Contributions to a system for Open Reproducible Publication Research

Topic Classification of Publications

Dayoung Lim <D.Lim-2@student.tudelft.nl>

1. Introduction

Background

 Volume of published journals and difficulty in finding journals are increasing $[1] \rightarrow$ correctly classify publications

Research Gap

- Existing classification works with short text are mainly sentence based [2]
- Abstract based classifications are mainly domain specific [3]

Research Question: How can publication topics be identified and matched based on existing journal topic values?

April 2022 Public Data File from Crossref:

including abstracts, titles, and topic values

Extract works that have an abstract, titles,

unnecessary aspects* for the model are

removed (e.g., HTML tags, trailing

Considered the nature of the data set

includes data of multilingual journals,

2. Methodology

- Date Crossref
- Data Selection

- OpenAl Embeddings (text-embeddingada-002)

Model Training

XGBoost XGBoost GridSearchCV: hyper-parameter tuning

whitespace)

- Weighted F1: Harmonic mean of precision and recall
- Total TP Micro-average precision: Total TP +Total FP Micro-average recall:
 Total TP+Total FN

3. Results

1.00

Veighted F1

Performance - Initial Run

- 10,000 data and 50 topic values
- Grid search → max_depth=6, eta=0.5, n_estimators=500
 - max depth: depth of the tree
 - eta: learning rate
 - n estimators: number of boosting rounds or trees to build
- Baseline model (BM25 + XGBoost) comparison
 - Difference is in data cleaning stage
 - XGBoost parameters for both experiment are the same
- Different Features: Abstract, Abstract + Title, Abstract + Title + Author



0.75 0.5624 0.5152 0.50 0.25 0.00 BM25 + XGBoost OpenAI Embeddings + XGBoost

Figure 1. Comparison of weighted f1 for baseline and proposed model

4. Conclusion

Research Question Answer

OpenAl Embeddings + XGBoost combination can be used for publication topic classification when the right features are chosen

Limitations

- High computational cost → only on a sample of Crossref
 - · Classification verified on data with work names
- Correctness of original data has not been checked

Future works

- Test on works without work names
- · Verify its performance on other publication data set
- · Usage of newer model for embeddings: text-embedding-3small/large [5]

Performance – Final Run

- 50,000 stratified data
- Abstract + Title
- Grid search \rightarrow max_depth=20, eta=0.8, n_estimators=1000

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Figure 2. Performance comparison of initial runs with different features and the final run

Cost

• \$0.0001/1k token

- For 10,000 data (50 topic values): ~\$0.2
- For 50,000 stratified data~\$2.8

References

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and topic values Use of Alexandria3k: provides efficient querying on large publication open data sets [4] After examining the data format,



