A Chinese Corpus for Fine-grained Entity Typing

Chin Lee¹, Hongliang Dai¹, Yangqiu Song¹, Xin Li²
¹HKUST
²Tencent Technology (SZ) Co., Ltd.
cleeag@ust.hk, {hdai,yqsong}@cse.ust, alonsoli@tencent.com

Abstract
Fine-grained entity typing is a challenging task with wide applications. However, most existing datasets for this task are in English. In this paper, we introduce a corpus for Chinese fine-grained entity typing that contains 4,800 mentions manually labeled through crowdsourcing. Each mention is annotated with free-form entity types. To make our dataset useful in more possible scenarios, we also categorize all the fine-grained types into 10 general types. Finally, we conduct experiments with some neural models whose structures are typical in fine-grained entity typing and show how well they perform on our dataset. We also show the possibility of improving Chinese fine-grained entity typing through cross-lingual transfer learning.

Keywords: Fine-grained entity typing, Entity typing

1. Introduction
The task of fine-grained entity typing [Ling and Weld, 2012; Gillick et al., 2014] assigns fine-grained types such as /person/politician, /organization/company to entity mentions in texts. It provides additional details to entity mentions compared with the typing in traditional named entity recognition tasks [Chinchor, 1998; Finkel et al., 2005], which typically categorize entity mentions into very general types such as person, location, or organization.

Ultra-fine Entity Typing [Choi et al., 2018] introduces a new fine-grained entity typing task that requires to predict an open set of types for entity mentions. The dataset constructed for this task uses a very large tag set that contains around 10k fine-grained entity typing datasets usually use tag sets with no greater than 200 types. This task presents a much closer view for each entity mention. Consider the sentence: “Tim Cook announced the new iPhone this morning.” With the dataset constructed by [Gillick et al., 2014], the mention “Tim Cook” can only be identified as /person/business. But with ultra-fine entity typing, “Tim Cook” can be categorized under types such as businessman, executive, public figure, etc. These free-form type phrases provide a more comprehensive and detailed description on the entity mention.

Unfortunately, most corpora [Ling and Weld, 2012; Weischedel and Brunstein, 2005; Gillick et al., 2014; Choi et al., 2018] of fine-grained entity typing are in English. To our knowledge, there doesn’t exist a large-scale fine-grained entity typing dataset exclusively in Chinese. In view of the growth of the research in Chinese NLP, a dataset for Chinese fine-grained entity typing will provide great value. Thus, in this paper, we present a Chinese corpus of extremely fine-grained entity typing containing over 7,100 unique entity types. We adopt a similar policy as the Ultra-fine Entity Typing corpus [Choi et al., 2018] by allowing an open set of entity types for each entity mention. In addition, we construct 10 general types, and mapped each fine-grained type to them. This provides a simple hierarchy and

| Sentence with Mention | Label Types |
|-----------------------|-------------|
| 高尔基大街（现易名为特维尔大街）是莫斯科一条最主要的大街Gorky Street (now as known as Tverskaya Street) is one of the main streets in Moscow. | 街道/street, 路/road, 旅游景点/tourist attraction, 街/street, 大街/thoroughfare, 道路/path |
| 腾讯，天猫或许将成为最大的受益者。 | 品牌/brand, 公司/company |
| 欧佩克去年11月份决定今年上半年该组织原油日产限额从2503万桶提高到2750万桶。OPEC decided to increase the limit of daily production unit for the organization. | 国际组织/international organization, 组织/organization, 联盟/league |
| 我在西堤牛排上海虹口梦之店：同学小聚丫丫哈哈 | 品牌/brand, 地方/location, 餐馆/restaurant, 位置/location |
| I’m at Tasty Shanghai store: Friends gathering, haha | 人/person, 老师/teacher, 教师/school teacher |
| 嘿嘿，比赛前厚着脸皮拉着顾老师合了好几张嘿嘿，took some pictures with Mr. Gu before the game, haha |  |

Table 1: Samples from our crowdsourced dataset. Each example contains an entity mention, the context sentence, and the annotated labels. The entity mentions are highlighted in blue. The first three rows are from news or magazines; the last two rows are from Weibo, a Chinese social media platform similar to Twitter.

Table 1: Samples from our crowdsourced dataset. Each example contains an entity mention, the context sentence, and the annotated labels. The entity mentions are highlighted in blue. The first three rows are from news or magazines; the last two rows are from Weibo, a Chinese social media platform similar to Twitter.

can also be useful for downstream tasks.

Our dataset consists of two parts: a relatively small set of examples annotated via crowdsourcing that contains 4,800 entity mention examples, and a large corpus annotated via distant supervision with 1.9M entity mentions. The former is accurate and can be used for both training and evaluation; the latter can only be used for training. Different from the dataset in [Choi et al., 2018], in addition to news, maga-
zines and web articles, we also include samples from social media which contains informal texts. Table 1 lists some examples from our crowdsourced dataset.

Our code and dataset are available at https://github.com/HKUST-KnowComp/cfet

2. Dataset Construction

We annotate an open type set for each entity mention with a procedure similar to the Ultra-Fine Entity Typing task (Choi et al., 2018). This annotation procedure benefits from having greater overall type coverage, and the types also produce a more comprehensive description for each of the entity mentions. Our dataset is generated with two different methods: crowdsourcing via Amazon Mechanical Turk, and entity linking between Wikipedia and Wikidata. Crowdsourcing can provide an accurate dataset for both training and evaluation, distant supervision via entity linking can create a large corpus for training. On top of that, we provide a mapping between the fine-grained types and the 10 general types defined by us.

2.1. Annotation Via Crowdsourcing

We gather our entity mentions from four different sources: Golden Horse (He and Sun, 2016), Boson dataset provided by BosonNLP, MSRA’s open source NER dataset, and PKU’s Corpus of Multi-level Processing for Modern Chinese (Yu et al., 2018). Each source has distinct semantic and lexical characteristics, which diversifies the dataset. For the Boson, MSRA and PKU’s dataset, the sentences are mostly extracted from news or magazines, and thus are more formal and detailed. For the Golden Horse dataset, most of them are extracted from Weibo (a Chinese social media website similar to Twitter) posts, which are far more informal. We extract mentions from these sources and amass around 4,800 entity mentions with context sentences. 80% of the mentions are named entities (e.g. 香港/Hong Kong, 苹果公司/Apple Inc., 勒布朗·詹姆斯/LeBron James) and 20% of them are pronouns.

Our crowdsourcing procedure consists of two steps. In step one, we let the annotators annotate entity mentions based on a type vocabulary we provide. The type vocabulary is constructed with types extracted from Wikidata and types provided by Ultra-Fine Entity Typing (Choi et al., 2018). It contains around 14K distinct types. We also provide a mapping from simplified Chinese to both English and Traditional Chinese and let the annotators decide which language to use. We require 3 different annotators to annotate 2 types for each entity mention, i.e., there will be at most 6 distinct labels for each entity mention. Similar to previous work (Gillick et al., 2014), the label for each entity mention should be context dependent. If an entity mention has many eligible types (e.g., Donald Trump can be politician, businessman, or television host), we ask the annotators to annotate the types that most closely reflect the context. If the context does not provide any relevant information for annotating the mention, the annotators are asked to label them with the most well-known types at their discretion.

In step two, we present all the types annotated for each entity mention in step one and let five different annotators determine if each type of annotation is valid or not. We analyze this validation result and find that each pair of annotators agreed on 67.2% of the validation results they made. The disagreements result from a different understanding of certain entity terms, on the task definition, and on whether an entity belongs to a type. Our final dataset consists of only the types approved by more than 3/5 of the annotators. In total, we obtain around 4,800 unique examples and 1,300 unique types. The left side of Figure 1 shows the 50 most occurring fine-grained types in this dataset.

2.2. Annotation Via Distant Supervision

We construct our distant supervision dataset with the combination of Wikipedia and Wikidata. Inspired by prior work (Ling and Weld, 2012; Mintz et al., 2009), we use the anchor links in the Wikipedia data as our entity mentions. We explore all the items (each item in Wikidata may corresponds to an entity) in Wikidata and select those with a Chinese Wikipedia page as possible entities. Since each Wikipedia page title is unique, we can then link the entity mentions from Wikipedia to Wikidata and utilize the fields and properties in Wikidata to obtain the types for each mention. For each entity in Wikidata, we take the following properties as their types: instance of, subclass of, and occupation. For example, Leonardo DiCaprio has an instance of human, with occupations of actor, film actor, screenwriter, television actor, film producer, and stage actor. This distantly annotates an entity mention with types, and we can extract its context sentence to form a training sample. In total, we gather 1.9M training examples and 5,975 unique types with this approach. The 50 most occurring fine-grained types in this dataset is shown in the right side of Figure 1. Although a large number of samples can be obtained this way, it has the limitation that the labeled types for an entity mention do not reflect the context. Also, each entity mention normally possesses less than 3
2.3. General Type Mapping

Both our crowdsourced and distant supervision method provide great varieties of fine-grained types. However, we also believe that assigning a high-level, more general type to each entity mention is a necessity, since it may be required by some certain applications. Thus, all the fine-grained types are categorized into 10 general types defined by us: person, living thing, organization, location, group, event, concept, goods, others.

In order to find the corresponding general type for each fine-grained type, we first use the type hierarchy provided in Wikidata to perform automatic type mapping. A large number of the fine-grained types in our dataset are from Wikidata, where we can find properties such as subclass of and instance of for them. The values of these properties are usually higher-level types. For example, the type “company” is a subclass of “organization.” Thus, we first manually assign a number of relatively coarse-grained types in Wikidata to our 10 general types. Then, for each fine-grained type in our dataset that can be found in Wikidata, we recursively search through its higher-level types to find a general type for it. This approach also introduces noise, so some mappings may be incorrect.

Finally, we manually inspected all the type mappings and fix the incorrect ones to ensure quality. Out of 7182 mappings, we found 1516 incorrect ones. Table 2 shows the number of fine-grained types in each general type. On average, in our crowdsourced dataset, each mention has 3.1 fine-grained entity types and 1.3 general types. In our distant supervision dataset, each mention has around 1.6 fine-grained types, and 1 general type. Figure 2 shows the visualization of the occurrence of general types in our datasets.

3. Experiments

Experiments are conducted with neural entity typing models that follow the design of previous works (Dai et al., 2019; Shimaoka et al., 2016). We experimented with structures such as bi-LSTM and BERT (Devlin et al., 2019). We also trained both models on the Ultra fine-grained dataset (Choi et al., 2018) for comparison.

3.1. Experimental Settings

Similar to the typical neural entity typing models, the architecture of the models we experimented consist of three parts: context sequence representation, mention representation, and the final inference layer. We adapted certain model architectures to better match our Fine-grained typing objective. We use fastText (Mikolov et al., 2018) for Chinese word embedding and Glove (Pennington et al., 2014) for English word Embedding.

Both BERT implementation from HuggingFace and bidirectional LSTM are experimented to construct the context representation. Given a sentence $x_1, ..., x_n$, we aim to construct a representation of the mention $x_m$ with the informa-

| GT | #FGT | FGT Examples |
|----|------|--------------|
| person | 1305 | 交易员/trader, 女儿/daughter, 地质学家/geologist |
| living thing | 98 | 梨/pear,狗/dog, 象/elephant |
| location | 917 | 住宅/residence, 地区/region, 首府/district capital, 胡同/hutong |
| organization | 651 | 中学/secondary school, 银行/bank, 医院/hospital |
| group | 45 | 群众/community, 原住民/indigenous people |
| event | 686 | 意外事故/accident, 经济危机/economic crisis |
| concept | 735 | 时间/time, 经济理论/theoretical economics |
| creation | 824 | 社论/editorial, 文件/file, 世界地图/world map |
| goods | 1273 | 打字机/typewriter, 菜肴/dish, 电脑/computer |
| others | 648 | 青霉素/penicillin, 非蛋白胺基酸/non-proteinogenic amino acids |

Table 2: Number and examples of fine-grained types in each general type. “GT” denotes general type; “FGT” denotes fine-grained type.

| Dataset | Crowdsourced | Distant |
|---------|--------------|---------|
| Mentions | 4,798 | 1,908,481 |
| Unique FGT | 1,307 | 5,975 |
| GT per mention | 1.6 | 1.0 |
| FGT per mention | 3.1 | 1.3 |

Table 3: Statistics for our crowdsourced and distant dataset.
| Dataset                        | Method                  | Our dataset | Ultra-fine dataset |
|-------------------------------|-------------------------|-------------|--------------------|
|                               |                         | MRR | P   | R   | F1 | MRR | P   | R   | F1 |
| BiLSTM                        | 0.199                   | 30.5 | 14.6 | 19.8 |     | 0.160 | 27.0 | 16.2 | 20.3 |
| BiLSTM + General Types        | 0.200                   | 46.6 | 17.5 | 25.5 |     | -    | -    | -    | -    |
| BERT                          | 0.281                   | 42.2 | 30.9 | 35.7 |     | 0.221 | 47.9 | 20.6 | 28.8 |
| BERT + General Types          | 0.310                   | 64.1 | 38.2 | 47.9 |     | -    | -    | -    | -    |

Table 4: Fine-grained entity typing performance on the test set. We report mean reciprocal rank (MRR), macro-averaged precision, recall and F1 score. “+ General Types” indicates adding the general type mapping.

We first split the 4,800 crowdsourced examples equally into train, dev and test. Each training batch then comprises equal number of distant supervision data and randomly sampled crowdsourced data from its training set. The development and test set only contain the crowdsourced data. For comparison, we also trained the same model on the Ultra-fine dataset. When training on the Ultra-fine dataset, we followed their original training method, mixing the distant supervision dataset and the crowdsourced dataset to form the training set [Choi et al., 2018]. The dev set and test set are also only consisting of their crowdsourced data.

**BERT** We use BERT-base-Chinese for our dataset and BERT-base-Cased for the Ultra-fine dataset. We fine-tune BERT on both of the datasets for 5 epochs. We use Adam as optimizer with the learning rate set at 3e-5, $\beta_1 = 0.9$ and $\beta_2 = 0.99$. The batch size is 32 and max sequence length is set at 128.

**BiLSTM** We train the whole dataset with bidirectional-LSTM for 15 epochs. The configuration of Adam optimizer is the same as above, with learning rate set at 0.001. We set the batch size at 256 and max sequence length remains the same.

Both models are tested on our dataset and the Ultra-fine dataset. We also experiment training with and without the general types on our dataset with both models. The evaluation criteria are defined the same as previous work [Shimaoka et al., 2016, Choi et al., 2018]. Macro-averaged precision, recall, F1-score, and MRR (average mean reciprocal rank) are reported.

### 3.2 Training with Distant Supervision Dataset

We first split the 4,800 crowdsourced examples equally into train, dev and test. Each training batch then comprises equal number of distant supervision data and randomly sampled crowdsourced data from its training set. The development and test set only contain the crowdsourced data. For comparison, we also trained the same model on the Ultra-fine dataset. When training on the Ultra-fine dataset, we followed their original training method, mixing the distant supervision dataset and the crowdsourced dataset to form the training set [Choi et al., 2018]. The dev set and test set are also only consisting of their crowdsourced data.
Table 5: Test samples of model prediction when training on our distant supervision dataset with general type mapping. Light blue color denotes incorrect predictions.

| No. | Sentence                                                                 | Label                                                                 | Prediction                                                                 |
|-----|---------------------------------------------------------------------------|----------------------------------------------------------------------|----------------------------------------------------------------------------|
| 1.  | 澳大利亚队夺得女子4×100米自由泳接力前三名。The Australian team won the top three prizes for 400m freestyle women swimming. | 职业运动队/professional sports team, 团队/team, 体育队/sports team, 组织/organization, 国家队/national sports team | 职业运动队/professional sports team, 团队/team, 体育队/sports team, 组织/organization, 国家队/national sports team |
| 2.  | 北京大学20多个院系的1000多名大学生参加升旗仪式。More than 1000 Peking University's students from more than 20 faculties attended the flag raising ceremony. | 教学机构/educational institution, 大学/university, 教育机构/educational institution, 组织/organization, 学院/institute | 大学/university, 组织/organization |
| 3.  | 对于苹果已收购Chomp的报道，Chomp拒加置评，苹果亦尚未就此发表评论。Regarding the news of Apple acquiring Chomp, Chomp refuse to comment, and neither did Apple issue any statement. | 品牌/brand, 公司/company, 上市公司/public company, 科技公司/technology company, 组织/organization | 公司/company, 组织/organization |
| 4.  | 对此，德拉吉表示，未与英国央行或中国央行在常规操作外进行协作。Draghi said he did not illegally work with the Bank of England or People’s Bank of China. | 银行/bank, 政府机构/government agency, 组织/organization, 金融机构/financial institution | 银行/bank, 金融机构/financial institution, 政府机构/government agency, 组织/organization, 金融管理局/monetary authority |
| 5.  | 万里长城和太阳金字塔，迄今仍巍然屹立，成为人类文明进步的永恒标志。The Great Wall and the Pyramids are still standing today, becoming a symbol of human civilization. | 地标/landmark, 地点/location, 旅游景点/tourist attraction, 文化遗产/cultural heritage, 墙/wall, 位置/location | 地点/location, 旅游景点/tourist attraction, 建筑/architecture, 组织/organization |

| Level | P   | R   | F1  |
|-------|-----|-----|-----|
| General | 79.9 | 74.9 | 77.3 |
| Fine-grained | 28.6 | 22.1 | 24.9 |
| All    | 64.1 | 38.2 | 47.9 |

Table 6: Breakdown of the prediction results from BERT+General from Table 4

Even with a relatively high number of labels (five labels), Example 2 and 3 are situations when entity mentions are labeled more comprehensively, and the model is not able to pick up all the labeled types. The last two examples show situations when the model predicts some types that are not labeled in the ground truth.

Similar to the Ultra-fine dataset (Choi et al., 2018), we find that the type labels of some mentions may be incomplete. This is also similar to a common scenario in recommendation, where only some of the positive examples (the items that users like) are known (Heckel et al., 2017; Pan et al., 2008). For our data, it is hard to define “complete” and is almost impossible to construct it for every entity mention.

Improving type coverage for each entity mention is an interesting but challenging topic for future work. Nonetheless, our crowdsourced dataset provides high precision on the labeled types, along with a great amount and variety of types for each entity mention. Methods to address the recall issue of incomplete label set should be conducted depending on the use case of this dataset.

Examples in Table 5 show the models are able to learn to predict fine-grained types from our training dataset even with the simplest structures and parameter tunings.

3.4. Transfer Learning

Finally, we would like to see whether English fine-grained entity typing data can be used to improve the performance on Chinese data. We experiment transfer learning with Babylon word embedding (Smith et al., 2017) between English and Chinese. We first trained the Ultra-fine dataset on English with the English Babylon word embedding. We then extract the weights of the BiLSTMs and continue training on our Chinese dataset. We experiment transfer learning with entity typing data can be used to improve the performance on Chinese data.

We follow our setup in 3.2, splitting the crowdsourced dataset equally to form the train, dev and test set. The results are shown in Table 7. All the experiments are conducted with the general type mapping. The result shows improvements under both scenarios. Since most entity typing resources are in English, using transfer learning to improve model

| No. | Sentence                                                                 | Label                                                                 | Prediction                                                                 |
|-----|---------------------------------------------------------------------------|----------------------------------------------------------------------|----------------------------------------------------------------------------|
| 1.  | 澳大利亚队夺得女子4×100米自由泳接力前三名。The Australian team won the top three prizes for 400m freestyle women swimming. | 职业运动队/professional sports team, 团队/team, 体育队/sports team, 组织/organization, 国家队/national sports team | 职业运动队/professional sports team, 团队/team, 体育队/sports team, 组织/organization, 国家队/national sports team |
| 2.  | 北京大学20多个院系的1000多名大学生参加升旗仪式。More than 1000 Peking University's students from more than 20 faculties attended the flag raising ceremony. | 教学机构/educational institution, 大学/university, 教育机构/educational institution, 组织/organization, 学院/institute | 大学/university, 组织/organization |
| 3.  | 对于苹果已收购Chomp的报道，Chomp拒加置评，苹果亦尚未就此发表评论。Regarding the news of Apple acquiring Chomp, Chomp refuse to comment, and neither did Apple issue any statement. | 品牌/brand, 公司/company, 上市公司/public company, 科技公司/technology company, 组织/organization | 公司/company, 组织/organization |
| 4.  | 对此，德拉吉表示，未与英国央行或中国央行在常规操作外进行协作。Draghi said he did not illegally work with the Bank of England or People’s Bank of China. | 银行/bank, 政府机构/government agency, 组织/organization, 金融机构/financial institution | 银行/bank, 金融机构/financial institution, 政府机构/government agency, 组织/organization, 金融管理局/monetary authority |
| 5.  | 万里长城和太阳金字塔，迄今仍巍然屹立，成为人类文明进步的永恒标志。The Great Wall and the Pyramids are still standing today, becoming a symbol of human civilization. | 地标/landmark, 地点/location, 旅游景点/tourist attraction, 文化遗产/cultural heritage, 墙/wall, 位置/location | 地点/location, 旅游景点/tourist attraction, 建筑/architecture, 组织/organization |

| Level | P   | R   | F1  |
|-------|-----|-----|-----|
| General | 79.9 | 74.9 | 77.3 |
| Fine-grained | 28.6 | 22.1 | 24.9 |
| All    | 64.1 | 38.2 | 47.9 |
performance on low-resource Chinese entity typing tasks is an interesting topic for future work.

| Method       | Dataset | MRR  | P   | R   | F1  |
|--------------|---------|------|-----|-----|-----|
| BiLSTM       | crowd   | 0.254| 58.1| 22.9| 32.9|
| BiLSTM + T   | crowd   | 0.279| 58.5| 26.9| 36.9|
| BiLSTM       | distant | 0.200| 46.6| 17.5| 25.5|
| BiLSTM + T   | distant | 0.225| 57.3| 22.1| 31.9|

Table 7: Experiment results of transfer learning. “T” indicates transferring the trained BiLSTM weights. “Dataset” indicates the source of training data. Note that the upper half and the lower half are results from different test data and the figures are not comparable between the two halves.

4. Conclusion

We create a Chinese fine-grained entity typing dataset with each entity mention having an open number of entity types. The dataset contains a large distantly supervised dataset with 1.9M examples, and a smaller crowdsourced dataset containing 4,800 examples with 1,300 unique entity types. In total, our dataset contains 7,100 unique entity types. In addition, a mapping between fine-grained types and general types is established, creating a hierarchical relationship between the large number of types. We test the data on a number of models and show the usability of our dataset.

5. Acknowledgements

This paper was supported by the Early Career Scheme (ECS, No. 26206717) from Research Grants Council in Hong Kong and WeChat-HKUST WHAT Lab on Artificial Intelligence Technology.

6. Bibliographical References

Abhishek, A., Anand, A., and Awekar, A. (2017). Fine-grained entity type classification by jointly learning representations and label embeddings. In Proceedings ACL, pages 797–807, Valencia, Spain, April. Association for Computational Linguistics.

Chinchor, N. (1998). Overview of muc-7. In Proceedings of MUC-7.

Choi, E., Levy, O., Choi, Y., and Zettlemoyer, L. (2018). Ultra-fine entity typing. In Proceedings of ACL, pages 87–96.

Dai, H., Du, D., Li, X., and Song, Y. (2019). Improving fine-grained entity typing with entity linking. In Proceedings of EMNLP, pages 6211–6216, Hong Kong, China, November. Association for Computational Linguistics.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2019). Bert: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of NAACL, pages 4171–4186.

Finkel, J. R., Grenager, T., and Manning, C. (2005). Incorporating non-local information into information extraction systems by gibbs sampling. In Proceedings of the ACL, pages 363–370. Association for Computational Linguistics.

Gillick, D., Lazic, N., Ganchev, K., Kirchner, J., and Huynh, D. (2014). Context-dependent fine-grained entity type tagging. arXiv preprint arXiv:1412.1820.

He, H. and Sun, X. (2016). F-score driven max margin neural network for named entity recognition in chinese social media. CoRR, abs/1611.04234.

Heckel, R., Vlachos, M., Parnell, T., and D¨unner, C. (2017). Scalable and interpretable product recommendations via overlapping co-clustering. In ICDE, pages 1033–1044. IEEE.

Ling, X. and Weld, D. S. (2012). Fine-grained entity recognition. In Proceedings of AAAI.

Mikolov, T., Grave, E., Bojanowski, P., Puhrsch, C., and Joulin, A. (2018). Advances in pre-training distributed word representations. In Proceedings of LREC.

Mintz, M., Bills, S., Snow, R., and Jurafsky, D. (2009). Distant supervision for relation extraction without labeled data. In Proceedings of ACL-AFNLP, pages 1003–1011, Suntec, Singapore, August. Association for Computational Linguistics.

Pan, R., Zhou, Y., Cao, B., Liu, N. N., Lukose, R., Scholz, M., and Yang, Q. (2008). One-class collaborative filtering. In ICDM, pages 502–511. IEEE.

Pennington, J., Socher, R., and Manning, C. D. (2014). Glove: Global vectors for word representation. In Proceedings of EMNLP, pages 1532–1543.

Shimaoka, S., Stenetorp, P., Inui, K., and Riedel, S. (2016). An attentive neural architecture for fine-grained entity type classification. In Proceedings of AKBC, pages 69–74, San Diego, CA, June. Association for Computational Linguistics.

Smith, S. L., Turban, D. H., Hamblin, S., and Hammerla, N. Y. (2017). Offline bilingual word vectors, orthogonal transformations and the inverted softmax. arXiv preprint arXiv:1702.03859.

Weischedel, R. and Brunstein, A. (2005). Bbn pronoun coreference and entity type corpus. Linguistic Data Consortium, Philadelphia.

Yogatama, D., Gillick, D., and Lazic, N. (2015). Embedding methods for fine grained entity type classification. In Proceedings of ACL-IJCNLP, pages 291–296.

Yu, S., Duan, H., and Wu, Y. (2018). Corpus of Multi-level Processing for Modern Chinese.