A Trigger Word Mining Method Based on Activation Force

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Abstract

A specific relation is mostly indicated by some trigger words in information extraction domain. Trigger word mining becomes an important part in relation extraction. In this paper, based on activation force, we present a novel method for trigger word mining. For a specific relation, strengths of activation that an entity exerts on trigger words and activations that a trigger word exerts on attribute-values can be considered as evaluation criterions for identifying trigger words. Based on these two activation forces, we introduce a new criterion, Trigger Force, to evaluate trigger words. With Trigger Force for trigger words evaluation, we choose words with high Trigger Force as trigger words for specific relations. Experiments on extracting top number trigger words on training data show that the new trigger word mining method gives a good performance for 10 relations of PER entity and ORG entity.

1 Introduction

The goal of Information Extraction (IE) is to extract entities and the relations that join them, transforming a large corpus of unstructured text into a relational data with entries. Many NLP applications, such as question answering and summarization, would benefit from large knowledge bases of relational information about entities (Wu and Weld, 2010).

In relation extraction domain, a specific relation is mostly indicated by some words with semantic information. These words are commonly called trigger words, which can trigger different relations. For pattern learning method (Zelenko et al., 2003; Culotta and Sorensen, 2004; Sergey, 1998; Agichtein and Gravano, 2000), which is a mainly used method for relation extraction, trigger words activate patterns for a specific relation and act as the patterns conceptual anchor points (Cardie, 1997). With a list of trigger words of a specific relation, relation extraction systems can extract much more high quality patterns and obtain relation information about entities. For example, by using a pattern learning method based on trigger words in TAC-KBP2012 Slot Filling task, we won the first prize with precision of 67.6%, recall of 41.9% and F1 value of 51.7%, much higher than the second team with the same parameters of 48.9%, 21.2% and 29.4%.

In this paper, we present a novel method based on activation force for trigger word mining. Regarding the activation that a word exerts on another as an imaginary force (Guo et al., 2011; Guo et al., 2012), we assume that an entity fires and evokes a trigger word, the trigger word fires and stimulates the attribute-value of the entity in a specific relation. Strengths of activation that an entity exerts on trigger words and activation that a trigger word exerts on attribute-values can be considered as evaluation criterions for identifying trigger words. Based on these two activation forces, we introduce a new criterion, Trigger Force, to evaluate trigger words. With the new criterion to evaluate trigger words, we choose words with high Trigger Force as trigger words for specific relations.

To evaluate our framework for trigger word mining, we conducted experiments in relations which are involved in TAC-KBP English Slot Filling task (Joe Ellis, 2012). We group attributes of PER entity and ORG entity in TAC-KBP English Slot Filling task into different relation classes and choose the most representative 10 relations to extract trigger words. The training data is made up by sentences which are correspondingly matched with entity and attribute-value pairs. The entities and attribute values include two parts: 278 entities from TAC-KBP English Slot Filling task of 2009-2012 and their attribute values extracted from assessment data (NIST, 2012) of Slot Filling; 200 entities (Fortune, 2012) (Time, 2010) and their attribute values from Wikipedia Infobox. Results show that the new trigger word mining method gives a good performance for 10 relations of PER entity and ORG entity.

2 Related Work

Since it is important to extract trigger words in relation extraction, some related work has been done to extract trigger words for specific relations.

WordNet (Miller, 1990) plays important role in trigger words extraction methods. For example, WordNet predicates are used as trigger words to establish relations between words and concepts of a language independent ontology in (Negri and Magnini, 2004); A trigger word list is gathered from WordNet by checking whether a word has the semantic class person|...|relative to personal social relation subtypes in (GuoDong et al., 2005).

There are some other trigger words mining method besides using WordNet. Detecting event triggers is defined as a multiclass classification problem and a binary classifier is trained for each event type in (Cardie, 1997). It computes the trigger power of a word by TF-IRFw, TextRank and their product methods to suggest tags according to the words in a resource description in (Liu et al., 2011). A generative model for relation extraction defines trigger words as all the words on the dependency path except stop words in (Yao et al., 2011). In the method of learning patterns for a particular domain in (Xu et al., 2006), it chooses the most frequent words as trigger words and clusters the rules with the same trigger words.

Most of these methods are manual or semi-automatical extraction methods for trigger words. In this paper we present a full-automatic method.

3 Trigger Word Mining Method

In this section, we give a detail description for trigger word mining method based on activation force.

3.1 Activation Force

Regarding the activation that a word exerts on another as an imaginary force, Guo (2011; 2012) proposed activation forces to describe the strength of the links of complex networks, which conveys an activation from node *i* to node *j* after the former fires. And the activation forces are formulated in terms of imaginary mass and distance that originate from the human language experience. Given the frequencies f_i and f_j and co-occurrence frequency f_{ij} of a pair of nodes *i* and *j*, the activation force is defined as

$$a_{ij} = (f_{ij}/f_i)(f_{ij}/f_j)/(d_{ij}^2) \tag{1}$$

where d_{ij} is the average distance by which node *i* precedes node *j* in their co-occurrences.

3.2 Trigger Force

Based on the theory of activation force, we assume that the pairs of entity and attribute-value and words between them may have some association, which all indicate a specific relation. So, we define Trigger Force as a criterion for trigger word evaluation .

3.3 Principle of Trigger Force

For all words in training data set, map entity *e*, candidate trigger word w_i, attribute-value *v* into the conditional probabilities $p(\{e, \cdots w_i\}^L|e)$ and $p(\{w_i \cdots v\}^L|v)$, where $\{e, \cdots w_i\}^L$ denotes a consecutive word sequence with maximum length of *L* (no punctuates) that contains the entity e at the head, w_i at the end, and 0 to *L-2* intervening words excluding e and w_i, we estimate the activation force that e exerts on w_i by the statistic:

$$af(e, w_i) = (f_{e,w_i}/f_e)(f_{e,w_i}/f_{w_i})/d_{e,w_i}^2 \tag{2}$$

Similarly, $\{w_i, \cdots v\}^L$ denotes a consecutive word sequence with maximum length of L (no punctuates) that contains the word w_i at the head, *v* at the end, and 0 to *L-2* intervening words excluding w_i and *v* , the activation force between word w_i and attribute-value v is:

$$af(w_i, v) = (f_{w_i,v}/f_{w_i})(f_{w_i.v}/f_v)/d_{w_i,v}^2 \tag{3}$$

In Formulae (2) and (3), f_e, f_{w_i}, f_v are the occurrence frequencies of entity *e*, candidate trigger word w_i and attribute-value *v*, respectively, f_{e,w_i} co-occurrence frequency of entity *e* and word w_i,

$f_{w_i,v}$ co-occurrence frequency of candidate trigger word w_i and attribute-value *v*, d_{e,w_i} distance between *e* and w_i , and $d_{w_i,v}$ distance between w_i and *v*.

Specially, the length of *L* is adaptive. It should be with lengths of sentences. Word frequencies are counted under the condition without stemming verbs or changing nouns between plural and singular forms but with changing all upper cases into lower cases (Guo et al., 2012). For example, *die*, *dies*, *died*, *dead*, *death* terms were treated as 5 different words, but *President* and *president* the same word *president*. Based on activation forces among entities, words and attribute-values, we define the Trigger Force of a trigger word:

$$Trigger\_Force(w_i) = \lambda af(e, w_i)+(1-\lambda)af(w_i, v) \quad (4)$$

λ is a parameter belonging to [0,1], which is used to adjust the importance of $af(e, w_i)$ and $af(w_i, v)$. According to the definition, the magnitude of Trigger Force is unitarily quantified in [0, 1]. Taking $Trigger\_Force(w_i)$ for example, zero means that word *i* is never followed by the entity and attribute-value pair closer than *L* words in the language experience, word *i* can not trigger the entity and attribute-value pair in current relation. While one means that words *i*, entity and attribute-value pairs are always immediately adjacent like a compound, so word *i* is the best trigger word for the current relation.

3.4 Trigger Words Judgment

There are two methods for trigger words judgment: hard decision and soft decision.

For the hard decision, choose the top *n* number words with high Trigger Force; For the soft decision, we set a threshold tf_0, which can be used to judge a candidate trigger words as a trigger word or not. If

$$Trigger\_Force(w_i) \geq tf_0 \quad (5)$$

word w_i is added to trigger word set as a trigger word.

The number *n* and threshold tf_0 are depending on different relations and different training data.

4 Experiment

To evaluate the framework of trigger word mining, we conducted experiments on relations which are involved in TAC-KBP English Slot Filling task.

Relations	Training data 1	Training data 2	Total number
PER			
alternate_name	1670	3750	5420
cause_of_death	1851	2500	4351
charges	1070	1750	2820
employee _of	3238	4250	7488
school_attend	1006	3500	4506
spouse	1690	3000	4690
ORG			
alternate_name	2109	2750	4859
founded_or_founded_by	2756	4500	7256
members_or_employees	1998	2250	4248
place_of_headquarters	2250	3750	6000

Table 1: Sentence distributions of 6 PER and 4 ORG relations.

Relation: *cause_of_death*	
Raw sentences	**Preprocessed sentences**
1. **Juanita Millender-McDonald** a seven-term California Democrat who chaired the Committee on House Administration died of **cancer** April 22 at her home in Carson California.	1. **E** a seven-term California Democrat who chaired the Committee on House Administration died of **V**.
2. A Democratic congresswoman **Juanita Millender-McDonald** has died of **cancer**.	2. **E** has died of **V**.
3. US Republican congresswoman **Jo Ann Davis** dies after fight with **breast cancer**.	3. **E** has died after a two-year battle with **V**.
4. Chadian Prime Minister Pascal **Yoadimnadji** died Friday at a Paris hospital following a **brain hemorrhage** the African nation's ambassador to France said.	4. **E** died Friday at a Paris hospital following a **V**.
5. Opera star Lincoln Center head Beverly Sills dies of cancer at78 the manager says.	5. **E** dies of **V**

Table 2: Illustration for preprocessing of example sentences.

For TAC-KBP Slot filing task, there are 26 attributes for PER entity and 17 attributes for ORG entity (Joe Ellis, 2012). We group these attributes into different relation classes and choose the most representative 10 relations, 6 for PER entity and 4 for ORG entity, to extract trigger words.

4.1 Training Data

The training data is made up by sentences which are correspondingly matched with entity and attribute-value pairs. The entity and attribute value pairs include two parts: 278 entities from TAC-KBP English Slot Filling task of 2009-2012 and their attribute values extracted from assessment data (NIST, 2012) of Slot Filling; 200 entities and their attribute values from Wikipedia Infobox. Corresponding sentences matched with these two parts of entity and attribute-value pairs respectively make up training data 1 and training data 2. The sentences distributions of different relations are shown in Table 1. The training data 1 is got by matching entity and attribute-value pairs with corresponding sentences in documents of TAC-KBP English Slot Filling corpus of 2009-2012, which are mainly Newswire and Web Text. There are 278 entities in TAC-KBP Slot Filling of 2009-2012, consist of 132 PER entities and 146 ORG entities. The entity and attribute-value pairs are extracted from assessment data of TAC-KBP Slot Filling of 2009-2012. The training data 1 is obtained as following: firstly, retrieval all entities in TAC-KBP corpus and find relevant documents; secondly, match corresponding sentences with entity and attribute-value pairs for 10 different relations in relevant documents. And then we get our training data 1, which contains 19638 sentences in all.

The training data 2 is got by matching 200 entities and their attribute-value pairs, which are extracted from Wikipedia Infobox, with corresponding sentences in Google. We choose the 20th century's most influential 100 people (Time, 2010) as PER entity and top 100 companies of 2012 Fortune 500 in Fortune Magazine (Fortune, 2012) as ORG entity. The training data 2 is obtained as following: firstly, extract the 200 entities attribute values in Wikipedia Infobox; secondly, search these entity and attribute-value pairs in Google to match sentences including these entity-value pairs; lastly, choose top 50 corresponding sentences as training data for each entity-value pairs. And then, we get the training data 2, which contains 32000 sentences in all.

4.2 Sentences preprocessing

Since our goal is to extract trigger words, we do some special process on sentences in training data (shown in Table 2):

- To give expression to statistic information of pairs of entity and attribute-value and trigger words, we replace all entity and attribute-value pairs in corresponding sentences with signs of **E** and **V**.
- We assume that trigger words of a specific relation are all between entities and their attribute-values in corresponding sentences and we just take words between entities and their attribute-values as candidate trigger words for evaluation.

4.3 Results

Because of different data set scale, we observe that thresholds of relations are changed a lot. In order to uniform standard, we just choose top 20 words as trigger words for each relation. To judge the result, we do manual annotation for the data set and determine trigger words set for each relation. We carry out the experiments to investigate the impact of different λ on the performance by changing it from 0 to 1 incrementally. Figure 2 presents the results for PER relation *emplyee_of*, *cause_of_death*

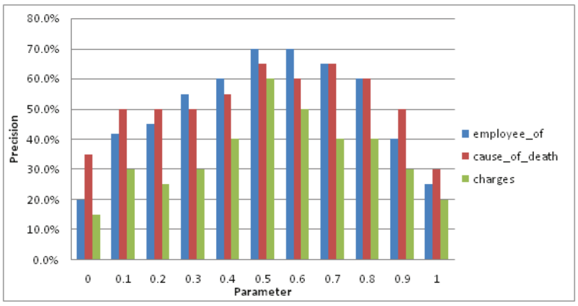

Figure 1: Impact of parameter λ for relation *employee_of*, *cause_of_death* and *charges*.

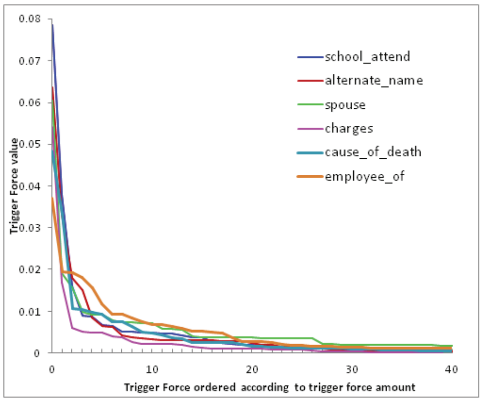

Figure 2: Distributions of Trigger Force amounts over the top 40 Trigger Forces of all PER relations.

and *charges* from the experiments. From Figure 2, we can see that with the adding of λ, Precisions of all three relations increase roughly befor $\lambda = 0.5$, and then decrease roughly after $\lambda = 0.5$. The results show that we can get the best performance at $\lambda = 0.5$. Based on the result of Figure 2, we conduct following experiments by setting $\lambda = 0.5$ We report precision, recall, F1 of top ranked 20 trigger words for each relation in Table 3. To show the effectiveness of the Trigger Force method (TF), we select term frequency (tf) results for comparison. From Table 3, we can see that results of all relations using Trigger Force outperform results using term frequency. The recall of PER relation *alternate_name* reaches 100%, which means that all trigger words are all included in top 20 trigger words. In average, the precision of our method achieves 20% improvement over the term frequency method to PER relations and 21.2% to ORG relations. The average F1 value of our method outperforms the term frequency method by 17.6% in all relations.

Why does the Trigger Force method help to improve trigger words extraction? Because excep-

Relation	Precision (%)		Recall (%)		F1 (%)	
	TF	tf	TF	tf	TF	tf
PER						
alternate_name	70.0	40.0	100	57.1	82.4	47.0
cause_of_death	65.0	50.0	86.7	66.7	74.3	57.2
charges	60.0	50.0	36.4	30.3	45.3	37.7
employee_of	70.0	70.0	58.3	58.3	63.6	63.6
school_attend	60.0	55.0	46.2	42.3	52.2	47.8
spouse	50.0	30.0	66.7	40.0	57.2	34.3
ORG						
alternate_name	60.0	20.0	92.3	30.8	72.7	24.3
founded_or_founded_by	40.0	25.0	44.4	27.8	41.9	26.3
members_or_employees	60.0	50.0	92.3	76.9	72.7	60.6
palce_of_headquarters	30.0	20.0	50.0	33.3	37.5	24.9

Table 3: Precision, recall and F1 value for all relations when $\lambda = 0.5$.

t for term frequency of words, the co-occurrence and distance with entities and their attribute-values are also playing an important role for triggering a specific relation. The trigger force method takes all these factors in consideration and predicts the Trigger Force of a word by weighting the activation that an entity exerts on the trigger word and the activation that the trigger word exerts on the attribute-value of the entity through the statistics of training data.

In the further investigation into the Trigger Force, by ordering the Trigger Forces of trigger words corresponding to a specific relation, we found an excellent nature of the Trigger Force: The Trigger Forces of trigger words related to a relation are very selective, forming a sharply skewed distribution over the trigger words. The major amount of all the forces is only related to very few words, which have close syntactic or semantic associations with the specific relation. Figure 3 shows the Trigger Force distributions of all PER relations.

As shown in Figure 3, the Trigger Force amounts descend very sharply along with the ordered trigger word identifiers at the beginning, and then maintain an obvious long-tail nature (power-law-like distribution). The top 10 trigger words of relations *alternate_name*, *cause_of_death*, *school_attend* and *spouse* are shown in Figure 4 (The sizes of ball are used to label term frequency, the thickness of a link represents the strength of the Trigger Force for its relation, but the length means nothing. The central nodes in networks are enlarged to promote ease of reading). The visible Trigger words distribution (the weighted links are higher than the threshold (1.0e-3)) of the PER relation *alternate_name* is shown in Figure 4. From Figure 5, we can see that in addition to high

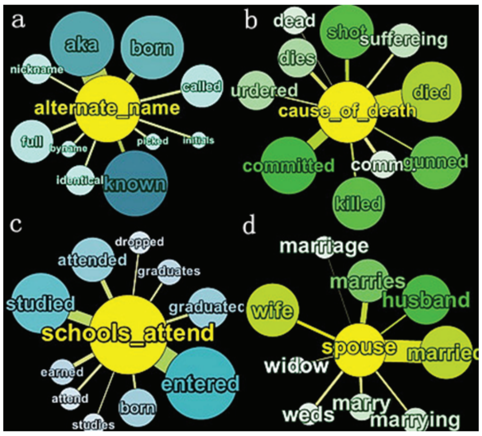

Figure 3: Top 10 trigger words identified by Trigger Forces in each relation.

frequency words, some low frequency words also have higher Trigger Force, such as *byname*, *early*, *picked*, *initials*, and *nickname*.

All these suggest that one can acquire the most forceful trigger words of a relation just by glancing at the top part of its Trigger Force which has been sorted in descending order.

5 Conclusions

In this paper we investigated trigger words mining for relation extraction and explored a new criterion for trigger words evaluation. Different to previous work, we introduced Trigger Force criterion based on activation force. The results showed that strengths of activation that an entity exerts on trigger words and activations that a trigger word exerts on attribute-values are all contribute to the capacity of trigger words for a specific relation and the criterion of Trigger Force do exhibit good performance. We also investigated the impact of parameter λ on the Trigger Force. Results show that the activation that an entity exerts on trigger word-

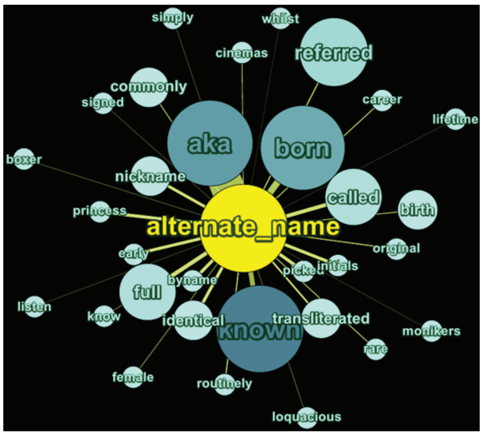

Figure 4: The visible Trigger words distribution of the PER relation *alternate_name*.

s and the activation that a trigger word exerts on attribute-values are the same important for Trigger Forces. Further investigation to the Trigger Force shows that the Trigger Force amounts of every relation meet power-law-like distribution.

Future work on using Trigger Forces for relation extraction needs to address several issues. Firstly, we should optimize our training data in sentences quality and quantity. Without doing textual coreference, there are some corresponding sentences matched with entity-value pairs missing. We plan to extend our method to evaluate bigger training data. Secondly, the threshold should be evaluated to find a good strategy for trigger words chosen in future work. Another interesting future work is to integrate the automatic trigger words mining with relation pattern learning for relation extraction, which would be more realistic than the experiments described in this paper where learning relation patterns is based on bootstrapping strategy. It would also be interesting to apply patterns learning model on TAC-KBP2013 Slot Filling task.

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