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Identification of an Anonymous Reviewer of an Academic Paper

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Introduction

- Commonly, as part of the process of publishing a scientific paper, the work undergoes peer review.
- “Double Blind” – the author and the reviewer are anonymous to each other.
- Today, due to transparency reasons, several well-known journals publish their reviews.

Goals

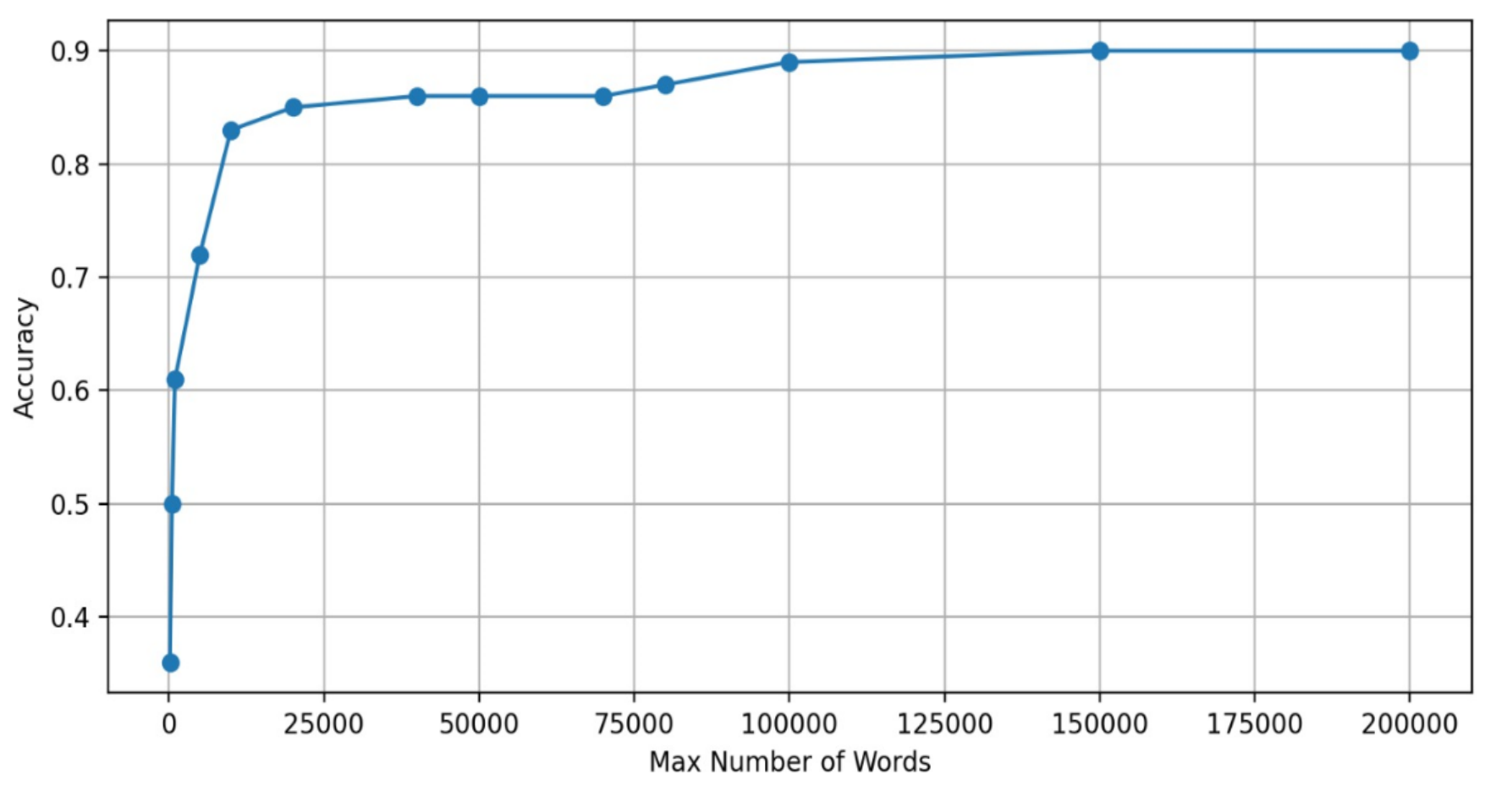
- Study the domain of a new problem – reviews on academic articles.
- Research how to perform authorship attribution on this domain by learning a different domain.
- Stepping-stone towards the following:
    - Obfuscation of reviews’ authors.
    - Dealing with the cross-domain problem – learning on articles and inferring on reviews.

Challenges

- No existing labeled ground truth.
- Reviews are short texts.
- Reviews and academic papers are topic related.
- Cross domain work.
- Most articles are written by multiple authors.

Toy Problem

- Small dataset: 100 texts – 10 Authors x 10 books (Guttenberg project).
- **Goal: create an author classifier (90% Acc.).**
- Accuracy vs. text length:

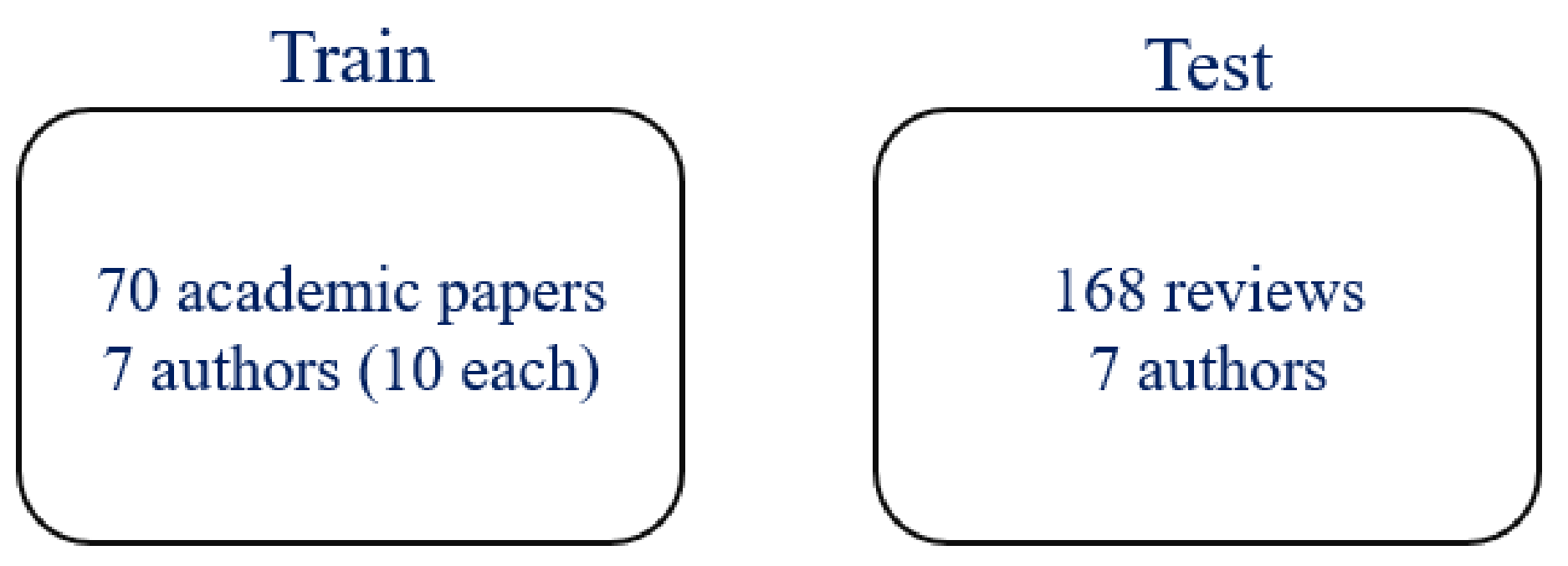


Dataset

Challenges:

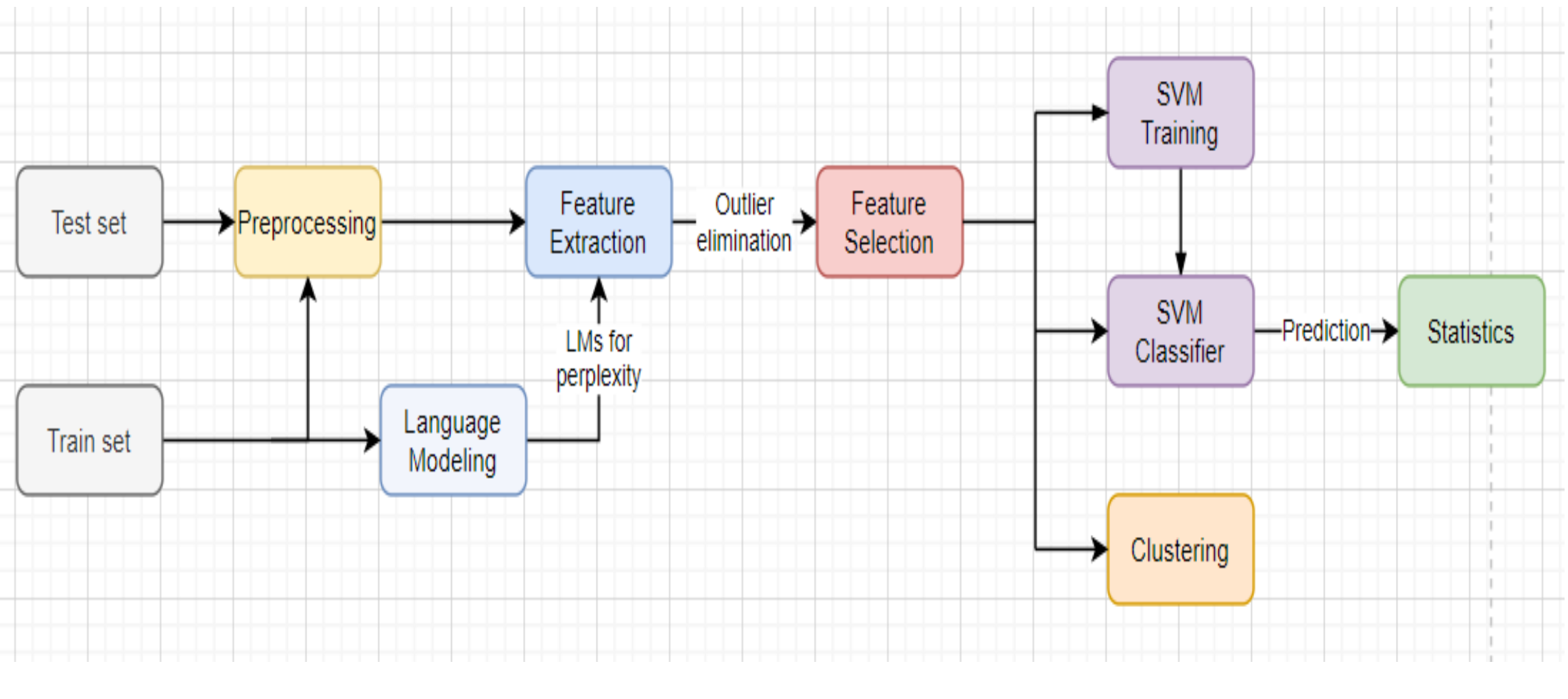
- Hard to find (especially labeled ones).
- Review’s authors write only few reviews in total.
- Short texts without meaningful context.
- Different text structures – hard for automation.
- Difficulty to obtain papers of a specific person.

Structure:


Train
70 academic papers
7 authors (10 each)
Test
168 reviews
7 authors

- Reviews - BMJ (British Medical Journal).
- Articles - various sources.

Project Diagram



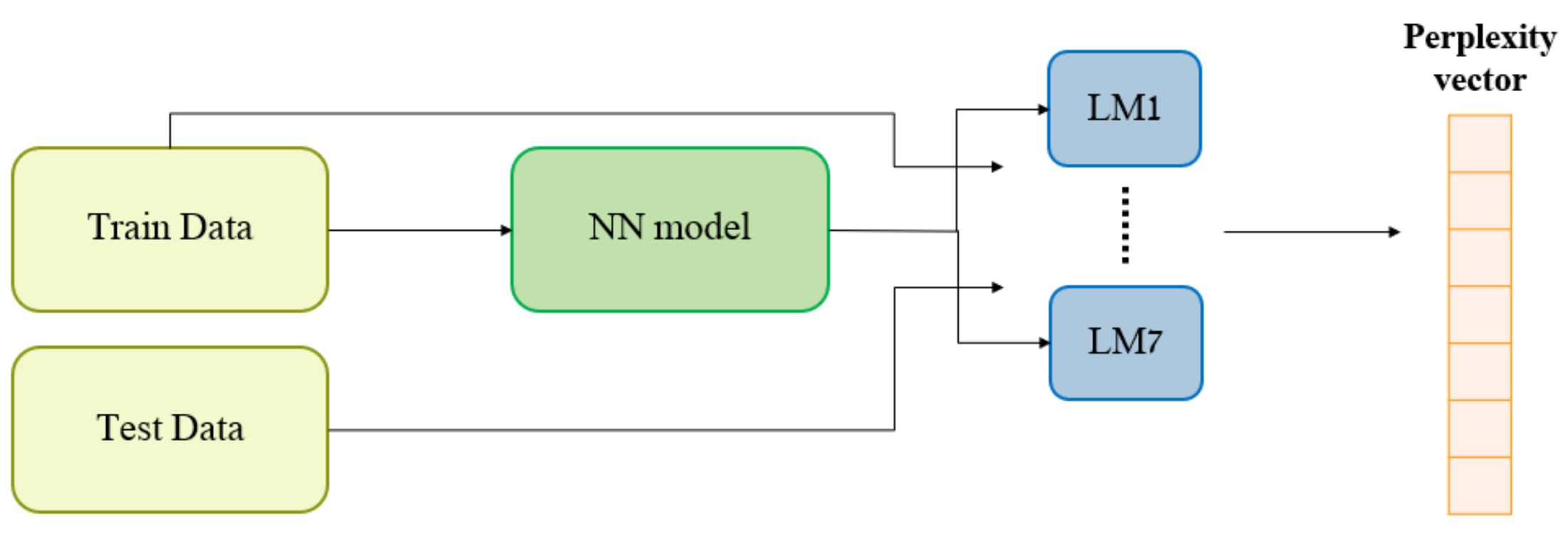
Preprocessing

- Tokenizing.
- Ignoring stop words.
- Lemmatization.
- Replacing numbers and signs with ‘<UNK>’.

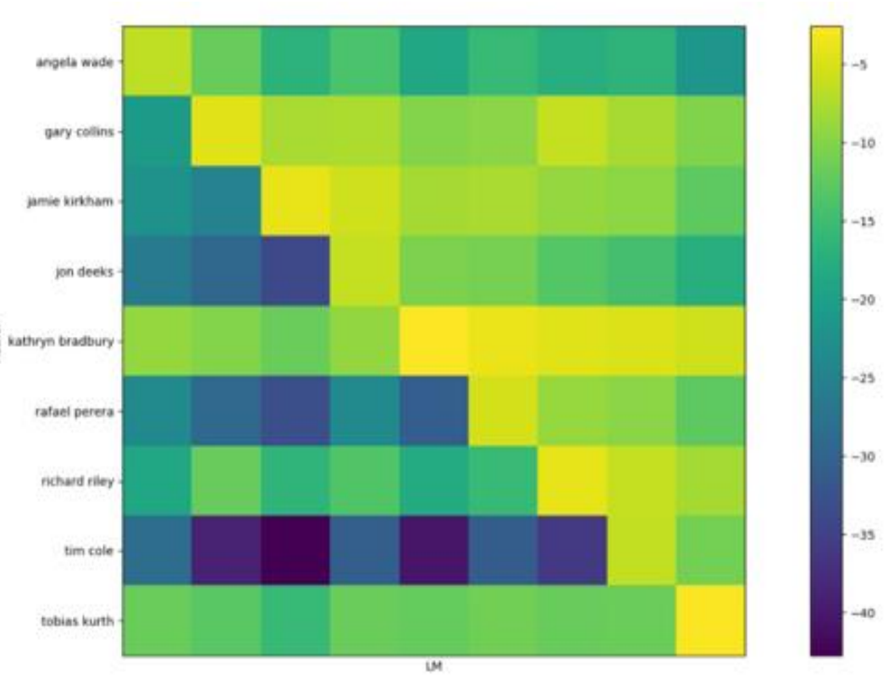
Features

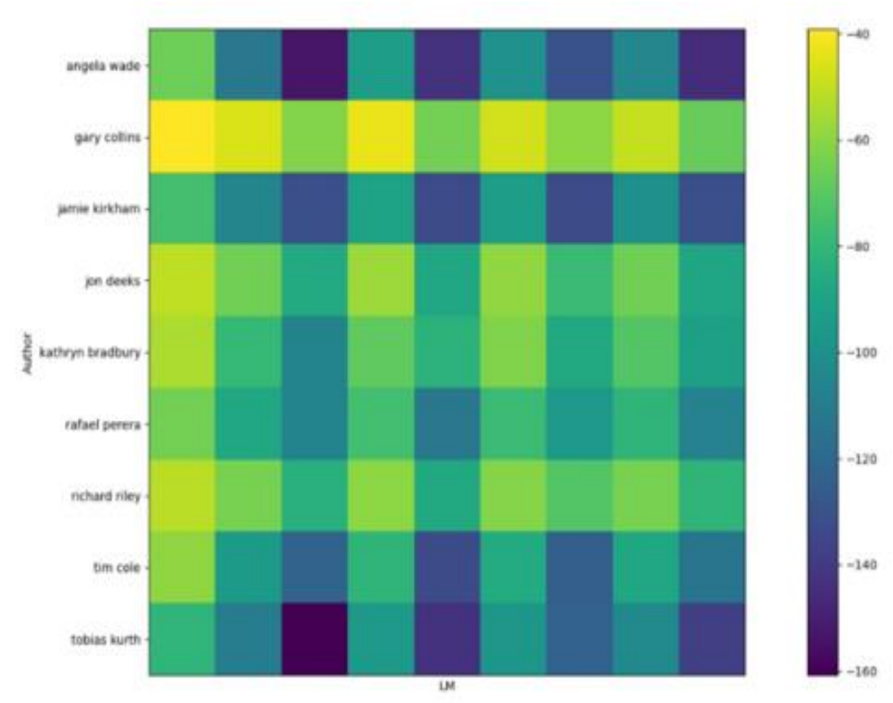
- n-gram histograms:
    - $n \in \{1,2,3,4,5\}$
    - TF-IDF normalization: $h[i] = \frac{n_i}{N} \cdot \log\left(\frac{D}{N_i}\right)$
- Average word length.
- Number of words.
- Average number of words in a sentence.
- Histogram of the following punctuation signs: , ; : -

Features – Language Models



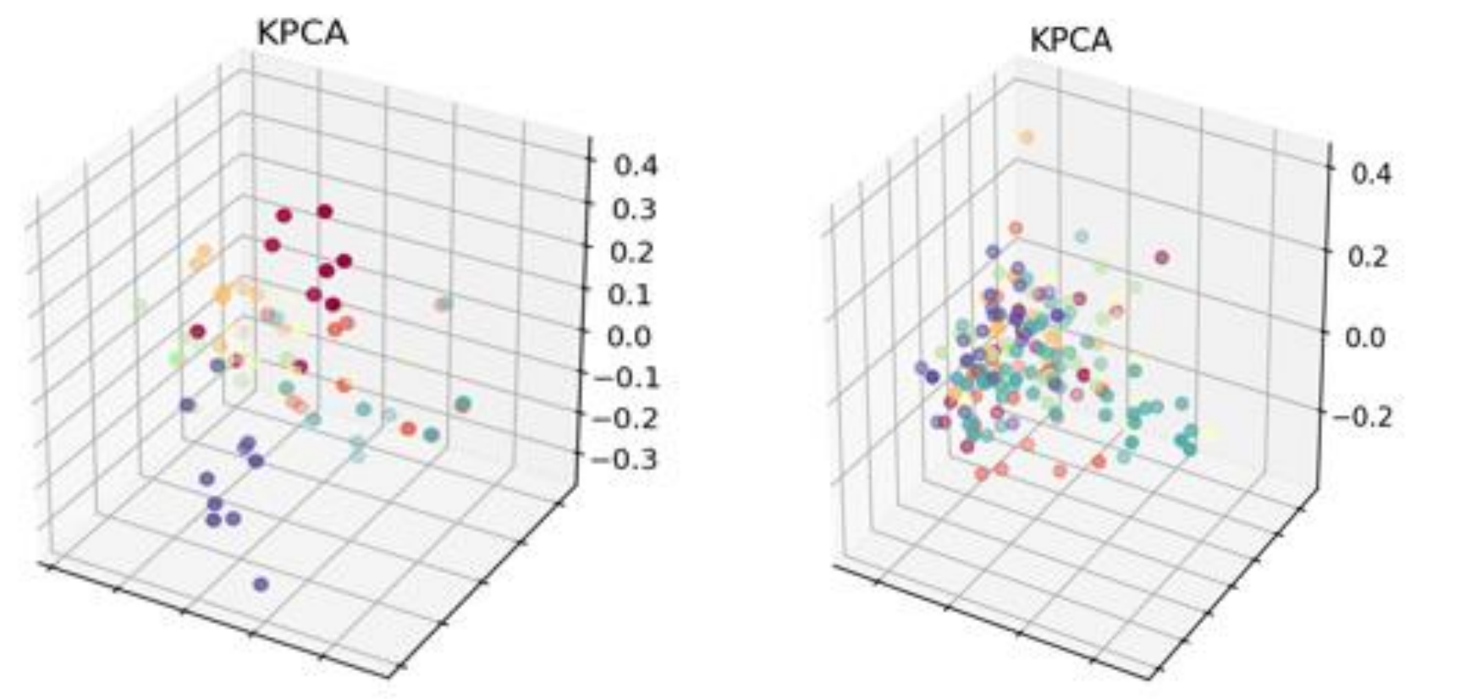
- Language model for each author.
- Calculates the probability for the next word.
- LSTM – Huggingfaces’ Transformers with GPT2.
- Perplexity as feature: $perp(x) = e^{-\frac{1}{N}\sum_{i=1}^{N}\log(P_\theta(x_i))}$
- Perplxity indicates the likelihood of a text to be associated with a language model.
- Gives understanding of vocabulary, writing style and more.


Articles - Articles


Articles - Reviews

Clustering

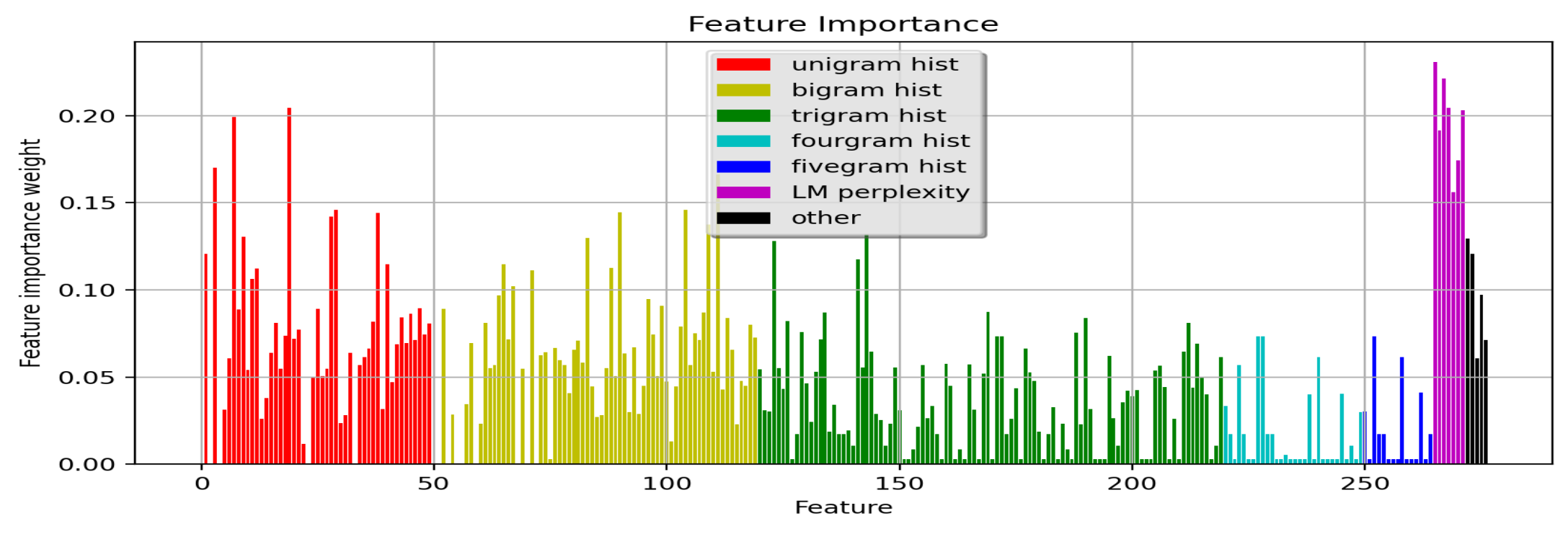
- Finding outliers in dataset – OPTICS algorithm.
- Samples visualization.
- Manifold learning – learning the feature space of the train set and the test set.



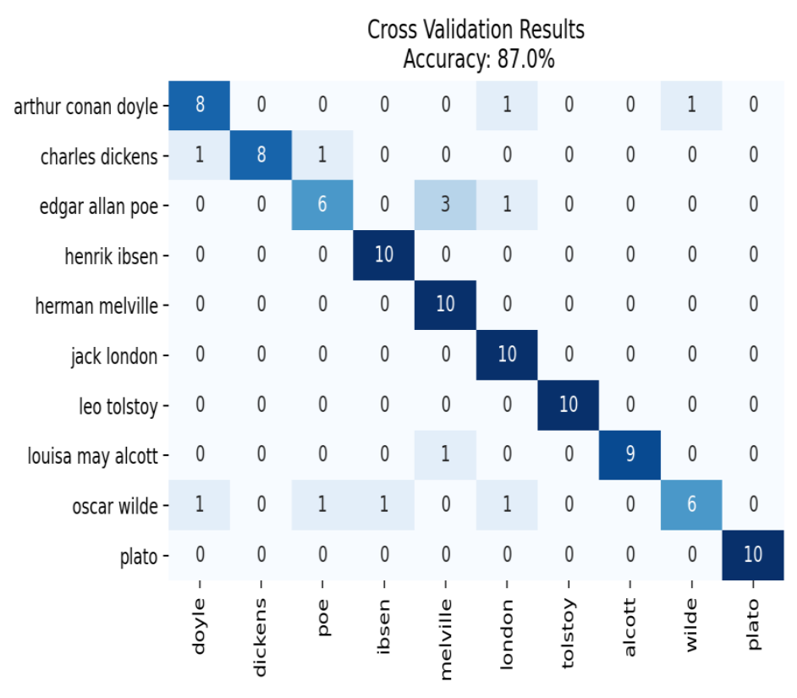
Articles
Reviews

Feature Selection

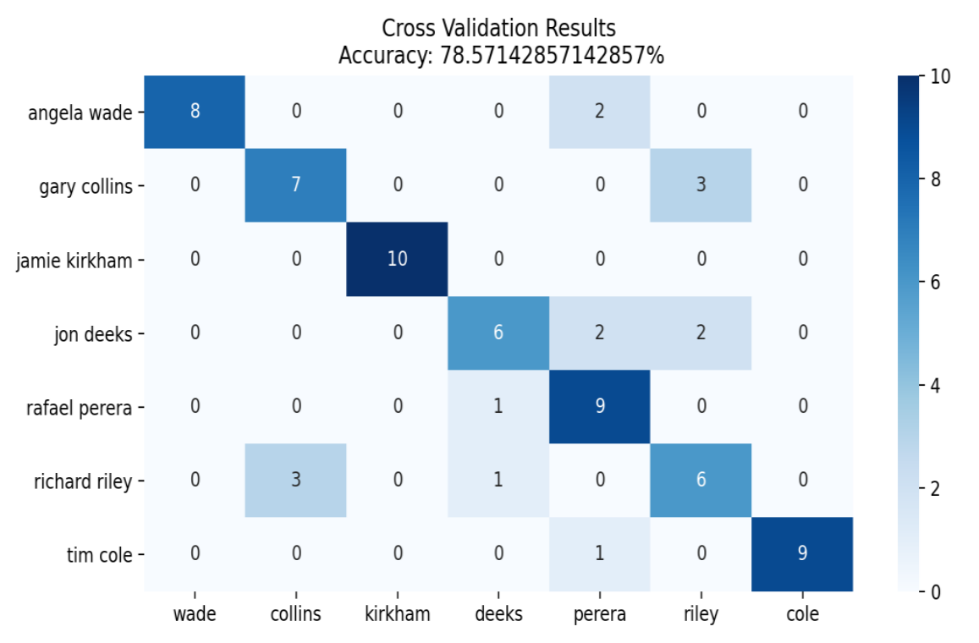
- Eliminate bad features (for both domains) with reliefF algorithm.
- For example – articles:



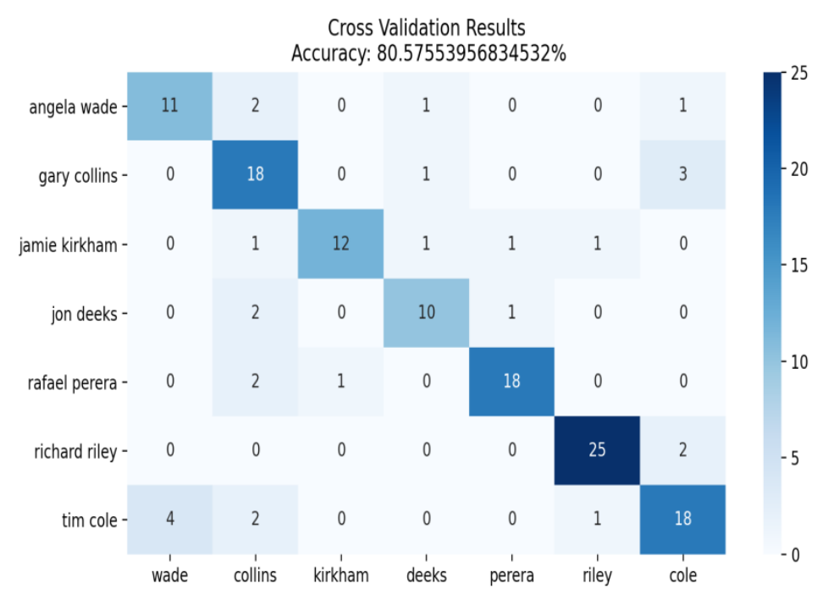
Results



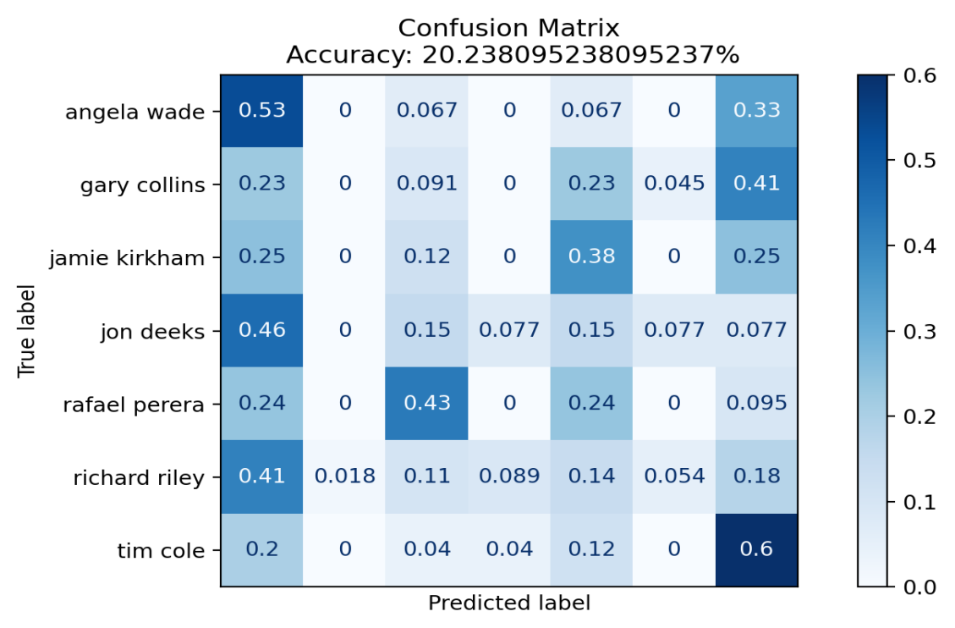
Toy problem



Articles - Articles



Reviews - Reviews



Articles - Reviews

- Indicates on the stability of our model for various problems.
- Stepping-stone for possible future work.
- Cross-domain problem hasn’t been dealt with – for future work.

Conclusions

- Good results on a naturally challenging domain.
- Future work – domain adaptation.
- The quality and size of the dataset have impact on the results.
- Text length may have a great impact on results.
- Using language models and perplexity is a highly valuable feature for this task.
- Feature selection is important when dealing with high feature dimension.

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