Transparent Similarity Estimation of Medieval Pen Flourishing via Local Visual Patterns

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Source: Klosterneuburg Abbey

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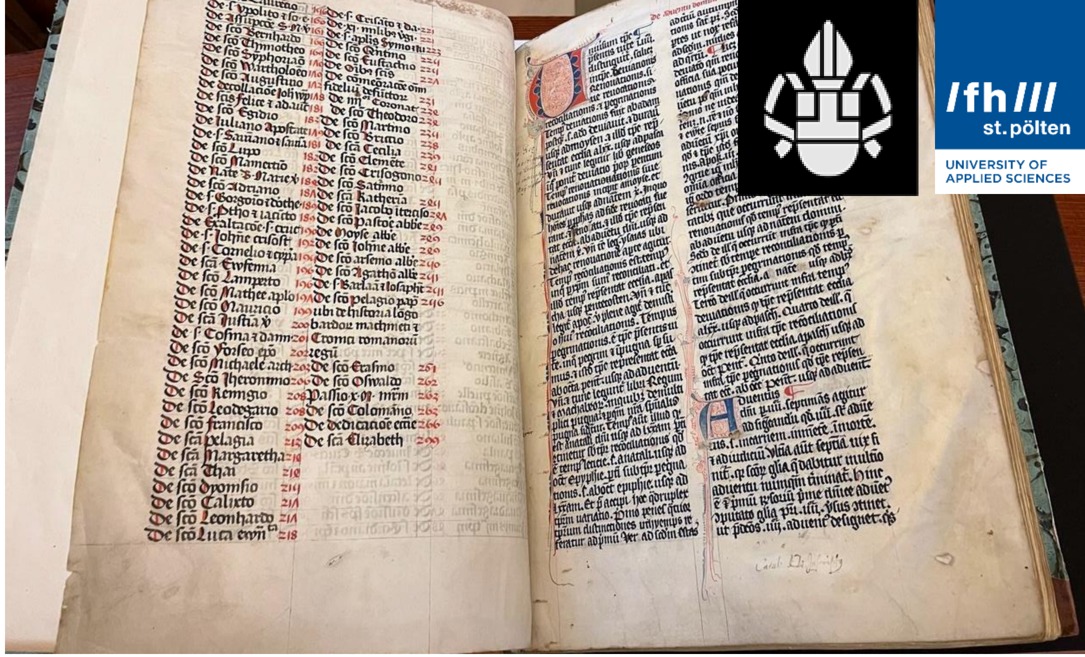
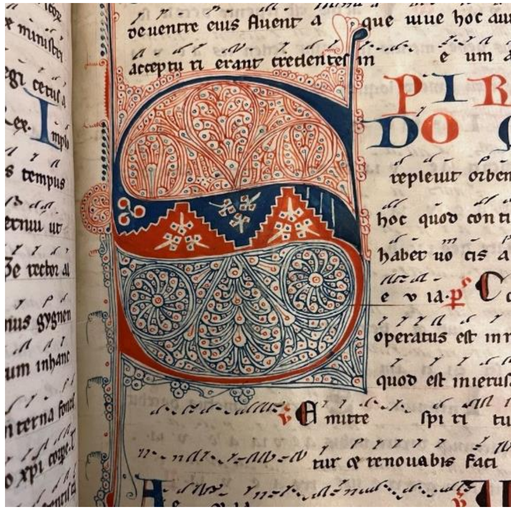
Medieval Manuscripts and Decoration

- Medieval manuscripts are central cultural assets that not only transmit texts but also communicate through their visual design [1,2].
- Decorations acted as navigational and aesthetic markers, guiding reading and emphasizing hierarchy or meaning [1,2].
- Decoration included *initials*, *miniatures*, or ***pen flourishing***.



Source: Klosterneuburg Abbey

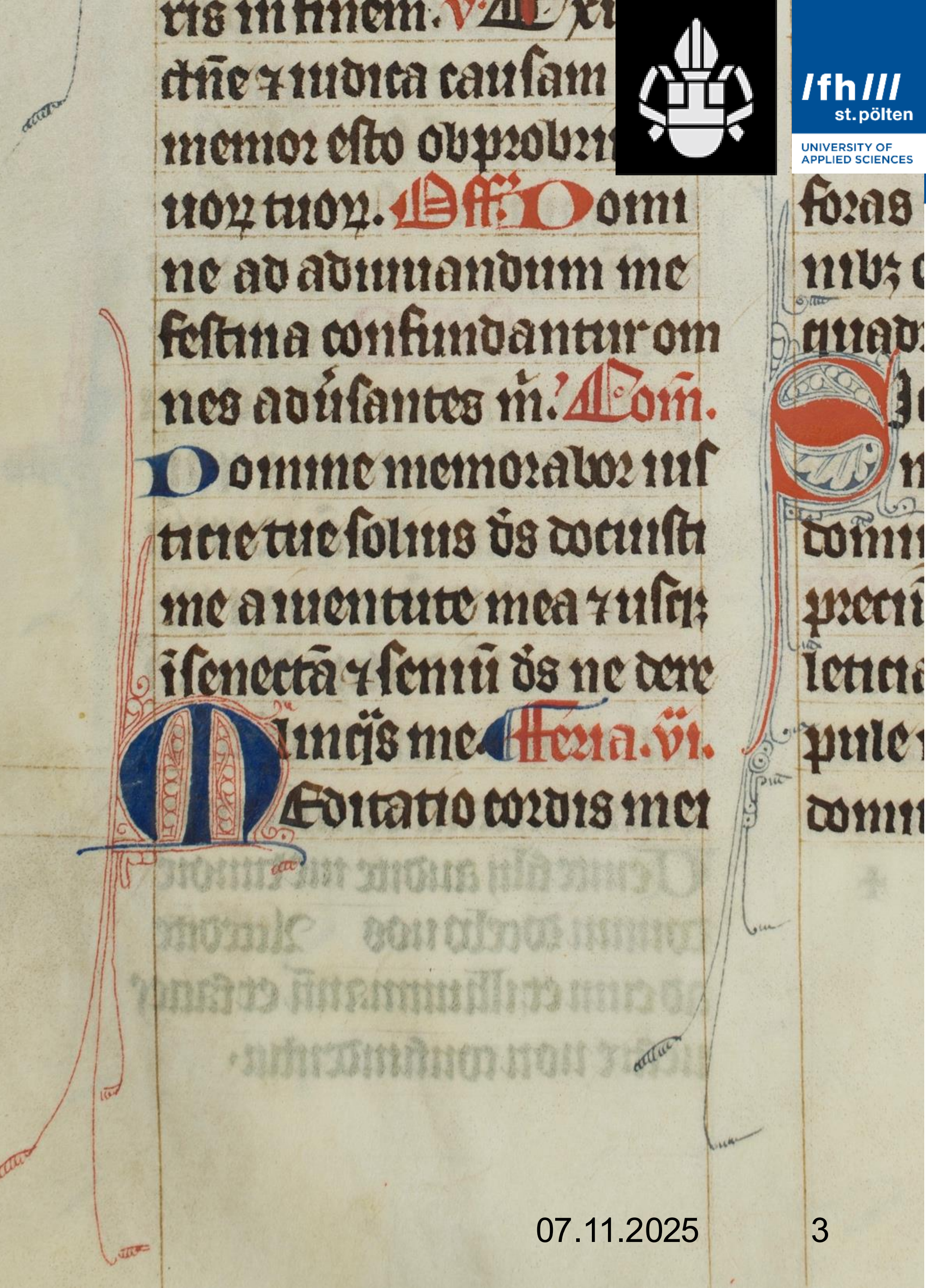
Source: Clementinae, and other text(s) von Clemens V. - Leiden University Libraries, Netherlands - Public Domain.



Source: Klosterneuburg Abbey

What is Pen Flourishing?

- Decorative ink line ornamentation (often red/blue) added after text was written [1,2, 3].
- Pen flourishing can take highly complex, interwoven shapes
- Created by rubricators (specialized scribes/artists) [4,5,6].
- Carried no narrative meaning, but expressed stylistic identity and workshop practice [1,2].
- Domain experts (art historians) use execution details of the flourishing to identify *rubricator groups* [4,5,6].
- Grouping rubricators by shared stylistic features allows for insight into medieval social structures and trading networks [1,2].



Source: Klosterneuburg Abbey (CCl 71 fol. 32v (Group B)

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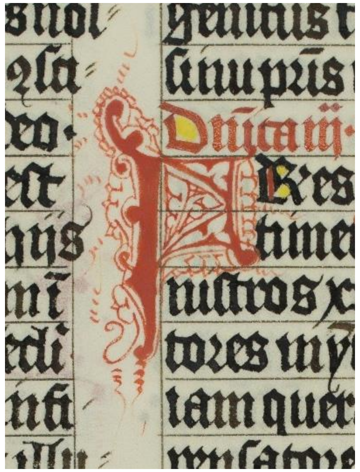
Rubricator Group A

CCl 71 fol. 108v

CCl 71 fol. 5r

CCl 71 fol. 4r

Rubricator Group D



CCl 71 fol. 217r

CCl 71 fol. 221r

CCl 71 fol. 240v

Source: Klosterneuburg Abbey

Research Context

Problem and Motivation

- Many manuscripts available, however …
- Few labeled examples - little ground truth to learn from.
- Hardly any studies on which groups belong together.
- Domain experts face too much data, need help exploring it.
- A tool is needed that is **explorative**, **explainable** to foster trust in experts.

Source: Klosterneuburg Abbey

State of the Art

- **Historical manuscript analysis**
  - **Early**: hand-crafted stroke/contour features + Bag-of-Features + SVM for writer dating/ID [7].
  - **Recent**: CNNs (AlexNet, Inception-ResNet), hybrids with transformers + keypoints, and self-/metric-learning (e.g., Online-Bag-of-Words) for stronger embeddings [8, 9, 10].
- **Illumination and decoration detection**
  - Region proposals + dense SIFT/VLAD + template matching → later Convolutional Neural Networks / Feature Pyramid Network pipelines and similarity-based retrieval improve detection [11, 12, 13].
- **Unsupervised art-style analysis (for paintings)**
  - Clustering & retrieval with deep embeddings (Deep Embedded Clustering / Deep Convolutional Embedded Clustering / DELIUS), multi-style feature aggregation, adversarial/contrastive training [14 ,15, 16, 17, 18].

State of the Art: Status for pen flourishing

- Little dedicated attention in prior work; usually folded into general illumination studies [19, 20, 21].
- Pen flourishing can take highly complex, interwoven shapes; style cues live in the strokes and micro-motifs [1].
- Global appearance is secondary for stylistic analysis - local, stroke-level features are primary cues for similarity.
- Methods emphasize global image features → limited interpretability for stroke-level comparisons.
- Hierarchical models (e.g., Feature Pyramid Networks, hierarchical transformers) offer finer multi-scale processing, but still lack transparency and interpretable region-level attributions.
- **Need for local modeling of motifs of arbitrary shape, transparent similarity attribution (region-level), and approaches that work with limited labels while aligning with expert reasoning.**

Gap / Our Contribution

- **Motif-level representation for pen flourishing**: Patch-based system that focuses on local stroke motifs rather than whole-page cues.
- **Transparent similarity & explainability**: Region/feature type attributions and visual overlays that show *why* two items match at the stroke level.
- **Label-efficient learning**: Works with scarce ground truth via self/metric learning and unsupervised clustering steps; robust with few labels.

Approach

Approach

Data

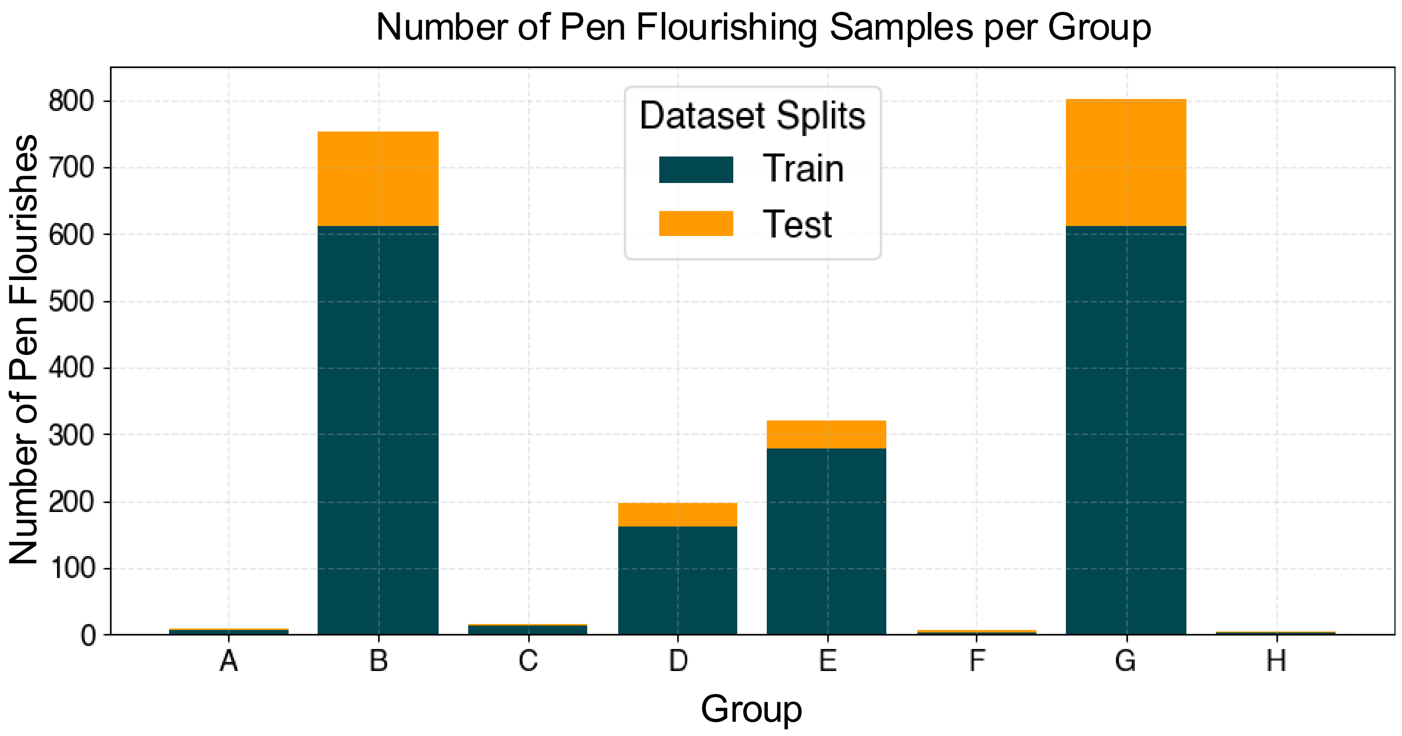
Total Number of Rubricator Groups	Total Number of Pen Flourishes
8	**2,102**

Total Number of Rubricator Groups (Used)	Total Number of Pen Flourishes (Used)
4	**788**

Source: Klosterneuburg Abbey

Data

Total Number of Rubricator Groups **8**	Total Number of Pen Flourishes **2,102**
Total Number of Rubricator Groups (Used) **4**	Total Number of Pen Flourishes (Used) **788**



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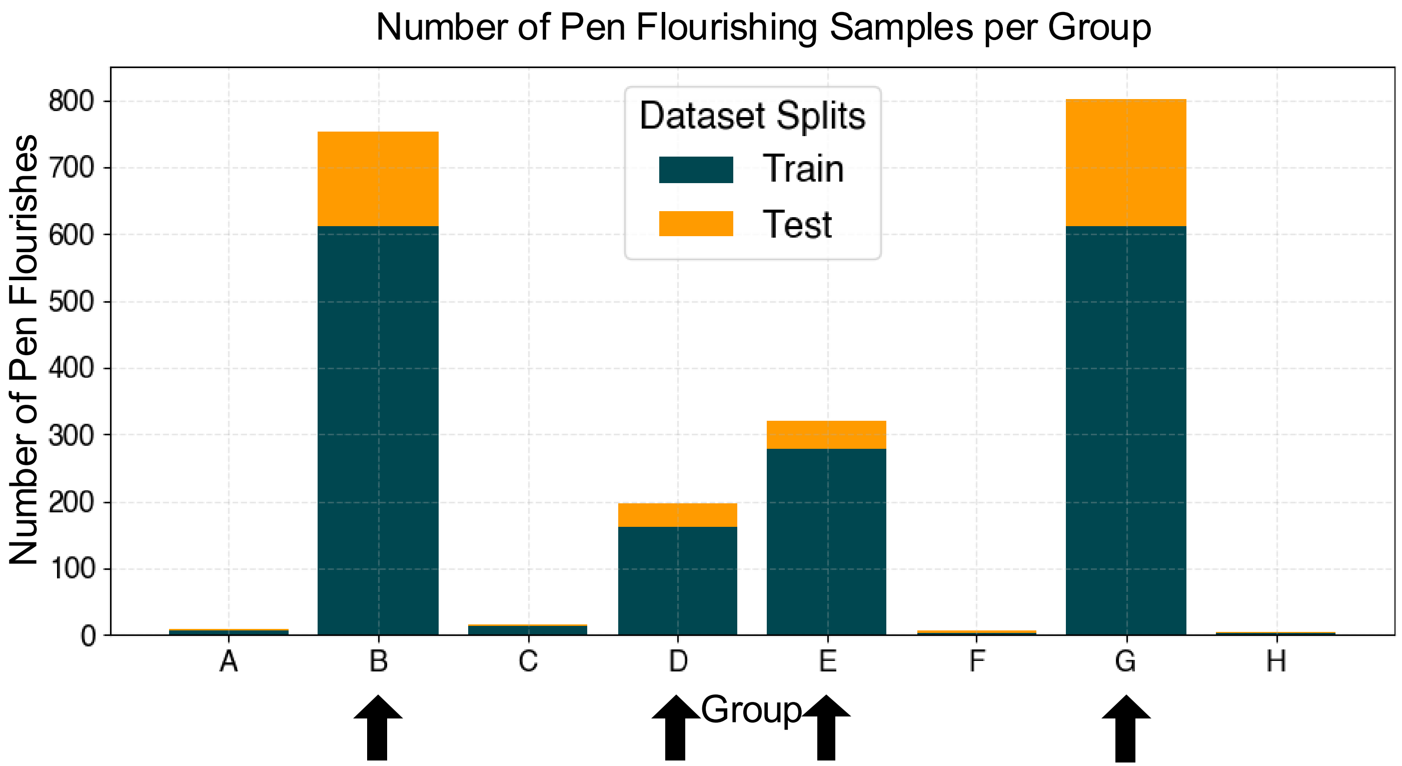

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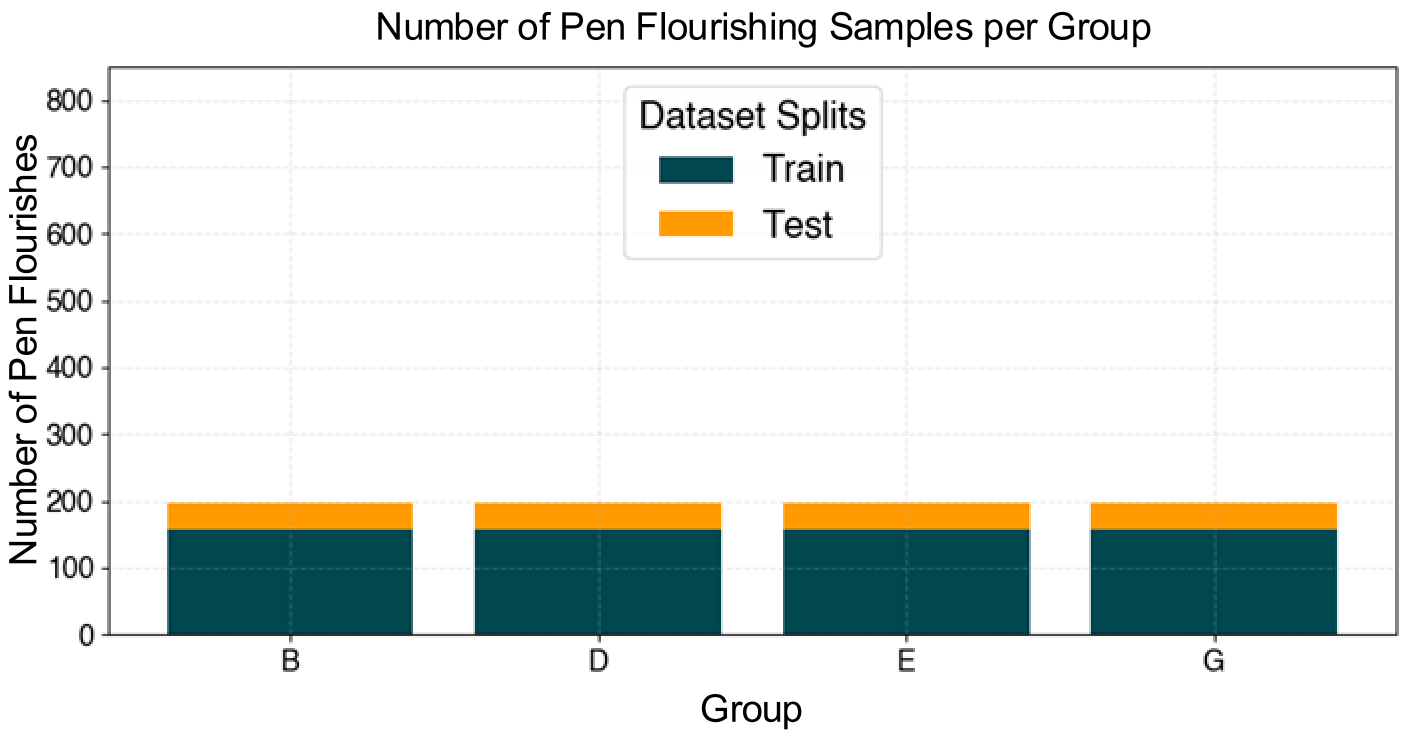

Data

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Pen Flourishing Example per Group

Group B CCl 71 fol. 23v3 | Group D CCl 71 fol. 226v1 | Group E CCl 73 fol. 43r2 | Group G CCl 73 fol. 158v3

Image Source: Klosterneuburg Abbey

Architecture

Segmentation

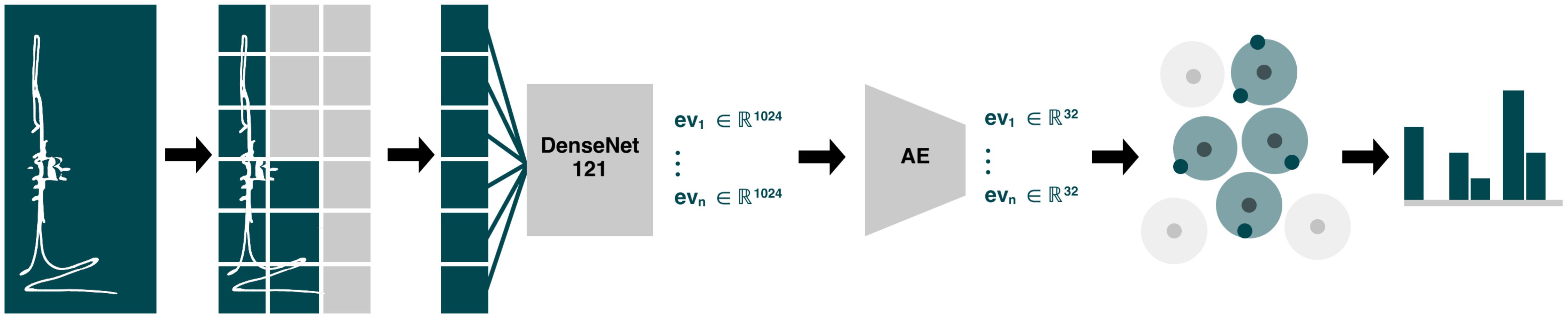
Dense Patching

Deep Feature Embedding

Dimensionality Reduction

Codebook Generation (K-Means)

Descriptor Encoding



Architecture

- Scanned in high-resolution (4435px × 5975px)
- Pen flourishing masks created by automated segmentation
- Gaussian blur applied to non-flourishing areas
- Pages are split by flourishes

CCl 71 fol. 17v3 (B)

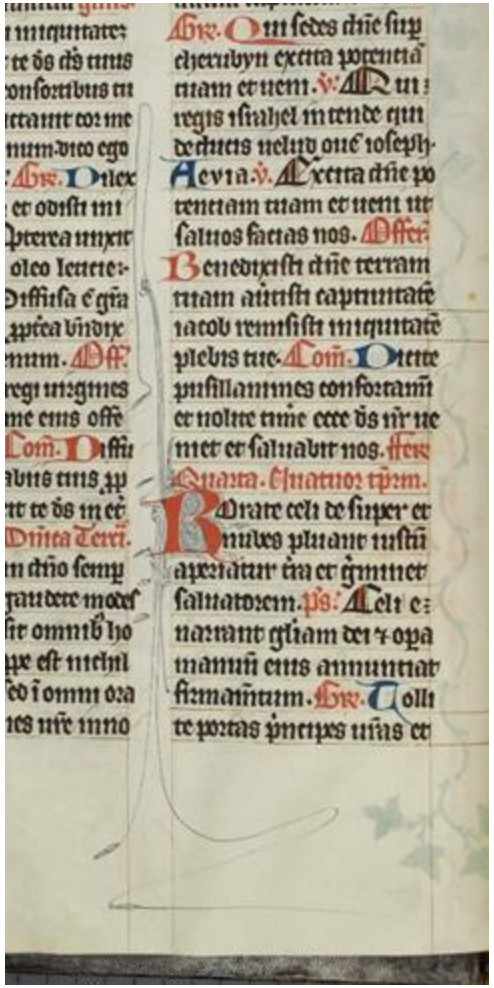


Image Source: Klosterneuburg Abbey

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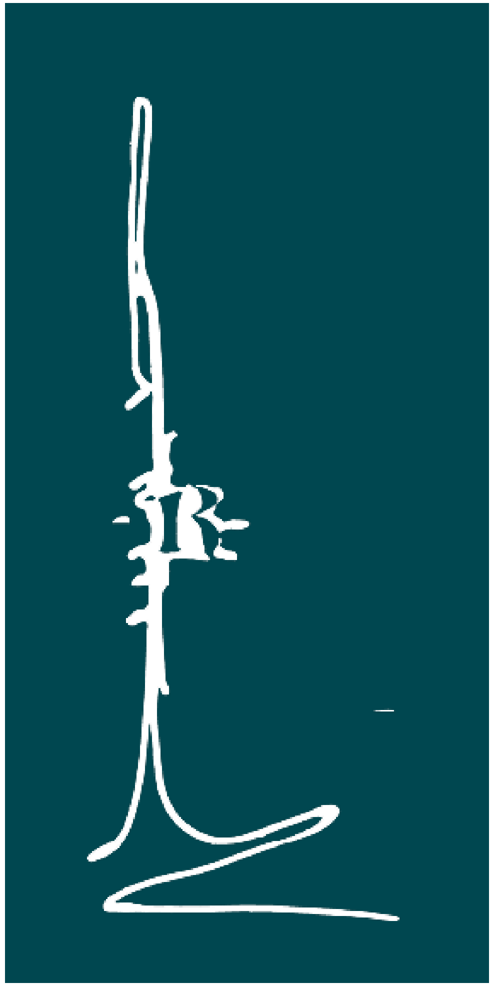
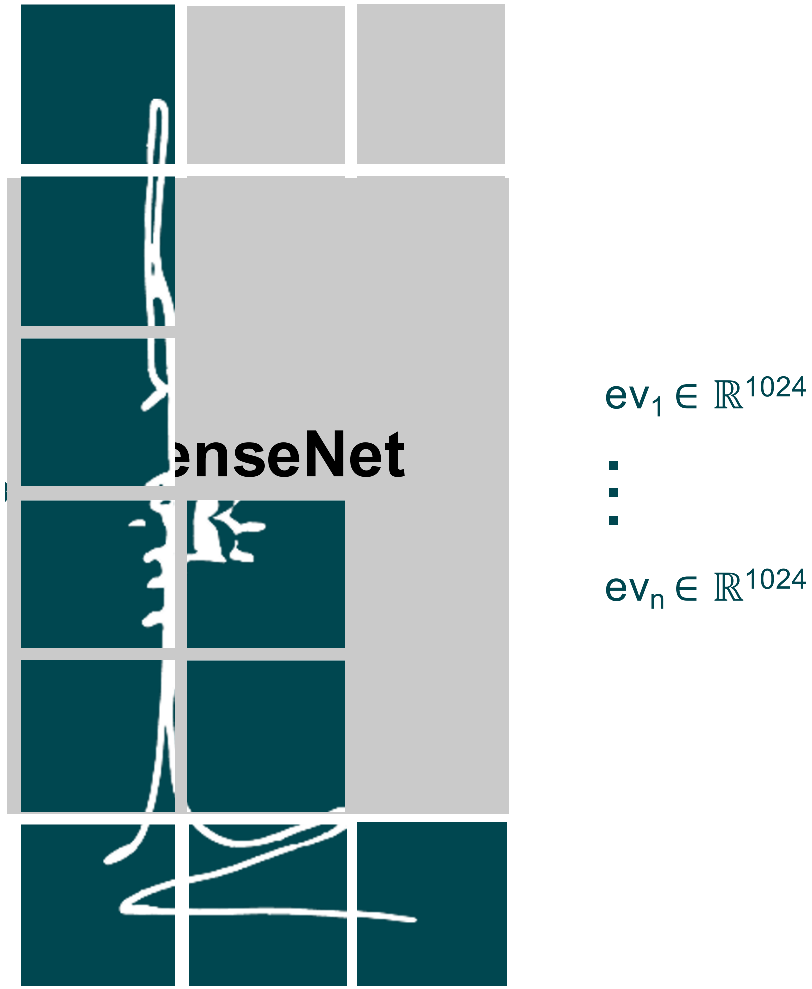


Architecture

- Patches extracted from a regular overlapping grid
  - Patch size set to 224px × 224px
  - Overlap of 1/3 of the patch size (74px)
  - Ensures independence from pen flourishing shape
  - Focusses on local features
- Patches with >20% pen flourishing foreground (masks) are retained

Architecture

- DenseNet-121 [22] used to embed patches
  - Cut off at the global average pooling layer
- Subsequent non-linear dimensionality reduction with fully connected autoencoder
  - Four-layered architecture: 500-500-2000-32 (3.57M parameters)
  - ReLU activations for non-linearity
  - Trained with mean squared error objective



Approach

Architecture

- DenseNet-121 [22] used to embed patches.
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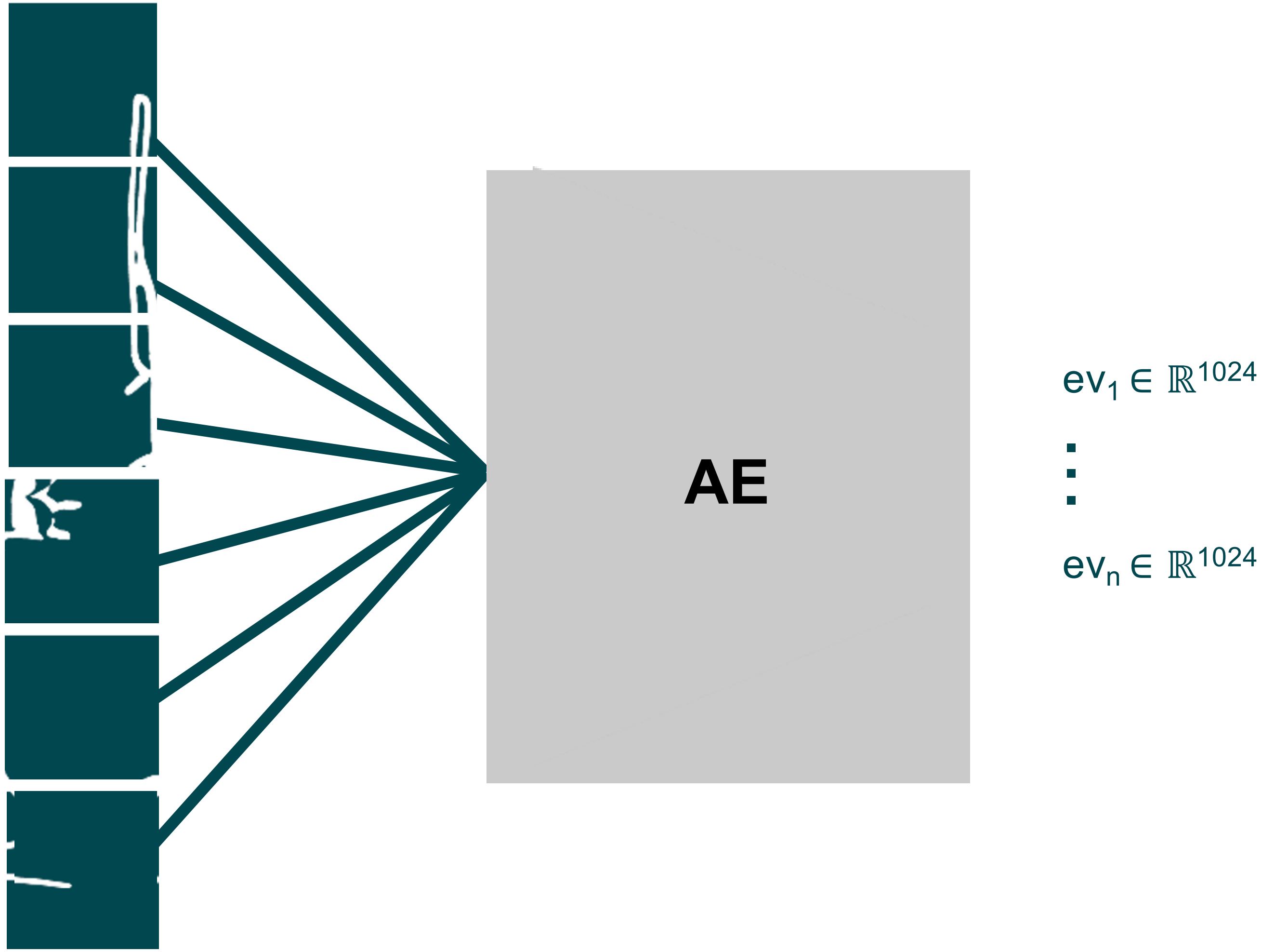
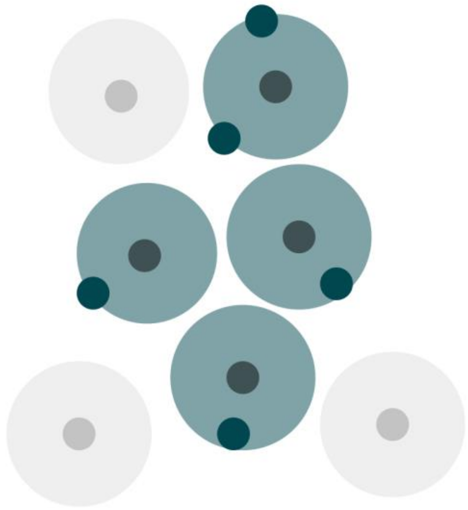
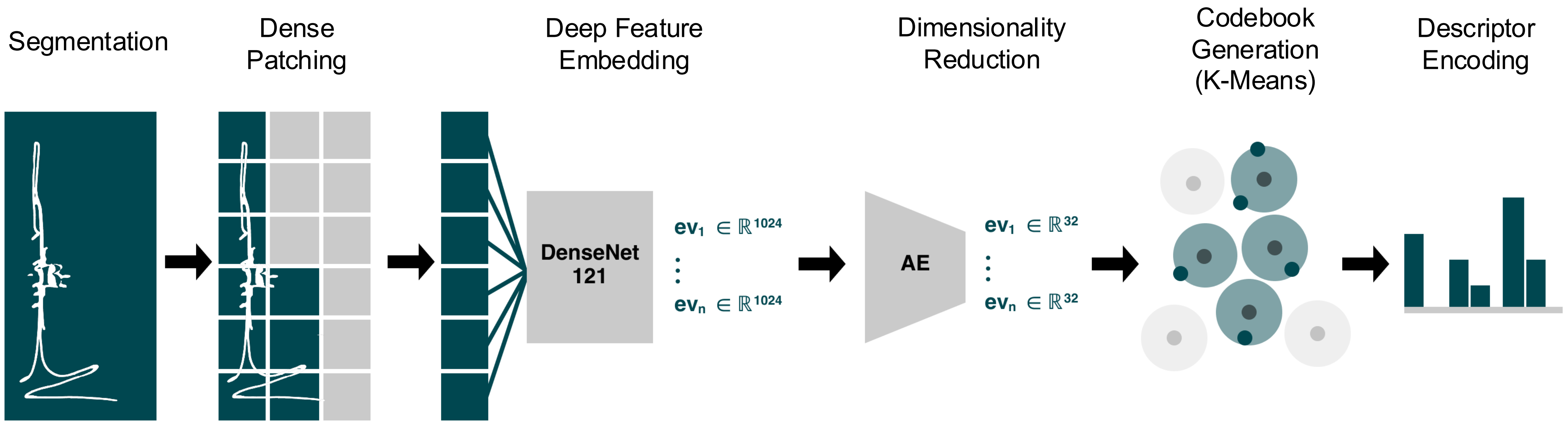


Architecture

- Computation of Bag-of-Features [23] codebook of size 100 with K-Means [24] clustering.
- Computation of global histogram vectors based on codebook.
- Root and L_2 normalization applied to the histogram vectors.

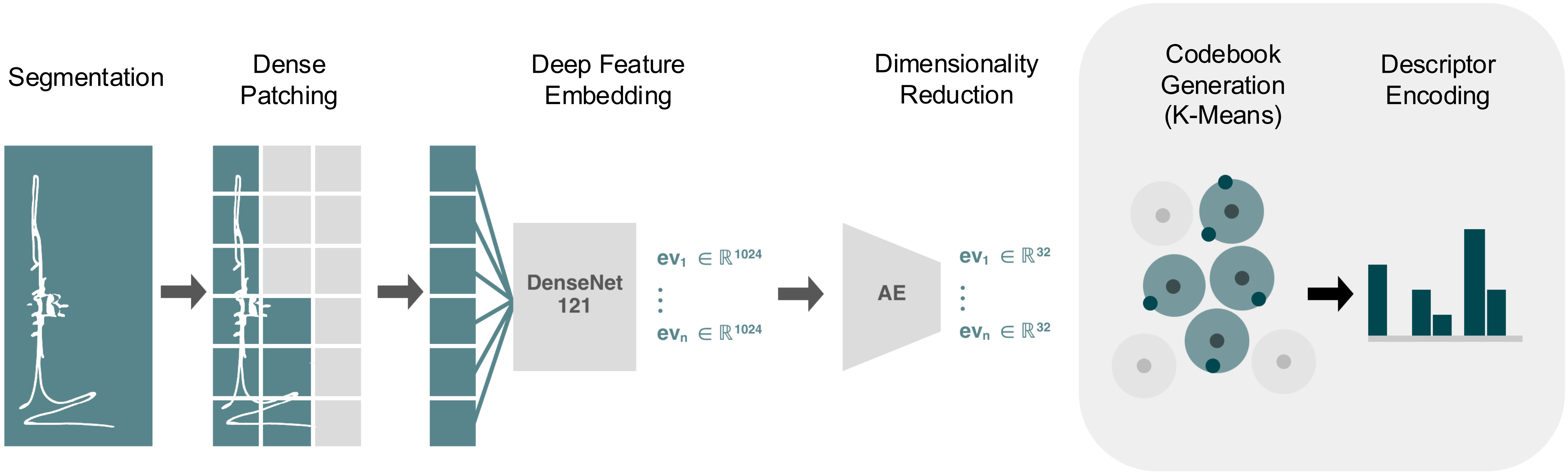


Architecture



Approach

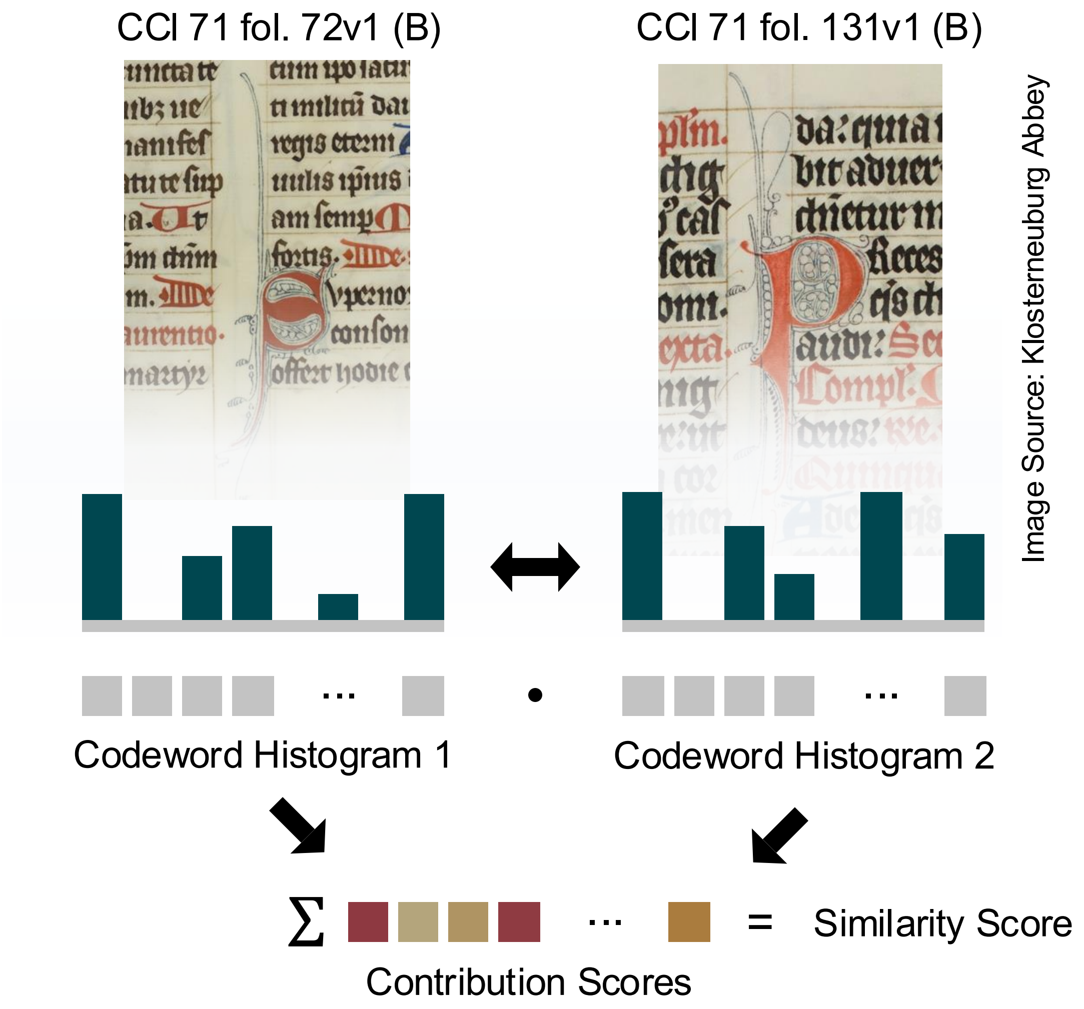
Model Transparency



Similarity described by single scalar

Approach

Model Transparency



1 Similarity-Level Transparency

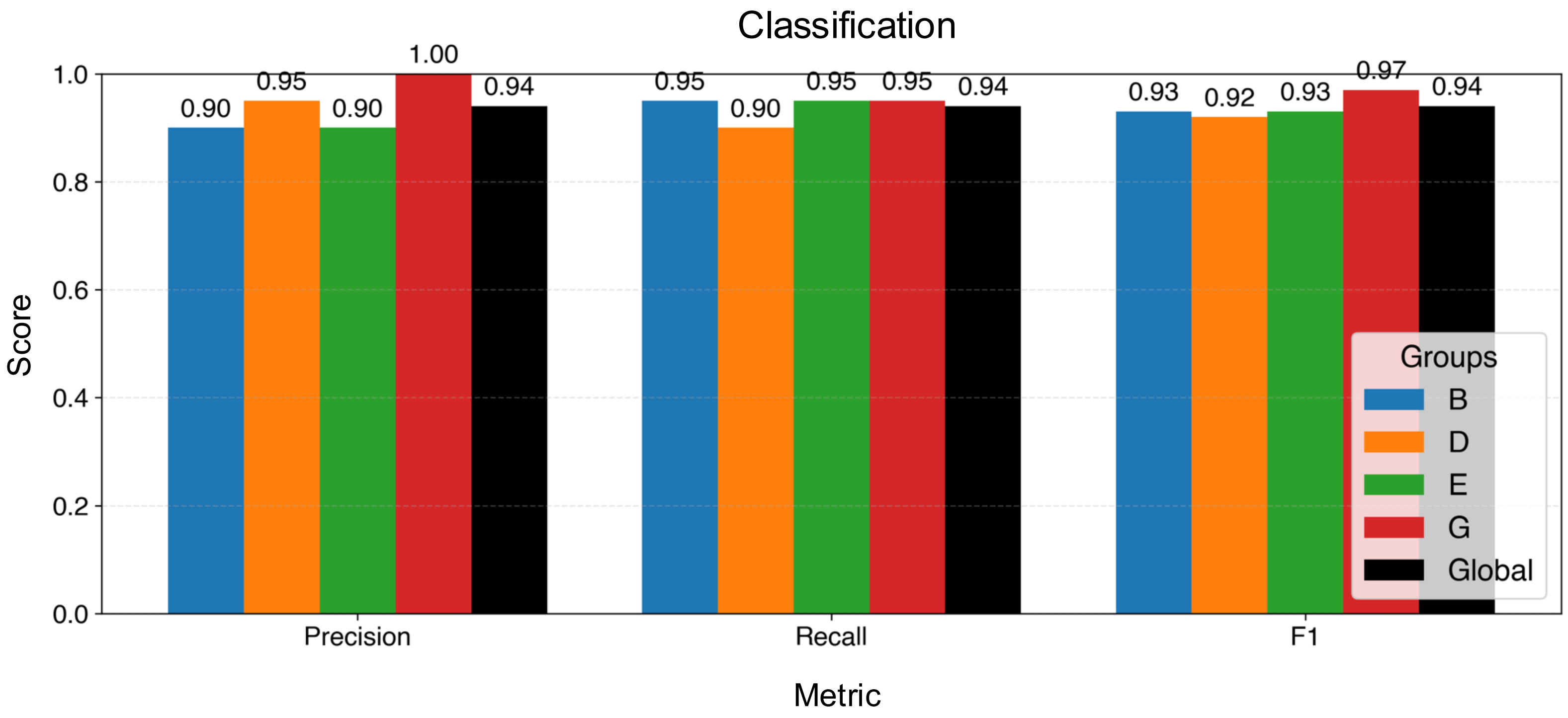
Why are flourishes similar?

2 Cluster-Level Transparency

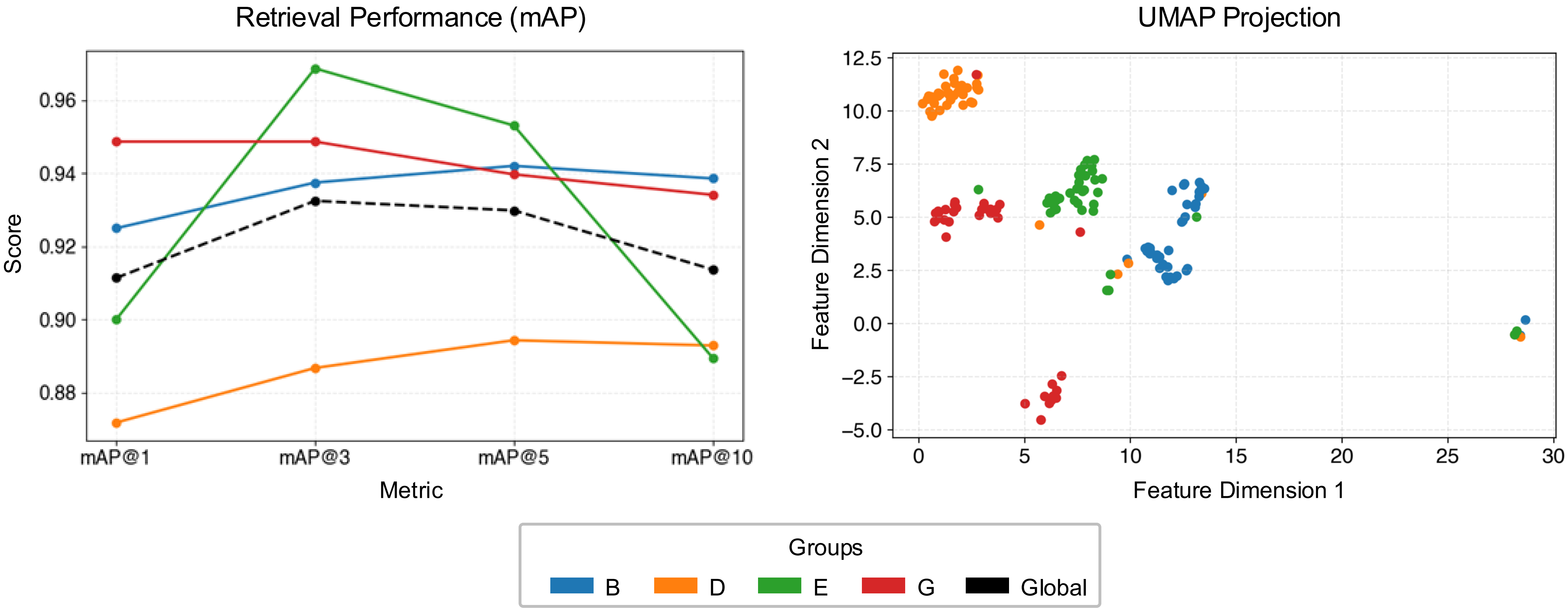
Which features are most characteristic for each group?

Classification

- Classification performance measured by a k-Nearest neighbor classifier [25] trained on top of the codeword histograms.



Feature Space



Similarity-Level Transparency

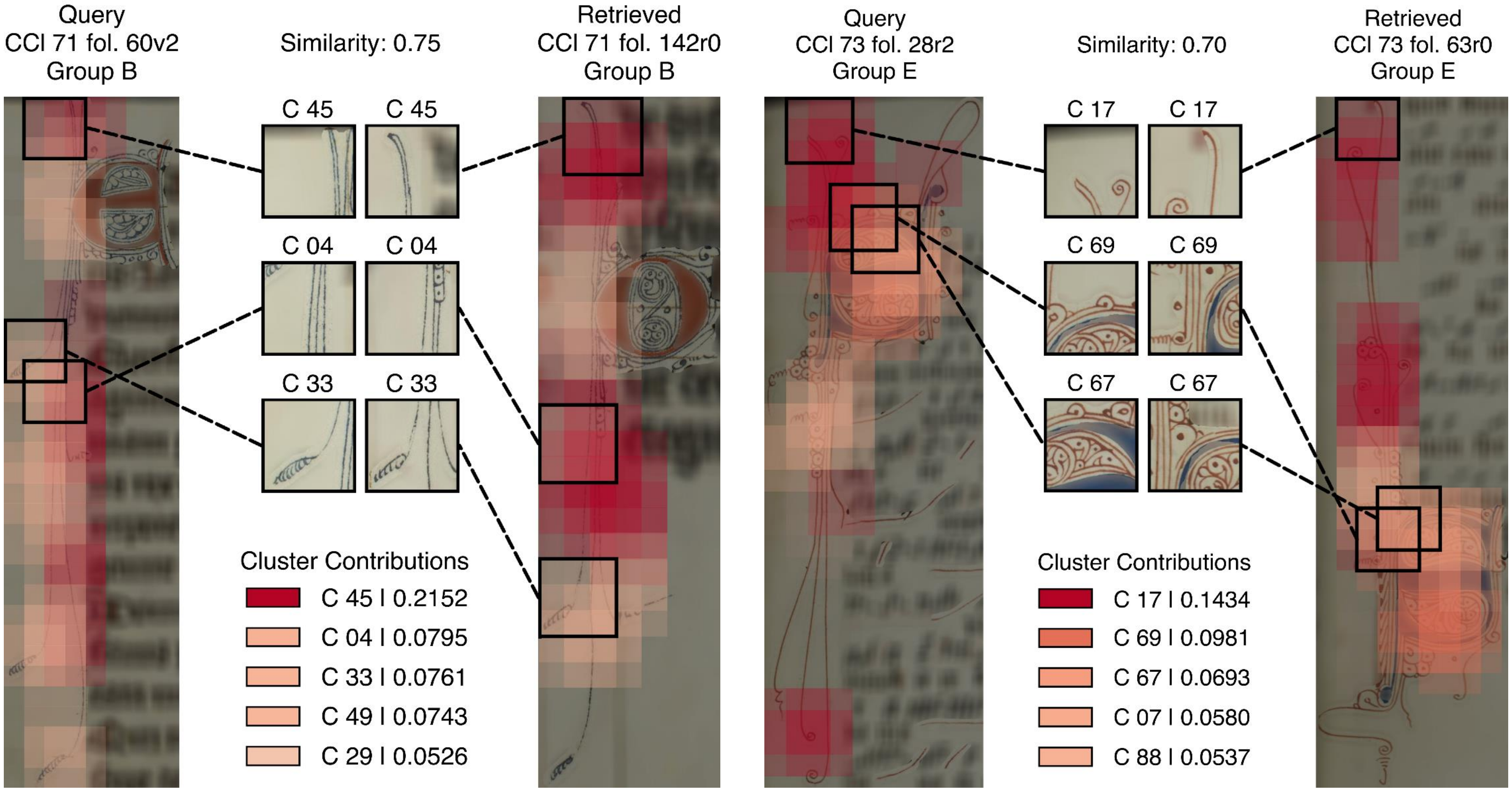
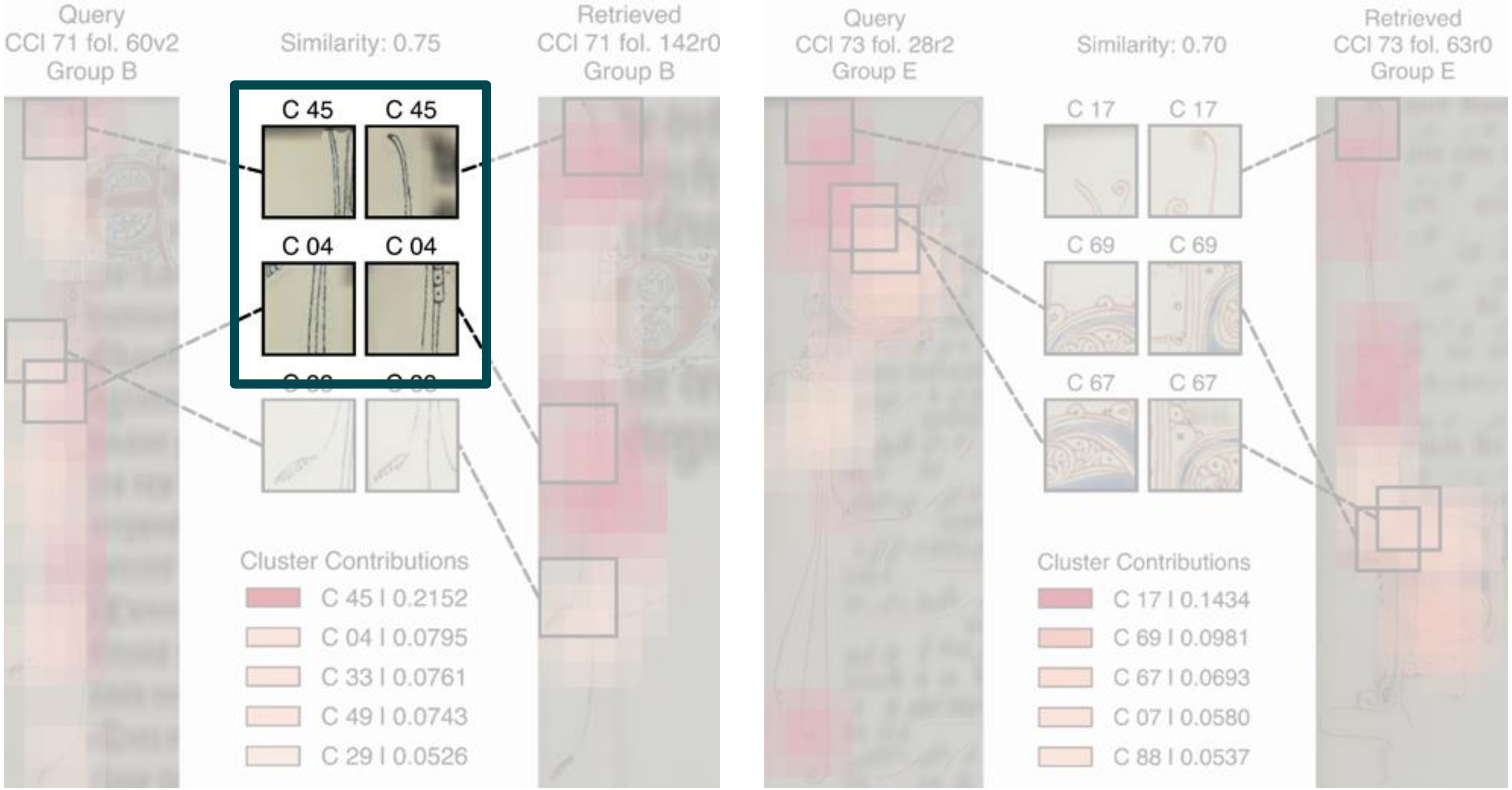


Image Source: Klosterneuburg Abbey

Similarity-Level Transparency



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Similarity-Level Transparency

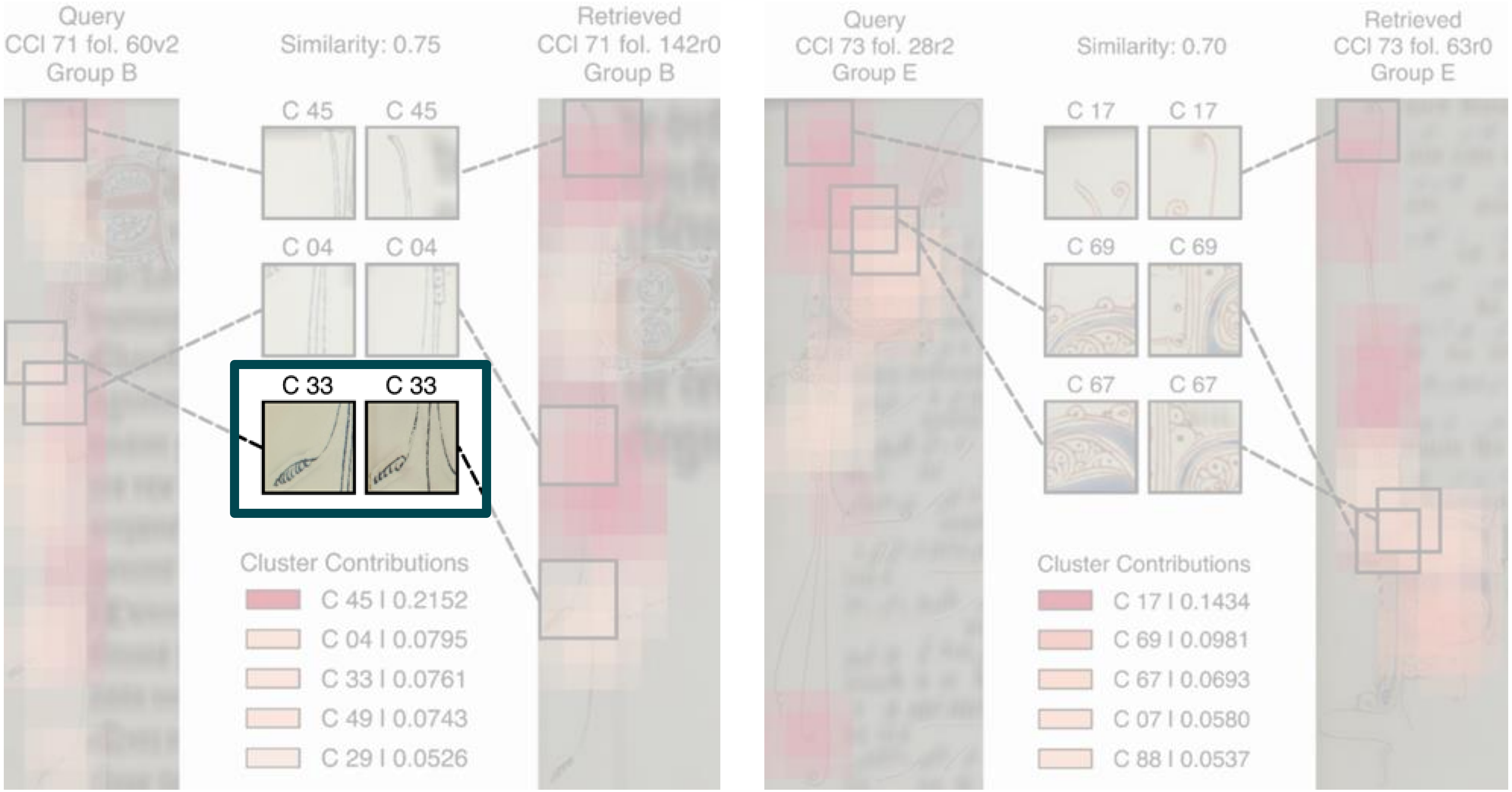


Image Source: Klosterneuburg Abbey

Evaluation

Similarity-Level Transparency

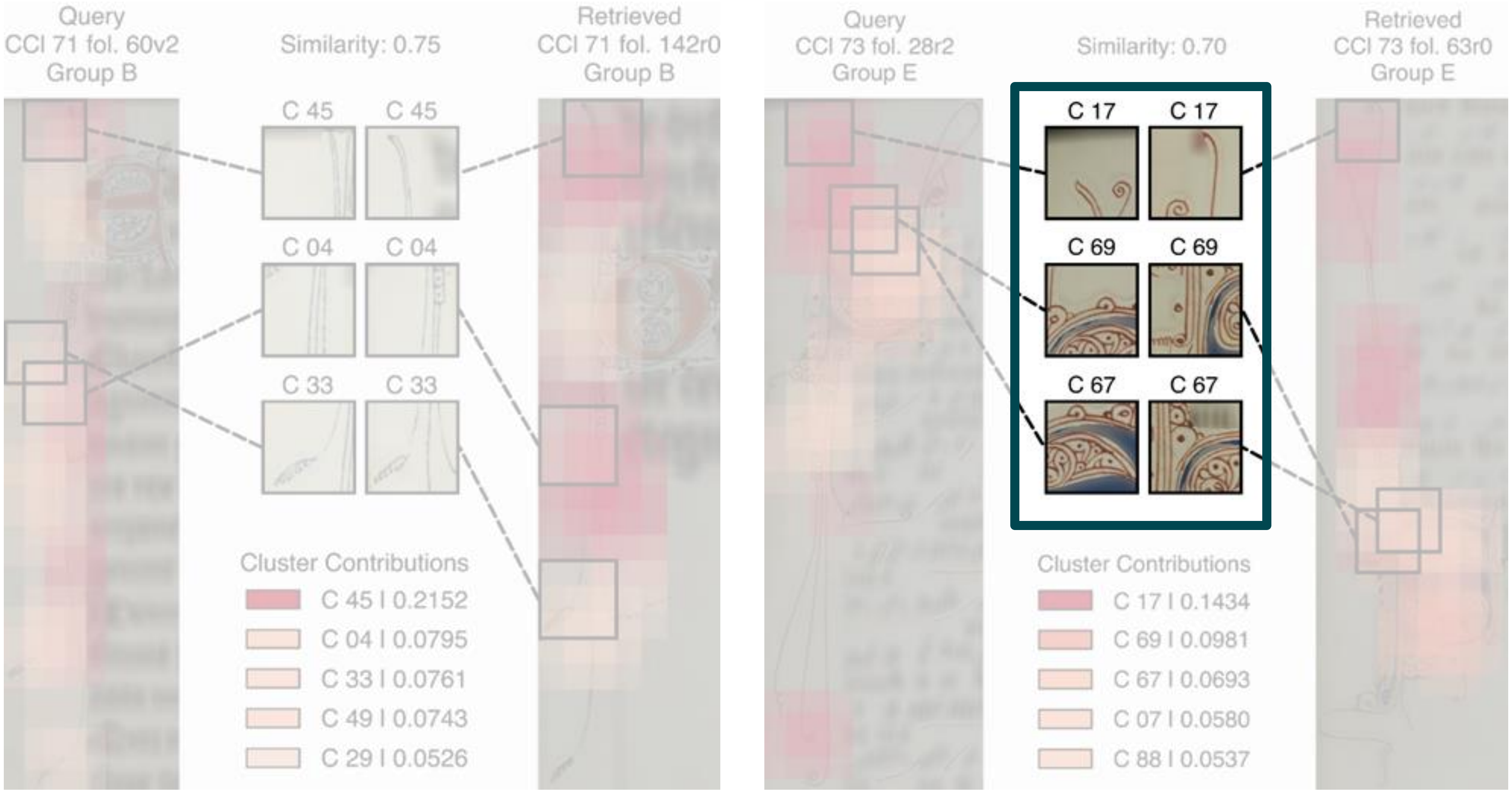
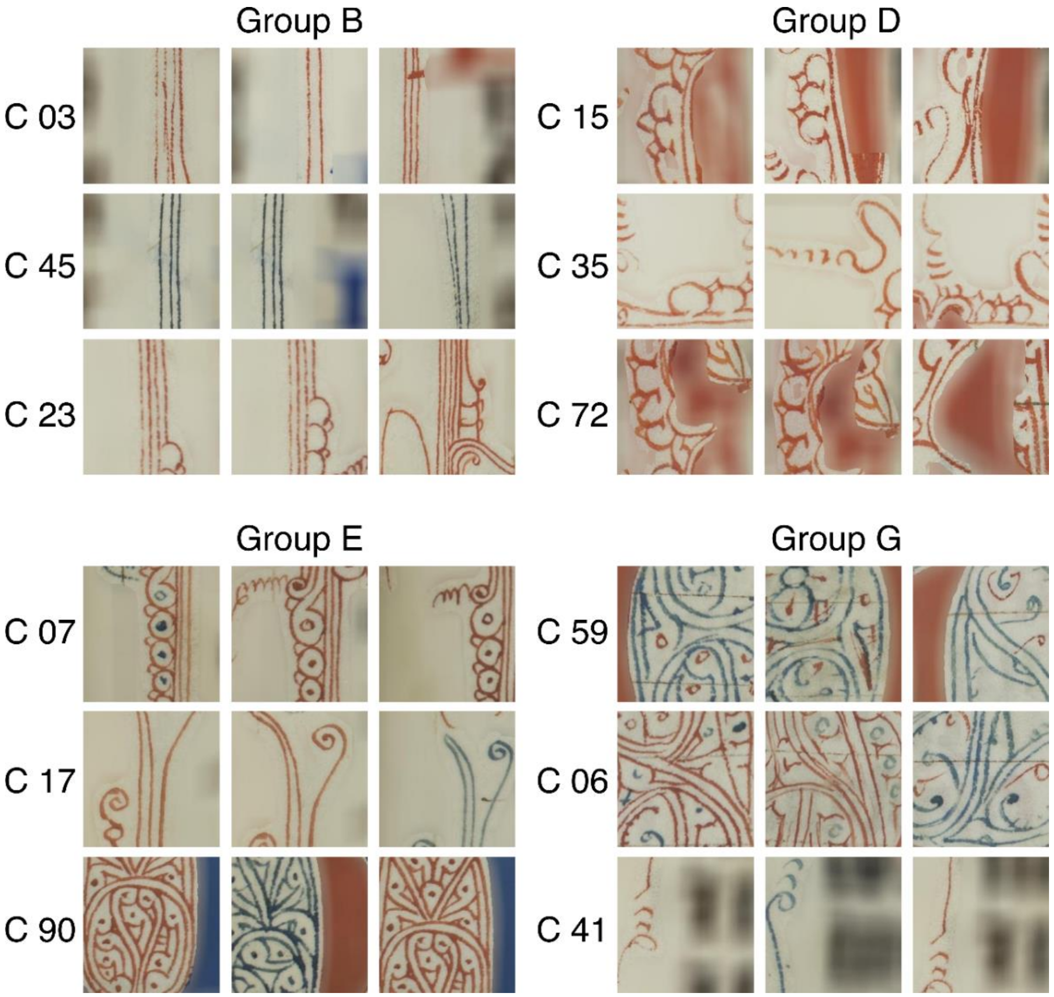


Image Source: Klosterneuburg Abbey

Evaluation

Cluster-Level Transparency



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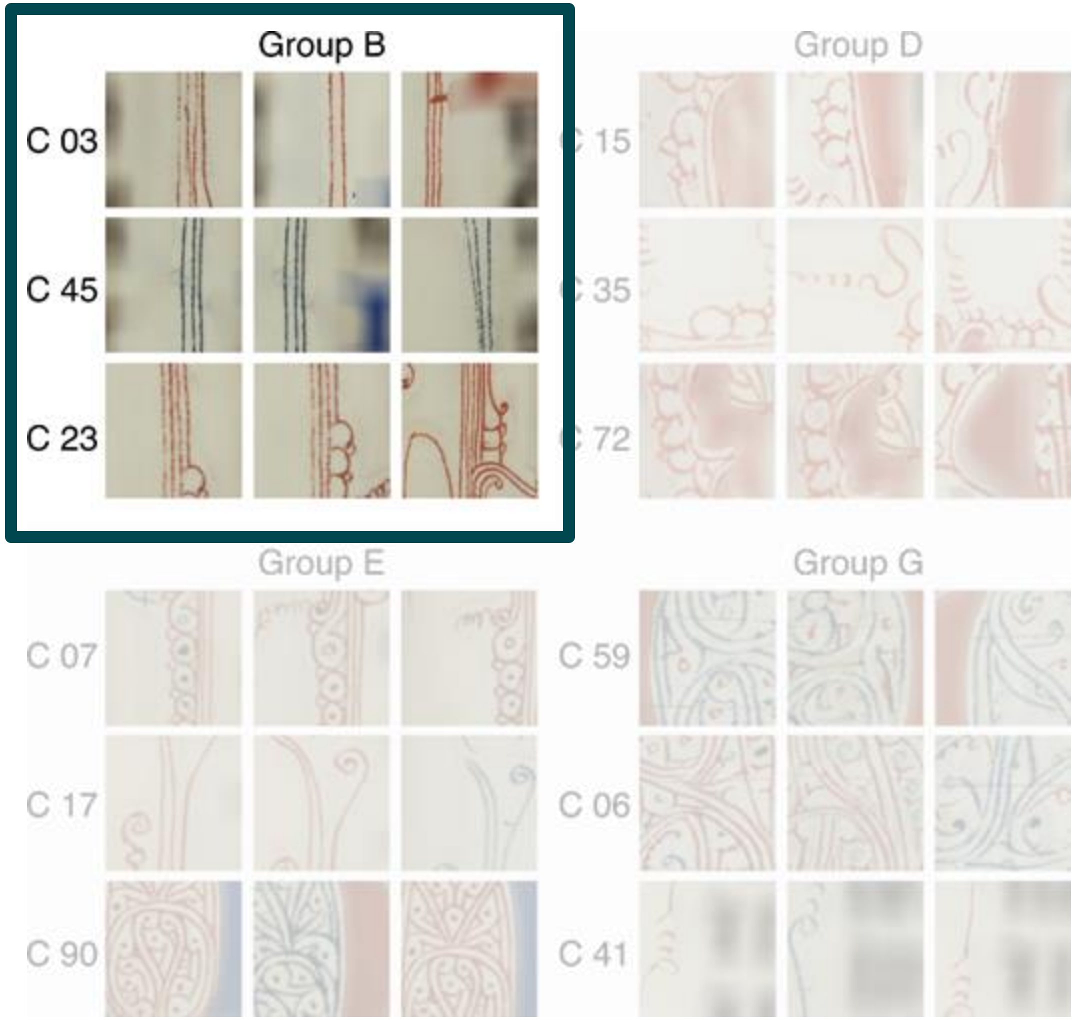
Cluster-Level Transparency



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Cluster-Level Transparency

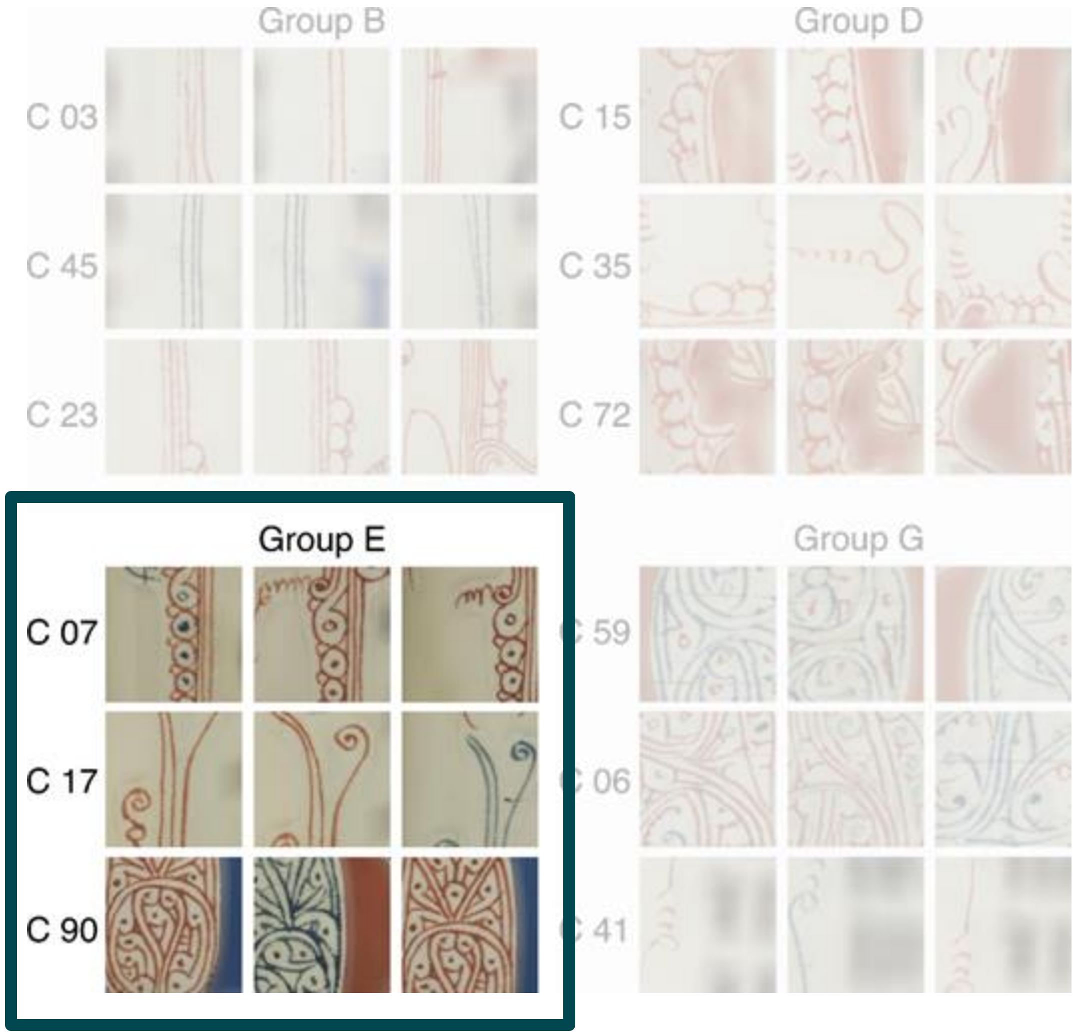

Image Source: Klosterneuburg Abbey

Domain Expert Annotations

Our Approach | Expert Annotations

CCl 71 folio 120v0 (C)

Our Approach | Expert Annotations

CCl 71 fol. 214r3 (E)

Image Source: Klosterneuburg Abbey

Domain Expert Annotations

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CCl 71 folio 120v0 (C)

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Image Source: Klosterneuburg Abbey

Takeaways

1 We presented a Bag-of-Features approach which allows both high quantitative performance and qualitative interpretability in visual style analysis of pen flourishing.

2 A codeword-contribution-based transparency layer reveals which visual motifs drive similarity - enabling explainable, expert-aligned results.

3 We identified that the *discriminative visual vocabulary* corresponds closely to art-historical motifs.

Outlook

1. **Scale up**: Extend dataset to more manuscripts, periods, and stylistic schools for broader validation.
2. **Benchmarking**: Compare against end-to-end architectures to better contextualize model performance.
3. **Interactive Tool**: Develop an expert-in-the-loop interface for similarity search, visual exploration, and motif comparison.

Thank you!

Acknowledgements

We thank the art historians of our “Ornament & Algorithm Workshop” and acknowledge Gesellschaft für Forschungsförderung Niederösterreich (GFF) for funding.

Code and dataset

Research project

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Appendix

Patching

CCl 71 fol. 169r1 (B)

CCl 73 fol. 143v2 (G)

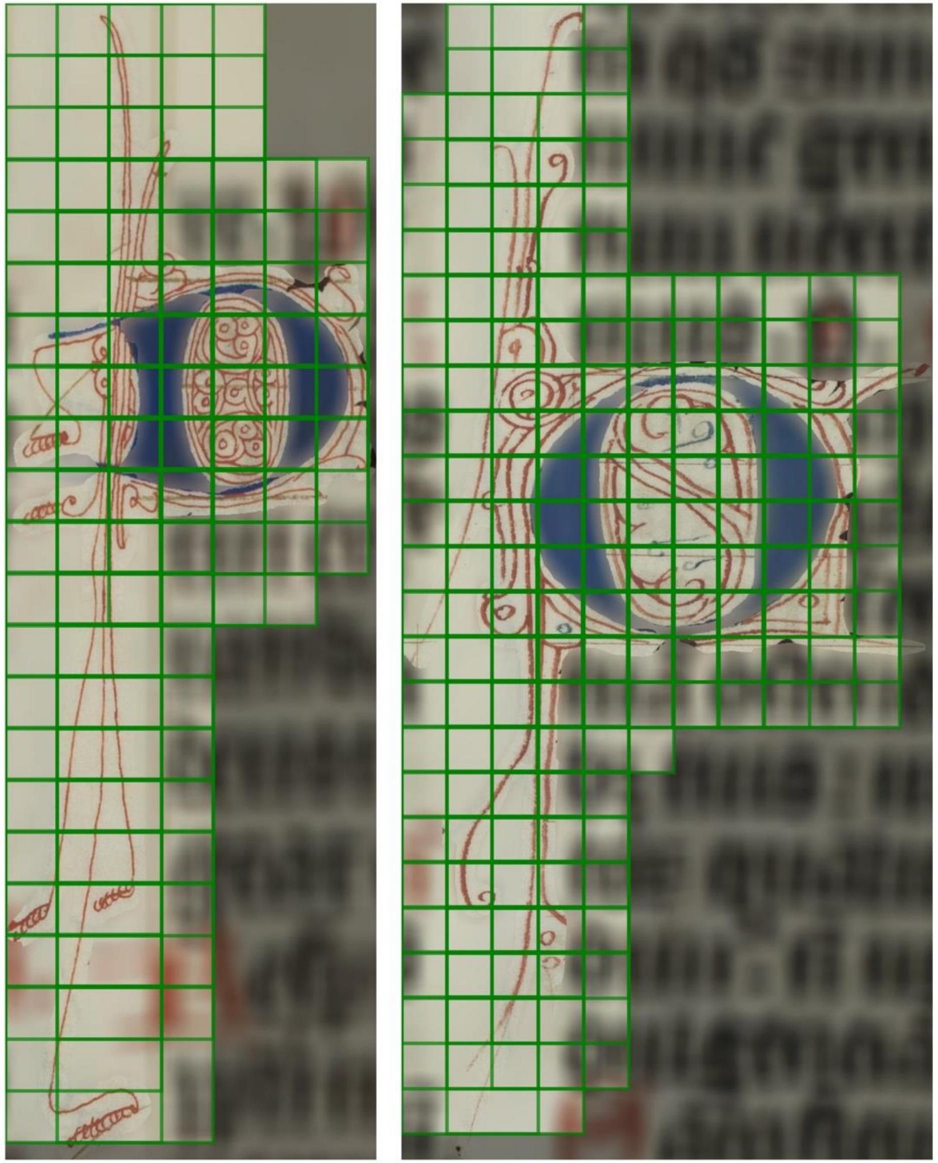

Image Source: Klosterneuburg Abbey

Similarity-Level Transparency

$$\mathbf{h}^{(i)} = \left[h_1^{(i)},\ h_2^{(i)},\ \ldots,\ h_K^{(i)}\right]^\top, \quad h_d^{(i)} \geq 0, \quad \|\mathbf{h}^{(i)}\|_2 = 1$$

$$S\big(\mathbf{h}^{(i)}, \mathbf{h}^{(j)}\big) = \langle \mathbf{h}^{(i)}, \mathbf{h}^{(j)} \rangle = \sum_{d=1}^{K} h_d^{(i)}\, h_d^{(j)}$$

$$c_d = h_d^{(i)}\, h_d^{(j)}$$

$$\sum_{d=1}^{K} c_d = S\big(\mathbf{h}^{(i)}, \mathbf{h}^{(j)}\big)$$

$\mathbf{h}^{(i)}$	Histogram for the i-th sample
S	Similarity of two histograms
K	Total number of codewords
d	Codeword (dimension)
c	Contribution score

Cluster-Level Transparency

$$\mathcal{I}_g = \{\, i : x_i \text{ has label } g\}, \quad \mathcal{I}_{\neg g} = \{\, i : x_i \text{ has label } \neq g\}$$

$$\mathcal{P}_g = \{(i,j) : i < j,\ i,j \in \mathcal{I}_g\}, \quad \mathcal{Q}_g = \{(i,j) : i \in \mathcal{I}_g,\ j \in \mathcal{I}_{\neg g}\}$$

$$\bar{c}_d^{\text{within}}(g) = \frac{1}{|\mathcal{P}_g|} \sum_{(i,j)\in\mathcal{P}_g} c_d\big(\mathbf{h}^{(i)}, \mathbf{h}^{(j)}\big)$$

$$\bar{c}_d^{\text{between}}(g) = \frac{1}{|\mathcal{Q}_g|} \sum_{(i,j)\in\mathcal{Q}_g} c_d\big(\mathbf{h}^{(i)}, \mathbf{h}^{(j)}\big)$$

$$\delta_d(g) = \bar{c}_d^{\text{within}}(g) \ - \ \bar{c}_d^{\text{between}}(g)$$

I_g, I_{-g}	Set of Images with / without group label *g*
P_g, Q_g	Within and between-group pairs
$c_d^{within}(g)$	Within-group contribution for codeword *d*
$c_d^{between}(g)$	Between-group contribution for codeword *d*
d	Codeword
$\delta_d(g)$	Discriminative score for codeword *d* and group *g*
$\mathbf{h}^{(i)}$	Histogram for the i-th sample

Codeword Assignment Balance