Supervised Contrastive Learning for Multi-Author Writing Style Analysis

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Keywords:
Supervised Contrastive Learning , Prompt base

*1 corresponding author

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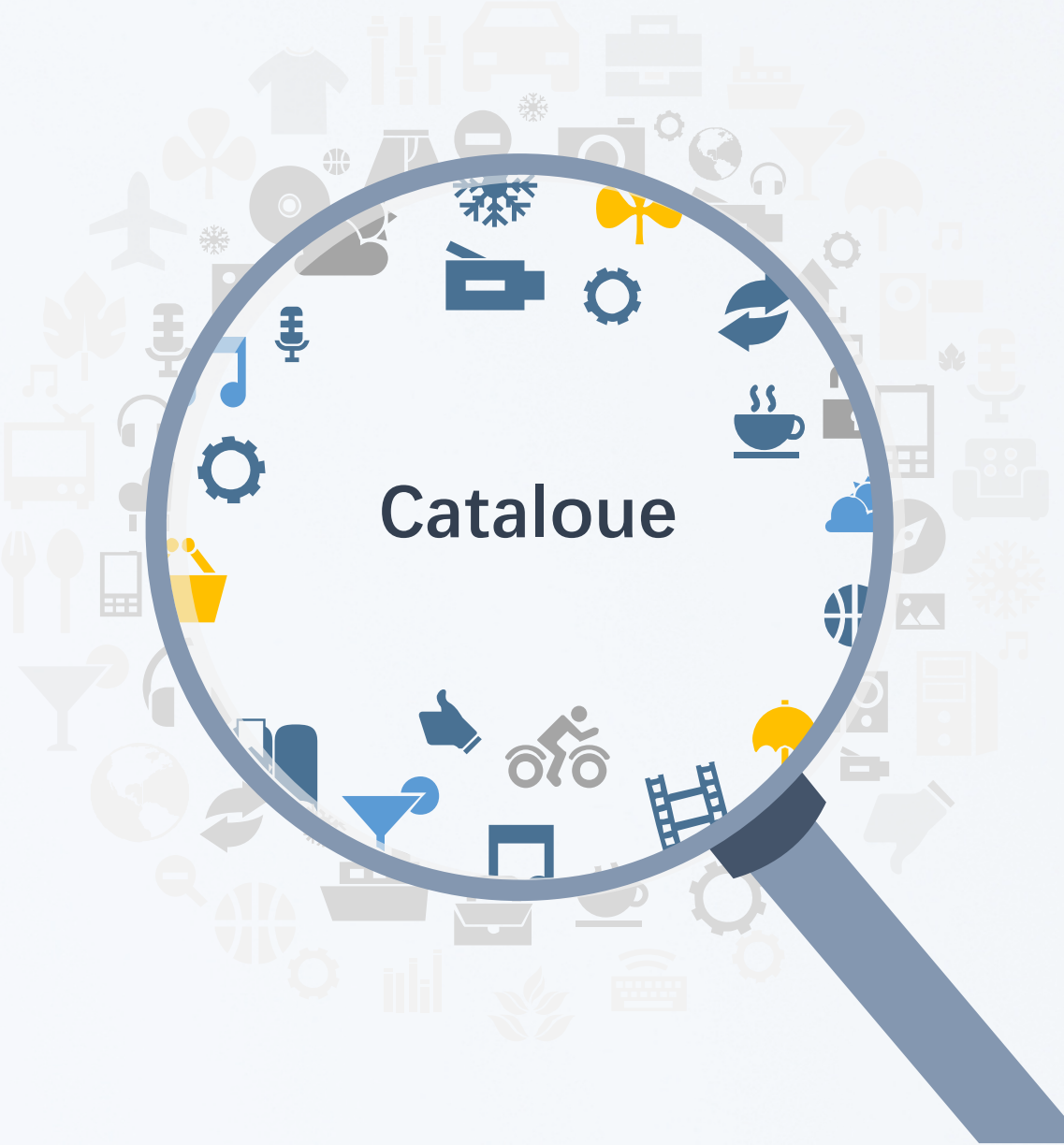
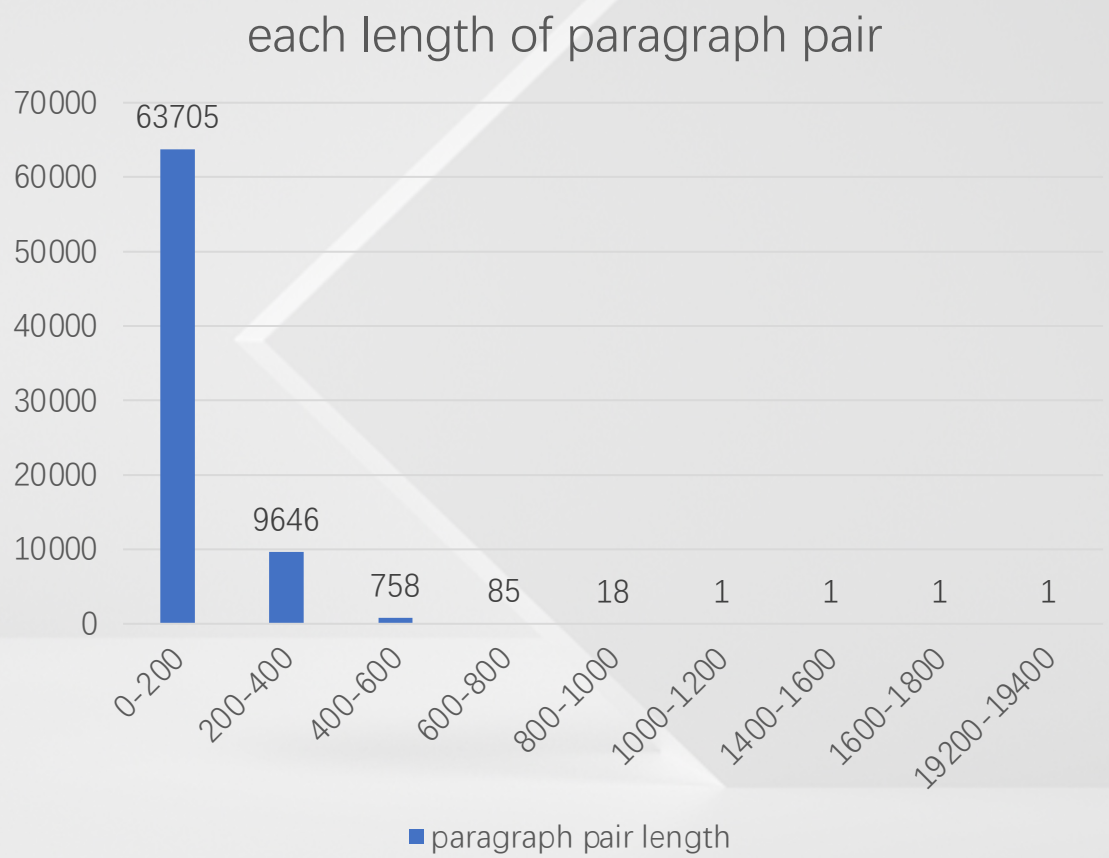
04 Conclusion

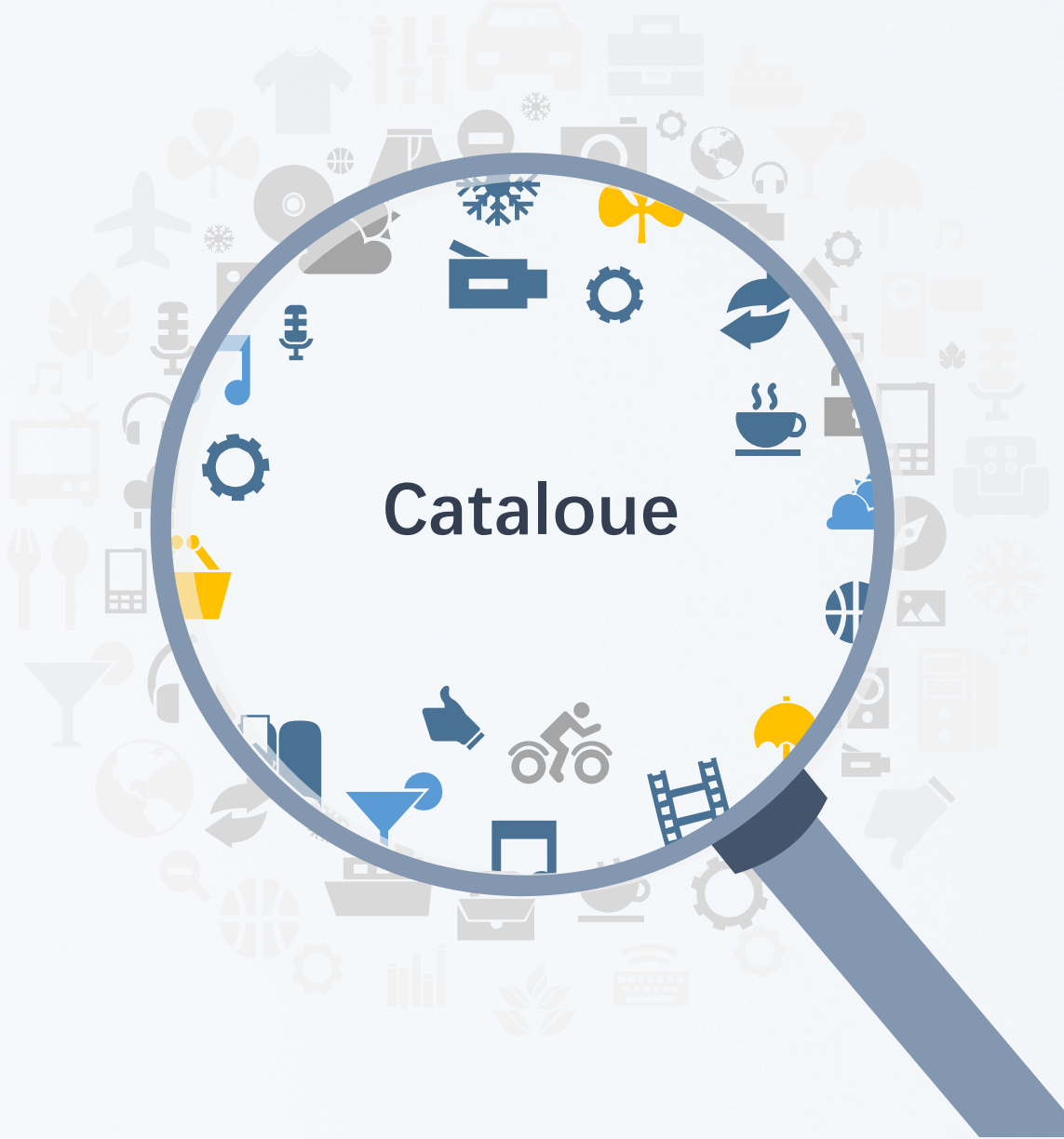


01 Background

Overview of datasets

- dataset 1(easy): The document's paragraphs cover diverse topics, which can help detect authorship changes.
- dataset 2(medium): The document has limited topical variety, pushing approaches to rely more on style for detection.
- dataset 3(hard): All paragraphs in a document are on the same topic.
- Describe: Identify whether two consecutive paragraphs in each document in the given dataset are written by the same author.
- Dataset: about 74,139 consecutive paragraphs





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Supervised Contrastive learning[1]

assumption

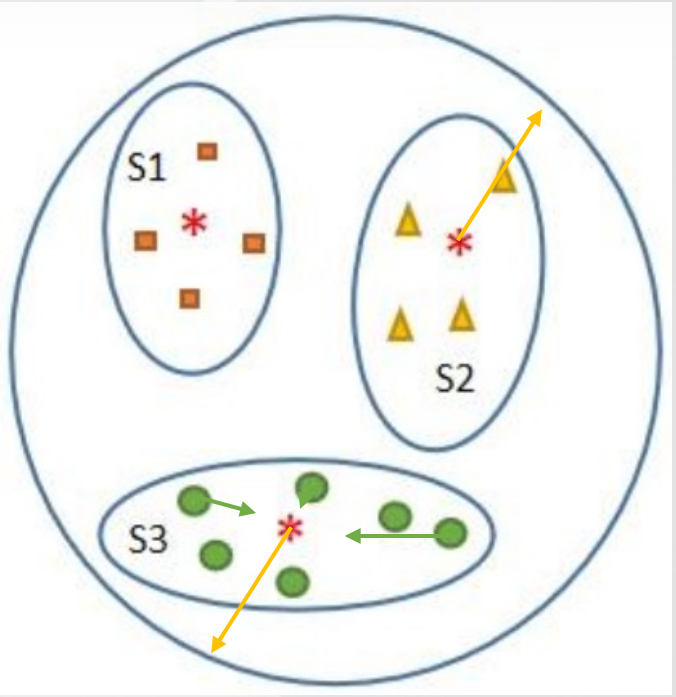
We assume that paragraph with the same topic but different subtle features are usually very similar in semantic space. This will cause the deep model to be unable to well determine whether the author of the consecutive paragraph pairs has changed.

Why supervised contrastive learning?

Because Supervised contrastive learning can enable deep models to better distinguish differences in some subtle features, such as writing styles, habits, etc.

Why can better distinguish capacity ?

Because supervised contrastive learning can use label information to make the same label as close as possible in semantic space, otherwise it is far away. Therefore, the model can distinguish subtle changes in features that were previously indistinguishable during training.



[1]Khosla P, Teterwak P, Wang C, et al. Supervised contrastive learning[J]. Advances in neural information processing systems, 2020, 33: 18661-18673.

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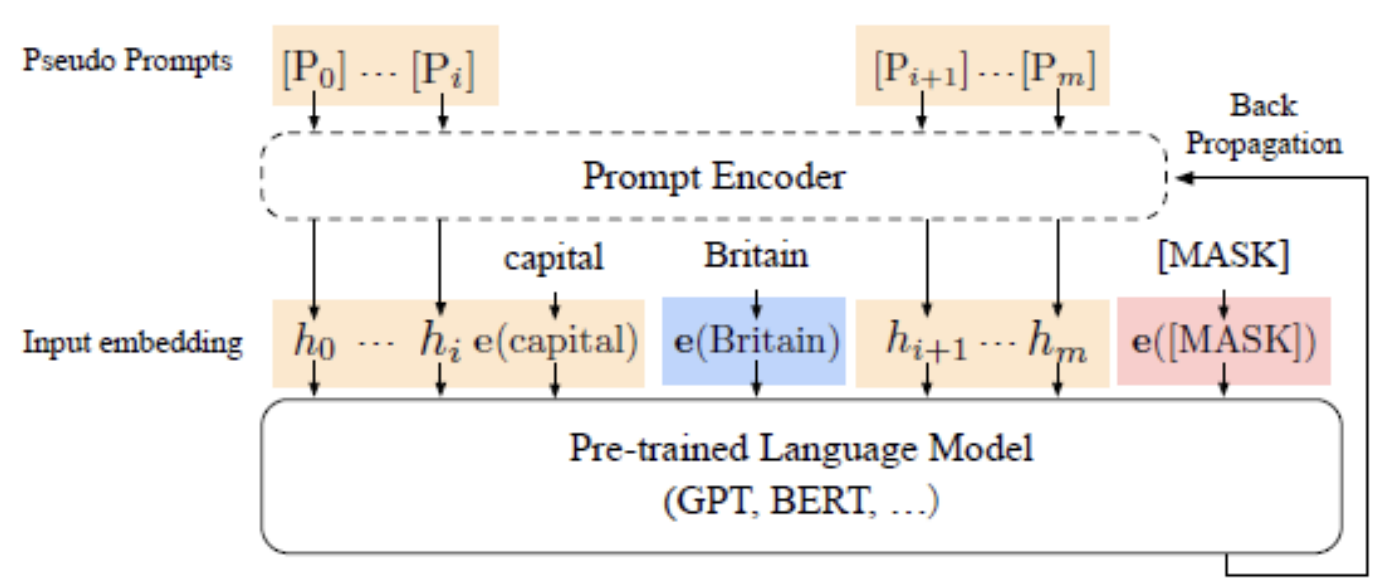
Methods

P-tuning[1] advantages:

- Part of the prompt words organize itself through downstream tasks, which can boost performance[1] and further explore the potential of deep learning models[2][3][4].



[1] Liu X, Zheng Y, Du Z, et al. GPT understands, too[J]. AI Open, 2023.
[2]Zhou J, Tian L, Yu H, et al. Dual context-guided continuous prompt tuning for few-shot learning[C]//Findings of the Association for Computational Linguistics: ACL 2022. 2022: 79-84.
[3]Schick T, Schütze H. It's not just size that matters: Small language models are also few-shot learners[J]. arXiv preprint arXiv:2009.07118, 2020.
[4]Schick T, Schütze H. Exploiting cloze questions for few shot text classification and natural language inference[J]. arXiv preprint arXiv:2001.07676, 2020.

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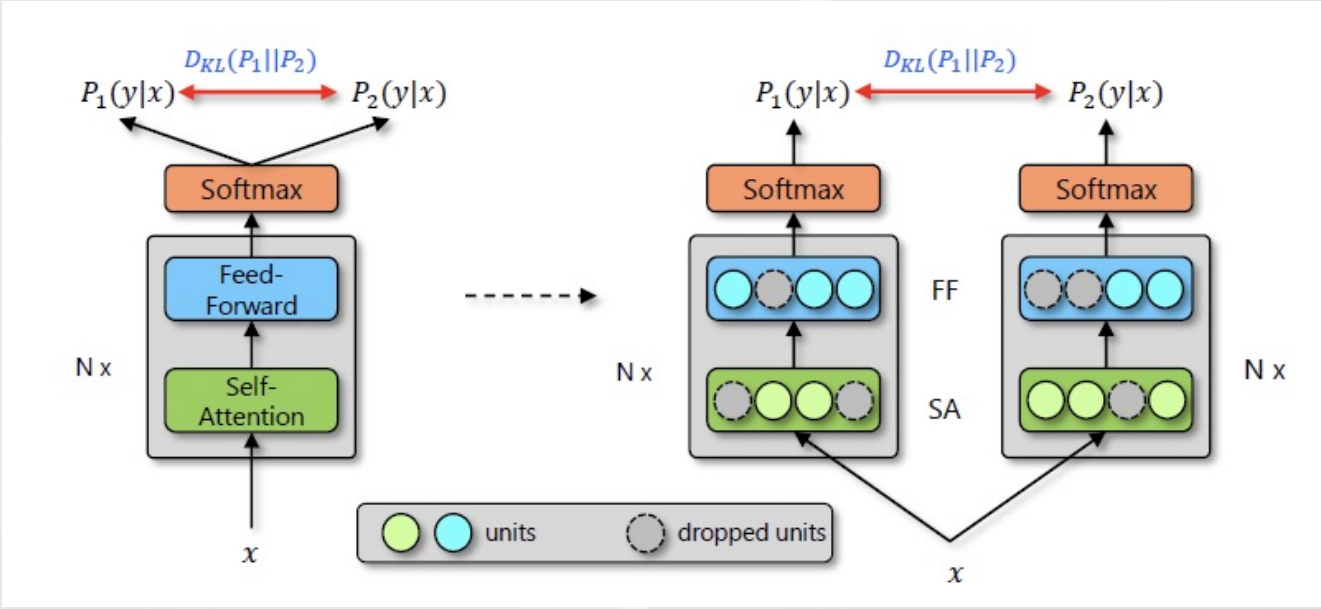
Methods

R-Drop[1] advantages:

- R-Drop can reduce the inconsistency between training and inference of the dropout based models.



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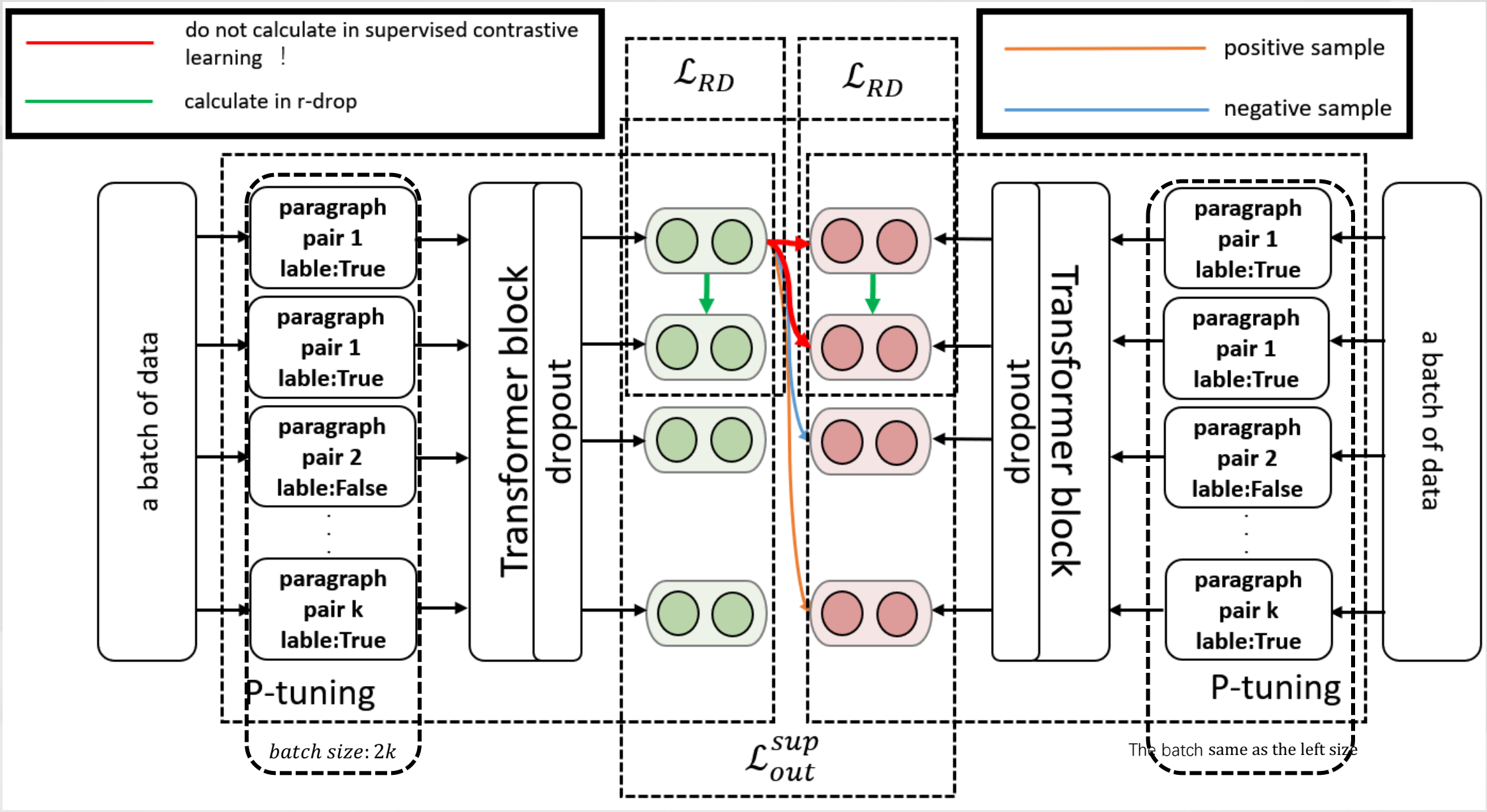
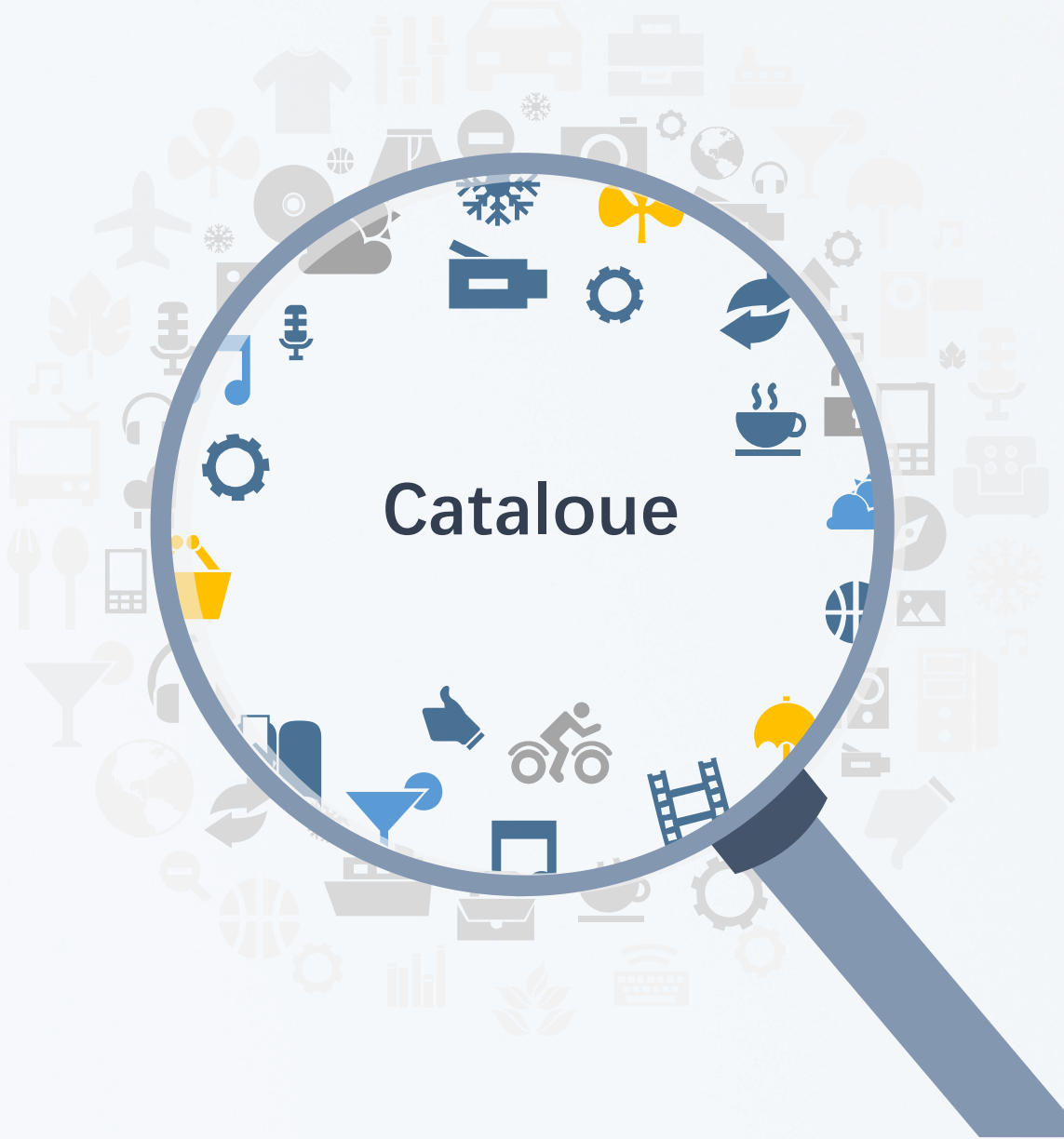
Our model and methods expiations



$\mathcal{L}_{out}^{sup}$: supervised contrastive learning loss

$\mathcal{L}_{RD}$: r-drop loss (including the downstream task loss)



Best performance：

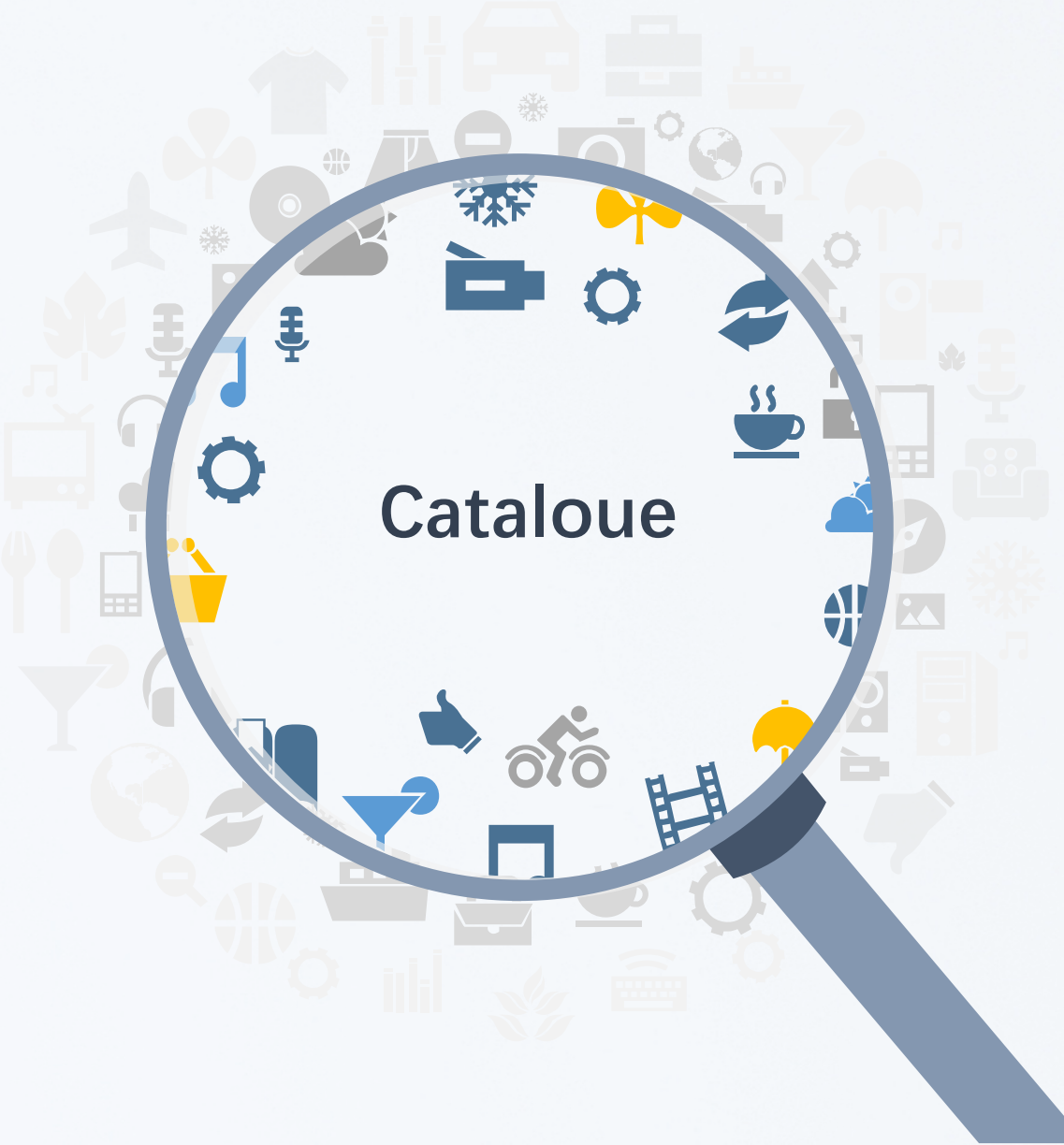
the score in the different difficulty test sets

	dataset1@ F1-SCORE	dataset2@ F1-SCORE	dataset3@ F1-SCORE
Test set	98.280	83.035	82.081

ablation experiments：

ablation experiment in different difficulty development sets

	dataset1 @ F1-SCORE	dataset2 @ F1-SCORE	dataset3 @ F1-SCORE
Our method	99.078	83.034	82.0
Without SupCon	96.902	81.016	78.623
Without SupCon & Rdrop	96.849	81.407	73.448



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Conclusion

- We use p-tuning, r-drop, supervised contrastive learning for solving the task of locating the author changes

- Experimental results show that exert supervised contrastive learning and r-drop methods to high-dimensional features can make the model better distinguish some subtle features, such as writing style and habits, etc.

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Have a nice day!