Attribute Acquisition in Ontology based on Representation Learning of Hierarchical Classes and Attributes

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Abstract

Attribute acquisition for classes is a key step in ontology construction, which is often achieved by community members manually. This paper investigates an attention-based automatic paradigm called TransATT for attribute acquisition, by learning the representation of hierarchical classes and attributes in Chinese ontology. The attributes of an entity can be acquired by merely inspecting its classes, because the entity can be regarded as the instance of its classes and inherit their attributes. For explicitly describing of the class of an entity unambiguously, we propose class-path to represent the hierarchical classes in ontology, instead of the terminal class word of the hypernym-hyponym relation (i.e., is-a relation) based hierarchy. The high performance of TransATT on attribute acquisition indicates the promising ability of the learned representation of class-paths and attributes. Moreover, we construct a dataset named BigCilin11k. To the best of our knowledge, this is the first Chinese dataset with abundant hierarchical classes and entities with attributes.

1 Introduction

For Artificial Intelligence and Semantic Web researchers, an ontology is a document or database that formally defines the characteristic of terms and relations among them for knowledge base (Berners-Lee et al., 2001; Shadbolt et al., 2006; Lehmann et al., 2015), like the schema for relational database. Attribute plays a crucial role in ontology, describing the characteristic of given class and connects different entities in knowledge base (for example, “director” is an attribute for class “film”, which also connects entities of class “film” and “person”), here class means the word describing type of an entity. Thus attribute acquisition is essential for the task of ontology construction, acquiring attributes for the given hierarchical classes formed by hypernym-hyponym relation (i.e., is-a relation). The task shown in Fig. 1.

Here, we think the entity can be regarded as instance of its classes, thus the attributes of an entity can be acquired by inspecting its classes. For an enclosed or specific domain knowledge base, experts could acquire the attributes by combing the guidance of the meaning of classes in ontology and their expert-level background knowledge, however, such approach is label intensive and time-consuming, which is not scalable for an open domain knowledge base, due to the continuous update of domain categories and entity classes.

An effective and simple solution for attribute acquisition in open domain knowledge base is community-collaborated method. The typical examples are DBpedia (Lehmann et al., 2015), FreeBase (Bollacker et al., 2008) and Wikidata (Vrandečić and Krötzsch, 2014) etc. However, for Chinese knowledge bases, there is no such huge community to build and maintain the ontology within short time. Although various data-driven methods, deriving a large number of facts from large-scale corpora by automatic extraction, have been utilized to build large-scale open domain Chinese language knowledge bases (Niu et al., 2011) [Wang et al., 2013] [Xu et al., 2017], most of them reuse the existing taxonomy of online encyclopedias (such as Baidubaik1) to build ontology, which is static and usually coverage-limited.

1https://baike.baidu.com/, one of the largest Chinese language encyclopedias.
In this paper, we attempt to propose an automatic paradigm to acquire attributes depending on hierarchical classes, further for significantly improve the scalability of ontology and efficiency of building a knowledge base. Typically, compared with the meaning expressed by only one word to represent one class (e.g., “university” to indicate this class is a school for high education), the meaning of one class-path (several words connected through a path, e.g. “institute/school/university”, the former one is the hypernym of the latter one) is more explicit and solid. For example, “university” also means the body of faculty and students at a university, with the help of “institute” and “school”, the meaning of university is refined. For this reason, we utilize class-path to represent the hierarchical classes in ontology, instead of the terminal class word of the hypernym-hyponym relation (i.e., is-a relation) based hierarchy. Inspired by recent representation learning of knowledge base (Bordes et al., 2013; Wang et al., 2014; Lin et al., 2015; Xiao et al., 2015), we consider mapping the hierarchical classes and attributes into continuous vector space, and transforming the attribute acquisition problem into a prediction task.

Traditional data-driven method for knowledge base construction mostly allocate attributes to entities, which is damaged by the inconvenience so called multi-role entities. (e.g. there are two classes for every entity on average in BigCilin2, a Chinese open domain hypernym-hyponym based knowledge base, with nearly 4.5 million entities having more than two classes). For example, the entity “apple” can refer to both fruit and company, or even a movie, actually, there are about 12 meanings for the entity “apple” in Baidubaike. Some entities referring to the same things might also have different roles, such as the entity “Ronald Wilson Reagan”, can indicate both actor and president of American. In fact, unlike the value of attribute, e.g. the concrete “color”, like “green”, is the value of the attribute “color” of the entity “apple”, the attribute is more general. For the entities in the same class, they almost share the same attribute sets. For example, “apple” and “pear” under the class “fruit” have the same attribute sets. That means different from allocating attribute to entities, allocating attribute to class seems more sense.

Ambiguous attributes-allocation problem caused by multi-role entities between classes and attributes is the major challenge of our work. For instance, there is an attribute of “director” for entity “apple”, but the actual class for the attribute is unknown, due to the multiple roles of “apple”. such as “fruit”, “film”, or “company”, etc. Directly obtaining the corresponding pair of classes and attribute will lead to much noises during the training process, for example, “director” is not an attribute for “fruit”, even they are bridged by entity “apple”. In this paper, we propose a translation-based embedding method based on selective attention model, called TransAtt, with the ability of representation learning of hierarchical classes and attributes. Though our work is focused on Chinese, the proposed method is language-independent for attribute acquisition in ontology of knowledge base.

The main contributions of this paper are as follows:

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2http://www.bigcilin.com/. BigCilin contains over 9 millions entities and about 12 millions hypernym-hyponym relation (i.e., “is-a” relation) pairs with over 45 thousands classes concept.
i) Constructing a dataset called BigCilin11K, to the best of our knowledge, this is the first dataset with abundant hierarchical classes and attributes of entities in Chinese language.

ii) Presenting an automatic paradigm for attribute acquisition by learning the continuous representation of hierarchical classes and attributes, called TransAtt, which certainly relieves the burden of manual attribute acquisition.

2 Related Work

2.1 Ontology Construction

For an open domain knowledge base, the ontology cannot be modeled once for all, because it changes when new facts populated. The light-weight knowledge base YAGO is constructed based on WordNet (Miller, 1995) and Wikipedia (Suchanek et al., 2007), but it is limited in coverage of ontology when new facts emerge. Many other popular knowledge bases, like DBpedia (Lehmann et al., 2015), FreeBase (Bollacker et al., 2008) and Wikidata (Vrandečić and Krötzsch, 2014) etc., adapt community-collaborated method to maintain and extend the ontology on a website. As time goes on, a mass of volunteers have been accumulated for English knowledge base. However, for Chinese knowledge bases there is no such huge community to construct such a satisfactory ontology.

In recent year, there are many Chinese knowledge base being developed, but there still a huge research gap in the construction of ontology. Some famous Chinese language knowledge bases, like zhishi.me (Niu et al., 2011), XLore (Wang et al., 2013), and CN-pedia (Xu et al., 2017), focus on the extraction of entity-relation triples without constructing powerful and dynamic ontology. They utilize existing category information provided in encyclopedias (e.g., Wikipedia, Baidubaike) to construct ontology, which will be failed when new classes injected. BigCilin is a Chinese open domain hypernym-hyponym based knowledge base developed by Harbin Institute of Technology, which will dynamically construct its architecture of hierarchical classes when new entities are injected. However BigCilin does not have a complete ontology even with a hierarchical classes architecture, such as attribute-allocation of the classes.

2.2 Knowledge Base Representation Learning

Knowledge base representation learning aims at offering a continuous knowledge representation paradigm by transforming the entities and relations into continuous vector space. Translation-based embedding methods are adopted extensively in representation learning of knowledge base (Bordes et al., 2013; Wang et al., 2014; Lin et al., 2015; Xiao et al., 2015), sharing the core translation principle \( h + r = t \) (Bordes et al., 2013) for the triple \((h, r, t)\), where \(h, r, t\) indicate a head entity, a relation, and a tail entity, respectively, and their embedding vectors are \(h, r, t\). The basic idea behind the principle is that the relation \(r\) corresponds to a translation of the embeddings, translating the head entity to a tail entity. Unlike the entity-relation triple, class-attribute tuple has no explicit translation operator. So we just induce an attribute-corresponding matrix as translation operator, mapping given class to attributes space.

Besides, getting the corresponding pairs of class and attribute for training is unobtainable, due to the ambiguous attribute-allocation problem between class and attribute in data-driven knowledge bases. For this issue, a representation learning method with the ability of selection over classes should be considered, as this paper to be discussed.

3 Preliminaries

In this section, firstly, we introduce some concepts occurred in this paper and a brief overview of the notation representation of the subset of knowledge base. Then, formal description of our task will be presented.

**Ontology** We refer ontology as an architecture of knowledge base defining the characteristic of terms and relations among them. like the schema for relational database.

**Class** A class is the word describing the type of an entity, for example, “fruit” is a class of the entity “apple”, and they form a hypernym-hyponym relation.
Class-Path Representing the hierarchical classes of hypernym-hyponym based relations. The nodes of the path are classes, and the edges represent hypernym-hyponym relations between the nodes.

We investigate a subset of knowledge base involving classes and attributes information of entities, without the relational facts of entities. Formally, the subset denoted as \( K \), and \( K = \{ E, C, A, R_1, R_2, R_3 \} \), where \( E \), \( C \) and \( A \) are the set of entities, classes and attribute name respectively. \( R_1 \) is the set of hypernym-hyponym relation in ontology with two elements denoted as \((e_k, e_i)\) and \((c_j, c_i)\) respectively, where \( e_i \in E \), \( c_j \in C \), and their classes \( c_k, c_j \in C \). \( R_2 \) is the attribute-allocation for entities where each tuple element is denoted as \((e_i, a_j)\), where \( e_i \in E \), and \( a_j \in A \), which means that the entity \( e_i \) has the attribute \( a_j \).

![Diagram](image-url)

Figure 2: Formal Task Definition with Notation Representation of \( K \).

Given \( E, C, R_1 \), we can get some class-paths for \( \forall e \in E \), the \( k \)-th class-path of \( e \) is represented by \( p_k^e \), and \( p_k^e = (c_{i_1}^e, c_{i_2}^e, \ldots, c_{i_{n-1}}^e, c_{i_n}^e), \) where \( n \) is the length of class-path \( p_k^e \), also the number of classes in the path. For \( i \in [1, n-1], c_i^e, c_{i+1}^e \in C \) and \((c_i^e, c_{i+1}^e, e) \in R_1 \). One of class-paths is labeled with shadow in Fig. 2. In the remainder part, we use class-paths to represent the hierarchical classes. And \( R_3 \) is the attribute-allocation for class-paths with each tuple element denoted as \((p_i, a_j)\), where \( p_i \) is one of class-path in \( K \) and \( a_j \in A \), meaning the class-path \( p_i \) has the attribute \( a_j \). The left part of arrow in Fig. 2 illustrates the notation representation of \( K \).

Task definition Formally, given \( \{ E, C, A, R_1, R_2 \} \) of \( K \) from knowledge base, we are supposed to predict \( R_3 \), and further use \( R_3 \) for \( R_2 \) completion. The prediction of \( R_3 \) can be regarded as attributes prediction for class-paths, and the completion of \( R_2 \) based on \( R_3 \) is attributes prediction of entities, which is achieved by inspecting their classes. This procedure is illustrated in Fig. 2.

4 Methodology

The main idea is to apply a sequence model to the class-path, then jointly learn both representation of attributes and class-paths based on a translation-based embedding model together with selective attention over the class-paths, called TransAtt, to deal with ambiguous attributes-allocation problem between class-paths and attributes. In the end of this section, the training algorithm of TransAtt will be presented.

4.1 Representation Learning of Class-Path via LSTM

Since a class-path is a sequence of class words, a sequence model could be considered. Recurrent Neural Network (RNN) [Mikolov et al., 2010] is a type of artificial neural network whose connections between neurons form a directed cycle, and create a hidden state of the network which allows it to exhibit dynamic temporal behavior according to the history information. This feature makes RNN suitable for sequential data such as unsegmented connected handwriting or speech recognition. The most representative variant of RNN is Long Short Term Memory (LSTM) [Hochreiter and Schmidhuber, 1997] which is capable of learning long-term dependencies.
In this paper, we use LSTM to learn the representation of class-path. LSTM is nearly identical as RNN, except that the updates in hidden layer are replaced by different types of memory cells to store information, which makes it better at exploiting long term context. The LSTM-cell is implemented as Graves et al. (2005). Fig. 3 shows a LSTM sequence model which employs aforementioned LSTM-cell (light gray boxes), applied by the class-path "/抽象事物/机构/教育机构/学校/大学", which means "/abstraction/organization/educational institution/school/university" in English. The input is pre-Strained embedding vectors (Mikolov et al., 2013) of the class words in class-path, and the final output (dark gray boxes) of the sequence model is the vector representation of a given class-path.

4.2 TransAtt: a Translation-Based Embedding via Selective Attention Model

Unlike conventional translation-based embedding methods which focus on entity-relation triples \((h, r, t)\), the focus in our work is the two-elements tuples \((p, a)\) formed by different class-path and its attribute. Therefore, there is no explicit translation operator like \(r\) in triple \((h, r, t)\). To solve this problem, we construct a mapping-matrix for each attribute, and the translation process is \(pM_a = a\), where \(p\), \(a\), \(M\) are the embedding vectors of class-path, attribute and its mapping-matrix respectively.

From \(K\), we can get a set of tuples in form of \((P_e, a)\), where \(P_e\) is the set of class-paths for a given entity \(e\) and \(a\) is an attribute the entity. However, we do not know which of these class-paths in the \(P_e\) has attribute \(a\). In order to deal with the ambiguous problem between class-path and attribute as well as to learn their representation jointly, we propose an attention-based translation embedding model, called TransAtt, which is composed of three parts: (i) representation learning model for class-path; (ii) selective attention model over class-paths; and (iii) translation-based embedding model to predict attributes. An overview of TransAtt is shown in Fig. 4. Part (i) have been introduced in Sec. 4.1, and we now proceed to some details for the last two parts.

**Selective attention model over class-paths** As we have mentioned, \(P_e\) is the set of class-path for a given entity \(e\), i.e., \(P_e = \{p^e_1, p^e_2, ..., p^e_k, ..., p^n_e\}\), where \(p^e_i\) is one of class-paths of \(e\), and there are a

![Figure 3: A LSTM network for Class-Path Representation.](image)

![Figure 4: Translation-Based Embedding via Selective Attention Model.](image)
total of $n$ class-paths of $e$. To exploit the information of all class-paths, our model represents the set $P_e$ with a real-valued vector $p_e$ during the prediction of attribute $a$. $p_e$ depends on the representations of all class-paths $p^1_e, p^2_e, \ldots, p^i_e, \ldots, p^n_e$, thus it can be computed as a weighted sum of these representations by $p_e = \sum_i \alpha_i p^i_e$, where $\alpha_i$ is the weight of each representation $p^i_e$. Due to the ambiguous attributes-allocation between class-path and attribute, we cannot regard each class-path equally because of all class-paths $p_e$. Hence, we use the selective attention to de-emphasize the noisy class-path, and set $\alpha_i = \frac{\exp(s_i)}{\sum_i \exp(s_i)}$, where $s_i$ is used to score how well the input class-path $p^i_e$ and the predict attribute $a$ matches. We select the bilinear form which achieves the best performance among different alternatives: $s_i = p^i_e A a$, where $A$ is a learnable weighted matrix, and $a$ is the embedding vector of attribute $a$.

**Translation-based embedding model to predict attributes** For the given attention-based representation $p_e$, the set of class-paths, the translation-based embedding model first utilizes the simple linear transformation to map the attention-based representation $p_e$ into attribute vector space, then predict the attribute name based on some distance measure in the vector space. Now we can rewrite the previous simple translation process as $p_e M_a = a$, where $p$ is replaced by $p_e$ and $M_a$ is the attribute-corresponding mapping-matrix.

### 4.3 Training Algorithm

According to the translation-based embedding model, we want $pM_a = a$ when $(p, a)$ holds (i.e., $a$ should be one of the nearest neighbors of $pM_a$), otherwise $pM_a$ should be far away from $a$. To achieve that, we need an energy-based framework, the energy of a tuple is equal to $d(pM_a, a)$ for some dissimilarity measure $d$, which we set to either L1 or L2-norm.

Given $\mathcal{K}$, we can collect a set of tuples $(P_e, a)$ as training set $\Omega$, where $P_e$ is the set of class-path for a given entity $e$ and $a$ is an attribute of $e$. We then minimize a margin-based ranking criteria over the training set to jointly learn the representation of class-paths and attributes:

$$\mathcal{L} = \sum_{(P_e, a) \in \Omega} \sum_{(P_e, a') \in \Omega'} [\gamma + d(p_e M_a, a) - d(p_e M_{a'}, a')]_+$$

where $[x]_+$ denotes the positive part of $x$, $\gamma > 0$ is a margin hyperparameter, $a'$ is the corrupted attribute for $P_e$, and the set of corrupted tuples $\Omega'_{(P_e, a)} = \{(P_e, a') | a' \in A\}$, is composed of training tuples with attribute replaced by a corrupted attribute, which is selected from $A$ randomly.

To train the neural networks in TransAtt, we utilize backpropagation [Rumelhart et al., 1985] to compute the gradient of parameters. We then apply Adadelta [Zeiler, 2012] to perform optimization. Adadelta is an extension of Adagrad [Dhillon et al., 2011] that aims to reduce its aggressive, monotonically decreasing learning rate. Instead of accumulating all past squared gradients, Adadelta restricts the window of accumulated past gradients to a certain fixed size.

### 5 Experiments

In the experimental stage, we implement and train the TransAtt to learn the embedding representations of class-paths and attributes. We first outline the preparation in experimental setup, including a dataset called BigCilin11K which we construct manually, as well as the evaluation metrics. We empirically study and evaluate TransAtt on two tasks: attributes prediction for entity (abbr. APE), and attributes prediction for class-path (abbr. APC). These two tasks evaluate the performances of our representative method from two diverse directions. In detail, APE focuses on evaluating TransAtt’s capacity of selection over classes for attributes of multi-roles entities, while APC focuses on the precision of attributes prediction for class-path based on TransAtt’s representation learning. Finally, we report the performance and perform visualization on our model.

#### 5.1 Dataset Construction

BigCilin has abundant information of hierarchical classes and the capacity of dynamically building the hierarchical structure given unknown entities. Furthermore, BigCilin is a data-driven knowledge base
which extracts attribute facts from encyclopedias (like info-box of Baidubaike). Based on BigCilin, we construct a dataset called **BigCilin11K** as follow:

1. Randomly extract 20,000 entities and their classes. Based on these classes, obtain the entire database of hypernym-hyponym relations in the class-level from BigCilin, i.e., $E, C, R$ of $K$. Then, filter the entities without attribute and approximately 11,000 entities are left. i.e., $A, R$ of $K$.

2. Construct and store the class-paths of every entity based on the extracted hypernym-hyponym relation set $R$ at entity-level and class-level.

3. Filter the attributes with low frequency. Select the attributes which have appeared in at least 20 entities (the threshold is determined by the coverage of entity with attributes).

We also randomly select 3,000 entities to evaluate the task of attributes prediction for entities and construct a class-path set including 240 class-paths that are unseen in training stage. The statistics of the dataset BigCilin11K is shown in Tab.1, where APE and APC represent the tasks of attributes prediction for entities and class-path respectively.

| -           | # Class-Paths | # Entities       | # attributes |
|-------------|---------------|------------------|--------------|
| Trian       | 5,174         | 11,161           | 286          |
| Test        | 240 (for APC) | 3,000 (for APE)  |              |

Table 1: The Statistics of BigCilin11K.

5.2 Evaluation Metrics

We adopt evaluation criteria in information retrieval field, because the tasks of attributes prediction from a candidate attribute set are considered as retrieval tasks. In this paper, $P@k$ and $Hits@k$ are utilized to evaluate performance in the two tasks.

$P@k$ measures the precision of top-$k$ returned results, corresponding to the number of relevant attributes in top-$k$ returned results. e.g., $P@10$ calculates the proportion of relevant attributes in top-10 returned results, if there are 7 relevant attributes, $P@10$ equals to $7/10 = 0.7$. In order to measure the overall performance on $P@k$, we calculate the mean value as $\sum_{n=1}^{Q} P@k(q)/Q$, where $Q$ is the number of entities or class-path.

$Hits@k$ measures the proportion of entities attaining at least one relevant attribute in the top-$k$ returned results. e.g. if there are 100 entities and 88 of them attain at least one relevant attribute in the top-10 returned results, then the $Hits@10$ is $88/100 = 0.88$.

5.3 Attributes Prediction for Entity (APE)

Viewing from an entity, predicting attributes for it is undoubtedly necessary and important. A more exciting work is bonding the predicted attributes with some class-paths of the entity, because the entity might have multi-roles, like the example of “苹果(apple)” mentioned before. Therefore, we propose the task of attributes prediction for entities (abbr. APE), in order to predict the attributes for given entity as well as bond them with relative class-paths.

Since the entity is regarded as instance of its classes, the set of attributes for an entity can be obtained by merely inspecting its classes, especially for fine-grained classes. In APE, for a given entity, we first obtain its class-paths from $K$, then use them to predict the attributes of entity. The prediction phase utilizes the entire TransAtt model with parameters and representation learned. $Hits@k$ evaluation method is adapted for APE (filtering of common attributes, like “中文名(Chinese name), “外文名(English name), etc.) because there is no complete standard entity-attribute dataset but only some incomplete entities’ information extracted from Baidubaike’s info-box for the 3,000 test entities (Tab.1) in the evaluation stage.

Besides inspecting $Hits@k$ on overall entities, different categories of entities are also considered (i.e., “Things”, “Abstraction”, “Person”). Final results are shown in Tab.2 where number in brackets are the number of entities of corresponding category. Results indicate that nearly 76% of overall entities have obtained at least one info-box attribute in top-20 predicted attributes. For entities of “Person”
type, the results of Hits@k are all over 80% except Hits@1. For the other two categories, the performance is poor as compared to overall evaluation. The results in Tab. 2 is evaluated under the worse situation, due to the incompleteness of info-box producing such as false negative noise. A more suitable method P@k will be manually evaluated in task APC, but it is not automated and hence time-consuming.

Figure 5: Visualization of top Predicted attributes of Multi-Roles Entities.

Since we are more concerned about multi-roles entities in APE, which requires bonding predicted attributes with relative class-paths, we further illustrate the predicted attributes by our model for two multi-roles entity samples in Fig. 5, namely, “苹果 (apple)” and “利华 (Li Hua)”. Class-paths for the two entities revealing the multi-roles nature are illustrated on the left hand side (e.g., tree class-paths for entity “苹果 (apple)” representing roles of fruit, film, and company respectively). Following the arrow, we outline the top predicted attributes and two matrices representing the selective class-paths attention weights of entities. Different columns of matrix represents the attention of predicted attributes for different class-paths, where darker cell indicates higher weights. From the attention matrices, it is observed that the predicted attributes attend the relative class-paths and nearly zero on uncorrelated ones, e.g., an accurate example is the class-path “/abstraction/film”, which gets the attentions of attributes “length, production company, producer”. However, there are also some mistakes: the attributes “Chinese name” and “English name” only attend one of the class “person” or “company”, which is inaccurate because both of them should have these two attributes in common sense. Fortunately, such mistake can be remedied by the task of APC, which is from viewpoint of class to execute the prediction.

| Hits@k | Thing | Abstr. | Person | Overall |
|--------|-------|--------|--------|---------|
| (848)  | (1,505) | (727)  | (2,641) |
| Hits@1 | 26.30 | 26.51  | 64.37  | 36.80   |
| Hits@5 | 50.71 | 46.18  | 80.47  | 56.57   |
| Hits@10| 60.73 | 56.35  | 84.73  | 65.05   |
| Hits@15| 67.92 | 63.85  | 87.48  | 71.34   |
| Hits@20| 73.58 | 73.58  | 89.27  | 75.99   |

| mean P@k | Thing | Abstr. | Person | Overall |
|-----------|-------|--------|--------|---------|
| (59)      | (71)  | (15)   | (184)  |
| mean P@1 | 77.97 | 83.10  | 73.33  | 78.26   |
| mean P@5 | 70.85 | 77.46  | 68.00  | 73.37   |
| mean P@10| 65.08 | 68.73  | 72.67  | 67.45   |
| mean P@15| 60.34 | 62.63  | 68.89  | 62.43   |
| mean P@20| 53.64 | 55.92  | 61.67  | 55.76   |

Table 2: Hits@k Evaluation on APE task.

Table 3: P@k Evaluation on APC task.

5.4 Attributes Prediction for Class-Path (APC)

In the viewpoint of class-path, we propose the task of attributes prediction for class-path (abbr. APC) in order to evaluate the capacity of model for mapping class-paths to attributes, which is helpful for dynamic ontology construction. During the prediction process of this task, we utilize TransAtt model without selective attention model over class-paths, as each prediction only involves a unique class-path and hence selective attention is not needed.
Currently, there is lack of support for standard complete class-attribute pairs dataset in Chinese language, so we manually label “True” or “False” for top-k predicted attributes (excluding common attributes such as “中文名(Chinese name), “外文名(English name)”). The manual labeling principles are follows:

(1) Filter inaccurate class-paths that include fake class word or are not consistent with the hierarchy of hypernym-hyponym.

(2) Filter class-path that are used to describe an abstract concept but not concrete entity, e.g., “抽象事物/能力/竞争力(/abstraction/capacity/competitiveness)”.

(3) Utilize search engine if meet with any unfamiliar domain or word.

After filtering, 184 of 240 test class-paths (see Tab. 1) are included in $P@k$ evaluation. Final results are shown in Tab. 2 where number in brackets are the number of entities of corresponding category after filtering. From the results, it is observed that the continuous representation learned can be utilized to predict attributes accurately for class, with higher than 75% of $P@1$ in overall class-paths and nearly 70% of $P@10$ of different categories. These given class-paths are unseen in training stage, but can be mapped to relatively accurate set of attributes, which indicates that the construction of ontology can be dynamic. We also outline some examples from prediction results in Tab. 4 with Chinese and English language labeled. Note that they are in different domains, but our model can predict domain relative attributes for them accurately.

| Class-Path: /抽象事物/电影/歌曲/名曲(/abstraction/drama/songs/famous songs) |
|---------------------------------|---------------------------------|
| top-10 attributes: 发行时间(issuem date), 歌曲时长(duration), 编曲(arranger), 歌曲语言(language), 填词(lyricist), 所属专辑(album), 歌曲原唱(original singer), 演唱风格(style), 出生日期(birth date) |

| Class-Path: /抽象事物/组织/医院/烟台市医院(/abstraction/organization/hospital/hospital of Yantai) |
|---------------------------------|---------------------------------|
| top-10 attributes: 地理位置(location), 成立时间(founding time), 所属地区(affiliating area), 地址(address), 医院等级(hospital level), 医院类型(type of hospital), 性质(attribute), 占地面积(floor space), 归属(affiliate), 行政区类别(type of administrative region) |

| Class-Path: /物/药品/精神药品(/thing/drug/spirit drug) |
|---------------------------------|---------------------------------|
| top-10 attributes: 药品类型(drug type), 用途分类(purpose), 规格(specification), 药品名称(name), 药型(dosage form), 用途用量(usage and dosage), 批准文号/license permission number, 别称(alias), 性质(nature) |

| Class-Path: /物/植物/树木/花卉(/thing/biology/botany/tree/flower tree) |
|---------------------------------|---------------------------------|
| top-10 attributes: 门(phyllum), 科(class), 目(order), 属(genus), 种(kingdom), 中文名称(Chinese scientific name), 拉丁学名(Latin scientific name), 科(family), 属(subclass), 种(species) |

| Class-Path: /人/名人/明星/亚洲明星(/person/famous person/star/Asia star) |
|---------------------------------|---------------------------------|
| top-10 attributes: 国籍(nationality), 出生地(birthplace), 出生日期(date of birth), 毕业院校(graduate institution), 职业(profession), 主要成就(achievements), 民族(ethnicity), 性别(gender), 代表作品(representative work), 逝世日期(death date) |

Table 4: Cases of top-10 Predicted attributes of different domain Class-Path samples.

6 Conclusion

This paper investigates an automatic paradigm of attribute acquisition in ontology by learning the continuous representation of class-paths and attributes, which is called TransAtt. To solve the problem of ambiguous allocating attributes to classes in data-driven knowledge bases, TransAtt utilizes selective attention over class-paths. Throughout the entire experiment, we construct a dataset called BigCilin11K and design two different attribute acquisition tasks to evaluate the performance of TransAtt and the learned distribution representation from different viewpoints and application context. The results show that TransAtt has the ability of selecting over class-paths for attributes prediction of multi-roles entity, and predicting attributes accurately for given class-paths even not seen before. The mechanism of automatic attribute acquisition can help ontology construction achieve automatic attribute acquisition to further improve the scalability of ontology and efficiency of building a knowledge base. Besides, though this work focus on Chinese ontology, our proposed method is language-independent for automatic attribute prediction.
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