

A Stylometric Application of Large Language Models

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Abstract

Stylometry is the quantitative analysis of writing style. In this paper we show that large language models can be used to distinguish the writings of different authors. Specifically, an individual model, trained on the works of one author, will predict held-out text from that author more accurately than held-out text from other authors. We suggest that, in this way, a model trained on one author's works embodies the unique writing style of that author. In our primary example, we use this approach to confirm R. P. Thompson's authorship of the well-studied 15th book of the "Oz" series, originally attributed to F. L. Baum. We also include other (known) authorship comparison pairs.

1 Introduction

The quantitative measure of writing style — stylometry — has a long history, and generally elides the complex collection of factors that may go into an author's "voice", focusing instead on statistics derived from the text (Neal et al., 2017). In literature, "style" refers to the distinctive manner in which language is used. It encompasses choices in vocabulary, sentence structure, tone, and the use of rhetorical devices. Style is distinct from semantics, which is concerned with the meaning and interpretation of text. In brief, content is what you say, and style is the way you say it. Many mark the birth of the subject with the late nineteenth century work of the philologist Wincenty Lutosławski, who had an interest in finding a statistical basis for addressing a long-standing problem in Classics of estimating the temporal order of Plato's Dialogues (Howland, 1991). Toward this end, Lutosławski measured hundreds of variables to arrive at his conclusions (Lutosławski, 1897).

An ability to quantify authorial voice is also useful for authorship attribution and is perhaps the most common application of stylometric techniques (Juola, 2008). Among the most famous results to date is Mosteller and Wallace's work on determining the authorship of The Federalist Papers, eighty-five essays in support of ratification of the Constitution, authored by the anonymous "Publius" over 1787-1788, but known to have been (individually) written by John Jay, James Madison, and Alexander Hamilton. Mosteller and Wallace used Bayesian techniques directed at simple word frequency statistics to hypothesize attribution of the essays, and their results are generally accepted by domain experts in political history (Mosteller and Wallace, 1963, 1984). Other approaches of note work with feature vectors whose entries record word frequencies in the texts, with works of known attribution giving ground-truth and disputed attributions resolved according to their similarity to the known. The words under consideration are picked according to a range of criteria. A common choice is the use of function words¹ used to build a simple classifier with feature vectors of word frequencies (Binongo and Smith, 1999). Famously, this was used to help settle uncertainty around the authorship of the 15th book in the 31 book *Oz* series (Binongo, 2003). In Hughes et al. (2012), feature vectors constructed from the frequencies of function words are used to show evidence for an evolutionary pattern of writing style in the text corpus comprised by the Gutenberg.org collection. See Neal et al. (2017) for a relatively recent survey of stylometric techniques. More generally, stylometric analysis is among the techniques available to those

¹"Function words" are words that have no particular contextual information (e.g., prepositions, articles, conjunctions).

whose work engages with the practice of “distant reading” (Moretti, 2017, 2000) (the machine reading of text at large scales) which is a part of the broader digital humanities and the practices of cultural analytics.

2 Methods

In this section, we outline our methodology for identifying stylometric signatures using large language models. For each selected author, we train a GPT-2 model on that author’s corpus. We then use the trained model to compute the prediction loss on some held-out texts from both the target author and other authors in the dataset. By comparing these losses, we assess whether the model captures author-specific stylistic patterns: a model trained on a given author should exhibit lower loss when predicting that author’s own texts compared to those of others.

We begin by applying this approach to compare the works of Thompson and Baum, both authors of books in the *Oz* series. We then extend our analysis to a broader set of eight authors.

2.1 Data and Data Preprocessing

We begin our stylometric analysis with Frank Baum and Rosemary Plumly Thompson, both contributors to the *Oz* series. We then expand our study to include a broader set of eight authors: Jane Austen, L. Frank Baum, Charles Dickens, F. Scott Fitzgerald, Herman Melville, Rosemary Plumly Thompson, Mark Twain, and H. G. Wells. These authors were selected because their works are well-represented on Project Gutenberg, are all in the public domain, and are written in English—eliminating any confounds due to translation. For each book, we pre-process the text by stripping Project Gutenberg metadata, publisher information, illustration tags, transcriber notes, prefaces, tables of contents, and chapter headings. We standardize whitespace, remove non-ASCII characters, and lowercase all alphabetic characters. Basic statistics on token lengths and the full list of books used are provided in Appendix A.

2.2 Model Training

For each author, we train GPT language models from scratch using the GPT2LMHeadModel class from the Hugging Face Transformers library with custom architecture settings: a context window of 1024

tokens, an embedding dimension of 128, 8 transformer layers, and 8 attention heads per layer. Training uses a batch size of 16 and the AdamW optimizer (Loshchilov and Hutter, 2019) with a learning rate of 5×10^{-5} .

To construct the training data for each author, we randomly select one book to hold out for evaluation, and the other books are considered as corpus. To ensure a fair comparison across authors, we standardize the number of training tokens per author. Specifically, we truncate each author’s corpus so that every model is trained on an equal number of tokens. This token budget is determined by removing the longest book from each author’s set and then taking the smallest remaining total token count across all authors. For our dataset, this yields a training token budget of 643,041 tokens for each training.

To construct a truncated corpus of 643,041 tokens for each author, we sample one contiguous subsequence from each book in the corpus (i.e., remaining books after holding out a book). The length of the subsequence sampled from book i is proportional to its original length, computed as:

$$\text{length}_i = 643,041 \times \frac{\text{tokens in book } i}{\text{total tokens in corpus}}.$$

The starting position of each subsequence is chosen uniformly at random, ensuring the sample fits within the book’s bounds.

Training data is then constructed by shuffling, concatenating, and then sampling 1024-token chunks from the truncated corpus. For evaluation, we do not sample randomly; instead, we apply a sliding window approach to ensure that each token in the evaluation set contributes to the computed loss.

We repeat the full process—including selecting a held-out book and training a model—across 10 different random seeds. To ensure comparability across authors, we stop training after the first epoch where the training loss drops to 3.0 or lower. We decided on this threshold after taking random draws from the models trained on Baum’s and Thompson’s *Oz* books and manually inspecting the quality of the resulting samples.

158 **2.3 Predictive Comparison Testing**

159 **2.3.1 Baum vs. Thompson**

160 After each training epoch, we compute the loss of
161 every model on its corresponding held-out book as
162 well as on one randomly selected book from the
163 other author’s corpora. For the specific case of Baum
164 and Thompson, we include three additional evalua-
165 tion texts: the contested 15th *Oz* book (authorship
166 disputed between Baum and Thompson), a non-*Oz*
167 book authored by Thompson, and a non-*Oz* book
168 authored by Baum. For all texts used for predic-
169 tive comparison, we compute the average next-token
170 cross-entropy loss using a sliding window approach.

171 Figure 1A presents the evaluation results for
172 models trained on Baum and Thompson. The
173 top left panel (labeled “Train”) confirms that both
174 models converge to similar training loss, ensur-
175 ing a fair basis for comparison. The top center
176 panel (labeled “Baum”) shows that the Baum-trained
177 model achieves lower loss on Baum’s held-out book
178 than the Thompson-trained model. Conversely, the
179 top right panel (labeled “Thompson”) shows that
180 the Thompson-trained model yields lower loss on
181 Thompson’s held-out book than the Baum-trained
182 model.

183 Notably, the bottom left panel (labeled “Con-
184 tested”) shows that the Thompson-trained models
185 consistently achieve lower loss on the contested 15th
186 *Oz* book, aligning with the prevailing literary con-
187 sensus that Thompson was its author. The bottom
188 center and bottom right panels show the models’ per-
189 formance on non-*Oz* books by Baum and Thompson,
190 respectively. As expected, the Baum-trained model
191 performs better on Baum’s non-*Oz* text, while the
192 Thompson-trained model performs better on Thomp-
193 son’s.

194 These results collectively support the conclusion
195 that the trained GPT-2 models are able to capture
196 distinct stylometric patterns associated with each
197 author.

198 **2.3.2 Eight-Author Comparison**

199 We then extend our predictive comparison frame-
200 work to a broader set of eight authors. For each
201 author, we compute the predictive loss of the corre-
202 sponding model on a held-out book by that author,
203 as well as on one randomly selected book from each

204 of the other authors. As before, evaluation is based
205 on average next-token cross-entropy loss computed
206 using a sliding window.

207 Figure 1B presents the evaluation results across all
208 eight authors. Training losses are again comparable
209 across models, ensuring a fair basis for comparison.
210 For each author, we compare the predictive losses
211 of all models on that author’s held-out text. For ev-
212 ery author’s held-out text, the model trained on the
213 matching author achieves the lowest loss, indicat-
214 ing a clear preference for its own author’s stylistic
215 patterns. This consistent alignment provides strong
216 evidence that the GPT-2 models have learned to en-
217 code author-specific stylometric features.

218 **2.4 *t*-tests**

219 To validate our findings in the comparison between
220 Baum and Thompson, we conduct a paired *t*-test
221 on the average cross-entropy losses of the two mod-
222 els evaluated on the contested 15th *Oz* book. The
223 test revealed a statistically significant difference in
224 predictive performance, $t(9) = 20.723, p = 6.6 \times$
225 10^{-9} . These results provide strong evidence that the
226 Thompson-trained models predict the contested text
227 more accurately, aligning with the prevailing literary
228 consensus regarding its authorship.

229 We also conduct a *t*-test for the eight-author com-
230 parison. Specifically, for each author’s model, we
231 perform *t*-tests for (i) the loss values computed by
232 using the author’s models to predict the author’s held-
233 out text and (ii) the loss values computed by using
234 the author’s models to predict the other authors’ ran-
235 domly sampled texts. Table 1 shows the results of
236 the *t*-tests computed for each author using the final
237 losses. These results demonstrate that the trained
238 GPT-2 models reliably distinguish the stylometric
239 features of the corresponding author with high statis-
240 tical significance.

241 In addition, we perform the same paired *t*-test
242 at each of the first 500 training epochs, comparing
243 losses on the author’s own held-out texts to losses
244 on texts from other authors. Figure 1C shows the *t*-
245 values as training progresses. For all authors except
246 Twain, the *t*-statistic exceeds the threshold corre-
247 sponding to $p < 0.001$ after just one epoch, indicat-
248 ing rapid acquisition of author-specific stylometry.
249 For Twain, this threshold is crossed at epoch 47. Fig-
250 ure 1D plots the average *t*-statistic across all eight

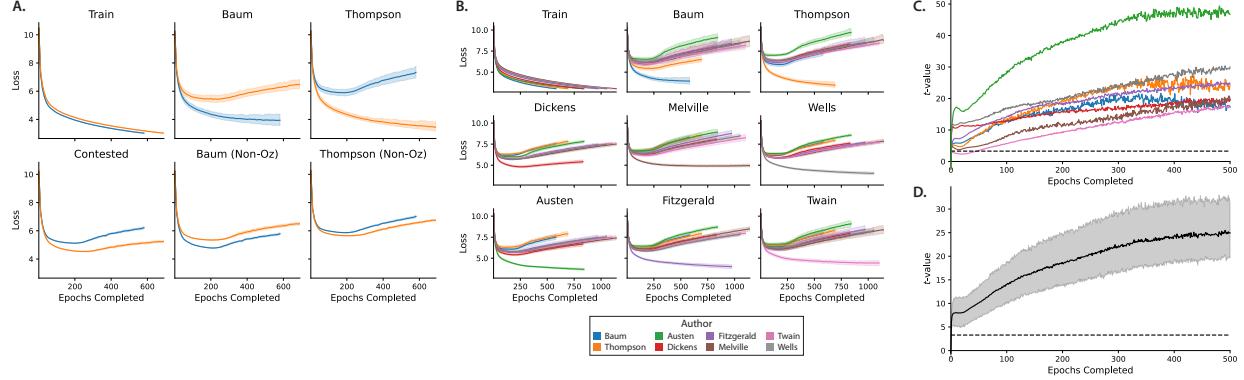


Figure 1: **A.** Average cross-entropy loss on evaluation texts for models trained on Baum and Thompson. Each model is trained with a different random seed; we report the mean cross-entropy loss across 10 random seeds, with error bars indicating a 95% confidence interval. **B.** Average cross-entropy loss on evaluation texts across all eight authors. Error bars denote 95% confidence intervals over 10 random seeds. **C.** t -test results by author for the first 500 training epochs. **D.** Averaged t -test results for the first 500 training epochs.

Author	t -stat	p-value	df
Baum	16.96	5.78×10^{-9}	10.49
Thompson	21.50	6.84×10^{-12}	13.60
Dickens	18.36	6.52×10^{-17}	27.36
Melville	24.15	1.87×10^{-27}	45.15
Wells	35.17	1.16×10^{-23}	26.33
Austen	47.29	4.38×10^{-46}	54.75
Fitzgerald	26.03	2.22×10^{-18}	22.66
Twain	20.13	9.67×10^{-11}	12.22

Table 1: t -test results for each author on final losses

authors over training epochs, further illustrating the early emergence of stylistic differentiation in the models.

2.5 Classification

For each author and each random seed, we compute loss on each evaluation text. The “predicted” author is the author of the evaluation text that has the lowest loss. Under this classification procedure, we have 100% accuracy.

2.6 Stylometric Distance

Predictive comparison suggests a natural notion of distance between authorial styles – if the loss of predicting tokens in a work of author j from a model derived from the work of author i is close to predicting tokens for the work of author i and vice-versa, one could say that their writing styles are sim-

ilar or nearby. Let $L_i(j)$ denote the average loss of a work of author j for a model trained on author i (the i, j -entry of the heatmap/average loss matrix in Figure 2A). Let $\bar{L}_i(j) = L_i(j) - L_i(i)$, normalizing the entries by subtracting the native author baseline. Then define the LLM-based *stylometric distance*, $d(i, j) = \frac{1}{2} (\bar{L}_i(j) + \bar{L}_j(i))$. Figure 2B is a visualization of the relative “distances” among our author set.

Conclusions

In this paper we introduce *predictive comparison*, a new LLM-based relative stylometric measure. It derives from a simple idea, that if an LLM can be fine-tuned to write like – i.e., in the style of – a given author by training on the work of an author, then the degree to which such a fine-tuned model can predict another author’s work could be a measure of stylistic similarity. In this paper we show using a small set of authors and their works, that this thesis is borne out. This in turn suggests a notion of stylometric distance which we produce. Lastly, this further suggest a literary authentication tool that would assign an unknown or contested work to the model which predictive comparison generates the smallest loss. We use this on a well-known and once contested book in the *Oz* series, confirming what is now accepted attribution. We believe this new idea could be of use in considering questions of authorial influence and stylistic evolution.

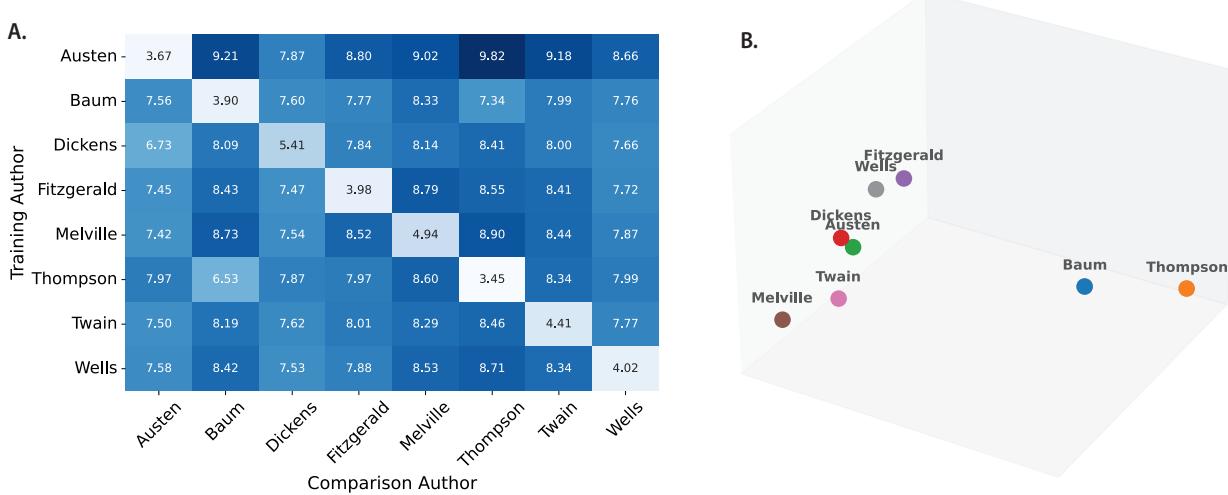


Figure 2: **A.** A heatmap of the average loss values when we compute losses on comparison texts (x -axis) language models trained on the 8 authors' texts (y -axis). Each cell represents the mean loss value across 10 training seeds, with lower values (lighter colors) indicating better model performance. The diagonal elements show how well models perform on their training author's own texts. **B.** Multidimensional scaling plot, where the distances between the authors are proportional to the correlations between the corresponding rows in the loss matrix shown in Panel A, excluding diagonal entries.

Limitations

The main limitations of this paper are the breadth of experiments as well as the oft-acknowledged opacity of the LLM. The results in this paper serve as a proof-of-concept for the idea of using the structure of a bespoke trained LLM as a stylometric engine. Only a handful of examples have been tested, but the results on a classic stylometric test are promising. Also, further testing is needed to understand what kinds of writing features are being picked up by the LLM.

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A Authors, Books, Tokens

Charles Dickens	Tokens	Herman Melville	Tokens
A Christmas Carol	38,906	I and My Chimney	15,341
Oliver Twist	216,100	Bartleby, the Scrivener	19,112
The Old Curiosity Shop	285,895	Israel Potter	88,570
Bleak House	471,630	Omoo	134,628
Dombeey and Son	482,161	Mardi, Vol. II	150,347
David Copperfield	479,387	The Confidence-Man	129,059
A Tale of Two Cities	181,593	White Jacket	190,577
Nicholas Nickleby	446,457	Mardi, Vol. I	132,358
American Notes	129,214	Moby-Dick	285,066
The Pickwick Papers	432,546	Typee	114,239
Great Expectations	244,897		
Martin Chuzzlewit	455,995		
Little Dorrit	449,230		
Hard Times	142,759		
Total	4,456,770	Total	1,259,297

L. Frank Baum	Tokens	Ruth Plumly Thompson	Tokens
Ozma of Oz	52,039	The Giant Horse of Oz	51,036
Dorothy and the Wizard in Oz	53,849	The Cowardly Lion of Oz	61,666
Tik-Tok of Oz	63,781	Handy Mandy in Oz	44,778
The Road to Oz	52,866	The Gnome King of Oz	51,687
The Magic of Oz	51,166	Grampa in Oz	55,169
The Patchwork Girl of Oz	75,703	Captain Salt in Oz	61,797
The Wonderful Wizard of Oz	49,686	Ozoplaning with the Wizard of Oz	50,660
The Lost Princess of Oz	60,418	The Wishing Horse of Oz	59,490
The Emerald City of Oz	70,781	The Lost King of Oz	58,105
The Tin Woodman of Oz	57,338	The Hungry Tiger of Oz	53,543
Rinkitink in Oz	62,241	The Silver Princess in Oz	47,964
The Marvelous Land of Oz	54,733	Kabumpo in Oz	62,693
Glinda of Oz	51,218	Jack Pumpkinhead of Oz	49,661
The Scarecrow of Oz	59,593		
Total	815,412	Total	708,249

Austen	Tokens	Twain	Tokens
Sense And Sensibility	153,718	Adventures Of Huckleberry Finn	147,655
Mansfield Park	201,611	A Connecticut Yankee In King Arthur'S Court	150,327
Lady Susan	29,043	Roughing It	208,545
Northanger Abbey	98,090	The Innocents Abroad	246,321
Emma	207,830	The Adventures Of Tom Sawyer, Complete	95,059
Pride And Prejudice	157,777	The Prince And The Pauper	88,409
Persuasion	106,027		
Total	954,096	Total	936,316

Fitzgerald	Tokens	Wells	Tokens
The Beautiful And Damned	168,147	The Red Room	4,944
Flappers And Philosophers	84,707	The First Men In The Moon	87,615
This Side Of Paradise	100,796	The Island Of Doctor Moreau	55,967
All The Sad Young Men	85,411	The Open Conspiracy	40,271
Tales Of The Jazz Age	109,997	A Modern Utopia	105,810
The Pat Hobby Stories	51,069	The Sleeper Awakes	98,228
The Great Gatsby	65,136	The New Machiavelli	185,158
Tender Is The Night	145,925	The War Of The Worlds	75,727
		Tales Of Space And Time	94,711
		The Invisible Man: A Grotesque Romance	65,584
		The Time Machine	40,184
		The World Set Free	80,518
Total	811,188	Total	934,717