Course Project

Review of LowFER: Low-rank Bilinear Pooling for Link Prediction

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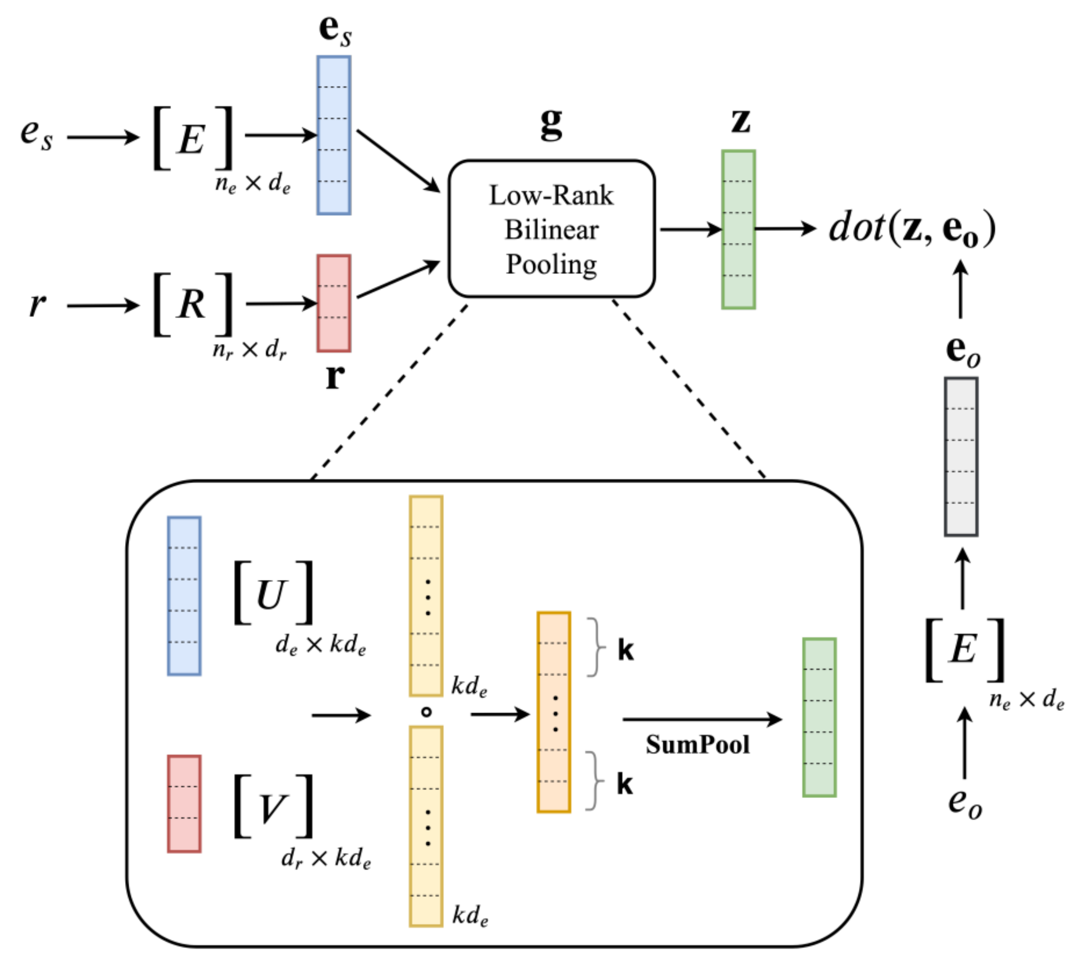
Introduction

Today, deep research is used to solve problems of big data analysis. Big data, often collected in so-called Knowledge Graphs, is used to analyze and predict events, predictive search and reveal hidden connections. Organized as object and subject Entities and Relations between them, they lose their usefulness when incomplete.

There are many different algorithms for KG complement. Both linear and non-linear models have been proposed to solve the problem. Bilinear models, while expressive, are prone to overfitting and lead to quadratic growth of parameters in the number of relations. Simpler models have become more standard, with certain constraints on bilinear maps as relation parameters. In this paper, we will consider a specific bilinear model.

Model

The LowFER model is a bilinear algorithm aimed at solving KG. Organized as object and subject Entities and Relations between them, they lose their usefulness when incomplete. The model from the original study is based on the TuckER algorithm and aims to predict multimodal relationships for knowledge graphs (in this particular case for thesauri and language KGs).



Pic.1 - LowFER model

Consider that entities and relations are not intrinsically bound and come from two different modalities, such that good fusion between them can potentially result in a knowledge graph of fact triples. Entities and relations can be shown to possess certain properties that allow them to function similarly to others within the same modality. For example, the relation "place-of-birth" shares inherent properties with the relation "residence". As such, similar entity pairs can yield similar relations, given appropriate shared properties. Like in multi-modal auditory-visual fusion, where the sound of a roar may better predict a resulting image within the distribution of animals that roar, a relation such as place-of-birth, can better predict an entity pair within a distribution of (person, place) entity pairs. In link prediction, we assume that the latent decomposition with MFB can help the model capture different aspects of interactions between an entity and a relation, which can lead to better scoring with the missing entity. We therefore apply the Low-rank Factorization trick of bilinear maps with k-sized non-overlapping summation pooling to Entities and Relations (LowFER).

Experimental result

For experimental testing, a dataset called RuWN-2021 was chosen. This dataset is the Russian version of the WordNet thesaurus from Princeton University. The Russian version contains 12 million parameters for the model (as opposed to 8 million for the VN from the original study). In this regard, we decided to conduct a partial comparative analysis of the application of the model, reducing the number of iterations to 30 for the original dataset and the Russian one.

We have obtained the following results:

```
INFO - main.py -   Training the LowFER model...
INFO - main.py -   Number of training data points: 282884
INFO - main.py -   Starting training...
INFO - main.py -   Params: 8650480
INFO - main.py -   Iteration numer 1 is running
INFO - main.py -   Epoch 1 / time 90.53296 / loss 0.013521139
INFO - main.py -   Iteration numer 2 is running
INFO - main.py -   Epoch 2 / time 90.88446 / loss 0.000688367
INFO - main.py -   Final Validation:
INFO - main.py -   Number of data points: 10000
INFO - main.py -   Hits @10: 0.0263
INFO - main.py -   Hits @3: 0.013
INFO - main.py -   Hits @1: 0.0048
INFO - main.py -   Mean rank: 15105.2795
INFO - main.py -   Mean reciprocal rank: 0.012298810894385266
INFO - main.py -   Final Test:
INFO - main.py -   Number of data points: 10000
INFO - main.py -   Hits @10: 0.0242
INFO - main.py -   Hits @3: 0.014
INFO - main.py -   Hits @1: 0.0059
INFO - main.py -   Mean rank: 15198.1264
INFO - main.py -   Mean reciprocal rank: 0.012848643358805293
```

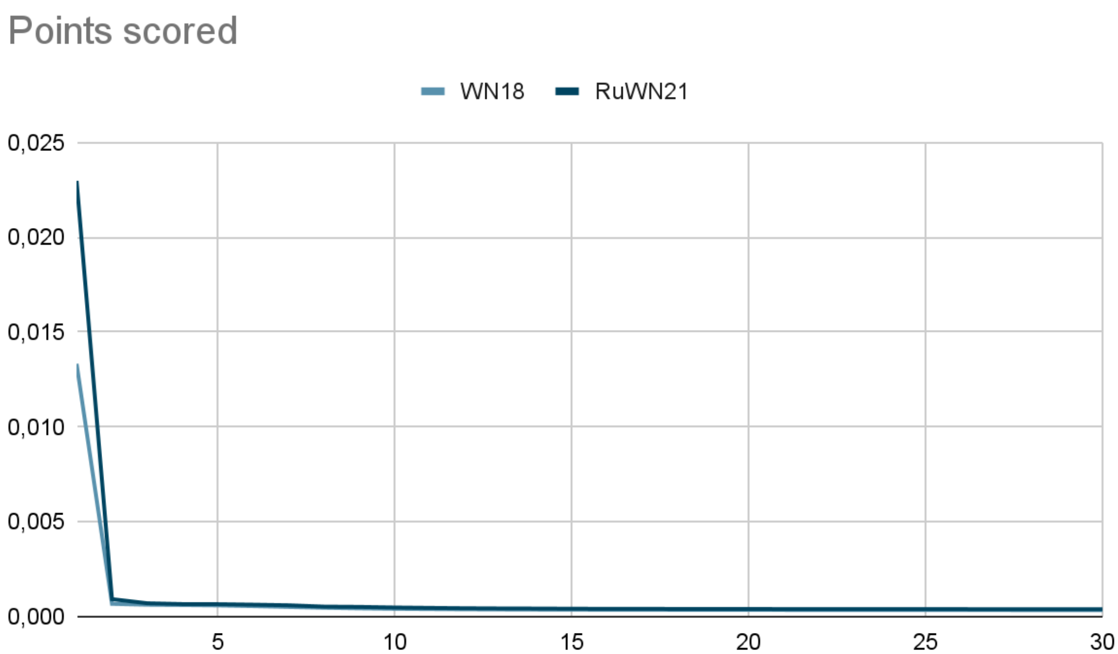
Pic.2 - Output example for original data (WN18)

After training the model, we conducted a comparative analysis of the results for both datasets:

Parameter	10th iteration		20th iteration		30th iteration	
DS	WN	**rWN**	WN	**rWN**	WN	**rWN**
H@10	0,87	**0,75**	0,95	**0,93**	0,95	**0,94**
H@3	0,83	**0,71**	0,95	**0,92**	0,95	**0,94**
H@1	0,75	**0,68**	0,94	**0,91**	0,94	**0,92**
MR	804	**890**	686	**704**	600	**622**

MRR	0,79	**0,76**	0,94	**0,89**	0,95	**0,91**
Loss 10^{-5}	4,1	**4,6**	3,5	**4**	3,4	**3,9**

Tab.1 - Results comparison



Pic.3 - Graph of loss parameter changes by iterations

Full results data could be found in logsWN18.txt and logsRWN21.txt files in the project folder.

Conclusion

In this work, the article "An Unsupervised Deep Learning Approach For Real-World Image Denoising" was studied and reviewed. The aims of the work and the advantages and disadvantages of the proposed approach were described. The proposed model is briefly described. The model has shown its effectiveness when working with the Russian-language thesaurus, and therefore can be used for its full analysis and machine learning of Linear models. The iterative graph (Pic.3) of the growth of parameters for RuWN-2021 very closely coincides with the growth for WN18, which allows us to make an assumption about similar results with a full cycle of 500 iterations.

Links

Original article: Amin, S., Varanasi, S., Dunfield, K., & Neumann, G. (2020). LowFER: Low-rank Bilinear Pooling for Link Prediction. In Proceedings of the 37th International Conference on Machine Learning (pp. 257–268). PMLR.

http://proceedings.mlr.press/v119/amin20a/amin20a.pdf

Original repo: Code for the paper "LowFER: Low-rank Bilinear Pooling for Link Prediction", ICML 2020

https://github.com/suamin/LowFER

Dataset: Loukachevitch N., Lashevich G. Multiword expressions in Russian Thesauri RuThes and RuWordNet. Proceedings of the AINL FRUCT 2016, 2016. pp.66-71.

http://www.labinform.ru/pub/ruthes/

Our repo: Testing the algorithm proposed in the article "LowFER: Low-rank Bilinear Pooling for Link Prediction", ICML 2020 on the Russian-language thesaurus of the WN format - RuWordNet for 2021.

https://github.com/zer0deck/LowFER

References

[1] Amin, S., Varanasi, S., Dunfield, K., & Neumann, G. (2020). LowFER: Low-rank Bilinear Pooling for Link Prediction. In Proceedings of the 37th International Conference on Machine Learning (pp. 257–268). PMLR.

[2] Dikeoulias, I., Amin, S., & Neumann, G. (2022). Temporal Knowledge Graph Reasoning with Low-rank and Model-agnostic Representations. In Proceedings of the 7th Workshop on Representation Learning for NLP (pp. 111–120). Association for Computational Linguistics.

[3] Balaževic, I., Allen, C., & Hospedales, T. (2019). TuckER: Tensor Factorization for Knowledge Graph Completion. In Empirical Methods in Natural Language Processing.

[4] Loukachevitch N., Lashevich G. Multiword expressions in Russian Thesauri RuThes and RuWordNet. Proceedings of the AINL FRUCT 2016, 2016. pp.66-71.