Chinese Named Entity Abbreviation Generation Using First-Order Logic

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Abstract

Normalizing named entity abbreviations to their standard forms is an important preprocessing task for question answering, entity retrieval, event detection, microblog processing, and many other applications. Along with the quick expansion of microblogs, this task has received more and more attentions in recent years. In this paper, we propose a novel entity abbreviation generation method using first-order logic to model long distance constraints. In order to reduce the human effort of manual annotating corpus, we also introduce an automatically training data construction method with simple strategies. Experimental results demonstrate that the proposed method achieves better performance than state-of-the-art approaches.

1 Introduction

Twitter and other social media services have received considerable attentions in recent years. Users provide hundreds of millions microblogs through them everyday. The informative data has been relied on by many applications, such as sentiment analysis (Jiang et al., 2011; Meng et al., 2012), event detection (Sakaki et al., 2010; Lin et al., 2010), stock market predication (Bollen et al., 2011), and so on. However, due to the constraint on the length of characters, abbreviations frequently occur in microblogs. According to a statistic, approximately 20% of sentences in news articles have abbreviated words (Chang and Lai, 2004). The frequency of abbreviation has become even more popular along with the rapid increment of user generated contents. Without pre-normalizing these abbreviations, most of the natural language processing systems may heavily suffer from them.

The goal of entity abbreviation generation is to produce abbreviated equivalents of the original entities. Table 1 shows several examples of entities and their corresponding abbreviations. A few of approaches have been done on this task. Li and Yarowsky (Li and Yarowsky, 2008b) introduced an unsupervised method used to extract phrases and their abbreviation pair using parallel dataset and monolingual corpora. Xie et al. (2011) proposed to use weighted bipartite graph to extract definition and corresponding abbreviation pairs from anchor texts. Since these methods rely heavily on lexical/phonetic similarity, substitution of characters and portion may not be correctly identified through them. Yang et al. (2009) studied the Chinese entity name abbreviation problem. They formulated the abbreviation task as a sequence labeling problem and used the conditional random fields (CRFs) to model it. However the long distance and global constraint can not be easily modeled thorough CRFs.

| Entity                                      | Abbr.         |
|---------------------------------------------|---------------|
| 北京大学 北大                               | (Peking University)北大 |
| 中国石油天然气集团公 中石油                 | (China National Petroleum Corporation)中石油 |
| 国际航空公司 北大                           | (Air China)国航 |

Table 1: Abbreviation examples

To overcome these limitations, in this paper, we propose a novel entity abbreviation generation method, which combines first-order logic and rich linguistic features. To the best of our knowledge, our approach is the first work of using first-order logic for this entity abbreviation. Abbreviation generation is converted to character deletion and
keep operations which are modeled by logic formula. Linguistic features and relations between different operations are represented by local and global logic formulas respectively. Markov Logic Networks (MLN) (Richardson and Domingos, 2006) is adopted for learning and predication. To reduce the human effort in constructing the training data, we collect standard forms of entities from online encyclopedia and introduce a few of simple patterns to extract abbreviations from documents and search engine snippets with high precision as training data. Experimental results show that the proposed methods achieve better performance than state-of-the-art methods and can efficiently process large volumes of data.

The remainder of the paper is organized as follows: In section 2, we review a number of related works and the state-of-the-art approaches in related areas. Section 3 presents the proposed method. Experimental results in test collections and analyses are shown in section 4. Section 5 concludes this paper.

2 Related Work

The proposed approach builds on contributions from two research communities: text normalization, and Markov Logic Networks. In the following of this section, we give brief description of previous works on these areas.

2.1 Text Normalization

Named entity normalization, abbreviation generation, and lexical normalization are related to this task. These problems have been recognized as important problems for various languages. Since different languages have their own peculiarities, many approaches have been proposed to handle variants of words (Aw et al., 2006; Liu et al., 2012; Han et al., 2012) and named entities (Yang et al., 2009; Xie et al., 2011; Li and Yarowsky, 2008b).

Chang and Teng (2006) introduced an HMM-based single character recovery model to extract character level abbreviation pairs for textual corpus. Okazaki et al. (2008) also used discriminative approach for this task. They formalized the abbreviation recognition task as a binary classification problem and used Support Vector Machines to model it. Yang et al. (2012) also treated the abbreviation generation problem as a labeling task and used Conditional Random Fields (CRFs) to do it. They also proposed to re-rank candidates by a length model and web information.

Li and Yarowsky (2008b) proposed an unsupervised method extracting the relation between a full-form phrase and its abbreviation from monolingual corpora. They used data co-occurrence intuition to identify relations between abbreviation and full names. They also improved a statistical machine translation by incorporating the extracted relations into the baseline translation system. Based on the data co-occurrence phenomena, they introduced a bootstrapping procedure to identify formal-informal relations informal phrases in web corpora (Li and Yarowsky, 2008a). They used search engine to extract contextual instances of the given an informal phrase, and ranked the candidate relation pairs using conditional log-linear model. Xie et al. (2011) proposed to extract Chinese abbreviations and their corresponding definitions based on anchor texts. They constructed a weighted URL-AnchorText bipartite graph from anchor texts and applied co-frequency based measures to quantify the relatedness between two anchor texts.

For lexical normalisation, Aw et al. (2006) treated the lexical normalisation problem as a translation problem from the informal language to the formal English language and adapted a phrase-based method to do it. Han and Baldwin (2011) proposed a supervised method to detect ill-formed words and used morphophonemic similarity to generate correction candidates. Liu et al. (2012) proposed to use a broad coverage lexical normalization method consisting three key components enhanced letter transformation, visual priming, and string/phonetic similarity. Han et al. (2012) introduced a dictionary based method and an automatic normalisation-dictionary construction method. They assumed that lexical variants and their standard forms occur in similar contexts.

In this paper, we focused on named entity abbreviation generation problem and treated the problem as a labeling task. Due to the flexibilities of Markov Logic Networks on capturing local and global linguistic feature, we adopted it to model the supervised classification procedure. To reduce the human effort in constructing training data, we also introduced a sample rule based method to find relations between standard forms and abbreviations.
2.2 Markov Logic Networks

Richardson and Domingos (2006) proposed Markov Logic Networks (MLN), which combines first-order logic and probabilistic graphical models. MLN framework has been adopted for several natural language processing tasks and achieved a certain level of success (Singla and Domingos, 2006; Riedel and Meza-Ruiz, 2008; Yoshikawa et al., 2009; Andrzejewski et al., 2011; Jiang et al., 2012; Huang et al., 2012).

Singla and Domingos (2006) modeled the entity resolution problem with MLN. They demonstrated the capability of MLN to seamlessly combine a number of previous approaches. Poon and Domingos (2008) proposed to use MLN for joint unsupervised coreference resolution. Yoshikawa et al. (2009) proposed to use Markov logic to incorporate both local features and global constraints that hold between temporal relations. Andrzejewski et al. (2011) introduced a framework for incorporating general domain knowledge, which is represented by First-Order Logic (FOL) rules, into LDA inference to produce topics shaped by both the data and the rules.

3 The Proposed Approach

In this section, firstly, we briefly describe the Markov Logic Networks framework. Then, we present the first-order logic formulas including local formulas and global formulas we used in this work.

3.1 Markov Logic Networks

A MLN consists of a set of logic formulas that describe first-order knowledge base. Each formula consists of a set of first-order predicates, logical connectors and variables. Different with first-order logic, these hard logic formulas are softened and can be violated with some penalty (the weight of formula) in MLN.

We use $\mathcal{M}$ to represent a MLN and $\{(\phi_i, w_i)\}$ to represent formula $\phi_i$ and its weight $w_i$. These weighted formulas define a probability distribution over sets of possible worlds. Let $y$ denote a possible world, the $p(y)$ is defined as follows (Richardson and Domingos, 2006):

$$p(y) = \frac{1}{Z} \exp \left( \sum_{(\phi_i, w_i) \in \mathcal{M}} w_i \sum_{c \in O^{\phi_i}} f_{\phi_i}^c(y) \right),$$

where each $c$ is a binding of free variable in $\phi_i$ to constraints; $f_{\phi_i}^c(y)$ is a binary feature function that
returns 1 if the true value is obtained in the ground formula we get by replacing the free variables in $\phi_i$ with the constants in $c$ under the given possible world $y$, and 0 otherwise; $C^m\phi_i$ is all possible bindings of variables to constants, and $Z$ is a normalization constant.

Many methods have been proposed to learn the weights of MLNs using both generative and discriminative approaches (Richardson and Domingos, 2006; Singla and Domingos, 2006). There are also several MLNs learning packages available online such as thebeast, Tuffy, PyMLNs, Alchemy, and so on.

### 3.2 MLN for Abbreviation Generation

In this work, we convert the abbreviation generation problem as a labeling task for every characters in entities. Predicate $drop(i)$ indicates that the character at position $i$ is omitted in the abbreviation. Previous works (Chang and Lai, 2004; Yang et al., 2009) show that Chinese named entities can be further segmented into words. Words also provide important information for abbreviation generation. Hence, in this work, we also segment named entities into words and propose an observed predict to connect words and characters.

#### 3.2.1 Local Formulas

The local formulas relate one or more observed predicates to exactly one hidden predicate. In this work, we define a list of observed predicates to describe the properties of individual characters. Table 2 shows the list. For this task, there is only one hidden predicate $drop$.

Table 3 lists the local formulas used in this work. The “+” notation in the formulas indicates that the each constant of the logic variable should be weighted separately. For example, formula $character(2,\_\_)+ isNumber(2) \Rightarrow drop(2)$ and $character(2,\_\_)+ isNumber(2) \Rightarrow drop(2)$ may have different weights as inferred by formula $character(i, c\_+) + isNumber(i) \Rightarrow drop(i)$.

Three kinds of local formulas are introduced in this work. Lexical features are used to capture the context information based on both character and word level information. Distance and position features are helpful in determining which parts of a entity may be removed. Hence, we also incorporate position information of word into local formulas. For example, “大学(University)” is usually omitted when it is at the end of the entity. In practice, abbreviations of some kinds of entities can be generated through several strategies. So we introduce several local formulas to handle a group of related entities with similar suffix.

#### 3.2.2 Global Formulas

Global formulas are designed to handle deletion of multiple characters. Since in this work, we only have one hidden predicate, $drop$, the global formulas incorporate correlations among different ground atoms of the $drop$ predicate.

We propose to use global formulas to force the abbreviations to contain at least 2 characters and to make sure that at least one character is deleted. The following formulas are implemented:

$$|character(i, c) \land drop(i)| \land \forall i \geq 1$$

$$|character(i, c) \land \neg drop(i)| \land \forall i \geq 2$$

Another constraint is that for the characters in some particular words should by dropped or kept simultaneously. So we add two formulas to model this:

$$character(i, c1) \land cwMap(i, j) \land drop(i) \land$$

$$character(i + 1, c2) \land cwMap(i + 1, j) \Rightarrow drop(i + 1)$$

$$character(i, c1) \land cwMap(i, j) \land \neg drop(i) \land$$

$$character(i + 1, c2) \land cwMap(i + 1, j) \Rightarrow \neg drop(i + 1)$$

### 4 Experiments

In this section, we first describe the dataset construction method, evaluation metrics, and experimental configurations. We then describe the evaluation results and analysis.

#### 4.1 Data Set

For training and evaluating the performance the proposed method, we need a large number of abbreviation and corresponding standard form pairs. However, manually labeling is a laborious and time consuming work. To reduce human effort, we propose to construct annotated dataset with two steps. Firstly, we collect entities from Baidu

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1. http://code.google.com/p/thebeast
2. http://hazy.cs.wisc.edu/hazy/tuffy/
3. http://www9-old.in.tum.de/people/jain/mlns/
4. http://alchemy.cs.washington.edu/
Lexical Features
character(i,c+) ∧ entityType(t+)⇒ drop(i)
character(i,c+) ∧ isNumber(i)⇒ drop(i)
character(i,c+) ∧ entityType(t+) ⇒ drop(i)
cwMap(i,j) ∧ (j=0) ∧ word(j,w) ∧ entityType(t+) ⇒ drop(i)

Table 3: Descriptions of local formulas.

Distance and Position Features
character(i,c) ∧ lenWord(wn+) ∧ cwPosition(i,wp+) ⇒ drop(i)
character(i,c) ∧ lenChar(cn+) ∧ cwPosition(i,wp+) ⇒ drop(i)
character(i,c) ∧ cwMap(i,j) ∧ word(j,w+) ∧ cwPosition(i,wp+) ⇒ drop(i)
character(i,c) ∧ cwMap(i,j) ∧ word(j,w+) ∧ lenWord(wn+) ⇒ drop(i)

Features for Entity with Special Suffixes
character(i,c+) ∧ cwMap(i,j) ∧ word(j,w+) ∧ lenWord(l+) ∧ entityType(t+) ⇒ drop(i)
character(i,c+) ∧ isCity(j) ∧ cwMap(i,j) ∧ word(j+1,w+) ∧ entityType(t+) ⇒ drop(i)
character(i,c) ∧ isCity(j) ∧ cwMap(i,j) ∧ word(j+1,w+) ∧ word(j+1,w2+) ∧ entityType(t+) ⇒ drop(i)
character(i,c) ∧ cwPosition(i,p+) ∧ ¬ isCity(j) ∧ cwMap(i,j) ∧ word(j+1,w+) ∧
(sufSchool(j+1) ∨ sufOrg(j+1) ∨ sufGov(j+1)) ⇒ drop(i)
character(i,c+) ∧ cwMap(i,j) ∧ word(j+1,w+) ∧ (sufSchool(j+1) ∧ sufOrg(j+1) ∧ sufGov(j+1)) ⇒ drop(i)
character(i,c+) ∧ cwMap(i,j) ∧ word(j-1,w+) ∧ (sufSchool(j) ∧ sufOrg(j) ∧ sufGov(j)) ⇒ drop(i)
character(i,c+) ∧ cwMap(i,j) ∧ word(j-2,w+) ∧ (sufSchool(j) ∧ sufOrg(j) ∧ sufGov(j)) ⇒ drop(i)
character(i,c+) ∧ cwMap(i,j) ∧ word(j+1,w1+) ∧ cwMap(ip,j-1) ∧ city(ip,p) ∧
(sufSchool(j+1) ∨ sufOrg(j+1) ∨ sufGov(j+1)) ⇒ drop(i)

Table 3: Descriptions of local formulas.
表4：词汇级别正则表达式用于匹配实体和缩写对。

Baike\(^5\)，是其中一个最受欢迎的维基百科为基础的中文百科全书，包含超过600万项内容。其次，我们使用一些简单的正则表达式从爬取的百科全书和搜索引擎片段中提取实体的缩写。

我们爬取了3200万篇来自百度百科的文章。接下来，我们清理了HTML标签，并从每篇文章中提取了标题、类别和文本内容。百度百科的结构类似于维基百科，标题是文章的主题，或者可能是话题的描述。因此，标题可以被认为是实体的标准形式。我们选择标题，其类别属于位置、组织和设施，以构建标准形式列表。该列表总共有302,633项。

下一步是使用标题和相应的文章来提取缩写。通过分析数据集，我们观察到大多数带有显式描述的缩写可以通过少量的词汇级别正则表达式匹配。表4显示了我们在工作中使用的正则表达式。通过此步骤，我们得到了30,701个缩写对。我们随机选择了500对，并手动检查其正确性。提取的对的准确度约为98.2%。

为了进一步增加提取的数量，我们使用Web作为语料库，并从搜索结果片段中提取缩写和实体对。对于每个实体，如果其缩写不能通过上述正则表达式识别，我们将组合实体和"简称"作为查询来检索。表4中的前三个正则表达式用于匹配缩写和实体对。通过此步骤，我们得到了另一个19,531个缩写。我们也随机选择了500对，并手动检查其正确性。准确率为95.2%。最后，我们将从百科全书和搜索结果片段提取的对合并，并构造一个包含50,232个缩写实体对的列表。列表的准确度为97.03%。

4.2 实验设置

为了评估所提出方法的性能，我们对自动构建的数据进行了实验。总实例随机分为75%用于训练，5%用于开发，其余20%用于测试。

我们比较了所提出的模型与现有的系统。Yang et al. (2009) 提出使用CRFs来建模这一过程。在本工作，我们重实现了他们提出的特征。为了公平比较两个模型，我们也扩展了他们的工作，包括了我们在工作中使用的所有局部公式作为特征。

在我们的设置中，我们使用了FudanNLP\(^6\)工具包和thebeast\(^7\)Markov Logic引擎。FudanNLP是为中文自然语言处理开发的。我们使用其默认设置下的中文分词。thebeast引擎的详细设置如下：推断算法是MAP推断，使用切割平面方法。对于参数学习，公式权重由在线学习算法更新，MIRA更新规则。所有初始权重设置为0。迭代次数设定为10个周期。

对于评估指标，我们使用精度、召回和F-分数来评估字符删除操作的性能。为了评估整个生成的缩写，我们也提出了使用准确性来评估。这意味着生成的缩写被认为是正确的，如果其标准形式的所有字符都被正确分类。

\(^5\)http://baike.baidu.com
\(^6\)http://code.google.com/p/fudannlp
\(^7\)http://code.google.com/p/thebeast
### Methods

| Methods            | P     | R     | F     | A     |
|--------------------|-------|-------|-------|-------|
| MLN-LF             | 83.2% | 81.1% | 82.1% | 42.2% |
| MLN-LF+DPF         | 80.9% | 84.3% | 82.6% | 45.7% |
| MLN-Local          | 82.4% | 85.4% | 83.9% | 54.7% |
| MLN-Local+Global   | 81.6% | 85.9% | 83.7% | 56.8% |
| CRFs-Yang          | 82.9% | 83.6% | 83.2% | 39.7% |
| CRFs-LF            | 84.9% | 83.7% | 84.3% | 40.5% |
| CRFs-LF+DPF        | 85.5% | 83.5% | 84.5% | 40.6% |
| CRFs-Local         | 84.9% | 83.8% | 84.3% | 40.8% |

**Table 5**: The lexical level regular expressions used to match entity and abbreviation pairs.

#### 4.3 Results

To evaluate the performance of our method, we set up several variants of the proposed method to compare with performances of CRFs. The **MLN-LF** method uses only the lexical features described in the **Table 3**. The **MLN-LF+DPF** method uses both lexical features and distance and position features. The **MLN-Local** method uses all local formulas described in the **Table 3**. The **MLN-Local+Global** methods combine both local formulas and global formulas together. For Yang’s system, we use **CRFs-Yang** to represent the re-implemented method with feature set proposed by them and **CRFs-LF**, **CRFs-LF+DPF**, and **CRFs-Local** to represent feature sets similar as used by MLN.

Table 5 shows the performances of different methods. We can see that **MLN-Local+Global** achieve the best accuracy of entire abbreviation among all the methods. Although, the F-score of **MLN-Local+Global** is slightly worse than **MLN-Local**. We think that the global formulas contribute a lot for the entire accuracy. However, since the constraint of simultaneously dropping or keeping characters does not consider context, it may also bring some false matches. We can also see that, the methods modeled by MLN significantly outperform the performances of CRFs no matter which feature sets are used (base on a paired 2-tailed t-test with \( p < 0.05 \)). We think that overfitting may be one of the main reasons.

From the perspective of entire accuracy, comparing the performances of **MLN-LF+DPF** and **MLN-Local**, we can see that features for entities with special suffixes contribute a lot. The relative improvement of **MLN-Local** is around 19.7%. It shows that the explicit rules are useful for improving the performance. However, these explicit rules only bring a small improvement to the accuracy of CRFs.

Comparing the performances of CRFs and MLNs, we can observe that CRFs achieve slightly better performance in classifying single characters. However MLNs achieve significantly better results of the entire accuracies. We think that these kinds of long distance features can be well handled by MLNs. These features are useful to capture the global constraints. Hence, MLNs can achieve better accuracy of the entire abbreviations.

In this paper, we also investigate the performance of different methods as the training data size are varied. Figure 1 shows the results. All full lines show the results of MLNs with different feature sets. The dot dash lines show the results of CRFs. From the results, we can observe that MLNs perform better than CRFs in most of cases. Except that MLNs with only lexical features work slightly worse than CRFs with small number of training data. From the figure, we also observe that the performance improvement of CRFs are not significant when the number of training data is larger than 35,000. However, methods using MLNs benefit a lot from the increasing data size. If more training instances are given, the performance of MLNs can still be improved.

![Figure 1: The impacts of training data size.](image-url)
of MLNs is fast. To evaluate the convergence rate, we also evaluate the dependence of the performances of MLNs on the number of training epochs. Figure 2 shows the results of MLN-Local and MLN-Local+Global. From the results, we can observe that the best performances can be achieved when the number of training epochs is more than nine. Hence, in this work, we set the number of iterations to be 10.

![Figure 2: The performance curves on the number of training epochs.](image)

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5 Conclusions

In this paper, we focus on named entity abbreviation generation problem. We propose to use first-order logic to model rich linguistic features and global constraints. We convert the abbreviation generation to character deletion and keep operations. Linguistic features and relations between different operations are represented by local and global logic formulas respectively. Markov Logic Network frameworks is adopted for learning and predication. To reduce the human effort in constructing the training data, we also introduce an automatical training data construction methods with sample strategies. We collect standard forms of entities from online encyclopedia, use a few simple patterns to extract abbreviations from documents and search engine snippets with high precision as training data. Experimental results show that the proposed methods achieve better performance than state-of-the-art methods and can efficiently process large volumes of data.

6 References

David Andrzejewski, Xiaojin Zhu, Mark Craven, and Benjamin Recht. 2011. A framework for incorporating general domain knowledge into latent dirichlet allocation using first-order logic. In Proceedings of the Twenty-Second international joint conference on Artificial Intelligence - Volume Two, IJCAI'11, pages 1171–1177. AAAI Press.

AiTi Aw, Min Zhang, Juan Xiao, and Jian Su. 2006. A phrase-based statistical model for sms text normalization. In Proceedings of the COLING/ACL 2006 Main Conference Poster Sessions, pages 33–40, Sydney, Australia, July. Association for Computational Linguistics.

Johan Bollen, Huina Mao, and Xiaojun Zeng. 2011. Twitter mood predicts the stock market. Journal of Computational Science, 2(1):1 – 8.

Jing-shin Chang and Yu-Tso Lai. 2004. A preliminary study on probabilistic models for chinese abbreviations. In Proceedings of the Third SIGHAN Workshop on Chinese Language Learning, pages 9–16.

Jing-Shin Chang and Wei-Lun Teng. 2006. Mining atomic chinese abbreviations with a probabilistic single character recovery model. Language Resources and Evaluation, 40(3-4):367–374.

Bo Han and Timothy Baldwin. 2011. Lexical normalisation of short text messages: Maka sens a #twitter. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, pages 368–378, Portland, Oregon, USA, June. Association for Computational Linguistics.

Bo Han, Paul Cook, and Timothy Baldwin. 2012. Automatically constructing a normalisation dictionary for microblogs. In Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning. EMNLP-CoNLL ’12, pages
421–432, Stroudsburg, PA, USA. Association for Computational Linguistics.

Minlie Huang, Xing Shi, Feng Jin, and Xiaoyan Zhu. 2012. Using first-order logic to compress sentences. In Proceedings of the Twenty-Sixth AAAI Conference on Artificial Intelligence.

Long Jiang, Mo Yu, Ming Zhou, Xiaohua Liu, and Tiejun Zhao. 2011. Target-dependent twitter sentiment classification. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, pages 151–160, Portland, Oregon, USA, June. Association for Computational Linguistics.

Shangpu Jiang, D. Lowd, and Dejing Dou. 2012. Learning to refine an automatically extracted knowledge base using markov logic. In Data Mining (ICDM), 2012 IEEE 12th International Conference on, pages 912–917.

Zhifei Li and David Yarowsky. 2008a. Mining and modeling relations between formal and informal Chinese phrases from web corpora. In Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing, pages 1031–1040, Honolulu, Hawaii, October. Association for Computational Linguistics.

Zhifei Li and David Yarowsky. 2008b. Unsupervised translation induction for chinese abbreviations using monolingual corpora. In Proceedings of ACL-'08: HLT, pages 425–433, Columbus, Ohio, June. Association for Computational Linguistics.

Cindy Xide Lin, Bo Zhao, Qiaozhu Mei, and Jiawei Han. 2010. Pet: a statistical model for popular events tracking in social communities. In Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining, KDD ’10, pages 929–938, New York, NY, USA. ACM.

Fei Liu, Fuliang Weng, and Xiao Jiang. 2012. A broad-coverage normalization system for social media language. In Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Long Papers - Volume 1, ACL ’12, pages 1035–1044, Stroudsburg, PA, USA. Association for Computational Linguistics.

Xinfan Meng, Furu Wei, Xiaohua Liu, Ming Zhou, Sujian Li, and Houfeng Wang. 2012. Entity-centric topic-oriented opinion summarization in twitter. In Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining, KDD ’12, pages 379–387, New York, NY, USA. ACM.

Naoaki Okazaki, Mitsuru Ishizuka, and Jun’ichi Tsujii. 2008. A discriminative approach to japanese abbreviation extraction. In Proceedings of the Third International Joint Conference on Natural Language Processing (IJCNLP 2008), pages 889–894.

Hoifung Poon and Pedro Domingos. 2008. Joint unsupervised coreference resolution with markov logic. In Proceedings of the Conference on Empirical Methods in Natural Language Processing, EMNLP ’08, pages 650–659, Stroudsburg, PA, USA. Association for Computational Linguistics.

Matthew Richardson and Pedro Domingos. 2006. Markov logic networks. Machine Learning, 62(1-2):107–136.

Sebastian Riedel and Ivan Meza-Ruiz. 2008. Collective semantic role labelling with markov logic. In Proceedings of the Twelfth Conference on Computational Natural Language Learning, CoNLL ’08, pages 193–197, Stroudsburg, PA, USA. Association for Computational Linguistics.

Takeshi Sakaki, Makoto Okazaki, and Yutaka Matsuo. 2010. Earthquake shakes twitter users: real-time event detection by social sensors. In Proceedings of the 19th international conference on World wide web, WWW ’10, pages 851–860, New York, NY, USA. ACM.

P. Singla and P. Domingos. 2006. Entity resolution with markov logic. In Data Mining, 2006. ICDM ’06. Sixth International Conference on, pages 572–582.

Li-Xing Xie, Ya-Bin Zheng, Zhi-Yuan Liu, Mao-Song Sun, and Can-Hui Wang. 2011. Extracting chinese abbreviation-definition pairs from anchor texts. In Machine Learning and Cybernetics (ICMLC), volume 4, pages 1485–1491.

Dong Yang, Yi-cheng Pan, and Sadaoki Furui. 2009. Automatic chinese abbreviation generation using conditional random field. In Proceedings of Human Language Technologies: The 2009 Annual Conference of the North American Chapter of the Association for Computational Linguistics, Companion Volume: Short Papers, NAACL-Short ’09, pages 273–276, Stroudsburg, PA, USA. Association for Computational Linguistics.

Dong Yang, Yi-Cheng Pan, and Sadaoki Furui. 2012. Vocabulary expansion through automatic abbreviation generation for chinese voice search. Computer Speech & Language, 26(5):321 – 335.

Katsumasa Yoshikawa, Sebastian Riedel, Masayuki Asahara, and Yuki Matsumoto. 2009. Jointly identifying temporal relations with markov logic. In Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP: Volume 1 - Volume 1, ACL ’09, pages 405–413, Stroudsburg, PA, USA. Association for Computational Linguistics.