# Towards Large-Scale Unsupervised Relation Extraction from the Web

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## ABSTRACT

The Web brings an open-ended set of semantic relations. Discovering the significant types is very challenging. Unsupervised algorithms have been developed to extract relations from a corpus without knowing the relation types in advance, but most of them rely on tagging arguments of predefined types. One recently reported system is able to jointly extract relations and their argument semantic classes, taking a set of relation instances extracted by an open IE (Information Extraction) algorithm as input. However, it cannot handle polysemy of relation phrases and fails to group many similar ("synonymous") relation instances because of the sparseness of features. In this paper, we present a novel unsupervised algorithm that provides a more general treatment of the polysemy and synonymy problems. The algorithm incorporates various knowledge sources which we will show to be very effective for unsupervised relation extraction. Moreover, it explicitly disambiguates polysemous relation phrases and groups synonymous ones. While maintaining approximately the same precision, the algorithm achieves significant improvement on recall compared to the previous method. It is also very efficient. Experiments on a real-world dataset show that it can handle 14.7 million relation instances and extract a very large set of relations from the Web.

***Keywords:*** Information Extraction, semantics, Web, large-scale, unsupervised learning, relation extraction

## INTRODUCTION

Relation extraction aims at discovering semantic relations between entities. It is an important task that has many applications in answering factoid questions, building knowledge bases and improving search engine relevance. In the era of the Internet, the Web has become a massive potential source of such relations. However, there are challenges for Web-scale open-domain relation extraction: the huge and fast-growing scale, a mixed genre of documents and potentially infinite types of relations it carries. To extract these relations, a system should not assume a fixed set of relation types, nor rely on a fixed set of relation argument types. It also should be able to efficiently handle a very large amount of data.

The past decade has seen some promising solutions. Unsupervised relation extraction (URE) algorithms extract relations from a corpus without knowing the relations in advance. However,

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most algorithms (Hasegawa et al., 2004, Shinyama and Sekine, 2006, Chen et. al, 2005) rely on tagging predefined types of entities as relation arguments, and thus are not well-suited for open domain relation extraction.

Recently, Kok and Domingos (2008) proposed Semantic Network Extractor (SNE), which generates argument semantic classes and sets of synonymous relation phrases at the same time. It avoids the requirement of tagging relation arguments of predefined types. However, SNE has 2 limitations: 1) following previous URE algorithms, it only uses features from the set of input relation instances for clustering. Empirically we found that it fails to group many relevant relation instances. These features, such as the surface forms of arguments and lexical sequences in between, are very sparse in practice. In contrast, there exist several well-known corpus-level semantic resources that can be automatically derived from a source corpus and are shown to be useful for generating the key elements of a relation: its 2 argument semantic classes and a set of synonymous phrases. For example, semantic classes can be derived from a source corpus with contextual distributional similarity and web table co-occurrences. The "*synonymy*" [2] problem for clustering relation instances could potentially be better solved by adding these resources. 2) SNE assumes that each entity or relation phrase belongs to exactly one cluster, thus is not able to effectively handle *polysemy* of relation phrases[3]. An example of a polysemous phrase is *be the currency of* as in 2 triples <*Euro, be the currency of, Germany*> and <*authorship, be the currency of, science*>. As the target corpus expands from mostly news to the open web, polysemy becomes more important as input covers a wider range of domains. In practice, around 22% (section 3) of relation phrases are polysemous. Failure to handle these cases significantly limits its effectiveness.

To move towards a more general treatment of the *polysemy* and *synonymy* problems, we present a novel algorithm WEBRE for open-domain large-scale unsupervised relation extraction without predefined relation or argument types (initially presented in Min et al., 2012). The major contributions of this work are:

- WEBRE incorporates a wide range of corpus-level semantic resources for improving relation extraction. The effectiveness of each knowledge source and their combination are studied and compared. To the best of our knowledge, it is the first to combine and compare them for unsupervised relation extraction.
- WEBRE explicitly disambiguates polysemous relation phrases and groups synonymous phrases, thus it fundamentally avoids the limitation of previous methods.
- Experiments on the Clueweb09 dataset (lemurproject.org/clueweb09.php) show that WEBRE is effective and efficient. We present a large-scale evaluation and show that WEBRE can extract a very large set of high-quality relations. Compared to the closest prior work, WEBRE significantly improves recall while maintaining the same level of precision. WEBRE is efficient. To the best of our knowledge, it handles the largest triple set to date (7-fold larger than largest previous effort). Taking 14.7 million triples as input, a complete run with one CPU core takes about a day.

## RELATED WORK

[2] We use the term *synonymy* broadly as defined in Section 3.

[3] A cluster of relation phrases can, however, act as a whole as the phrase cluster for 2 different relations in SNE. However, this only accounts for 4.8% of the polysemous cases.

Unsupervised relation extraction (URE) algorithms (Hasegawa et al., 2004; Chen et al., 2005; Shinyama and Sekine, 2006) collect pairs of co-occurring entities as relation instances, extract features for instances and then apply unsupervised clustering techniques to find the major relations of a corpus. These UREs rely on tagging a predefined set of argument types, such as Person, Organization, and Location, in advance. Yao et al. 2011 proposed several generative models, largely similar to LDA (Blei et al, 2003), for relation extraction. One of their models learns fine-grained semantic classes as relation arguments, but they share the similar requirement of tagging coarse-grained argument types. Most UREs use a quadratic clustering algorithm such as Hierarchical Agglomerate Clustering (Hasegawa et al., 2004, Shinyama and Sekine, 2006), K-Means (Chen et al., 2005), or both (Rosenfeld and Feldman, 2007); thus they are not scalable to very large corpora.

As the target domain shifts to the Web, new methods are proposed without requiring predefined entity types. Resolver (Yates and Etzioni, 2007) resolves objects and relation synonyms. Kok and Domingos (2008) proposed Semantic Network Extractor (SNE) to extract concepts and relations. Based on second-order Markov logic, SNE used a bottom-up agglomerative clustering algorithm to jointly cluster relation phrases and argument entities. However, both Resolver and SNE require each entity and relation phrase to belong to exactly one cluster. This limits their ability to handle polysemous relation phrases. Moreover, SNE only uses features in the input set of relation instances for clustering, thus it fails to group many relevant instances. Resolver has the same sparseness problem but it is not affected as much as SNE because of its different goal (synonym resolution).

As the preprocessing instance-detection step for the problem studied in this paper, open IE algorithms extracts relation instances (in the form of triples) from the open domain (Etzioni et al., 2004; Banko et al., 2007; Fader et al., 2011). For efficiency, they only use shallow features. Reverb (Fader et al., 2011) is a state-of-the-art open domain extractor that targets verb-centric relations, which have been shown in Banko and Etzioni (2008) to cover over 70% of open domain relations. Wang et al. (2011) filtered relation instances by using a few heuristics and a learning algorithm. Taking the relation instances extracted by open IE algorithms as input, algorithms have been proposed to resolve objects and relation synonyms (Resolver), extract semantic networks (SNE), and map extracted relations into an existing ontology (Soderland and Mandhani, 2007).

Recent work shows that it is possible to construct semantic classes automatically with data-driven approaches. They generally fall into three categories. The first category is based on the distributional hypothesis, which states that similar terms tend to appear with similar contexts (Harris 1985), so that it is possible to group similar terms if their contexts are similar. Several previous efforts aimed at utilizing the distributional hypothesis for constructing semantic classes (Pasca, 2007; Pantel et al., 2009). The second category (Pasca 2004; Sarmento et al., 2007) uses patterns to find similar terms. The third category is language independent approaches (Wang and Cohen 2007, 2009). For example, Wang and Cohen (2007) use HTML wrappers to find similar terms. Pennacchiotti and Pantel (2009) combine several sources and features for extracting entity classes.

Two tasks are closely related to the task of finding similar phrases for a relation: paraphrase discovery and recognizing textual entailment. Data-driven paraphrase discovery methods (Lin and Pantel, 2001; Pasca and Dienes, 2005; Wu and Zhou, 2003; Sekine, 2005) find paraphrases by extending the idea of distributional similarity to phrases. The Recognizing Textual Entailment

algorithms (Berant et al. 2011) can be used for finding related phrases since they find pairs of phrases in which one entails the other.

To efficiently cluster high-dimensional datasets, canopy clustering (McCallum et al., 2000) uses a cheap, approximate distance measure to divide data into smaller subsets, and then clusters each subset using an exact distance measure. It has been applied to reference matching. The second phase of WEBRE applies a similar high-level idea of partition-then-cluster for speeding up relation clustering. We design a graph-based partitioning subroutine that uses various types of evidence, such as shared hypernyms. To the best of our knowledge, we have applied the efficient clustering algorithm on the largest set of relation instances extracted from the open domain to date.

## PROBLEM ANALYSIS

The basic input is a collection of relation instances (triples) of the form <$ent_1$, *ctx*, $ent_2$>. For each triple, *ctx* is a relation phrase expressing the relation between the first argument $ent_1$ and the second argument $ent_2$. An example triple is <*Obama, win in, NY*>. The triples can be generated by an open IE extractor such as TextRunner or Reverb. Our goal is to automatically build a list of relations, each with the form[4] $\{< \text{ent}_1, ctx, \text{ent}_2 >\}$ or $< C_1, P, C_2 >$ ($P$ is the set of relation phrases, and $C_1$ and $C_2$ are two argument classes). Examples of triples and relations $R$ (as Type B) are shown in Figure 1.

There are two major challenges for building such a list of relations. The first problem is the *polysemy* of relation phrases, which means that a relation phrase *ctx* can express different relations in different triples. For example, the meaning of *be the currency of* in the following two triples is quite different: <*Euro, be the currency of, Germany*> and <*authorship, be the currency of, science*>. It is more appropriate to assign these 2 triples to 2 relations "*a currency is the currency of a country*" and "*a factor is important in an area*" than to merge them into one. Formally, a relation phrase *ctx* is *polysemous* if there exist 2 different relations $< C_1, P, C_2 >$ and $< C_1^{'}, P^{'}, C_2^{'} >$ where $ctx \in P \cap P^{'}$. In the previous example, *be the currency of* is polysemous because it appears in 2 different relations.

Polysemy of relation phrases is not uncommon. We generated clusters from a large sample of triples with the assistance of a soft clustering algorithm, and found that around 22% of relation phrases can be put into at least 2 disjoint clusters that represent different relations. More importantly, manual inspection reveals that some common phrases are polysemous. For example, *be part of* can be put into a relation "a *city is located in a county"* when connecting *Cities* to *Counties*, and another relation *"a company is a subsidiary of a parent company"* when connecting *Companies* to *Companies*. Failure to handle polysemous relation phrases fundamentally limits the effectiveness of an algorithm. The WEBRE algorithm described later explicitly handles polysemy and synonymy of relation phrases in its first and second phase respectively.

The second problem is the "*synonymy"* of relation instances. We use the term *synonymy* broadly and we say 2 relation instances are synonymous if they express the same semantic relation between the same pair of semantic classes. For example, both <*Euro, be the currency used in, Germany*> and <*Dinar, be legal tender in, Iraq*> express the relation <*Currencies, be*

[4] There are 2 possible representations of a relation: as a set of triple instances or a triple with 2 entity classes and a relation phrase class.

*currency of, Countries*>. Solving this problem requires grouping synonymous relation phrases and identifying argument semantic classes for the relation.

Various knowledge sources can be derived from the source corpus for this purpose. In this paper we pay special attention to incorporating various semantic resources for relation extraction. We will show that these semantic sources can significantly improve the coverage of extracted relations and the best performance is achieved when various resources are combined together.

## MINING RELATIONS FROM THE WEB

In this section, we first describe the knowledge sources that are used in the relation extraction algorithm, and then introduce the WEBRE algorithm, followed by a brief analysis on its computational complexity.

### Knowledge Sources

**Entity similarity graph:** We build two similarity graphs for entities: a distributional similarity (DS) graph and a pattern-similarity (PS) graph. The DS graph is based on the distributional hypothesis (Harris, 1985), saying that terms sharing similar contexts tend to be similar. We use a text window of size 4 as the context of a term, use Pointwise Mutual Information (PMI) to weight context features, and use Jaccard similarity to measure the similarity of term vectors. The PS graph is generated by adopting both sentence lexical patterns and HTML tag patterns (Hearst, 1992; Kozareva et al., 2008; Zhang et al., 2009). Two terms (*T*) tend to be semantically similar if they co-occur in multiple patterns. One example of sentence lexical patterns is *(such as | including) T{,T}* (and|,|.)*. HTML tag patterns include tables, dropdown boxes, etc.

**Hypernymy graph:** Hypernymy relations are very useful for finding semantically similar term pairs. For example, we observed that a small city in UK and another small city in Germany share common hypernyms such as *city*, *location*, and *place*. Therefore the similarity between the two cities is large according to the hypernymy graph, while their similarity in the DS graph and the PS graph may be very small. Following existing work (Hearst, 1992, Pantel & Ravichandran 2004; Snow et al., 2005; Talukdar et al., 2008), we adopt a list of lexical patterns to extract hypernyms. The patterns include *NP {,} (such as) {NP,}* {and|or} NP*, *NP (is|are|was|were|being) (a|an|the) NP*, etc. In this paper, we use the terms *hypernym* and *label* interchangeably.

**Relation phrase similarity:** To generate the pairwise similarity graph for relation phrases with regard to the probability of expressing the same relations, we apply a variant of the DIRT algorithm (Lin and Pantel, 2001):

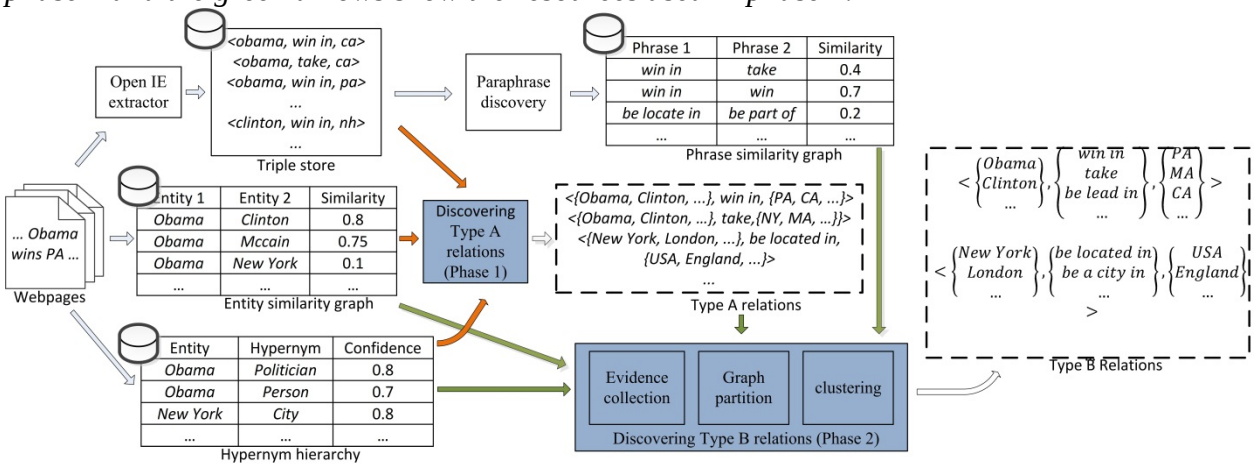
| Algorithm ***ParaphraseDiscovery*** | |
|---|---|
| Input: | Set of triples *{<$ent_1$, ctx, $ent_2$>}* |
| Output: | Similarity matrix of phrases *M* |
| Steps: | |
| 01. | For each *<$ent_1$, ctx, $ent_2$>* in *{<$ent_1$, ctx, $ent_2$>}* |
| 02. | Collect *< $ent_1$, $ent_2$>* as features for *ctx* |
| 03. | *Vec(ctx)* = feature vector of *ctx* |
| 04. | For each phrase *$ctx_1$* in *{ctx}* |

05. For each phrase $ctx_2$ in $\{ctx\}$
06. $Sim(ctx_1, ctx_2) = Jaccard(Vec(ctx_1), Vec(ctx_2))$
07. Add $Sim(ctx_1, ctx_2)$ into $M$
08. Return $M$

Like DIRT, the paraphrase discovery relies on the distributional hypothesis, but there are a few differences: 1) we use stemmed lexical sequences instead of dependency paths as relation phrase candidates. There are two reasons. First, although dependency parsing produces less sparse phrase candidates, it is not applicable to a very large corpus. Second, the impact of the data sparseness problem is reduced in a large corpus. 2) We used ordered pairs of arguments as features of phrases while DIRT uses them as independent features. We empirically tested both feature schemes and found that using ordered pairs results in likely paraphrases but using independent features the result contains general inference rules[5].

## WEBRE for Relation Extraction

*Figure 1. Overview of the WEBRE algorithm (Illustrated with examples sampled from experiment results). The tables and rectangles with a database sign show knowledge sources, shaded rectangles show the 2 phases, and the dotted shapes show the system output, a set of Type A relations and a set of Type B relations. The orange arrows denote resources used in phase 1 and the green arrows show the resources used in phase 2.*




WEBRE consists of two phases. In the first phase, a set of semantic classes are discovered and used as argument classes for each relation phrase. This results in a large collection of relations whose arguments are pairs of semantic classes and which have exactly one relation phrase. We call these relations the *Type A* relations. An example Type A relation is *<{New York, London…}, be located in, {USA, England, …}>*. During this phase, polysemous relation phrases are disambiguated and placed into multiple Type A relations. The second phase is an efficient algorithm which groups similar Type A relations together. This step enriches the argument semantic classes and groups synonymous relation phrases to form relations with multiple

[5] For example, *be part of* has ordered argument pairs *<A, B>* and *<C, D>*, and *be not part of* has ordered argument pairs *<A, D>* and *<B, C>*. If arguments are used as independent features, these two phrases shared the same set of features *{A, B, C, D}*. However, they are inferential (complement relationship) rather than being similar phrases.

expressions, which we called *Type B* relations. Both Type A and Type B relations are system outputs since both are valuable resources for downstream applications such as Question Answering and Web Search. An overview of the algorithm is shown in Figure 1. Here we first briefly describe a clustering subroutine that is used in both phases, and then describe the algorithm in detail.

To handle polysemy of objects (e.g., entities or relations) during the clustering procedure, a key building block is an effective Multi-Membership Clustering algorithm (*MMClustering*). For simplicity and effectiveness, we use a variant of Hierarchical Agglomerative Clustering (HAC), in which we first cluster objects with HAC, and then reassign each object to additional clusters when its similarities with these clusters exceed a certain threshold[6]. The algorithm is as follow:

| Algorithm ***MMClustering*** | |
|---|---|
| Input: | Vector of objects *{I}*<br>Objects similarity function *SimFunc*<br>Similarity threshold $\alpha$ and $\beta$ |
| Output: | Clusters of objects *{C}* |
| Steps: | |
| 01. | *{C}* = set each object in *{I}* as a unit cluster |
| 02. | *{C} = HAC({C}, α)* |
| 03. | For each *I* in *{I}* |
| 04. | For each *C* in *{C}* |
| 05. | If *SimFunc(I, C)* > $\beta$ |
| 06. | Insert *I* into *C* |
| 07. | Return *{C}* |

An object can be an entity as in phase 1, or a relation for phase 2. Empirically β should be greater than α to avoid generating duplicated clusters.

**Discovering Type A Relations** The first phase of the relation extraction algorithm generates Type A relations, which have exactly one relation phrase and two argument entity semantic classes. For each relation phrase, we apply a clustering algorithm on each of its two argument sets to generate argument semantic classes. The *Phase 1* algorithm processes relation phrases one by one. For each relation phrase *ctx*, step 4 (refer to the "Algorithm Phase 1" figure below) clusters the set $\{ent_1\}$ using *MMClustering* to find left-hand-side argument semantic classes $\{C_1\}$. Then for each cluster *C* in $\{C_1\}$, it gathers the right-hand-side arguments which appeared in some triples whose left hand-side-side argument are in *C*, and puts them into $\{ent_2'\}$. Following this, it clusters $\{ent_2'\}$ to find right-hand-side argument semantic classes. This results in pairs of semantic classes which are arguments of *ctx*. Each relation phrase can appear in multiple Type A relations. For example, <*Cities, be part of, Counties*> and <*Companies, be part of, Companies*> are different Type A relations which share the same relation phrase *be part of*. In the pseudo code, *SimEntFunc* is encoded in the entity similarity graphs.

| Algorithm ***Phase 1: Discovering Type A relations*** | |
|---|---|
| Input: | set of triples $T=\{<ent_1, ctx, ent_2>\}$<br>entity similarity function *SimEntFunc*<br>Similarity threshold $\alpha$ |

[6] This threshold should be slightly greater than the clustering threshold for HAC to avoid generating duplicated clusters.

Output: list of Type A relations $\{<C_1, ctx, C_2>\}$
Steps:
01. For each relation phrase *ctx*
02. $\{<ent_1, ctx, ent_2>\}$ = set of triples sharing *ctx*
03. $\{ent_1\}$ = set of $ent_1$ in $\{<ent_1, ctx, ent_2>\}$
04. $\{C_1\} = MMClustering(\{ent_1\}, SimEntFunc, \alpha)$
05. For each $C_1$ in $\{C_1\}$
06. $\{ent_2'\} = set\ of\ ent_2\ s.t. \exists < ent_1, ctx, ent_2 > \in T \wedge ent_1 \in C_1$
07. $\{C_2\} = MMClustering(\{ent_2'\}, SimEntFunc, \alpha)$
08. For each $C_2$ in $\{C_2\}$
09. Add $<C_1, ctx, C_2>$ into $\{<C_1, ctx, C_2>\}$
10. Return $\{<C_1, ctx, C_2>\}$

**Discovering Type B Relations** The goal of *phase 2* is to merge similar Type A relations, such as <*Cities, be located in, Countries*> and <*Cities, be city of, Countries*>, to produce Type B relations, which have a set of synonymous relation phrases and more complete argument entity classes. The challenge for this phase is to cluster a very large set of Type A relations, on which it is infeasible to run a clustering algorithm that does pairwise comparison. Therefore, we designed an evidence-based partition-then-cluster algorithm.

The basic idea is to heuristically partition the large set of Type A relations into small subsets, and run clustering algorithms on each subset. It is based on the observation that most pairs of Type A relations are not similar because of the sparseness in the entity class and the relation semantic space. If there is little or no evidence showing that two Type A relations are similar, they can be put into different partitions. Once partitioned, the clustering algorithm only has to be run on each much smaller subset, thus computation complexity is reduced.

We use 2 types of evidence. They are shared members and shared hypernyms of relation arguments. For example, 2 Type A relations $r_1$=<*Cities, be city of, Countries*> and $r_2$=<*Cities, be located in, Countries*> share a pair of arguments <*Tokyo, Japan*>, and a pair of hypernyms <"*city*", "*country*">. These pieces of evidence give us hints that they are likely to be similar. As shown in the pseudo code, shared arguments and hypernyms are used as independent evidence to reduce sparseness.

Algorithm ***Phase 2: Discovering Type B relations***

Input: Set of Type A relations $\{r\}=\{<C_1, ctx, C_2>\}$
Relation similarity function *SimRelationFunc*
Map from entities to their hypernyms: $M_{entity2label}$
Similarity threshold $\alpha$
Edge weight threshold $\mu$
Variables $G(V, E)$ = weighted graph in which $V=\{r\}$
Output: Set of Type B relations $\{<C_1, P, C_2>\}$
Steps:
01. $\{<ent, \{r'\}>\}$ = build inverted index from argument *ent* to set of Type A relations $\{r'\}$ on $\{<C_1, ctx, C_2>\}$
02 $\{<l, \{r'\}>\}$ = build inverted index from hypernym *l* of arguments to set of Type A relations $\{r'\}$ on $\{<C_1, ctx, C_2>\}$ with map $M_{entity2label}$
03. For each *ent* in $\{<ent, \{r'\}>\}$

04. For each pair of $r_1$ and $r_2$ s.t. $r_1 \in \{r'\} \wedge r_2 \in \{r'\}$
05. *weight_edge(<$r_1$, $r_2$>) += weight (ent)*
06. For each *l* in *{<l, {r'}>}*
07. For each pair of $r_1$ and $r_2$ s.t. $r_1 \in \{r'\} \wedge r_2 \in \{r'\}$
08. *weight_edge(<$r_1$, $r_2$>) += weight (l)*
09. For each edge <$r_1$, $r_2$> in *G*
10. If *weight_edge(<$r_1$, $r_2$>) < $\mu$*
11. Remove edge <$r_1$, $r_2$> from *G*
12. *{CC}= DFS(G)*
13. For each connected component *CC* in *{CC}*
14. *{<$C_1$, ctx, $C_2$>}* = vertices in *CC*
15. *{<$C_1$', P', $C_2$'>} = MMClustering({<$C_1$, ctx, $C_2$>}, SimRelationFunc, α)*
16. Add *{<$C_1$', P', $C_2$'>}* into *{<$C_1$, P, $C_2$>}*
17. Return *{<$C_1$, P, $C_2$>}*

Steps 1 and 2 build an inverted index from evidence to sets of Type A relations. On the graph *G* whose vertices are Type A relations, steps 3 to 8 set the value of edge weights based on the strength of evidence that shows the end-points are related. The weight of evidence *E* is calculated as follows:

$$weight(E) = \frac{\#\ shared\ triples\ in\ which\ E\ appears\ in}{\max(\#\ classes\ E\ appears\ in)}$$

The idea behind this weighting scheme is similar to that of TF-IDF in that the weight of evidence is higher if it appears more frequently and is less ambiguous (appeared in fewer semantic classes during clustering of phase 1). The weighting scheme is applied to both shared arguments and labels.

After collecting evidence, we prune (steps 9 to 11) the edges with a weight less than a threshold $\mu$ to remove noise. Then a Depth-First Search (DFS) is called on *G* to find all Connected Components *CC* of the graph. These *CC*s are the partitions of likely-similar Type A relations. We run *MMClustering* on each *CC* in *{CC}* and generate Type B relations (step 13 to step 16). The similarity of two relations (*SimRelationFunc*) is defined as follows:

$$sim(< C_1, P, C_2 >, < C_1', P', C_2' >) = \begin{cases} 0, & if\ sim(P, P') < \sigma \\ \min\left(sim(C_1, C_1'), sim(C_2, C_2')\right), & else \end{cases}$$

in which $\boldsymbol{sim(P, P')}$ is the average similarity of the 2 sets of relation phrases in the 2 relations, and $\boldsymbol{sim(C_1, C_1')}$ is the average similarity of the 2 sets of argument entities in the 2 relations. These similarities are looked up from the similarity graphs (phrase and entities) constructed with techniques described in Section 4.1.

## Computational Complexity

WEBRE is very efficient since both phases decompose the large clustering task into much smaller clustering tasks over partitions. Given $n$ objects for clustering, a hierarchical agglomerative clustering algorithm requires $O(n^2)$ pairwise comparisons. Assuming the clustering task is split into subtasks of size $n_1, n_2, \ldots, n_k$, thus the computational complexity is reduced to $O(\sum_1^k n_i^2)$. Ideally each subtask has an equal size of $n/k$, so the computational

complexity is reduced to $O(n^2/k)$, a factor of $k$ speed up. In practice, the sizes of partitions are not equal. Taking the partition sizes observed in the experiment with 0.2 million Type A relations as input, the phase 2 algorithm achieves around a 100-fold reduction in pairwise comparisons compared to the agglomerative clustering algorithm. The combination of phase 1 and phase 2 achieves more than a 1000-fold reduction in pairwise comparison, compared to running an agglomerative clustering algorithm directly on 14.7 million triples. This reduction of computational complexity makes the unsupervised extraction of relations on a large dataset a reality. In the experiments with 14.7 million triples as input, phase 1 finished in 22 hours, and the phase 2 algorithm finished in 4 hours with one CPU core.

Furthermore, both phases can be run in parallel in a distributed computing environment because data is partitioned. Therefore it is scalable and efficient for clustering a very large number of relation instances from a large-scale corpus like the Web.

## EXPERIMENT

**Data preparation** We tested WEBRE on resources extracted from the English subset of the Clueweb09 dataset, which contains 503 million webpages. For building knowledge resources, all webpages are cleaned, POS tagged and chunked with in-house tools. We implemented the algorithms described in section 4.1 to generate the knowledge sources, including a hypernym graph, two entity similarity graphs and a relation phrase similarity graph.

We used Reverb Clueweb09 Extractions 1.1 (downloaded from *reverb.cs.washington.edu*) as the triple store (relation instances). It is the complete extraction of Reverb over Clueweb09 after filtering low confidence and low frequency triples. It contains 14.7 million distinct triples with 3.3 million entities and 1.3 million relation phrases. We choose it because 1) it is extracted by a state-of-the-art open IE extractor from the open-domain, and 2) to the best of our knowledge, it contains the largest number of distinct triples extracted from the open-domain and which is publicly available. Reverb triples are in the form of triples <*argument1, relation phrase, argument2*> in which the 2 arguments are noun phrases and relation phrases are the lexical sequence in between. An example triple is <*Boston, is located north of, New York*>. To reduce sparseness of the relation phrases, we apply a dictionary-based stemmer to reduce the inflected form of each word to its base form. We also remove stop words (semantically empty words) from the relation phrases.

**Evaluation setup** The evaluations are organized as follows: we evaluate Type A relation extraction and Type B relation extraction separately, and then we compare WEBRE to its closest prior work SNE. Since both phases are essentially clustering algorithms, we compare the output clusters with human labeled gold standards and report performance measures, following most previous work such as Kok and Domingos (2008) and Hasegawa et al. (2004). Three gold standards are created for evaluating Type A relations, Type B relations and the comparison to SNE, respectively. In the experiments, we set $\alpha=0.6$, $\mu=0.1$ and $\sigma=0.02$ based on trial runs on a small development set of 10k relation instances. We filtered out the Type A relations and Type B relations which only contain 1 or 2 triples since most of these relations are not different from a single relation instance and are not very interesting. Table 1 shows the overall statistics of the experiment. 201,246 Type A relations and 84,126 Type B relations are extracted.

*Table 1. Overall statistics of the experiment. The Type A relations are generated with the Label+SIM method and must contain at least 2 triples.*

| Type | Distinct # of instances |
|---|---|
| Triple | 14,728,268 |
| Entity | 3,326,830 |
| Relation phrase | 1,299,841 |
| Type A relation | 201,246 |
| Type B relation | 84,126 |

**Evaluating Type A relations** To understand the effectiveness of knowledge sources, we run *Phase 1* multiple times taking entity similarity graphs (matrices) constructed with resources listed below:

- **TS**: Distributional similarity based on the triple store. For each triple <$ent_1$, *ctx*, $ent_2$>, features of $ent_1$ are *{ctx}* and *{ctx* $ent_2$*}*; features of $ent_2$ are *{ctx}* and *{*$ent_1$ *ctx}*. Features are weighted with PMI. Cosine is used as similarity measure.
- **LABEL:** The similarity between two entities is computed according to the percentage of top hypernyms they share.
- **SIM:** The similarity between two entities is the linear combination of their similarity scores in the distributional similarity graph and in the pattern similarity graph.
- **SIM+LABEL** SIM and LABEL are combined. Observing that SIM generates high quality but overly fine-grained semantic classes, we modify the entity clustering procedure to cluster argument entities based on SIM first, and then further clustering the results based on LABEL.

The outputs of these runs are pooled and mixed for labeling. We randomly sampled 60 relation phrases. For each phrase, we select the 5 most frequent Type A relations from each run ($4\times5=20$[7] Type A relations in all). For each relation phrase, we ask a human labeler to label the mixed pool of Type A relations that share the phrase: 1) The labelers[8] are asked to first determine the major semantic relation of each Type A relation, and then label the triples as *good*, *fair* or *bad* based on whether they express the major relation. 2) The labeler also reads all Type A relations and manually merges the ones that express the same relation. These 2 steps are repeated for each phrase. After labeling, we create a gold standard *GS1*, which contains roughly 10,000 triples for 60 relation phrases. On average, close to 200 triples are manually labeled and clustered for each phrase. This creates a large data set for evaluation.

We report micro-average of precision, recall and F1 on the 60 relation phrases for each method. Precision (P) and Recall (R) of a given relation phrase is defined as follows. Here $R_A$ and $R_A^{'}$ represents a Type A relation in the algorithm output and *GS1*, respectively. We use *t* for triples and *s(t)* to represent the score of the labeled triple *t*.

$$P = \frac{\sum_{R_A}\sum_{t\in R_A} s(t)}{\sum_{R_A}|R_A|},\ R = \frac{\sum_{R_A}\sum_{t\in R_A} s(t)}{\sum_{R_A^{'}}\sum_{t^{'}\in R_A^{'}} s(t^{'})}$$

*s(t) is* set to *1.0*, *0.5* or *0* for *t* labeled as good, fair and bad, respectively. Examples of labels assigned to triples are listed in following table:

*Table 2. Scores for human judgments on triples. The labels are assigned according to whether they belongs to the main relation <Cities, be capital of, Countries>. The second entry is rated 'Fair' because it's not clear that Abkhazia should be classified as a country.*

[7] Here 4 means the 4 methods (the bullet items above) of computing similarity.

[8] 4 human labelers perform the task. A portion of the judgments were independently dual annotated; inter-annotator agreement is 79%. Moreover, each judgment is cross-checked by at least one more annotator, further improving quality.

| Label | Score | Example triple (<*Cities, be capital of, Countries*>) |
|---|---|---|
| Good | 1.0 | <*Baghdad, Iraq*> |
| Fair | 0.5 | <*Sukhumi, Abkhazia*> |
| Bad | 0.0 | <*Bangalore, Karnataka State*> |

The results are in table 3. Overall, LABEL performs 53% better than TS in F-measure, and SIM+LABEL performs the best, 8% better than LABEL. Applying a simple sign test shows both differences are clearly significant ($p<0.001$). Surprisingly, SIM, which uses the similarity matrix extracted from full text, has a F1 of 0.277, which is lower than TS. We also tried combining TS and LABEL but did not find encouraging performance compared to SIM+LABEL.

Among the 4 methods, SIM has the highest precision (0.964) when relation phrases for which it fails to generate any Type A relations are excluded, but its recall is low. Manual checking shows that SIM tends to generate overly fine-grained argument classes. If fine-grained argument classes or extremely high-precision Type A relations are preferred, SIM is a good choice. LABEL performs significantly better than TS, which shows that hypernymy information is very useful for finding argument semantic classes. However, it has coverage problems in that the hypernym finding algorithm failed to find any hypernym from the corpus for some entities. Following up, we found that SIM+LABEL has similar precision and the highest recall. This shows that the combination of semantic spaces is very helpful. The significant recall improvement from TS to SIM+LABEL shows that the corpus-based knowledge resources significantly reduce the data sparseness, compared to using features extracted from the triple store only. The result of the phase 1 algorithm with SIM+LABEL is used as input for phase 2.

*Table 3. Phase 1 performance (averaged on multiple runs) of the 4 methods. The highest performance numbers are in bold. (The number in parenthesis is the micro-average when empty-result relation phrases are not considered for the method).*

| Algorithm | Precision | Recall | F1 |
|---|---|---|---|
| TS | 0.842 (0.886) | 0.266 | 0.388 |
| LABEL | 0.855 (0.870) | 0.481 | 0.596 |
| SIM | 0.755 (**0.964**) | 0.178 | 0.277 |
| SIM+LABEL | 0.843 (0.872) | **0.540** | **0.643** |

**Evaluating Type B relations** The goal is 2-fold: 1) to evaluate the phase 2 algorithm. This involves comparing system output to a gold standard constructed by hand, and reporting performance; 2) to evaluate the quality of Type B relations. For this, we will also report triple-level precision.

We construct a gold standard *GS2*[9] for evaluating Type B relations as follows: We randomly sampled 178 Type B relations, which contain 1547 Type A relations and more than 100,000 triples. Since the number of triples is very large, it is infeasible for labelers to manually cluster triples to construct a gold standard. To report precision, we asked the labelers to label each Type A relation (as a whole rather than label each of its triples) contained in this Type B relation as good, fair or bad based on whether it expresses the same relation. For recall evaluation, we need to know how many Type A relations are missing from each Type B relation. We provide the full

[9] 3 human labelers performed the task. A portion of the judgments were independently dual annotated; inter-annotator agreement is 73%. Similar to labeling Type A relations, each judgment is cross-checked by at least one more annotator, further improving quality.

data set of Type A relations along with three additional resources: 1) a tool which, given a Type A relation, returns a ranked list of similar Type A relations based on the pairwise relation similarity metric in section 4, 2) DIRT paraphrase collection, 3) WordNet (Fellbaum, 1998) synsets. The labelers are asked to find similar phrases by checking phrases which contain synonyms of the tokens in the query phrase. Given a Type B relation, ideally we expect the labelers to find all missing Type A relations using these resources. We report precision (P) and recall (R) as follows. Here $R_B$ and $R_B^{'}$ represent Type B relations in the algorithm output and *GS2*, respectively. $R_A$ and $R_A^{'}$ represent Type A relations. $s(R_A)$ denotes the score of $R_A$.

$$P = \frac{\sum_{R_B} \sum_{R_A \in R_B} |R_A| \cdot s(R_A)}{\sum_{R_B} \sum_{R_A \in R_B} |R_A|}, \; R = \frac{\sum_{R_B} \sum_{R_A \in R_B} |R_A| \cdot s(R_A)}{\sum_{R_B^{'}} \sum_{R_A^{'} \in R_B^{'}} |R_A^{'}|}$$

$s(R_A)$ is set to 1.0, 0.5 and 0 for good, fair or bad respectively. Examples of labels assigned to type A relations are listed in following table:

*Table 4. Scores for human judgments on Type A relations. The labels are assigned to each Type A relation according to whether they express the main relation in the Type B relation. The main relations in the third columns are the human perceived major relations.*

| Label | Score | Example Type A relation | Main relation in Type B |
|---|---|---|---|
| Good | 1.0 | *<{Ben, Aaron,…}, be younger brother of, {Harish, Curt, …}>* | *{Ben, Chris, …}"is brother of" {Tim, John Wesley, …}* |
| Fair | 0.5 | *<{Bill Richardson, Edwards, Gore}, should endorse, {Hilary Clinton, Obama, Romney}>* | *{Gore, Edwards, …}"supports" {Clinton, Obama, …}* |
| Bad | 0.0 | *<{Josh, James, …}, never like, {Jamie, Simon, …}>* | *{Ben, Chris, …} "is brother of" {Tim, John Wesley, …}* |

We also ask the labeler to label at most 50 randomly sampled triples from each Type B relation, and calculate triple-level precision as the ratio of the sum of scores of triples over the number of sampled triples. We use $P_{ins}$ to represent the precision calculated based on labeled triples. Moreover, as we are interested in how many phrases are found by our algorithm, we also include $R_{phrase}$, which is the recall of synonymous phrases. Results are shown in Table 5.

*Table 5. Performance for Type B relation extraction. The first column shows the range of the maximum sizes of Type A relations in the Type B relation. The last column shows the number of Type B relations that are in this range. The number in parenthesis in the third column is the recall of phrases.*

| Interval | *P* | *R* ($R_{phrase}$) | *F1* | $P_{ins}$ | count |
|---|---|---|---|---|---|
| [3, 5) | 0.913 | 0.426 (0.026) | 0.581 | 0.872 | 52149 |
| [5, 10) | 0.834 | 0.514 (0.074) | 0.636 | 0.863 | 21981 |
| [10, 20) | 0.854 | 0.569 (0.066) | 0.683 | 0.883 | 6277 |
| [20, 50) | 0.899 | 0.675 (0.406) | 0.771 | 0.894 | 2630 |
| [50, +∞) | 0.922 | 0.825 (0.594) | 0.871 | 0.929 | 1089 |
| Overall | 0.897 | 0.684 (0.324) | 0.776 | 0.898 | 84126 |

The result shows that WEBRE can extract Type B relations at high precision (both $P$ and $P_{ins}$). The overall recall is 0.684. Table 5 also shows a trend that if the maximum number of Type A relation in the target Type B relation is larger, the recall is better. This shows that the recall of Type B relations depends on the amount of data available for that relation. Some examples of Type B relations extracted are shown in Table 9.

**Phrase synonymy and polysemy** WEBRE disambiguates polysemous relation phrases and groups synonymous ones with the phase 1 and phase 2 algorithms respectively. In table 6, we show the type A relations generated for two relation phrases *withdraw from* and *be a unit of*. We can see that phase 1 effectively placed the phrases into several type A relations with different meanings. For instance, "*withdraw from*" can represent the relationship between two countries (meaning one country withdraws its forces from the other), a country and an organization (showing that the country is no longer a member of the organization), a player and an event, a team and a sport, etc. Multiple meanings of a relation phrase are successfully identified in the first phase of our algorithm, and multiple type A relations are generated accordingly.

*Table 6. Sample relation phrases and their corresponding type A relations. The second column shows the argument class names (assigned "label" pairs) and the third column shows sample argument pairs.*

| Relation phrases | Type A relations | Argument pairs samples |
|---|---|---|
| *withdraw from* | <country, country> | *<America, Vietnam>; <Israel, Lebanon>* |
| | <country, organization> | *<Albania, the Warsaw Pact>; <Zimbabwe, the Commonwealth>* |
| | <force, country> | *<American forces, Vietnam>; <Roman Legions, Britain>* |
| | <player, event> | *<Brandon Bass, the NBA draft>; <Agassi, Wimbledon>* |
| | <car, sport>* | *<Chrysler, NASCAR >; <Porsche, Grand Prix racing>* |
| *be a unit of* | <company, company> | *<ABC, the Walt Disney co.>; <American Airlines, AMR Corp.>* |
| | <unit, concept> | *<Celsius, temperature>; <pounds, weight>* |

*A wrong pair of labels was assigned by WEBRE based on the hypernym hierarchy, The correct one should be "<team, sport>"

We also show the top neighbors (the list of most similar phrase or type A relations, sorted in descending order by their similarities to the query phrase) of a common phrase *be part of* and two Type A relations *<companies, be part of, companies>* and *<cities, be part of, counties>* in Table 7. The top neighbors of *be part of* show a mix of two meanings of *be part of*: "*a company is a part of its parent company*", or "*a city is a part of a county*", whereas the top neighbors of the two type A relations (*be part of* applied to pairs of arguments *<companies, companies>* and *<cities, counties>* respectively) diverge and show a clear split in the meaning of the relations they express. This further shows the importance of applying phase 1 to disambiguate relation phrases.

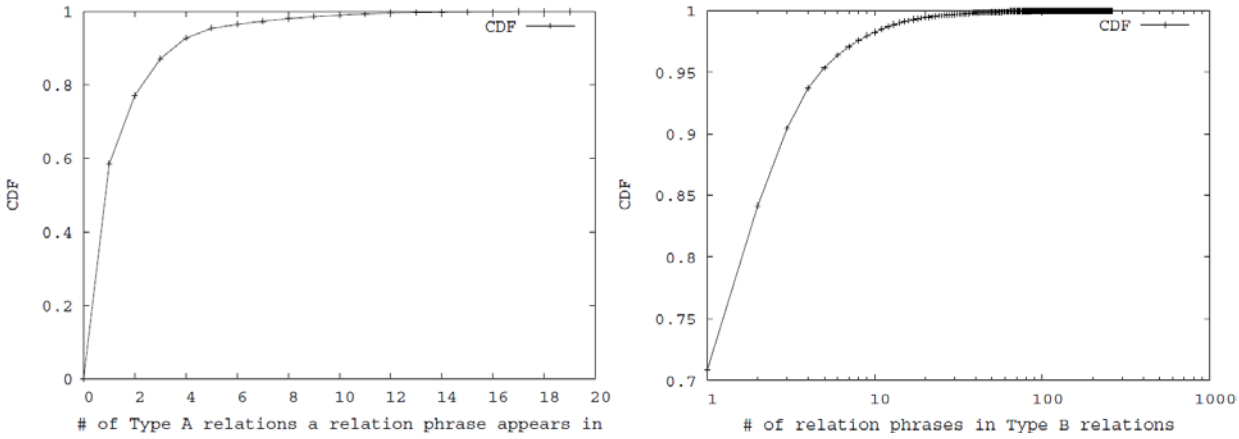
*Table 7. Top neighbors of a relation phrase and the 2 type A relations it appears in (I: top-10 similar relation phrases of "be part of"; II: top-10 similar type A relations of <companies, be part of, companies>; III: top-10 similar type A relations of <cities, be part of, counties>). To emphasize our focus on the relation phrases, in this table we show the relation phrase first, and then 2 argument classes (assigned "labels"). This is different from previous notation <Argument class1, relation phrases, Argument class2>.*

| *be part of* | *<be part of, company, company>* | *<be part of, city, county>* |
|---|---|---|
| *be a part of* | *<be owned by, company, company>* | *<be located in, city, county>* |
| *be a city in* | *<be a division of, company, company>* | *<be the county seat of, city, county>* |
| *be a town in* | *<be a unit of, company, company>* | *<be a township in, city, county>* |
| *be a city located in* | *<be a subsidiary of, company, company>* | *<be in, city, county>* |
| *be a village in* | *<will be acquired by, company, company>* | *<be a village in, city, county>* |
| *be a division of* | *<will be purchased by, company, company>* | *<be located in, city, city>* |
| *be a town located in* | *<will be bought by, company, company>* | *<be a city located in, city, county>* |
| *be located in* | *<be now part of, company, company>* | *<be a city in, city, county>* |
| *be a fact of* | *<be a part of, company, company>* | *<be a town located in, town, county>* |
| *be a subsidiary of* | *<be recently sold to, company, company>* | *<be a town in, town, county>* |
| (I) | (II) | (III) |

Using the large set of Type A and Type B relations extracted by WEBRE, we generate the Cumulative Distribution of Frequency (CDF) of the number of Type A relations the relation phrases belong to, and the CDF of the number of synonymous relation phrases each Type B relation has, and plot them in figure 2 to shows the distribution of polysemy and synonymy of relation phrases empirically.

Figure 2 (I) shows the CDF of the number of Type A relations to which a relation phrase belongs. Around 40% of phrases can be put into 2 Type A relations, and around 8% of them can be put into at least 5 Type A relations. It shows that WEBRE can disambiguate a large number of relation phrases. In figure 2 (II), we plot the CDF of the number of synonymous phrases in Type B relations. Close to 30% of Type B relations have at least 2 relation phrases (Note: x-axis of figure II starts from 1 not 0). Some Type B relations have more than 200 relation phrases. Coupled with the phrase level recall shown in Table 5, this demonstrates WEBRE's ability to find synonymous relation phrases.

*Figure 2. Figure (I) shows the Cumulative Distribution of Frequency (CDF) of the number of distinct Type A relations in which a relation phrase appears, and figure (II) shows the CDF of the number of synonymous relation phrases that are in the same Type B relation. Note: x-axis of (II) is in log-scale for presentation.*




(I) (II)

**Comparison with SNE** We compare Type B relations extracted by WEBRE to the relations extracted by its closest prior work, SNE[10]. We found SNE is not able to handle the 14.7 million triples in a foreseeable amount of time, so we randomly sampled 1 million (1M) triples[11] and test both algorithms on this set. We also filtered out resulting clusters which have only 1 or 2 triples from both system outputs. For comparison purposes, we constructed a gold standard *GS3* as follows: randomly select 30 clusters from both system outputs, and then find similar clusters from the other system output, followed by manually refining the clusters by merging similar ones and splitting non-coherent clusters. *GS3* contains 742 triples and 135 clusters. We report triple-level pairwise precision, recall and F1 for both algorithms against *GS3*, and report results in Table 8. We fine-tuned SNE (using grid search, internal cross-validation, and coarse-to-fine parameter tuning), and report its best performance.

*Table 8. Pairwise precision/recall/F1 of WEBRE and SNE.*

| Algorithm | Precision | Recall | F1 |
|---|---|---|---|
| WEBRE | 0.848 | 0.734 | 0.787 |
| SNE | 0.850 | 0.080 | 0.146 |

Table 8 shows that WEBRE outperforms SNE significantly in pairwise recall while having similar precision. There are two reasons. First, WEBRE makes use of several corpus-level semantic sources extracted from the corpus for clustering entities and phrases while SNE uses only features in the triple store. These semantic resources significantly reduced data sparseness. Examination of the output shows that SNE is unable to group many triples from the same generally-recognized fine-grained relations. For example, SNE placed relation instances *<Barbara, grow up in, Santa Fe>* and *<John, be raised mostly in, Santa Barbara>* into 2 different clusters because the arguments and phrases do not share features nor could be grouped by SNE's mutual clustering. In contrast, WEBRE groups them together. Second, SNE assumes a relation phrase to be in exactly one cluster. For example, SNE placed *be part of* in the phrase cluster *be city of* and failed to place it in another cluster *be subsidiary of*. This limits SNE's ability to place relation instances with polysemous phrases into correct relation clusters.

It should be emphasized that we use pairwise precision and recall in table 8 to be consistent with the original SNE paper. Pairwise metrics are much more sensitive than instance-level metrics, and penalize recall exponentially in the worst case[12] if an algorithm incorrectly splits a coherent cluster; therefore the absolute pairwise recall difference should not be interpreted as the same as the instance-level recall reported in previous experiments. On 1 million triples, WEBRE generates 12179 triple clusters with an average size[13] of 13 while SNE generate 53270 clusters with an average size of 5.1. In consequence, pairwise recall drops significantly. Nonetheless, at above 80% pairwise precision, it demonstrates that WEBRE can group more related triples by adding rich semantics harvested from the Web and employing a more general treatment of polysemous relation phrases. On 1M triples, WEBRE finished in 40 minutes, while the run time of SNE varies from 3 hours to a few days.

[10] Obtained from alchemy.cs.washington.edu/papers/kok08

[11] We found that SNE's runtime on 1M triples varies from several hours to over a week, depending on the parameters. The best performance is achieved with runtime of approximately 3 days. We also tried SNE with 2M triples, on which many runs take several days and show no sign of convergence. For fairness, the comparison was done on 1M triples.

[12] Pairwise precision and recall are calculated on all pairs that are in the same cluster, thus are very sensitive to cluster sizes. For example, if an algorithm incorrectly split a cluster of size *N* to a smaller main cluster of size *N/2* and some constant-size clusters, pairwise recall could drop to as much as ¼ of its original value.

[13] The clusters which have only 1 or 2 triples are removed and not counted here for both algorithms.

## Discussion

**Domain of the relations** The harvested relations are from a wide range of domains. To show the breadth of coverage, we sample a few Type B relations and map them into the relation types defined in a benchmark evaluation, and those defined for two domains, business news and clinical text:

- Automatic Content Extraction (ACE) 2005[14]: ACE is an evaluation on information extraction organized by the U.S. National Institute of Standards and Technology (NIST). It is the standard benchmark for most research in relation extraction. ACE 2005 defines 5 major types and 18 subtypes. They come from a wide range of domains.
- OpenCalais[15] is a service by Thomson Reuters that automatically extracts entities, facts and events from the news domain. A fraction of its facts are similar to relations.
- The 2010 i2b2/VA[16] workshop on Natural Language Processing Challenges for Clinical Records: it defines a few relation types in the clinical record domain.

Table 9 presents the Type B relations that can be mapped into relation types defined in ACE 2005, Calais (OpenCalais) or i2b2. Except for "artifact" subtypes, we found WEBRE extraction covered all relation subtypes defined in ACE 2005. This demonstrates that WEBRE's extraction contains lots of relations of interest in a wide range of topics. Furthermore, we show the extracted results contain relations which can be mapped to the representative relations ("facts") from Calais and major types in the 2010 i2b2 challenge. In fact, WEBRE extraction covers more than half of the "facts" (it is sometimes hard to differentiate events from "facts" in Calais) of Calais and all the three major types in i2b2. This further shows WEBRE extraction's wide coverage. We also included two relations that could not be mapped into any types that are defined in the known set.

As a fully unsupervised algorithm, WEBRE extracts a wide range of relations that can be mapped into existing human-defined relation types from a diverse set of domains. This shows it is useful for real-world applications. Furthermore, we show that WEBRE can find relations that have not been defined in previous evaluations (systems). This shows it has the flexibility to discover new open-domain relations.

*Table 9. A list of relations that maps into the ACE 2005 subtypes, representative Calais relation types from news, and i2b2 types from the clinical data domain. The types with "(Calais)" are representative "fact" types from Calais. The types with "(i2b2)" are the major relation types from the 2010 i2b2/VA challenge in clinical text. All other types are relation subtypes defined in ACE 2005. "-" shows no relations matched. We also show 2 interesting relations that cannot map into the types previously defined. At most 2 relation phrases are shown for each relation.*

| Types | Type B relations | | |
|---|---|---|---|
| | Argument 1 | Relation phrase | Argument 3 |
| user-owner-inventor-manufacturer | *Charlie, Luke, Barbara* | *drive* | *a Porsche, a Corvette, an Audi* |
| | *AutoCAD, Java, PlayStation* | *be a trademark of, be a product of* | *Autodesk, Sun Microsystems, Sony Corporation* |

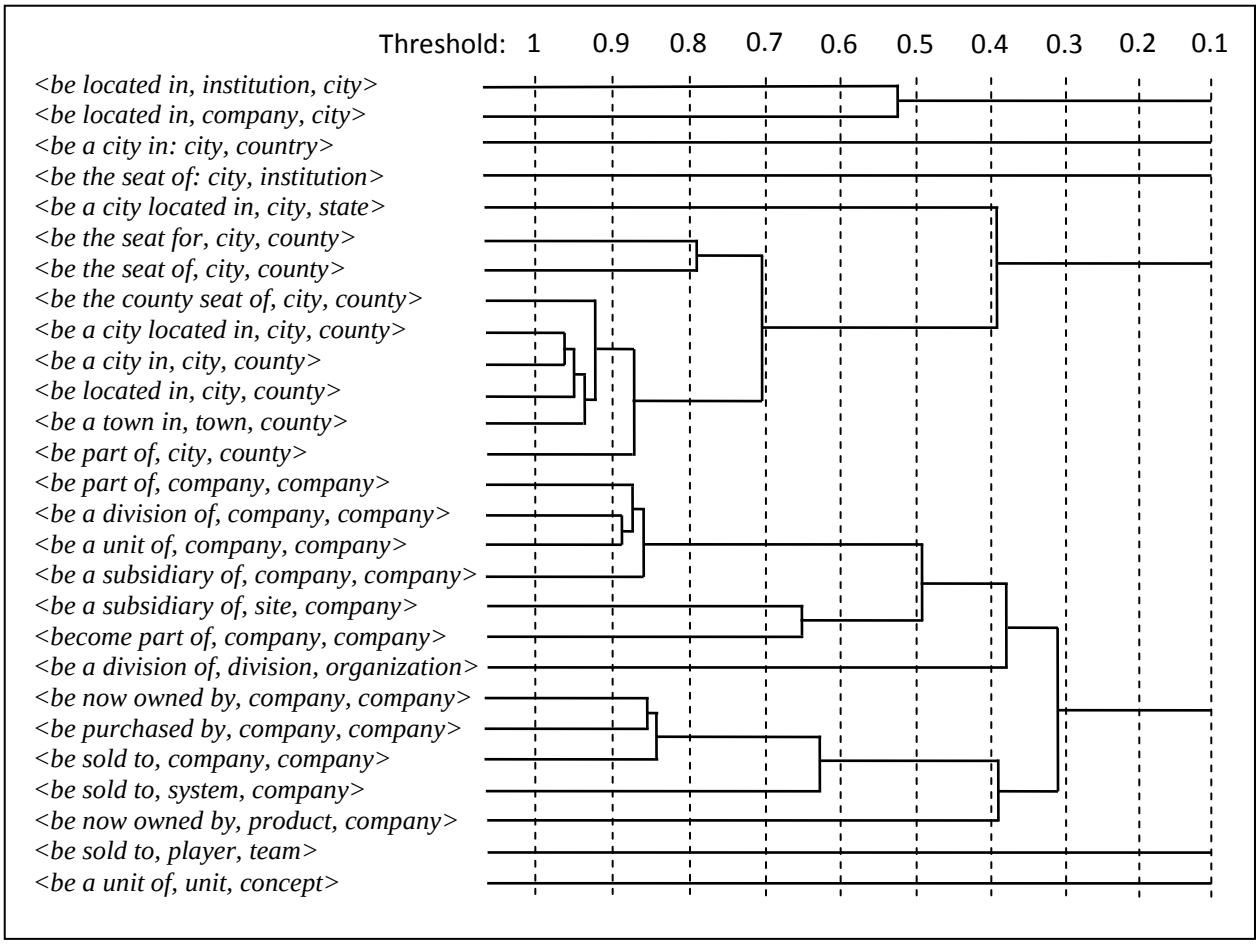
[14] http://www.itl.nist.gov/iad/mig/tests/ace/ace05/
[15] http://www.opencalais.com/
[16] https://www.i2b2.org/NLP/Relations/

| | | | |
|---|---|---|---|
| | *Tim Berners-Lee, Philot. Farnsworth, Thomas Alva Edison* | *be the inventor of, have invented* | *the World Wide Web, Television, electricity* |
| | *Rockwell Automation, Lexar, HoMedics* | *be a manufacturer of, be a big name in* | *programmable controllers, flash memory, massage equipment* |
| citizen-resident-religion-ethnicity | *Larry, Grace, Anna* | *reside in, be a legal resident of* | *Tulsa, Boulder, Denver* |
| | *David, Henry, Charlotte* | *convert to, be a convert to* | *Islam, Buddism, Mormonism* |
| org-location | *AuctionDrop, BMI, Dr. Pepper* | *be headquartered in, be a company in* | *Menlo Park, New York, Plano* |
| employment | *Michael Smith, Michael Goldfarb, Matthew Brown* | *work at, be an employee of* | *Radioshack, Starbucks, Renaissance magazine* |
| founder | *Brzezinski, Larson, Bokaer* | *be founder of, be founding director of* | *The Trilateral Commission, LINC, Chez Bushwick* |
| ownership | *United Online, Saks Inc., Lockheed Martin* | *be the parent company to, be the owner of* | *NetZero, Saks Fifth Avenue, Savi Technology* |
| student-alum | *Barnard, Axelrod, Doug* | *graduate from, be a student at* | *Simon Fraser University, George Washington University, The University of Maryland* |
| sports-affiliation | *Boyd, Mccovey, Tom Brady* | *sign with, play for* | *the Boston Red Sox, the San Francisco Giants, the Patriots* |
| investor-shareholder | *bond funds, international funds, mutual fund* | *invest only in, invest primarily in* | *bonds , foreign stocks, commodities* |
| membership | *Elsie, Henry, Boyd* | *remain a member of, be a member of* | *Chi Omega Sorority, The Labour Party, Greenpeace* |
| artifact | - | - | - |
| geographical | *Lacey Township, Vernon Township, Woodbridge Township* | *be a township in, be located in* | *Ocean County, Sussex County, Middlesex County* |
| subsidiary | *STM, Stock Building Supply, FedEx Ground* | *be a subsidiary of, be a part of* | *SunTrust bank, Wolseley, Federal Express* |
| business | *Bohm, Robert, Mike* | *be a colleague of* | *Albert Einstein, Werner Heisenberg, Jack Canfield* |
| family | *Jean Grey, Jillian, Anne* | *be a daughter of, be the younger daughter of* | *John Grey, Jonathan Lee, James* |
| lasting-personal | *Paul, Curtis, Kerr* | *have a close friendship with, developed a friendship with* | *Michael Jackson, Roosevelt, Bas Rutten* |
| located | *David, Henry, Antoine* | *live in, have resided in* | *New York, Buffalo, San Francisco* |
| near | *Seattle, Samaria, Yorkton* | *be near, be north of* | *Portland, Jerusalem, Minot* |
| (Calais) acquisition | *Philip Morris, Ingersoll Rand, The Coca-Cola Company* | *acquire, be buying* | *Kraft, Trane, Columbia Pictures* |
| (Calais) alliance | *Microsoft, Mitsubishi Motors, Enventis* | *be a strategic partner of* | *Hewlett-Packard, DaimlerChrysler, Cisco Systems* |
| (Calais) bankruptcy | *Lehman Brothers, Penn Central, Syntax-Brillian* | *go bankrupt in, declare bankruptcy in* | *September 2008, June 1970, July 2008* |
| (i2b2) medical | *Albuterol, Imipramine,* | *be used for treating, be a* | *Emphysema, depression,* |

| | | | |
|---|---|---|---|
| problems and treatments | *Darifenacin* | *medication used to treat* | *Overactive bladder* |
| (i2b2) test relations with medical problems | *Biopsy, blood tests, amnio* | *come back positive for, confirm the presence of* | *Breast cancer, Anthrax, Down syndrome* |
| (i2b2) medical problem relations with other medical problems | *high blood pressure, Menorrhagia, Chronic Infections* | *can lead to, may raise the risk of* | *congestive heart failure, Iron deficiency anemia, weight loss* |
| | *C# 2.0, PHP5, Java, C++* | *allow the use of, also use* | *destructors, interfaces, template* |
| | *Clinton, Obama, McCain, …* | *win in, take* | *CA, DC, FL, NH, PA, VA, GA, IL* |

**A hierarchy of relations** We evaluate relations (Type B) as a flat set of relations following common practice. However, in practice we observe that some Type A relations gradually merged together when we lowered the threshold in the phase 2 clustering algorithm. In other words, different thresholds can lead to relations at different target granularities. This indicates that relations could form a hierarchy and provides us the ability to query them at different granularity. The following figure illustrates this with sampled results. Building the hierarchy remains an open research topic which we will study in the near future.

*Figure 3. A hierarchy built from a small sample of type A relations using hierarchical clustering. The top shows the different threshold we used to cluster type A relations. The merging of lines represents the merging of type A relations into the one cluster. To emphasize the meaning of relation phrases applied to a pair of argument classes, in this table we show the relation phrase first, and then 2 argument classes (assigned "labels"). This is different from previous notation <Argument class1, relation phrases, Argument class2>.*




## CONCLUSION

We have proposed an unsupervised algorithm that can extract relations without predefined types of relations and entities. Compared to previous work, the algorithm handles polysemy of relation instances and achieves a significant improvement in recall while maintaining the same level of precision. We applied the algorithm on a very large web-based dataset and did a large-scale evaluation to show its effectiveness. We analyzed the harvested set of relations in detail and provided some insights into future research on open-domain relation extraction.

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