Joint Learning Templates and Slots for Event Schema Induction

Lei Sha, Sujian Li, Baobao Chang, Zhifang Sui
Key Laboratory of Computational Linguistics, Ministry of Education
School of Electronics Engineering and Computer Science, Peking University
Collaborative Innovation Center for Language Ability, Xuzhou 221009 China
shalei, lisujian, chbb, szf@pku.edu.cn

Abstract

Automatic event schema induction (AESI) means to extract meta-event from raw text, in other words, to find out what types (templates) of event may exist in the raw text and what roles (slots) may exist in each event type. In this paper, we propose a joint entity-driven model to learn templates and slots simultaneously based on the constraints of templates and slots in the same sentence. In addition, the entities’ semantic information is also considered for the inner connectivity of the entities. We borrow the normalized cut criteria in image segmentation to divide the entities into more accurate template clusters and slot clusters. The experiment shows that our model gains a relatively higher result than previous work.

1 Introduction

Event schema is a high-level representation of a bunch of similar events. It is very useful for the traditional information extraction (IE) task. An example of event schema is shown in Table 1. Given the bombing schema, we only need to find proper words to fill the slots when extracting a bombing event.

| Bombing Template |
|------------------|
| Perpetrator:     |
| Victim:          |
| Target:          |
| Instrument:      |
| person           |
| person           |
| public           |
| bomb             |

Table 1: The event schema of bombing event in MUC-4, it has a bombing template and four main slots that best explains the text. However, the graphical models considers the entities independently and do not take the interrelationship between entities into account. Another method relies on ad-hoc clustering algorithms (Filatova et al., 2006; Sekine, 2006; Chambers and Jurafsky, 2011). (Chambers and Jurafsky, 2011) is a pipelined approach. In the first step, it uses pointwise mutual information (PMI) between any two clauses in the same document to learn events, and then learns syntactic patterns as fillers. However, the pipelined approach suffers from the error propagation problem, which means the errors in the template clustering can lead to more errors in the slot clustering.

This paper proposes an entity-driven model which jointly learns templates and slots for event schema induction. The main contribution of this paper are as follows:

- To better model the inner connectivity between entities, we borrow the normalized cut in image segmentation as the clustering criteria.
- We use constraints between templates and between slots in one sentence to improve AESI result.
2 Task Definition

Our model is an entity-driven model. This model represents a document \( d \) as a series of entities \( E_d = \{ e_i | i = 1, 2, \ldots \} \). Each entity is a quadruple \( e = (h, p, d, f) \). Here, \( h \) represents the head word of an entity, \( p \) represents its predicate, and \( d \) represents the dependency path between the predicate and the head word, \( f \) contains the features of the entity (such as the direct hypernyms of the head word), the sentence id where \( e \) occurred and the document id where \( e \) occurred. A simple example is Fig 1.

Our ultimate goal is to assign two labels, a slot variable \( s \) and a template variable \( t \), to each entity. After that, we can summarize all of them to get event schemas.

3 Automatic Event Schema Induction

3.1 Inner Connectivity Between Entities

We focus on two types of inner connectivity: (1) the likelihood of two entities to belong to the same template; (2) the likelihood of two entities to belong to the same slot;

3.1.1 Template Level Connectivity

It is easy to understand that entities occurred near each other are more likely to belong to the same template. Therefore, \( \text{PMI} \) uses PMI to measure the correlation of two words in the same document, but it cannot put two words from different documents together. In the Bayesian model of \( \text{PMI} \), \( p(\text{predicate}) \) is the key factor to decide the template, but it ignores the fact that entities occurring nearby should belong to the same template. In this paper, we try to put two measures together. That is, if two entities occurred nearby, they can belong to the same template; if they have similar meaning, they can also belong to the same template. We use PMI to measure the distance similarity and use word vector \( \text{PMI} \) to calculate the semantic similarity.

A word vector can well represent the meaning of a word. So we concatenate the word vector of the \( j \)-th entity’s head word and its predicate, denoted as \( vec_{hp}(i) \). We use the cosine distance \( \cos_{hp}(i, j) \) to measure the difference of two vectors.

Then we can get the template level connectivity formula as shown in Eq (1). The \( \text{PMI}(i, j) \) is calculated by the head words of entity mention \( i \) and \( j \).

\[
W_T(i, j) = \text{PMI}(i, j) + \cos_{hp}(i, j)
\]  

3.1.2 Slot Level Connectivity

If two entities can play similar role in an event, they are likely to fill the same slot. We know that if two entities can play similar role, their head words may have the same hypernyms. We only consider the direct hypernyms here. Also, their predicates may have similar meaning and the entities may have the same dependency path to their predicate. Therefore, we give the factors equal weights and add them together to get the slot level similarity.

\[
W_S(i, j) = \cos_p(i, j) + \delta(\text{depend}_i = \text{depend}_j) + \delta(\text{hypernym}_i \cap \text{hypernym}_j \neq \emptyset)
\]  

Here, the \( \delta(\cdot) \) has value 1 when the inner expression is true and 0 otherwise. The “hypernym” is derived from Wordnet, so it is a set of direct hypernyms. If two entities’ head words have at least one common direct hypernym, then they may belong to the same slot. And again \( \cos_p(i, j) \) represents the cosine distance between the predicates’ word vector of entity \( i \) and entity \( j \).

3.2 Template and Slot Clustering Using Normalized Cut

Normalized cut intend to maximize the intra-class similarity while minimize the inter class similarity, which deals well with the connectivity between entities.
We represent each entity as a point in a high-dimension space. The edge weight between two points is their template level similarity / slot level similarity. Then the larger the similarity value is, the more likely the two entities (point) belong to the same template / slot, which is also our basis intuition.

For simplicity, denote the entity set as \( E = \{e_1, \cdots, e_{|E|}\} \), and the template set as \( T \). We use the \([E] \times [T]\) partition matrix \( X_T \) to represent the template clustering result. Let \( X_T = [X_{T_1}, \cdots, X_{T_{|T|}}] \), where \( X_{T_l} \) is a binary indicator for template \( l(T_l) \).

\[
X_T(i, l) = \begin{cases} 
1 & e_i \in T_l \\
0 & \text{otherwise}
\end{cases} \quad (3)
\]

Usually, we define the degree matrix \( D_T \) as: \( D_T(i, i) = \sum_{j \in E} W_T(i, j), i = 1, \cdots, |E| \). Obviously, \( D_T \) is a diagonal matrix. It contains information about the weight sum of edges attached to each vertex. Then we have the template clustering optimization as shown in Eq (4) according to Shi and Malik, 2000.

\[
\max \: \varepsilon_1(X_T) = \frac{1}{|T|} \sum_{l=1}^{|T|} X_T^T l W_T X_T l \\
s.t. \: X_T \in \{0, 1\}^{|E| \times |T|} \: X_T 1_{|T|} = 1_{|E|} \quad (4)
\]

where \( 1_{|E|} \) represents the \(|E| \times 1\) vector of all 1’s.

For the slot clustering, we have a similar optimization as shown in Eq (5).

\[
\max \: \varepsilon_2(X_S) = \frac{1}{|S|} \sum_{l=1}^{|S|} X_S^T l W_S X_S l \\
s.t. \: X_S \in \{0, 1\}^{|E| \times |S|} \: X_S 1_{|S|} = 1_{|E|} \quad (5)
\]

where \( S \) represents the slot set, \( X_S \) is the slot clustering result with \( X_S = [X_{S_1}, \cdots, X_{S_{|S|}}] \), where \( X_{S_l} \) is a binary indicator for slot \( l(S_l) \).

\[
X_S(i, l) = \begin{cases} 
1 & e_i \in S_l \\
0 & \text{otherwise}
\end{cases} \quad (6)
\]

### 3.3 Joint Model With Sentence Constraints

For event schema induction, we find an important property and we name it “Sentence constraint”. The entities in one sentence often belong to one template but different slots.

The sentence constraint contains two types of constraint, “template constraint” and “slot constraint”.

1. **Template constraint**: Entities in the same sentence are usually in the same template. Hence we should make the templates taken by a sentence as few as possible.

2. **Slot constraint**: Entities in the same sentence are usually in different slots. Hence we should make the slots taken by a sentence as many as possible.

Based on these consideration, we can add an extra item to the optimization object. Let \( N_{\text{sentence}} \) be the number of sentences. Define \( N_{\text{sentence}} \times |E| \) matrix \( J \) as the sentence constraint matrix, the entries of \( J \) is as following:

\[
J(i, j) = \begin{cases} 
1 & e_i \in \text{Sentence}_j \\
0 & \text{otherwise}
\end{cases} \quad (7)
\]

Easy to show, the product \( G_T = J^T X_T \) represents the relation between sentences and templates. In matrix \( G_T \), the \((i, j)\)-th entry represents how many entities in sentence \( i \) are belong to \( T_j \).

Using \( G_T \), we can construct our objective. To represent the two constraints, the best objective we have found is the trace value: \( tr(G_T G_T^T) \). Each entry on the diagonal of matrix \( G_T G_T^T \) is the sum of all the entries in the corresponding line in \( G_T \), and the larger the value is, the less templates the sentence would taken. Since \( tr(G_T G_T^T) \) is the sum of the diagonal elements, we only need to maximize the value \( tr(G_T G_T^T) \) to meet the template constraint. For the same reason, we need to minimize the value \( tr(G_S G_S^T) \) to meet the slot constraint.

Generally, we have the following optimization objective:

\[
\varepsilon_3(X_T, X_S) = \frac{tr(X_T^T J J^T X_T)}{tr(X_S^T J J^T X_S)} \quad (8)
\]

The whole joint model is shown in Eq (8). The solving
method is in the attachment file.

\[
X_T, X_S = \arg \max_{X_T, X_S} \varepsilon_1(X_T) + \varepsilon_2(X_S) + \varepsilon_3(X_T, X_S)
\]

\[
s.t. X_T \in \{0, 1\}^{|E| \times |T|} X_T 1_{|T|} = 1_{|E|}
\]

\[
X_S \in \{0, 1\}^{|E| \times |S|} X_S 1_{|S|} = 1_{|E|}
\]

(9)

4 Experiment

4.1 Dataset

In this paper, we use MUC-4 (Sundheim, 1991) as our dataset, which is the same as previous works (Chambers and Jurafsky, 2011; Chambers, 2013). MUC-4 corpus contains 1300 documents in the training set, 200 in development set (TS1, TS2) and 200 in testing set (TS3, TS4) about Latin American news of terrorism events. We ran several times on the 1500 documents (training/dev set) and choose the best \(|T|\) and \(|S|\) as \(|T| = 6, |S| = 4\). Then we report the performance of test set. For each document, it provides a series of hand-constructed event schemas, which are called gold schemas. With these gold schemas we can evaluate our results. The MUC-4 corpus contains six template types: Attack, Kidnapping, Bombing, Arson, Robbery, and Forced Work Stoppage, and for each template, there are 25 slots. Since most previous works do not evaluate their performance on all the 25 slots, they instead focus on 4 main slots like Table 1, we will also focus on these four slots. We use the Stanford CoreNLP toolkit to parse the MUC-4 corpus.

4.2 Performance

Fig 2 shows two examples of our learned schemas: Bombing and Attacking. The five words in each slot are the five randomly picked entities from the mapped slots. The templates and slots that were joint learned seem reasonable.

We compare our results with four works (Chambers and Jurafsky, 2011; Cheung, 2013; Chambers, 2013; Nguyen et al., 2015) as is shown in Table 2. Our model has outperformed all of the previous methods. The improvement of recall is due to the normalized cut criteria, which can better use the inner connectivity between entities. The sentence constraint improves the result one step further.

| Perpetrator | Victim | Target | Instrument |
|-------------|--------|--------|------------|
| El salvador | The police chief | ministry | explosives |
| The guerrillas | Students | The embassy | car bomb |
| The drag mafia | The Peruvian embassy | The police station | dynamite |
| Drug traffickers | The diplomat soldiers | organization bridge | incendiary bomb |
| The Attacall battalion | | | vehicle bomb |

Figure 2: Part of the result

| Prec | Recall | F1 |
|------|--------|----|
| C&J (2011) | 0.48 0.25 0.33 |
| Cheung (2013) | 0.32 0.37 0.34 |
| Chambers (2013) | 0.41 0.41 0.41 |
| Nguyen et al. (2015) | 0.36 0.54 0.43 |
| Our Model-SC | 0.38 0.68 0.49 |
| Our Model | 0.39 0.70 0.50 |

Table 2: Comparison to state-of-the-art unsupervised systems, “-SC” means without sentence constraint

5 Related Works

AESI task has been researched for many years. Shinya and Sekine (2006) proposed an approach to learn templates with unlabeled corpus. They use unrestricted relation discovery to discover relations in unlabeled corpus as well as extract their fillers. Their constraints are that they need redundant documents and their relations are binary over repeated named entities. Chen et al., 2011 also extract binary relations using generative model.

Kasch and Oates (2010), Chambers and Jurafsky (2008), Chambers and Jurafsky (2009), Balasubramanian et al. (2013) captures template-like knowledge from unlabeled text by large-scale learning of scripts and narrative schemas. However, their structures (template/slot) are limited to frequent topics in a large corpus. Chambers and Jurafsky (2011) uses their idea, and their goal is to characterize a specific domain with limited data using a three-stage clustering algorithm.
Also, there are some state-of-the-art works using probabilistic graphic model [Chambers, 2013; Cheung, 2013; Nguyen et al., 2015].

6 Conclusion

This paper presented a joint entity-driven model to induct event schemas automatically.

This model uses word embedding as well as PMI to measure the inner connection of entities and uses normalized cut for more accurate clustering. Finally, our model uses sentence constraint to extract templates and slots simultaneously. The experiment has proved the effectiveness of our model.

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The Solving Method of the Event Schema Induction Joint Model

Lei Sha
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1 The Model

Template clustering optimization is shown in Eq 1.

\[
\begin{align*}
\max & \quad \varepsilon_1(X_T) = \frac{1}{|T|} \sum_{i=1}^{|T|} X_{T_i}^T W_T X_{T_i} \\
\text{s.t.} & \quad X_T \in \{0,1\}^{|E| \times |T|}, \quad X_T 1_{|T|} = 1_{|E|}
\end{align*}
\] (1)

Here, \(1_{|E|}\) represents the \(|E| \times 1\) vector of all 1’s.

Slot clustering optimization is shown in Eq 2.

\[
\begin{align*}
\max & \quad \varepsilon_2(X_S) = \frac{1}{|S|} \sum_{i=1}^{|S|} X_{S_i}^T W_S X_{S_i} \\
\text{s.t.} & \quad X_S \in \{0,1\}^{|E| \times |S|}, \quad X_S 1_{|S|} = 1_{|E|}
\end{align*}
\] (2)

Here, \(S\) represents the slot set, \(X_S\) is the slot clustering result with \(X_S = [X_{S_1}, \cdots, X_{S_{|S|}}]\), where \(X_{S_i}\) is a binary indicator for slot \(l(S_i)\).

\[
X_S(i, l) = \begin{cases} 
1 & e_i \in S_l \\
0 & \text{otherwise}
\end{cases}
\] (3)

The original sentence constraint model is shown as follows:

\[
\varepsilon_3(X_T, X_S) = \frac{\text{tr}(X_T^T J J^T X_T)}{\text{tr}(X_S^T J J^T X_S)}
\] (4)

However, this form of objective is hard to optimize, we can transfer the slot constraint objective \(\text{tr}(G_S G_S^T) (G_S = J^T X_S)\) to something that should be maximized. Since \(\text{tr}(G_S G_S^T) = \text{tr}(X_S^T J J^T X_S)\), to minimize \(\text{tr}(X_S^T J J^T X_S)\) is the same as to maximize \(\text{tr}(X_S^T (E - J J^T) X_S)\) \((E = 1 \cdot 1^T)\). \(1\) represents an all 1 vector. It can be proved that \(\text{tr}(X_S^T (E - J J^T) X_S)\) is positive.
Generally, we have the following optimization objective:

$$\max \varepsilon_3(X_T, X_S) = \text{tr}(X_T^T J J^T X_T) \text{tr}(X_S^T (E - J J^T) X_S)$$

$$\text{s.t. } X_T \in \{0, 1\}^{|E|\times|T|} \quad X_T 1_{|T|} = 1_{|E|}$$

$$X_S \in \{0, 1\}^{|E|\times|S|} \quad X_S 1_{|S|} = 1_{|E|}$$

(5)

The whole joint model is shown in Eq (6). The first item represents the goodness of the templates clustering. The second item represents the goodness of the slot clustering. The third item is the sentence constraint item. However, this model is too complex to be solved by normal optimization method. Therefore, we use the Alternating Maximization Procedure [2] to solve this problem in the following section.

$$X_T, X_S = \arg\max_{X_T, X_S} \varepsilon_1(X_T) + \varepsilon_2(X_S) + \varepsilon_3(X_T, X_S)$$

$$\text{s.t. } X_T \in \{0, 1\}^{|E|\times|T|} \quad X_T 1_{|T|} = 1_{|E|}$$

$$X_S \in \{0, 1\}^{|E|\times|S|} \quad X_S 1_{|S|} = 1_{|E|}$$

(6)

2 Solving Method: Alternating Maximization Procedure (AMP)

In this section, the detailed solving method of the complex model shown in Eq (6) will be illustrated. The ultimate objective in Eq (6) is the combination of optimization objective in Eq (1), Eq (2) and Eq (5).

The first two items in Eq (6) is the form of generalized Rayleigh quotient and can be solved using the method in [3], which mainly contains two steps: 1) find the continuous optimal value 2) discretization. We use the AMP method to get the numerical solution of Eq (6). The AMP algorithm can be viewed as a joint maximization method by fixing one argument and maximizing over the other. After we fixed $X_S$ or $X_T$, we can transform the objective to the form of generalized Rayleigh quotient which could be solved by the method in [3].

When $X_T$ is fixed The first term in Eq (6) is a constant in this case, so that we ignore it for simplicity. Let $f(X_T) = \text{tr}(X_T^T J J^T X_T)$, then Eq (6) becomes:

$$\max \varepsilon(X_S; X_T) = \frac{1}{|S|} \sum_{l=1}^{|S|} \frac{X_S^T W S X_{S_l}}{X_{S_l}^T D_S X_{S_l}} + f(X_T) \sum_{l=1}^{|S|} X_{S_l}^T (E - J J^T) X_{S_l}$$

(7)

We can reduce the fractions to a common denominator, then Eq (7) becomes:

$$\sum_{l=1}^{|S|} \frac{X_{S_l}^T W S X_{S_l}}{X_{S_l}^T D_S X_{S_l}} + f(X_T) \sum_{l=1}^{|S|} X_{S_l}^T (E - J J^T) X_{S_l} X_{S_l}^T D_S X_{S_l}$$

(8)
Note that the term $X_S^T (E - JJ^T) X_S X_S^T D_S X_S$ is a scalar, so that we can take it as a trace of a $1 \times 1$ matrix as shown in Eq 9.

$$
X_S^T (E - JJ^T) X_S X_S^T D_S X_S = tr(X_S^T (E - JJ^T) X_S X_S^T D_S X_S)
$$

Here, $\Omega_S = X_S^T X_S$ is a diagonal matrix. Each diagonal entry is the number of entities in the corresponding slot.

In order to represent Eq 8 to the form of Eq 10, we need to keep $D^*_S = D_S$, and the $W^*_S$ is as Eq 11. In order to keep $W^*_S$ a symmetric matrix, we add $\frac{1}{2}$ of Eq 9 to both sides of $X_S^T W_S X_S$.

$$
\varepsilon(X_S; X_T) = \sum_{l=1}^{[S]} \frac{X_S^T W_S X_S}{X_S^T D_S^* X_S}
$$

$$
W^*_S = \frac{1}{2} f(X_T) D_S (E - JJ^T) \Omega_S + \frac{1}{|S|} W_S
$$

$$
D^*_S = D_S
$$

**When $X_S$ is fixed** Using the same method as the above, in order to get the form of Eq 12, the value of $W^*_T$ and $D^*_T$ are calculated as Eq 13.

$$
\varepsilon(X_T; X_S) = \sum_{l=1}^{[T]} \frac{X_T^T W^*_T X_T}{X_T^T D_T^* X_T}
$$

$$
W^*_T = \frac{1}{2} J J^T D_T \Omega_T + \frac{1}{|T|} W_T
$$

$$
D^*_T = D_T
$$

**Stopping criteria** According to [3], if $X_T, X_S$ is a feasible solution to Eq 8, so is $\{X_T R_T, X_S R_S | R_T^T R_T = I, R_S^T R_S = I\}$, and they have the same objective value: $\varepsilon(X_T R_T, X_S R_S) = \varepsilon(X_T, X_S)$. Therefore, if Eq 14 is satisfied, the loop ends.

$$
\|X_T^{new} - X_T^{old} R_T\| = 0
$$

$$
\|X_S^{new} - X_S^{old} R_S\| = 0
$$

We can get the closed form of $R_T$ and $R_S$ as shown in Eq 15.

$$
R_T = (X_T^{(new)} X_T^{(new)T})^{-1} X_T^{(new)T} X_T^{(old)}
$$

$$
R_S = (X_S^{(new)} X_S^{(new)T})^{-1} X_S^{(new)T} X_S^{(old)}
$$
Therefore, the ultimate stop criteria becomes \[ \| R_T^T R_T - I \| + \| R_S^T R_S - I \| < \epsilon, \]
\( \epsilon \) is very close to 0.

The total algorithm of the whole process is shown as Algorithm 1. Since the optimization objective is a differentiable function, the convergence to the optimum solution can be guaranteed by \[2, 1\].

**Algorithm 1:** The pseudo code of the optimum value finding process

**Input:**
- Template level similarity matrix, \( W_T \);
- Slot level similarity matrix, \( W_S \);
- sentence constraint matrix, \( J \).

**Output:**
- The partition matrix of template, \( X_T \);
- The partition matrix of slot, \( X_S \);

**begin**
- Randomly initialize \( X_T \) and \( X_S \);
- **while** \[ \| R_T^T R_T - I \| + \| R_S^T R_S - I \| > \epsilon \] **do**
  - Fix \( X_T \), calculate Eq 11;
  - Find \( X_S \) which can maximize Eq 10;
  - Fix \( X_S \), calculate Eq 12;
  - Find \( X_T \) which can maximize Eq 12;
  - Calculate \( R_T \) and \( R_S \) by Eq 15;
- **end while**
- Discretize \( X_T \) and \( X_S \);
- **return** \( X_T \) and \( X_S \);

**end**

3 Experiment Setting

The \( \Omega_T \) and \( \Omega_S \) in Eq 13 and Eq 11 can be seen as a prior of the template cluster size and slot cluster size. We use the most naive prior that all clusters are of the same size.

References

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[3] Stella X Yu and Jianbo Shi. Multiclass spectral clustering. In *Computer Vision, 2003. Proceedings. Ninth IEEE International Conference on*, pages 313–319. IEEE, 2003.