Attention Understands Semantic Relations
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Introduction

LMs are used in almost every NLP tasks, yet they are often criticized for memorizing instead of generalizing knowledge. As a result, model interpretation research area has been actively developing. Existing papers mostly focus on investigating grammatical relations, while semantic knowledge remains less studied.

To narrow the gap, we propose a simple Relation Extraction (RE) approach and interpret our outcomes. We perform on and analyze the behaviour of the BERT self-attention mechanisms.

Data and Methodology

Data: subset of the TREX dataset with texts annotated for relation triplets of 95 semantic relation types from WikiData.

RE Pipeline:
1) collect a vector of attention weights for each triplet from every attention map in the model
2) binary classifier identifies if a triplet has a semantic relation between its tokens
3) multiclass classifier labels meaningful triplets with a relation Id

Performance of our RE pipeline compared with the REBEL (Cabot andNavigli, 2021) performance on two datasets

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Results

Table: Comparing the performance of different models on the test set.

| Model    | Dataset | Pr | Rec | F1  |
|----------|---------|----|-----|-----|
| Our REBEL | TREX   | 0.223 | 0.534 | 0.312 |
| REBEL    | TREX   | 0.223 | 0.375 | 0.276 |
| Our      | DocRed | 0.294 | 0.437 | 0.363 |
| REBEL    | DocRed | 0.594 | 0.347 | 0.563 |

Classifiers performance on a test set compared with a randomly initialised BERT. Probes are selective.

Conclusion

We introduce a novel approach to interpreting Language models and use it to study BERT’s awareness of semantic relations.

We find that:
- semantic relations of different types are encoded with a combination of attention weights provided by different heads
- attention weights are not as informative as layers’ units activations but provide a reliable, straightforward approach to ranking the layers’ awareness of relational linguistic features
- none of the layers and attentions must be neglected while developing an unsupervised approach to relation extraction
- there are no individual relation-specific heads, yet one could meaningfully group relations by the heads’ relevance for them
- graphs are available through the link via QR code

The results of agglomerative clustering of the feature importance weights with cosine distance shows that the relation types are logically organised into semantic groups. A complicated way of how knowledge is structured inside language models is not purely stochastic but can be interpreted.

We find no strict mapping between the attention heads and the semantic relation types.