A survey of embedding models of entities and relationships for knowledge graph completion: Supplementary

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Triple Classification

Task Description

The triple classification task was first introduced by Socher et al. (2013), and since then it has been used to evaluate various embedding models. The aim of this task is to predict whether a triple \((h, r, t)\) is correct or not. For classification, a relation-specific threshold \(\theta_r\) is set for each relation type \(r\). If the plausibility score of an unseen test triple \((h, r, t)\) is higher than \(\theta_r\), then the triple will be classified as correct, otherwise incorrect. Following Socher et al. (2013), the relation-specific thresholds are determined by maximizing the micro-averaged accuracy, which is a per-triple average, on the validation set.

| Dataset          | \(|E|\) | \(|R|\) | #Triples in train/valid/test |
|------------------|-------|-------|-------------------------------|
| FB13 (Socher et al., 2013) | 75,043 | 13    | 316,232 5,908 23,733 |
| WN11 (Socher et al., 2013) | 38,696 | 11    | 112,581 2,609 10,544 |

Table 1: Statistics of the benchmark datasets for triple classification. In both WN11 and FB13, each validation and test set also contains the same number of incorrect triples as the number of correct triples.

Datasets

Information about benchmark datasets for the triple classification task is given in Table 1. FB13 and WN11 (Socher et al., 2013) are derived from the large real-world KG Freebase (Bollacker et al., 2008) and the large lexical KG WordNet (Miller, 1995), respectively. Note that when creating the FB13 and WN11 datasets, Socher et al. (2013) already filtered out triples from the test set if either or both of their head and tail entities also appear in the training set in a different relation type or order.

Main Results

Table 2 presents the triple classification results of KG completion models on the WN11 and FB13 datasets. The first 9 rows report the performance of models that use TransE/DISTMULT to initialize the entity and relation vectors. The last 12 rows present the accuracy of models with randomly initialized parameters. Note that there are higher triple classification results computed for NTN, Bilinear-COMP and TransE-COMP when entity vectors are initialized by averaging the pre-trained GloVe word vectors (Pennington et al., 2014). It is not surprising because many entity names in WordNet and Freebase are lexically meaningful. However, this is not always the case w.r.t. many domain-specific KGs.

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| Method                          | W11  | F13  | Avg.  |
|--------------------------------|------|------|-------|
| CTransR (Lin et al., 2015)    | 85.7 | -    | -     |
| TransR (Lin et al., 2015)     | 85.9 | 82.5 | 84.2  |
| TransD (Ji et al., 2015)      | 86.4 | 89.1 | 87.8  |
| TEKE, (Wang and Li, 2016)     | 84.8 | 84.2 | 84.5  |
| TranSparse-S (Ji et al., 2016)| 86.4 | 88.2 | 87.3  |
| TranSparse-US (Ji et al., 2016)| 86.8 | 87.5 | 87.2  |
| ConvKB (Nguyen et al., 2018)  | 87.6 | 88.8 | 88.2  |
| TransE-HRS (Zhang et al., 2018)| 86.8 | 88.4 | 87.6  |
| DISTMULT-HRS (Zhang et al., 2018)| 88.9 | 89.0 | 89.0  |
| NTN (Socher et al., 2013)     | 70.6 | 87.2 | 78.9  |
| TransH (Wang et al., 2014)    | 78.8 | 83.3 | 81.1  |
| SLogAn (Liang and Forbus, 2015)| 75.3 | 85.3 | 80.3  |
| KG2E (He et al., 2015)        | 85.4 | 85.3 | 85.4  |
| Bilinear-COMP (Guu et al., 2015)| 77.6 | 86.1 | 81.9  |
| TransE-COMP (Guu et al., 2015)| 80.3 | 87.6 | 84.0  |
| TransR-FT (Feng et al., 2016) | 86.6 | 82.9 | 84.8  |
| TransG (Xiao et al., 2016)    | 87.4 | 87.3 | 87.4  |
| lppTransD (Yoon et al., 2016) | 86.2 | 88.6 | 87.4  |
| TransE (Bordes et al., 2013)  | 86.5 | 87.5 | 87.0  |
| TransE-NMM (Nguyen et al., 2016)| 86.8 | 88.6 | 87.7  |
| TranSparse-DT (Chang et al., 2017)| 87.1 | 87.9 | 87.5  |

Table 2: Accuracy results (in %) for triple classification on WN11 (labeled as W11) and FB13 (labeled as F13) test sets, which are taken from the corresponding papers. “Avg.” denotes the averaged accuracy. [*] denotes that scores are taken from Nguyen et al. (2019).

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