Twenty-One* Pseudo-Chrysostoms and More

Authorship Verification in the Patristic World

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Patristics & Chrysostom

Vocabulary

Late Antiquity classification of the litterature based on the period (incl. christ. litt)

Patristics study of the texts and influence of Church Fathers Church Father vs. ecclesiastic author Doctrinal influence and recognition by the institution

Christian litterature in the first millenium

- First in Ancient Greek, then in Latin (first texts are Paul's *Epistles* (51-55 CE))
- Chronological coverage 1st-8th century CE (more or less)
- "Golden age": 4th century

- Born in 349 CE
- Various high ranked positions in the Church (Antioch Diaconate and Priest, Archbishop of Constantinople)
- Exiled twice (fights between his supporters and others ended up costing the walls of a cathedral (burnt technically))
- Dies in an exile from exile (further banished because he had too much influence remaining in Constantinople)
- Wrote a lot, was very influential (very high h-index potential)

One way to present him, the first time it was introduced to me, is that Chrysostom is the **Greek-speaking equivalent of Augustine** (and I love this comparison).



The issue with writing a lot

- Around 300 works written by Chrysostom (which we are more or less sure of, 18 volumes of the Patrologia Graeca)
- S. J. Voicu [4] estimates that a little more than 1000 works are wrongly attributed to Chrysostom (and as such are Pseudo-Chrysostomian), including Armenian and Latin translation.
- Some authors have been namely identified, such as Severian of Gabala (originally friendly with C, ended up judging him for exile) who wrote around 60 homelia ending up attributed to Chrysostom (irony ?)

UNE NOMENCLATURE POUR LES ANONYMES DU CORPUS PSEUDO-CHRYSOSTOMIEN

Plus d'un millier d'ouvrages (1) sont attribués à tort à Jean Chrysostome, en grec ou en d'autres langues orientales (2).

Mais ces textes - dont l'écrasante majorité se présente sous forme d'homélies - n'appartiennent pas tous au même titre au corpus pseudo-chrysostomien.

Il y a lieù en effet de distinguer parmi eux trois grandes catégories (Vocru, 1981): a) les ouvrages composites : b) oux pour lesquets nous pouvons remonter à un état plus ancien que l'état chrysostomien : c) au moins 300 pièces qui ne semblent appartenir à aucun des deux groupes précédents.

Ce sont ces derniers ouvrages, ceux dont l'intégrité ne parait pas contestible et dont nous ne connaissons auura dist pré-chrysostomien, qui sont le terrain de choix de la recherche pseudochrysostomienne. Puisque, du moirs pour l'instant, aucune autre attibution ne vient remplacer colle des manuscris, manifestement erronte, nous avons choisi d'appler, avec un brin d'oxymoron, aunonymes pseudo-chrysostomients les auteurs de ces textes (P).

(1) Nous appelors «cuvrago» toute forme textuelle qui se présente comme étant indépendante – à l'exclusion donc des citations et extraits, et des démanguages et paraphraises dans le corps de pièces positirieures : mais en incluant certaines formes littéraires bien définies, comme les evice.

123 Accurate repertisons an dense un chilffer tanti soli per perick dei testas pessoloticitato e la provincia del la soli bosti difficia della la no tere petedere. Peri testaste, la mediore approximizioni perali fere l'additori dei latos survintati al Acassati della periodi della de

(3) Dans l'état actuel de nos connaissanoss il parait qu'il faile accepter cet anonymat comme la condition définitive de maint dossier. Au moins deux auteurs

1000 pseudo-chrysostomian works ?

In 1981, S. J. Voicu provides a summary of the status of attribution of pseudonymous work into anonymous clusters (PCn). It covers around 21 PC, for which some hypothesis date back to the 17th century, and features argument based on various features: style, theological, extra-textual (references or cites something posterior to Chrysostom) and sequentiality (texts clearly continuing each others).

Cluster	Number of texts	Original Hypothesis	Confidence	Additional analysis	Confidence	Argument type
1	2	Montfaucon		Altendorf	Refuted	theological
2	2	Montfaucon		Voicu	Confirmed	continuity
3	3	Montfaucon		Voicu	Refuted	
4	7	Montfaucon		Voicu	Low	
5	3	Montfaucon		Voicu	Partially refuted	
6	3	Montfaucon		Voicu	Low	
7	7	Montfaucon		Voicu	Possible	
8	2	Montfaucon		Voicu	Refuted	stylistic
9	5	Marx		Voicu	Refuted	
10	2	Weyer				
11	3	Nautin				
12	2*	Liébart				theologic
13	3	Leroy		Voicu	Refuted	
14	4	Voicu	High			
15	5	Voicu	Mostly high			
16	5	Voicu	High	Wenger	Partially Possible	
17	2	Voicu	High			
18	2	Voicu	Possible			stylistic,theologic
19	2*	Rilliet	High			
20	5	Datema	High	Voicu		
20b	12	Datema	Possible	Voicu		
21	2	Voicu	High			extra-textual

Authorship verification

We have very small samples of texts (between 2 and 7 texts per Pseudo-Chrysostom, one exception with 20b being 12 texts): so classification is nearly out of the question (hard to test accuracy on a two text sample).

We propose to approach this with authorship verification, and specifically, we want to merge approaches from NLP and Computer Vision (using Siamese Networks, specific distance) and features usually used in DH (avoid to use complete sentences, prefer style markers that are (nearly) atopical such as function words, POS 3-grams, affixes [2].

Siamese network ?

Architecture of our models: vectors are passed in parallel in the embedding projection layer and a distance vector is then computed.



Siamese network ?

Architecture of our models: vectors are passed in parallel in the embedding projection layer and a distance vector is then computed. Input layer MF(W,P,T) Embedding Text 1 Text 1 SNR Distance Batch norm Loss Vector T1,2 Dropout Linear 2100 SNR Input layer MF(W,P,T) Embedding Text 2 Text 2 64 2100



If we consider T_i as the features representing a text, $f(T_i)$ a function reducing it as a vector E_i , we can optimize f towards the enhancement of the authorial signal (or stylome) A_y and the reduction of noise N_i around it¹ such that $E_i = N_i + A_y$ where $N_i \approx 0$ if f converges.

Given two texts *i* and *j*, if they are from the same author *y*,

 $E_i - E_j = N_i + A_y - N_j - A_y = N_i - N_j$. If the function *f* converges, given $g(T_i, T_j) = var(f(T_i) - f(T_j))$, then $g(T_i, T_j) \approx 0$. As a result, considering the signal-to-noise ratio $SNR(E_i, E_j) = \frac{var(E_i)}{g(E_i, E_j)}$, then the distance $SNRD = \frac{1}{SNR} \approx 0$ for the same author.

If $E_k = N_k + A_z$, $g(E_i, E_k) = var(N_i + A_y - N_k - A_z)$, given $N \approx 0$, f should optimize such that $var(A_y - A_z) > var(A_y)$ and as such, $SNRD(E_i, E_k) > 1^2$

¹The noise could then be considered as containing remaining information about the genre, the period, the topic, etc.

²Many thanks to Pierre Mercuriali for our discussions which led to this slide.

Parameters finding

Input concatenation of

- 1. 0, 100 and 200 most frequent POS-trigrams using a Greek BERT [3]³
- 2. 0, 250, 500, 750, 1000 most frequent words⁴
- 3. 0, 250, 500, 750, 1000 most frequent affixes.

Distance SNR-D [5], Manhattan (L1), Euclidean (L2)

Hyper-params: Adam, $lr = 1e^4$, embedding size of 64, batch size of 64, .3 dropout, class sampling of 2, and a minimum of 100 epochs for training. Early stopping 20 epochs using dev loss

Trainable on CPU "quickly", on GPU in a shorter amount of time..

³All most frequent classes on a large corpus of Christian litterature ⁴We maxed our value at the size of our sample, 1000 words.

Corpus



Results

Mean of standard-deviation across the parameters sweep depending on distances.

	Dev Mean	±	Test Mean	±
Distance				
L2	1.04	0.55	1.82	1.02
Manhattan	1.09	0.59	1.84	1.29
STN	1.18	0.68	1.14	0.59

Fleiss Kappa using 1000 models as annotators on the test set.

Development Precision	100%	99%	95%	90%	85%	80%
			Fleiss I	Kappa		
Manhattan	0.18	0.18	0.20	0.29	0.40	0.50
STN	0.50	0.60	0.69	0.72	0.72	0.72

Top 10 architectures

	P	arameter	De	v	Test			
POS	FW	Affixes	Distance	mean	std	mean	std	
100	1000	1000	Manhattan	88.04	0.58	86.01	0.53	
200	1000	750	Manhattan	87.63	0.83	85.88	2.03	
100	750	1000	Manhattan	86.75	0.80	85.12	1.67	
100	1000	750	STN	85.77	1.91	84.51	0.93	
100	1000	1000	STN	87.03	0.65	84.42	1.31	
100	1000	750	Manhattan	87.19	1.25	84.33	4.10	
100	750	1000	STN	85.38	0.33	84.23	0.63	
200	1000	750	STN	85.81	0.15	84.15	0.81	
100	1000	500	Manhattan	86.85	1.44	83.68	4.48	
200	750	750	Manhattan	86.64	0.51	83.63	1.08	

- L2 is bad (what a surprise)
- Manhattan is more unstable in this setting
- Discrepancy between dev and test are lower for STN
- 100, 1000, 1000 seems to hit the spot



Evaluation on the 21* pseudo-Chrysostoms

The model does not output a probability (future work ?) but does provite a distance.

What we do:

- Distance is deemed positive based on the given precision on the dev or test set
- We look for each PC what's the percentage of pairs
- We plot.

Overall

DevPre:0.75	- 1	0.5	0	0.55	0	0.33	0.4	0	0.05	0.5	1	0	0.33	1	1	0.5	0	0.17	1		
DevPre:0.8	- 1		0		0	0.33	0.4	0	0.05	0.5		0	0.33				0	0.1	1		
DevPre:0.85	- 1		0		0	0.33	0.38	0	0	0.5		0	0.17	1			0	0.07	1		- 0.8
DevPre:0.9	- 1		0	0.4	0	0.33	0.38	0	0	0.5		0	0.17	0.92			0	0.04	1		
DevPre:0.95	- 0.5	0	0	0.36	0	0.17	0.38	0	0	0.5		0	0.17	0.92			0	0.01	1		
DevPre:0.99	- 0	0	0	0.19	0	0.17	0.36	0	0	0.5		0	0				0	0			- 0.6
DevPre:1.0	- 0	0	0	0	0	0	0.26	0	0	0	0	0	0	0.08	0	0	0	0	0		
TestPre:0.75	- 1		0		0	0.33	0.38	0	0.05	0.5	1	0	0.33	1		0.5	0	0.11	1		
TestPre:0.8	- 1		0	0.45	0	0.33	0.36	0	0	0.5		0	0.17	0.92			0	0.06	1		- 0.4
TestPre:0.85	- 1	0.5	0	0.4	0	0.33	0.36	0	0	0.5	1	0	0.17	0.92			0	0.03	1		
TestPre:0.9	- 0	0	0	0.29	0	0.17	0.36	0	0	0.5		0	0	0.83			0	0.01			
TestPre:0.95	- 0	0	0	0.14	0	0.17	0.26	0	0	0.5		0	0	0.75		0	0	0			- 0.2
TestPre:0.99	- 0	0	0	0.05	0	0.17	0.26	0	0	0	0	0	0	0.42	0	0	0	0	0		
TestPre:1.0	- 0	0	0	0.05	0	0	0.26	0	0	0	0	0	0	0.33	0	0	0	0	0		
	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10 PC	PC12	PC13	PC15	PC16	PC17	PC18	PC20	PC20b	PC21		- 0.0

14

1.0

Zooming in



(a) Precision threshold matrix for Pseudo-Chrysostoms 13, 14, and 16.



(b) Pseudo-Chrysostom 7

Conclusion

- It works, maybe more tuning and work around the question of prediction as a probability would be interesting.
- It can serves as a confirmation tool, but should not be used as THE single tool in an analysis (too much false negatives).
- We mostly align with Voicu and its peers.
- We have two very *bizarre* results:
 - We have more or less confirmation of a single author behind PC1, which was refuted by Altendorf [1].
 - We are completely unable to confirm PC20, which was a strong hypothesis of Voicu.

Questions?

https://github.com/PonteIneptique/Chryso-Voicu

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