Abstract

Author profiling classifies author characteristics by analyzing how language is shared among people. In this work, we study that task from a low-resource viewpoint: using little or no training data. We explore different zero and few-shot models based on entailment and evaluate our systems on several profiling tasks in Spanish and English. In addition, we study the effect of both the entailment hypothesis and the size of the few-shot training sample. We find that entailment-based models outperform supervised text classifiers based on roberta-XLM and that we can reach 80% of the accuracy of previous approaches using less than 50% of the training data on average.

1 Introduction

Author profiling (Rangel et al., 2013) aims to identify the characteristics or traits of an author by analyzing its sociolect, i.e., how language is shared among people. It is used to determine traits such as age, gender, personality, or language variety. The popularity of this task has increased notably in the last years. Since 2013, the Uncovering Plagiarism Authorship and Social Software Misuse (PAN) Lab at CLEF conference organized annual shared tasks focused on different traits, e.g. age, gender, language variety, bots, or hate speech and fake news spreaders.

Data annotation for author profiling is a challenging task. Aspects such as the economic and temporal cost, the psychological and linguistic expertise needed by the annotator, and the congenital subjectivity involved in the annotation task, make it difficult to obtain large amounts of high quality data (Bobicev and Sokolova, 2017; Troiano et al., 2021). Furthermore, with few exceptions for some tasks (e.g. PAN), most of the research has been conducted on English corpora, while other languages are under-resourced.

Few-shot (FS) learning aims to train classifiers with little training data. The extreme case, zero-shot (ZS) learning (Larochelle et al., 2008; Chang et al., 2008), does not use any labeled data. This is usually achieved by representing the labels of the task in a textual form, which can either be the name of the label or a concise textual description. One popular approach (Yin et al., 2019, 2020; Halder et al., 2020; Wang et al., 2021) is based on textual entailment. That task, a.k.a. Natural Language Inference (NLI) (Dagan et al., 2006; Bowman et al., 2015), aims to predict whether a textual premise implies a textual hypothesis in a logical sense, e.g. Emma loves cats implies that Emma likes cats. The entailment approach for text classification uses the input text as the premise, and the text representing the label as the hypothesis. An NLI model is then applied to each premise-hypothesis pair, and the entailment probability is used to get the best matching label.

Our contributions are as follows: (i) We study author profiling from a low-resourced viewpoint and explore different zero and few-shot models based on textual entailment. This is, to the best of our knowledge, the first attempt to use zero and few-shot learning for author profiling. (ii) We study the identification of age, gender, hate speech spreaders, fake news spreaders, bots, or depression, in English and Spanish. (iii) We analyze the effect of the entailment hypothesis and the size of the few-shot training sample on the system’s performance. (iv) Our novel author instance selection method allows to identify the most relevant texts of each author. Our experiments show that on average we can reach 80% of the accuracy of the top PAN systems using less than 50% of the training data.
2 Zero and Few-shot Author Profiling Approach

In this section, we give details zero and few-shot text classification based on textual entailment and describe how we apply it to author profiling.

2.1 Zero and Few-shot Text Classification

We follow the so called entailment approach (Yin et al., 2019, 2020; Halder et al., 2020; Wang et al., 2021) to zero-shot text classification. The approach relies on the capabilities of neural language models such as BERT (Devlin et al., 2019) trained on large NLI datasets such as Stanford NLI (Bowman et al., 2015). These models are trained to predict whether a hypothesis text follows from a premise text. The entailment approach consists of using the input text of a classification problem as the premise. A hypothesis in textual form is then defined for each label. The model is applied to each text-hypothesis pair and the label with the highest entailment probability is chosen as the predicted class.

To use this approach in a few-shot setup, we need to create a training set. We follow the related work (Wang et al., 2021) and generate the examples in the following manner: Given an text instance and its reference label, we create an instance of class contradicted using the premise of the hypothesis of the reference label. For every other label hypothesis, we create an instance of class entailed.

The neural models used for entailment classification are usually based on cross attention which means that both inputs (premise and hypothesis) are encoded jointly and their tokens can attend to each other. However, recent work (Chu et al., 2020; Müller et al., 2022) has shown that Siamese networks can also work well if pre-trained on NLI data. A Siamese network encodes premise and hypotheses into a high dimensional vector space and uses a similarity function such as the dot-product means that both inputs (premise and hypothesis) are encoded jointly and their tokens can attend to each other. However, recent work (Chu et al., 2020; Müller et al., 2022) has shown that Siamese networks can also work well if pre-trained on NLI data. A Siamese network encodes premise and hypotheses into a high dimensional vector space and uses a similarity function such as the dot-product.

2.2 Author Profiling

Author profiling represents each author as a collection of texts. The objective is to assign each author to a label of a given set. As the transformer models we employ in this study are large and scale quadratically with the input length we process each text as a separate instance. Following the literature (Franco-Salvador et al., 2015), we determine an author’s class \( y \) in function of the probabilities of classification of its texts:

\[
y = \arg\max_{c \in C} \sum_{i=1}^{n} P(c \mid t_i)
\]

Where \( C \) is the total number of classes and \([t_1, ..., t_n]\) is the list of texts of that specific author.

Typically, the labeled texts of an author are random and might thus not be representative of the author’s label. Especially, when separating the texts into individual training instances, this might produce noisy or misleading instances. In this work, we propose an instance selection method to mitigate this effect. Given the texts \( T \), it returns the set of texts \( T' = \{t_1, ..., t_m\} \) where each text \( t_i \) is the closest to the \( i^{th} \) centroid \( d_i \in D \). The cluster set \( D \) results of applying the Agglomerative Clustering method with cosine distance to the texts in \( T \). Following other work\(^3\), we use scikit-learn (Pedregosa et al., 2011) and a distance threshold of 1.5 to get a dynamic number of clusters depending on the author and its information.

3 Related Work

Early Author Profiling attempts focused on blogs and formal text (Argamon et al., 2003; Koppel et al., 2004) based on Pennebaker’s (Pennebaker et al., 2003) theory, which connects the use of the language with the personality traits of the authors. With the rise of social media, researchers proposed methodologies to profile the authors of posts where the language is more informal (Burger et al., 2011). Since then, several approaches have been explored. For instance, based on second order representation which relates documents and user profiles (Lopez-Monroy et al., 2013), the Emograph graph-based approach enriched with topics

\(^3\)https://tinyurl.com/st-agg-cluster
and emotions (Rangel and Rosso, 2016), or the LDSE (Rangel et al., 2016), commonly used as a baseline at PAN. Recently, the research has focused on the identification of bots and users who spread harmful information (e.g. fake news and hate speech). In addition, there has been work to leverage the impact of personality traits and emotions to discriminate between classes (Ghanem et al., 2020).

Zero and Few-shot Text Classification has been explored in different manners. Semantic similarity methods use the explicit meaning of the label names to compute the similarity with the input text (Reimers and Gurevych, 2019). Prompt-based methods (Schick and Schütze, 2021) use natural language generation models, such as GPT-3 (Brown et al., 2020), to get the most likely label to be associated with the input text. In this work, we use entailment methods (Yin et al., 2019; Halder et al., 2020). Recently, Siamese Networks have been found to give similar accuracy while being much faster (Müller et al., 2022).

4 Experimental setup

4.1 Dataset

We conduct a comprehensive study in 2 languages (English and Spanish) and 7 author profiling tasks: demographics (gender, age), hate-speech spreaders, bot detection, fake news spreaders, and depression level. We use datasets from the PAN and early risk prediction on the internet (eRisk) (Parapar et al., 2021) shared tasks. Table 1 gives details on the datasets.

4.2 Entailment Models for Zero and Few Shot

In our experiments, we use pretrained models hosted on Hugging Face (Wolf et al., 2020). Based on our prototyping experimentation, for the Cross Attention (CA) models, we use a BART large (Nie et al., 2019) model for English and a XLM roberta-large (Liu et al., 2019) model for Spanish. Following (Müller et al., 2022), for the Siamese Networks (SN) model, we use paraphrase-multilingual-mpnet-base-v2, a sentence transformer model (Reimers and Gurevych, 2019), for English and Spanish. All models have been trained on NLI data. The SN models has additionally been trained on paraphrase data.

4.3 Baseline and Compared Approaches

- Best performing system (winner): We show the test results of the system that ranked first at each shared task overview paper. The reference to those specific systems can be found in the Appendix (S. 7).

- Sentence-Transformers with logistic regression (ST-lr): We use the scikit-learn logistic regression classifier (Pedregosa et al., 2011) on top of the embeddings of the Sentence Transformer model used for the Siamese Network experiments.

- Character n-grams with logistic regression (user-char-lr): We use [1..5] character n-grams with a TF-IDF weighting calculated using all texts. Note that n – grams and logistic regression are predominant among the best systems in the different PAN shared tasks (Rangel and Rosso, 2019; Rangel et al., 2020).

- XLM-RoBERTa (xlm-roberta): Model based on the pre-trained XLM roberta-base (Liu et al., 2019). Trained for 2 epochs, batch size of 32, and learning rate of 2e-4.

- Low-Dimensionality Statistical Embedding (LDSE): This method (Rangel et al., 2016) represents texts based on the probability distribution of the occurrence of their terms in the different classes. Key of LDSE is to weight the probability of a term to belong to each class. Note that this is one of the best ranked baselines at different PAN editions.

4.4 Methodology and Parameters

We conduct our validation experiments using 5-fold cross-validation. We report the mean and standard deviation among folds. Using this scheme we fine-tune the few-shot models in terms of users per label ($n \in [8, 16, 32, 48, 64, 128, 256, 512]$), best entailment hypothesis, learning rate, and user instance selection method. Following the literature (Müller et al., 2022), SN uses a batch size equal to the number of labels and trains for 10 epochs. CA uses a batch size of 8 and trains for 10 epochs.

We compare our author Instance Selection (IS) method (Section 2.2) with two baseline methods
that respectively select 1 and 50 random instances from the author text list (Ra1 and Ra50). We use the paraphrase-multilingual-mpnet-base-v2 model to obtain the instance embeddings required by IS. The resulting tuned CA learning rates are 1e-8 and 1-e6 for Ra1 and IS, respectively. For SN they are 2e-5 and 2e-6.

We use macro F1-score ($F_1$) as our main evaluation metric and accuracy (Acc.) to compare with the official shared task results.

### 4.5 Hypotheses of the Entailment Models

We compared 68 different hypotheses for the CA and SN entailment models. We included the identity hypothesis: represent the label using its raw string label. Table 2 shows the best performing hypothesis for each task and model. We use those for the rest of the evaluation. See the Appendix (S. 7) for a complete list with results of all the hypotheses explored in our experiments.

### 5 Results and Analysis

In this section, we analyze the results of the Siamese networks (SN) and the Cross-Attention (CA) models among different author profiling tasks in English and Spanish. We compare the performance in function of the number of training users ($n$), author instance selection method (Inst. sel.), and total training size ($s$). The few-shot results of user-char-lr can be found in the Appendix (S. 7).

Table 3 shows the English validation results. Regarding the zero-shot setting ($n = 0$), SN outperforms CA in Age and Bots. However, it obtains lower numbers in tasks such as Gender and Hate Speech. Regarding the few-shot setting ($n > 0$), the Ra50 author instance selection method outperforms Ra1 in combination with SN. Interestingly, the contrary happens for CA, where Ra50 is only superior in Bots. Comparing Ra_x and IS, with SN both obtain similar results in four tasks and the later exceeds in two. For the CA model, IS is superior in three tasks and similar in the rest. IS uses much less training data ($s$) than Ra50 in all cases and thus reduces training time and cost. Looking at the overall English few-shot results, SN outperforms CA in four tasks (Age, Hate Speech, Fake News and Depression) and is out-performed in two (Gender and Bots). However, there exist overlaps between some confidence intervals, suggesting a low significance. SN gives more stable results across tasks. Finally, there is a general trend of more training users giving better results. Nevertheless, as proved by our IS method the information used from those users matters.

Table 4 shows the Spanish validation results. Regarding the zero-shot setting, similarly to English, SN outperforms CA in Age and Bots. In addition, it also improves in Fake News. Looking at the few-shot setting, the results also show a clear improvement trend while increasing the number of training users. This is more clear for SN, improving from the beginning ($n = 8$), than for CA, which sometimes requires additional training users and failed at improving the Age zero-shot results. Regarding the author instance selection method, in general, IS in combination with CA outperforms random selection on most datasets. For SN, we find similar results for Ra50 and IS, while IS uses 75% less training instances. This highlights again its capability to select the most relevant training
instances. Looking at the overall Spanish few-shot results, SN outperforms in three tasks (Age, Hate Speech and Fake News) and CA in two (Gender and Bots). However, both models offer a similar performance; with the exception of Age, where CA failed to converge. This, together with the English results, leave SN as the most stable across tasks and languages.

The few-shot experiments with the test sets use the best configurations obtained at our validation phase, i.e., the number of training users ($n =$ best) and author instance selection method for each language and task. Table 5 compares the test set results of CA and SN with several baselines and reference approaches (see Section 4.3). Note that the baselines use all the available training data ($n =$ all) and that we show both the SN and CA zero and few-shot results. As you can see, the zero-shot models outperform xlm-roberta in English. CA also does it for Spanish. Comparing them against other approaches, including the shared task top systems (winner), we find encouraging results: the zero-shot models ranked third at some tasks, e.g. EN CA Hate Speech, EN CA Gender, and EN CA Depression. This is remarkable considering that those models did not use any training data, and shows their potential for low-resource author profil-
Table 3: English Validation results of the CA and SN models. \( n \) shows the number of training users and \( s \) the total training size. Top results are highlighted with bold.
| n | Inst. Sel. | Gender | Age | Hate Speech | Bots | Fake News |
|---|-----------|--------|-----|-------------|------|-----------|
| 0 | 0         | 68.126 | 0   | 38.101 22  | 38.101 | 38.101 22 |
| 8 | Ra1       | 65.109 | 26  | 14.023     | 16   | 36.187 22 |
|    | Ra50      | 63.126 | 1.2k | 12.304     | 32   | 35.125 22 |
|    | IS        | 64.073 | 248 | 24.178     | 272  | 33.125 22 |
| 16| Ra1       | 67.126 | 30  | 14.023     | 32   | 35.125 22 |
|    | Ra50      | 56.126 | 1.9k | 12.304     | 1.6k | 35.125 22 |
|    | IS        | 65.122 | 474 | 18.81      | 542  | 35.125 22 |
| 32| Ra1       | 67.126 | 40  | 14.023     | 32   | 35.125 22 |
|    | Ra50      | 59.126 | 3.2k | 50.508     | 4.8k | 65.125 22 |
|    | IS        | 69.122 | 1.9k | 75.82      | 1.6k | 75.125 22 |
| 48| Ra1       | 67.126 | 40  | 14.023     | 96   | 35.125 22 |
|    | Ra50      | 61.126 | 4.8k | 94.145     | 6.4k | 67.125 22 |
|    | IS        | 69.122 | 2.2k | 77.120     | 1.3k | 75.125 22 |
| 64| Ra1       | 67.126 | 40  | 14.023     | 128  | 35.125 22 |
|    | Ra50      | 61.126 | 6.4k | 49.145     | 6.4k | 67.125 22 |
|    | IS        | 69.122 | 2.2k | 77.120     | 1.3k | 75.125 22 |
| 128| Ra1      | 55.107 | 12.8k | 1.9k | 2.6k | 89.125 22 |
|    | Ra50      | 72.107 | 3.3k | 72.102     | -    | -         |
|    | IS        | 51.107 | 1.0k | 61.109     | -    | -         |
| 256| Ra1     | 63.141 | 51.2k | 68.126     | 97.147 | -         |
|    | Ra50      | 70.141 | 6.4k | 64.145     | 6.4k | 67.125 22 |
|    | IS        | 97.141 | 10.3k | 94.145     | 1.3k | 75.125 22 |

Table 4: Spanish Validation results of the CA and SN models. n shows the number of training users and s the total training size. Top results are highlighted with bold.
Table 5: **Test set results** of CA and SN compared to several baseline and reference approaches. ₙ shows the number of training users. Per-block top results without confidence interval overlaps are highlighted with **bold**.

### **English dataset results**

| System       | n  | Gender Acc. | Gender F₁ | Age Acc. | Age F₁ | Hate Speech Acc. | Hate Speech F₁ | Bots Acc. | Bots F₁ | Fake News Acc. | Fake News F₁ | Depression Acc. | Depression F₁ |
|--------------|----|-------------|-----------|----------|--------|------------------|----------------|-----------|--------|----------------|---------------|----------------|---------------|
| winner       | all| **82.3**    | 83.8      | 74.0     | 96.0   | **75.0**         | 41.3           | 68.0      | 67.8   | **80.0**       | 28.0          | 20.2           |                |
| ST-Lr        | all| 76.0        | 76.0      | 72.1     | 47.4   | 64.0             | 92.0           | 68.0      | 60.3   | **82.0**       | 38.2          |                |                |
| xlm-roberta  | all| 53.2        | 39.5      | 73.1     | 41.9   | 52.6             | 90.2           | 57.4      | 47.4   | **33.8**       | 21.3          |                |                |
| user-char-lr | all| 79.2        | 79.2      | 73.9     | 45.0   | 62.4             | 91.2           | 70.5      | 70.4   | **35.2**       | 24.0          |                |                |
| LDSE         | all| 74.7        | 74.7      | **85.2** | **76.5**| 70.0             | 90.6           | 74.5      | 74.5   | **45.0**       | 38.2          |                |                |
| CA           | 0  | **75.3**    | **75.2**  | **63.4** | **35.1**| 70.0             | **69.9**       | 64.0      | 63.9   | **36.2**       | **25.5**      |                |                |
| SN           | 0  | 38.0        | 37.6      | 38.7     | 29.7   | 45.0             | 44.1           | 60.0      | 56.3   | 17.5           | 15.9          |                |                |
| CA           | all| **76.1**    | 76.0      | 65.9     | 36.6   | **63.4**         | **63.3**       | 59.3      | 56.2   | **34.2**       | 19.4          |                |                |
| SN           | all| 76.0        | 76.0      | **78.3** | **61.5**| 60.4             | 60.2           | 65.7      | 65.6   | 32.1           | 22.9          |                |                |
| CA           | best| **77.3**   | **77.3**  | 72.3     | 44.6   | 70.0             | **69.9**       | 62.6      | 61.7   | **33.5**       | 24.7          |                |                |
| SN           | best| 76.3        | 76.3      | **72.4** | **61.2**| 62.2             | 62.1           | **65.5**  | **65.1**| 29.8           | **25.7**      |                |                |

### **Spanish dataset results**

| System       | n  | Gender Acc. | Gender F₁ | Age Acc. | Age F₁ | Hate Speech Acc. | Hate Speech F₁ | Bots Acc. | Bots F₁ | Fake News Acc. | Fake News F₁ | Depression Acc. | Depression F₁ |
|--------------|----|-------------|-----------|----------|--------|------------------|----------------|-----------|--------|----------------|---------------|----------------|---------------|
| winner       | all| **83.2**    | **79.6**  | **85.0** | **93.3**| **82.0**         | **76.5**       | 87.3      | 87.3   | 75.6           | 75.6          |                |                |
| ST-Lr        | all| 70.3        | 70.3      | 62.7     | 48.7   | 80.8             | 80.6           | 86.2      | 86.1   | 71.4           | 67.9          |                |                |
| xlm-roberta  | all| 53.8        | 42.2      | 50.0     | 16.7   | 75.6             | 75.2           | 86.2      | 86.1   | 71.4           | 67.9          |                |                |
| user-char-lr | all| 77.8        | 77.8      | 69.5     | 56.5   | 80.0             | 79.9           | 92.5      | 92.5   | 75.6           | 75.4          |                |                |
| LDSE         | all| 71.9        | 71.9      | 78.4     | 64.9   | 82.0             | 82.0           | 79.0      | 78.9   | 79.0           | 79.0          |                |                |
| CA           | 0  | **68.3**    | **68.2**  | 21.6     | 16.4   | **79.0**         | **78.6**       | 33.6      | 33.6   | **51.0**       | 36.3          |                |                |
| SN           | 0  | 38.1        | 33.9      | **48.6** | **32.6**| 49.0             | 34.5           | 41.5      | 34.8   | 49.5           | **44.3**      |                |                |
| CA           | all| **71.7**    | **71.7**  | 66.4     | 51.1   | 76.6             | 76.4           | **87.1**  | **87.0**| **78.3**       | **78.0**      |                |                |
| SN           | all| 71.0        | 71.0      | **66.8** | **51.6**| 77.4             | **77.1**       | 83.6      | 83.2   | 77.8           | 77.6          |                |                |
| CA           | best| **73.7**   | **73.4**  | 40.9     | 27.8   | 80.0             | 79.8           | **88.3**  | **88.2**| 74.7           | 74.4          |                |                |
| SN           | best| 72.7        | 72.5      | **66.8** | **56.0**| **80.8**         | **80.7**       | 86.5      | 86.4   | **76.3**       | **76.2**      |                |                |

₈The accuracy of the eRisk SOTA system corresponds to the DCHR metric used in the shared task.

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### 6 Conclusions

In this work, we studied author profiling from a low-resource perspective: with little or no training data. We addressed the task using zero and few-shot text classification. We studied the identification of age, gender, hate speech spreaders, fake news spreaders, bots, and depression. In addition, we analyzed the effect of the entailment hypothesis and the size of the few-shot training sample on the system’s performance. We evaluated corpora both in Spanish and English.

On the comparison of Cross Attention and Siamese networks, we find that the former performs better in the zero-shot scenario while the latter gives more stable few-shot results across the evaluated tasks and languages. We find that entailment-based models out-perform supervised text classifiers based on roberta-XLM and that we can reach 80% of the state-of-the-art accuracy us-
ing less than 50% of the training data on average. This highlights their potential for low-resource author profiling scenarios.

7 Appendix

The repository at https://tinyurl.com/ZSandFS-author-profiling contains experimental details and results.

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References

Shlomo Argamon, Moshe Koppel, Jonathan Fine, and Anat Rachel Shimoni. 2003. Gender, genre, and writing style in formal written texts. TEXT, 23:321–346.

Victoria Bobicev and Marina Sokolova. 2017. Inter-annotator agreement in sentiment analysis: Machine learning perspective. In Proceedings of the RANLP, pages 97–102.

Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. 2015. A large annotated corpus for learning natural language inference. In Proc. of the EMNLP, pages 632–642.

Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. In Advances in Neural Information Processing Systems, volume 33, pages 1877–1901.

John D. Burger, John Henderson, George Kim, and Guido Zarrella. 2011. Discriminating gender on twitter. In Proc. of the EMNLP, pages 1301–1309.

Ming-Wei Chang, Lev-Arie Ratinov, D. Roth, and Vivek Srikrumar. 2008. Importance of semantic representation: Dataless classification. In AAAI, volume 2, pages 830–835.

Zewei Chu, Karl Stratos, and Kevin Gimpel. 2020. Unsupervised label refinement improves dataless text classification. arXiv preprint arXiv:2012.04194.

Ido Dagan, Oren Glickman, and Bernardo Magnini. 2006. The pascal recognising textual entailment challenge. In Machine Learning Challenges. Evaluating Predictive Uncertainty, Visual Object Classification, and Recognising Tectual Entailment, pages 177–190.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proc. of the NAACL-HLT, pages 4171–4186.

Marc Franco-Salvador, Francisco Rangel, Paolo Rosso, Mariona Taulí, and M Antònia Martit. 2015. Language variety identification using distributed representations of words and documents. In Proc. of International conference of the cross-language evaluation forum for European languages, pages 28–40.

Bilal Ghanem, Paolo Rosso, and Francisco Rangel. 2020. An Emotional Analysis of False Information in Social Media and News Articles. ACM Transactions on Internet Technology, 20(2):1–18.

Kishaloy Halder, Alan Akbik, Josip Krapac, and Roland Vollgraf. 2020. Task-aware representation of sentences for generic text classification. In Proc. of the COLING, pages 3202–3213.

Matthew L. Henderson, Rami Al-Rfou, Brian Strope, Yun-Hsuan Sung, et al. 2017. Efficient natural language response suggestion for smart reply. arXiv preprint arXiv:1705.00652.

Moshe Koppel, Shlomo Argamon, and Anat Rachel Shimoni. 2004. Automatically categorizing written texts by author gender. To appear in Literary and Linguistic Computing, 17:4.

Hugo Larochelle, Dumitru Erhan, and Yoshua Bengio. 2008. Zero-data learning of new tasks. In Proc. of the National Conference on Artificial Intelligence, page 646–651.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, et al. 2019. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

A. Pastor Lopez-Monroy, Manuel Montes-Y-Gomez, Hugo Jair Escalante, Luis Villasenor-Pineda, and Esau Villatoro-Tello. 2013. INAOE’s participation at PAN’13: author profiling task. In Proc. of CLEF.

Thomas Müller, Guillermo Pérez-Torró, and Marc Franco-Salvador. 2022. Few-Shot Learning with Siamese Networks and Label Tuning. In ACL.

Yixin Nie, Adina Williams, Emily Dinan, Mohit Bansal, Jason Weston, and Douwe Kiela. 2019. Adversarial nli: A new benchmark for natural language understanding. arXiv preprint arXiv:1910.14599.

Javier Parapar, Patricia Martín-Rodilla, David E Losada, and Fabio Crestani. 2021. Overview of erisk at clef 2021: Early risk prediction on the internet. In Proc. of CLEF.
F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, et al. 2011. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*.

James W. Pennebaker, Mathias R. Mehl, and Kate G. Niederhoffer. 2003. Psychological aspects of natural language use: Our words, our selves. *Annual review of psychology*, 54(1):547–577.

Francisco Rangel, Anastasia Giachanou, Bilal Hisham Hasan Ghanem, and Paolo Rosso. 2020. Overview of the 8th author profiling task at pan 2020: profiling fake news spreaders on twitter. In *CEUR Workshop Proceedings*, pages 1–18.

Francisco Rangel and Paolo Rosso. 2016. On the impact of emotions on author profiling. *Information processing & management*, 52(1):73–92.

Francisco Rangel and Paolo Rosso. 2019. Overview of the 7th author profiling task at pan 2019: bots and gender profiling in twitter. In *Proceedings of the CEUR Workshop*, pages 1–36.

Francisco Rangel, Paolo Rosso, and Marc Franco-Salvador. 2016. A low dimensionality representation for language variety identification. In *Proc. of the International Conference on Intelligent Text Processing and Computational Linguistics*, pages 156–169.

Francisco Rangel, Paolo Rosso, Moshe Koppel, Efstatios Stamatakos, and Giacomo Inches. 2013. Overview of the author profiling task at pan 2013. In *Proc. of CLEF*, pages 352–365.

Francisco Rangel, Paolo Rosso, Martin Potthast, and Benno Stein. 2017. Overview of the 5th author profiling task at pan 2017: Gender and language variety identification in twitter. *Working notes papers of the CLEF*, pages 1613–0073.

Francisco Rangel, Paolo Rosso, Martin Potthast, Benno Stein, and Walter Daelemans. 2015. Overview of the 3rd author profiling task at pan 2015. In *Proc. of CLEF*.

Francisco Rangel, GLDLP Sarracén, BERTa Chulvi, Elisabetta Fersini, and Paolo Rosso. 2021. Profiling hate speech spreaders on twitter task at pan 2021. In *Proc. of CLEF*.

Nils Reimers and Iryna Gurevych. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. In *Proc. of the EMNLP*.

Timo Schick and Hinrich Schütze. 2021. Exploiting cloze-questions for few-shot text classification and natural language inference. In *Proc. of the EACL*, pages 255–269.

Enrica Troiano, Sebastian Padó, and Roman Klinger. 2021. Emotion ratings: How intensity, annotation confidence and agreements are entangled. In *Proc. of the Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*, pages 40–49.

Sinong Wang, Han Fang, Madian Khabsa, Hanzi Mao, and Hao Ma. 2021. Entailment as few-shot learner. *arXiv preprint arXiv:2104.14690*.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, et al. 2020. Transformers: State-of-the-art natural language processing. In *EMNLP*.

Wenpeng Yin, Jamaal Hay, and Dan Roth. 2019. Benchmarking zero-shot text classification: Datasets, evaluation and entailment approach. In *Proc. of the EMNLP and the IJCNLP*, pages 3914–3923.

Wenpeng Yin, Nazneen Fatema Rajani, Dragomir Radev, Richard Socher, and Caiming Xiong. 2020. Universal natural language processing with limited annotations: Try few-shot textual entailment as a start. In *Proc. of the EMNLP*, pages 8229–8239.