Joint Intent Detection and Entity Linking on Spatial Domain Queries

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1 Appendix

1.1 Setting

When training, the queries were further flattened with the way we described in section 5.2.2. We record L^{int}, L^{el}, L^{qt}, L^{mt} as the loss functions for query intent detection task, entity linking task, query type prediction task and mention type prediction task respectively. The final loss function is defined as follows.

$$L = \lambda_1(L^{int} + L^{el}) + \lambda_2(L^{qt} + L^{mt}), \qquad (1)$$

We jointly trained the two main task and two auxiliary task with the loss function Eqn. 1. λ_1 was 1 and λ_2 was 0.6. The hidden state size d is 300 for all CNN and RCNN modules. The Chinese word embedding modules were all initialed with Word2Vec(Li et al., 2018; Qiu et al., 2018). The GCN layer number in the SGCN pre-training model was 2. The N_{qi} was 100. The learning rate was set as 0.001 for RCNN, 0.0001 for CNN in query intent detection module and 0.01 for entity linking module. All the parameters were optimized with Adam optimizer(Kingma and Ba, 2014) and the batch size was 16. We trained the model with 20 epochs and an early stop mechanism was used when the accuracy on the validation set did not increase over ten batches. The hyper-parameters were evaluated on validation results.

1.2 Analysis

In order to further study the ability of MELIP on different query types, we divided test dataset into seven groups by query type. Then, we tested query intent detection and entity linking performances on them. The results are shown in Table 1.

For the query intent detection task, we can easily find that MELIP has the best performance on query type 6. This is because query type 6 is easier than other types and we also generated more data on it.

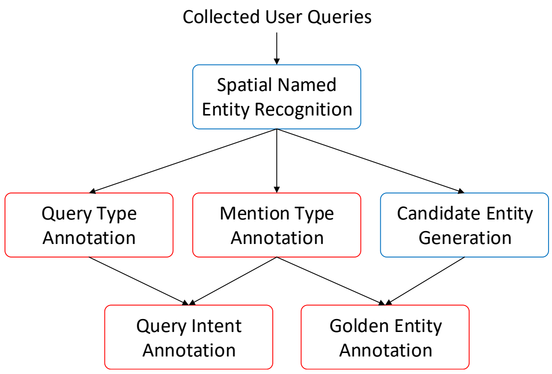


Figure 1: The generation process of our *SMQ*

For query type 2 and 4, there are less training and testing data on them. More data should be extracted on them to improve the MELIP performance. For query types 1, 3 and 5, we believe our MELIP could solve them well, with an accuracy close to 80%. For query type 0 with an accuracy of 57.23%, the worst performance is mainly because it is harder than other types. We will focus on dealing with it in our future work.

For the entity linking task, the accuracy of all query types is higher than 85%, which means that our MELIP has the powerful ability to handle entity linking task in the spatial domain.

1.3 Dataset Annotation

As illustrated in Figure 1, we develop *SMQ* dataset with six processes. We have explained these blue processes. Now, we will describe these res processes in detail as follows.

Query Type Annotation This step marks each query as one of the query types described in Table 2. We sent the query to three trained annotators to accomplish this task. We consider this query a valid query only if more than two annotators have labeled the same type for the same query. Queries labeled for different types by three annotators are

Query Type	0	1	2	3	4	5	6
Train Number	4352	11364	1062	4872	102	4657	17590
Test Number	352	1482	72	766	24	498	2305
QI Acc.(%)	57.23	80.75	69.38	83.21	80.33	79.77	89.48
EL Acc.(%)	85.07	87.82	91.00	87.89	86.53	95.40	89.96

Table 1: .The results of query intent detection and entity linking on different query types."QI" means query type prediction task while "EL" means entity linking task. The query type index is the same as Table 2

Type index	Query Type	Example
0	Ask for the distance information between two places	从上海到北京多少公里
1	Ask for the information between two places except distance and time	从上海到北京最近线路
2	Ask for the time information between two places	从上海到北京要多长时间
3	Ask for the location information of one place	上海市的准确位置在哪里
4	Ask for the information of one place except location	上海的土地面积
5	Ask for a recommendation	上海有哪些景点
6	Only one entity	上海迪士尼酒店

Table 2: The defined seven query types and their examples.

Type index	Mention Type	Type index	Mention Type
0	POI	5	BRAND
1	AREA	6	PROVINCE
2	AOI	7	AROUND
3	TAG	8	TIME
4	CITY	9	PERSON GROUP

Table 3: The defined ten mention types. The meaning of each type can be found in section 3.1

discarded. We also gave up those queries that could not be classified as one of the seven query types.

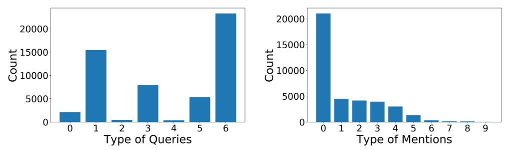
Mention Type Annotation Now, we annotate each mention generated from spatial named entity recognition as one of the ten mention types shown in Table 3. Three trained annotators are employed for this work and the annotation rules are the same with the query type annotation. Those mentions that do not fall into one of the ten mention types will be considered as common words in the query.

Query Intent Annotation After annotating all query types and mention types, we provide these results to three annotators to annotate the final query intent. The query intent is combined with query type and mention type with some easy rules. Some examples of query intent are shown in Table 4. The query intent annotation rules are the same as we described above. However, after labeling all queries, we will only keep the first 100 query intents in the order of their corresponding query numbers. Those query intents with fewer queries will be discarded.

Golden Entity Annotation In the last step, we will annotate the golden entity of each mention corresponding to. Three trained annotators are employed to do this work and the generation rules are the same as above. Besides the original query, mentions and candidate entities, annotators are provided with more entity attributes to help them distinguish candidate entities. Finally, each mention in the query will be labeled to a certain candidate entity as its corresponding entity in the POI-KB.

1.4 Dataset Statistics

We summarize the more statistics of *SMQ* in Figure 2. From Figure 2(a), we can find that the "only one entity" query has the highest weight. This is because many users only ask a simple entity as a query. In Figure 2(b), the mention type *POI* has the highest weight. This is the characteristic of spatial domain data that usually contains some special entity that is a certain point on the map.



(a) (b)

Figure 2: The more data statistics on *SMQ*. The type indexes in (a) and (b) are the same as Table 2 & 3

References

Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

Shen Li, Zhe Zhao, Renfen Hu, Wensi Li, Tao Liu, and Xiaoyong Du. 2018. Analogical reasoning on chinese morphological and semantic relations. *arXiv preprint arXiv:1805.06504*.

Query Type	Mention Type	Query Intent
Ask for the distance information between two place	AROUND, AOI	Ask for the distant from AROUND to AOI
Ask for the time information between two place	CITY, PROVINCE	Ask for the time from CITY to PROVINCE
Ask for the location information of one place	POI	Ask for the location information of POI
Ask for the information of one place except location	POI	Ask for evaluation of POI
Ask for a recommendation	TAG	Ask for recommendations for attractions
Only one entity	POI	Ask for the information of POI

Table 4: The examples of defined query intents.

Yuanyuan Qiu, Hongzheng Li, Shen Li, Yingdi Jiang, Renfen Hu, and Lijiao Yang. 2018. Revisiting correlations between intrinsic and extrinsic evaluations of word embeddings. In *Chinese Computational Linguistics and Natural Language Processing Based on Naturally Annotated Big Data(CCL)*.