"If not yours… then whose kid?" - A Replication of Quantitative Authorship Attribution Methods

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1 Introduction

Authorship attribution is an age old problem that relates to the study of (writing) style where style is a unique variety of language use in an individual. (Crystal, 2008) The previous sentence implies that there is a unique set of stylistic markers that an author habitually or unconsciously employs in their writing, and that style is something that can be attributed back to an individual. In real-life applications, however, it is hard to simply say that, since multiple questions are usually intertwined to form one problem: for example, how many candidates are there, how long are the documents in question, and how old are they?

Two famous authorship attribution cases show the variability of questions in application: Shakespeare's authorship problem and the Unabomber case. The two cases show a similarity in that there are multiple lengthy documents to assign, but they are different in that the primary objective of the former is to verify whether the documents share the same author, or whether the proposed candidate (William Shakespeare, or someone else) is the correct author, while that for the latter is finding a certain individual(s) that is likely to have written the document, among an open pool of candidates. What features we consider more important than others can drastically change the approach to the solution, too. Are some features more reflective of the author than others? Is it realistically possible to assign a correct author to an unattributed text with them?

With this essay, I aim to attempt to answer such questions, tying together the readings to get an overview of the matter at hand and reporting the procedures and results from my own experiments based on the methods mentioned in the readings. In the grand scheme of things, the semester was divided into two parts that virtually progressed at the same time: first, finding and reading previous studies, and second, replicating methods from the readings, including learning to code in Python and collecting data to test them on.

There were clear limitations to this endeavor: to name a few, I could not verify the reliability of each method using valid statistical methods due to lack of time, and I did not replicate methods employing machine learning techniques. Discussions and reflections on the procedures will follow

in more detail in the final section. Still, the semester as well as the replication attempts were a good opportunity to investigate a topic, which could potentially lead to more in-depth studies in the future: I plan to continue the research, as this small project left more questions than there were before.

The report is structured as the following: I first piece together several previous studies related to the topic and explain central issues of authorship. Then I explain the methods I replicated in more detail with actual codes I used. Finally, I present the results and evaluate the successfulness and limitations of the project.

2 Background

2.1 Problems and paradigms in stylometry

Authorship attribution, in the sense it has in the present essay, is a quantitative approach to the study of stylistics, and the goal of authorship attribution is to assign correct author(s) to the unattributed text. In automated authorship attribution tasks, "text" refers to written documents and this does not include texts produced and conveyed using other media such as pictures, audio, or video. Stylistics could be understood as an intersection of literary analysis and linguistics, but it is widely applicable in a variety of other contexts as well, such as historical/religious studies, authorship credits/plagiarism-related controversies, political discourse analysis, and criminal investigations (including online attacks and feuds).

Different situations call for different approaches, as Koppel et al. (2013) classify typical attribution problems like the following (the names in parentheses are taken from Koppel et al. (2013, p. 318)):

1. Problems where the goal is to find a most likely author among a closed set of candidate authors and an abundance of sample text is available ("simple authorship attribution"),
2. problems where the goal is to identify if two long texts are written by the same author ("long-text verification"): in other words, it is a binary question, and
3. problems where the goal is to attribute a text to one author among a large set of candidates ("many-candidates problem").

In addition to this, there are problems where there are very many candidates among which we do not even know if the true author is included, or the candidates' samples or the unattributed texts are too short for comparison. Koppel et al. poses "the fundamental problem" which is a problem of determining whether two (shorter) texts were written by the same person or two different authors.

There are two main paradigms in authorship attribution that is considered, which can (and should) be modified depending on the type of task at hand: similarity-based approach on one hand and machine-learning methods on the other. A similarity-based method relies on the similarity between the query text (the anonymous text to be attributed) and a known author's style profile – all available writing by that author is considered like a single document. "Similarity" can be defined in a variety of ways. A machine-learning method use writings of a candidate author as training data to construct a classifier that categorizes anonymous documents. (Koppel et al., 2013; Koppel et al., 2012; Koppel & Winter, 2014)

2.2 Stylistic features

Which linguistic features represent the individual writing better than others is the central question in authorship attribution, especially in similarity-based methods. Here, I introduce two concepts proposed in previous studies with varying reliability: the methods I replicate are presented in more detail in the next section.

CUSUM method (Morton, 1991; Morton and Michaelson, 1990), which is short for cumulative sum analysis, considers the occurrence of several variables within a sentence, such as the words starting with a vowel or words that are two or three letters long. The cumulative sum of to what degree these measurements as well as the sentence length deviate from the average of the whole text is calculated and compared to known author profiles that are calculated the same way. The assumption that forms the basis of this method is that language habits are constant, and the two profiles would match each other if the same author wrote both. (Coulthard et al., 2017) This method was accepted in court multiple times from 1991, before its reliability and the validity of its assumptions were refuted (Hardcastle, 1993, 1997; Totty et al., 1987).

Zipf's law (1932) provide us with useful insights about the pattern of how word-types in a (natural language) text are distributed. Zipf found that when we rank all word-types in order of frequency, the frequency of the type at ith rank is inversely proportional of the rank. Put differently, the frequency of the most common word is about twice as much as the second most common word. From this, we can predict that a few word-types cover a majority of tokens in a corpus: just 150 most frequent word-types account for 50-65% of a text. (Savoy, 2020)

This inspires using word frequency as an important variable in characterizing a certain individual's language habit. Various measurement methods were since proposed with relation to word frequency, each with a different view on what words are more meaningful to measure frequency of: type-token ratio is a classic index; Burrows (2002) takes the most frequent word-types, Labbé (2007) considers all word-types, and so on.

Several non-linguistic aspects influence one's writing style, including gender, period in which the text is written, age, and genre. In what form these aspects are reflected in statistically measurable linguistic features, and to what extent those linguistic features are chosen consciously, and therefore to what extent these stylistic preferences reflect cognitive processes or social backgrounds, are all unclear. The endeavor to find answers to these questions might cross the boundaries of stylistics.

3 Methods

In this section, I explain in detail the data collection procedure and methods of analysis. As was mentioned in the previous section, there are various types of tasks in authorship attribution: simple closed-set problem, verification problems with a binary question, many-candidates problems are the common types of stylometry tasks. In real-world authorship attribution problems, however, there are also instances of co-authorship, which requires more complex methods of analysis which will not dealt with in the present paper.

The methods employed in the replications illustrated in this section are applicable for closed-set, single-author problems, and the data were collected accordingly. The methods can be divided to two large sections: lexical analysis and distance-based analysis. I collected data and wrote the

codes myself, but the formula for each quantitative analysis largely followed chapters 2 and 3 from Savoy(2020).

3.1 Data collection

Two sets of data consisted with texts from three authors each were collected. I call them `data1` and `data2` respectively. As the writing style of an individual varies across themes (what the text is about) and channels (what platform the text was intended for), I decided one channel and two themes: about gardening and true crime, on blogs run by private individuals. Sample blogs are found by several simple google search sessions using keywords "gardening" and "true crime". Three random blogs each with enough amount of text were selected. In total, texts from 3 gardening-related blogs were included in the first dataset (`data1`), and three true-crime blogs were included in the other (`data2`). Texts were manually collected going from reverse chronological order. A short excerpt from each author were stored separately as test(query) text. The query text is not included in the sample text. (In this essay, "text" refer to each sample text whose author is the same, unless otherwise noted.)

Things worth noting about texts and collecting them:

1. I do not personally know any of the blog owners that were included in the sample. (Links to the source blogs are included in the bibliography.)
2. Author C in data1 was one of three co-writers in the blog, so I filtered out the two other authors and only included one.
3. Some manual processing was involved to delete links, advertisement, mentions of the names of the blog owners.

3.2 Blog posts as text

I use blog posts as sample texts for the experiment. Blogs, like other channels, show several characteristic features which should be considered when analyzed:

1. Blogs are online platforms for individuals or groups of people to share thoughts, experiences, or knowledge on various topics. Blog posts are typically reverse-chronologically organized, though there is no set rule for organizing posts.
2. There is no set rules for the type of content, formality or layout for blog posts. Therefore, blog writers have a flexibility of writing styles. Some blogs deal with a single topic seriously, while others have different purposes.
3. Many different types of media including images, audio files, and videos can be incorporated into the posts. These can be embedded inside the posts so that the readers can directly check them out without leaving the page, or provided as hyperlinks to external websites. This implies that a lot can be explained without using written words, and there can be mixed-medium contexts where the context cannot be understood entirely if only the text is considered.
4. It is a platform for relatively casual writings, and thus blog posts include words and phrases characteristic of casual online texts. At the same time, blogs are usually for long-form contents: language use characteristic of short-form text platforms such as YouTube comment sections and Twitter is rarely present in blog posts. It is difficult to generalize linguistic

features specific for blog posts since there is a great variety of forms and themes across blogs, but the blogs included in the sample tended to be casual and long-form.

I presumed that inter-genre variability within a single individual would be bigger than interpersonal variability within a single genre, but blogs might be a different story. Blogs operate under self-determined rules, which might lead us to predict that there can be more room for variability between blogs than, say, tweets.

Sample texts as well as full codes can be seen on `https://github.com/jhshlee/ling4181-progress/tree/main`. Codes are in addition attached as appendix.

Table 1. Data summary (type, token)

	token	type
a	21654	3560
b	22897	3640
c	15234	2287
d	51333	4848
e	51063	6679
f	50910	7382

- Texts a, b, c belong to `data1`, while d, e, f belong to `data2`).

3.3 Preparation

First, necessary packages are installed:

[32]:
```
import nltk
import os
import random
import pandas as pd
import collections
import string
import numpy as np
from nltk.tokenize import sent_tokenize, word_tokenize
from nltk.probability import FreqDist

nltk.download('punkt')
print("Done!")
```

```
Done!

[nltk_data] Downloading package punkt to /home/jupyter/nltk_data…
[nltk_data]   Package punkt is already up-to-date!
```

3.4 Preprocessing

Each text went through preprocessing as follows:

[33]:
```
def preprocess(filename):
    text = open(filename, 'r').read().replace("\n"," ").lower()
    return text.translate(str.maketrans("","", string.punctuation)).split()
```

As such, all letters were converted to lowercase letters, and was removed punctuation marks (more about this later), then split to word units instead of letter unit strings. In other words, all texts after this are a list of all the words it contains, not a string of letters, as seen below:

[34]:
```
text_a = preprocess('author_a.txt')
text_b = preprocess('author_b.txt')
text_c = preprocess('author_c.txt')
text_d = preprocess('author_d.txt')
text_e = preprocess('author_e.txt')
text_f = preprocess('author_f.txt')
print(text_a[0:50]) # processed text looks like this
```

```
['these', 'weeks', 'just', 'after', 'the', 'calendar', 'turns', 'from', 'one',
'year', 'to', 'the', 'next', 'are', 'the', 'perfect', 'time', 'to', 'think',
'about', 'your', 'goals', 'for', 'the', 'coming', 'gardening', 'season', 'on',
'this', 'week's', 'podcast', 'i', 'discuss', 'plotting', 'out', 'plans', 'for',
'doubling', 'down', 'on', 'what', 'worked', 'well', 'in', 'the', 'garden',
'while', 'also', 'deciding', 'on']
```

3.5 Lexical Analysis

Lexical analysis methods refer to methods that make use of surface lexical information. They all have in common the fact that they utilize some aspect of word frequency in a given corpus(text). Several such methods have been proposed that consider different aspects of the word frequency distribution.

3.5.1 Lexical Diversity

One way of quantitatively evaluating word choice is to measure the diversity of word use - in other words, how many types of words were used in relation to the total length (number of word-tokens) in a text.

Type-token ratio Type-token ratio is a simple index for measuring lexical diversity in a given text. A low type-token ratio indicates low degree of diversity in the choice of words the author made. It can be simply calculated as the following:

[ ]:
```
def typetoken_ratio(text):
    return round(len(set(text))/len(text),4)
```

And thus Table 1 is completed as the following:

Table 2. Type-token ratio

	token	type	ratio
a	21654	3560	0.1644
b	22897	3640	0.1590
c	15234	2287	0.1501
d	51333	4848	0.0944
e	51063	6679	0.1308
f	50910	7382	0.1450

The number of all word-types is divided by the number of all tokens to calculate type-token ratio, and more nuanced information such as the frequency of each word-type is not reflected.

Simpson's D Simpson's D (1949) is another indicator of lexical diversity. It was not created specifically to measure lexical diversity, but a diversity in a group in general. It is a useful index that is less influenced by the text length(=sample size). Simpson's D measures vocabulary richness by calculating the sum of probabilities of selecting the same word twice in two separate trials.

The formula is as follows (taken from Savoy(2020):

(1)

$$Simpson'sD(T) = \sum_{r=1} \frac{r}{n} \cdot \frac{r-1}{n-1} \cdot \mid Voc_r(T) \mid$$

- T refers to the text.
- n refers to the corpus size, i.e. the number of tokens in T.
- r refers to the number of times a given word type appears in T.
- VOCr(T) refers to the number of word types that appear in T exactly r times.

When there is no diversity in the usage of words, i.e. there are only one word that is used throughout the entire text ($ r=n $), the formula returns 1, which is the maximum value, Hence, the closer to 0 Simpson's D value is, the richer the vocabulary use is for the given text. The formula in **(1)** is rewritten as codes as follows:

[ ]:
```
def simpson_D(text):
    count = collections.Counter(text)
    types = set(text)
    n = len(text)
    def VOC(r):
        VOC = 0
        for i in types: # i is a word(type)
            if count.get(i) == r:
                VOC += 1
        return VOC
```

```
    if sum(VOC(r) for r in range(1, n)) == 0:
        return 1
    else:
        return round(sum(VOC(r) * (r**2 - r) / (n**2 - n) for r in␣
↪range(1,n+1)),4)
```

The function `simpson_D(text)` takes a preprocessed text as its argument. `collections.Counter` function creates a dictionary type data where the key is the word type and the value is its occurence in the text. `VOC(r)` is an inner function that is defined as the number of word types(`i`) in `text` that appears r times. Since it presupposes `i` appears at least once in `text`, `VOC(r)` always appears as a positive number. Hence the absolute value sign in **(1)** is unnecessary. The function, then, calculates the sum of $\frac{r}{n} \cdot \frac{r-1}{n-1} \cdot Voc_r$ for all r.

By definition, the function should return 1 when $r = n$. However, the code above somehow always returns `0.0`. From a practical point of view, $ r=n $ is unlikely to happen, since we are dealing with a real-life language use where there are more than 1 word type in a text. But for the sake of completing the equation, the following lines were added,

```
if sum(VOC(r) for r in range(1, n)) == 0:
        return 1
```

which returns 1 if there is all `r` is zero until $r = n - 1$. Simpson's D can be used to compare the query text to candidate texts to find out which candidate text is the closest in terms of lexical diversity. Results will be discussed in section 4.

3.5.2 Other lexical stylometric measures

Big Words Index Big Words Index is defined as the percentage of words consisted of 6 letters or more in a given text.

A text with high percentage of big words require more cognitive resources to process, effectively meaning more difficult to read. (Savoy, 2020) I used 7 letters as the threshold instead, because I was sceptical of the significance of 6 letter words, since 4-5 character long nouns can take plural form and become 6 character long. The same applies for verbs and a few other parts of speech.

The function `BWI` illustrated below takes a text as its argument. The text will have been preprocessed and made into a list type data before being put. If a word in that text is 7 letters or longer, `big_word` is increased by 1, and after going through all items in the list, the function returns the percentage of 'big words'.

[ ]:
```
def BWI(text):
    big_word = 0
    for word in text:
        if len(word) >= 7:
            big_word += 1
    return big_word / len(text)
```

Mean sentence length In a similar way to big words, mean sentence length can help us understand the complexity of the text, as longer sentences are more difficult to understand than short ones. Sentence length can also reflect syntactical choices made by the writer; phrase-structuring habits like *'Tom's'* as opposed to *'of Tom'* can influence the length of the sentence. The codes below show how it is calculated:

```
[ ]: def mean_sent(filename): # put raw text, not split by space or deleted␣
      ↪punctuation marks!
        text = open(filename, 'r').read().replace("\n"," ").lower()
        t = sent_tokenize(text)
        split = []
        for sent in t:
            a = sent.translate(str.maketrans("","", string.punctuation)).split()
            split.append(a)
        return sum(len(sent) for sent in split) / len(split)
```

The function `mean_sent` takes a raw, unprocessed text as its argument and preprocesses the text inside itself. I used sentence tokenizer provided in the Natural Language ToolKit(NLTK), which turns the original text into a list of sentences, split by full stops, question marks and other common sentence-ending punctuation marks.

Then each item in the list(each sentence) is split by spaces. At this point, the text is a multi-dimensional list where each item(sentence) is again a list of words. It is then possible to calculate how many items(words) there are inside each item(sentence), and calculating mean sentence length is as simple as dividing the sum of sentence lengths by the length of the text(number of sentences).

Mean word length To make a fairer comparison for mean word length between sample texts, I took the first 15,000 words from each text of `data1`, since the shortest text of data1 (`text_c`) has about 15,000 tokens. The sample texts in `data2` do not have to go through this process, since they all contain more than 50,000 tokens each and there are small differences between the lengths.

```
[ ]: text_a_split = text_a[:15000]
     text_b_split = text_b[:15000]
     text_c_split = text_c[:15000]
```

Calculating mean word length is simpler and more precise than calculating mean sentence length:

```
[ ]: def mean_word(text):
         return sum(len(word) for word in text) / len(text)
```

Word length distribution Another way of taking word length into consideration is checking word length distribution.

The function `wordlength` presented below shows how many words that are exactly `r` letters long are in a given text. It creates a list `X` of integers from 1 to the maximum word length in the text (`n`). The internal function `length` counts the number of words that consist of exactly `r` letters. Then `X`,which contains all possible word length, is paired with the the values from the internal function `length` and turned into a dictionary-type data.

```
[ ]: def wordlength(text):
         dist = {}
         n = len(max(text, key=len))
         X = list(i for i in range(1,n+1))
         def length(r):
             length = 0
             for word in text:
                 if len(word) == r:
                     length += 1
             return length
         for x in X:
             dist[x] = length(x)
         return dist
```

The dictionary returned at the end, `dist`, has the word length in natural numbers as keys and the number of words as long as that as values. We can then compare it to another text's word length distribution.

Lexical Density Lexical density (LD) is the ratio between the number of lexical items (1-functional words) and the text length.

Functional words (stop words) include frequently used words that carry little meaning but grammatical information. Here, I used a predefined list of stop words provided in NLTK and selected English.

```
[ ]: from nltk.corpus import stopwords
     stopwords = set(stopwords.words('english'))

     def l_density(text):
         filtered = []
         for w in text:
             if w not in stopwords:
                 filtered.append(w)
         return round(len(filtered) / len(text),4)
```

The function `l_density` filters out function words from a text and computes the percentage for the remainder against the number of all tokens in the text. Therefore, the closer to 1 the value is, the 'denser' the text is.

3.6 Distance-based Analysis

Distance-based methods establish a profile for each candidate author to which we can compare the query text's profile.

Burrows' Delta (Savoy 2020: 34-36) is one of such methods: it considers 40-150 most frequent word types, and the style is reflected through the word choice. According to Savoy(34), 150 most frequent word types cover 50-65% of all tokens in a certain text, with the percentage varying depending on the theme, genre, etc. of the text.

The following is the formula for Delta (taken from Savoy(p.37)):

(2)

$$Burrow's Delta(A_j, Q) = \frac{1}{m} \cdot \sum_{i=1}^{m} \mid Zscore(t_{i,Aj}) - Zscore(t_{i,Q}) \mid$$

- Aj is a candidate author A's profile.
- Q is the query text.
- t is a set of word-types in the MFW list.

Each t in the MFW list has the same importance, but the impact depends on their Z score values.

To get the Delta value between the query text and a sample text, a list of most frequent word-types is necessary. A relative frequency value for each term can be calculated for each text: the number of occurrences for a certain word-type in a certain text is divided by the length of the text.

Then the relative frequency values are compared against each other to get mean and standard deviation values. This is to get Z score for each term in each text: Z score is the relative frequency minus mean divided by standard deviation. Z score helps us understand where a certain value lies in relation to the entire sample. By comparing a Z score for a certain term in both texts, we know how much difference in using that word there is, and the bigger the sum is, the bigger the difference in word choices between the texts will be.

The function `MFW` below returns a list of 300 most frequent words and their frequency. The number 300 can be changed if necessary. Frequency here is absolute frequency, i.e. how many times it appears in the text.

Function `MFW_100` returns the percentage of MFW tokens in relation to the entire text.

[ ]:
```
def MFW(text):
    freq = FreqDist(text)
    MFWlist = freq.most_common(300)
    return MFWlist

def MFW_100(text):
    return 100 * sum(i[1] for i in MFW(text)) / len(text)
```

The codes below create a table of most frequent words (MFW) with their absolute frequency in the three respective texts. Obviously, the MFW list is different for each of the text with some overlap, and to be able to compare to each other, I took only MFWs that are present in all three lists, which makes the list shorter than the original.

[ ]:
```
def abs_table(xa, xb, xc):
    dict_b = (dict(MFW(xb)))
    dict_c = (dict(MFW(xc)))
    table = pd.DataFrame(MFW(xa)).rename(columns={0: 'word', 1:'a'})
    table.set_index('word',inplace=True)
    table["b"] = ""
    table["c"] = ""
    for n in MFW(xa):
        word = n[0]
```

```
        if dict_b.get(word) != None and dict_c.get(word) != None:
            table.loc[word,"b"] = dict_b.get(word)
            table.loc[word,"c"] = dict_c.get(word)
        else:
            table.loc[word,"b"] = np.nan
            table.loc[word,"c"] = np.nan
        table.dropna(inplace= True)
    return table
```

The table we get from `abs_table` is then turned into a relative frequency table. Relative frequency table takes each text's length (number of tokens) into consideration. Since the absolute frequency of MFW will be heavily influenced by the size of the corpus, a relative term frequency is more useful.

[ ]:
```
def rel_table(xa, xb, xc):
    table = abs_table(xa, xb, xc)
    table = table.astype(float)
    table["words"] = table.index
    table.loc[:,"a"] = round(table["a"] / len(xa),5)
    table.loc[:,"b"] = round(table["b"] / len(xb),5)
    table.loc[:,"c"] = round(table["c"] / len(xc),5)
    table.loc[:,"mean"] = table.mean(axis='columns')
    table.loc[:,"sd"] = table.std(axis='columns')
    return table

table = rel_table(text_a,text_b,text_c)
```

Finally, the codes below calculate z-score and eventually Delta score. The query text has to be preprocessed before running these lines.

Since the function `zscore_table` takes the result from `abs_table` and calculates relative frequency in itself, the function `rel_table` above is not required if the goal is to calculate the Delta score.

[ ]:
```
def zscore_table(a,b,c):
    dict_q = dict(collections.Counter(q))
    table = abs_table(a, b, c)
    table = table.astype(float)
    table["words"] = table.index
    table["q"] = ""
    table.loc[:,"a"] = round(table["a"] / len(a),5)
    table.loc[:,"b"] = round(table["b"] / len(b),5)
    table.loc[:,"c"] = round(table["c"] / len(c),5)
    table.loc[:,"mean"] = table.mean(axis='columns')
    table.loc[:,"sd"] = table.std(axis='columns')
    for word in table["words"]:
        if dict_q.get(word) != None:
            table.loc[word,"q"] = round((dict_q.get(word) / len(q)),5)
        else:
```

```
            table.loc[word,"q"] = np.nan
    table.loc[:,"z_a"] = (table["a"] - table["mean"]) / table["sd"] #␣
↪calculates z-scores for columns a,b,c,q
    table.loc[:,"z_b"] = (table["b"] - table["mean"]) / table["sd"]
    table.loc[:,"z_c"] = (table["c"] - table["mean"]) / table["sd"]
    table.loc[:,"z_q"] = (table["q"] - table["mean"]) / table["sd"]
    table.dropna(inplace= True) # deletes rows that contain NaN
    table.drop('words', axis = 'columns',inplace= True) # deletes the redundant␣
↪column
    return table
```

[ ]:
```
def delta(df): # calculates delta score between the column a in the given␣
↪dataframe and the query text
    delta_a = round(sum(list(abs(df["z_a"]-df["z_q"]))) / len(df),5)
    delta_b = round(sum(list(abs(df["z_b"]-df["z_q"]))) / len(df),5)
    delta_c = round(sum(list(abs(df["z_c"]-df["z_q"]))) / len(df),5)
    return delta_a, delta_b, delta_c
```

4 Discussion

In the previous section, several methods of characterizing writing styles for each author were introduced. In this section, I present results and examine the possibility of attributing correct authors to the query texts based on each index.

Query texts are from the same blogs the sample texts are from, but collected separately so that the query texts are not included in the sample. First, importing the query texts the same way as the sample texts, using `preprocess` function defined earlier: the query text names indicate which author it was written by, for example `q_a` was written by `author_a`.

[ ]:
```
# query text preprocessing

q_a = preprocess('q1.txt')
q_b = preprocess('q2.txt')
q_c = preprocess('q3.txt')
q_d = preprocess('q4.txt')
q_e = preprocess('q5.txt')
q_f = preprocess('q6.txt')
```

4.1 Results

In this section, results from each method performed on 6 sample texts and 6 query texts are presented. The accuracy level of each model is also evaluated. A more detailed perfomance evaluation and comparison between the models are presented in the next section.

4.1.1 Lexical analysis

Evaluation method For evaluation of each lexical analysis method, a simple distance calculation was done like **(3)**:

(3)

$$Distance(A, Q) = \mid Value(A) - Value(Q) \mid$$

- A is a sample text.
- Q is a query text.
- Value(A) is the value of the result when sample text A goes through a formula.

Since there were three sample texts, each query text had three distance values, and the smallest among them was regarded as the model's answer, i.e. the model's prediction as to who the correct author of the query text is. Each correct and wrong answers were marked with different colors (see Table 4) and counted separately. Full evaluation chart can be found in the same link.

Type-token ratio Type-token ratio was not a useful tool for authorship attribution, for two reasons:

1. The type-token ratio difference between the sample texts as well as between the query texts were not big enough to be able to assign any query text to any sample text.
2. The type-token ratio of the query texts were much bigger than the sample texts. (see Figure 1 below)

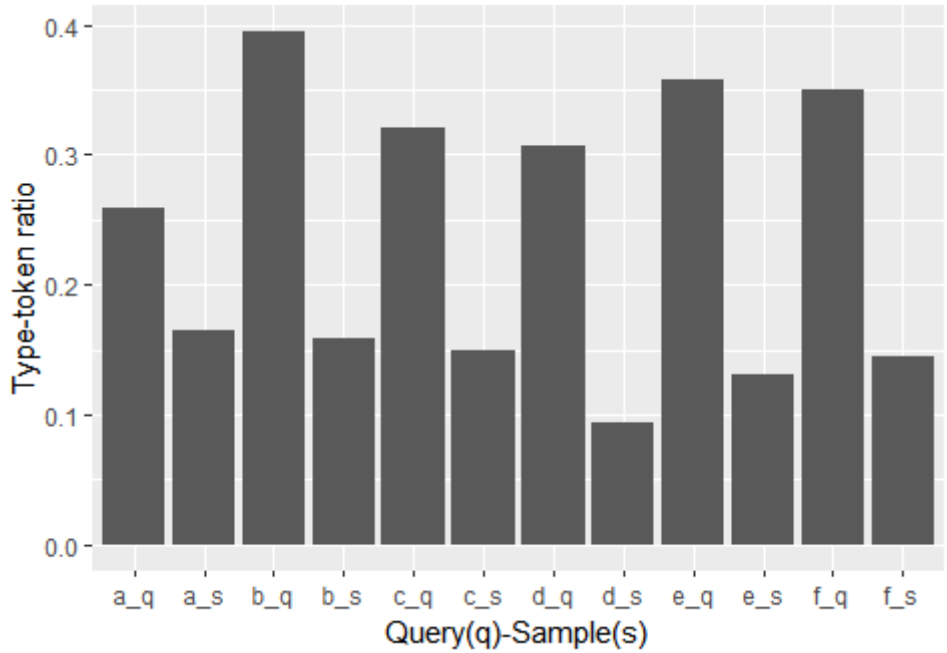
Both are caused by the fact the query texts are much shorter than the sample texts. Type-token ratio is heavily influenced by the text length, because the number of word-types used in a text does not increase in the same rate as the text gets longer.

Table 3. Type-token ratio of all sample and query texts

	sample	query
a	0.1644	0.2593
b	0.1590	0.3952
c	0.1501	0.3203
d	0.0944	0.3065
e	0.1308	0.3578
f	0.1450	0.3496

Figure 1 visualizes Table 3:

Figure 1. Type-token ratio difference between sample/query texts



- `a_q` refers to the query text written by author A, and `a_s` refers to the sample text written by author A.

Table 4. Performance of the method using type-token ratio

ttratio	a_q	b_q	c_q	d_q	e_q	f_q
a_s	0.0949	0.2308	0.1559	1	1	1
b_s	0.1003	0.2362	0.1613	1	1	1
c_s	0.1092	0.2451	0.1702	1	1	1
d_s	1	1	1	0.2121	0.2634	0.2552
e_s	1	1	1	0.1757	0.227	0.2188
f_s	1	1	1	0.1615	0.2128	0.2046

- Cells highlighted in pink are correctly attributed instances: the model attributed the query text to the correct author.
- Cells highlighted in blue are correct answers that were not chosen by the model.
- Cells highlighted in orange are incorrectly attributed instances: the model ignored the correct answer and chose a wrong author.
- Cells highlighted in white are incorrect answers that were not chosen by the model: the model predicted that they are not the answer, which is a correct decision.
- Cells highlighted in gray are dummy values.

Two query texts out of six, `a_q` and `f_q`, were correctly attributed to their authors by comparing type-token ratio, which make its correctness probability 1/3, similar to that of randomly guessing.

Simpson's D Simpson's D values from each sample text and query text are shown in Table 5.

Table 5. Simpson's D values of all sample and query texts

index	sample	query
a	0.0071	0.0080
b	0.0065	0.0085
c	0.0098	0.0205
d	0.0101	0.0108
e	0.0080	0.0104
f	0.0076	0.0096

Table 6. Performance of the method using Simpson's D

SimpsonD	a_q	b_q	c_q	d_q	e_q	f_q
a_s	0.0009	0.0014	0.0134	1	1	1
b_s	0.0015	0.002	0.014	1	1	1
c_s	0.0018	0.0013	0.0107	1	1	1
d_s	1	1	1	0.0007	0.0003	0.0005
e_s	1	1	1	0.0028	0.0024	0.0016
f_s	1	1	1	0.0032	0.0028	0.002

Three query texts out of six (50%) were correctly attributed (highlighted in pink) by Simpson's D values.

Big words index (BWI) Table 7 shows the percentage of words that consist of 7 letters or longer in all 12 texts:

Table 7. BWI values of all sample and query texts

index	sample	query
a	0.1906	0.1992
b	0.2172	0.1808
c	0.2306	0.1369
d	0.1596	0.1310
e	0.2229	0.2044
f	0.1949	0.2089

Table 8. Performance of the method using BWI

BWI	a_q	b_q	c_q	d_q	e_q	f_q
a_s	0.008584	0.009835	0.053773	1	1	1
b_s	0.017971	0.03639	0.080329	1	1	1
c_s	0.031384	0.049803	0.093741	1	1	1
d_s	1	1	1	0.028646	0.044787	0.049273
e_s	1	1	1	0.091903	0.01847	0.013984
f_s	1	1	1	0.063934	0.009499	0.013985

Using BWI as a metric for authorship attribution was as (un)successful as using type-token ratio, with the success rate of 33%. However, the BWI distance value difference between query text F (`f_q`) and sample texts E and F (`e_s` and `f_s`) was observed 7 digits under the decimal point; it was a narrow margin of 0.0000008.

Mean sentence length (MSL) MSL measures the length of the sentences by word count.

The preprocessing method used to calculate mean sentence length had its flaws, specficially because blog posts utilize section titles, which typically do not end with a punctuation mark. As a result, the section titles were processed as if they were included in the sentence that came after them, which could make the sentence longer and affect the mean. However, since all blogs included in the datasets used section titles and there were not so many section titles compared to the number of sentences, I did not add any manual correction or change the preprocessing method.

Table 9. MSL values of all sample and query texts

index	sample	query
a	22.232033	21.445026
b	18.158604	17.857143
c	19.018727	19.927273
d	16.016537	15.862069
e	18.101028	20.816327
f	19.196833	19.148148

It is difficult to judge the effectivity of MSL from seeing the values in Table 9, but Table 10 makes it clearer:

Table 10. Performance of the method using MSL

MSL	a_q	b_q	c_q	d_q	e_q	f_q
a_s	0.787007	4.37489	2.30476	10	10	10
b_s	3.286422	0.301461	1.768668	10	10	10
c_s	2.4263	1.161584	0.908546	10	10	10
d_s	10	10	10	0.154468	4.79979	3.131611
e_s	10	10	10	2.238959	2.715299	1.04712
f_s	10	10	10	3.334764	1.619494	0.048684

Mean sentence length turned out to be fairly effective, with five correct answers out of six (83%).

Mean word length (MWL) As can be seen in Table 11, the difference between the MWL values are marginal, which is confirmed by the evaluation table provided in Table 12:

Table 11. MWL values of all sample and query texts

index	sample	query
a	4.521467	4.522461
b	4.681867	4.572800
c	4.804867	4.564797
d	4.290885	4.203804
e	4.729687	4.575980
f	4.532508	4.564797

Table 12. Performance of the method using MWL

MWL	a_q	b_q	c_q	d_q	e_q	f_q
a_s	0.000994	0.051333	0.04333	1	1	1
b_s	0.159406	0.109067	0.11707	1	1	1
c_s	0.282406	0.232067	0.24007	1	1	1
d_s	1	1	1	0.087081	0.285095	0.273912
e_s	1	1	1	0.525883	0.153706	0.16489
f_s	1	1	1	0.328704	0.043472	0.032289

Using mean word length was not useful in authorship attribution: the model had 50% success rate.

Word length distribution Word length distribution looks at word lengths like MWL, but their distribution instead of average.

By using the function `wordlength`, I could obtain a dictionary-type data where the number of words with exactly `r` letters is stored as values.

The longest dictionary was from sample text F: it had a 58-letter-long word. This clearly indicates the word-splitting process from at the beginning was incomplete. These (incorrectly) wrong words are few enough to not affect other lexical method results, but they could be confusing when plotting a word length distribution graph. I used the following function `find_length` to find what the abnormally long words were:

[ ]:
```
def find_length(text,r):
    word = []
    for i in text:
        if len(i) == r:
            word.append(i)
    return word
```

Long words in sample text F were, for example, like the following:

[ ]:
```
print(find_length(text_f,54))
print(find_length(text_f,58))
```

Longer words than 40 letters were all website links and were deleted. Other words included two words connected by a hyphen(-) where hyphens were deleted in the preprocessing stage. I manually parsed them and added them to correct numbers. The longest word in the entire dataset (query texts included) without a hyphen was "compartmentalized" (17 letters) from query text A.

Figures 2 and 3 show how word lengths measured by the number of letters are distributed in both sample and query texts.

Figure 2. Word length distribution for authors and query texts A-C

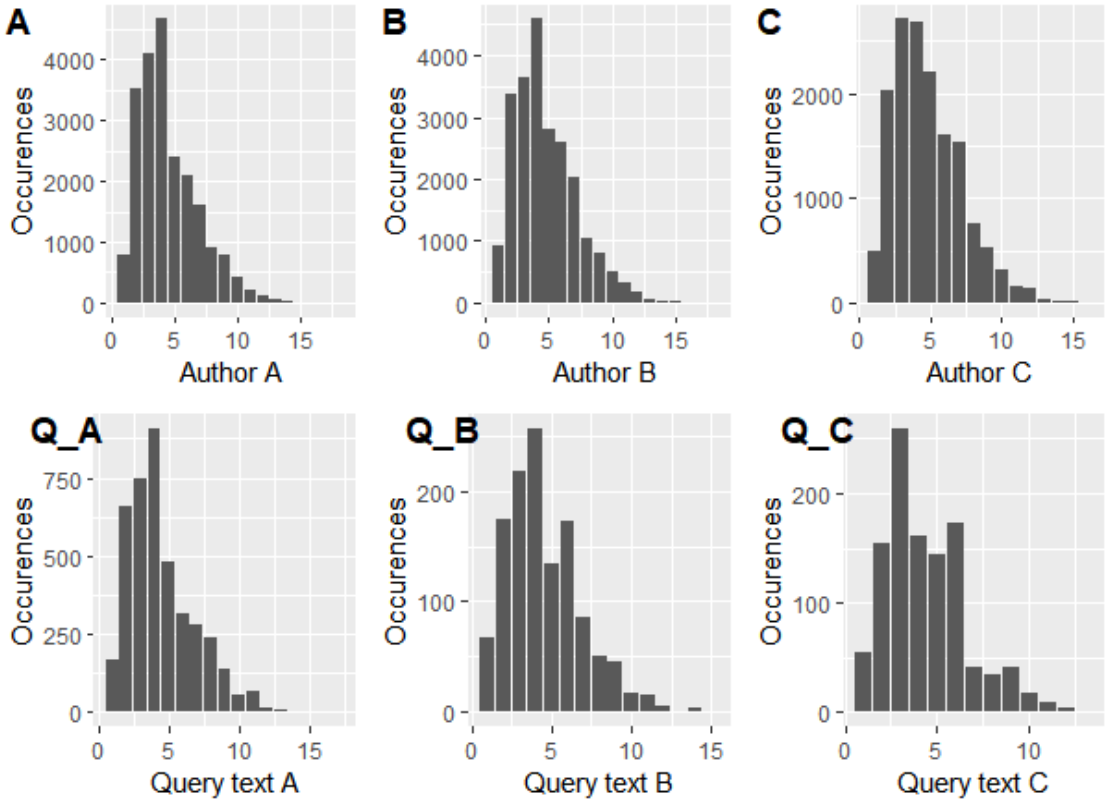
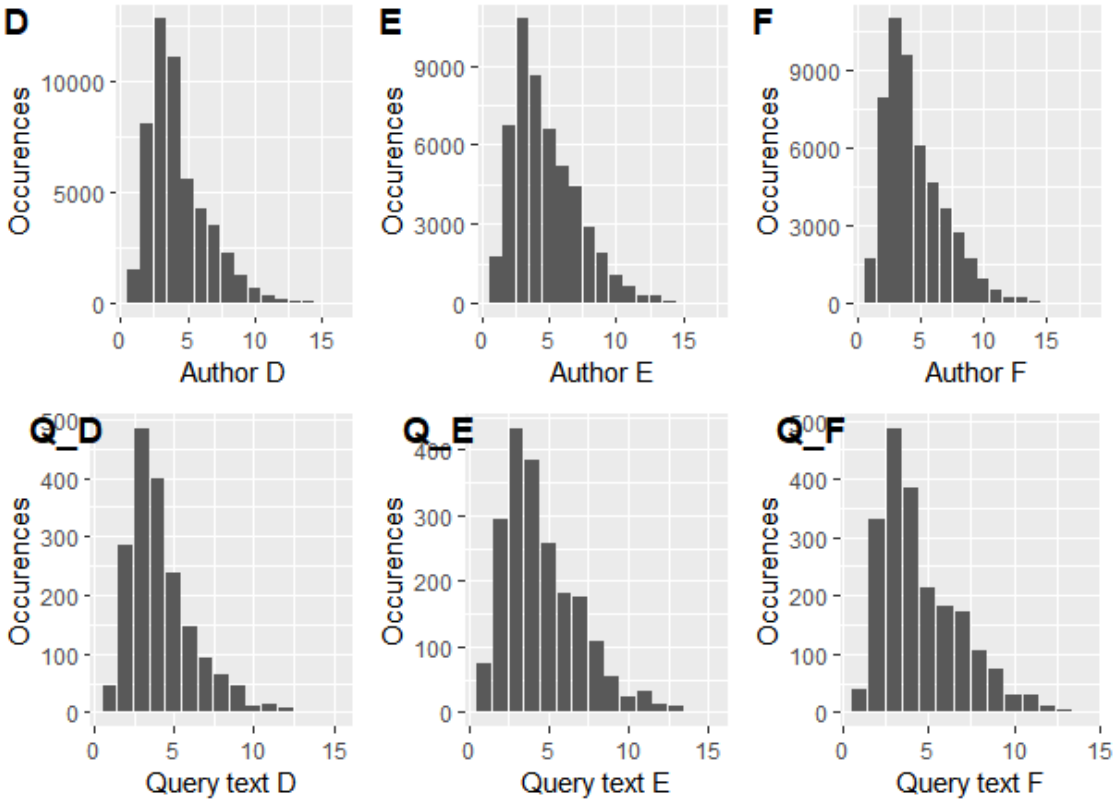


Figure 3. Word length distribution for authors and query texts D-F



From the graphs, we can observe how the word length distribution is similar across the texts; there are differences, for examples between `A` and `B`, but `Q_A` and `Q_B` are both similar to `A`. This indicates word length distribution must not be effective in attributing a text to its author. A statistical significance test would have confirmed this, but because of the way the dataframe was created (a single-column dataframe) and lack of time, I could not test whether the word length distribution of a query text can be associated to that of the sample text. If it can be done, we will be able to find out if word length distribution is fairly similar across different texts or unique to an author.

Lexical Density Lexical density is an index for the percentage of words that are meaningful, calculated by subtracting the percentage of function words from 1. Table 13 shows the summary of lexical density in the texts:

Table 13. Lexical density values of all sample and query texts

index	sample	query
a	0.5389	0.5439
b	0.5947	0.5784
c	0.6211	0.6223
d	0.4825	0.4924
e	0.5664	0.5392
f	0.5513	0.5551

Some comparative values are necessary to know whether a lexical density value defies the normal range: I follow Savoy(2020, p.30)'s guideline that an LD value of around 0.3 for an oral production and around 0.4 and higher for writings are the norm. As can be seen from Table 13, all sample and query texts have an LD value of more than 0.4.

Table 14. Performance of the method using lexical density

LD	a_q	b_q	c_q	d_q	e_q	f_q
a_s	0.005	0.0395	0.0834	1	1	1
b_s	0.0508	0.0163	0.0276	1	1	1
c_s	0.0772	0.0427	0.0012	1	1	1
d_s	1	1	1	0.0099	0.0567	0.0726
e_s	1	1	1	0.074	0.0272	0.0113
f_s	1	1	1	0.0589	0.0121	0.0038

Using lexical density values, five out of six query texts were correctly attributed (success rate of 83%). Interestingly, it failed to attribute the same query text to the correct author as using MSL (see Table 10). The two models chose the same wrong answer, as well.

4.1.2 Distance-based analysis (Burrows' Delta)

Burrows' Delta takes a certain number of most frequently occurring words (MFWs) and computes the distance value between two texts based on Z-scores of the relative frequency of each MFW from both texts.

The functions created for Delta take four arguments: the three author profiles and the query text `q`. Hence, I had to manually define a new `q` for each trial, and that created six similar-looking dataframes like shown in Table 15, which includes relative frequency and Z-scores for each MFW in each text:

[ ]:
```
q = q_a
abc_a = zscore_table(text_a, text_b, text_c)
abc_a
```

Table 15. Z-score table for query text A

word	a	b	c	q	mean	sd	z_a	z_b	z_c	z_q
the	0.04221	0.03389	0.06525	0.03931	0.047117	0.013264	-0.369911	-0.997151	1.367061	-0.58854
and	0.03131	0.02638	0.03020	0.02563	0.029297	0.002112	0.953467	-1.381264	0.427797	-1.736446
to	0.03094	0.02913	0.03164	0.03491	0.030570	0.001058	0.349857	-1.361604	1.011748	4.103725
of	0.02106	0.02371	0.02107	0.01709	0.021947	0.001247	-0.711113	1.414206	-0.703093	-3.895082
a	0.02064	0.03000	0.02704	0.02563	0.025893	0.003906	-1.344843	1.051299	0.293544	-0.067413
...	...	...	...	...	...	...	...	...	...	...
start	0.00055	0.00109	0.00092	0.00269	0.000853	0.000225	-1.345530	1.049809	0.295721	8.147109
planted	0.00055	0.00100	0.00085	0.00049	0.000800	0.000187	-1.336306	1.069045	0.267261	-1.65702
green	0.00055	0.00074	0.00210	0.00049	0.001130	0.000690	-0.840256	-0.565000	1.405256	-0.927179
watering	0.00046	0.00070	0.00085	0.00244	0.000670	0.000161	-1.307403	0.186772	1.120631	11.019539
easy	0.00046	0.00122	0.00217	0.00073	0.001283	0.000700	-1.176965	-0.090536	1.267500	-0.790997

103 rows × 10 columns

Table 16. Burrows' Delta values for between sample and query texts

Delta	a_q	b_q	c_q	d_q	e_q	f_q
a_s	2.49817	3.11836	4.97545	10	10	10
b_s	2.73929	2.72426	4.91509	10	10	10
c_s	3.01049	3.34396	4.62071	10	10	10
d_s	10	10	10	3.65058	4.93397	3.9648
e_s	10	10	10	4.21731	4.54952	3.74926
f_s	10	10	10	4.50348	5.04095	3.4331

The model using Burrows' Delta as an attribution metric was the most successful among all the methods I replicated. It correctly attributed authorship to all query texts (100%).

4.1.3 Comparative Evaluation

F-1 score Based on the results (Tables 4, 6, 8, 10, 12, 14, 16), Table 17 could be computed:

Table 17. Confusion matrix and F1-score

index	ttratio	SimpsonD	BWI	MSL	MWL	LD	Delta
TP	2.000000	3.000000	2.000000	5.000000	3.000000	5.000000	6
TN	8.000000	9.000000	8.000000	11.000000	9.000000	11.000000	12
FP	4.000000	3.000000	4.000000	1.000000	3.000000	1.000000	0
FN	4.000000	3.000000	4.000000	1.000000	3.000000	1.000000	0
Accuracy	0.555556	0.666667	0.555556	0.888889	0.666667	0.888889	1
Precision	0.333333	0.500000	0.333333	0.833333	0.500000	0.833333	1
Recall	0.333333	0.500000	0.333333	0.833333	0.500000	0.833333	1
F1	0.333333	0.500000	0.333333	0.833333	0.500000	0.833333	1

Since there are only three options (authors) and only one correct answer, false positive and false negative always have the same value, and precision, recall and eventually F1-score all have the same value, which is also the same with the success rate discussed in sections `4.1.1` and `4.1.2`.

Other statistics Table 18 below shows how many times each sample text (`a_s` to `f_s`) was chosen by the models using each method, correctly or incorrectly.

data	ttratio	SimpsonD	BWI	MSL	MWL	LD	Delta	sum	token
a_s	3	1	3	1	3	1	1	13	21654
b_s	0	0	0	1	0	1	1	3	22897
c_s	0	2	0	1	0	1	1	5	15234
d_s	0	3	1	1	1	1	1	8	51333
e_s	0	0	1	0	0	0	1	2	51063
f_s	3	0	1	2	2	2	1	11	50910

Table 19 shows to what percentage each text was correctly attributed by each model (column `cor_att`).

data	ttratio	SimpsonD	BWI	MSL	MWL	LD	Delta	cor_att
a_q	1	1	1	1	1	1	1	1.000000
b_q	0	0	0	1	0	1	1	0.428571
c_q	0	1	0	1	0	1	1	0.571429
d_q	0	1	1	1	1	1	1	0.857143
e_q	0	0	0	0	0	0	1	0.142857
f_q	1	0	0	1	1	1	1	0.714286

According to Table 19, Query text A (`a_q`) was correctly attributed to its author by all models (100%), but Table 18 indicates that that may have been because of the fact all models were inclined

to attribute all query texts to author A. Same observation can be found in Query text D and F with high `cor_att` values, whose source texts were assigned 8 and 11 times, respectively. Considering 7 times is the maximum when every model has 100% accuracy, this is a meaningful difference. However, what caused the models to attribute more query texts to these specific sample texts is unclear - the token size turned out not to be a significant factor with regard to this. (For example, the sample text E had as many tokens as the other two texts from the same dataset, but it was correctly attributed only by Delta.) A possibility is that the difference lies in the query text rather than the sample text, but it remains unconfirmed.

5 Reflection

5.1 Limitations

Due to lack of resources and the premise of the project, there were several limitations as to the procedures as well as the analyses.

1. The datasets were too small to test the potential of these models. Indexes like type-token ratio might have a better accuracy rate when both the sample and query texts are long. Furthermore, the fact that there were only three candidates per problem made it difficult to know if the models actually correctly attributed the query texts to the authors or some luck played in the decisions.
2. The way I replicated the methods are only suitable for 3-candidate simple attribution problems, and is not flexible for application for any other type of authorship attribution problems. For example, the function `delta` takes three sample texts as arguments, and a large part of the codes has to be revised in order to apply it to more than 3 candidate authors. In addition, the premise is that the true author definitely exists among the candidates - if there were a query text whose author does not exist among the candidates, it is easily predictable that the overall accuracy will drop significantly due to the small candidate set.
3. The statistical analysis method leaves room for improvement. For one, the method for calculating distance values for lexical analysis methods might have been inappropriate, considering the fact Delta performed successfully on all texts without any error. The normalization process (z-scores) could be key. Secondly, the distance value differences between the wrong answers and between the correctly unchosen values were not considered, which might have led to a more nuanced interpretation.
4. Machine learning models were not tested. In recent years, machine learning models trained on large language data are proving to be more accurate in authorship attribution than the classic quantitative methods I replicated in the present paper. It tends to be difficult to know what process inside the model is exactly enabling such performances, but in investigating authorship attribution methods, machine learning models cannot be overlooked.

5.2 Ways forward

It is clear from the results that some of these methods can relatively effectively function as an authorship attribution metric, but not reliable enough. A more integrative model might perform better than each individual methods that were unsuccessful. The findings from the replications could then be useful in deciding how much each method should weigh in that model.

Going forward, I am interested in further research with the following questions, with the basic knowledge earned from these replications and background readings:

1. What makes humans think a text looks like somebody specific wrote it, and how is it different from statistical measures or machine learning models?

In an experiment where the genre, theme and length of the texts are controlled, quantitative attribution models will perform better than humans. However, I hypothesize humans will perform better if the texts are of different genres, themes, lengths as well as platforms, but with the same author. If this is true, it could mean there is more to authorship attribution than what can be measured on the surface.

2. Is it possible to characterize an idiolect or a sociolect based on quantitative text analyses, taking both linguistic marks and personal/social background into consideration?

It has been shown in many studies in sociolinguistics that differences in people's backgrounds (gender, economic status, education, etc.) play a role in their language. Would it hold in the opposite direction, i.e. predict the author's background based on their writing? This would require a large corpus specific for the sociological feature of choice.

5.3 Summary

Among the seven methods (type-token ratio, Simpson's D, Big word index, mean sentence length, mean word length, lexical diversity and Burrows' Delta), Burrow's Delta was the most successful in attributing correct authors to the query text with 100% accuracy. Mean sentence length and lexical diversity came in second, with both having 83% accuracy. Type-token ratio and Big word index was not effective in attributing authorship in this experiment, each having as good an accuracy rate as purely guessing.

In addition, the results showed certain sample texts were assigned more query texts than others: author A were associated with 13 query texts and had a perfect accuracy rate (meaning query text A was always attributed to author A), while author E were only chosen twice and had an accuracy rate of 0.14. I did not find a satisfying explanation concerning this. There were also several limitations in this project, mostly pertaining to statistical analysis methods and sample size, which, if improved, could lead to better results in future studies.

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Data source

- Joe gardner: https://joegardener.com/blog/
- Savvy gardening: https://savvygardening.com/
- Family food garden blog: https://www.familyfoodgarden.com/
- The true crime blog: https://truecrime.blog/
- The killer queen blog: https://thekillerqueenblog.com/
- True crime society: https://truecrimesocietyblog.com/