

Joint task learning for relation extraction and named entity recognition

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In this work we present our system for RuREBus challenge held together with Dialog 2020 conference. The task consisted of 3 tracks: named entity recognition, relation extraction with provided named entity tags and end-to-end relation extraction. Our system took the first place in the named entity recognition track and the second place in the third track. For the second task we failed to submit the solution till the deadline but it was among the best systems. The systems for all tasks are based on Transformer models.

Key words: relation extraction, named entity recognition, transformer, bert

Совместное обучение моделей для извлечения отношений и именованных сущностей

Авторы

Организация

В данной работе мы представляем нашу систему для соревнования RuREBus, проводящегося совместно с конференцией Dialog 2020. Задача состояла из 3 дорожек: распознавание именованных сущностей, классификация отношений между заранее аннотированными именованными сущностями и извлечение отношений из неаннотированного текста. Наша система заняла первое место в задаче распознавания именованных сущностей и второе место на третьей дорожке. Для второй задачи мы не успели своевременно представить решение, но оно оказалось в числе лучших систем. Системы для всех задач основаны на моделях Transformer.

Ключевые слова: извлечение отношений, распознавание именованных сущностей, transformer, bert

1 Introduction

There are many ways to extract information from text. This task is often solved by extracting named entities and classifying relations between them. One of the most popular datasets for this task is TACRED [4] where semantic relations are understood as relations between two pairs of entities.

Nowadays, state-of-the art results for this dataset are achieved by using Transformer-based models [3]. The most advanced models (according to <https://paperswithcode.com/sota/relation-extraction-on-tacred>) use extra training data.

The authors of Matching the Blanks: Distributional Similarity for Relation Learning [1]. Knowledge Enhanced Contextual Word Representations

Among the systems that make use of only the provided data, the best results were achieved by Joshi et al. [2].

Unfortunately, such annotated datasets are scarce for most languages besides English. Some researchers have tried to solve this problem for the Russian language. They have used unsupervised approaches based on knowledge databases such as Wikidata and online encyclopedias such as Wikipedia. Models trained this way tend to be not specialized because the original database does not contain relations from the required domain. They also tend

to work only for the most popular relation types such as geographical or professional ones which are common to Wikipedia.

There are few annotated datasets for the Russian language. Among similar tasks to relation extraction there was held FactRuEval 2016 within the conference Dialog 2016. Within the competition contestants had to extract facts from news articles and to fill special slots in these facts (e.g. one of the fact types was 'Occupation' and its fields were 'POSITION', 'WHO', 'WHERE' and 'PHASE').

RuREBus competition was devoted to the problem of relation extraction and named entities recognition in a specialized business domain.

2 Shared task overview

The organizers of the competition have provided 188 annotated texts as the training dataset and 544 texts as the test dataset for the first and thirds tracks and $\langle N \rangle \langle N \rangle$ for the second track respectively. All texts were provided by the Ministry of Economic Development of the Russian Federation. The corpus consists of various regional and strategic plan reports. There are in total 8 named entity classes and 11 semantic relation classes. The organizers have also provided a large unannotated dataset for language model fine-tuning. However, we did not use it.

TEXT EXAMPLE

Named entity groups could contain rather broad types of entities, for example "SOC" entities contained social groups as well as various social attributes - phrases like 'blue collar workers' and 'housing accessibility' corresponded to this group.

2.1 Dataset

Type	Description
MET	Some quantitative metric
ECO	An economy entity or facility
BIN	A binary attribute
CMP	Comparative attribute
QUA	Qualitative attribute
ACT	Activity, actions, implemented policies
INST	Institutions and organizations
SOC	Social groups and characteristics

Table 1: Named entity types

Group	Type	Description
Current state of affairs	NNG	now negative
Current state of affairs	NNT	now neutral
Current state of affairs	NPS	now positive
Results	PNG	past negative
Results	PNT	past neutral
Results	PNS	past positive
Forecasts	FNG	future negative
Forecasts	FNT	future neutral
Forecasts	FNS	future positive
Goals	GOL	some abstract goals
Tasks	TSK	tasks and performed actions to achieve goals

Table 2: Semantic relation types

3 Our solution

3.1 Named entities recognition

3.2 Stand-alone relation extraction

3.3 Relation classification with provided named entity tags

4 Results

5 Conclusion

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