Towards Topic-Aware Slide Generation For Academic Papers With Unsupervised Mutual Learning

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Major Contribution

- We conduct an in-depth slide analysis, and have mined frequently covered topics into the slide generation process.
- We adopt mutual learning in the unsupervised setting, where we provide a general and flexible framework for integrating prior knowledge to initiate the training.

Slide Analysis and Dataset

- Analysis 50 presentations (1,127 slides in total) with corresponding papers.
- Measure Topic Popularity, Extraction Coverage, Extraction Distance to find our target.

Slide Topic	Popularity	Ext Cov. (#text bullets)	Ext Dist.
Task Background	100%	70.23%(1,154)	0.074
Related Work	86%	82.14%(1,034)	0.158
Contribution	90%	87.14%(995)	0.693
Approach	100%	74.39%(70)	0.481
Dataset	84%	89.12%(310)	0.298
Baseline	88%	90.17%(255)	0.121
Result	100%	72.33%(101)	0.248
Conclusion	76%	76.25%(258)	0.799
Future Work	72%	93.68%(186)	0.011

Figure 1. Slide Analysis

- We use the ACL Anthology Reference Corpus (Bird et al. 2008) [1] (22,878 publications) as training data.
- Select slide topic with high popularity and extraction coverage. (i.e. Bold slide topics in Figure 1.)

Task Formulation and Architecture

Given a slide topic T and a paper P with N sentences $\{S_1, S_2, \ldots, S_N\}$, the goal is to select topic-relevant sentences.

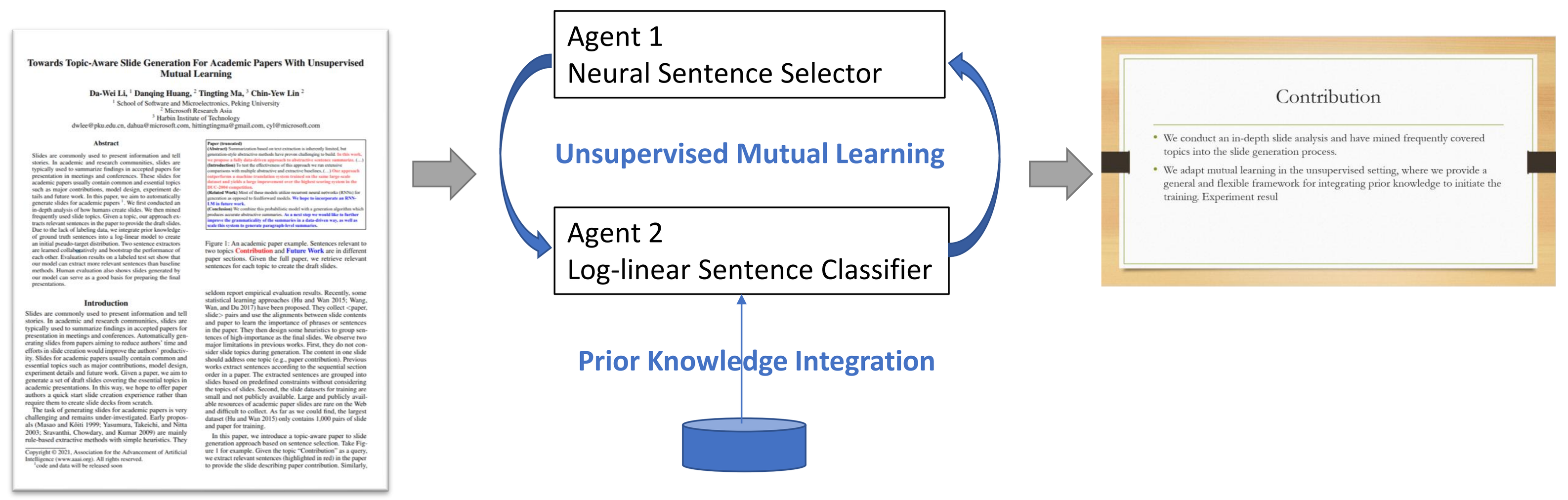


Figure 2. Overview

Neural Sentence Selection Model.

- Based on the work of Zhou et al. (2018) [2]
- Aims to capture the sentence semantic.

Log-Linear Classifier with Prior Knowledge.

- To provide initial guidance for unsupervised bootstrapping.
- Integrated features:
  - Task-specific features: Keywords, Belonging Section
  - General features: Sentence Position
  - Signal from general pre-trained model: BERT-QA

$$q(S_i|\gamma) = \frac{\exp(\gamma \cdot \phi(S_i, T))}{\sum_k \exp(\gamma \cdot \phi(S_k, T))}$$

Figure 3. Log-linear Model

Learning Algorithm

- Adopt mutual learning in our unsupervised training framework which trains two agents iteratively.
- The two-stage setting increases the robustness of the early-stage training, and let the model able to make use of a large amount of unlabeled data.

Algorithm Training paradigm based on mutual learning

Require: Unlabeled papers U, neural-based model C_1, log-linear model C_2

Create seed subset U' with keyword filtering

Initialize pseudo-target distribution with log-linear model weights γ;

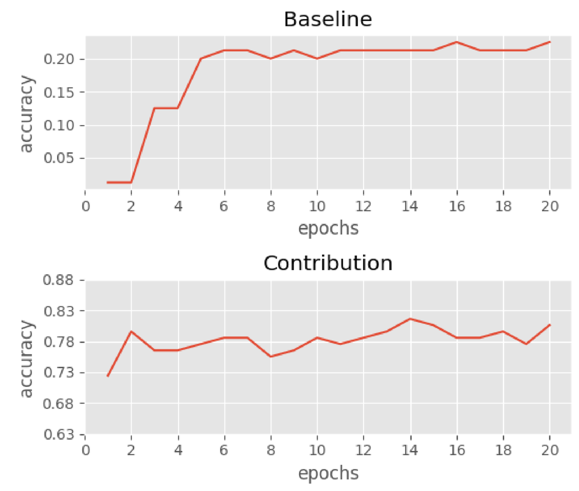
while $\mathcal{L}_{neural}$ not converges **do**
  Update C_1 with $\mathcal{L}_{neural}$, U';
  Update C_2 with $\mathcal{L}_{log\_linear}$, U';
end while

for timestep $t = 1, \cdots, T_1$ **do**
  Sample a batch of unlabeled papers U_t
  Update $U' = U' + U_t$;
  Use C_1 to label U';
  Update C_2 with pseudo-labeled U';
  Use C_2 to label U';
  Update C_1 with pseudo-labeled U';
end for

Figure 4. Training Framework

Experiment and Human Evaluation

- Both of our models obtain the best scores on precision and BLEU[Φ].
- The performance curve shows our models are learning stable and robustly.
- Human evaluation result shows that our model can provide good basis for generating slides.



	Relevance	Coverage	Overall
Author	4.33	3.99	-
Ours	3.56	3.52	3.54

Figure 4. Accuracy Curve and Human Evaluation Result

References

1. Bird, S.; Dale, R.; Dorr, B.; Gibson, B.; Joseph, M.; Kan, M. Y.; Lee, D.; Powley, B.; Radev, D.; and Tan, Y. F. 2008. The ACL Anthology Reference Corpus: A Reference Dataset for Bibliographic Research in Computational Linguistics.
2. Zhou, Q.; Yang, N.; Wei, F.; Huang, S.; Zhou, M.; and Zhao, T. 2018. Neural Document Summarization by Jointly Learning to Score and Select Sentences.

[Φ] The detail result and analysis can be found in the paper.