A Call for Clarity in Contemporary Authorship Attribution Evaluation

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Abstract

Recent research has documented that results reported in frequently-cited authorship attribution papers are difficult to reproduce. Inaccessible code and data are often proposed as factors which block successful reproductions. Even when original materials are available, problems remain which prevent researchers from comparing the effectiveness of different methods. To solve the remaining problems—the lack of fixed test sets and the use of inappropriately homogeneous corpora—our paper contributes materials for five closed-set authorship identification experiments. The five experiments feature texts from 106 distinct authors. Experiments involve a range of contemporary non-fiction American English prose. These experiments provide the foundation for comparable and reproducible authorship attribution research involving contemporary writing.

1 Introduction

Closed-set authorship attribution picks out the likely author of an unsigned document from a pool of candidate authors. Decades of research show that authors leave conspicuous “fingerprints” in their writing (Juola, 2006). A small amount of pre-existing prose (ca. 2,500 words) is often enough to learn enough about the writing “styles” of a set of candidate authors to correctly identify the author of an unsigned document. Authorship attribution techniques have found application in numerous domains. They have been used to resolve uncertainty about authorship in historical research (Mosteller and Wallace, 1964). For writers living today, widespread use of authorship attribution techniques—and related author profiling techniques (Argamon et al., 2009)—poses a privacy risk (Brennan et al., 2012). A better understanding of how authorship attribution techniques work can inform efforts to improve privacy-enhancing language technologies.

While there is no doubt that authorship attribution methods have improved over the past century, recent progress is harder to measure. Some of this difficulty is due to the field’s success. In recent decades, new methods improve on old ones by small amounts. Given small improvements, assessing whether or not the advance may be due to aleatory factors such as preprocessing or a particular dataset becomes difficult. Another reason recent progress is difficult to measure is the lack of standard benchmark tasks. Of 15 frequently-cited authorship attribution studies examined by Potthast et al. (2016), original corpora could be found for only 4 (27%) and code could be located for 0 (0%). While other fields, notably machine translation and language modeling, excel at organizing research activity around publicly-accessible benchmark tasks, contemporary authorship attribution research has no such tasks.

Recent experience suggests that without standard benchmarks—and evidence that researchers can consistently reproduce results using them—a field’s ability to self-assess progress on well-defined tasks can go astray. The field of recommender systems offers a cautionary tale. Rendle et al. (2019) documents a series of papers being published in prestigious journals over a five year period which do not, in fact, improve on earlier results. Notably, these papers used a standard dataset for their evaluations (Movielens 10M). Where these papers fell short was in their reproduction of previous results—to which their new methods were compared. The papers reported improvements on earlier results...
which were illusory; models used in earlier research, upon closer examination, outperformed the new methods. Analogous cases exist in other fields. In machine translation, although standard datasets were used, inconsistency in applying a key metric (BLEU) prevented researchers from easily reproducing or comparing results (Post, 2018).

Our paper supports reproducible research in authorship identification by introducing five standard benchmark tasks. Each task features fixed train and test sets. Four of the five tasks have a test set consisting of writing samples on fixed topics, guaranteeing that test set examples do not overlap with training set examples in terms of subject matter. Data for all tasks is available for download without any restrictions.

2 Problem Description

2.1 Problem: Models Cannot be Compared due to Unavailable or Under-specified Test Sets

Comparing the effectiveness of a new model with that of an existing model requires, at minimum, evaluating models on the same data. Because different models may perform differently when applied to texts by different authors or to texts in different genres by the same authors, comparing the performance of two models on a new dataset is often uninformative. Even when the new dataset resembles the original, researchers should worry that the poor performance of an earlier model may be due to accidental errors in re-implementation. Reliable comparisons of new models with previous baselines require that the original data be available.

Having the original data is not enough. The test set, the set of documents whose authorship a model must predict, must also be specified (Bouthillier et al., 2019). If cross-validation is used, the train/test splits must be known. Authorship attribution datasets typically feature a small number of authors (8-100) and much of the variability in model performance can be due to the idiosyncratic composition of cross-validation “folds.”

For an example, consider the task of reproducing the work of Abbasi and Chen (2008) with the Enron email corpus. Abbasi and Chen (2008) evaluate different techniques using ten-fold cross-validation with varying number of candidate authors. Comparing the performance of a new model with their result requires knowledge of the composition of the folds they used. Small improvements in classification accuracy could be due to different partitions of the set of authors into cross-validation folds. A different partition could, by chance, end up with folds featuring writers who have distinct writing styles, making achieving higher accuracy easier.

2.2 Problem: Inappropriately Homogeneous Training and Test Corpora

Evaluations of authorship attribution techniques often use corpora consisting of homogeneous texts. Corpora consisting of texts in a single genre (e.g., newspaper article, blog post, email message) are common. This method of evaluation is not ideal. It is at odds with traditional presentations of authorship attribution, which typically claim that methods work in a variety of settings (Koppel et al., 2009; Juola, 2006). To eliminate any doubt that methods are, in fact, picking up on content-independent authorial fingerprints, test set texts should not resemble training set texts.

For an illustration of the problem, consider the use of a corpus of 100 newspaper articles written by 10 different authors. Using such a corpus to evaluate the performance of an authorship attribution method may not yield the expected information: an estimate of how well the method will perform on similar authors in a different setting. The risk of a model using topical information is clear. Newspaper writers tend to have distinct areas of expertise (“beats”) which influence the types of subjects they write about. Writers from the same generation or similar social backgrounds may tend to write about certain topics. Senior writers may be more likely than junior writers to receive certain topics as assignments. Methods which appear to be using content-independent features may, in fact, be picking up on subtle signals of topic.

Unfortunately this kind of homogeneity in evaluation corpora is common. It features in all the corpora considered by Abbasi and Chen (2008) as well as the “C10” corpus drawn from Reuters (RCV1) (Potthast et al., 2016).

One method of addressing this problem is to use test set documents which are distinct from training set documents. Test set documents might be written in a different setting or different document genre. If, say, training set documents are work e-mails, then test set documents might be personal essays. Using test documents from a different time period would also help address the concern of topical homogeneity. Koppel et al. (2009) illustrate such a
division in a dataset involving two authors by using
e-mails written before a fixed date as training and
e-mails written after the date as testing.

Another method involves conducting a field
experiment and eliciting prose on a fixed topic from
writers. The elicited writing samples form the test
set. This method is expensive but guarantees that
models will not perform better by leveraging in-
formation about the topics specific authors tend to
write about. Both Juola (2004) and Brennan et al.
(2012) use this approach.

Authorship attribution methods are consistently
presented as relying on the identification of topic-
independent fingerprints. Evaluation tasks should
be aligned with this presentation.

2.3 Problem: Unavailable or Restricted
Corpora

The practice of restricting access to corpora appears
to be more common in authorship attribution re-
search than in the machine translation and language
modeling communities. We considered including
the C10, PAN12, and PAN13 authorship attribution
tasks in our suite of benchmark tasks but found
that all three are restricted and cannot be down-
loaded without permission.1 We know of no cases
in current machine translation or language model-
ing research where performing a standard evalua-
tion requires access to a restricted dataset. Data for
the news translation tasks distributed by the Con-
ference on Machine Translation are available for
immediate download.2 Data for the widely-used
language modeling benchmarks (GLUE, SQuAD)
are publicly available (Wang et al., 2018; Rajpurkar
et al., 2018). Of the 81 language modeling tasks
cataloged by the NYU-based team developing the
Jiant evaluation tool, 69 tasks (85%) can be down-
loaded automatically, that is, by the evaluation soft-
ware itself.3

Making a dataset publicly available increases the
likelihood that other researchers will reproduce re-

cable is higher than previously appreciated (less
than 70% according to Baker (2016)). The prob-
lem of non-reproducible results is sufficiently seri-
ous that certain conferences are exploring adopting
additional measures—beyond submission of code
and data—which will alleviate the problem.4

There is no reason to suspect that the repro-
ducibility rate of authorship attribution research is
conspicuously different from the rate in other areas
of computational linguistics. Indeed, in the
study of 15 frequently-cited authorship attribution
papers, Potthast et al. (2016) document one failure
to replicate results (Potthast et al., 2016, 403). If
reproducing or replicating results is difficult in as
many as 6% (1 in 15) of papers, then reproduction
(or replication) should be a regular practice. And
reproducing results requires that the original code
and data be easy to access.

3 Improving Authorship Attribution
Evaluation

The problems described in the previous section
complicate a range of authorship attribution re-
search (e.g., identification, verification, profiling).
We propose a suite of five tasks which address the
problems for one area of authorship attribution re-
search: closed-set author identification involving
contemporary English-language non-fiction prose.
Lessons learned developing standard benchmark
tasks in this area will, we hope, inform the devel-

ditional tasks in other areas.

Two arguments support our focus on contem-
porary non-fiction texts. First, collecting redis-
tributable non-fiction prose from a diverse set of
writers is relatively easy. A considerable share
of the English-using population writes non-fiction
prose. Demonstrating (some) competency in En-
glish composition is a requirement in secondary
education across the English-speaking world. Sec-
ond, many researchers are interested in the efficacy
of authorship attribution methods applied to con-
temporary non-fiction English prose. English is,
for the moment, the lingua franca of diplomacy,
science, and international business. Authorship at-
tribution methods which work on English therefore
enjoy broad applicability. The stakes of author pro-
filng research—research informed by authorship
attribution research—are also significantly higher
for research involving living writers than for writ-

1The restricted-download datasets may be found at the following
URLs: https://zenodo.org/record/3759064 (C10), https://zenodo.org/record/3713273 (PAN12), https://zenodo.org/record/3715864 (PAN13).
2For example, http://www.statmt.org/wmt18/translation-task.html
3See https://github.com/nyu-mll/jiant/blob/master/guides/tasks/supported_tasks.md for a list of the tasks.
4“ML Reproducibility Challenge,” https://paperswithcode.com/rc2020
ers active in previous centuries. Only in the former case is, say, an individual’s privacy at risk.

3.1 Reproducible Authorship Attribution Benchmark Tasks (RAABT)

Five closed-set authorship identification tasks make up the Reproducible Authorship Attribution Benchmark Tasks (RAABT). Table 1 summarizes the tasks. All tasks feature a fixed test set. Test set documents do not overlap with training set documents. In four out of five of the tasks, authors write test set documents on a fixed topic. Three of the tasks involve writing from a diverse set of adults living in North America. In aggregate, the tasks feature 106 different authors.

The tasks are published at https://zenodo.org/record/5213898.

3.2 Task descriptions

1. Ad-hoc Authorship Attribution Competition, fixed topic (AAAC–fixed-topic). The first task is “Problem A” from the 2004 Ad-hoc Authorship Attribution Competition (AAAC) (Juola, 2004, 2006). Texts were gathered from 13 authors in a 2013 undergraduate writing course at a university in the United States. For the test set documents, participants were asked to write on the topic of “work.”

2. Ad-hoc Authorship Attribution Competition, free topic (AAAC–free-topic) The second task is “Problem B” from the AAAC. Test documents are additional course essays on other topics. Test set documents do not overlap with training documents. Training documents are the same as in the first task.

3. Extended Brennan-Greenstadt Corpus, obfuscation condition (EBG–obfuscation) The Extended Brennan-Greenstadt Corpus (Brennan et al., 2012) (EBG) contains writing from 45 individuals contacted through the Amazon Mechanical Turk platform no later than the year 2012. Participants uploaded examples of their writing. The researchers asked for writing of a “scholarly” nature. Participants were then asked to write a short essay on a fixed topic. They were asked to describe their neighborhood to someone unfamiliar with the location. Notably, they were also asked to obscure their writing style. They were, however, not given any instructions on how to accomplish this. These essays form the test set.

Given prevailing norms on Amazon Mechanical Turk and the monetary incentive to finish quickly (payment did not depend on time spent on the task) we suspect many participants did not devote considerable time to de-
vising strategies for obscuring their writing style. We suggest that this task be treated as, in essence, an additional fixed topic task.

We note that the population of individuals who sell their labor on Amazon Mechanical Turk is quite diverse in terms of age, gender, and region (Coppock and McClellan, 2019).

4. Riddell-Juola Corpus, control condition (RJ–fixed-topic)

The Riddell-Juola Corpus collects texts using essentially the same techniques were used in Brennan et al. (2012). Responses were collected in March and June of 2019. According to self-reported gender and age, participant demographic characteristics are roughly balanced.

Participants were asked to respond to the same “describe your neighborhood” prompt mentioned earlier. No further instructions were given. (The instruction to obscure one’s writing style was not present.)

5. Riddell-Juola Corpus, obfuscation condition (RJ–obfuscation) This task is the same as RJ–fixed-topic with one difference. Participants were told to obscure their writing using the same instruction as found in EBG–obfuscation. Again, they were given no instructions on how to accomplish this task.

Participants were randomly assigned to receive the obfuscation instruction. Therefore the authors of the test set documents in this task do not overlap with the authors of the test set documents in RJ–fixed-topic.

The training sets for the two tasks involving the Riddell-Juola Corpus are the same.

4 Accuracy of Received Methods

Table 2 reports the performance of two classic methods on the five tasks. We use a familiar 512-word function word feature set with both methods (Koppel et al., 2009). For linear SVM we use the libSVM implementation with default cost parameter (C = 1) (Chang and Lin, 2011). For multiclass logistic regression we use L2 regularization (λ = 1) (Pedregosa et al., 2011).

These baselines are intended to be reference points. They are chosen because they should be particularly easy to reproduce.

5 Discussion

Perceptions of the importance of having reproducible measures of model performance on well-understood tasks have changed over the last decade. Previously regarded as something desirable but by no means essential, reproducible benchmarks are increasingly seen as indispensable. Experience has shown that without such benchmarks, researchers risk overestimating the reliability of existing results or gaining a false sense of a field’s progress on particular problems. Our paper contributes a suite of benchmarks which can be used to anchor future authorship attribution research.

These five tasks are a start. Additional tasks would be welcome. Many forms of writing and document types in widespread use today are not featured in the five tasks we introduce here. Short text messages and informal e-mails, in particular, are ubiquitous. Yet many individuals’ habits of composition vary dramatically when writing in such genres. Standard benchmarks for cross-register and cross-genre authorship attribution would likely yield new insights into the strengths and weaknesses of existing approaches.

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