Entity Alignment Method for Power Data Knowledge Graph of Semantic and Structural Information

Wang Zhiqiang¹, Wang Yuan²,³*, Zhao Kang²,³, Wang Xin⁴ and Hu Hui⁵

¹State Grid Zhejiang Information & Telecommunication Co., LTD, Hangzhou, Zhejiang, 310020, China
²NARI Group Corporation/State Grid Electric Power Research Institute, Nanjing, Jiangsu, 211000, China
³China Realtime Database Co., Ltd, Nanjing, Jiangsu, 211000, China
⁴State Grid Anhui Electric Power Co., LTD, Hefei, Anhui, 230061, China
⁵Xi’an Jiaotong University, Xi’an, Shanxi, 710049, China

* 406839653@qq.com

Abstract. With the continuous deepening of information construction of State Grid Corporation of China, organizing and utilizing the accumulated mass run data effectively and intelligently has become an urgent problem to solve. Knowledge graph has become an increasingly important hot technology for establishing semantic connection network for power data in full-service unified data centre. Entity alignment is one of the key steps for constructing high-quality power knowledge graph to solve the problem of a large number of entity heterogeneity and redundancy existing between different business systems. This paper proposes an entity alignment method for power data with semantic and structural information with a co-training framework. The semantic and structural models are complemented from the other after they are trained under their perspectives separately. The experiment shows the model achieves satisfactory results with higher accuracy and F1.

1. Introduction
STATE GRID Corporation of China has accumulated a huge amount of power data during the construction smart grid. With the continuous development of big data technology, the potential value of these data is being more and more valued by the corporation and academia. At present, SG Corporation has constructed a full-service unified data centre of electric power system to achieve unified storage and shared use of data, then the Knowledge Graph established in the data centre can establish semantic connections among the data and provide unified semantic-level data service. However, there are lots of heterogeneous and redundant entities and relationships extracted in the knowledge graph because the data in the data centre come from different business systems where the objects are defined and described according to their own business rules. Therefore, entities alignment that can clean and merge entities that point to the same objects and solve the problem of entity reuse has become one of the key processes of building a high-quality power knowledge graph.

Entity alignment technology is aimed at achieving high-quality links between data sources by recognizing those entities in different datasets that point to the same object and linking the entities to a unique one with unified global identity by constructing co-reference links such as owl:SameAs. The
inference is usually based on two kinds of methods: traditional and representing learning. The former one mainly depends on attribute similarity.

Based on the string similarity, ontologies and entities can be aligned by matching the literal quantities of the attributes[1-2]. Entity alignment problem is transformed into classification problem and established probability models[3], the weight coefficient is considered in [4] to promote alignment accuracy rate. The method based on attribute information is simple and easy to use and can usually achieves satisfactory results to construct general knowledge graphs, but in the face of heterogeneous power data, it becomes inefficient or even no longer applicable. Sarawagi proposed an active learning method, which requires manual labeling of some entities which are difficult to identify, and then uses artificial feedback to improve the system effect. Then Arasu added filtering operation to reduce the workload of manual data annotation by picking pairs of entities with large amount of information [6]. Song proposed Histsim and DisNgram algorithms for heterogeneous data based on PARIS[7-8], the former uses historical records of entity alignment to calculate entity similarity and the later calculates character set similarity to inference entity alignment. Similarity calculation functions need to be specially designed for different types of attributes, so it causes large amount of manual work. This kind of alignment is also based on attribute similarity, without the consideration of semantic similarity, the effect of entity alignment is limited.

In recent years, deep learning technology has developed rapidly and knowledge representation learning is proposed. It calculates and deduces in a low-dimensional dense vector space where the entities and relationships in knowledge graph are modeled and mapped. TransE[9] is the earliest knowledge representation learning model. It is simple and can achieve satisfactory result on large-scale data sets for one-to-one relationships. Then some extended models are proposed to compute more complex entity relationships on the basis of TransE, such as TransH, TransR and TransSparse, [10-12].

The data of knowledge graph of power grid full-service data comes from different service systems, so the entity alignment task is actually a cross-network relational inference process which is difficult to achieve satisfactory results only based on attribute or semantic information. Cross-KG method can be used for joint learning of two knowledge graphs because of the contribution of complementary information of two data sets in relationship inference[13]. This method works well in the construction of general knowledge graph, but the requirement of large number of labeled alignment data which in practice means a large amount of workload of business experts in power system is unrealistic.

Aiming at this problem, this paper proposes an entity alignment method for power full-service data. The model is trained under a co-training framework. We divide the data into two independent perspectives: semantic and structural. Select the reliable results from one perspective to assist the training of another one. Experiments show that this method can achieve higher accuracy and F1 value for power full-service data entity alignment.

2. Description of entity alignment for full-service power data

The task of entity alignment for full-service power data is to find record pairs in different service systems that point to the same physical object, that is, the entity alignment between data sets. Firstly, we give the formal definition of knowledge graph and knowledge graph entity alignment.

Knowledge graph. The knowledge graph is composed of triples as the following way: KG=(E, R, F), E={e1,e2,…,en} represents collection of entities. It includes instance and attribute values. R={r1,r2,…,rn} represents a set of binary relations. It describes the relationship between entities. F ⊆ E×R×E represents fact triple set.

Knowledge graph entity alignment. Supposing KG1 and KG2 are two given knowledge graphs, we find out all entities aligned to KG2 (or KG1) in KG1 (or KG2) respectively. Alignmany(KG1, KG2)= {(ei, e’), e ∈ E1, e’ ∈ E2}
3. Entity alignment method with semantic and structural information

3.1. Knowledge graph entity alignment of representation learning

Entity alignment using representation learning is mainly divided into two steps. Firstly, map KG1 and KG2 into a low-dimensional vector space and obtain corresponding knowledge representations KG1 and KG2. Then train the model to learn alignment relationship \( \phi \) between entities based on the labeled entity alignment data set N. \((e_1,e_2)\) represents a pair of entities in data set N, which means \((e_1,e_2)\in N \) and \(e_1\in E_1, \quad e_2\in E_2.\) The alignment of entities in two knowledge graphs can be considered as a special relationship \( r*=\text{SameAs} \) and it can form a triple \((e_1,\text{SameAs},e_2).\) Before the training, the embeddings of entities and relationships of KG1 and KG2 should be initialized by uniform distribution. Then the loss function of vector space representation is defined as:

\[
L = \sum_{(h,r,t) \in \Delta} \sum_{(h',r',t') \in \Delta'} [\phi(h,t) + \gamma - \phi(h',t')]_+
\]

\((h,r,t) \in \Delta \) represents the collection of positive triples. It means those existing triples in the real knowledge graph. \((h',r',t') \in \Delta' \) represents the collection of negative triples. It means the triples don’t exist in the real knowledge graph. The negative triples are generated by replacing the head or tail vector of positive triples. When constructing negative triples from positive triples with \( r*=\text{SameAs} \) relationship, the replaced head or tail entity should have the same type with the original entity in the data set. In another word, \( e_1 \) is replaced by another entity \( e_1' \) with the same data type in KG1 or \( e_2 \) is replaced by another entity \( e_2' \) with the same data type in KG2. \( \phi=|h+r\cdot t| \), it measures the degree of matching between two entities by regarding tail entity \( t \) as the translation process of head entity \( h \) through \( r \) according to the idea of translation model. \( \gamma \) is used for separating positive and negative entity pairs, \( \gamma>0 \)

When optimizing the loss function, constraint the relation vector \( r*=\text{SameAs} \) to be zero vector and set the maximum number of iterations of loss function or the threshold of stopping iteration. Each iteration updates the head entity vector, tail entity vector and relation vector. Vector gradient method can be used in updating as follows:

\[
\forall \ i \in \{0,1,2\ldots \text{dim}\}
\]

\[
\begin{align*}
    h_i &= h_i - \mu \cdot 2^* |t_i - h_i - r_i| \\
    r_i &= r_i - \mu \cdot 2^* |t_i - h_i - r_i| \\
    t_i &= t_i - \mu \cdot 2^* |t_i - h_i - r_i| \\
    h_i' &= h_i' - \mu \cdot 2^* |t_i' - h_i' - r_i'| \\
    r_i' &= r_i' - \mu \cdot 2^* |t_i' - h_i' - r_i'| \\
    t_i' &= t_i' - \mu \cdot 2^* |t_i' - h_i' - r_i'| 
\end{align*}
\]

\text{dim} \text{ represents the dimension of space vector. } h_i \text{ represents } i_{\text{th}} \text{ dimensional vector of } h, \mu \text{ represents the learning rate.}

It’s worth noting that some attributes can be aligned automatically by eliminating the ambiguity of attribute names and some entities with similar semantics are close in the semantic space for example “AC bus” and “AC line”

3.2. Co-training with semantic and structural perspectives

Models of semantic and structural features infer entity alignment relations from their respective perspectives. Both aspects of information are useful for inference in the construction of knowledge graph of full-service power data knowledge graph. Using Co-training framework to complement the inference results from two perspectives can improve the performance of entity alignment.

Specifically, we divide the training data into two independent perspectives, semantic perspective and structural perspective. Generate training data of the semantic perspective according to a small
labeled align data set \( L_{se} \). Then train and obtain the semantic perspective model \( m_{se} \). Predict the entity alignment relation for unlabeled data set \( X_s \) and pick out reliable entity pairs \( L_{se}' \). Put \( L_{se}' \) into labeled data of the structural perspective and obtain a new labeled data set \( X_s \). Then repeat a similar process, generate training data of the structural perspective according to \( X_s \). Then train and obtain the semantic perspective model \( m_{se} \). Predict the entity alignment relation for unlabeled data set \( X_s \) and pick out best results \( L_{se}' \). Put \( L_{se}' \) into labeled data of the structural perspective and obtain a new labeled data set \( X_s \). The two models are iterated until convergence.

### Algorithm

蛾 training with semantic and structural perspectives

**Input:** KG\(_1\) triples \( T_1=(h, r, t) \)
- Aligned Data Source 1 Entity Set \( L_1 \), Data Source 1 Entity Set to Align \( U_1 \)

KG\(_2\) triples \( T_2=(h, r, t) \)
- Aligned Data Source 2 Entity Set \( L_2 \), Data Source 2 Entity Set to Align \( U_2 \)
- Labeled aligned entity pairs \( L=(\{e_1, \text{SameAs}, e_2\}, e_1 \in L_1, e_2 \in L_2 \)

**Output:** Embedding vectors of entities and relationships after training

1. Construct a joint knowledge map \( T=T_1 \cup T_2 \cup L \)
2. Divide the training ternary triples into two perspectives. \( X_f=T_{se} \cup L, X_s=T_{se} \cup L \)
3. **Loop for k iterations:**
   4. Train entity alignment model \( m_1 \) under the first perspective according to \( X_1 \)
   5. Train entity alignment model \( m_1 \) under the second perspective according to \( X_2 \)
   6. Infer alignment entity pairs by \( m_1 \) and pick out reliable entity pairs \( L_1' \)
   7. Infer alignment entity pairs by \( m_1 \) and pick out reliable entity pairs \( L_1' \)
   8. \( X_f-X_1 \cup L_2' \)
   9. \( X_s=X_2 \cup L_1' \)
10. **End Loop**

#### 3.3. Entity Similarity Computing Based on Attribute Matching

Although the power data may be described in different formats in different business systems, they have common parts inevitably. Similarity calculation based on common attributes of different source entities can also provide some reference results. \( up(e_1, e_2) \) is defined as common set of attributes for entities \( e_1 \) and \( e_2 \):

\[
up(e_1, e_2) = property1 \cap property2
\]

\( property1 \) represents the attribute set of \( e_1 \). \( property2 \) represents the attribute set of \( e_2 \).

The similarity \( sim(p) \) of the common attribute \( p \) of two entities can be calculated by:

\[
Sim(p_i) = \frac{\text{lcs}(vlx, v2y)}{\max(\text{len}(vlx), \text{len}(v2y))}
\]

\( p_i \) corresponds to the \( x_i \) attribute of \( e_1 \) and the \( y_i \) attribute of \( e_2 \). \( p1x \) and \( p2y \) the values are \( v1x \) and \( v2y \) respectively. \( \text{lcs}(vlx, v2y) \) represents their longest common subsequence of attribute values.

The similarity of \( e_1 \) and \( e_2 \) is the average of similarity of their common attributes:

\[
Sim(e_1, e_2) = \text{average}(Sim(p_i))
\]

When inferring the entity \( h \) that align to the given entity \( t' \) in another data set, we score all entity relationships \( (h', \text{SameAs}, t') \) based on scoring function and choose the highest marked one as result. The scoring function is defined with vector representation similarity and attribute similarity.

\[
f_{\text{predict}}(h, r, t') = (1 + w \times Sim(h, t')) \left\| h - t' \right\|
\]

\( \left\| h - t' \right\| \) measures vector representation. \( Sim(h, t') \) represents attribute similarity. \( w \) is penalty coefficient ranging from 0 to 1. The value is determined by the reliability of attributes of data set.
4. experiment and result analysis

The experimental data set comes from full-service unified data centre in SG Zhejiang Electric Power Corporation. The running data of a region for a week is extracted from the buffer layer where the data of all the business systems are access directly and stored. There are 1,032 equipment entities recorded in Operation and Maintenance System and 876 in Material System. Altogether there are 1,448 different equipment entities recorded in the two systems. So, 460 equipment entities can be aligned. We select 160 entities as a training set, 150 as a validation set and 150 as a test set. There are altogether 178 supplier entities in the Marketing System and Material System. Among them, 104 are involved in the marketing system and 161 are involved in the material system. So, 87 supplier entities can be aligned. We select 47 entities as a training set, 20 as a validation set and 20 as a test set.

The experiment compares entity alignment method with attribute similarity LCS and the method with knowledge representation learning cross-KG and SEEA. The evaluation index are precision P, Recall R and F1.

Accuracy reflects the rate of extraction results. It is defined as:
\[
P = \frac{N_{\text{success}}}{N_{\text{total}}}
\]

\(N_{\text{total}}\) represents the total number of relationships inferred. \(N_{\text{success}}\) represents the total number of correct inferences.

Recall rate reflects the proportion of correct inferences to all existing alignment relationships. It is defined as:
\[
R = \frac{R_{\text{success}}}{R_{\text{total}}}
\]

\(R_{\text{success}}\) represents the correct inferences. \(R_{\text{total}}\) represents the number of all existing alignment relationships.

\(F1\) is an evaluation indicator of comprehensive accuracy and recall rate. It can reflect the overall effect.
\[
F1 = 2 \cdot R \cdot P / (R + P)
\]

The experimental results are shown in Table 1.

| method   | Alignment rate for equipment entities(%) | Alignment rate for supplier entities(%) |
|----------|----------------------------------------|---------------------------------------|
|          | P          | R          | F1         | P          | R          | F1          |
| LCS      | 80.37      | 86.67      | 83.40      | 77.78      | 70.00      | 73.69       |
| Cross KG | 92.74      | 90.00      | 91.35      | 80.00      | 80.00      | 80.00       |
| SEEA     | 90.66      | 89.33      | 89.99      | 78.95      | 75.00      | 76.92       |
| this paper| 98.68      | 97.33      | 98.00      | 95.00      | 95.00      | 95.00       |

The results of the experiment show that the method of entity alignment with semantic and structural information has achieved ideal results in entity alignment tasks of full-service power data. There is a comprehensive enhance in precision, recall and F1 compared to method with semantic or structural information. The reason for this is that both the semantic information and structural information are effective in entity alignment for power data. On one side, some physical concepts in the electrical industry are very similar in name but quite different in nature. They can be easily distinguished from their attribute structure. On the other side, entities pointing to the same areas or in hierarchical relationships may have common attributes, so they are easier to be distinguished from semantic perspective.

5. conclusion

The experiment shows that the method of entity alignment with semantic and structural information can work well in entity alignment for power data. The models are divided into two perspectives: semantics and structure. Training the two models separately from their perspectives, then select the best results from one perspective to supply another and iterate. Finally, the model is promoted with higher P, R and F1. In the construction of a knowledge graph in a specific field, both the semantic and structural information are important in entity alignment. Fully use of these two aspects of information
can theoretically achieve satisfactory effect. Therefore, this method has strong generality for the construction of a industry knowledge graph.

Acknowledgements
This work was financially supported by State Grid science and technology project: Research on key technologies and application of unified data model of power grid based on Knowledge Graph. (Project number: 5211XT180045) fund.

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