

Workshop on Computational Methods in the Humanities 2018 (COMHUM 2018), Lausanne.

Clustering Writing Components from Medieval Manuscripts



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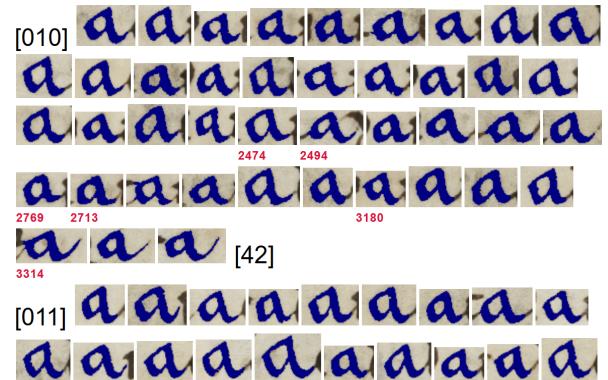
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Purpose

- ◊ Extraction and clustering of writing components.
- ◊ Partial transcription in combination with human annotation of the clusters.
- ◊ Qualitative palaeographic analysis.



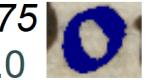
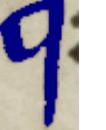
tum pnoꝝ p̄lit̄ tñanꝝ naui
gane p̄ot̄. quo audito p̄r
ſic pnoꝝ atun. Cuidam r̄co
& electo homini. qui ad noſ
arte uſꝝ p̄hiam p̄huln̄a.
Omnipot̄is tñan quillitat̄.
quam liba. In t̄mperat̄e
donauit. & Ecce eadē die

“Pipeline”

- ◊ **Extraction of components**
 - Binarization (ink-background separation)
 - Connected component labelling
 - Segmentation
- ◊ **Clustering**
 - Core clustering
 - Removal of small clusters
 - Extension by classification

In experiments, we took 20 000 components. 3

Overview of clusters, Gen. 1

1 1715 4.7		2 1171 5.9		3 827 4.6		4 755 6.0		5 675 4.0		6 667 4.6		7 460 6.8	
8 406 4.1		9 306 4.2		10 289 4.1		11 273 6.7		12 271 3.6		13 252 5.8		14 251 5.9	
15 204 4.3		16 112 5.4		17 101 4.8		18 90 6.8		19 65 5.5		20 54 6.7			

In cells: “central” instance, number, size, and width.
From experiment with our “baseline” settings.

Gen. 1, $\langle a \rangle$ whole cluster

[006]		[45]
[007]		[62]
[008]		[52]
[009]		[58]
[010]		[42]
[011]		[49]
[012]		[56]
[013]		[57]
[014]		[55]
[015]		[57]
[016]		[46]
[017]		[49]
[018]		[46]
[019]		[37]
[020]		[52]
[021]		[50]
[022]		[38]
[023]		[53]
[024]		[47]
[025]		[43]
[026]		[47]
[027]		[48]
[028]		[43]
[029]		[31]
[030]		[8]

Size=1171. (27 p.) High precision for $\langle a \rangle$.

Gen. 1, $\langle a \rangle$ cluster, subset

[021] 

[022] 
2433 2353

[023] 
2172

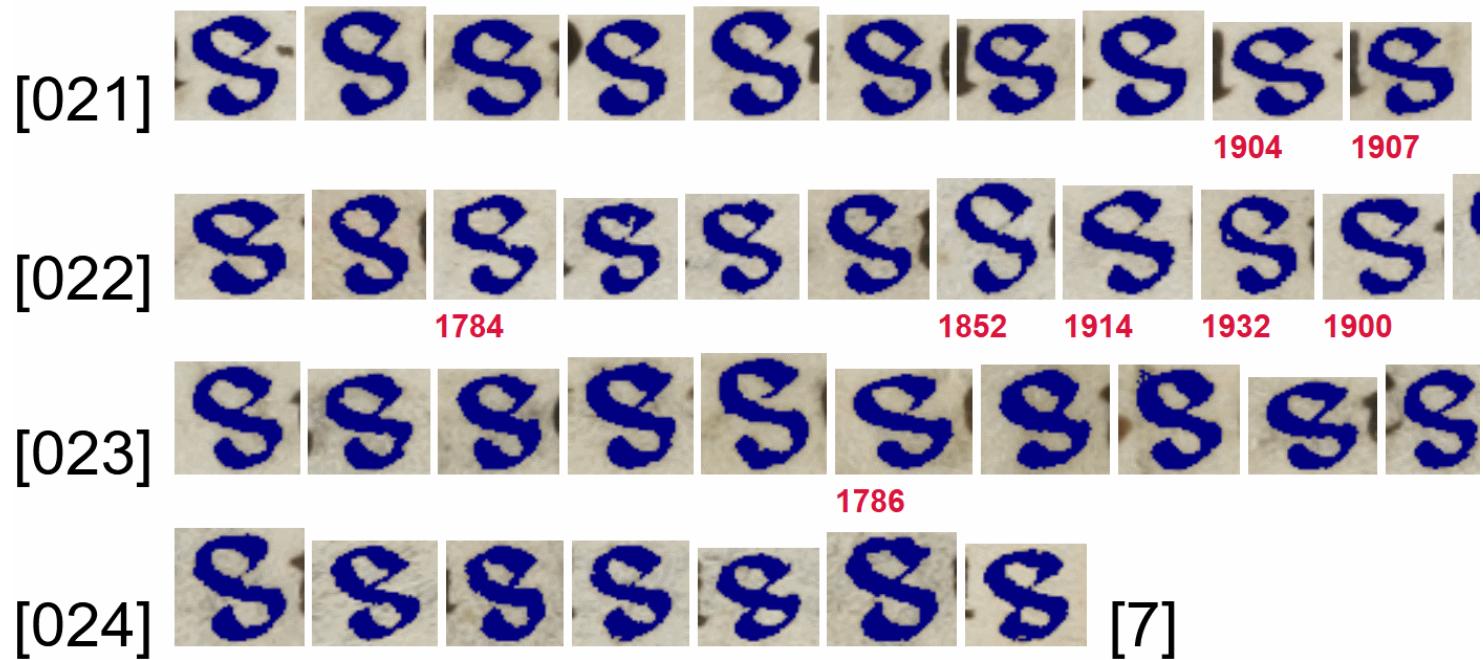
[024] 

[025] 
2121

[026] 

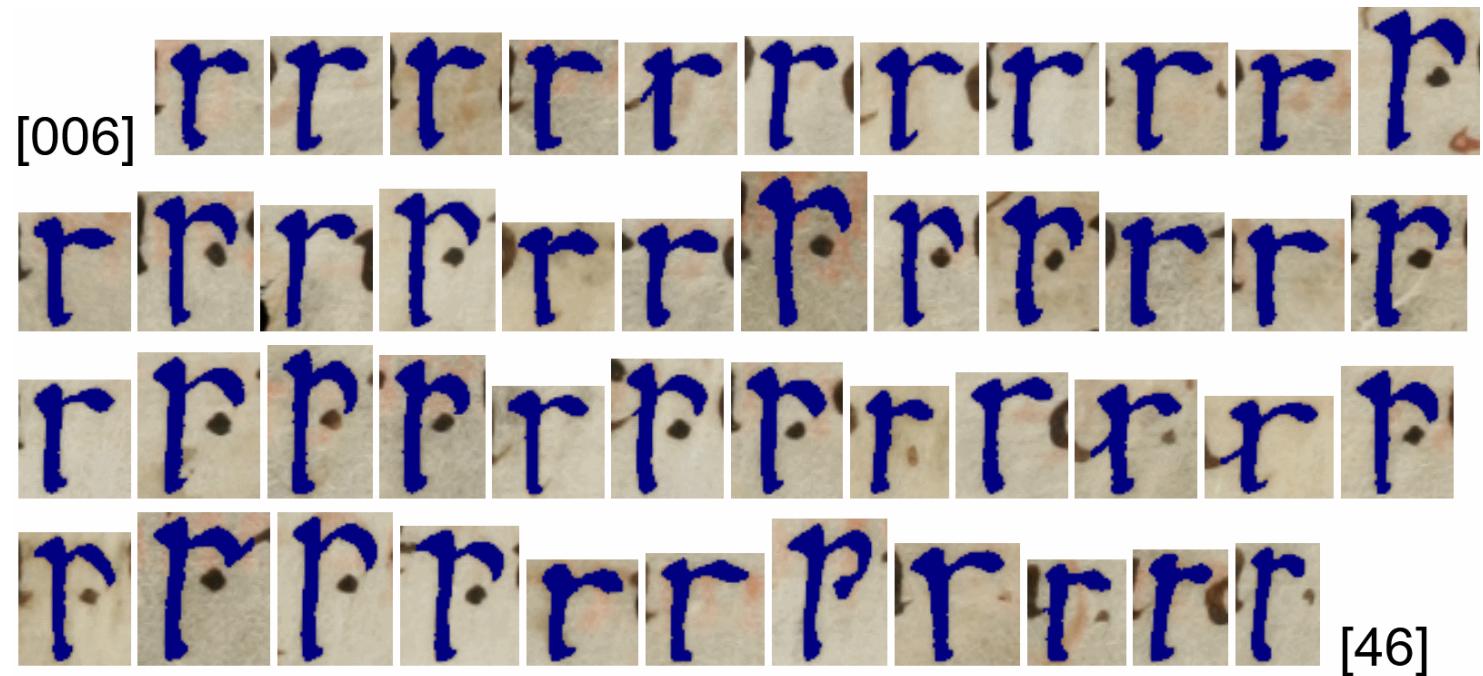
Size=1171. (27 p.) High precision for $\langle a \rangle$.

Gen. 1, $\langle s \rangle$ (one allograph) cluster



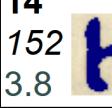
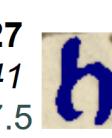
Size=101. 100% precision for this $\langle s \rangle$ allograph.

Gen. 1, largest cluster



Mixture of $\langle p \rangle$ and $\langle s \rangle$ (another allograph).

Another example: C 61 (b), clusters

1 2889 5.5		2 1594 3.7		3 1180 4.2		4 905 6.3		5 511 3.3		6 508 3.8		7 461 5.8	
8 456 3.9		9 436 3.2		10 261 5.1		11 237 4.1		12 205 6.6		13 158 6.8		14 152 3.8	
15 148 3.6		16 134 6.9		17 130 5.0		18 117 4.3		19 114 6.1		20 111 7.1		21 109 3.3	
22 94 7.5		23 88 5.3		24 63 6.0		25 60 6.6		26 52 5.7		27 41 7.5			

In cells: “central” instance, number, size, and width.

C 61 (b), cluster for $\langle \ddot{a} \rangle$

[275]		[12]	
	2939		
[276]		[13]	
	2907	3048	3077
[277]			
	2554	2758	2819
[278]		[14]	
	2794	3119	
[279]			
	2816		
[280]			
	2630	3076	

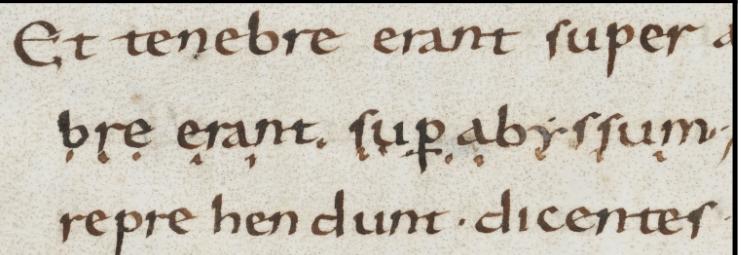
How to evaluate clustering results?

- ◊ **For which categories** are clusters established?
- ◊ **Precision** of a cluster: fraction of elements belonging to the right category.
- ◊ **Recall**: fraction of real instances of the right category assigned to the cluster.

Component Extraction

- ◊ **Binarization** (ink-background separation).
- ◊ **Connected component labelling** finds regions of ink.
- ◊ **Segmentation**, guided by estimated stroke width, w_s . (w_s is estimated as the most common width of sequences of continuous horizontal ink pixels separated by at least two pixels of background.)

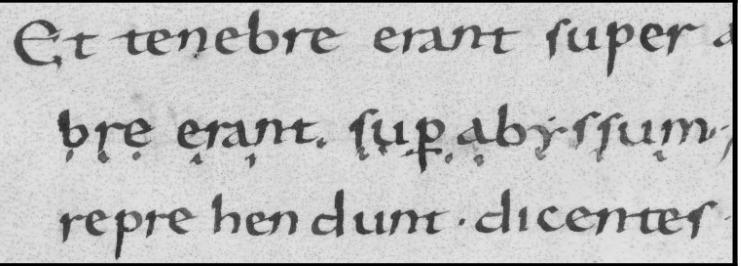
Binarization



Et tenebre erant super a
bre erant. sup. abyssum;
repre hen dunt. dicentes

colour

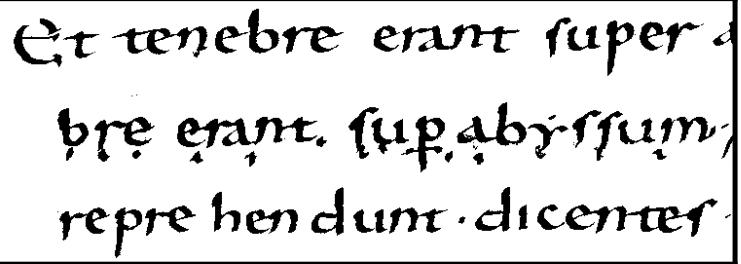
(red, green, blue)



Et tenebre erant super a
bre erant. sup. abyssum;
repre hen dunt. dicentes

greyscale

(dark–light)



Et tenebre erant super a
bre erant. sup. abyssum;
repre hen dunt. dicentes

binarized

(ink, background)

Segmentation, five parameters

- ◊ width $\in [w_{mn}, w_{mx}]$
- ◊ t_i is the thickest amount of ink that allows a cut to be made.
- ◊ height $\in [h_{mn}, h_{mx}]$
- ◊ In our experiments,
$$(t_i, w_{mn}, w_{mx}, h_{mn}, h_{mx}) =$$
$$(1.0w_s, 3.0w_s, 8.0w_s, 3.0w_s, 15.0w_s).$$

An example. C 61 (b)

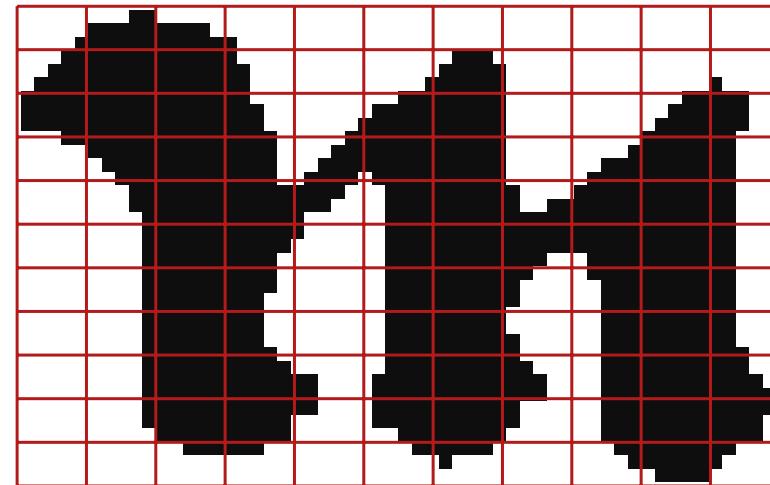
ſwa fuſſeoþlcga. inſaſte rom q
ſtræſſeim oppa ena marmorſte
neſſ qon genſtam þaſſ tæc bohe
modq̄t manu qwilka qenē ſtræſſ
reðqan oppa latimo. aþtæḡt h̄y rom

An example. C 61 (b)

ſi uia ſuſt' hōp' legea t' m' f'it' q' r'om' q'
g'z p'ff' u' m' opp' a' c'ha' t' m' u' m' o'z f'ci
p'ff' q' on' s'c' n' f' m' p'ff' t'c' B'oh'z
m' o'g' q'z m' n' u' l' f' u' l' t' a' q' c' n' c' p'ff'
g'z q' q' a' n' opp' p' n' h' m' o' p'ff' t'c' l' q' p'om'

Image features

Distribution of ink as captured by a grid of 11×11 equal subrectangles over the bounding box.



Each value is the ratio of the number of ink pixels to the size of the subrectangle region.

Similarity of components

- ◊ So, we associate each component with a 121-dimensional (11×11) vector.
- ◊ We apply Euclidean distance on these:

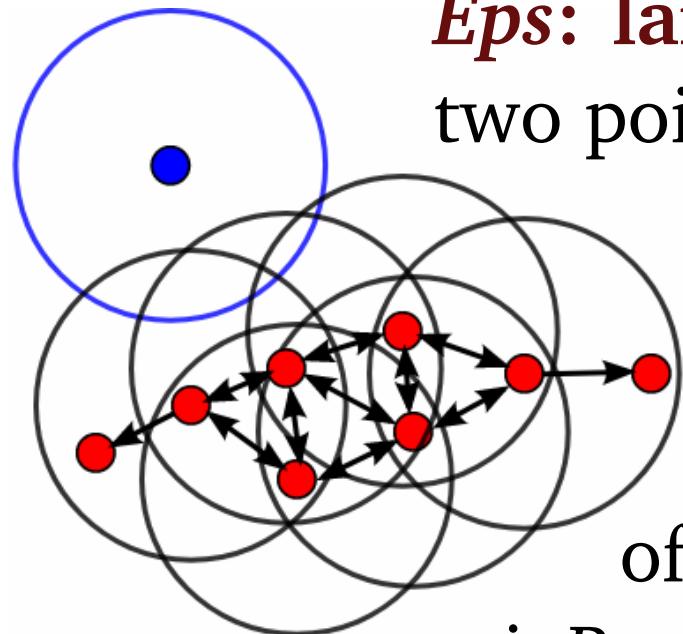
$$\text{distance}(I, J) = \sqrt{\sum_{i=1}^n (I_i - J_i)^2}$$

- ◊ **The feature model and distance metric define a distance** (dissimilarity) between any two image components.

Clustering

- ◊ “**Core**” **clustering** by density-based algorithm (DBSCAN).
- ◊ **Removal** of small clusters (size < 40 here).
- ◊ **Classification** assigns some not clustered components to the remaining core clusters (“nearest neighbour” to centroids).

DBSCAN guided by two parameters



Eps: largest distance between two points counted as neighbours.

minPts: minimal number of neighbouring points required for the formation of a same-cluster dense region.

$minPts = 11$ in our experiments.

(Illustration: $minPts = 4$.)

Eps estimation

- ◆ Image distance is difficult to “use” in an intuitive way.
- ◆ Eps estimated from the probability (p_{Eps}) that two randomly selected components are at least that close to each other.
- ◆ Baseline setting: $p_{Eps} = 0.0007$.
- ◆ This makes Eps sensitive to the data set.

Extension of clusters by classification

- ◊ DBSCAN typically leaves some data unclustered.
Small clusters are removed.
- ◊ In the last step some of the unclustered components are assigned to existing clusters. This is based on a “nearest neighbour” (to cluster centroids) procedure.

Data in experiments

- ◊ **Irish** (7th/8th C.): Gen. 1. and CS 60.
- ◊ **Carolingian minuscule** (St. Gallen)
CS 557 (9th C.) and CS 564 (12th C.).
- ◊ **Textualis** (14th C., Swedish): B 59 and B 10.
- ◊ **Cursiva recentior** (late 15th C., Swedish):
C 61(a) and C 61(b).

High-resolution images (JPEG or TIFF), published open access.

Two settings

CS 557 (44 p.).

*... tam militiam in adolescentia secutus
ter scolares alas sub rege constantio.
in. sub iuliano cesare militauit. Non*

Settings	letters	ligatures, bigrams	mixtures, etc.
Baseline $p_{Eps} = 0.0007$ 17 clusters 5.0k elements	b :241+93, d ₁ :273, g :64, h :84, l :85, m :585, n :144, o :676, p :597, q :195, r :409+86, s :1141, v :191	is :104, ss :56	–
More generous $p_{Eps} = 0.0014$ 27 clusters 9.5k elements	a :594, b :404, c :111, d ₁ :309, d ₂ :167, e :423, E :54, g :112, h :108, l :109 [*] , m :960, n :685, o :841, p :628, q :245, r :609+138 [†] , s :1149, t :64, u :969, v :229	co :104, er :184, & :104, is :113, ri :64, ss :66	–

Precision levels: default > 99.5%. ★: > 98%. †: > 80%. ($minPts = 11$.)

Recall and precision (%) – a few cases

	“Core” $p_{Eps} = 0.0007$			Baseline w. classif.			More generous $p_{Eps} = 0.0014$		
Manus.	e	m	o	e	m	o	e	m	o
Gen. 1 recall	10	46	54	14	54	58	46	68	83
prec.	100	100	100	100	100	100	100	100	100
CS 557 recall	0	13	46	0	44	61	8	71	76
prec.	–	100	100	–	100	100	100	100	100
CS 564 recall	0	46	1	4	58	17	7	61	36
prec.	–	97	100	100	65	100	100	57	100
C 61(b) recall	28	58	25	28	63	28	31	65	36
prec.	100	100	100	100	97	100	100	96	29

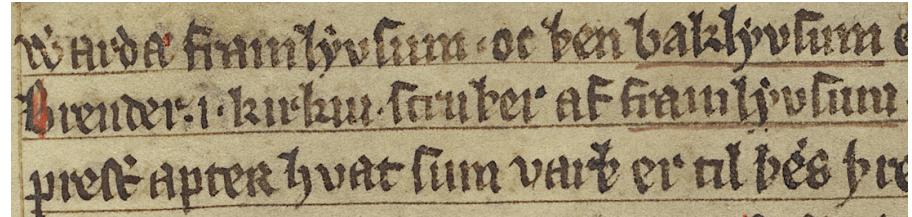
Overclustering (B 59, largest cluster)



Baseline settings. Size: 3846.

Three settings

B 59 (44 p.)



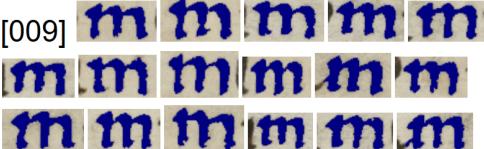
Manuscript	letters	ligatures, bigrams	mixtures, etc.
Baseline $p_{Eps} = 0.0007$ 23 clusters 14.8k elements	a :2938 [†] , m :361 [†] , n :1562 [‡] , o :488, s :1220 [‡]	al :57, bo :47, fa :105 [*] , fi :157, gh :63, gi :94 [†] , ll :71 [†] , sk :256 [†] , sti :53 [†]	a ... :367, ... a :290 [†] , e ... :110, sk U st :52 [†] . <i>Useless</i> : 3846+2172+223+ 190+109
More reluctant $p_{Eps} = 0.00035$ 18 clusters 8.9k elements	a :2634 [*] , d :200, h :71, k :456 [*] , m :289 [†] , n :1348 [‡] , o :359, s :1144 [‡] , p :355 [†]	ar :122 [*] , sk :236 [†] , ta :98 [†]	v U b :693 [‡] . <i>Useless</i> : 507+157+75+65+64
More reluctant $minPts = 22$ 16 clusters 6.6k elements	a :2852 [*] , h :93, k :477 [*] , m :335 [†] , n :1433 [‡] , o :455, s :1170 [‡] , p :386 [†] ,	ar :229 [‡] , fi :63, sk :223 [†] , ta :143 [†] ,	v U b :943 [‡] . <i>Useless</i> : 599+155+66

Precision levels: default > 99.5%. ^{*}: > 98%. [†]: > 80%. [‡]: > 60%.

Methodological overview

- ◆ “Unsupervised” learning.
- ◆ Theoretical and experimental tuning of parameters.
- ◆ Human interpretation of output.
- ◆ Useful precision, but possibly low recall.

tum proficit trans nauis
gane poterit quo audito per
sic proficitur. Cuidam rco
& electo homini. qui ad nos
ante usq; pham perhibuit.

[009] 

Conclusions

- ◊ Clustering allows us to find classes of letters and other writing elements in handwriting.
- ◊ Almost all components in the pipeline can be modified (binarization, segmentation, feature model, similarity metric, clustering algorithm and settings).

Thank you!

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