Automatic Recognition and Classification of Future Work Sentences in Academic Articles in a Specific Domain

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Introduction

Nowadays, various digital technologies promote the publication, diffusion, acquisition, and utilization of academic literature. Therefore, researchers, mainly those who are beginners in scientific research, are difficult to predict future research topics. The research paradigm characterized by ‘data-driven’ is emerging in the topic detection and tracking. Compared with the bibliographic information, full-text of academic papers contains more micro-semantic details. The ‘future work’ is a pivotal part of an academic paper, where the authors make suggestions for future research, point out what research is underway, or discuss the potential direction of the whole field. Taking the field of NLP as a case, this paper extracts Future Work Sentences (FWS) of articles, classifies them into different types, and then discusses the trends of future research in NLP field.

Related work

Recently, Hao et al. (2020) constructed a corpus, including FWS manually extracted from ACL papers published during 1990-2015, and constructed a classification system in accordance with grounded theory. Besides, most prior work is based on rules to identify FWS (Hu & Wan, 2015). However, manually established rules can hardly cover all the language features of FWS and are susceptible to subjective factors of experts. Therefore, we adopt machine learning methods realize automatic recognition and classification of FWS.

Method

Dataset

We download 11,952 conference papers of ACL, EMNLP, and NAACL during 2000-2019 from ACL Anthology (https://www.aclweb.org/anthology/). The manually annotated dataset consists of two parts: first, FWS of ACL during 2000-2015 are obtained from the ACL FWS-RC corpus (Hao et al., 2020). Second, we extract chapters related to future work in the other papers by manual reading. Subsequently, we annotate the FWS in the extracted chapters of EMNLP and NAACL according to the existing label specification and classification system. Cohen’s kappa coefficient (Cohen, 1960) is employed to measure the reliability of the labels and achieves over 0.75.

Model Selection

For automatic recognition of FWS, we use four traditional ML models, including Naïve Bayesian, Logistic Regression, Support Vector Machine and Random Forest, combining with three feature selection methods: filter, embedded, and wrapper. For automatic classification of FWS, we use the BERT pre-training model to represent the input data’s features and input the acquired feature vectors into the SoftMax layer for classification. We evaluate the model performance by Precision, Recall, and F1 score.

Result

Result of Automatic FWS recognition

The experiment result is shown in Table 2. Then we use the best model to recognize FWS from extracted chapters of ACL between 2016 and 2019. 1430 sentences are identified and we add them to our dataset. The ratio of FWS is used as an indicator, which is the share of papers that contain FWS. The result is shown in Figure 2.

Table 2. Performance of FWS recognition.

<table>
<thead>
<tr>
<th>Model</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>LR</td>
<td>92.46%</td>
<td>81.05%</td>
<td>85.35%</td>
</tr>
<tr>
<td>SVM</td>
<td>92.39%</td>
<td>86.87%</td>
<td>89.31%</td>
</tr>
<tr>
<td>RF</td>
<td>92.58%</td>
<td>92.63%</td>
<td>92.08%</td>
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<tr>
<td>NB</td>
<td>91.22%</td>
<td>97.58%</td>
<td>93.95%</td>
</tr>
</tbody>
</table>

References


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