Generating Handwriting via Decoupled Style Descriptors


Atsunobu Kotani

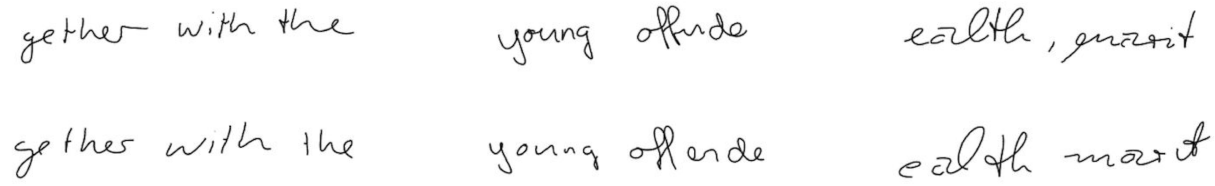

Stefanie Tellex


James Tompkin

BROWN
Computer Science


Target

Ours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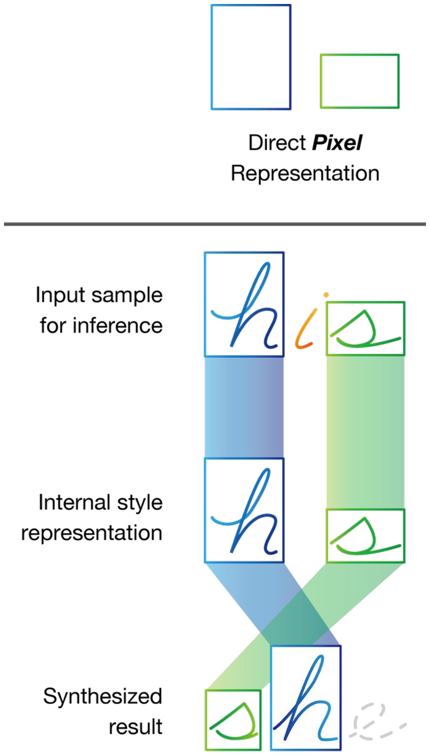
Handwriting generation:

- Pixel representation [2]



Haines et al. **[2]**

[1] Aksan, E., Pece, F., Hilliges, O.: DeepWriting: Making Digital Ink Editable via Deep Generative Modeling. SIGCHI (2018).
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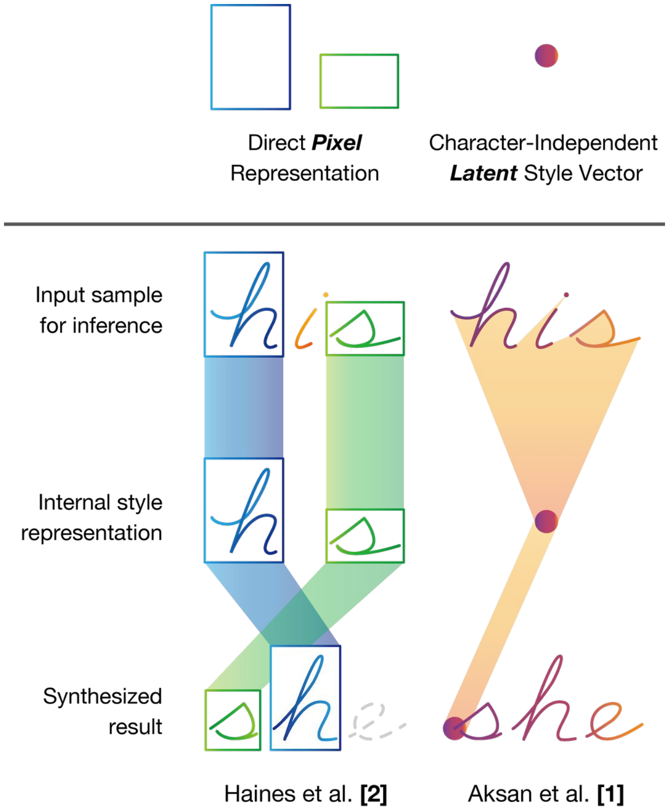
Handwriting generation:

- Pixel representation [2]
- Learned by neural networks [1]



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Handwriting generation:

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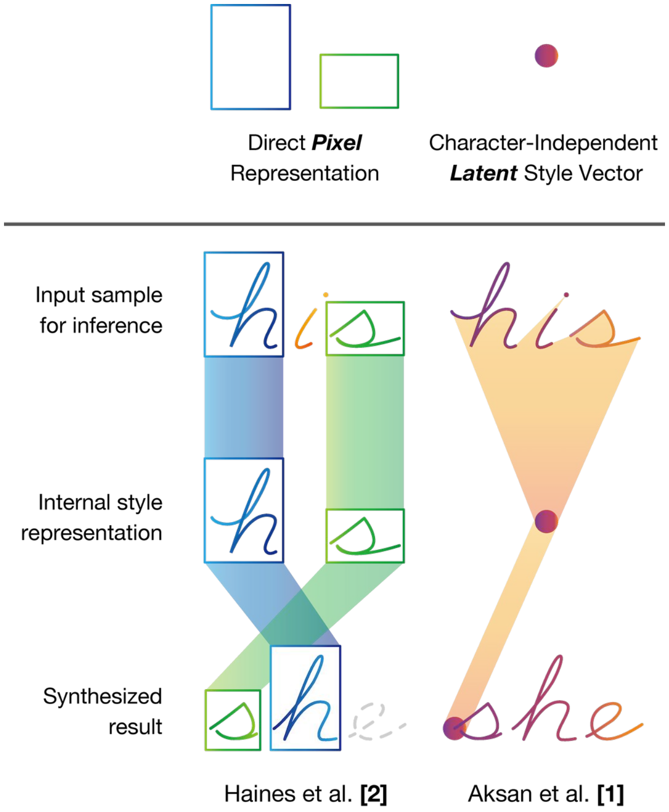
Limitations:

- Generating missing characters
- Generating fine details



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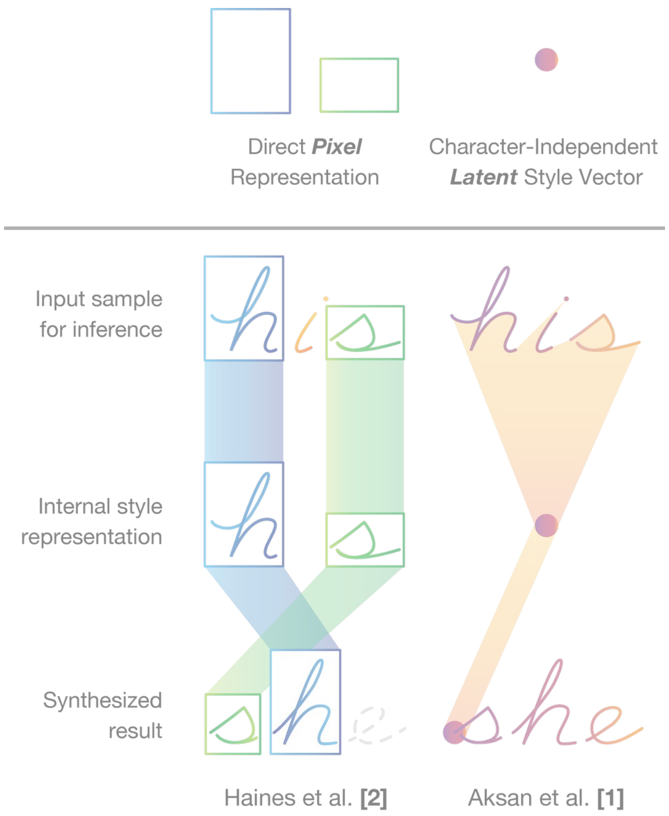
Underlying problem:
No explicit separation of writer style from character style.



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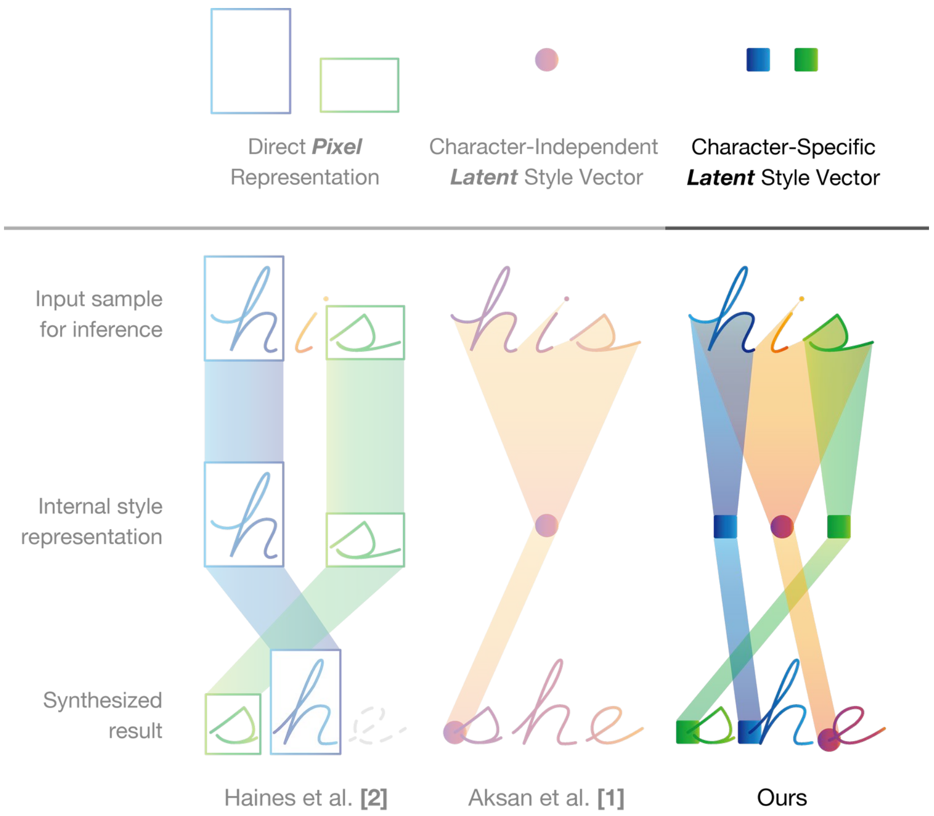
We learn to decouple writer and character style into specific vectors.



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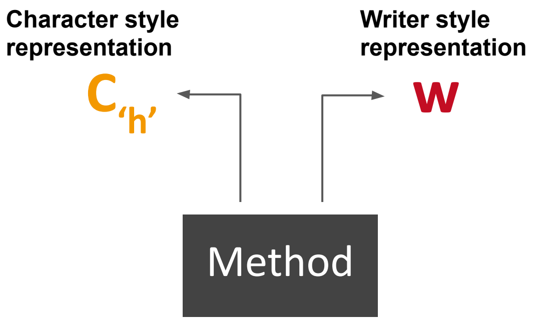
Problem statement

Desired output data:

- *Writer-independent* character style representation $c_{\text{'h'}}$
- *Character-independent* writer style representation $\mathbf{w}$



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- *Writer-independent* character style representation $C_{\text{‘h’}}$
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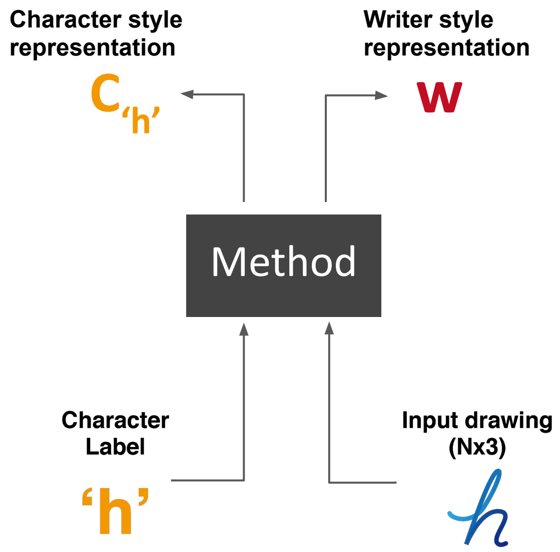
Input data:

- Strokes as point sequences (x, y, t)
- Character labels as one-hot vectors



Decoupled Style Descriptors (DSD)

We learn a ***linear*** relationship between

- Writer-DSD **w** and

- Character-DSD $\mathbf{C}_{\text{‘h’}}$

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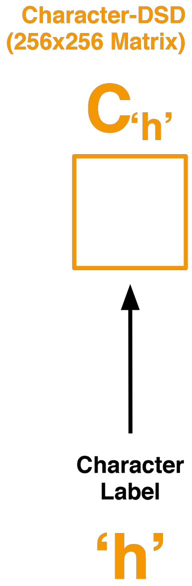

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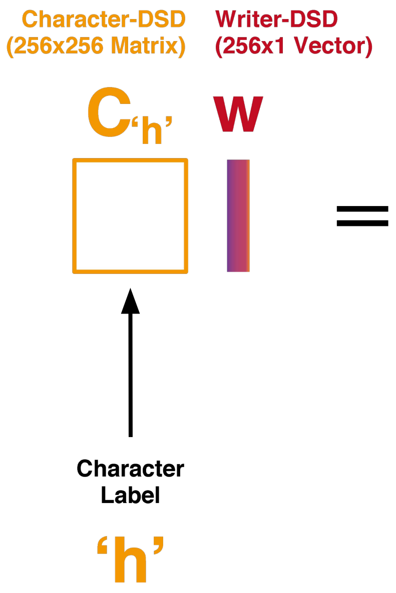

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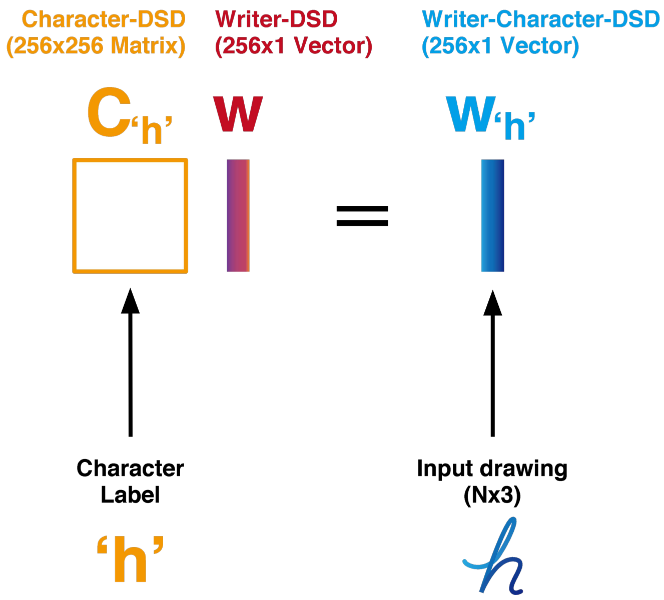

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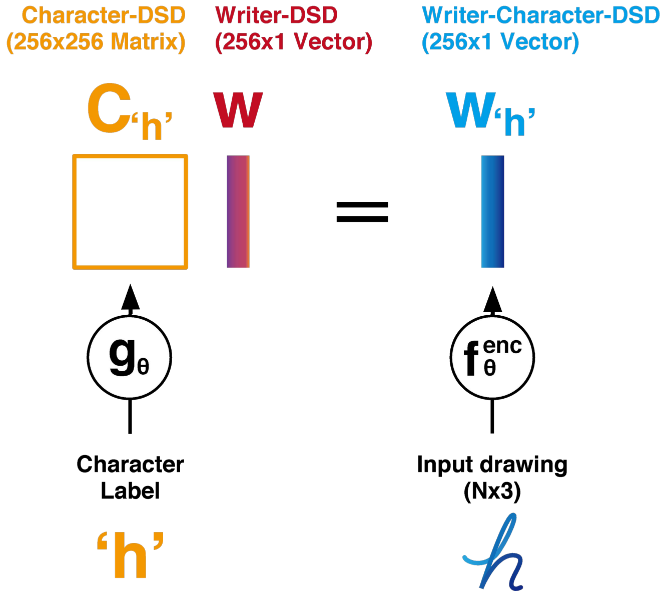

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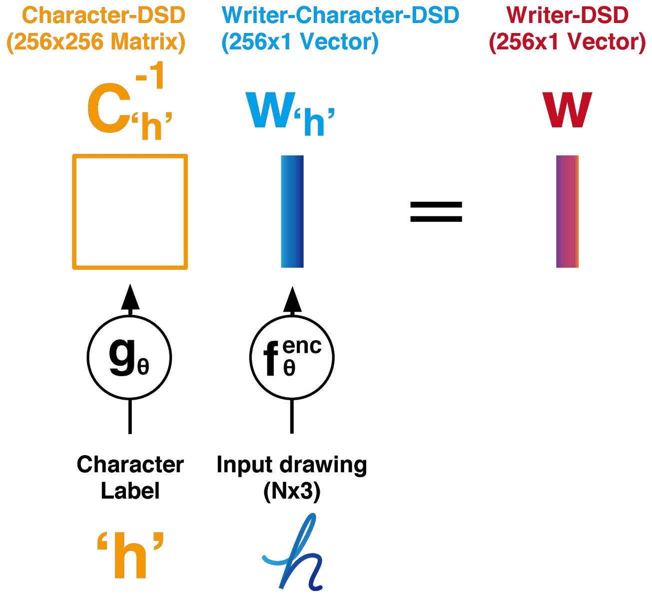
Simply invert $\mathbf{C}_{\text{'h'}}$ to recover **w** from $\mathbf{w}_{\text{'h'}}$.



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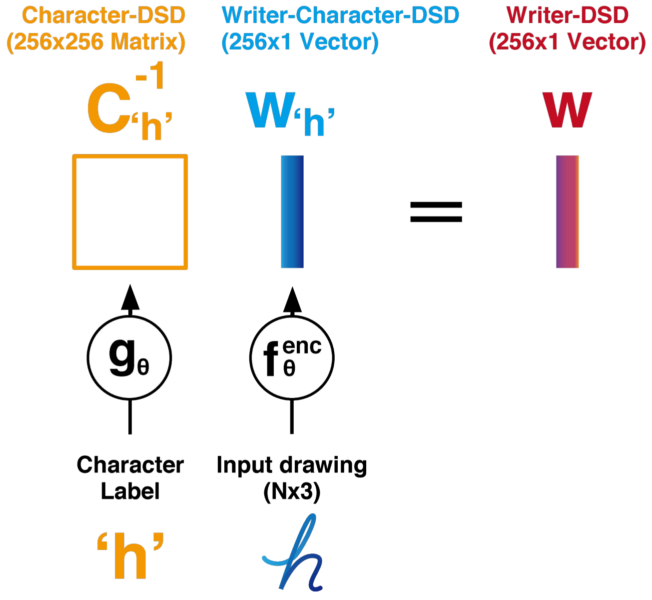
Simply invert $\mathbf{C}_{\text{‘h’}}$ to recover **w** from $\mathbf{w}_{\text{‘h’}}$.

Retains ***more fine detail***.

Allows ***few-shot learning*** for new characters,

and ***writer identification***.



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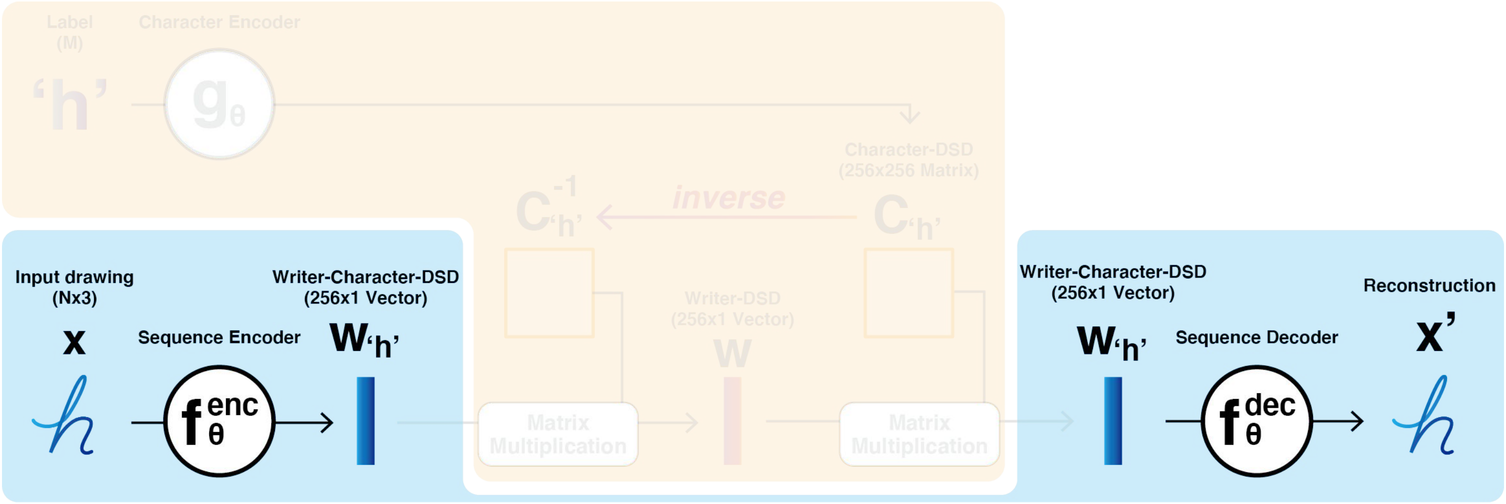

At the core, we have LSTM-based autoencoder, similar to the work by Graves [3].

[3] Graves, A.: Generating sequences with recurrent neural networks. arXiv preprint arXiv:1308.0850 (2013)

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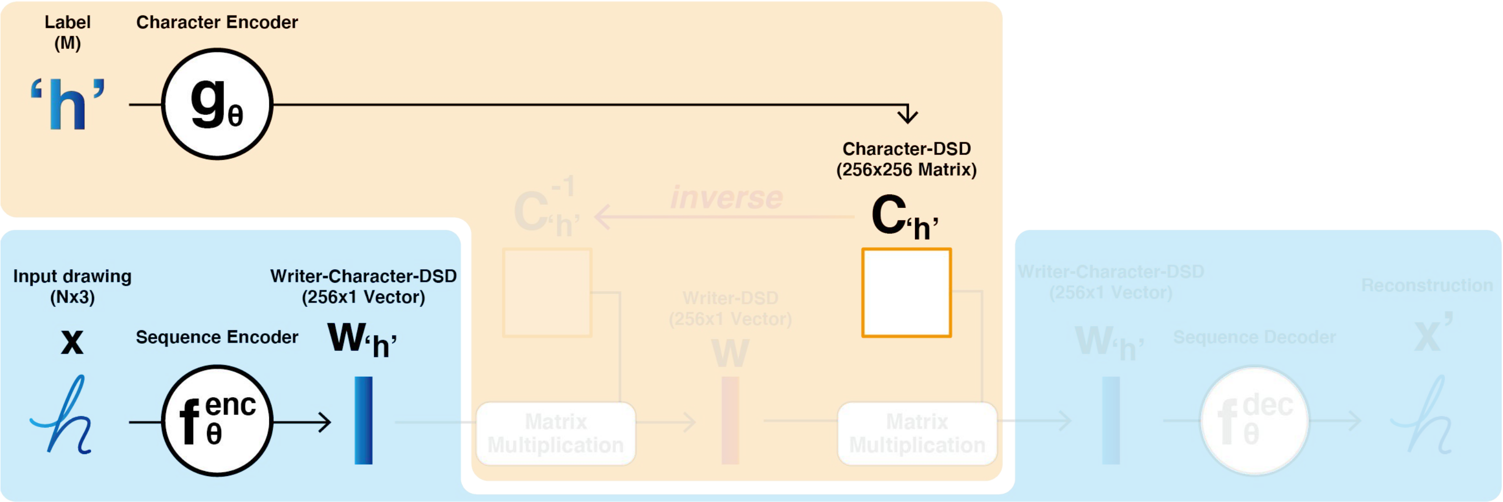

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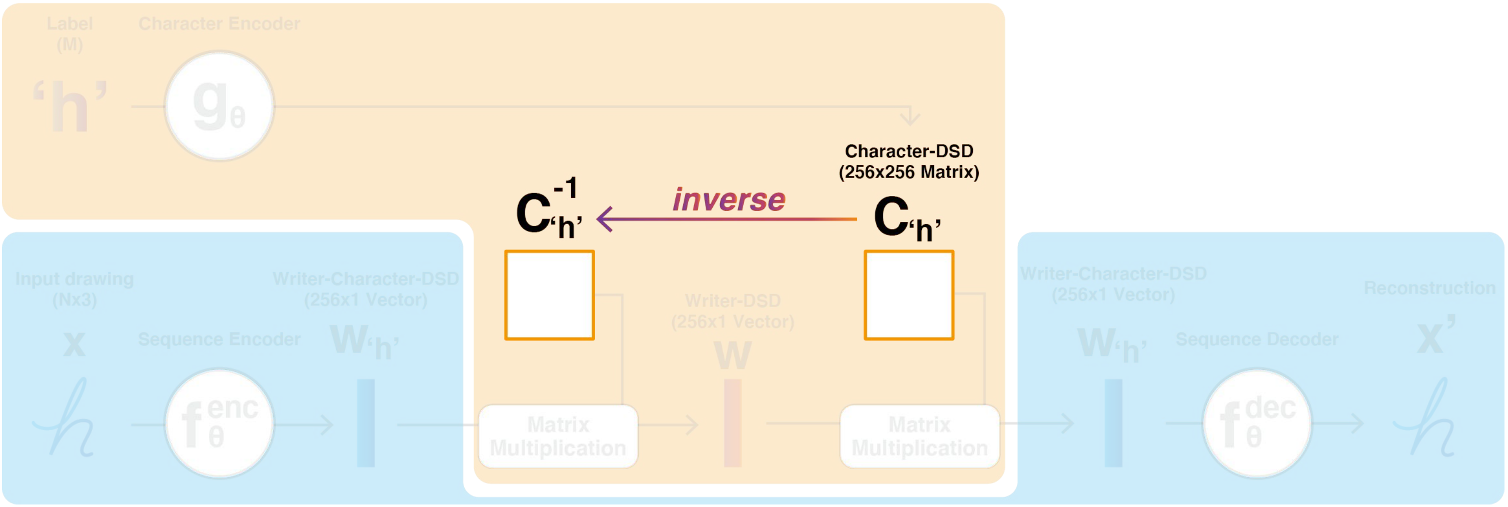

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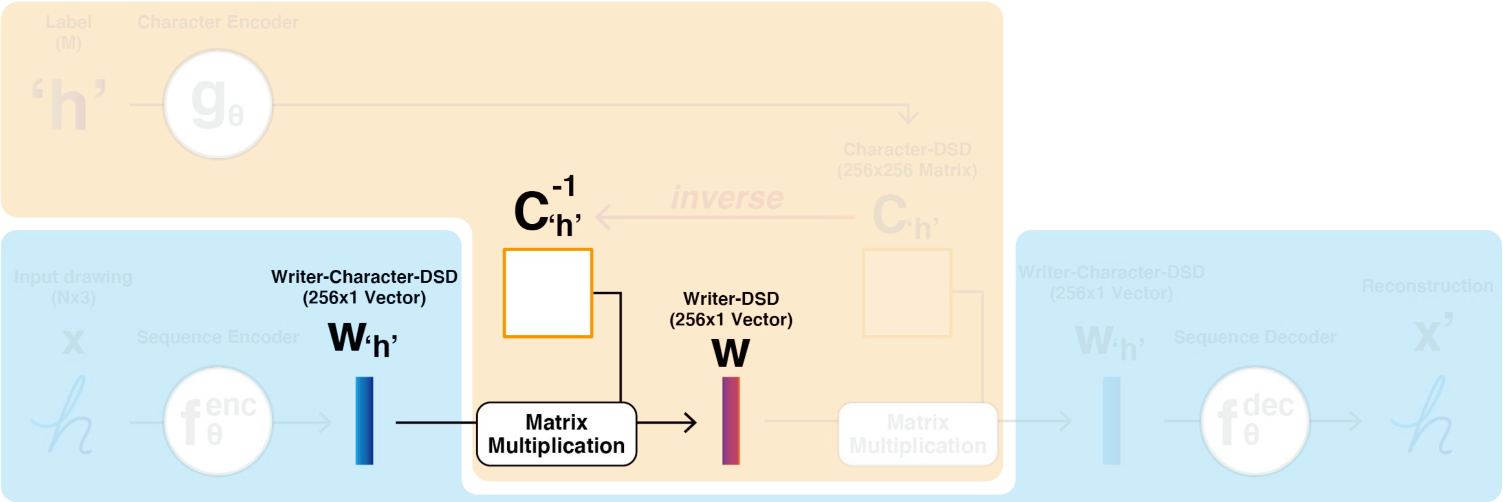

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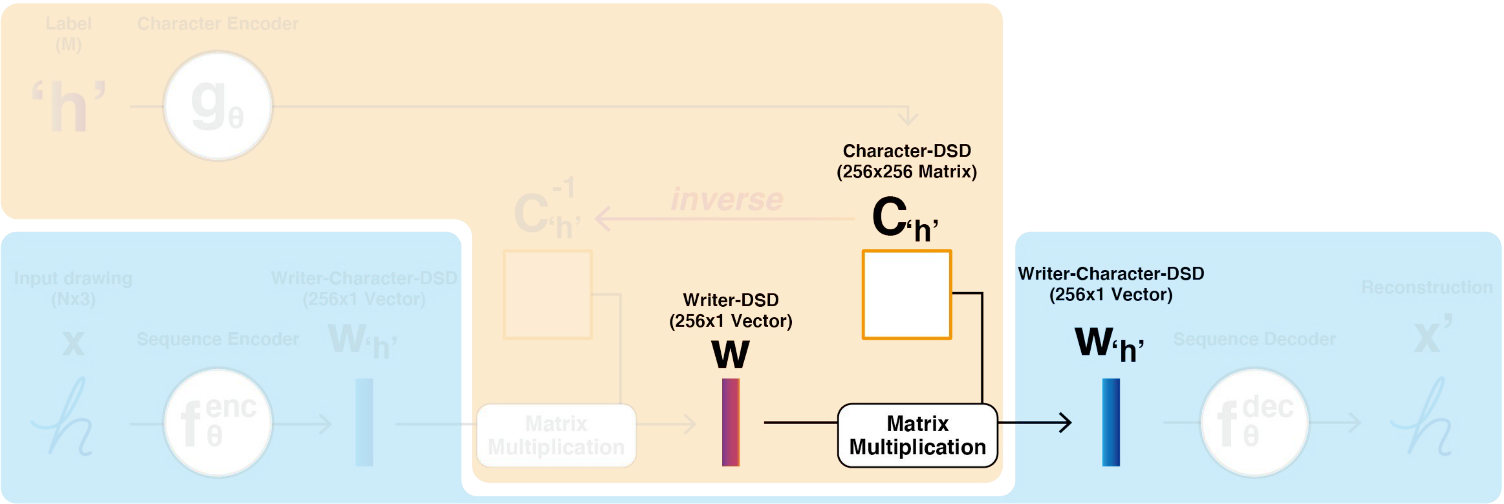

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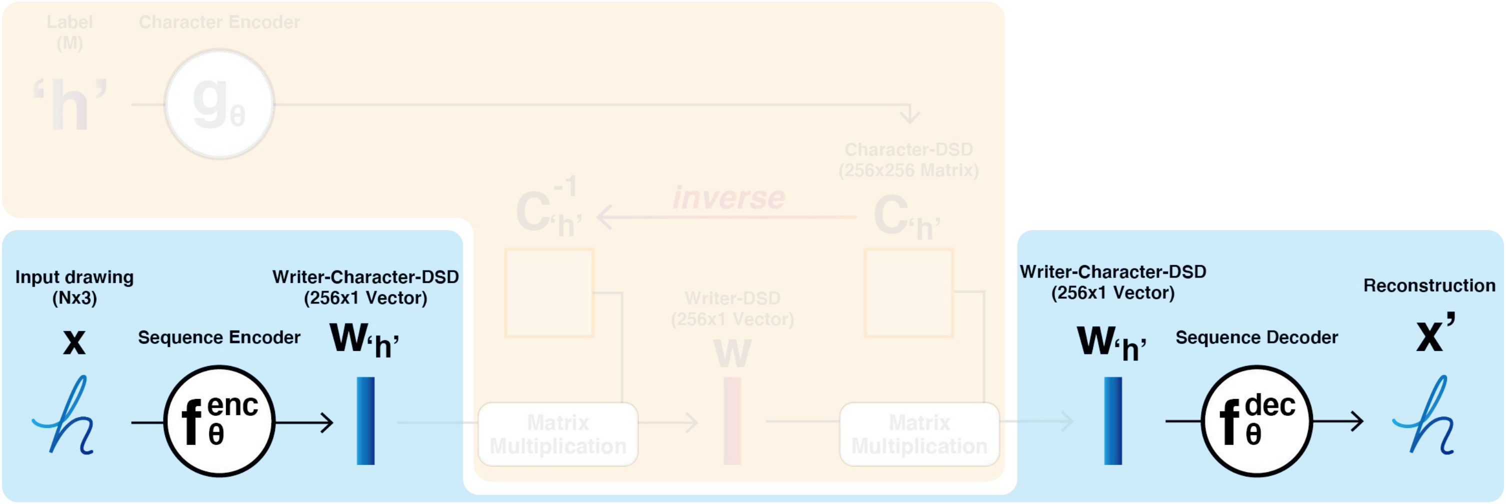

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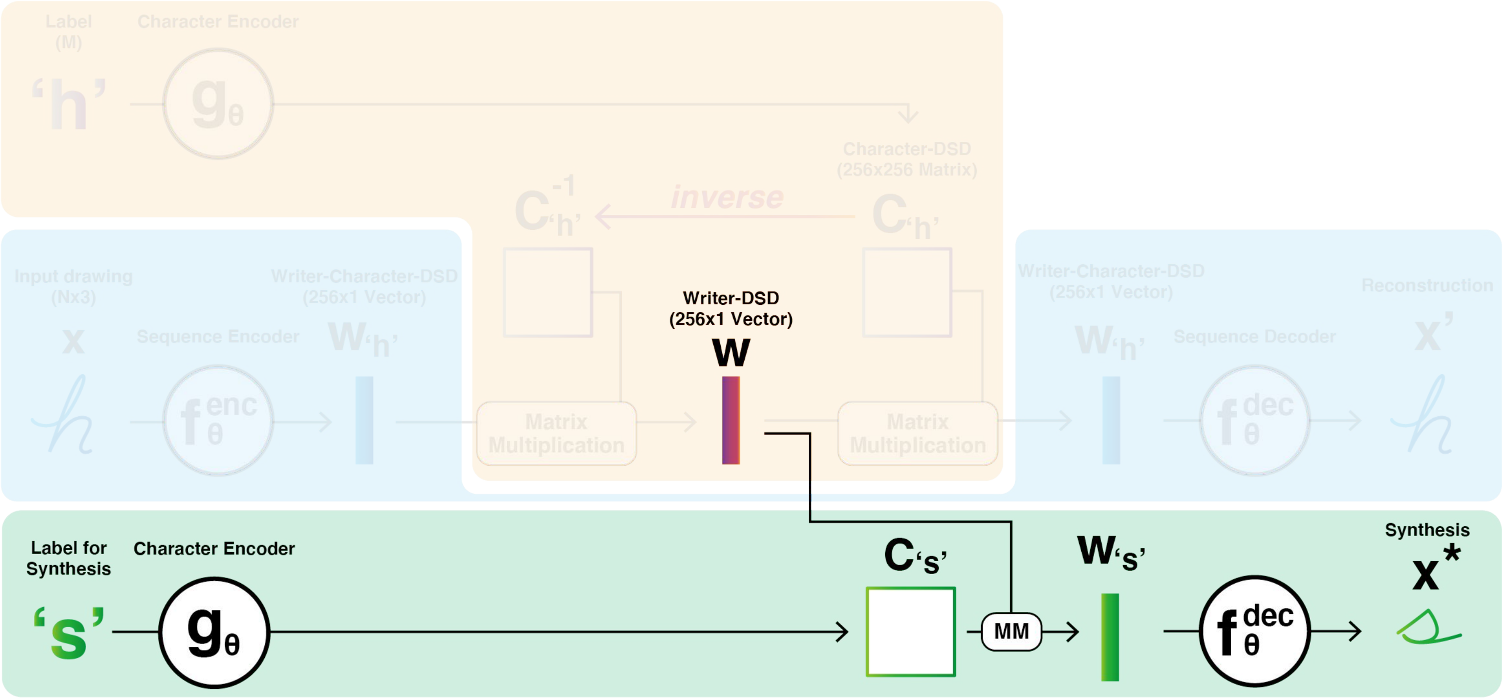

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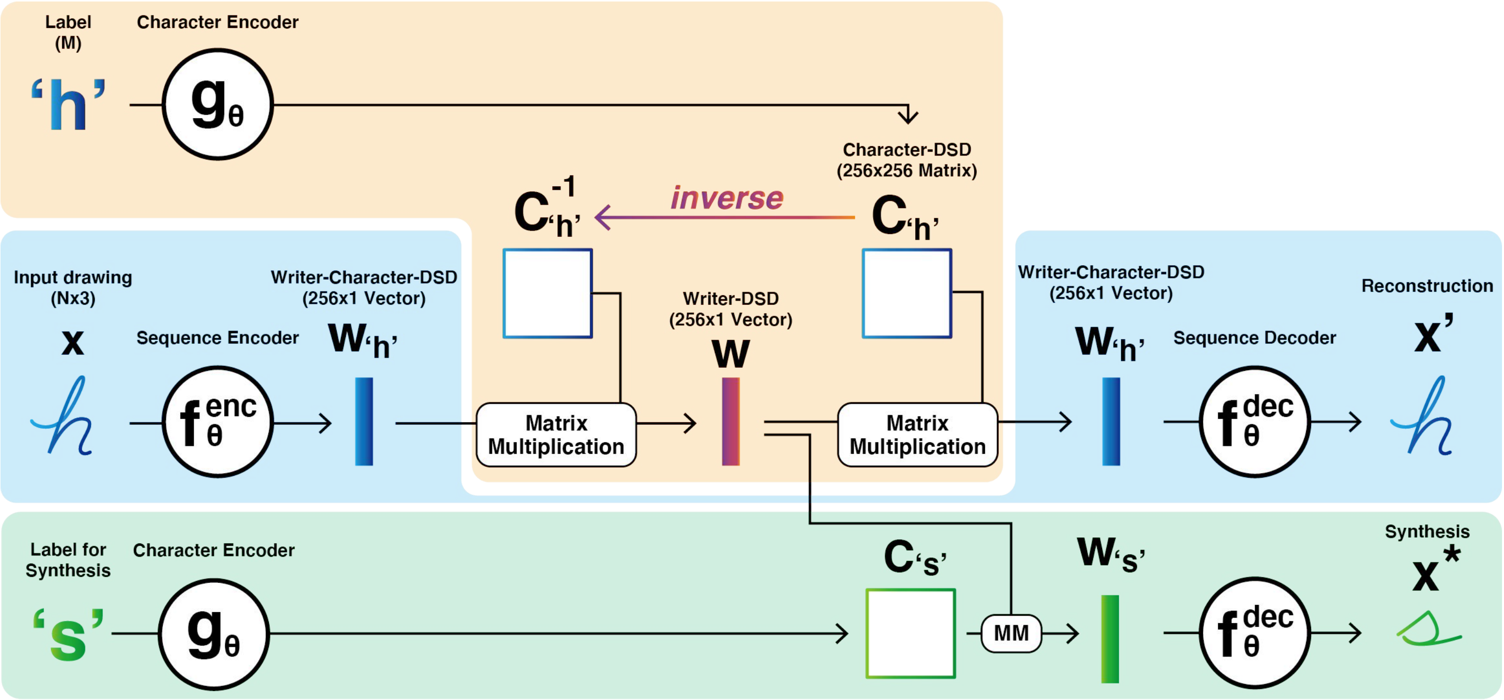

Subsequences rather than single characters

Writing is complex:

- Cursive
- Character pairs (ligatures)
- Delayed strokes (f, t, i, j)

Subsequences rather than single characters

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- Cursive
- Character pairs (ligatures)
- Delayed strokes (f, t, i, j)

Our approach actually represents latent space of *all subsequences of characters.*

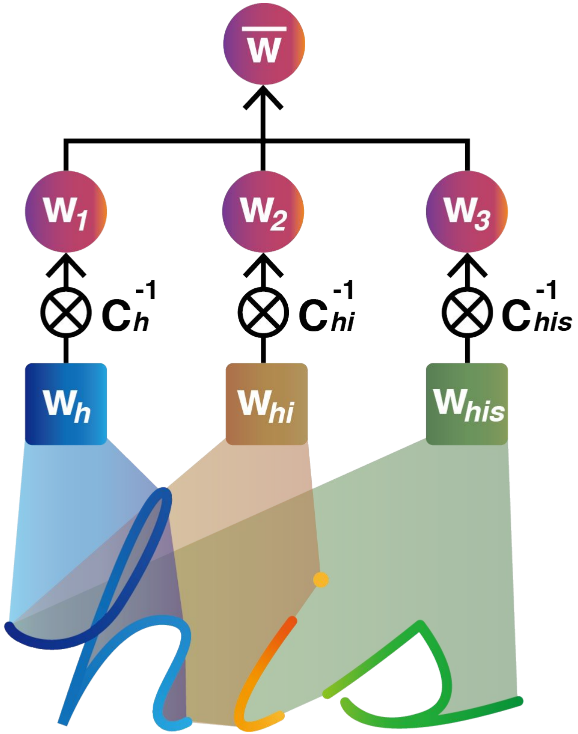
Word 'his' has representations $\mathbf{C}_{\text{'h'}}$, $\mathbf{C}_{\text{'hi'}}$, and $\mathbf{C}_{\text{'his'}}$.

and $\mathbf{w}_{\text{'h'}}$, $\mathbf{w}_{\text{'hi'}}$, and $\mathbf{w}_{\text{'his'}}$.

Recovering Writer-DSD **w** from handwriting samples

Take mean **w** over subsequences:

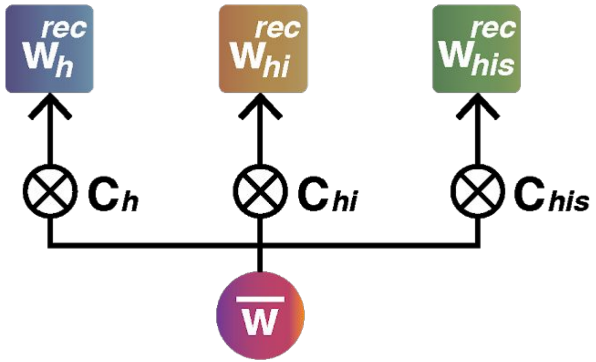
$$\overline{\mathbf{w}} = \frac{1}{M}\sum_{t=1}^{M}\mathbf{C}_{c_t}^{-1}\mathbf{w}_{c_t}$$



Generating handwriting using a *global* Writer-DSD **w**

Given a target word 'his':

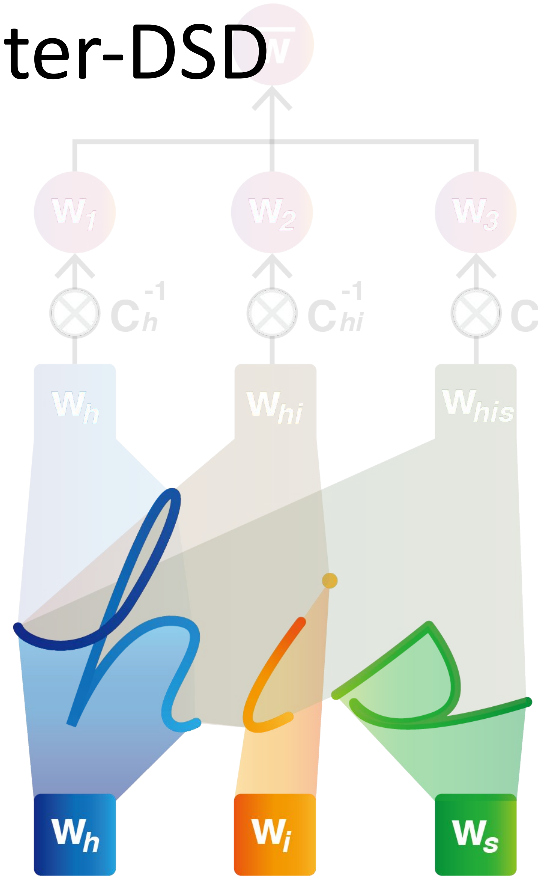
- Predict $\mathbf{C}_{\text{'h'}}$, $\mathbf{C}_{\text{'hi'}}$, and $\mathbf{C}_{\text{'his'}}$
- Multiply by **w** to create $\mathbf{w}_{\text{'h'}}$, $\mathbf{w}_{\text{'hi'}}$, and $\mathbf{w}_{\text{'his'}}$
- Decode ($\mathbf{w}_{\text{'h'}}, \mathbf{w}_{\text{'hi'}}, \mathbf{w}_{\text{'his'}}$) into stroke sequence



Single-character Writer-Character-DSD

There are relatively few single-character $\mathbf{w}_{\text{'h'}}$.

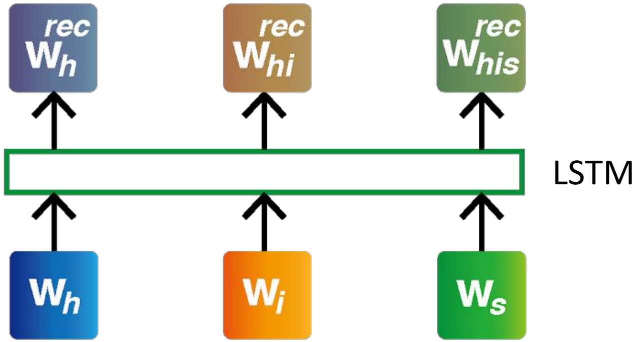
If we extract them from a writing sample, we can save them in a **database** and **sample** them during generation.



Generating handwriting using ***sampled*** Writer-Character-DSD

Retrieve relevant single-characters $\mathbf{w}_{\text{'h'}}$, $\mathbf{w}_{\text{'i'}}$, $\mathbf{w}_{\text{'s'}}$.

Restore temporal dependencies via LSTM.



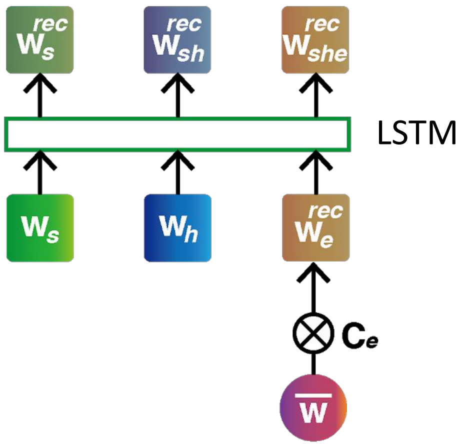
Cannot cope with any missing characters in reference handwriting samples.

Combined method with ***sampling***

Reference sample: ‘his’

Generation target: ‘she’

- Compute mean **w** from all substrings
- Predict $\mathbf{w}_{‘e’}$ with $\mathbf{C}_{‘e’}$ and the mean **w**
- Extract single-character Writer-Character-DSDs
- *Restore temporal dependencies with LSTM.*

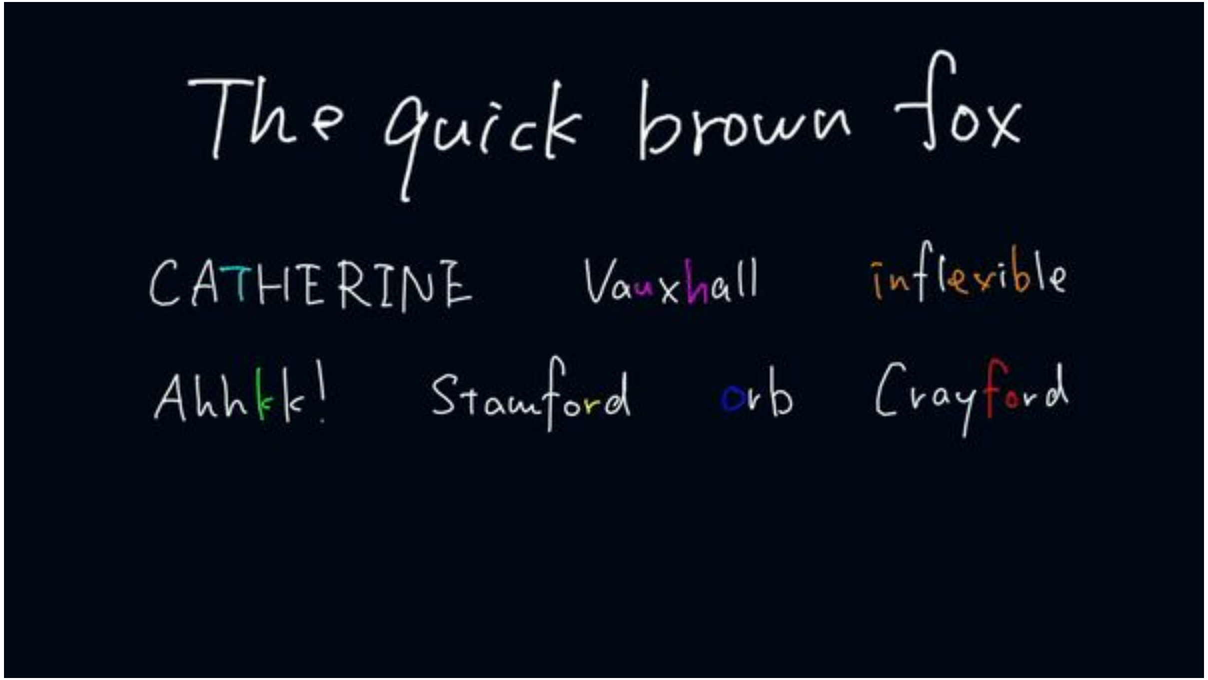


Generated Results

Colored characters match between provided writing samples and desired output.

These are generated from retrieved $\mathbf{w}_{\text{'h'}}$

Missing characters are generated from global $\mathbf{w}$



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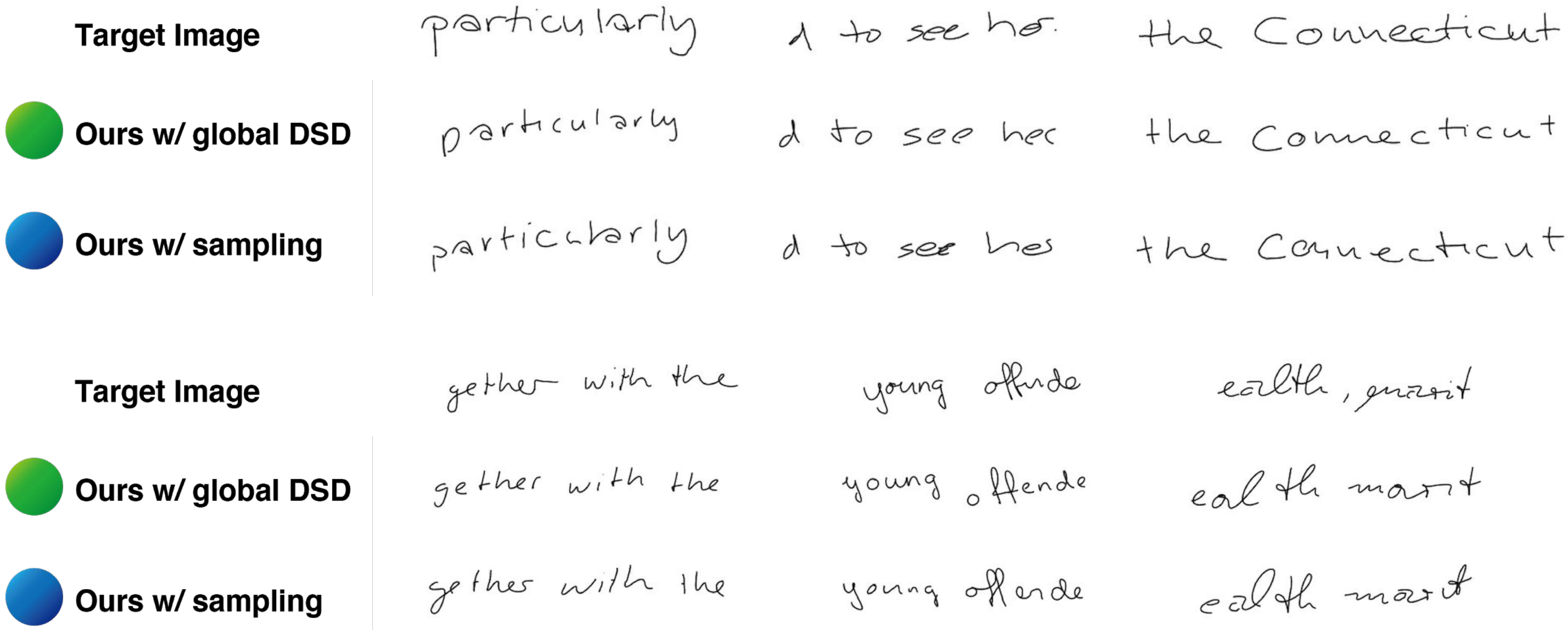
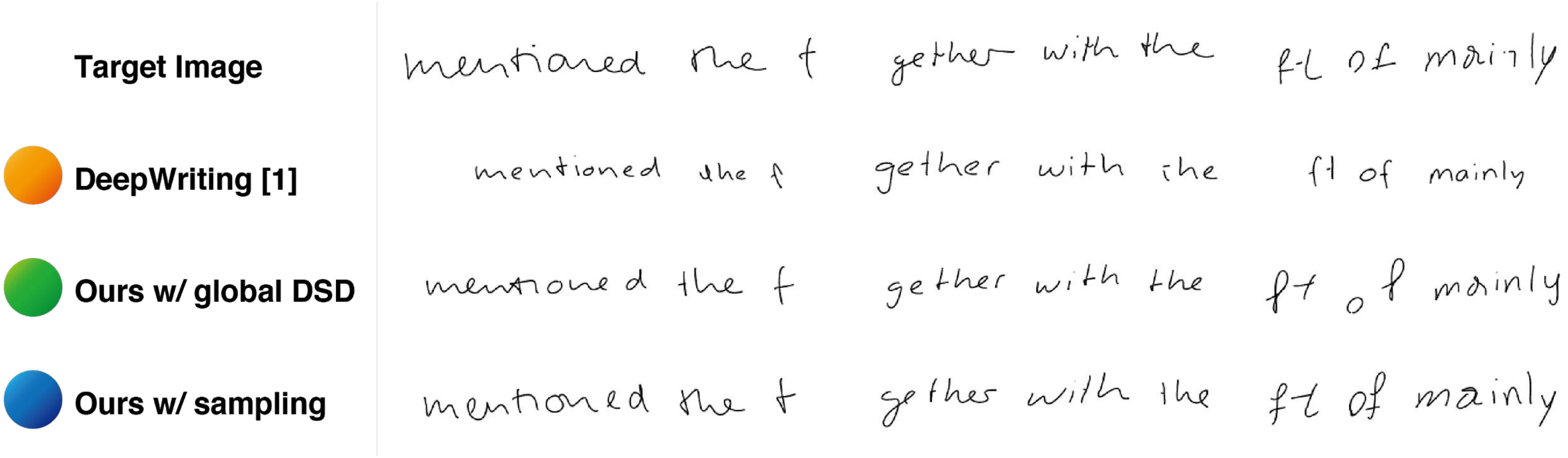


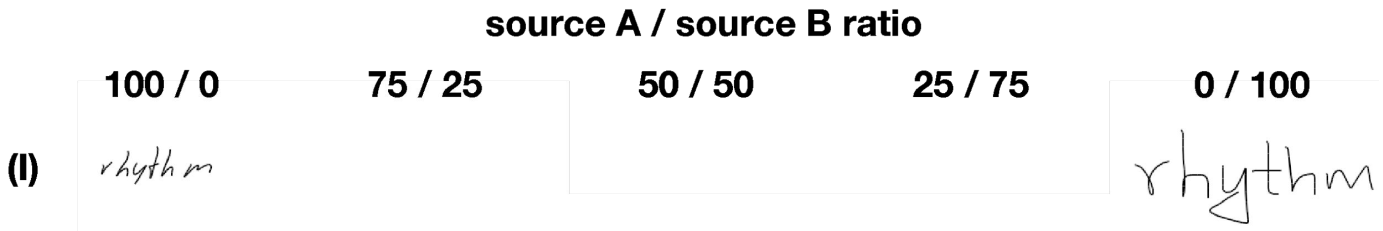
Generated Results - Comparison



[1] Aksan, E., Pece, F., Hilliges, O.: DeepWriting: Making Digital Ink Editable via Deep Generative Modeling. SIGCHI (2018).

Interpolation

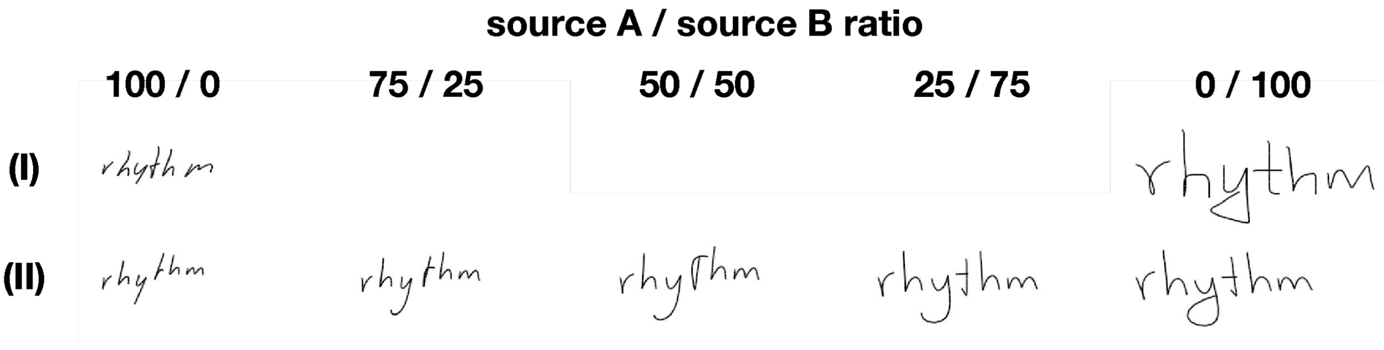
True samples



Interpolation

True samples

Writer-DSD level

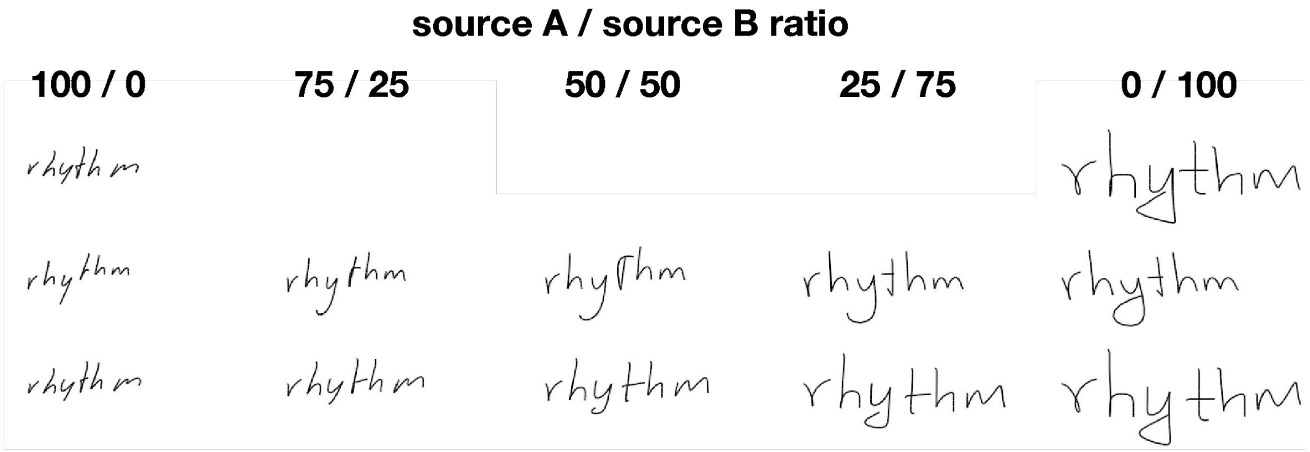


Interpolation

True samples (I)

Writer-DSD level (II)

Writer-Character-DSD level (III)



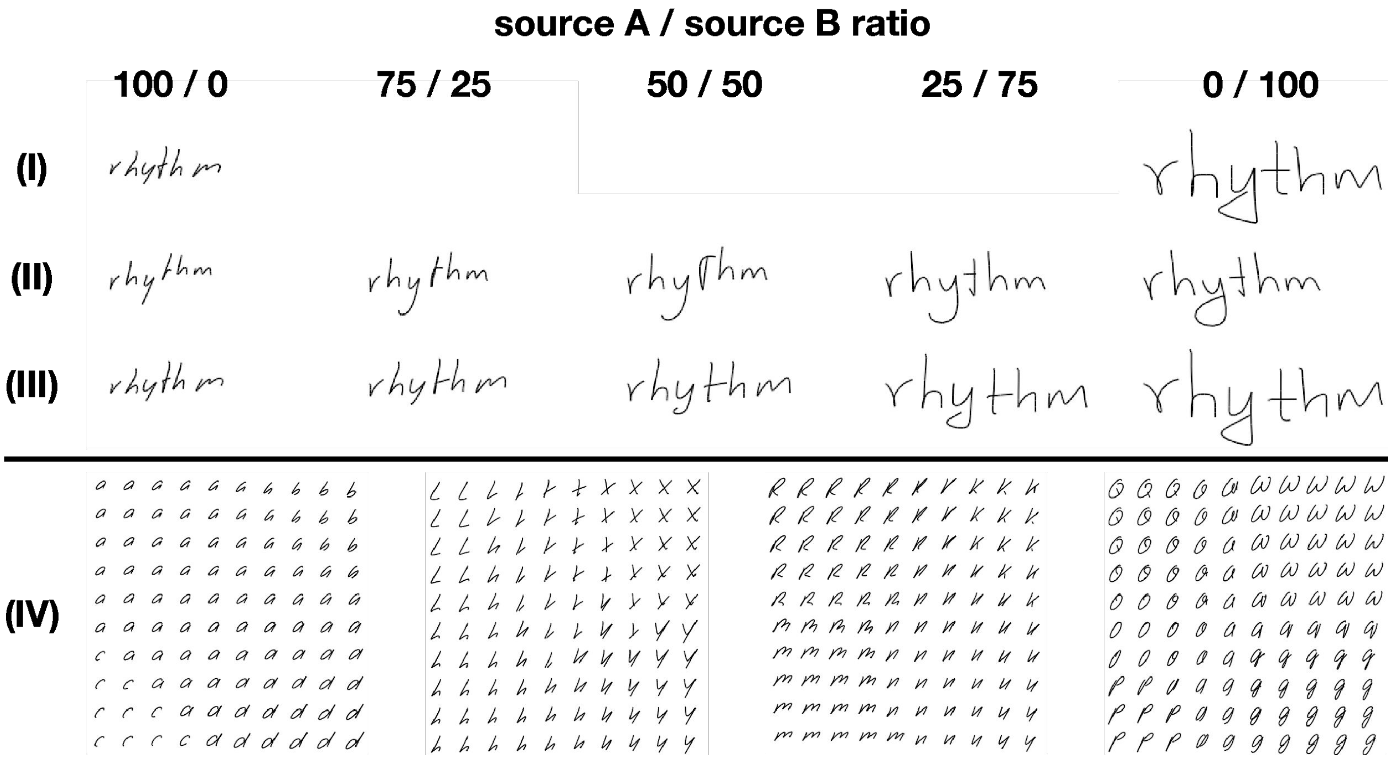
Interpolation

True samples

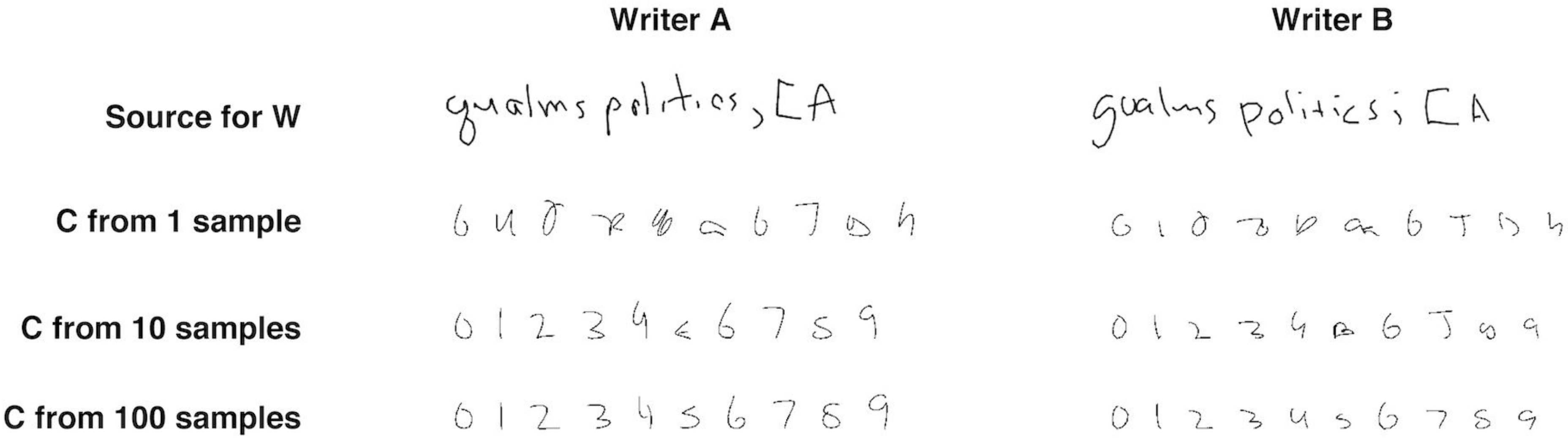
Writer-DSD level

Writer-Character-DSD level

Character-DSD level



Few-shot learning of New Characters



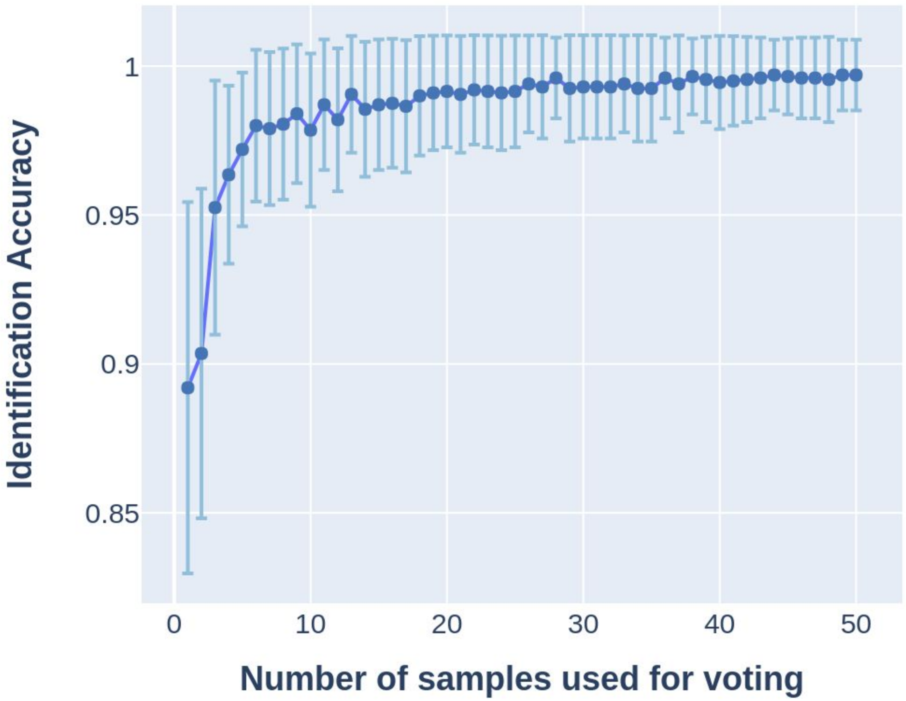
Writer Identification

In a 20-writer identification task,

our model achieved:

89.20% ± 6.23 for **1** word sample

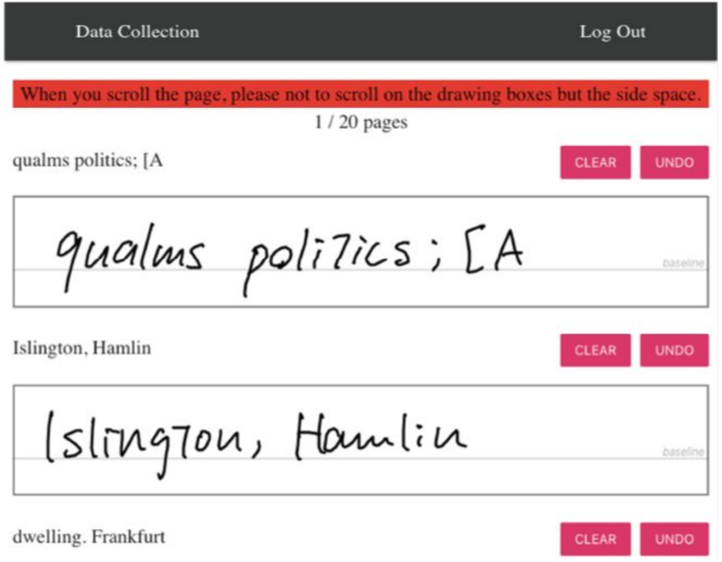
99.70% ± 1.18 for **50** word samples



BRUSH dataset

BRUSH dataset contains handwriting of:

- 170 writers, 86 Latin alphabet characters
- 488 common words written by all writers
  - 99.5% coverage of two-character letter space
- + 3668 rarer words written across writers
  - 99.9% coverage in total



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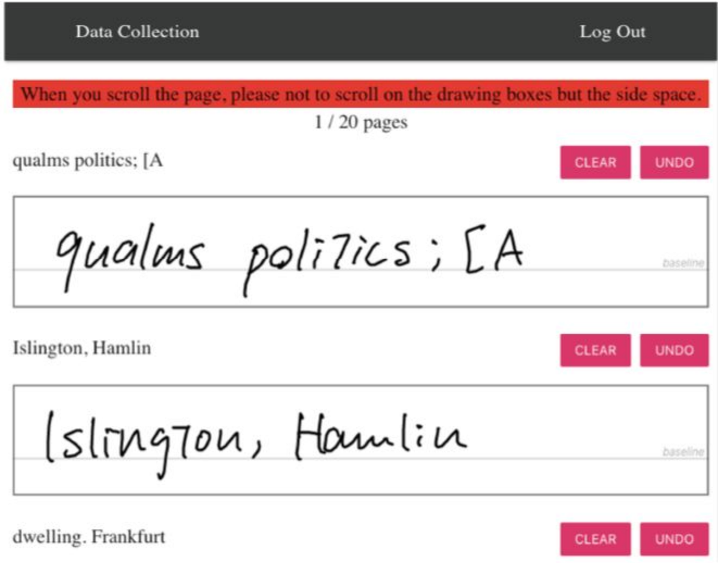

Common word samples & character-level labels

are not present in IAM dataset [4].

[4] Marti, U.V., Bunke, H.: The iam-database: an english sentence database for offline handwriting recognition. IJDAR (2002).

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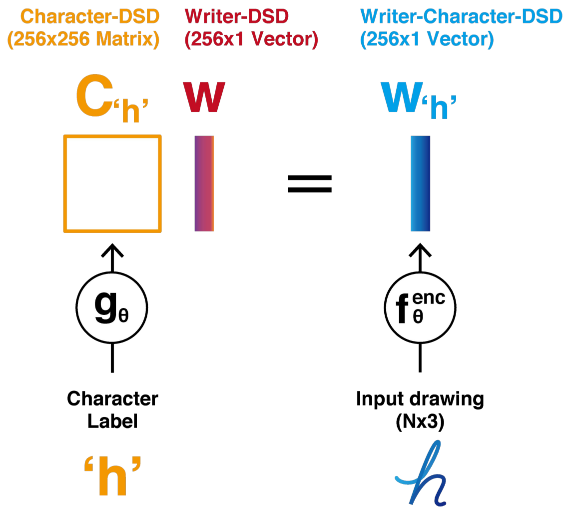
Contributions:

- DSDs decouple character style from writer style.
- Allow flexible handwriting generation.
- BRUSH: new dataset for online handwriting.



Code & dataset available at

http://dsd.cs.brown.edu

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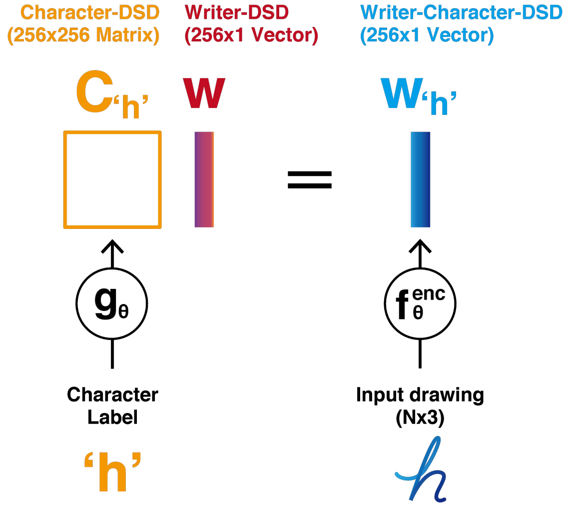
Potential Extension:

- Explicit decoupling may work better than implicit decoupling / disentanglement.
- DSDs could be applied to other sequential data (e.g. speech, motion capture data)



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