Collaborative Entity Extraction and Translation

HENG JI & RALPH GRISHMAN

New York University

Abstract

Entity extraction is the task of identifying names and nominal phrases (mentions) in a text and linking coreferring mentions. We propose the use of a new source of data for improving entity extraction: the information gleaned from large bitexts and captured by a statistical, phrase-based machine translation system. We translate the individual mentions and test properties of the translated mentions, as well as comparing the translations of coreferring mentions. The results provide feedback to improve source language entity extraction. Experiments on Chinese and English show that this approach can significantly improve Chinese entity extraction (2.2% relative improvement in name tagging F-measure, representing a 15.0% error reduction), as well as Chinese to English entity translation (9.1% relative improvement in F-measure), over state-of-the-art entity extraction and machine translation systems.

1 Introduction

Named entity tagging has become an essential component of many NLP systems, such as question answering and information extraction. Building a high-performance name tagger, however, remains a significant challenge. The challenge is greater for languages such as Chinese and Japanese with neither capitalization nor overt tokenization to aid name detection, or Semitic languages such as Arabic that do not exhibit differences in orthographic case.

This challenge is now generally addressed by constructing, by hand, a large name-annotated corpus. Because of the cost of such annotation, several recent studies have sought to augment this approach through the use of un-annotated data, for example by constructing word classes (Miller et al. 2004) or by annotating additional data automatically and selecting the most confident annotations as further training (Ji & Grishman 2006).

One further source of information for improving name taggers are bitexts: corpora pairing the text to be tagged with its translation into one or more other languages. Such bitexts are becoming increasingly available for many language pairs, and now play a central role in the creation of machine translation and name translation systems. By aligning the texts at the word level, we are able to infer properties of a sequence s in language S from the properties of the sequence of tokens t with which it is aligned in language T. For example, knowing that t is a name, or merely that it is capitalized (for T = English) makes it more likely that s is a name. So if we have multiple, closely competing name hypotheses in the source language S, we can use the bitext to select the correct analysis.

Huang and Vogel (2002) used these observations to improve the name tagging of a bitext, and the NE (named entity) dictionary learned from the bitext. We wish to take this one step further by using information which can be gleaned from bitexts to improve the tagging of data for which we do not have pre-existing parallel text. We will use a phrase-based statistical machine translation system trained from these bitexts; we will translate the source-language entities using the machine translation (MT) and name translation systems; and then we will use this translation to improve the tagging of the original text.

This approach is an example of joint inference across quite disparate knowledge sources: in this case, combining the knowledge from named entity tagging and translation to produce better results for each. Such symbiosis of analysis components will be essential for the creation of high-performance NLP systems.

The translation knowledge source has an additional benefit: because name variants in S may translate into the same form in T, translation can also aid in identifying name coreference in S.

2 Task and terminology

We shall use the terminology of ACE[1] to explain our central ideas.

entity: an object or a set of objects in one of the semantic categories of interest, referred to by a set of mentions.
mention: a reference to an entity (typically, a noun phrase).
name mention: a reference by name to an entity.
nominal mention: a reference by a common noun or noun phrase to an entity.

In this paper we consider five types of entities in ACE evaluation: PER (persons), ORG (organizations), GPE (geo-political entities — locations which are also political units, such as countries, counties, and cities), GPE (other locations), and GPE (facility). *Entity extraction* can then be viewed as a combination of mention detection and classification with coreference analysis, which links coreferring mentions.

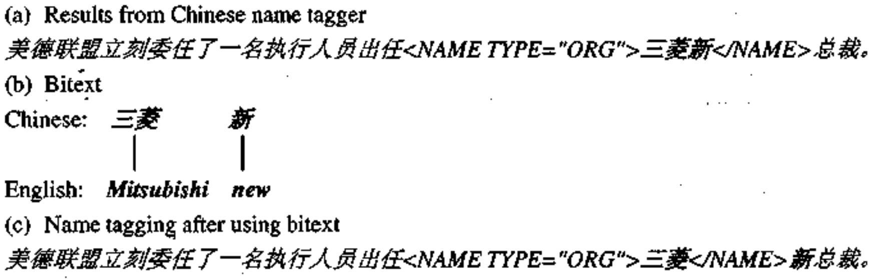
[1] The Automatic Content Extraction evaluation program of the U.S. Government. The ACE guidelines are at `http://www.ldc.upenn.edu/Projects/ACE/`

3 Motivation for using bitexts

We present first our motivation for using word-aligned bitexts to improve source language (S) entity extraction. Many languages have special features that can be employed for entity extraction. By using the alignment between the entity extraction results in language S and their translations in target language T, the language-specific information in T will enable the system to perform more accurate extraction than a model built from the monolingual corpus in S alone. In the following we present some examples for the Chinese-English language pair.

- Chinese → English

Chinese does not have white space for tokenization or capitalization, features which, for English, can help identify name boundaries and distinguish names from nominals. Using Chinese-English bitexts allows us to capture such indicative information to improve Chinese name tagging. For example,



(a) Results from Chinese name tagger

美德联盟立刻委任了一名执行人员出任<NAME TYPE="ORG">三菱新</NAME>总裁。

(b) Bitext

Chinese: *三菱* *新*

English: ***Mitsubishi*** ***new***

(c) Name tagging after using bitext

美德联盟立刻委任了一名执行人员出任<NAME TYPE="ORG">三菱</NAME>新总裁。

Based on the title context word *president* the Chinese name tagger mistakenly identifies *Mitsubish new* as an organization name. But the uncapitalized English translation of *new* can provide a useful clue to fix this boundary error.

- English → Chinese

On the other hand, Chinese has some useful language-specific properties for entity extraction. For example, standard Chinese family names are generally single characters drawn from a fixed set of 437 family names, and almost all first names include one or two characters. The suffix words (if there are any) of ORG and GPE names belong to relatively distinguishable fixed lists. This feature (particular character or word vocabulary for names) can be exploited as useful feedback for fixing name tagging errors.

Bank in English can be the suffix word of either a ORG or GPE name, while its Chinese translation *shore* indicates that *West Bank* is more likely to be a GPE name.

(a) Results from English name tagger

*The flashpoint in a week of bitter <NAME TYPE="ORG">**West Bank**</NAME> clashes ...*

(b) Bitext

English: ***West Bank***

Chinese: *西岸*

(c) Name tagging after using translation

*The flashpoint in a week of bitter <NAME TYPE="LOC">**West Bank**</NAME> clashes...*

These examples indicate how aligned bitexts can aid entity extraction. However, in most cases the texts from which we wish to extract entities will not be part of such bitexts. We shall instead use a statistical MT system which in effect distills the knowledge in its training bitexts. We will use this MT system to generate entity translations, and then use these translations as we did the bitexts in the examples above.

4 General approach

4.1 *Combining entity extraction and translation*

We propose a new framework to improve source language S entity extraction through the indirect use of bitexts as follows.

We first apply a source language *baseline* entity extraction system trained from a monolingual corpus to produce entities (*SEntities*), and then translate these entities into target language T (*TEntities*). Coreference decisions are made on the source language level. The *TEntities* carry information from a machine translation system trained from large bitexts, information which may not have been captured in the monolingual entity extraction. The *TEntities* can be used to provide *cross-lingual feedback* to confirm the results or repair the errors in SEntities. This feedback is provided by a set of rules which are applied iteratively.

However, in such a framework we face the problem that the translations produced by the MT system will not always be correct. In this paper we address this problem by using confidence estimation based on voting among translations of coreferring mentions, which we shall refer to as a *mention cache*. In section 4.2 and 4.3 we shall verify the two hypotheses which are required to apply the cache scheme, and in section 4.4 we shall explain the details of these caches.

4.2 *One translation per named entity*

Named entities may have many variants, for example, *IOC* and *International Olympic Committee* refer to the same entity; and *New York City* alternates with *New York*; but all these different variants tend to preserve *name heads* — a brief key alternation that represent the *naming function* (Carroll 1985). Unlike common words for which *fluency* and *vitality* are most required during translation, translating a named entity requires preserving its *functional* property — the real-world object that the name is referring to. Inspired by this linguistic property we propose a hypothesis:

- **Hypothesis (1).** *One Translation per Named Entity*:

The translation of different name mentions is highly consistent within an entity.

This hypothesis may seem intuitive, but it is important to verify its accuracy. On 50 English documents (4360 mention pairs) from ACE 2007 Chinese to English Entity Translation training data with human tagged entities, we measure the *accuracy* of this hypothesis by:

$$accuracy = \frac{|\text{ coreferred mention pairs with consistent translations }|}{|\text{ coreferred mention pairs }|}$$

We consider two translations *consistent* if one is a name component, acronym or adjective form of the other.

The *accuracy* of this hypothesis for different name types are: 99.6% for PER, 99.5% for GPE, 99.0% for ORG and 100% for GPE. This clearly indicates that Hypothesis (1) holds with high reliability.

4.3 *One source name per translation*

Based on Hypothesis (1), we can select a single best (maximal) name translation for each entity with a name; and this best translation can be used as *feedback* to determine whether the extracted name mentions in source language are correct or not. If they are incorrect (if their translations are not consistent with the best translation), they can be replaced by a best source language name. This is justified by:

- **Hypothesis (2).** *One Source Name per Translation*:

Names that have the same translation tend to exhibit *consistent* spellings in the source language.

In reviewing 101 Chinese documents (8931 mention pairs) with human translations from ACE'07 entity translation training data, the accuracy of this hypothesis for all entity types was close to 100%; the exceptions appeared to be clear translation errors.

Therefore, if we require the name mentions in one entity to achieve consistent translation as well as extraction (name boundary and type), then we can fix within-doc or cross-doc entity-level errors, with small sacrifice of (less than 1%) exceptional instances.

4.4 *Cross-lingual voted caches*

Given an entity in source language *SEntity* and its translation *TEntity*, let *SName(i)* be a name mention of *SEntity* and have translation *TName(i)*. Then the above two properties indicate that if string *TName(i)* appears frequently in *TEntity*, then *SName(i)* is likely to be correct. On the other hand, if *TName(i)* is infrequent in TEntity and conflicts with the most frequent translation in boundary or word morphology, then *SName(i)* is likely to be a wrong extraction.

For a pair of languages S (source language) → T (target language), we build the following voted cache models in order to get the best *assignment* (extraction or translation candidate) for each entity:

Inside-S-T-Cache: For each name mention of one entity (inside a single document), record its unique translations and frequencies;

Cross-S-T-Cache: Corpus-wide (across documents), for each name and its consistent variants, record its unique translations and their frequencies;

Cross-T-S-Cache: Corpus-wide, for each set of consistent name translations in T, record the corresponding names in S and their frequencies.

The caches incorporate simple filters based on properties of language T to exclude translations which are not likely to be names. For T = English, we exclude empty translations, translations which are single un-capitalized tokens, and, for person names, translations with any un-capitalized tokens. In addition, in counting translations in the cache, we group together consistent translations. For English, this includes combining person name translations if one is a subsequence of the tokens in the other. The goal of these simple heuristics is to take advantage of the general properties of language T in order to increase the likelihood that the most frequent entry in the cache is indeed the best translation.

For each entry in these caches, we get the frequency of each unique assignment, and then use the following margin measurement to compute the confidence of the best assignment:

$$Margin = Freq(Best\ Assignment) - Freq(Second\ Best\ Assignment)$$

A large margin indicates greater confidence in the assignment.

5 Inference rules

We can combine the language-specific information in *SEntity*, and its entry in the cross-lingual caches to detect potential extraction errors and take corresponding corrective measures. We construct the following inference rules and an example for some particular rules below.

Based on hypotheses (1) and (2), for a test corpus we aim to attain a group of entities in both source and target languages which have high consistency on the following levels:

Rule (1): *Adjust Source Language Annotations to Achieve Mention-level Consistency:*

Rule (1-1): *Adjust Mention Identification*
If a mention receives translation that has small margin as defined in Section 4.4 and violates the linguistic constraints in target language, then do not classify the mention as a name.

Rule (1-2): *Adjust Isolated Mention Boundary*
Adjust the boundary of each mention of SEntity to be consistent with the mention receiving the best translation.

Rule (1-3): *Adjust Adjacent Mention Boundary*
If two adjacent mentions receive the same translation with high confidence, merge them into one single mention.

Rule (2): *Adjust Source Language Annotations to Achieve Entity-level Consistency:*
If one entity is translated into two groups of different mentions, split it into two entities.

Rule (3): *Adjust Target Language Annotations to Achieve Mention-level Consistency:*
Enforce entity-level translation consistency by propagating the high-confidence best translation through coreferred mentions.

These inferences are formalized in Appendix A of (Ji & Grishman 2007). They are applied repeatedly until there are no further changes; improved translation in one iteration can lead to improved S entity extraction in a subsequent iteration.

6 System pipeline

The overall system pipeline for language pair (S, T) is summarized in Figure 1.

7 Experiments on Chinese to English

In this section we shall present an example of applying this method using Chinese-to-English translation to improve Chinese entity extraction.

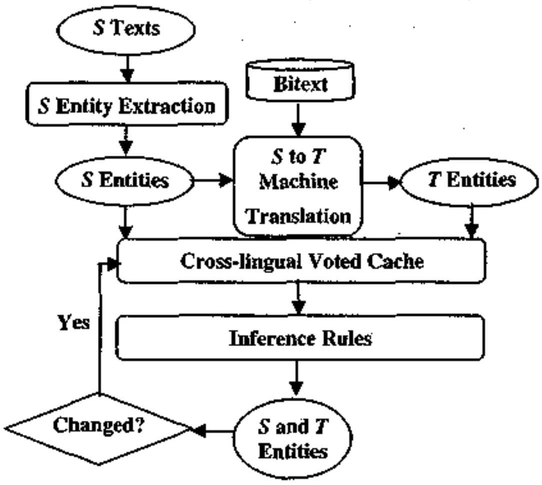


Fig. 1: *A symbiotic framework of entity extraction and translation*

7.1 *Baseline systems*

We used a Chinese entity extraction system described in (Ji et al. 2005) and a statistical, phrase-based machine translation system (Zens & Ney 2004) for our experiments. Each source mention is translated independently using the MT system[2].

7.2 *Data*

We took the Chinese newswire data from the ACE 2007 Entity Translation training and evaluation corpus as our blind test set, and evaluated our system. The test set includes 67 news texts, with 2077 name mentions and 1907 entities.

7.3 *Improvement in entity extraction*

The name tagging performance on different entity types is shown in Table 1 as follows.

[2] We tried an alternative approach in which mentions are translated in context and the mention translations are then extracted using word alignment information produced by the MT system, but it did not perform as well. The word alignments are indirectly derived from phrase alignment and can be quite noisy. As a result, noise in the form of words from the target language context is introduced into the mention translations. Manual evaluation on a small development set showed that isolated translation obtains (about 14%) better F-measure in translating names.

Type	Baseline	After Using Inference Rules
PER	89.9%	91.2%
GPE	87.0%	86.9%
ORG	85.7%	88.5%
LOC	89.7%	90.6%
FAC	80.9%	85.3%
ALL	87.3%	89.2%

Table 1: *F-measure of name tagging*

Except for the small loss for GPE names, our method achieved positive corrections on most entity types. Significant improvements were achieved on ORG and GPE names, mainly because organization and facility names in English texts have less boundary ambiguity than in Chinese texts. So they are better aligned in bitexts and easier to translate. The small loss in GPE names for the Chinese source is due to the poor quality of the translation of country name abbreviations. The rules can also improve nominal tagging by disambiguating mention types (name vs. nominal), and improve coreference by merging or splitting incorrect entity structures. All of these improvements benefit entity extraction.

7.4 *Improvement in entity translation*

A further benefit of our system is a boost in the translation quality of Chinese entities. We used the official ACE 2007-ET scorer[3] to measure the F-scores. The performance for translating different entity types is presented in Table 2.

Type	Baseline	After Using Inference Rules
PER	34.8%	36.7%
GPE	44.7%	49.8%
ORG	37.0%	39.9%
LOC	18.3%	18.1%
FAC	23.1%	23.3%
ALL	35.1%	38.3%

Table 2: *F-measure of entity translation*

The inference based on voting over mentions of an entity particularly improved GPE name abbreviation translation and fixed translated person foreign name boundaries. Thus we have succeeded in using the interaction of entity extraction and translation to improve the performance of both.

[3] The description of the ACE entity translation metric can be found at `http://www.nist.gov/speech/tests/ace/ace07/doc/ET07-evalplan-v1.6.pdf`.

7.5 *Error analysis*

The errors reveal both the shortcomings of the MT system and consistent difficulties across languages. For a name not seen in training bitexts the MT system tends to mistakenly align part of the name with an un-capitalized token. Also, there are words where the ambiguity between name and nominal exists in both Chinese and English. Rule (2) fails in these cases by mistakenly changing correct names into nominal mentions. In these and other cases, we could apply a separate name transliteration system developed from larger name-specific bitexts to re-translate these difficult names. Or we could incorporate the confidence values such as (Ueffing & Ney 2005) generated from the MT system into our cross-lingual cache model. Nevertheless, as Table 1 and 2 indicate, the rewards of using the bitext/translation information outweigh the risks.

8 Related work

The work described here complements the research described by (Huang & Vogel 2002). They presented an effective integrated approach that can improve the extracted named entity translation dictionary and the entity annotation in a bilingual training corpus. We expand their idea of alignment consistency to the task of entity extraction in a *monolingual test* corpus. Unlike their approach requiring reference translations in order to achieve highest alignment probability, we only need the source language unlabeled document. So our approach is more broadly applicable and also can be extended to additional information extraction tasks (nominal tagging and coreference).

Aligned bitexts have also been used to project name tags from French to English by Riloff et al. (2002) and from Japanese to English by Sudo et al. (2004), but their approaches only use the entity information from the source language.

In addition, our approach represents a form of cross-lingual joint inference, which complements the joint inference in the monolingual analysis pipeline as described in (Ji & Grishman 2005) and (Roth & Yi 2004).

9 Conclusion and future work

Bitexts can provide a valuable additional source of information for improving named entity tagging. We have demonstrated how the information from bitexts, as captured by a phrase-based statistical machine translation system, and then used to generate translations, can be used to correct errors made by a source-language named-entity tagger. While our approach has only been tested on Chinese and English so far, we can expect that it is applicable to other language pairs. The approach is independent of the baseline tagging/extraction system, and so can be used to improve systems with varied learning schemes or rules.

There are a number of natural extensions and generalizations of the current approach. In place of correction rules, we could adopt a joint inference approach based on generating alternative source language name tags (with probabilities), estimating the probabilities of the corresponding target language features, and seeking an optimal tag assignment. Although the current approach only relies on limited target language features, we could use a full target-language entity extractor (as Huang and Vogel (2002) did), providing more information as feedback (for example, name type information). Furthermore, we intend to pass the name tagging hypotheses to a name transliteration system and use the transliteration results as additional feedback in assessing name hypotheses.

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