

Improve the predictability of SmartFund

Yiwei Dong

ydong2@nd.edu

Supervisor: Meng Jiang, Qingkai Zeng

{mjiang2, qzeng}@nd.edu

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Introduction

- This project aims at improving the predictability of SmartFund, which is a model used for research outcomes prediction developed by Alvin Alaphat and Dr. Jiang. SmartFund leverages the past project data (award amount, investigators, university, and abstract) from the National Science Foundation (NSF) website, to predict the number of papers and corresponding citations a new project might produce, and thus it is expected to help NSF fund projects efficiently and cost-effectively. However, the performance of SmartFund model is not so satisfying, with coefficient of determination 0.348 for #papers prediction and 0.188 for #citations prediction. Therefore, it is important to enhance the predictability of SmartFund to make it useful in the real sense.

Motivations

- Textual features can be better extracted by SciBERT model

Textual features hidden in the abstract can be extracted more amply by SciBERT, the state-of-the-art natural language processing model.

Work of Alvin Alaphat and Dr. Jiang: LDA + regression Models

- Extract data from NSF¹ and Open Academic Data²
- Feature extraction
 - Bag-of-Words model
 - Latent Dirichlet Allocation (LDA)
 - Term Frequency-Inverse Document Frequency (TF-IDF)
 - AutoPhrase model: upgrading vocabulary from words only to words and phrases
- Feature selection
- Regression models

¹NSF Award Search: <https://www.nsf.gov/awardsearch/download.jsp>

²Open Academic Graph: <https://www.openacademic.ai/oag/>

Results of Topic Modeling + Regression Models

| Model | Features | MAE (dev) | MAE (test) | RMSE (dev) | RMSE (test) | R^2 (dev) | R^2 (test) | |
|-------------------------|----------------------------|-----------|--------------|------------|---------------|-------------|--------------|-------------|
| Linear Regression | Profiling | 7.714 | 7.758 | 13.542 | 13.760 | 0.106 | 0.097 | |
| | + best Bag-of-Words | 7.625 | 7.676 | 13.343 | 13.566 | 0.132 | 0.123 | 4 topics |
| | + best Bag-of-Phrases | 7.624 | 7.662 | 13.285 | 13.493 | 0.140 | 0.132 | 3 topics |
| | (All features) | 7.402 | 7.516 | 12.820 | 13.148 | 0.199 | 0.176 | |
| Single-Layer Perceptron | Profiling | 7.054 | 7.097 | 12.642 | 12.800 | 0.221 | 0.219 | |
| | + best BOW | 6.724 | 6.839 | 11.951 | 12.264 | 0.304 | 0.283 | 10 topics |
| | + best BOP | 6.596 | 6.641 | 12.073 | 12.277 | 0.290 | 0.281 | 5 topics |
| | + best BOW + best BOP | 6.395 | 6.514 | 11.663 | 11.994 | 0.337 | 0.314 | |
| | + top 10 BOW/BOP | 6.402 | 6.946 | 11.042 | 12.057 | 0.406 | 0.307 | overfitting |
| | (All features) | 4.737 | 11.438 | 6.581 | 16.192 | 0.789 | -0.250 | overfitting |
| Multi-Layer Perceptron | Profiling | 6.861 | 6.896 | 12.733 | 12.898 | 0.210 | 0.207 | |
| | + best BOW + best BOP | 6.348 | 6.462 | 11.554 | 11.948 | 0.350 | 0.319 | |
| | + top 10 BOW/BOP | 6.076 | 6.293 | 11.243 | 11.909 | 0.384 | 0.324 | |
| | (All features) | 6.503 | 6.914 | 11.508 | 12.601 | 0.355 | 0.243 | |
| | + top 10 correlated topics | 6.125 | 6.261 | 11.288 | 11.727 | 0.379 | 0.344 | |
| | + top 20 correlated topics | 6.229 | 6.371 | 11.331 | 11.742 | 0.374 | 0.343 | |
| | + top 30 correlated topics | 6.136 | 6.342 | 11.071 | 11.699 | 0.403 | 0.348 | |

Table 1: Performance on predicting the number of papers produced by an unseen project¹

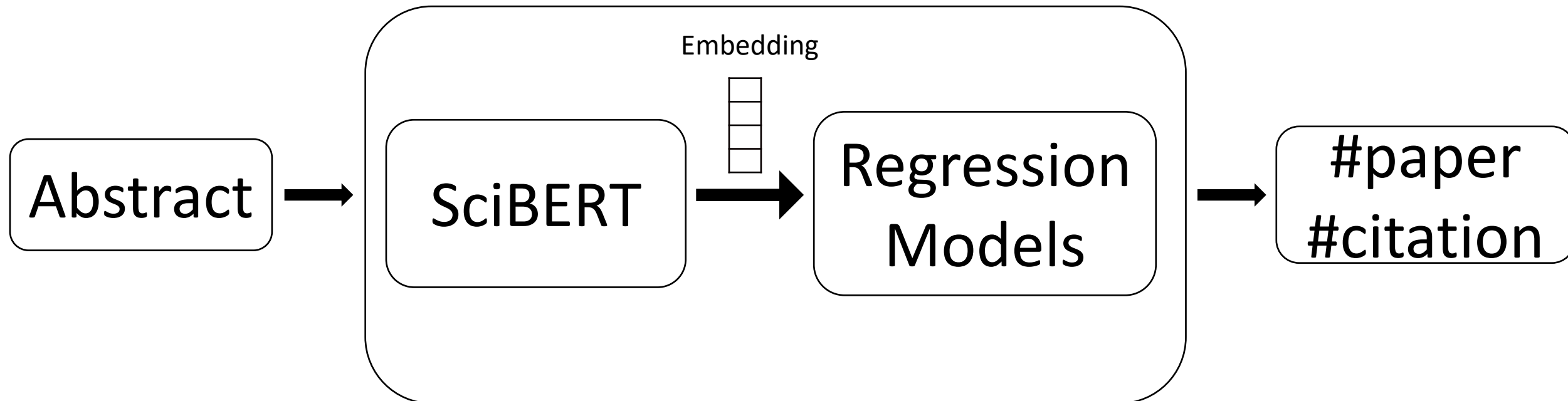
| Model | Features | MAE (dev) | MAE (test) | RMSE (dev) | RMSE (test) | R^2 (dev) | R^2 (test) | |
|-------------------------|----------------------------|-----------|--------------|------------|--------------|-------------|--------------|-------------|
| Linear Regression | Profiling | 224.2 | 224.8 | 503.6 | 501.1 | 0.041 | 0.040 | |
| | (All features) | 222.4 | 225.1 | 491.9 | 492.8 | 0.085 | 0.071 | |
| Single-Layer Perceptron | Profiling | 211.2 | 212.3 | 483.9 | 479.9 | 0.115 | 0.119 | |
| | + best BOW | 204.1 | 205.6 | 476.1 | 473.0 | 0.143 | 0.144 | 8 topics |
| | + best BOP | 206.5 | 208.0 | 475.8 | 472.0 | 0.144 | 0.148 | 8 topics |
| | (All features) | 192.3 | 299.3 | 342.5 | 522.8 | 0.556 | -0.046 | overfitting |
| Multi-Layer Perceptron | Profiling | 197.4 | 198.9 | 485.2 | 482.4 | 0.110 | 0.110 | |
| | (All features) | 204.6 | 209.9 | 485.3 | 492.7 | 0.109 | 0.071 | |
| | + top 30 correlated topics | 188.1 | 192.4 | 455.0 | 460.8 | 0.217 | 0.188 | |

Table 2: Performance on predicting the number of citations the produced papers can have²

^{1,2} from Alvin and Dr. Jiang

SciBERT Model + Regression Models

- Using SciBERT Model to get sentence embeddings of abstracts
- Feed the sentence embeddings to regression models



Data Processing

- Delete items with none abstract
- Tokenize abstract & Cut to 490 tokens (BERT model can tackle at most 512 tokens at one time. Here, we regard each abstract as one sentence, and take the sentence embedding as its feature)
- Split train, dev, and test

Use SciBERT to Embed All The Abstracts

| ID | Abstract | #paper | #citation | Sentence embeddings | | | |
|---------|---|--------|-----------|---------------------|---------|-----|---------|
| | | | | 0 | 1 | ... | 767 |
| 8854199 | This is a workshop on the use of mathematical and computer models in biological resource conservation. It is designed to... | 0 | 0 | -0.6507 | 0.0876 | ... | -0.8717 |
| 9012033 | The distribution of Ba in the ocean is similar to the refractory components, silica and alkalinity. Therefore reconstructions of Ba in ancient... | 1 | 90 | -0.6902 | -0.3954 | ... | -0.8150 |
| 1536005 | The research objective of this project is to investigate how performance can be made comparable across a wide range of construction project sizes and types. Performance... | 0 | 0 | 0.1398 | -0.3006 | ... | -0.5552 |
| ... | | ... | ... | ... | ... | ... | ... |

Feedforward Neural Network

- Pass the obtained sentence embedding as the input to the feedforward neural network
- Train & Save the model with the least MSE on validation set

Future Work

- Optimize the SciBERT + Feedforward neural network model
- Test the reasonability of each step(e.g. If it is reasonable to cut each long abstract to 490 words? If it is better to cut those abstracts backward so that we can get a better result?)

Conclusion

In this project:

- We propose to improve the predictability of SmartFund, to make it function better
- We propose to use SciBERT to extract the information contained in abstracts

Feel free to contact me at ydong2@nd.edu should you have any questions!