Pattern Recognition Lab

FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG
FACULTY OF ENGINEERING

Handwriting Generation

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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

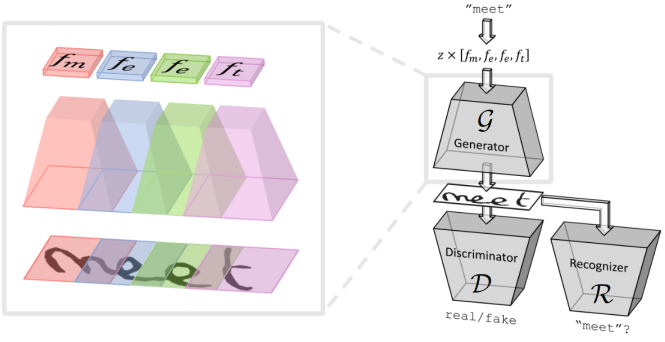
Source: https://commons.wikimedia.org/wiki/File:Broken_right_hand_in_orange_cast.jpg (CC-BY-SA) | https://www.pinterest.ru/pin/499125571171917604/

Outline

Word Generation

Method Overview

ScrabbleGAN - Synthesizing Handwriting



Sharon Fogel et al. "ScrabbleGAN: Semi-Supervised Varying Length Handwritten Text Generation". In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. June 2020

ScrabbleGAN

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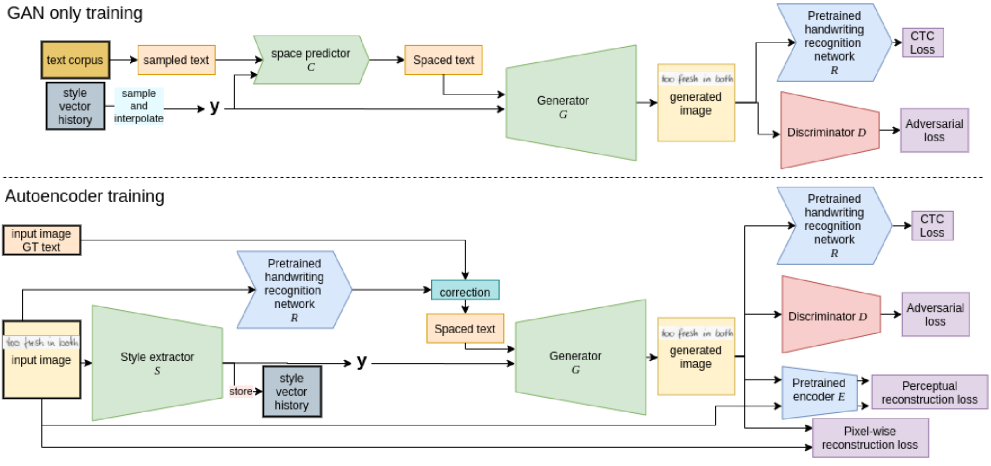
Davis et al.

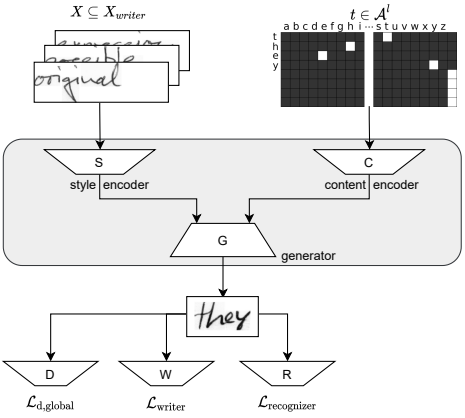


Brian Davis et al. "Text and Style Conditioned GAN for Generation of Offline Handwriting Lines". In: *British Machine Vision Conference (BMVC)*. 2020. arXiv: 2009.00678 [cs.CV]

ScrabbleGAN vs. Davis et al.

Brian Davis et al. "Text and Style Conditioned GAN for Generation of Offline Handwriting Lines". In: *British Machine Vision Conference (BMVC)*. 2020. arXiv: 2009.00678 [cs.CV]

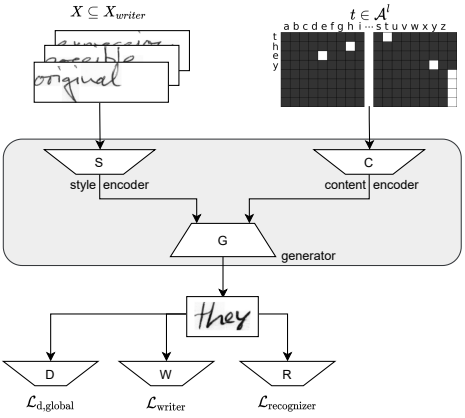
GANwriting - Handwriting Imitation



- Generator input: clear-text and word-images

Lei Kang et al. “GANwriting: Content-Conditioned Generation of Styled Handwritten Word Images”. In: *Computer Vision – ECCV 2020*. Ed. by Andrea Vedaldi et al. Cham: Springer International Publishing, 2020, pp. 273–289

GANwriting - Handwriting Imitation



- Generator input: clear-text and word-images
- Generator output: image with content of the clear-text and style of word-samples

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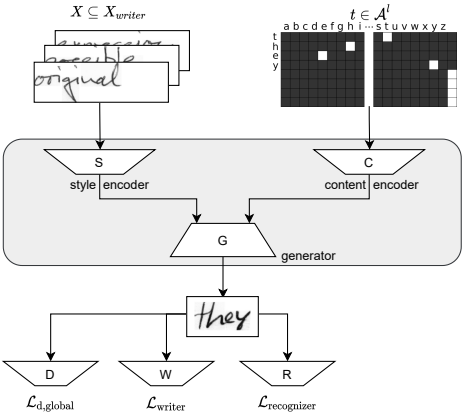

- Generator input: clear-text and word-images
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- GAN-discriminator

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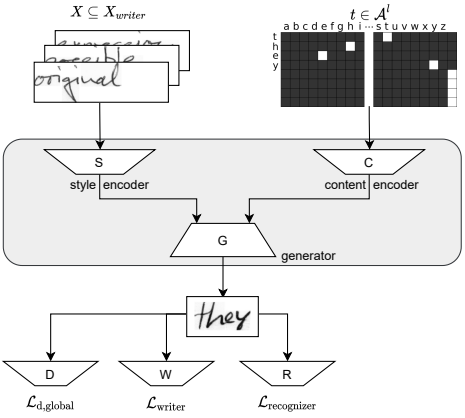

- Generator input: clear-text and word-images
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- GAN-discriminator
- HTR-model for content loss

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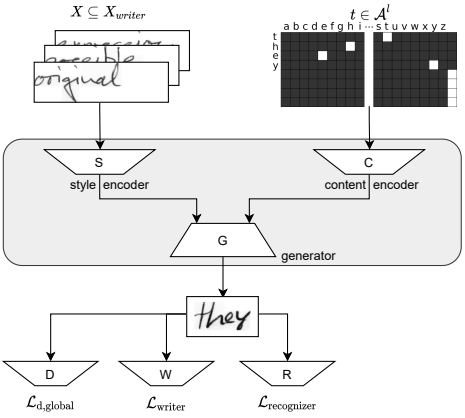
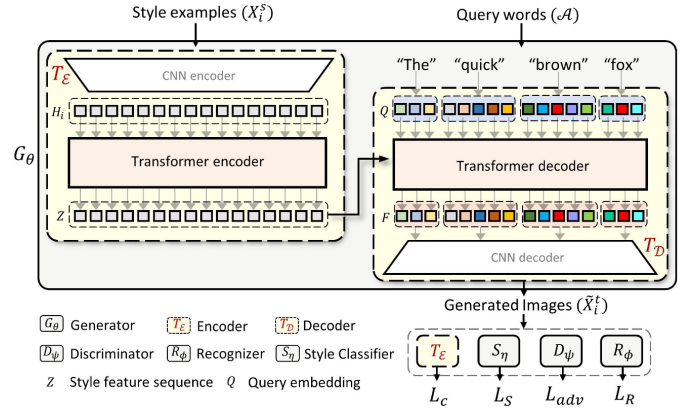
GANwriting - Handwriting Imitation



- Generator input: clear-text and word-images
- Generator output: image with content of the clear-text and style of word-samples
- GAN-discriminator
- HTR-model for content loss
- Writer-identification for style loss

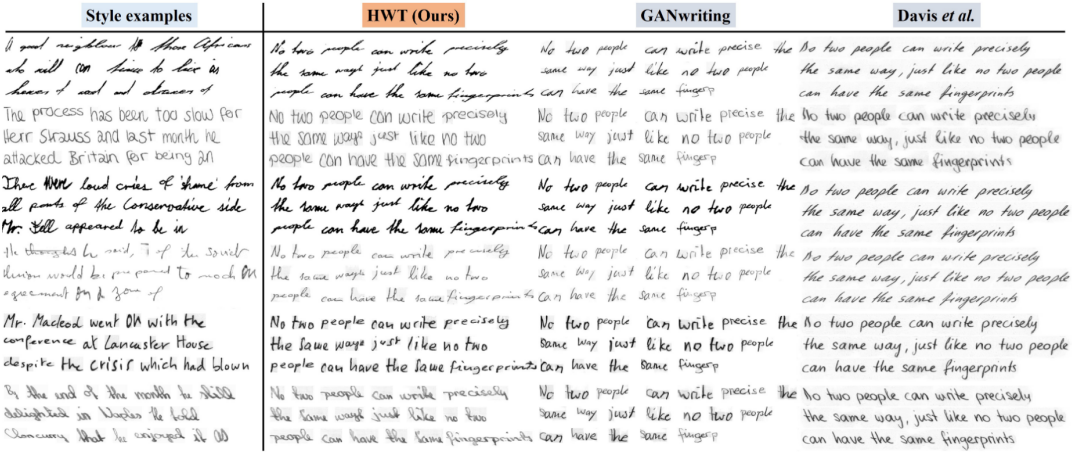
Lei Kang et al. “GANwriting: Content-Conditioned Generation of Styled Handwritten Word Images”. In: *Computer Vision – ECCV 2020*. Ed. by Andrea Vedaldi et al. Cham: Springer International Publishing, 2020, pp. 273–289

Handwriting Transformer



Ankan Kumar Bhunia et al. "Handwriting Transformers". In: *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*. Oct. 2021, pp. 1086–1094

Handwriting Transformer (HWT) vs. GANwriting vs. Davis et al.



Ankan Kumar Bhunia et al. "Handwriting Transformers". In: *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*. Oct. 2021, pp. 1086–1094

Defects of GANwriting

Figure: Frequently appearing artifacts in the outputs of GANwriting.

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- “stepping” artifacts

Defects of GANwriting

Figure: Frequently appearing artifacts in the outputs of GANwriting.

- “stepping” artifacts
- thin lines

Defects of GANwriting

Figure: Frequently appearing artifacts in the outputs of GANwriting.

- “stepping” artifacts
- thin lines
- smudged lines

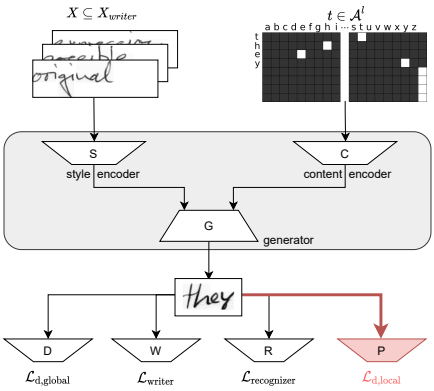
Defects of GANwriting

Figure: Frequently appearing artifacts in the outputs of GANwriting.

- “stepping” artifacts
- thin lines
- smudged lines
- unsteady lines

SmartPatch

SmartPatch



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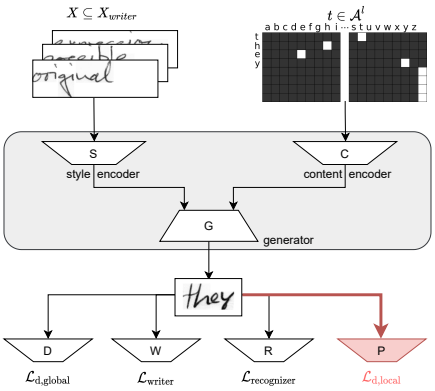
SmartPatch



- Dedicated discriminator for character level

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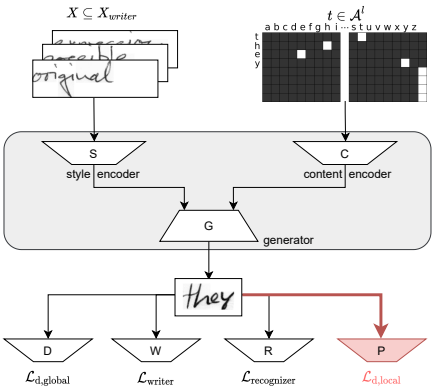

- Dedicated discriminator for character level
- Rolling patches: 64×64 patches with stride 32

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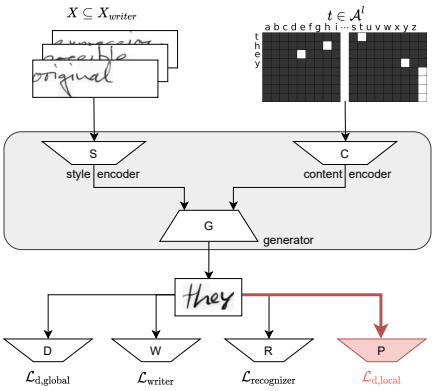

- Dedicated discriminator for character level
- Rolling patches: 64×64 patches with stride 32
- Discriminator: small pix2pix 70×70 receptive field

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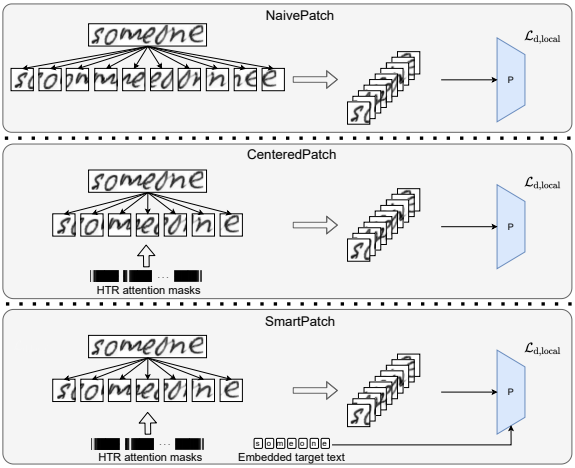
SmartPatch - Discriminator Designs



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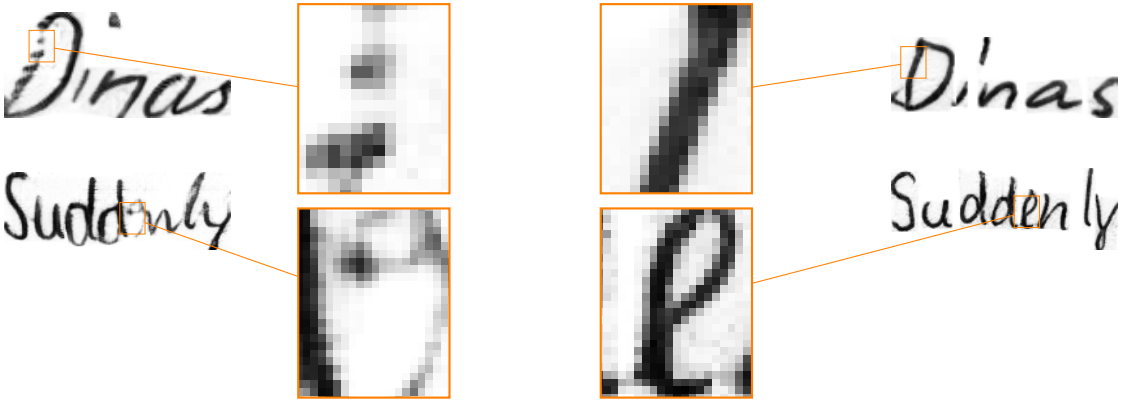
GANwriting vs. SmartPatch



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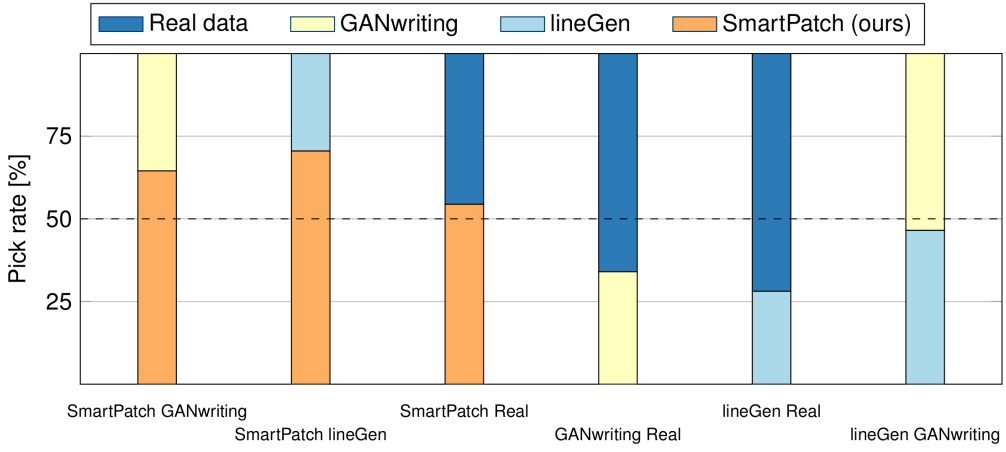
Results



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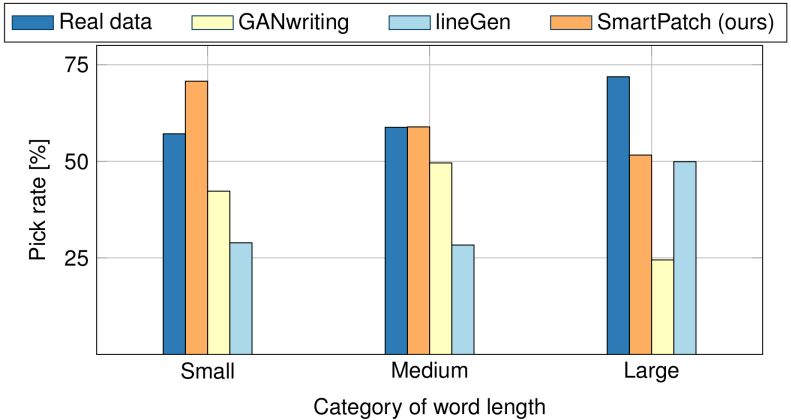

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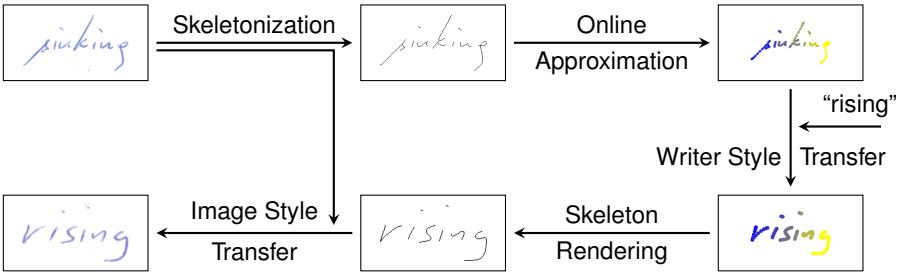
Full-Line Generation

Spatio-Temporal Handwriting Imitation

Overview

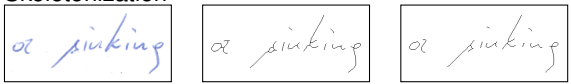


Martin Mayr et al. “Spatio-Temporal Handwriting Imitation”. In: *Computer Vision – ECCV 2020 Workshops*. 2020, pp. 528–543

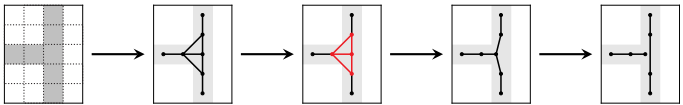
Spatio-Temporal Handwriting Imitation

From Offline to Online Data

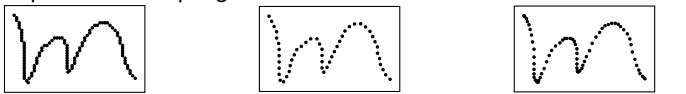
1. Skeletonization



2. Skeletons ➔ strokes



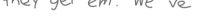
3. Importance sampling



Martin Mayr et al. “Spatio-Temporal Handwriting Imitation”. In: *Computer Vision – ECCV 2020 Workshops*. 2020, pp. 528–543

Writer Style Transfer

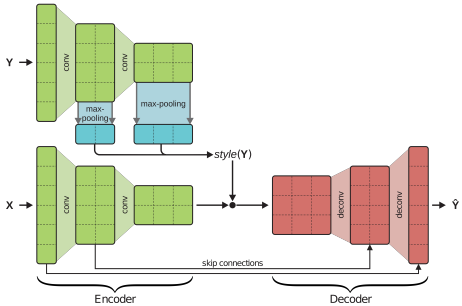
Online Handwriting Synthesis[1]

Style Input	Output
	I am a synthetic sample
	I am a synthetic sample
	I am a synthetic sample
	I am a synthetic sample
	I am a synthetic sample
	I am a synthetic sample

[1] Alex Graves. *Generating Sequences With Recurrent Neural Networks.* Aug. 2013. arXiv: 1308.0850 [cs.NE].

Image/Pen Style Transfer

- Extract style information of the input image
- Remove spatial information of style
- Add to generated image



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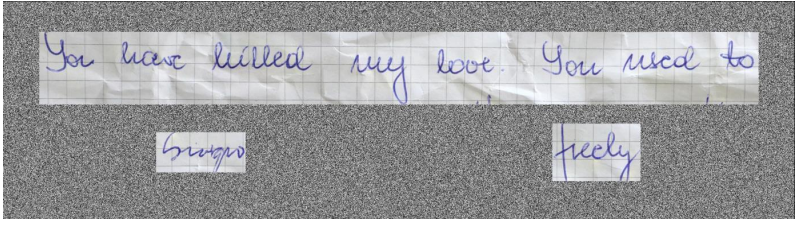
Results – User Study

- Turing task (32): Fake or Real?

- Style task (64):

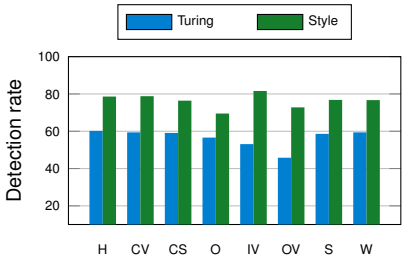


Results – User Study

- 59 participants
- Accuracy Turing task: 58.7 %
- Accuracy Style task: 76.8 %

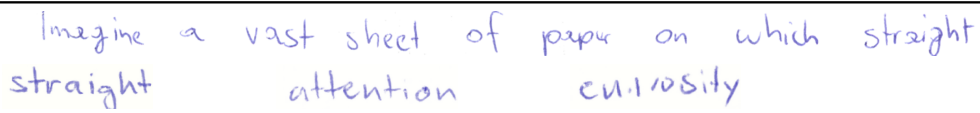
Results – User Study

- 59 participants
- Accuracy Turing task: 58.7 %
- Accuracy Style task: 76.8 %
- Humanities (H) have best performance (vs. CV, CS, O)
- Out-of-Vocabulary (OV) better imitated than in vocabulary (IV)
- No impact of synthetic background (S vs. W)

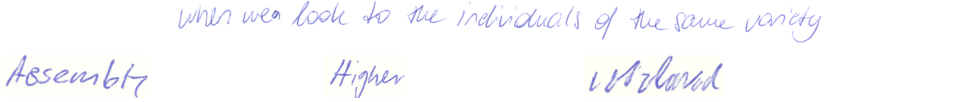


Qualitative Results

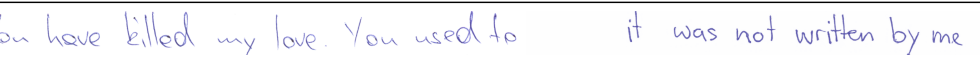
(a)



(b)



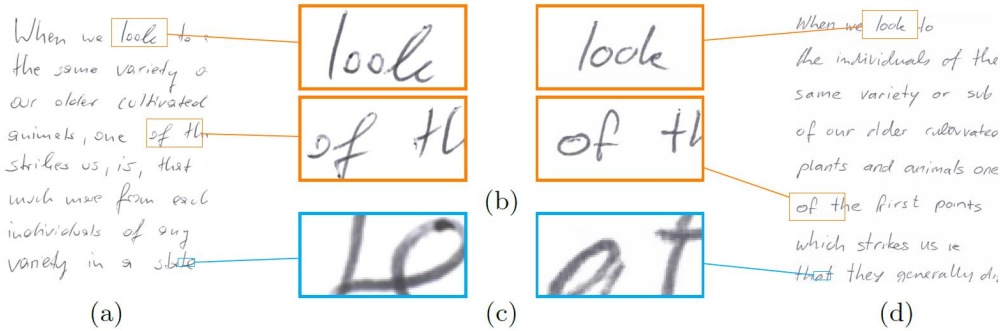
(c)



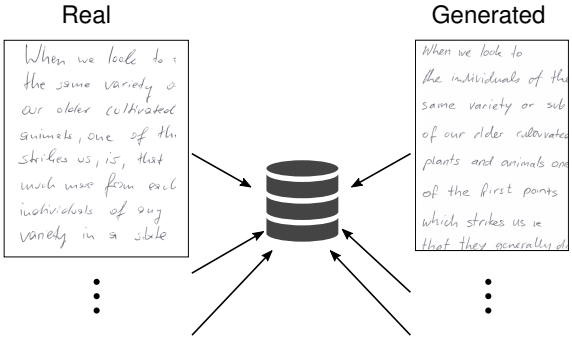
(d)

(e)

Qualitative Results



Results – Writer Identification



DB	mAP %	Acc. %
OV	29.66	14.82
IV	37.13	25.92

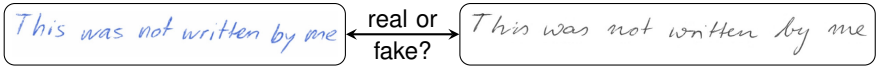
Source: https://iconscout.com/icons/database

Writer Identification in Generated Images

➔ A new layer for writer identification

Summary & Outlook

Summary & Outlook



Summary

- Rapidly improving results on word and line level
- Can be used for improving HTRs

Outlook

- Handwriting imitation of whole images

Questions?

Missed something? Please let us know!

References

References I

[Bhu+21] Ankan Kumar Bhunia, Salman Khan, Hisham Cholakkal, Rao Muhammad Anwer, Fahad Shahbaz Khan, and Mubarak Shah. “Handwriting Transformers”. In: *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*. Oct. 2021, pp. 1086–1094.

[Dav+20] Brian Davis, Chris Tensmeyer, Brian Price, Curtis Wigington, Bryan Morse, and Rajiv Jain. “Text and Style Conditioned GAN for Generation of Offline Handwriting Lines”. In: *British Machine Vision Conference (BMVC)*. 2020. arXiv: 2009.00678 [cs.CV].

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[Gra13] Alex Graves. *Generating Sequences With Recurrent Neural Networks*. Aug. 2013. arXiv: 1308.0850 [cs.NE].

References II

[Kan+20] Lei Kang, Pau Riba, Yaxing Wang, Marçal Rusiñol, Alicia Fornés, and Mauricio Villegas. “GANwriting: Content-Conditioned Generation of Styled Handwritten Word Images”. In: *Computer Vision – ECCV 2020*. Cham: Springer International Publishing, 2020, pp. 273–289.

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[May+20] Martin Mayr, Martin Stumpf, Anguelos Nicolaou, Mathias Seuret, Andreas Maier, and Vincent Christlein. “Spatio-Temporal Handwriting Imitation”. In: *Computer Vision – ECCV 2020 Workshops*. 2020, pp. 528–543.