A simple but effective solution for Task 1 of KDD Cup 2022 Challenge on improving product search

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The target of task 1

Given a user specified query and a list of matched products, the goal of this task is to rank the products so that the relevant products are ranked above the non-relevant ones[1]. Relevance is broken down into four classes, named Exact(E), Substitute(S), Complement(C) and Irrelevant(I).

Figure 1. The target of task 1.

Data distribution and supplement data

The train data distribution of task 1 is {'exact': 43.64%, 'substitute': 34.27%, 'irrelevant': 16.89%, 'complement': 5.187%}. we add the supplementary data from task 2 and task 3 to task1. All the data are listed in Figure 2.

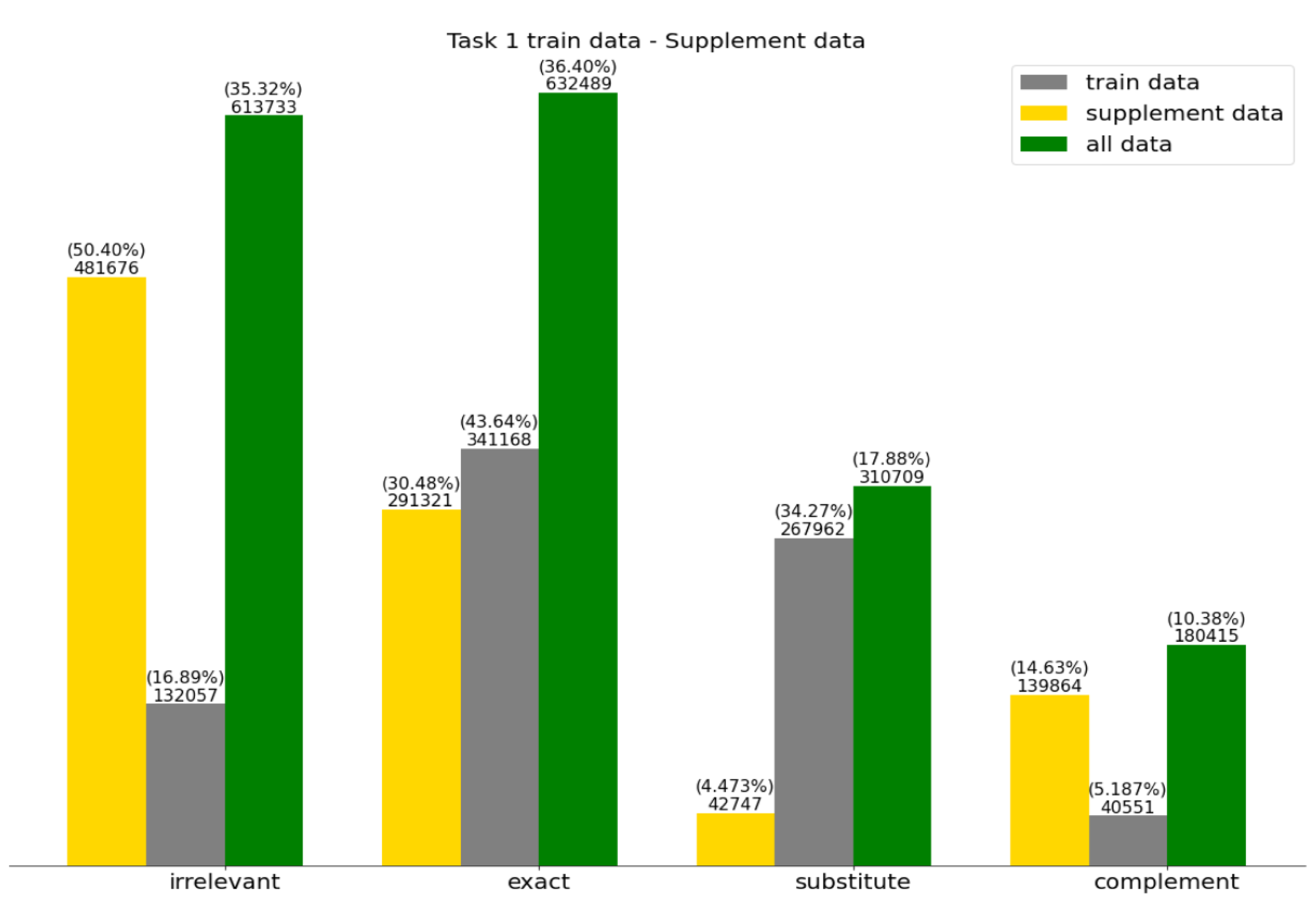

Figure 2. Data of task 1 distribution.

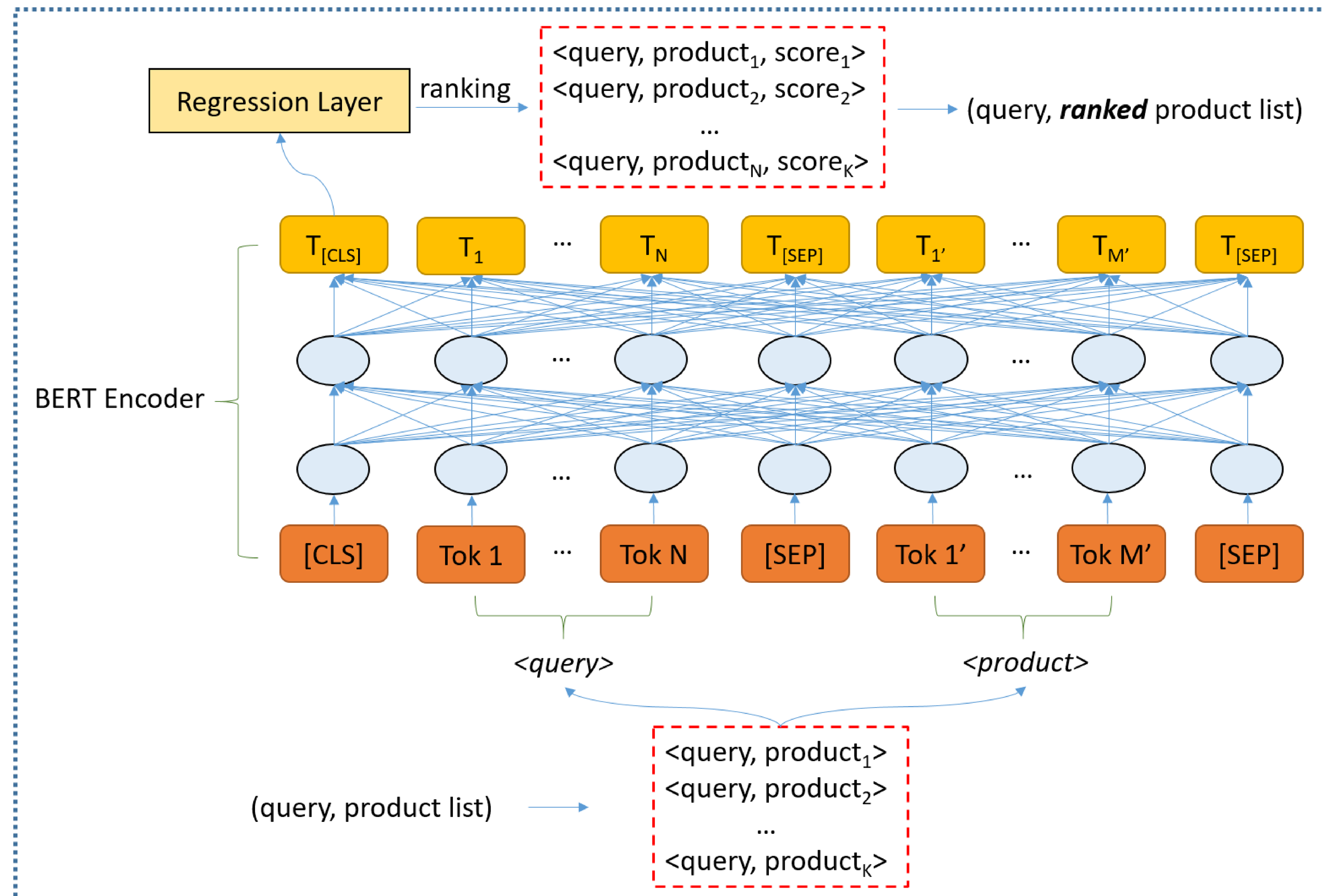

Figure 3. The model of our solution.

Our solution

In the modeling phase, we use a simple but effective unified paradigm, namely BERT Encoder + Regression Layer, where the regression layer is a normal fully connection layer. For different locales, we select different BERT Encoders. Summary information is shown in Figure 3. The unified framework is shown in Figure 4. We strictly follow the implementation described in the original paper[1] for the settings of the hyper-parameters.

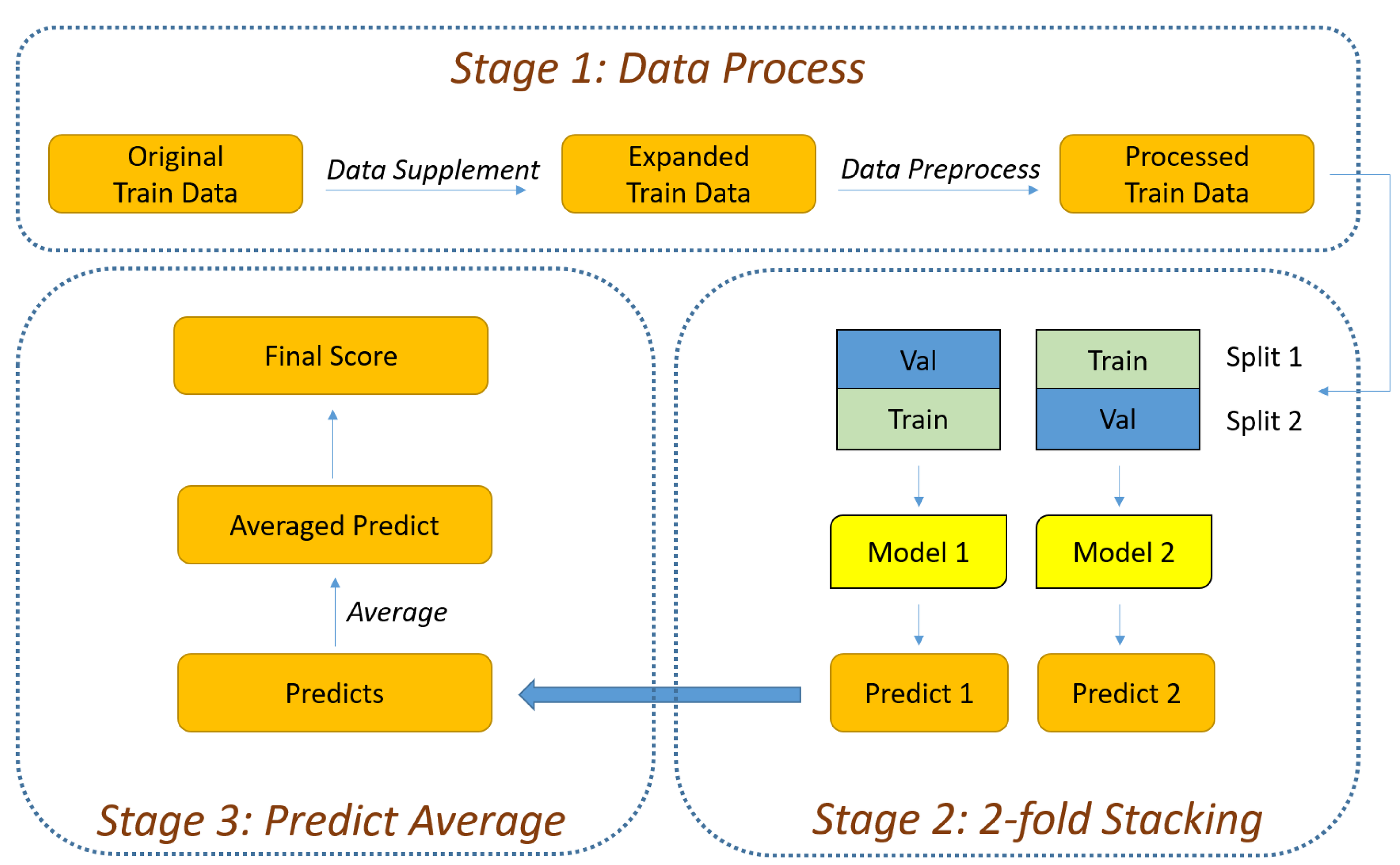

Figure 4. The unified framework of our solution.

Experimental results

Due to limited resources and time for verification, we set k=2 in k-fold cross validation and model ensemble (average results for each fold). The baseline is DeBERTaV3-large for the us locale, while mDeBERTaV3-base for the es locale and the jp locale. '-' in the Fold column means that the model do not use k-fold, and '-' in the Private Test nDCG column means that we can not get the result. Our final solution ***baseline-sup-2fold-all*** achieved a nDCG of **0.9012** in public test set and **0.9008** in private test set.

Model	Public Test nDCG	Private Test nDCG	
baseline(official)	0.8503	-	
baseline(ours)	0.8968	-	+0.0465
baseline-sup-us	0.8981	-	
baseline-sup-all	0.8983	-	+0.0480
baseline-2fold-us	0.8983	-	
baseline-2fold-all	0.8988	-	+0.0485
baseline-sup-2fold-us	0.9009	-	
baseline-sup-2fold-es-jp	0.9008	-	
baseline-sup-2fold-all	**0.9012**	**0.9008**	+0.0509

Figure 5. Online results.

Conclusions

According to our attempt and work, BERT Encoder + Regression layer also can get relatively good result.

Contact

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Acknowledgments

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References

[1] Pengcheng He, Jianfeng Gao, and Weizhu Chen. 2021. DeBERTaV3: Improving DeBERTa using ELECTRA-Style Pre-Training with Gradient-Disentangled Embedding Sharing.

[2] Chandan K. Reddy, Lluís Màrquez, Fran Valero, Nikhil Rao, Hugo Zaragoza, Sambaran Bandyopadhyay, Arnab Biswas, Anlu Xing, and Karthik Subbian. 2022.Shopping Queries Dataset: A Large-Scale ESCI Benchmark for Improving Product Search.