalized Max Pooling", ICDAR 2019

Global Embedding

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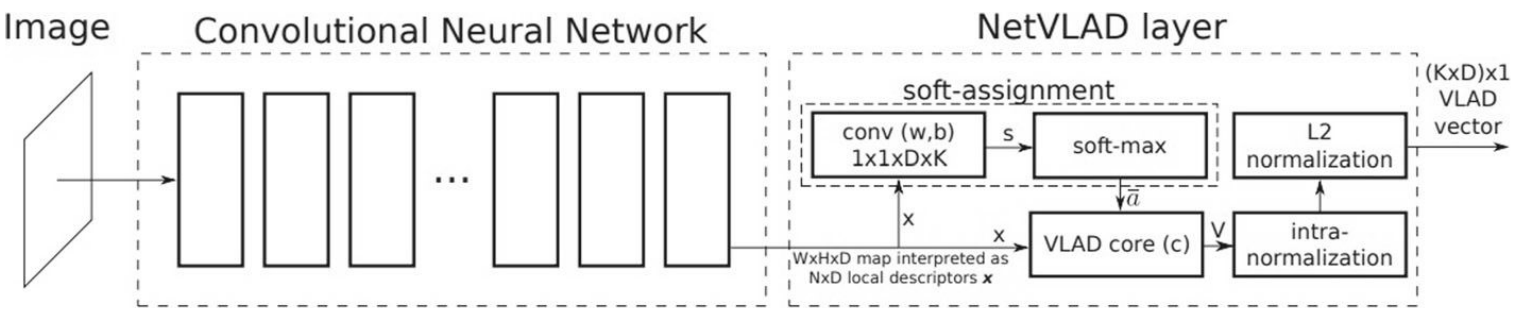
    - Multiple vocabularies
  - NetRVLAD[4]
    - Different normalization
  - DeepTEN[5]
- (Deep) Generalized Max-pooling[6]
- Transformers[7]
  - not as feature encoder but feature aggregation
    → performance potentially better than (Net)VLAD but needs a lot of compute



Source: Arandjelovic et al. “NetVLAD: CNN architecture for weakly supervised place recognition”, CVPR’16

[1]S. Rasoulzadeh & B. BabaAli, “Writer identification and writer retrieval based on NetVLAD with Re-ranking”, *IET Biometrics* 2021
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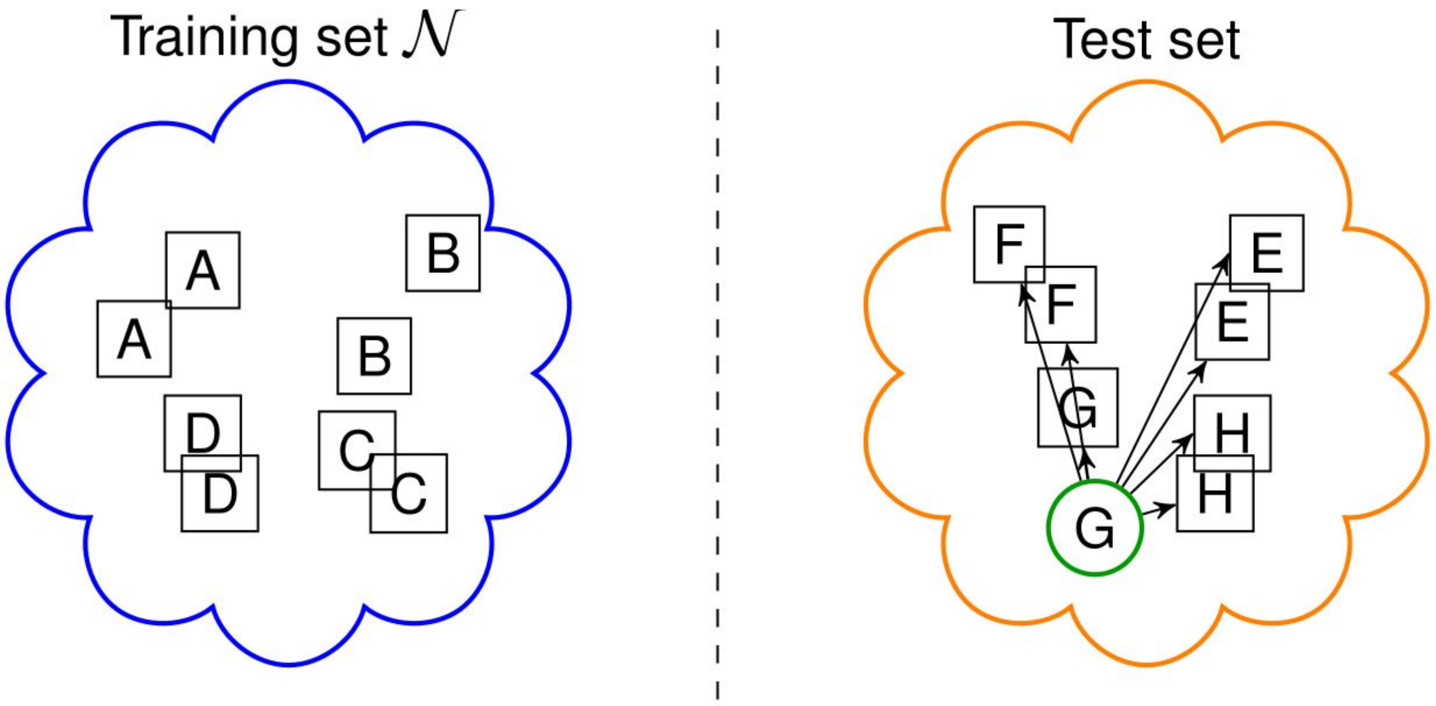
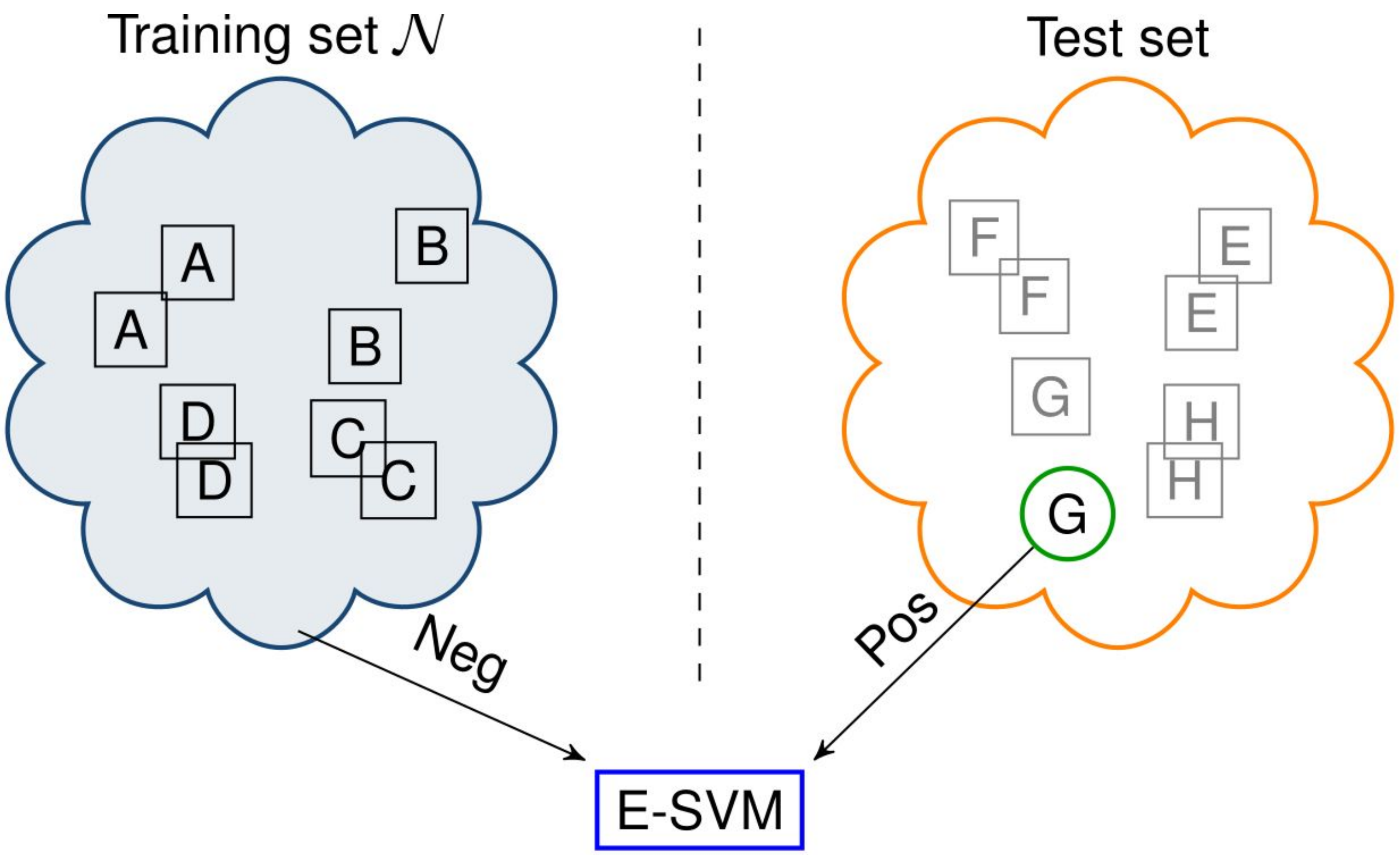
[3]M. Peer, F. Kleber and R. Sablatnig, "Writer Retrieval using Compact Convolutional Transformers and NetMVLAD", ICPR 2022
[4]M. Peer, F. Kleber, and R. Sablatnig, "Towards Writer Retrieval for Historical Datasets", *ICDAR 2023*
[5]Z. Wang, A. Maier, V. Christlein, “Towards End-to-End Deep Learning-based Writer Identification”, INFORMATIK 2020
[6]V. Christlein, L. Spranger, M. Seuret, A. Nicolaou, P. Král and A. Maier, "Deep Generalized Max Pooling", ICDAR 2019
[7]A Mattick, M Mayr, M Seuret, F Kordon, F Wu, V. Christlein, “Evaluating learned feature aggregators for writer retrieval”, IJDAR 2024

Exemplar SVM



V. Christlein, D. Bernecker, F. Hönig, A. Maier, and E. Angelopoulou, "Writer identification using GMM supervectors and exemplar-SVMs," Pattern Recognition 2017

Exemplar SVM

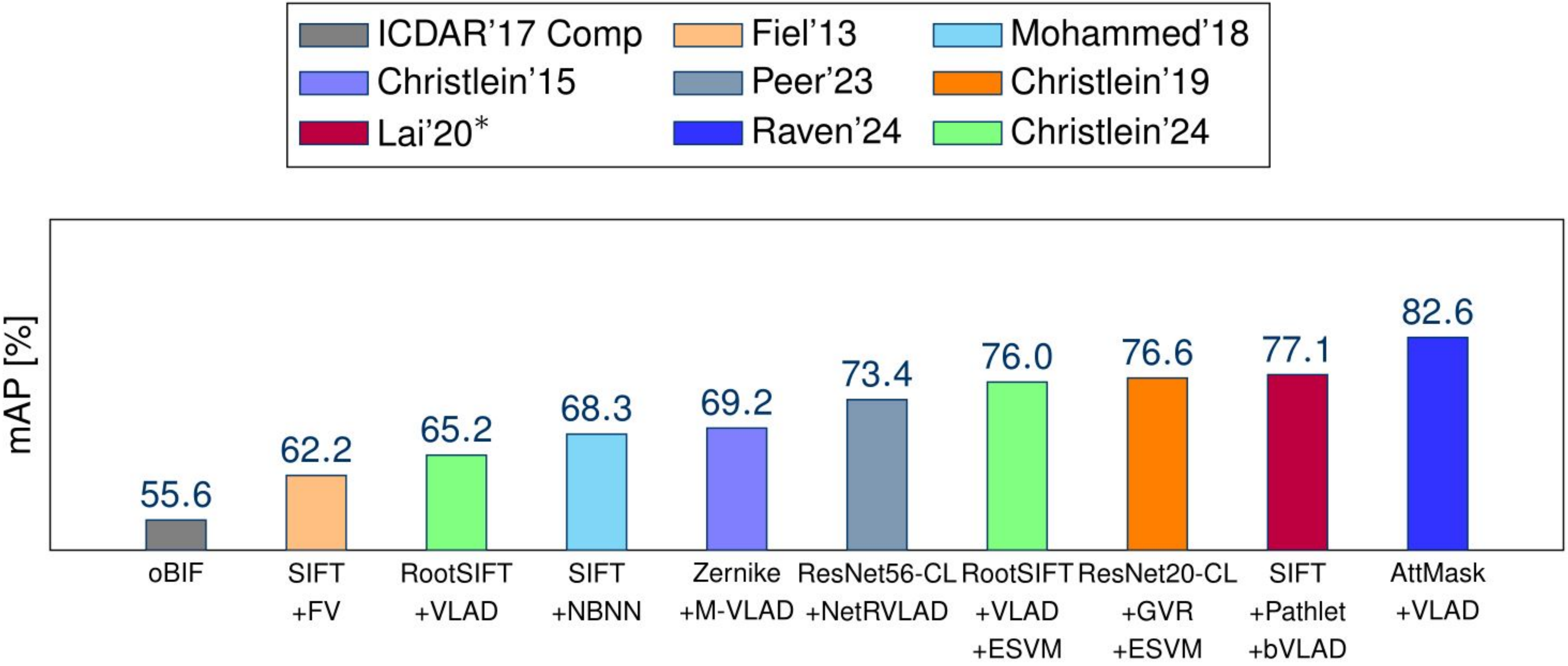


V. Christlein, D. Bernecker, F. Hönig, A. Maier, and E. Angelopoulou, "Writer identification using GMM supervectors and exemplar-SVMs," Pattern Recognition 2017

Some Results

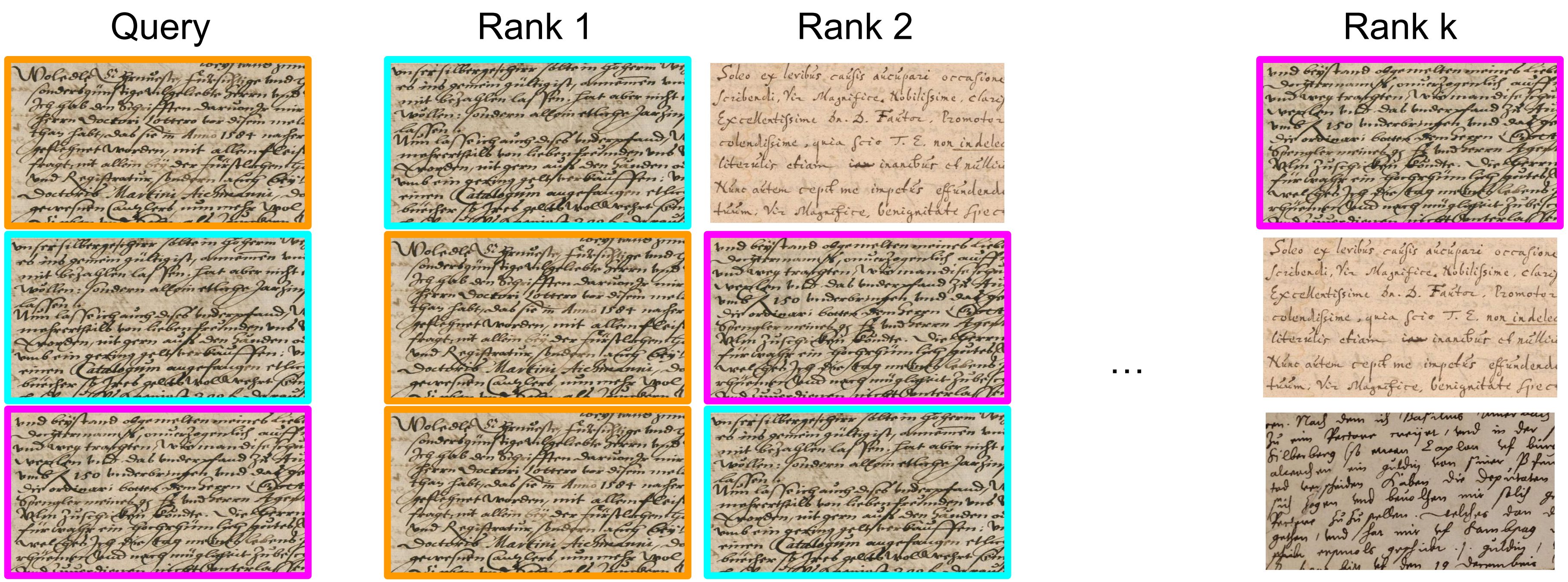
Writer Identification/Retrieval

ICDAR'17 WI Dataset



*Used differently binarized dataset

Re-ranking

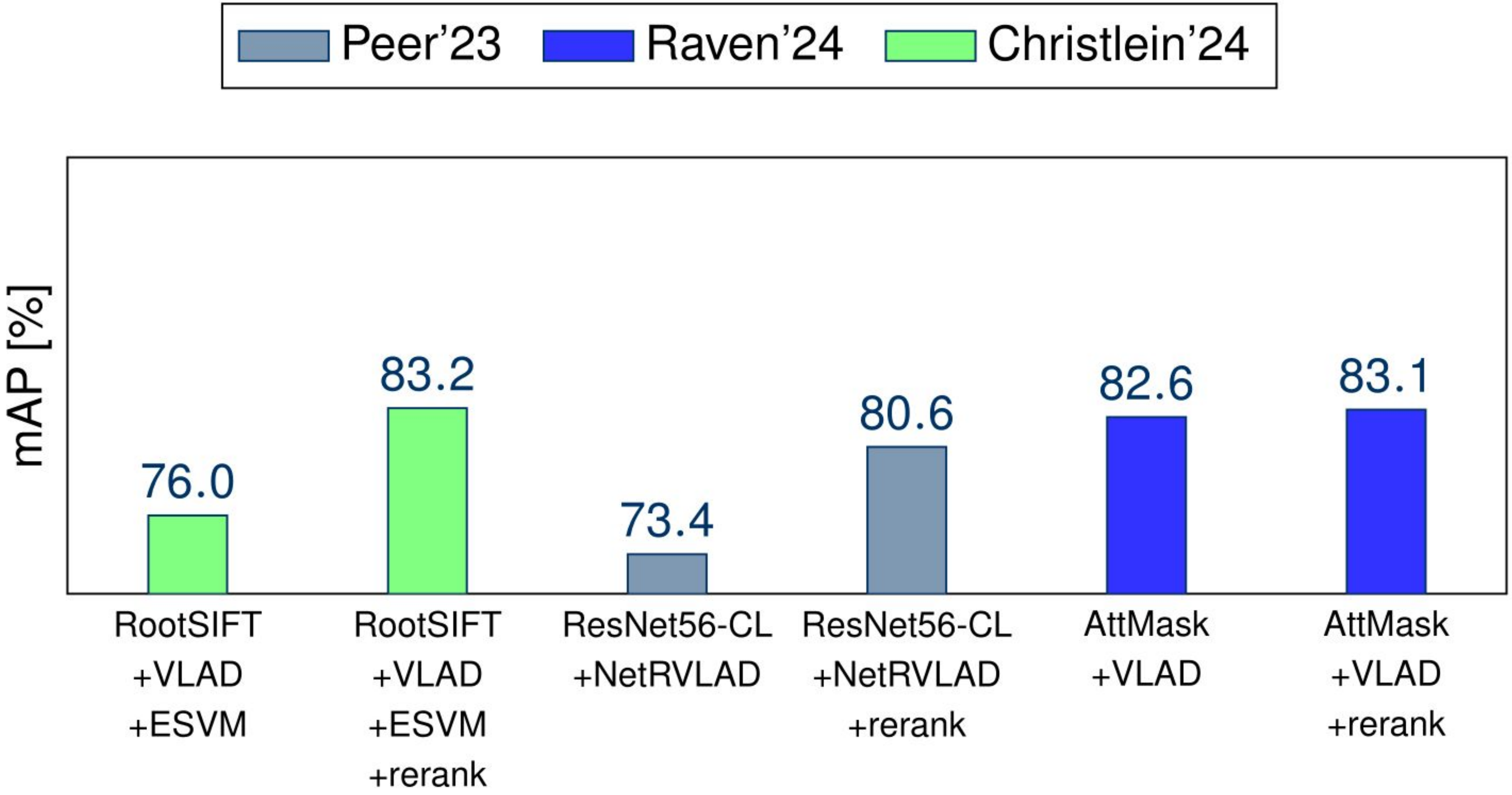


Different methods exist, e.g.,

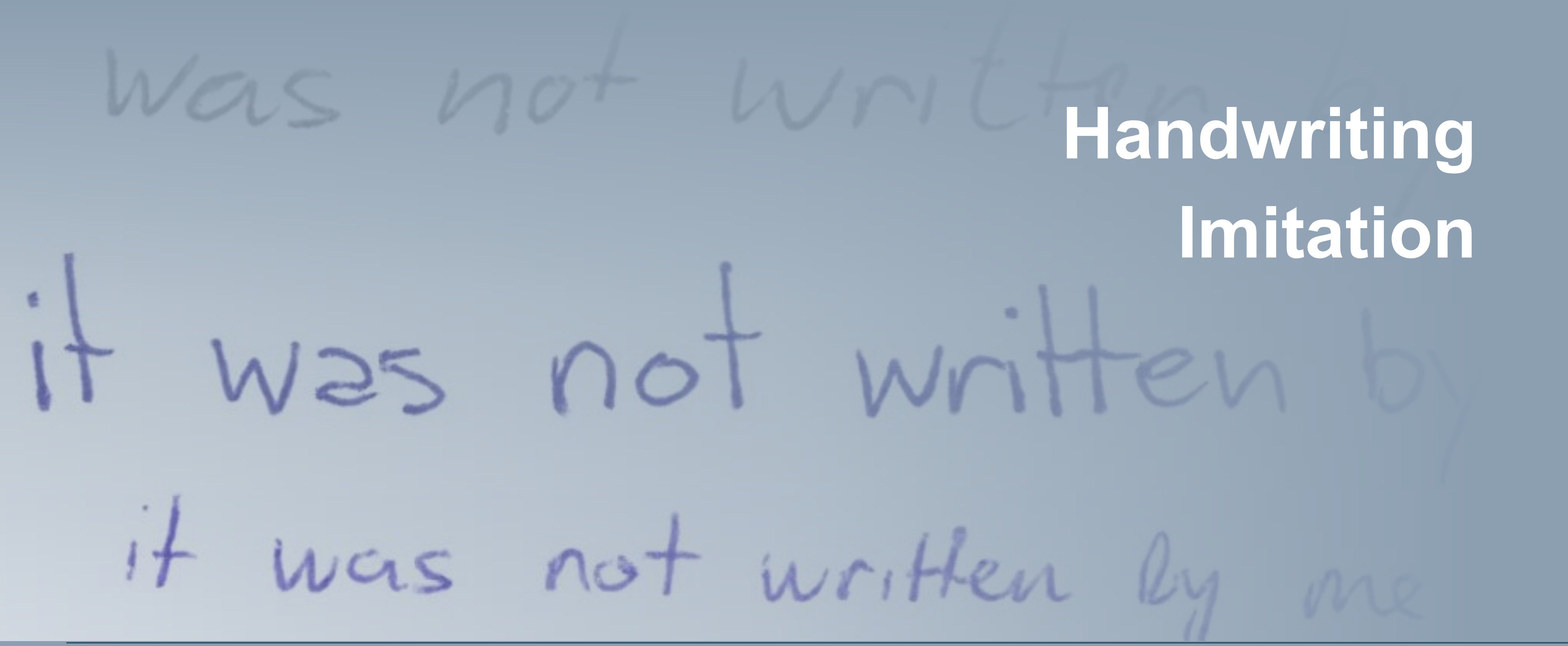
- *k*-reciprocal re-ranking[1]
- Similarity Graph re-ranking[2]

[1]S. Jordan, M. Seuret, P. Král, L. Lenc, J. Martínek, B. Wiermann, T. Schwinger, A. Maier & V. Christlein, “Re-Ranking for Writer Identification and Writer Retrieval”, DAS 2020
[2]M. Peer, F. Kleber, and R. Sablatnig, "Towards Writer Retrieval for Historical Datasets", *ICDAR 2023*

Re-ranking Results



Handwriting Imitation



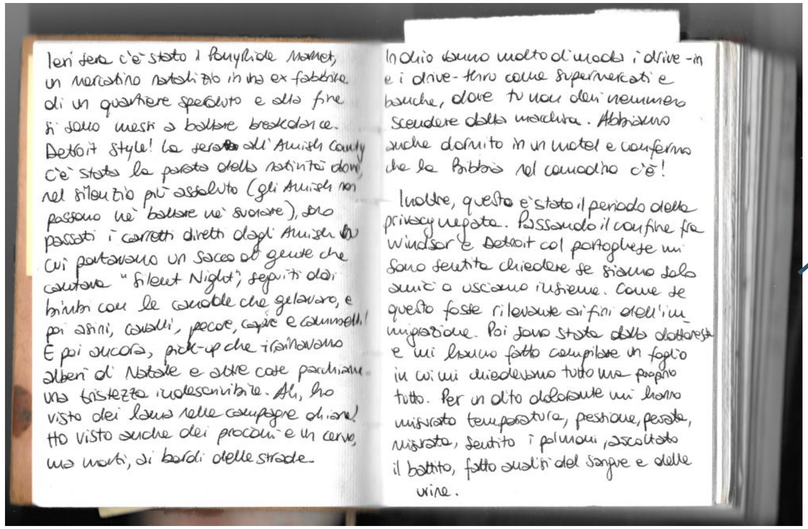
Motivation

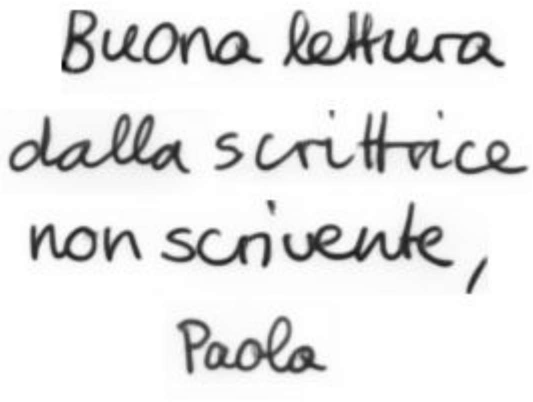
Generate handwriting without a pen

- Help people when writing is physically impaired

"Buona lettura dalla scrittrice non scrivente, Paola"

('Enjoy reading from the non-writing writer, Paola')





Paola Tellaroli

Source: https://www.intoscana.it/it/vince-il-premio-pieve-saverio-tutino-2023-paola-tellaroli-che-ha-raccontato-lictus-in-tutta-la-polvere-del-mondo-in-faccia/

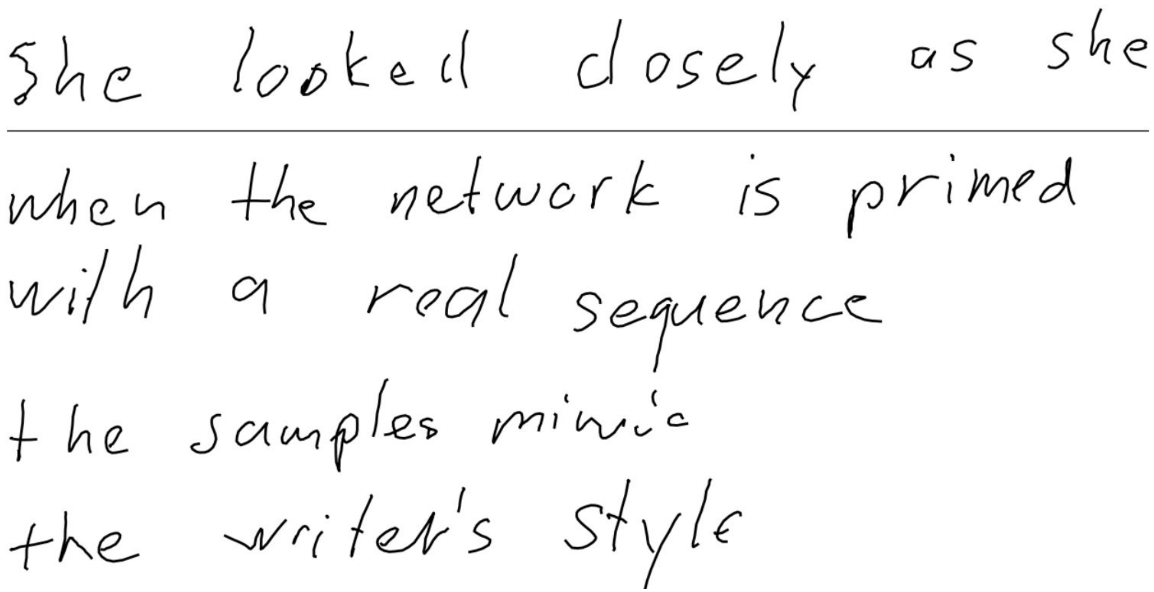
Motivation

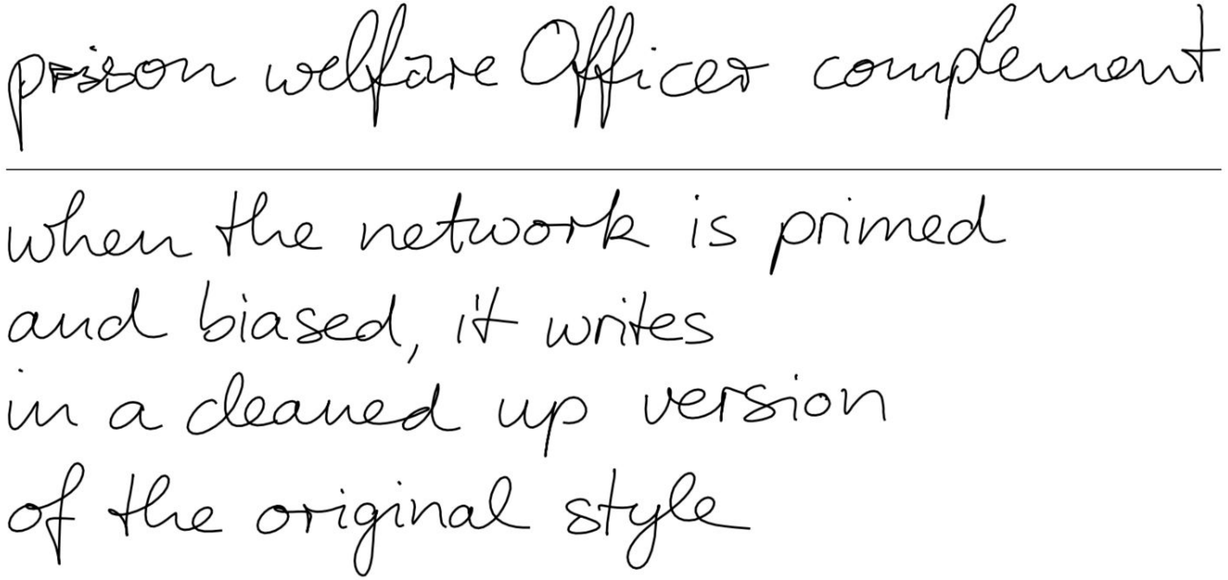
Generate handwriting without a pen

- Help people when writing is physically impaired
- Produce personalized cards / invitations
- Automatic manipulation of handwriting in movies to match the specific language
- Training data for automatic text recognition

Source: https://www.pinterest.ru/pin/499125571171917604/

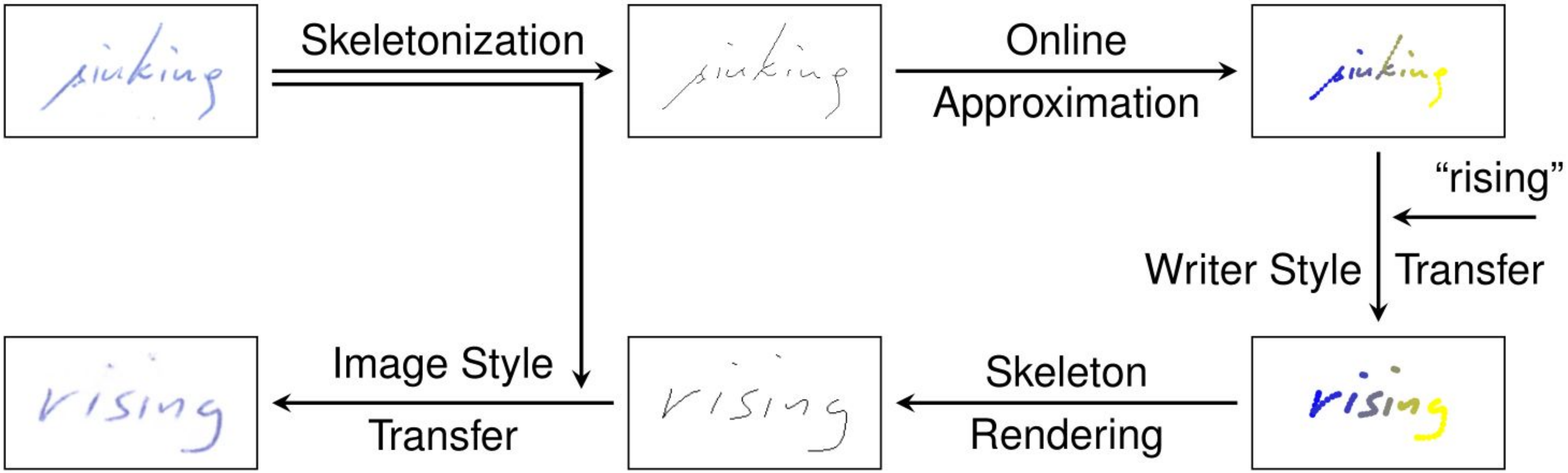
Online Text Generation





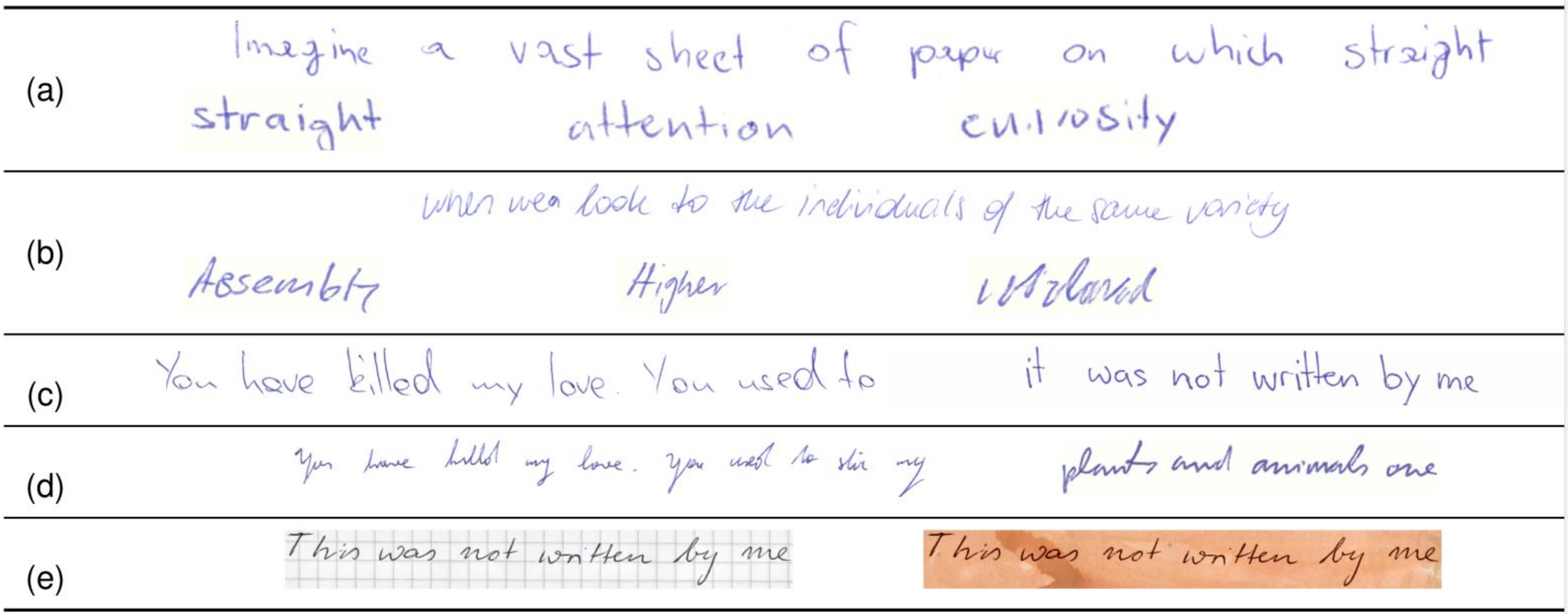
A. Graves "Generating Sequences With Recurrent Neural Networks”, arXiv 2013

Line-wise Imitation



M Mayr, M Stumpf, A Nicolaou, M Seuret, A. Maier, V. Christlein "Spatio-Temporal Handwriting Imitation". In: Computer Vision – ECCV 2020 Workshops 2020

Line-wise Imitation



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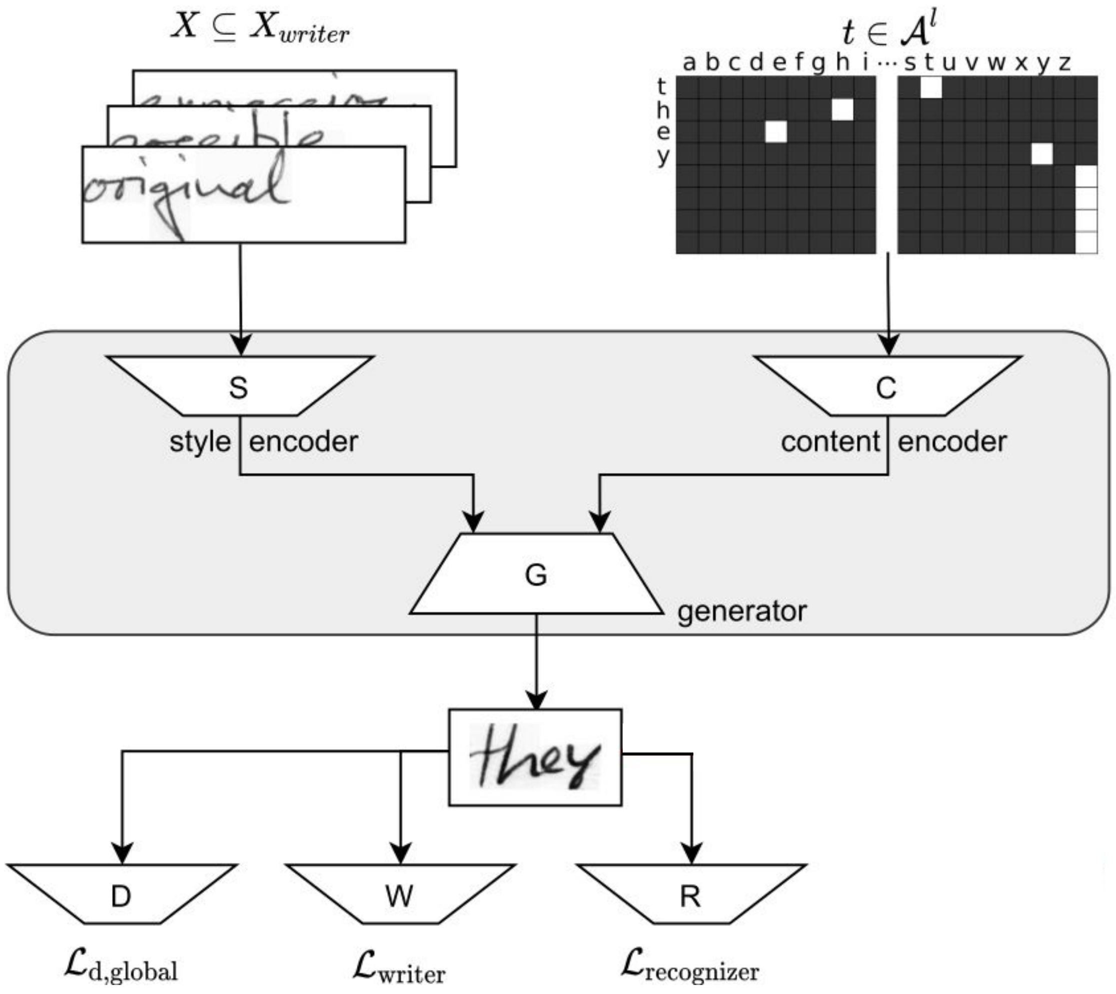
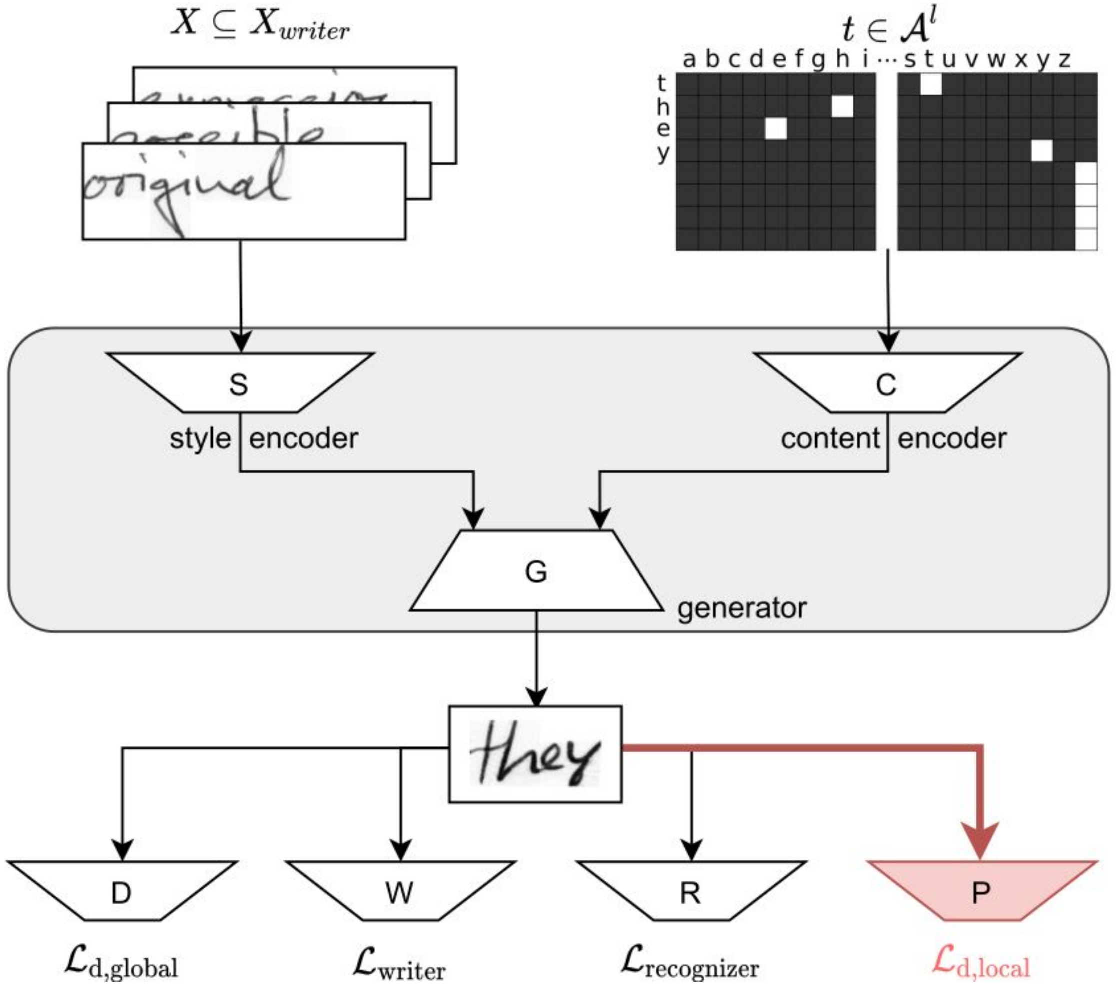
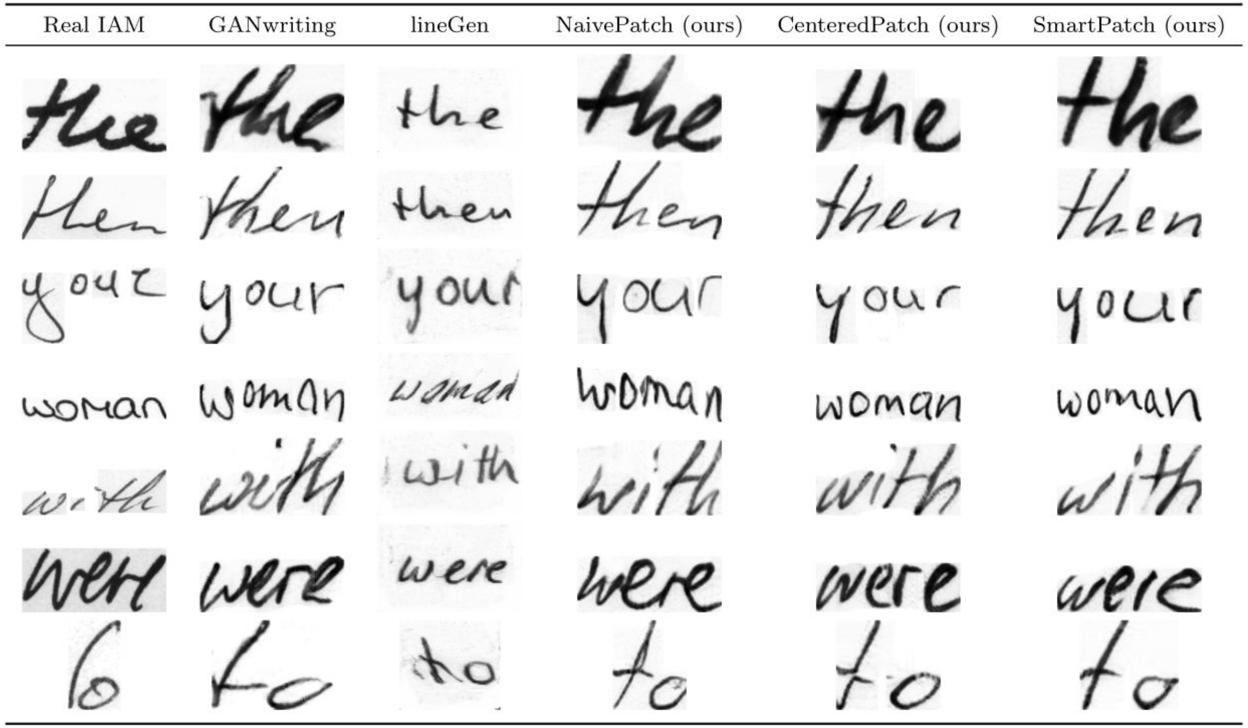
DeepWriter



Kang, L., Riba, P., Wang, Y., Rusinol, M., Fornés, A., & Villegas, M. “GANwriting: content-conditioned generation of styled handwritten word images.” ECCV 2020

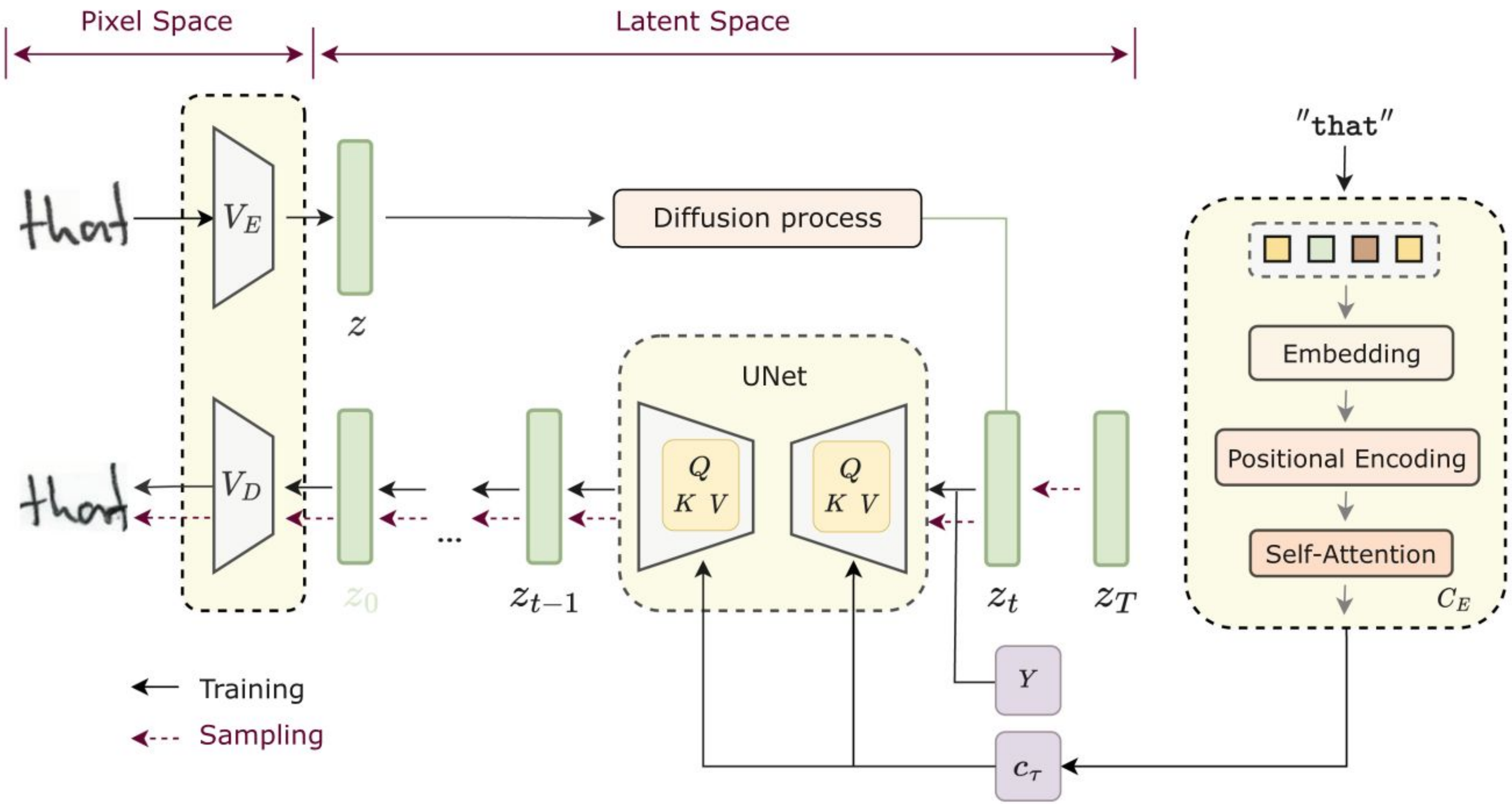
SmartPatch





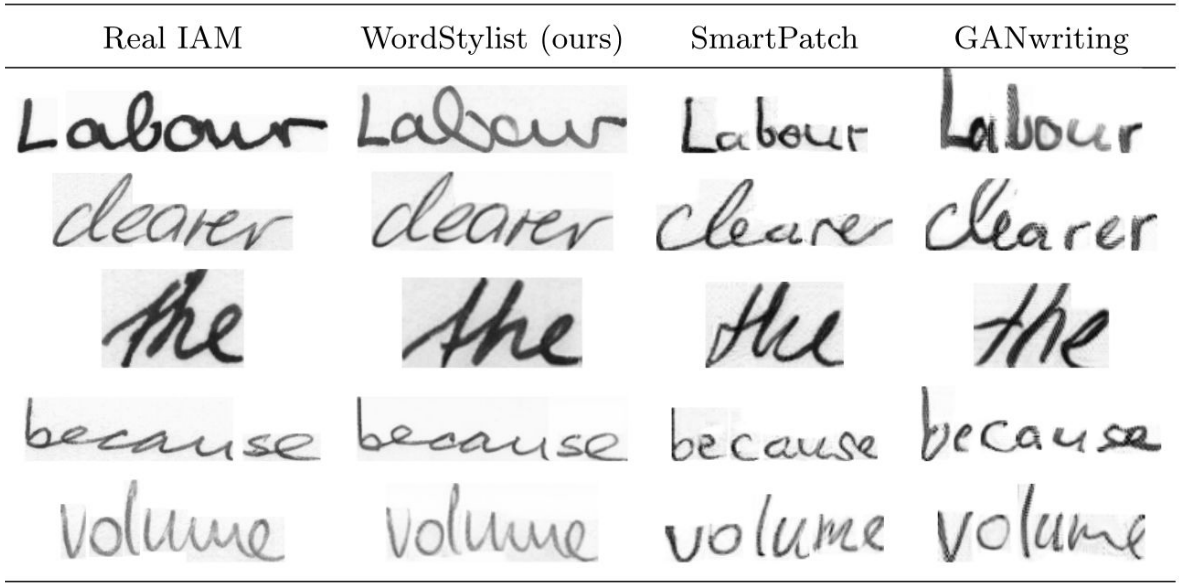
A. Mattick, M Mayr, M Seuret, A Maier, V.Christlein, “SmartPatch: Improving Handwritten Word Imitation with Patch Discriminators”. ICDAR 2021

WordStylist



Nikolaidou K., Retsinas G., Christlein V., Seuret M., Sfikas G., Barney Smith E., Mokayed H., Liwicki M.: "WordStylist: Styled Verbatim Handwritten Text Generation with Latent Diffusion Models", ICDAR 2023

WordStylist



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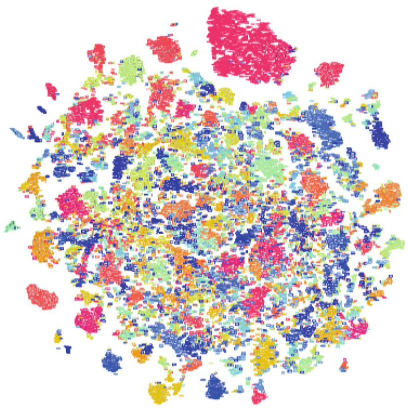
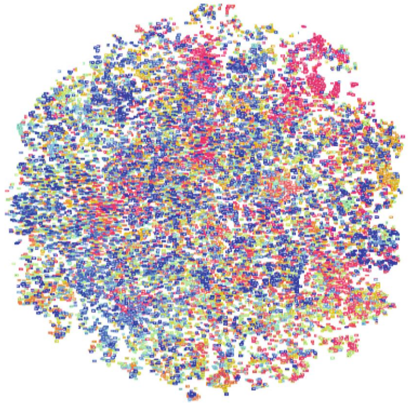
WordStylist

Writer Style

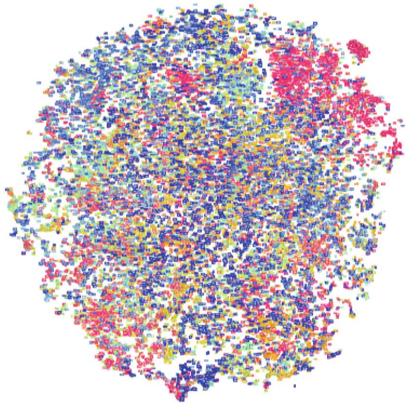
Real IAM



WordStylist



SmartPatch



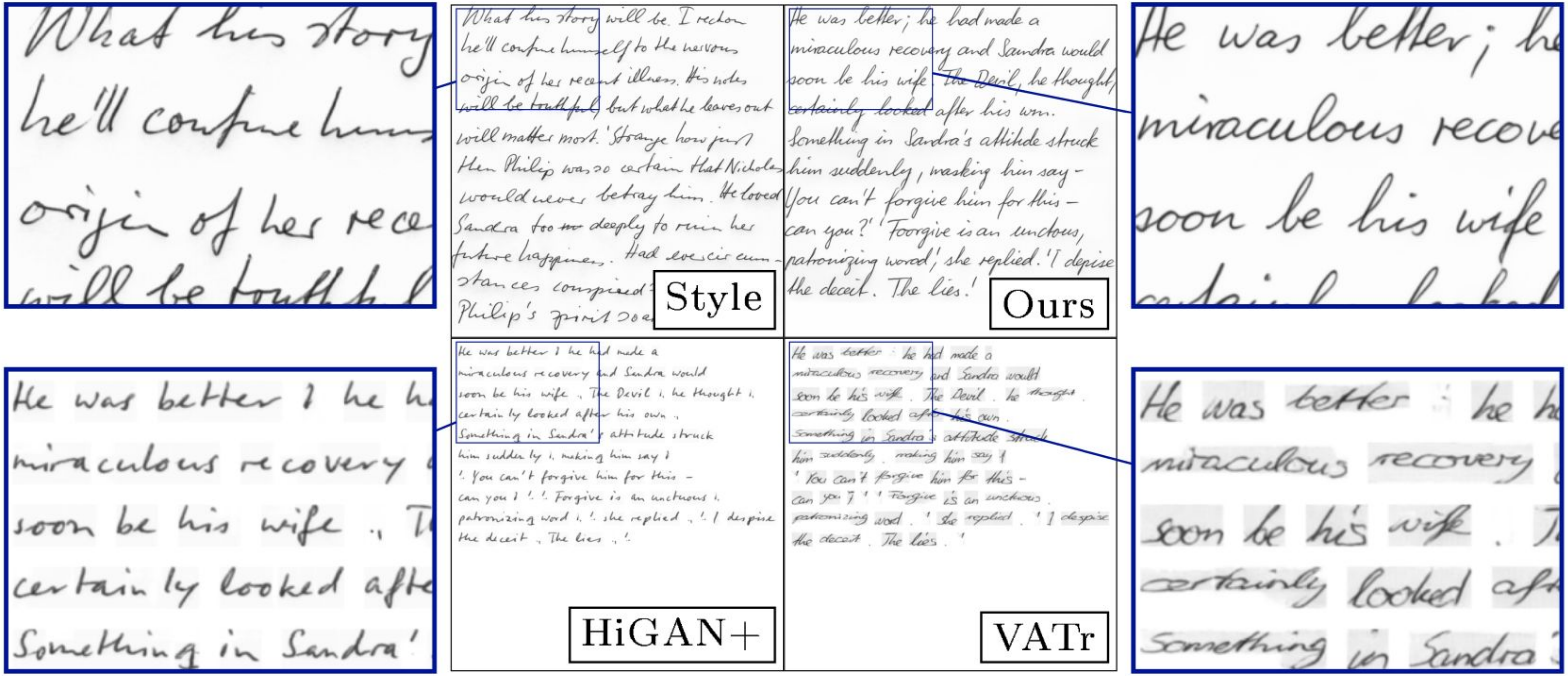
GANWriting

	Top-1 [%] ↑	mAP [%] ↑
IAM + IAM	97.45	97.61
IAM + GANwriting	3.18	7.23
IAM + SmartPatch	3.18	7.72
IAM + WordStylist (Ours)	**97.13**	**97.84**

- Preserves writing-style very well
- Only 96x96 dimension output
- Has to be trained for specific writer

Nikolaidou K., Retsinas G., Christlein V., Seuret M., Sfikas G., Barney Smith E., Mokayed H., Liwicki M.: “WordStylist: Styled Verbatim Handwritten Text Generation with Latent Diffusion Models”, ICDAR 2023

Paragraph-wise Imitation



M. Mayr, M. Dreier, F. Kordon, M. Seuret, J. Zöllner, F. Wu, A. Maier, V. Christlein "Zero-Shot Paragraph-level Handwriting Imitation with Latent Diffusion Models", arXiv 2409.00786 2024

Handwriting imitation meets Writer Retrieval

Writer retrieval for

- Assessing imitation quality
  - Should be the standard for evaluation, FID is (close to) meaningless for text
- Improving imitation quality (as additional loss)
  - → So far no sophisticated method used

Handwriting imitation meets Writer Retrieval

Writer retrieval for

- Assessing imitation quality
  - Should be the standard for evaluation, FID is (close to) meaningless for text
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- **A new frontier:** Detect generated imitations

Handwriting imitation meets Writer Retrieval

Writer retrieval for

- Assessing imitation quality
  - Should be the standard for evaluation, FID is (close to) meaningless for text
- Improving imitation quality (as additional loss)
  - → So far no sophisticated method used

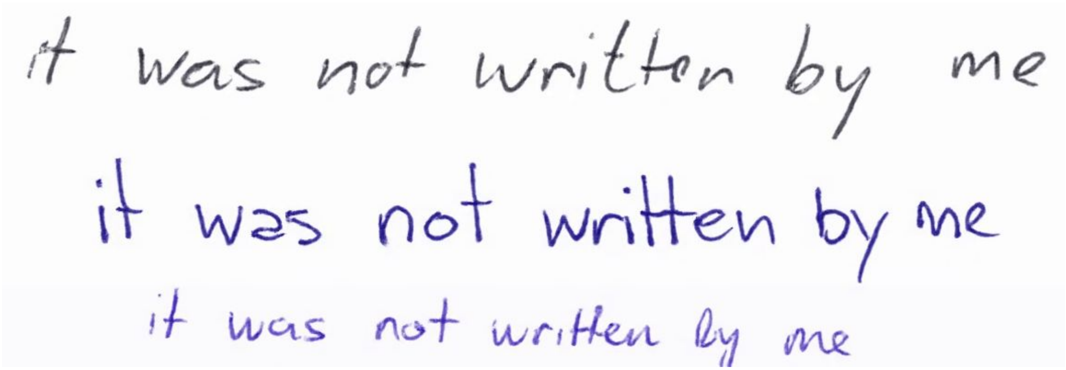
- **A new frontier:** Detect generated imitations
  - Diffusion-based generation can be detected by 90% with a simple ResNet18
  - Main factor: genuine samples are less clean

G. Carrière, K. Nikolaidou, F. Kordon, M. Mayr, M. Seuret, V. Christlein, “Beyond Human Forgeries: An Investigation into Detecting Diffusion-Generated Handwriting”, ICDAR - ADAPDA 2023

Research Frontiers:
- For the detection of forgeries
- For writer retrieval

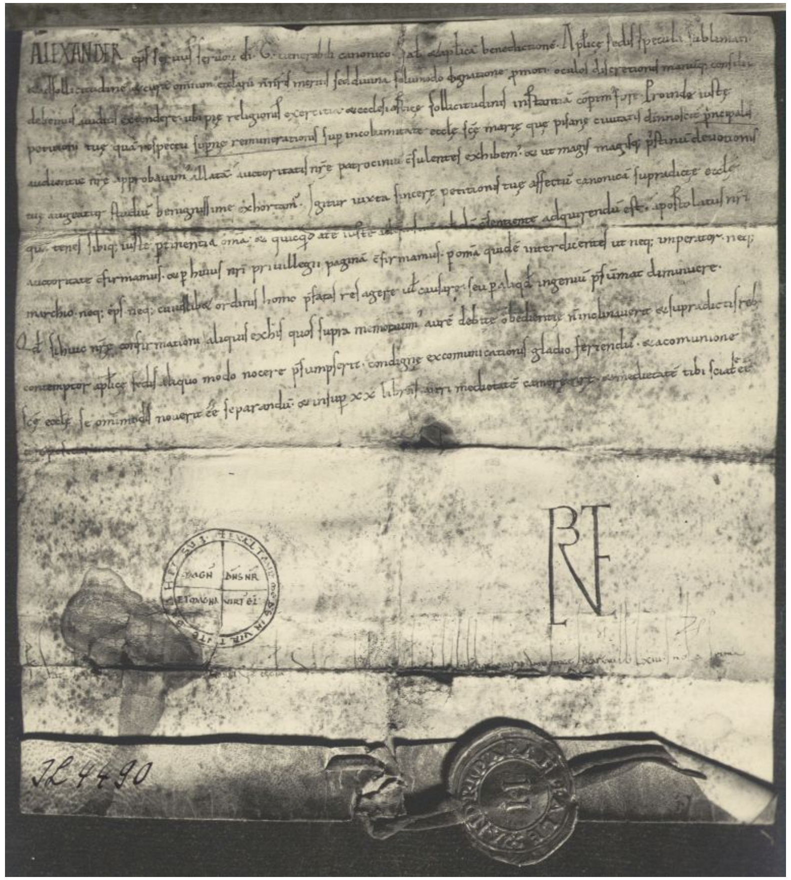
Research Frontiers

- New datasets
  - Genuine
  - Genuine + generated
- Increase robustness against noise/artifacts



Research Frontiers

- New datasets
  - Genuine
  - Genuine + generated
- Increase robustness against noise/artifacts
- Fine-grained identification/classification
  - Line-based
  - Word-based
- More realistic scenarios
  - OOD
  - Incremental learning
  - Identifying Imitations
- Improve interpretability

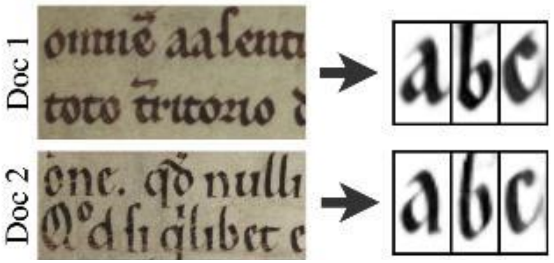


Source: Göttingen Academy of Sciences and Humanitie, JL 4490

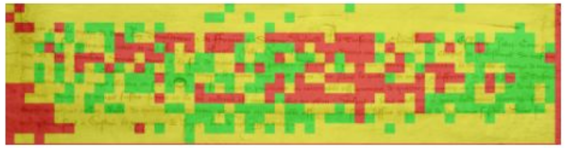
Interpretability

Several options

The Learnable Typewriter



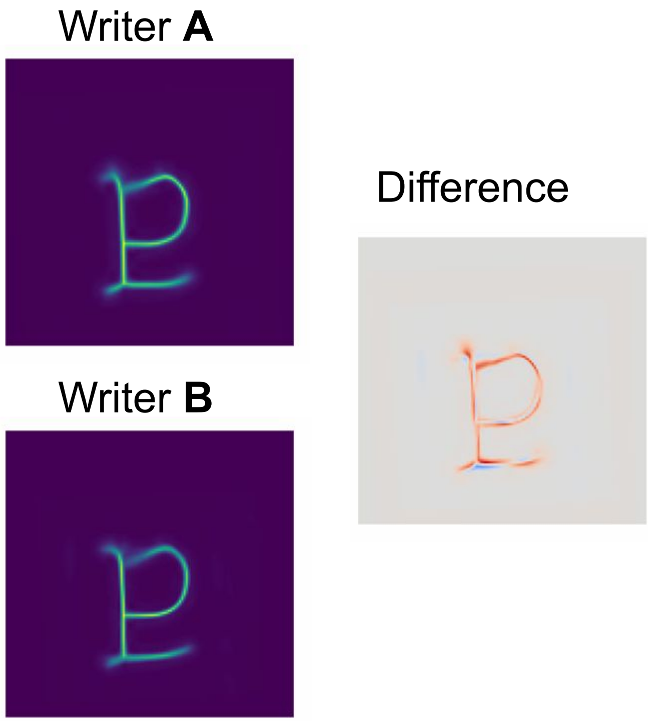
The Paleographer’s Eye



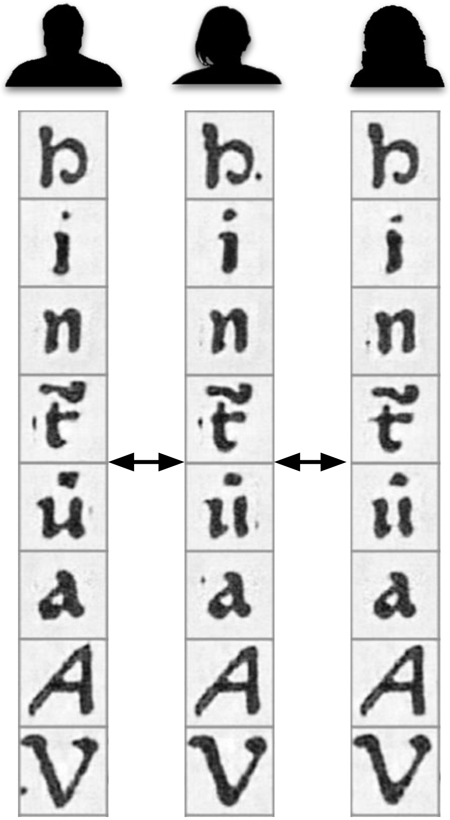
Hoccleve Example Compared to Hoccleve Template

Hoccleve Example Compared to Langeport Template

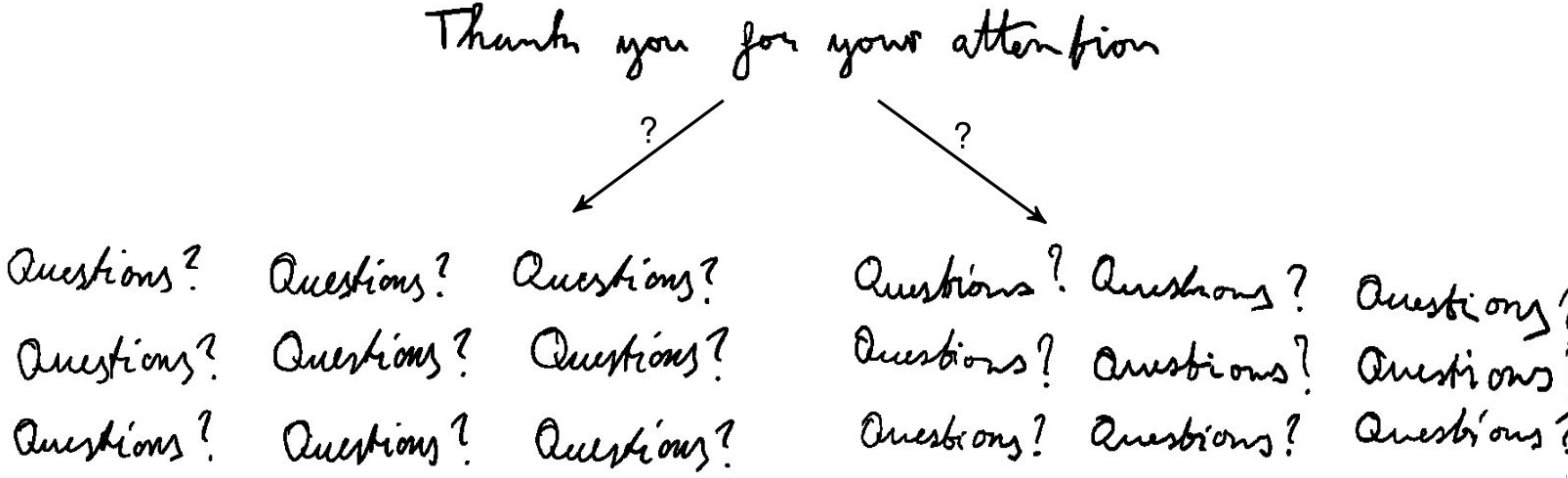
Inter-writer shape analysis using character skeletons



Comparison of class prototypes with high probability mass



I. Siglidis, N. Gonthier, J. Gaubil, T. Monnier, M. Aubry: “The Learnable Typewriter: A Generative Approach to Text Analysis”. *ICDAR,* 2024.
S. Grieggs, C. E. M. Henderson, S. Sobecki, A. Gillespie, W. Scheirer: "The Paleographer’s Eye ex machina: Using Computer Vision to Assist Humanists in Scribal Hand Identification". *WACV,* 2024.
F. Kordon, N. Weichselbaumer, R.I Herz, S. Mossman, E. Potten, M. Seuret, M. Mayr & V. Christlein “Classification of incunable glyphs and out-of-distribution detection with joint energy-based models”. IJDAR, 2023.

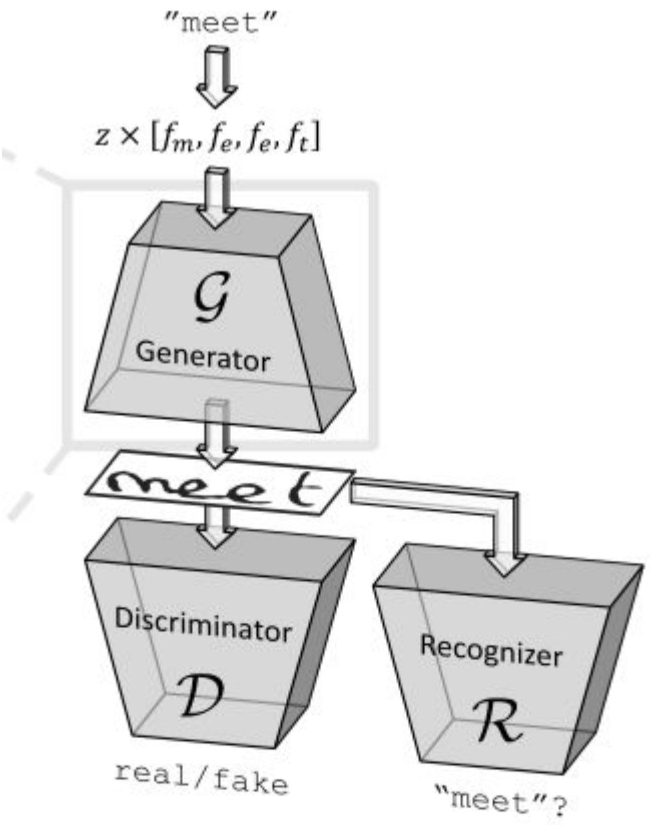


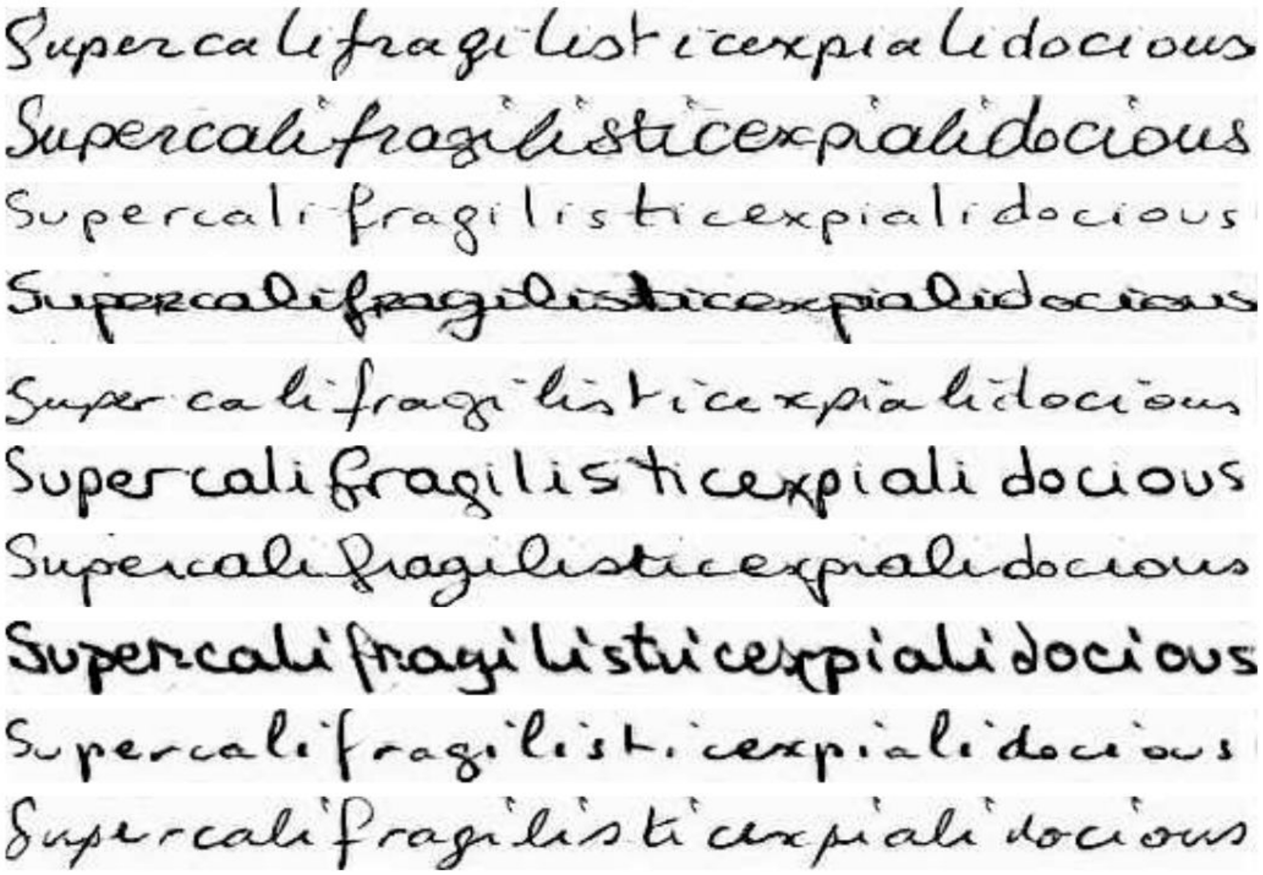
Slides + Code

https://github.com/VChristlein/icdar24keynote

From Handwriting Generation to Imitation

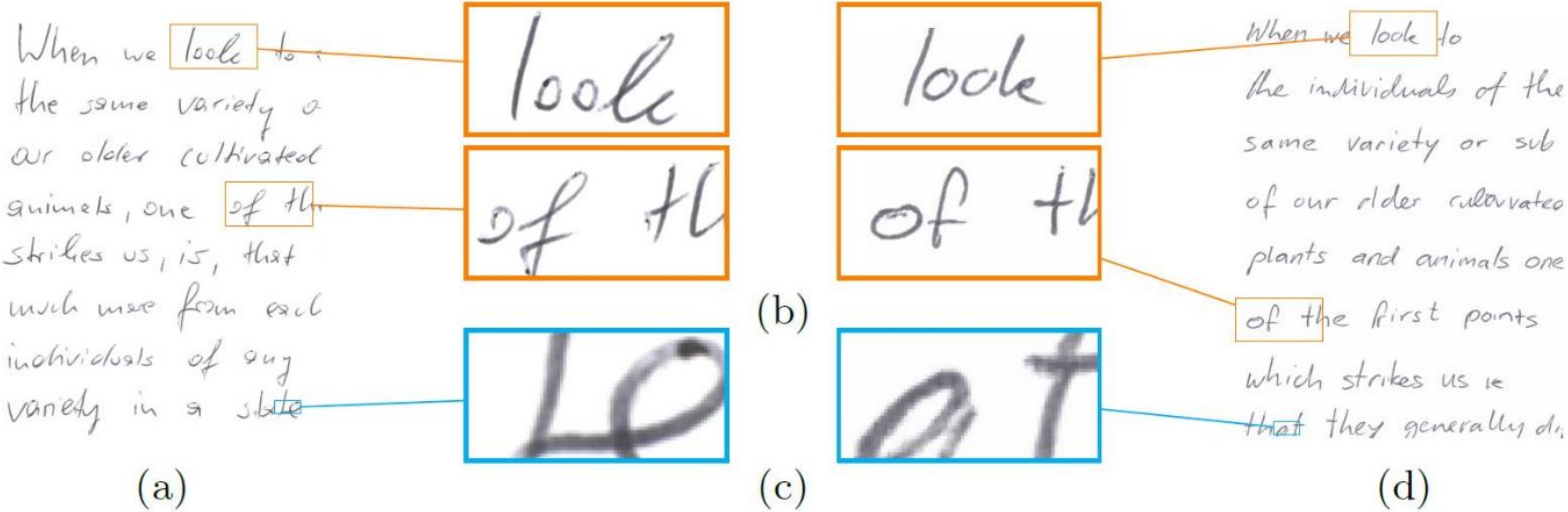
ScrabbleGAN





Fogel, S., Averbuch-Elor, H., Cohen, S., Mazor, S., & Litman, R. "ScrabbleGAN: Semi-supervised varying length handwritten text generation." CVPR 2020

Line-wise Imitation



M Mayr, M Stumpf, A Nicolaou, M Seuret, A. Maier, V. Christlein "Spatio-Temporal Handwriting Imitation". In: Computer Vision – ECCV 2020 Workshops 2020