

RAAMove: A Corpus for Analyzing Moves in Research Article Abstracts

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1. Introduction

Background:

(1) importance of research articles (RAs)

(2) move analysis for instructing,

assessing abstract writing

Gap:

(1) few move analysis targeting multi-

disciplinary RAs

(2) few large-scale annotated corpora for

RA abstracts

[Background]Large-scale pretrained language models have achieved SOTA results on NLP tasks. [Gap]However, they have been shown vulnerable to adversarial attacks especially for logographic languages like Chinese. [Purpose]In this work, we propose RoCBert: a pretrained Chinese Bert that is robust to various forms of adversarial attacks like word perturbation, synonyms, typos, etc. [Method]It is pretrained with the contrastive learning objective which maximizes the label consistency under different synthesized adversarial examples. [Result]Across 5 Chinese NLU tasks, RoCBert outperforms strong baselines under three blackbox adversarial algorithms without sacrificing the performance on clean testset.



1. Introduction

- We develop a multi-domain move structure annotation corpus for analyzing moves in RA abstracts.
- We suggest a revision of move structure categories based on Hyland's established move classification (Hyland, 2000).
- We propose an innovative **BERT-based automatic annotation model** that incorporates word level saliency attribution.



This section attempts to answer the following questions:

(1) Which rhetorical move theories could guide the construction of a corpus for analyzing moves in RA abstracts?(2) In what manner can these theories find greater relevance in our work?



2. Scheme

(1) Which rhetorical move theories could guide the construction of

a corpus for analyzing moves in RA abstracts?

| Move | Function |
|--------------|---|
| Introduction | Establishes context of the paper and motivates the research or discussion. |
| Purpose | Indicates purpose, thesis or hypothesis, outlines the intention behind the paper. |
| Method | Provides information on design, procedures, assumptions, approach, data, etc. |
| Product | States main findings or results, the argument, or what was accomplished. |
| Conclusion | Interprets or extends results beyond scope of paper, draws inferences, points to |
| | applications or wider implications. |

Table 1: Hyland's classification of rhetorical moves in RA abstracts



2. Scheme

(1) Which rhetorical move theories could guide the construction of

a corpus for analyzing moves in RA abstracts?

| | AI | | Engine | eering |
|--------|-------|------|--------|--------|
| Move | Freq. | % | Freq. | % |
| Intro. | 17 | 85% | 16 | 80% |
| Pur. | 20 | 100% | 19 | 95% |
| Met. | 19 | 95% | 19 | 95% |
| Pro. | 11 | 55% | 16 | 80% |
| Con. | 11 | 55% | 13 | 65% |

Table 2: Frequency of moves identified based on Hyland's classification in sample abstracts. Where the five moves correspond to those in Table 1. [Example 1]: These results can provide a better understanding of surfactants and guide the practical preparation of multicomponent fluids for boiling heat transfer enhancement.

[Example 2]: We release source code for our models and experiments at https://github.com/xxx.

[Example 3]: Undermining the impact of hateful content with informed and non-aggressive responses, called counter-narratives, has emerged as a possible solution for having healthier online communities.

[Example 4]: Although such studies have made an effort to build hate speech / counternarrative (HS/CN) datasets for neural generation, they fall short in reaching either high-quality and/or high-quantity.



2. Scheme

(2) In what manner can these theories find greater relevance in our

work?

| Move | Function |
|--------------|--|
| Background | States the research area and provides any historical, theoretical, or empirical related information. |
| Gap | Establishes a niche: indicates a gap, adds to what is known, presents positive justification (Swales, 2004). |
| Purpose | Indicates purpose, thesis or hypothesis, outlines the intention behind the paper. |
| Method | Provides information on design, procedures, assumptions, approach, data, etc. |
| Result | States main findings or results or what was accomplished. |
| Conclusion | Summarizes the results or extends results beyond scope of paper. |
| Implication | Draws inferences which has not been explicitly stated. |
| Contribution | Points out the theoretical and practical value. |

Table 3: Enriched move classification



Two phases:

(1) data selection and preprocessing

(2) process (manual annotation + automatic annotation)



(1) data selection and preprocessing

| Discipline | Journal/Conference |
|---------------------------|--|
| Artificial Intelligence | the Annual Meeting of the Association for Computational Linguistics (ACL) |
| Artificial Intelligence | Technical Track on CV on the AAAI Conference on Artificial Intelligence (AAAI) |
| Mechanical Engineering | Journal of Mechanical Design |
| Mechanical Engineering | International Journal of Heat and Mass Transfer |
| Communication Engineering | IEEE Journal on Selected Areas in Communications |

Table 4: Selected journals and conferences for annotation



(2) process: manual annotation

| Neu | ral abstractive summarization mo | odels are able to generate summaries which have high overlap with human references. |
|---------------|----------------------------------|--|
| •BA' | Select a label BAC | |
| Hov •GA | BAC | mized for factual correctness, a critical metric in real-world applications. |
| | GAP | |
| In th • PU | MTD | mework where we evaluate the factual correctness of a generated summary by fact-checking it automatically |
| | PUR | |
| aga | RST | ation extraction module. |
| We | CLN | which optimizes a neural summarization model with a factual correctness reward via reinforcement learning. |
| •M1 | IMP | |
| We | СТМ | summarization of radiology reports, where factual correctness is a key requirement. |

On two separate datasets collected from hospitals, we show via both automatic and human evaluation that the proposed approach substantially improves • CLN

the factual correctness and overall quality of outputs over a competitive neural summarization system, producing radiology summaries that approach the

quality of human-authored ones.

Figure 1: Screenshot of the doccano annotation platform

https://github.com/doccano/doccano



(2) process (manual annotation + automatic annotation): guidelines

| Label | Abbreviation |
|--------------|--------------|
| Background | BAC |
| Gap | GAP |
| Purpose | PUR |
| Method | MTD |
| Result | RST |
| Conclusion | CLN |
| Implication | IMP |
| Contribution | CTN |

Table 5: Annotation labels and their abbreviation

[BAC]While neural networks with attention mechanisms have achieved superior performance on many natural language processing tasks, [GAP]it remains unclear to which extent learned attention resembles human visual attention.



(2) process: manual annotation

expert team + weekly discussions + revision



(2) process:

automatic annotation: **BERT-based** model



Figure 2: An illustration of move saliency attribution



4. Corpus Statistics

(1) distribution of move types

| Label | Frequency | % |
|-------|-----------|-------|
| BAC | 6,466 | 19.02 |
| GAP | 3,272 | 9.63 |
| PUR | 4,874 | 14.34 |
| MTD | 11,526 | 33.91 |
| RST | 3,732 | 10.98 |
| CLN | 3,006 | 8.84 |
| IMP | 282 | 0.83 |
| CTN | 830 | 2.44 |
| Total | 33,988 | 100 |

Table 6: Frequency and distribution of moves identified in our corpus

(2) occurrence of move types

| | AI | | Engin | eering |
|------|-------|-------|-------|--------|
| Move | # | % | # | % |
| BAC | 2,003 | 75.02 | 1,528 | 76.29 |
| GAP | 1,518 | 56.85 | 891 | 44.48 |
| PUR | 2,333 | 87.38 | 1,901 | 94.91 |
| MTD | 2,245 | 84.08 | 1,873 | 93.51 |
| RST | 1,540 | 57.68 | 953 | 47.58 |
| CLN | 1,192 | 44.64 | 1,079 | 53.87 |
| IMP | 112 | 4.19 | 159 | 7.94 |
| CTN | 544 | 20.37 | 215 | 10.73 |

Table 7: Occurrence and distribution of each move type identified across the two fields in our corpus



4. Corpus Statistics

| | AI | Engineering |
|---------------------|---------|-------------|
| #Sent. | 17,391 | 16,597 |
| Average #Sent. | 6.51 | 8.29 |
| #Words | 381,734 | 406,244 |
| Average #Words | 142.97 | 202.82 |
| Average #Move types | 4.38 | 4.29 |

Table 8: The average number of sentences, words, and move types in each abstract within the two fields



5. Experiments

(1) move recognition

| Data | #Sentences |
|--------------|-------------------|
| Training set | 7,147 |
| Test set | 1,787 |

Table 9: Dataset statistics

| Method | P (%) | R (%) | F1 (%) |
|--------------|-------|-------|--------|
| BERT | 74.06 | 79.58 | 76.72 |
| BERT+Context | 74.55 | 81.23 | 77.60 |
| Our | 75.01 | 82.34 | 78.53 |

Table 10: Results of move structure identification

(2) comparison with ChatGPT

The move structure of a scientific paper refers to the categorical composition of the linguistic rhetorical components of the academic discourse in the paper. Move recognition is essentially a classification problem in sentences. Now the moves are background, gap, method, purpose, result, conclusion, contribution, and implication. Here are a few examples of move recognition: Detecting emotion in text allows social and computational scientists to study how people behave and react to online events. [background] However, developing these tools for different languages requires data that is not always available. [gap] This paper collects the available motion detection datasets across 19 languages. [purpose] We train a multilingual emotion prediction model for social media data, XLM-EMO. [method] The model shows competitive performance in a zero-shot setting, suggesting it is helpful in the context of low-resource languages. [results] We release our model to the community so that interested researchers can directly use it. [contribution] Below I will give you some sentences, these sentences are from scientific papers, please complete the step recognition.

"Input sentences"

What is the move of this sentence?

Figure 3: Instructions for ChatGPT

Our VS. ChatGPT 80 VS. 65



Thank you!