Automated Phrase Mining from Massive Text Corpora

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ABSTRACT

As one of the fundamental tasks in text analysis, phrase mining aims at extracting quality phrases from a text corpus. Phrase mining is important in various tasks including automatic term recognition, document indexing, keyphrase extraction, and topic modeling. Most existing methods rely on complex, trained linguistic analyzers, and thus likely have unsatisfactory performance on text corpora of new domains and genres without extra but expensive adaption. Recently, a few data-driven methods have been developed successfully for extraction of phrases from massive domain-specific text. However, none of the state-of-the-art models is fully automated because they require human experts for designing rules or labeling phrases.

In this paper, we propose a novel framework for automated phrase mining, AutoPhrase, which can achieve high performance with minimal human effort. Two new techniques have been developed: (1) by leveraging knowledge bases, a robust positive-only distant training method can avoid extra human labeling effort; and (2) when the part-of-speech (POS) tagger is available, a POS-guided phrasal segmentation model can better understand the syntactic information for the particular language and further enhance the performance by considering the context. Note that, AutoPhrase can support any language as long as a general knowledge base (*e.g.*, Wikipedia) in that language are available, while benefitting from, but not requiring, a POS tagger. Compared to the state-of-the-art methods, the new method has shown significant improvements on effectiveness on five real-world datasets in different domains and languages.

1. INTRODUCTION

Phrase mining refers to the process of automatic extraction of high-quality phrases (*e.g.*, scientific terms and general entity names) in a given corpus (*e.g.*, research papers and news). Representing the text with quality phrases instead of n-grams can improve computational models for applications such as automatic term recognition [9, 21, 27], document indexing, keyphrase extraction [18, 24, 15], and topic modeling [12, 26].

Almost all the state-of-the-art methods, however, require human experts at certain levels. Most existing methods [9, 21, 27] rely on *complex, trained linguistic analyzers* (*e.g.*, noun phrase chunkers or dependency parsers) to locate phrase mentions, and thus may have unsatisfactory performance on text corpora of new domains and genres without extra but expensive adaption. Our latest domain-independent method SegPhrase [14] outperforms many other approaches [9, 21, 27, 5, 20, 6], but still needs *domain experts* to annotate hundreds of varying -quality phrases with binary labels.

Such reliance on manual efforts by domain and linguistic experts becomes an impediment for timely analysis of massive, emerging text corpora in specific domains. An ideal *automated phrase mining* method is supposed to be *domain-independent, with minimal human involvement or reliance on linguistic analyzers.* Bearing this in mind, we propose a novel automated phrase mining framework AutoPhrase in this paper, going beyond SegPhrase, to further minimize the human effort and enhance the performance, mainly using the following two new techniques.

- *Robust Positive-Only Distant Training.* Utilizing a set of quality/inferior phrases as supervision is usually beneficial. Creating an effective set, however, might be very expensive, for example, in the biomedical domain. Considering the huge search space of phrases, to ensure the representativeness of such hand-crafted label set, domain experts have to invest protracted effort. We propose to minimize these domain expert labors by leveraging existing general knowledge bases, such as Wikipedia and Freebase, because the domain-specific corpus usually contains quality phrases encoded in general knowledge bases, and sometimes domain-specific knowledge bases might not exist. More specifically, for each base classifier, we independently sample positive labels from general knowledge bases and negative labels from the given corpus. Due to such independence among base classifiers, the noise from negative labels will be reduced when we aggregate their predictions.
- *POS-Guided Phrasal Segmentation.* There is a trade-off between the performance and domain-independence when incorporating linguistic processors in the phrase mining method. On the domain independence side, the accuracy might be limited without linguistic knowledge. It is difficult to support multiple languages, if the method

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is completely language-blind. On the accuracy side, relying on complex, trained linguistic analyzers may hurt the domain-independence of the phrase mining method. For example, it is expensive to adapt dependency parsers to special domains like clinical reports. As a compromise, we propose to incorporate the *pre-trained* part-of-speech (POS) tagger to further enhance the performance, when it is available. The POS-guided phrasal segmentation leverages the shallow syntactic information in POS tags to guide the phrasal segmentation model locating the boundaries of phrases more accurately.

In principle, AutoPhrase can support any language as long as a general knowledge base in that language are available. In fact, at least 58 languages have more than 100,000 articles in Wikipedia as of Feb, 2017[1]. Moreover, since pre-trained part-of-speech (POS) taggers are widely available in many languages (*e.g.*, more than 20 languages in TreeTagger [23][2]), the POS-guided phrasal segmentation can be applied in many scenarios. It is worth mentioning that for domain-specific knowledge bases (*e.g.*, MeSH terms in the biomedical domain) and trained POS taggers, the same paradigm applies. In this study, we focus on general knowledge bases and pre-trained POS taggers.

As demonstrated in our experiments, AutoPhrase not only works effectively in multiple domains like scientific papers, business reviews, and Wikipedia articles, but also supports multiple languages, such as English, Spanish, and Chinese. To our best knowledge, this is the first *domain-independent* phrase mining method that can *support multiple languages* with *minimal human effort*[3].

Our main contributions are highlighted as follows:

- We formulate an important problem, *automated phrase mining*, and analyze its major challenges as above.
- We propose a robust positive-only distant training method for phrase quality estimation to minimize the human effort.
- We develop a novel phrasal segmentation model to incorporate POS tags for a higher accuracy, when the POS tagger is available.
- We demonstrate the robustness and accuracy, showing improvements over prior methods, with results of experiments conducted on five real-world datasets in different domains (scientific papers, business reviews, and Wikipedia articles) and different languages (English, Spanish, and Chinese).

The rest of the paper is organized as follows. Sec. 2 positions our work relative to existing work. Sec. 3 defines basic concepts including four requirements of phrases. The details of our method are covered in Sec. 4. Extensive experiments and case studies are presented in Sec. 5. We discuss the single-word phrase modeling in Sec. 6 and conclude the study in Sec. 7.

2. RELATED WORK

Identifying quality phrases at the corpus scope gains increasing attention due to its value of handling increasingly massive text datasets. In contrast to keyphrase extraction [18, 24, 15], this task goes beyond document scope and provides useful cross-document signals. As the origin, the natural language processing (NLP) community has conducted extensive studies mostly known as automatic term recognition [9, 21, 27], referring to the task of extracting technical terms with the use of computers. This topic also attracts attention in the information retrieval (IR) community [7, 20] since selecting appropriate indexing terms is critical to the improvement of search engine where the ideal indexing units should represent the main concepts in a corpus, beyond the bag-of-words.

Linguistic processors are commonly used to filter out stop words and restrict candidate terms to noun phrases. With pre-defined part-of-speech (POS) rules, one can generate noun phrases as term candidates to each POS-tagged document. Supervised noun phrase chunking techniques [22, 25, 3] leverage annotated documents to automatically learn these rules. Other methods may utilize more sophisticated NLP features such as dependency parser to further enhance the precision [11, 17]. With candidate terms collected, the next step is to leverage certain statistical measures derived from the corpus to estimate phrase quality. Some methods further resort to reference corpus for the calibration of "termhood" [27]. The various kinds of linguistic processing, domain-dependent language rules, and expensive human labeling make it challenging to apply to emerging big and unrestricted corpora which possibly encompass many different domains, topics and languages.

To overcome this limitation, data-driven approaches are proposed by exploring frequency statistics in the corpus to address both candidate generation and quality estimation [5, 20, 6, 14]. They typically do not rely on complicated linguistic feature generation, domain-specific rules or heavy labeling efforts. Instead, a large corpus containing hundreds of thousands of documents is usually necessary to ensure superior performance [14]. In [20], several indicators, including frequency and comparison to super/sub-sequences, were proposed to extract n-grams that are not only popular but also concise as concepts. Deane [5] proposed a heuristic metric over frequency distribution based on Zipfian ranks, to measure lexical association for phrase candidates. As a preprocessing step towards topical phrase extraction, El-Kishky *et al.* [6] performed significant phrase mining based on frequency as well as document context following a bottom-up fashion. Our previous work [14] proposed to integrate phrase quality estimation with phrasal segmentation to further rectify the statistical features initially utilized, based on local occurrence context. Unlike previous methods which are purely unsupervised, a small set of phrase labels is required to train its phrase quality estimator. It is worth mentioning that all these approaches still depend on the human effort (*e.g.*, setting domain-sensitive thresholds) or language-dependent assumptions. Therefore, extending them to work automatically is a challenging task.

3. PRELIMINARIES

The goal of this paper is to develop an automated phrase mining method to extract quality phrases from a large collection of documents without any human effort and heavy linguistic reliance. The main input of the automated phrase mining task is a corpus with a knowledge base. The input corpus is a textual word sequence in a particular language and a specific domain with an arbitrary length. The output is a ranked list of phrases with decreasing quality.

The AutoPhrase framework is shown in Figure 1. The

[1] https://meta.wikimedia.org/wiki/List_of_Wikipedias

[2] http://www.cis.uni-muenchen.de/~schmid/tools/TreeTagger/

[3] The phrase "minimal human effort" indicates using only existing general knowledge bases without any other human effort.

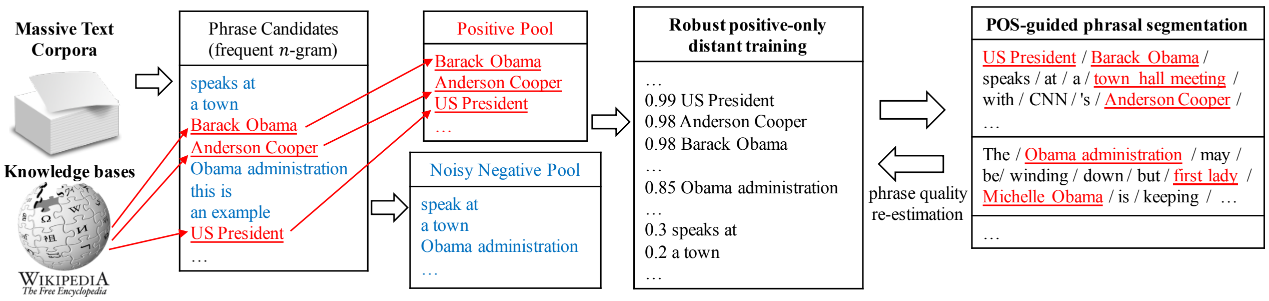

Massive Text Corpora
Knowledge bases
WIKIPEDIA
The Free Encyclopedia
Phrase Candidates (frequent n-gram)
speaks at
a town
Barack Obama
Anderson Cooper
Obama administration
this is
an example
US President
…
Positive Pool
Barack Obama
Anderson Cooper
US President
…
Noisy Negative Pool
speak at
a town
Obama administration
…
Robust positive-only distant training
…
0.99 US President
0.98 Anderson Cooper
0.98 Barack Obama
…
0.85 Obama administration
…
0.3 speaks at
0.2 a town
…
phrase quality re-estimation
POS-guided phrasal segmentation
US President / Barack Obama / speaks / at / a / town hall meeting / with / CNN / 's / Anderson Cooper / …
The / Obama administration / may / be/ winding / down / but / first lady / Michelle Obama / is / keeping / …
…

Figure 1: The overview of AutoPhrase. The two novel techniques developed in this paper are highlighted.

work flow is completely different form our previous domain-independent phrase mining method requiring human effort [14], although the phrase candidates and the features used during phrase quality (re-)estimation are same. In this paper, we propose a robust positive-only distant training to minimize the human effort and develop a POS-guided phrasal segmentation model to further improve the accuracy. In this section, we briefly introduce basic concepts and components as preliminaries.

A ***phrase*** is defined as a sequence of words that appear consecutively in the text, which serves as a complete semantic unit in certain contexts among given documents [8]. The ***phrase quality*** is defined to be the probability of a word sequence being a complete semantic unit, considering the following criteria [14].

- ***Popularity***: Quality phrases should occur with sufficient frequency in the given document collection.
- ***Concordance***: Concordance refers to the collocation of tokens in such frequency that is significantly higher than what is expected due to chance.
- ***Informativeness***: A phrase is informative if it is indicative of a specific topic or concept.
- ***Completeness***: Long frequent phrases and their subsets may both satisfy the above criteria. A complete phrase should be interpreted as a complete semantic unit in certain context. Note that a phrase and its subphrase can both be valid in appropriate context. For example, "*relational database system*", "*relational database*" and "*database system*" can all be valid in certain context.

Only the phrases satisfying all above requirements are recognized as ***quality phrases***.

EXAMPLE 1. "strong tea" *is a quality phrase while* "heavy tea" *is not because of the concordance.* "this paper" *is a popular and concordant phrase, but is not informative in research publication corpus.* "NP-complete in the strong sense" *is a quality phrase while* "NP-complete in the strong" *is not due to the completeness.* □

First of all, by meeting the popularity requirement, the ***phrase candidates*** contain all frequent n-grams over the minimum support threshold τ (*e.g.*, 30) in the corpus. Here, the frequency refers to ***raw frequency*** based on string matching. In practice, one can also set a length threshold (*e.g.*, $n \leq 6$) to restrict the number of words in any phrase. Given a phrase candidate $w_1w_2\ldots w_n$, its phrase quality is:

$$Q(w_1w_2\ldots w_n) = p(\lceil w_1w_2\ldots w_n\rfloor | w_1w_2\ldots w_n) \in [0,1]$$

where $\lceil w_1w_2\ldots w_n\rfloor$ refers to the event that these words compose a phrase. $Q(\cdot)$, also known as the ***phrase quality estimator***, is learned from data based on statistical features designed to model concordance and informativeness mentioned above. Note the phrase quality estimator does not contains any feature based on POS tags since the POS tagger is not required in AutoPhrase. For unigrams, we define their phrase quality as 1.

EXAMPLE 2. *A good quality estimator can return* $Q(\textit{relational database system}) \approx 1$, $Q(\textit{this paper}) \approx 0$. □

Then, to address the completeness criterion, the ***phrasal segmentation*** finds the best segmentation for each sentence.

EXAMPLE 3. *Ideal phrasal segmentation results are as follows.*

#1:	... / the / Great Firewall / is / ...
#2:	This / is / a / great / firewall software/ .
#3:	The / discriminative classifier / SVM / is / ...

□

During the ***phrase quality re-estimation***, related statistical features will be re-computed based on the ***rectified frequency*** of phrases, which means the number of times that a phrase becomes a complete semantic unit in the identified segmentation. After incorporating the rectified frequency, the phrase quality estimator also models the *completeness* in addition to *concordance* and *informativeness*.

EXAMPLE 4. *Continuing the previous example, the* raw frequency *of* "great firewall" *is* 2 *but its* rectified frequency *is* 1. *Both the* raw frequency *and the* rectified frequency *of* "firewall software" *are* 1. *The* raw frequency *of* "classifier SVM" *is* 1 *but its* rectified frequency *is* 0.

4. METHODOLOGY

In this section, we will focus on the two new techniques proposed in this paper.

4.1 Robust Positive-Only Distant Training

To assign the phrase quality to each phrase candidate, our previous work [14] requires hundreds of representative quality/interior phrases from domain experts. For example, for computer science papers, our domain experts give tens of positive labels (*e.g.*, "*spanning tree*" and "*computer science*") and hundreds of negative labels (*e.g.*, "*paper focuses*" and "*important form of*"). However, creating such a label set is expensive, especially in special domains like clinical reports and business reviews. In this paper, we introduce a method that only utilizes existing general knowledge bases without any other human effort.

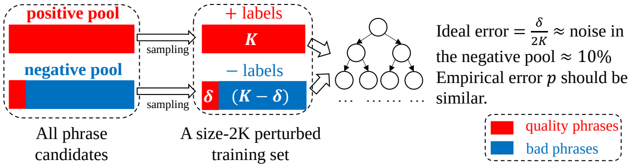

positive pool
negative pool
sampling
sampling
+ labels
K
− labels
δ
(K − δ)
All phrase candidates
A size-2K perturbed training set
Ideal error = δ/2K ≈ noise in the negative pool ≈ 10%
Empirical error p should be similar.
quality phrases
bad phrases

Figure 2: The illustration of each base classifier.

4.1.1 Label Pools

Public knowledge bases (*e.g.*, Wikipedia) usually encode a considerable number of high-quality phrases in the titles, keywords, and internal links of pages. For example, in Chinese, by analyzing the internal links and synonyms[4], more than 20,000 high-quality phrases could be discovered. These high-quality phrases can be safely treated as a ***positive pool***.

Knowledge bases, however, rarely tell about bad phrases. An important observation is that the number of phrase candidates is huge and the majority of them are actually poor in quality (*e.g.*, "Francisco opera and"). In practice, among millions of phrase candidates, usually, only about 10% are in good quality. Therefore, the remaining phrase candidates, which cannot be matched to any knowledge base, can serve as a large but noisy ***negative pool***.

4.1.2 Noise Reduction

Directly training a classifier based on the noisy label pools is not a wise choice because the false-negative labels may interfere the classifier and thus being inaccurate. Considering a balanced classification scenario, we propose to train the classifier by nearly balanced subsets.

As shown in Figure 2, we randomly draw K phrase candidates with replacement from the positive pool and the negative pool respectively. This size-$2K$ subset is called a ***perturbed training set*** [2], because the labels of some (δ in the figure) quality phrases are switched from positive to negative. In order for the final classifier to alleviate the effect of such noise, we need to use a base classifier that manages to obtain a training error as low as possible. The growth of an unpruned decision tree until all phrases have been separated meets this requirement. In fact, such decision tree always obtains 100% training accuracy if there are no two positive and negative phrases share identical feature values in the perturbed training set. In this case, its ideal error is $\frac{\delta}{2K}$, which approximately equals to the proportion of switched labels among all phrase candidates (*i.e.*, $\frac{\delta}{2K} \approx 10\%$). Assuming the extracted features are expressive, the test error p evaluating by all phrase candidates should be relatively small as well. Therefore, the value of K is not sensitive to the performance and is fixed as 100 in our implementation.

An interesting property of this sampling procedure is that the random selection of phrase candidates creates classifiers that have statistically independent errors and similar erring probability [2, 16]. Therefore, we naturally adopt random forest [10], which is verified to be robust and efficient in the literature. The ratio of positive predictions among all decision trees is interpreted as phrase quality. Suppose there are T trees in the random forest, the ensemble error can be estimated as the probability of having more than half of the classifiers misclassifying a given phrase candidate as follows.

$$\text{ensemble\_ error}(T) = \sum_{t=\lfloor 1+T/2 \rfloor}^{T} \binom{T}{t} p^t (1-p)^{T-t}$$

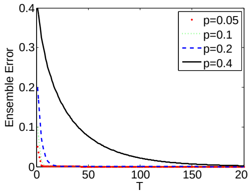


Figure 3: Ensemble errors of different p's varying T.

From Figure 3, one can easily observe that the error rate is approaching 0 when T grows. In practice, T can be set as 1000. Moreover, in our framework, we care about the relative order of the probabilistic scores instead of the binary predictions. Therefore, the noise reduction should be robust enough.

4.2 POS-Guided Phrasal Segmentation

Phrasal segmentation is proposed to tackle the challenge of measuring *completeness* through locating every phrase mention in the corpus and rectifying phrase mentions previously obtained via string matching.

The corpus is processed as a length-n POS-tagged word sequence $\Omega = \Omega_1\Omega_2 \ldots \Omega_n$, where Ω_i refers to a pair of words and its POS tag $\langle w_i, t_i \rangle$. A ***POS-guided phrasal segmentation*** is a partition of this sequence induced by a boundary index sequence $B = \{b_1, b_2, \ldots, b_{m+1}\}$ satisfying 1 = $b_1 < b_2 < \ldots < b_{m+1} = n$+1. The i-th segment refers to $\Omega_{b_i}\Omega_{b_i+1} \ldots \Omega_{b_{i+1}-1}$.

Compared to the phrasal segmentation in our previous work [14], the POS-guided phrasal segmentation addresses the completeness requirement in a *context-aware* way, instead of equivalently penalizing phrase candidates of the same length. In addition, POS tags provide language-specific knowledge at a certain level, which can improve the accuracy.

Given the whole POS tag sequence is $t = t_1t_2 \ldots t_n$, for the subsequence of $t_l \ldots t_{r-1}$ (denote as $t_{[l,r)}$ for clarity), the ***POS quality*** is defined to be the conditional probability of its corresponding word sequence being a complete semantic unit. Formally, we have

$$T(t_{[l,r)}) = p(\lceil w_l \ldots w_r \rfloor | t) \in [0, 1]$$

The POS quality score $T(\cdot)$ is designed to reward the phrases with meaningful POS patterns, as follows.

Example 5. *Suppose the whole POS tag sequence is "NN NN NN VB DT NN". A good POS sequence quality estimator can return T(NN NN NN) ≈ 1, T(NN VB) ≈ 0, and T(DT NN) ≈ 0, where NN refers to singular or mass noun (e.g., database), VB means verb in the base form (e.g., is), and DT is for determiner (e.g., the).*

The particular form of $T(\cdot)$ we have chosen is:

$$T(t_{[l,r)}) = (1 - \delta(t_{b_r-1}, t_{b_r})) \times \prod_{j=l+1}^{r-1} \delta(t_{j-1}, t_j)$$

where, $\delta(t_x, t_y)$ is the probability that the POS tag t_y is exactly after the POS tag t_x within a phrase in the given document collection. In this formula, the first term represents that there is a phrase boundary between $r - 1$ and r, while the latter product indicates that all POS tags among $t_{[l,r)}$ are in the same phrase. This POS quality score can naturally

[4] https://github.com/kno10/WikipediaEntities

counter the bias to longer segments because $\forall i > 1$, exactly one of $\delta(t_{i-1}, t_i)$ and $(1 - \delta(t_{i-1}, t_i))$ is always multiplied no matter how the corpus is segmented. Note that the length penalty model in our previous work [14] is a special case when all values of $\delta(t_x, t_y)$ are the same.

Mathematically, $\delta(t_x, t_y)$ is defined as:

$$\delta(t_x, t_y) = p(\lceil \dots w_1 w_2 \dots \rfloor | \Omega, \text{tag}(w_1) = t_x \wedge \text{tag}(w_2) = t_y)$$

As it depends on how documents are segmented into phrases, $\delta(t_x, t_y)$ will be learned during the POS-guided phrasal segmentation.

Now, after we have both phrase quality $Q(\cdot)$ and POS quality $T(\cdot)$ ready, we are able to formally define the POS-guided phrasal segmentation model. The joint probability of a POS tagged sequence Ω and a boundary index sequence $B = \{b_1, b_2, \dots, b_{m+1}\}$ is factorized as:

$$p(\Omega, B) = \prod_{i=1}^{m} p\left(b_{i+1}, \lceil w_{[b_i, b_{i+1})} \rfloor \middle| b_i, t\right)$$

where $p(b_{i+1}, \lceil w_{[b_i, b_{i+1})} \rfloor | b_i, t)$ is the probability of observing a word sequence $w_{[b_i, b_{i+1})}$ as the i-th quality segment given the previous boundary index b_i and the whole POS tag sequence t.

Since the phrase segments function as a constituent in the syntax of a sentence, they usually have weak dependence on each other [8, 14]. As a result, we assume these segments in the word sequence are generated one by one for the sake of both efficiency and simplicity.

For each segment, given the POS tag sequence t and the start index b_i, the generative process is defined as follows.

1. Generate the end index b_{i+1}, according to its POS quality

$$p(b_{i+1} | b_i, t) = T(t_{[b_i, b_{i+1})})$$

2. Given the two ends b_i and b_{i+1}, generate the word sequence $w_{[b_i, b_{i+1})}$ according to a multinomial distribution over all segments of length-$(b_{i+1} - b_i)$.

$$p(w_{[b_i, b_{i+1})} | b_i, b_{i+1}) = p(w_{[b_i, b_{i+1})} | b_{i+1} - b_i)$$

3. Finally, we generate an indicator whether $w_{[b_i, b_{i+1})}$ forms a quality segment according to its quality

$$p(\lceil w_{[b_i, b_{i+1})} \rfloor | w_{[b_i, b_{i+1})}) = Q(w_{[b_i, b_{i+1})})$$

We denote $p(w_{[b_i, b_{i+1})} | b_{i+1} - b_i)$ as $\theta_{w_{[b_i, b_{i+1})}}$ for convenience. Integrating the above three generative steps together, we have the following probabilistic factorization:

$$\begin{aligned} & p(b_{i+1}, \lceil w_{[b_i, b_{i+1})} \rfloor | b_i, t) \\ =& p(b_{i+1} | b_i, t) p(w_{[b_i, b_{i+1})} | b_i, b_{i+1}) p(\lceil w_{[b_i, b_{i+1})} \rfloor | w_{[b_i, b_{i+1})}) \\ =& T(t_{[b_i, b_{i+1})}) \theta_{w_{[b_i, b_{i+1})}} Q(w_{[b_i, b_{i+1})}) \end{aligned}$$

Therefore, there are three subproblems:

- Learn θ_u for each word and phrase candidate u;
- Learn $\delta(t_x, t_y)$ for every POS tag pair; and
- Infer B when θ_u and $\delta(t_x, t_y)$ are fixed.

We employ the maximum a posterior principle and maximize the joint log likelihood:

$$\log p(\Omega, B) = \sum_{i=1}^{m} \log p\left(b_{i+1}, \lceil w_{[b_i, b_{i+1})} \rfloor \middle| b_t, t\right) \quad (1)$$

Given θ_u and $\delta(t_x, t_y)$, to find the best segmentation that maximizes Equation (1), we develop an efficient dynamic programming algorithm for the POS-guided phrasal segmentation as shown in Algorithm 1.

Algorithm 1: POS-Guided Phrasal Segmentation (PGPS)

```
Input: Corpus $\Omega = \Omega_1 \Omega_2 \dots \Omega_n$, phrase quality $Q$,
  parameters $\theta_u$ and $\delta(t_x, t_y)$.
Output: Optimal boundary index sequence $B$.
// $h_i \equiv \max_B \quad p(\Omega_1 \Omega_2 \dots \Omega_{i-1}, B | Q, \theta, \delta)$
$h_1 \leftarrow 1$, $h_i \leftarrow 0$ $(1 < i \le n + 1)$
for $i = 1$ to $n$ do
    for $j = i + 1$ to $\min(i + \textit{length threshold}, n + 1)$ do
        // In practice, log and addition are used
           to avoid underflow.
        if $h_i \times p(j, \lceil w_{[i,j)} \rfloor | i, t_{[i,j)}) > h_j$ then
            $h_j \leftarrow h_i \times p(j, \lceil w_{[i,j)} \rfloor | i, t_{[i,j)})$
            $g_j \leftarrow i$
$j \leftarrow n + 1$, $m \leftarrow 0$
while $j > 1$ do
    $m \leftarrow m + 1$
    $b_m \leftarrow j$
    $j \leftarrow g_j$
return $B \leftarrow 1, b_m, b_{m-1}, \dots, b_1$
```

Algorithm 2: Viterbi Training (VT)

```
Input: Corpus $\Omega$ and phrase quality $Q$.
Output: $\theta_u$ and $\delta(t_x, t_y)$.
initialize $\theta$ with normalized raw frequencies in the corpus
while $\theta_u$ does not converge do
    while $\delta(t_x, t_y)$ does not converge do
        $B \leftarrow$ best segmentation via Alg. 1
        update $\delta(t_x, t_y)$ using $B$ according to Eq. (2)
    $B \leftarrow$ best segmentation via Alg. 1
    update $\theta_u$ using $B$ according to Eq. (3)
return $\theta_u$ and $\delta(t_x, t_y)$
```

When the segmentation S and the parameter θ are fixed, the closed-form solution of $\delta(t_x, t_y)$ is:

$$\delta(t_x, t_y) = \frac{\sum_{i=1}^{m} \sum_{j=b_i}^{b_{i+1}-2} \mathbb{1}(t_j = t_x \wedge t_{j+1} = t_y)}{\sum_{i=1}^{n-1} \mathbb{1}(t_i = t_x \wedge t_{i+1} = t_y)} \quad (2)$$

where $\mathbb{1}(\cdot)$ denotes the identity indicator. $\delta(t_x, t_y)$ is the unsegmented ratio among all $\langle t_x, t_y \rangle$ pairs in the given corpus.

Similarly, once the segmentation S and the parameter δ are fixed, the closed-form solution of θ_u can be derived as:

$$\theta_u = \frac{\sum_{i=1}^{m} \mathbb{1}(w_{[b_i, b_{i+1})} = u)}{\sum_{i=1}^{m} \mathbb{1}(b_{i+1} - b_i = |u|)} \quad (3)$$

We can see that θ_u is the times that u becomes a complete segment normalized by the number of the length-$|u|$ segments.

Similar to our previous work [14], as shown in Algorithm 2, we choose Viterbi Training, or Hard EM in literature [1] to iteratively optimize parameters, because Viterbi Training converges fast and results in sparse and simple models for Hidden Markov Model-like tasks [1].

4.3 Complexity Analysis

The time complexity of the most time consuming components in our framework, such as frequent n-gram, feature extraction, POS-guided phrasal segmentation, are all $O(|\Omega|)$ with the assumption that the maximum number of words in a phrase is a small constant (*e.g.*, $n \le 6$), where $|\Omega|$ is the

Table 1: Datasets and their statistics. $|\Omega|$ is the total number of words. $size_p$ is the size of positive pool.

Dataset	Domain	Language	$\|\Omega\|$	File size	$size_p$
DBLP	Scientific Paper	English	91.6M	618MB	29K
Yelp	Business Review	English	145.1M	749MB	22K
EN	Wikipedia Article	English	808.0M	3.94GB	184K
ES	Wikipedia Article	Spanish	791.2M	4.06GB	65K
CN	Wikipedia Article	Chinese	371.9M	1.56GB	29K

total number of words in the corpus. Therefore, AutoPhrase is linear to the corpus size and thus being very efficient and scalable. Meanwhile, every component can be parallelized in an almost lock-free way grouping by either phrases or sentences.

5. EXPERIMENTS

In this section, we will apply the proposed method to mine quality phrases from five massive text corpora in three domains (scientific papers, business reviews, and Wikipedia articles) and three languages (English, Spanish, and Chinese). We compare the proposed method with many other methods to demonstrate its high performance. Then, we explore the robustness of the distant training and its performance against the expert labeling. The advantage of incorporating POS tags in the phrasal segmentation has also been proved. In the end, we present case studies.

5.1 Datasets

To verify that the distant training can effectively work in different domains and the POS-guided phrasal segmentation supports multiple languages effectively, we have prepared five large collections of text in different domains and languages, as shown in Table 1: Abstracts of English computer science papers from **DBLP**[5], English business reviews from **Yelp**[6], Wikipedia articles[7] in English (**EN**), Spanish (**ES**), and Chinese (**CN**). From the existing general knowledge base Wikipedia, we extract popular mentions of entities by analyzing intra-Wiki citations within Wiki content[8]. On each dataset, the intersection between the extracted popular mentions and the generated phrase candidates forms the positive pool. Therefore, the size of positive pool may vary in different datasets of the same language.

5.2 Compared Methods

We compare **AutoPhrase** with three types of methods as follows. Every method returns a ranked list of phrases.

SegPhrase[9]**/WrapSegPhrae**[10]: In English domain-specific text corpora, our latest work SegPhrase outperformed phrase mining [6], keyphrase extraction [24, 20], and noun phrase chunking methods. For each dataset, we ask domain experts to give a representative set of 300 quality/interior phrases. Moreover, WrapSegPhrase extends SegPhrase to different languages by adding an encoding preprocessing to first transform non-English corpus using English characters and punctuation as well as a decoding postprocessing to later translate them back to the original language.

Parser-based Phrase Extraction: Using complicated linguistic processors, such as parsers, we can extract minimum phrase units (*e.g.*, NP) from the parsing trees as phrase candidates. Parsers of all three languages are available in Stanford NLP tools [19, 4, 13]. Two ranking heuristics are considered:

- **TF-IDF**: [14] shows that it is more effective than C-Value;
- **TextRank**: An unsupervised graph-based ranking model for keyword extraction [18].

Pre-trained Chinese Segmentation Models: Different from English and Spanish, phrasal segmentation in Chinese has been intensively studied because there is no whitespace in Chinese sentences. The most effective and popular segmentation methods are:

- **AnsjSeg**[11] is a popular text segmentation algorithm for Chinese corpus. It ensembles statistical modeling methods of Conditional Random Fields (CRF) and Hidden Markov Models (HMMs) based on the *n*-gram setting;
- **JiebaPSeg**[12] is a *Chinese* text segmentation method implemented in Python. It builds a directed acyclic graph for all possible phrase combinations based on a prefix dictionary structure to achieve efficient phrase graph scanning. Then it uses dynamic programming to find the most probable combination based on the phrase frequency. For unknown phrases, an HMM-based model is used with the Viterbi algorithm.

Note that all parser-based phrase extraction and Chinese segmentation models are pre-trained based on general corpus.

5.3 Experimental Settings

Implementation. The preprocessing includes tokenizers from Lucene and Stanford NLP as well as the POS tagger from TreeTagger. Our documented code package has been released and maintained in GitHub[13].

Default Parameters. We set the minimum support threshold σ as 30. The maximum number of words in a phrase is set as 6 according to labels from domain experts. These are two parameters required by all methods. Other parameters required by compared methods were set according to the open-source tools or the original papers.

Human Annotation. We rely on human evaluators to judge the quality of the phrases which cannot be matched to any knowledge base. More specifically, on each dataset, we randomly sample 500 such uncovered phrases from the returned phrases of each method in experiments. These selected phrases are shuffled as a *pool* and evaluated by 3 reviewers independently. We encourage reviewers to use search engines when unfamiliar phrases encountered. By the rule of majority voting, phrases in this pool received at least two positive annotations are *quality phrases.* The intra-class correlations (ICCs) are all more than 0.9 on all five datasets, which show the agreements.

Evaluation Metrics. For a list of phrases, *precision* is defined as the number of occurred quality phrases divided by the length of the list; *recall* is defined as the number of occurred quality phrases divided by the total number of quality phrases. We retrieve the ranked list of the pool from the outcome of each method. When a quality phrase encountered, we record the precision and recall of this prefix ranked list. In the end, we evaluate the *precision-recall*

[5] https://aminer.org/citation

[6] https://www.yelp.com/dataset_challenge

[7] https://dumps.wikimedia.org/

[8] https://github.com/kno10/WikipediaEntities

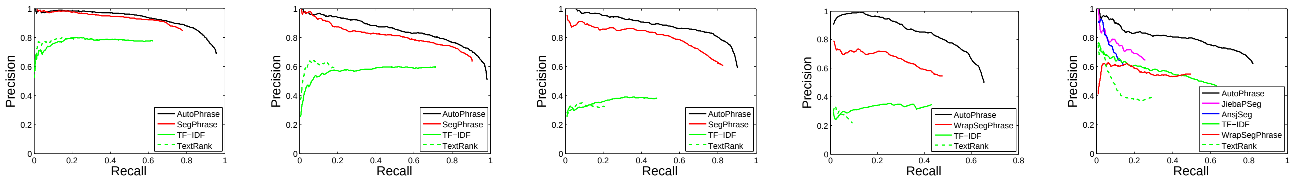
[9] https://github.com/shangjingbo1226/SegPhrase

[10] https://github.com/remenberl/SegPhrase-MultiLingual

[11] https://github.com/NLPchina/ansj_seg

[12] https://github.com/fxsjy/jieba

[13] https://github.com/shangjingbo1226/AutoPhrase



(a) DBLP (b) Yelp (c) EN (d) ES (e) CN

Figure 4: Precision-recall curves evaluated by human annotation.

curves using the records. In addition, we can calculate the *area under the curve (AUC)* as a quantitative measure for the precision-recall curve.

5.4 Overall Performance

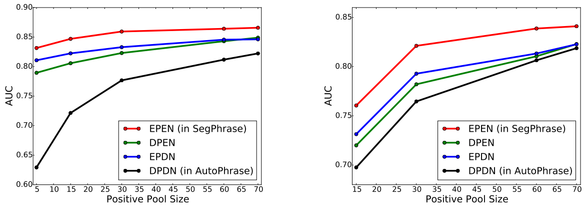
Precision-recall curves of all compared methods evaluated by human annotation on five datasets are presented in Figures 4. Overall, AutoPhrase always performs the best, in terms of not only precision but also recall. Significant recall advantages can be always observed, especially on the two non-English datasets *ES* and *CN*. For example, on the *ES* dataset, the recall of AutoPhrase is about 20% higher than the second best method (SegPhrase) in absolute value. Meanwhile, one can also observe that there is always a visible precision gap between AutoPhrase and the best baseline on all datasets. Without any surprise, the phrase chunking-based methods TF-IDF and TextRank work poorly, because the extraction and ranking are separated instead of unified. TextRank usually starts with a higher precision than TF-IDF, but its recall is very low because of the sparsity of the constructed co-occurrence graph. TF-IDF achieves a reasonable recall but unsatisfactory precision. On the *CN* dataset, the pre-trained Chinese segmentation models, JiebaSeg and AnsjSeg, are very competitive, because they not only leverage training data for segmentations, but also exhaust the engineering work, including a huge dictionary for popular Chinese entity names and specific rules for certain types of entities. As a consequence, they can easily extract tons of well-known terms and people/location names. Outperforming such a strong baseline further confirms the effectiveness of AutoPhrase.

The comparison among the English datasets in three domains (*i.e.*, *DBLP*, *Yelp*, and *EN*) demonstrates that AutoPhrase is *domain-independent*. The performance of parser-based methods TF-IDF and TextRank depends on the rigorous degree of the documents. For example, it works well on the *DBLP* dataset but poorly on the *Yelp* dataset. However, without any human effort, AutoPhrase can work effectively on domain-specific datasets, and even outperform SegPhrase, which is supervised by the domain experts.

The comparison among the Wikipedia article datasets in three languages (*i.e.*, *EN*, *ES*, and *CN*) shows that, first of all, AutoPhrase *supports multiple languages*. Secondly, the advantage of AutoPhrase over SegPhrase/WrapSegPhrase is more obvious on two non-English datasets *ES* and *CN* than the *EN* dataset, which proves that *the helpfulness of introducing the POS tagger*.

As conclusions, AutoPhrase is able to support different domains and support multiple languages with minimal human effort.

5.5 Distant Training Exploration



(a) DBLP (b) Yelp

Figure 5: When we have enough expert labels.

To compare the distant training and domain expert labeling, we choose the domain-specific datasets *DBLP* and *Yelp*. To be fair, everything in classifiers is same, except for the labels. More specifically,

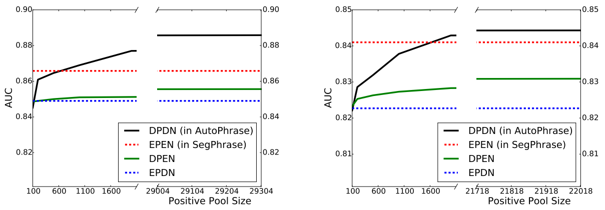
- **EP** means that domain experts give the positive pool.
- **DP** means that a sampled subset from existing general knowledge forms the positive pool.
- **EN** means that domain experts give the negative pool.
- **DN** means that all unknown phrase candidates form the negative pool.

By combining any pair of the positive and negative pools, we have four variations, **EPEN** (in SegPhrase), **DPDN** (in AutoPhrase), **EPDN**, and **DPEN**.

First of all, we evaluate the quality of positive pools sampled from existing general knowledge bases. Compared to EPEN, we evaluate DPEN, which adopts a positive pool sampled from knowledge bases instead of the well-designed positive pool given by domain experts. Note that the negative pool given by domain experts is shared. As shown in Figure 5, we vary the size of the positive pool and plot the AUC curves of EPEN and DPEN. We can find that EPEN has a better performance than DPEN and the trends of both curves are similar. Therefore, the positive pool generated from knowledge bases has a reasonable quality, although it works slightly worse without any surprise.

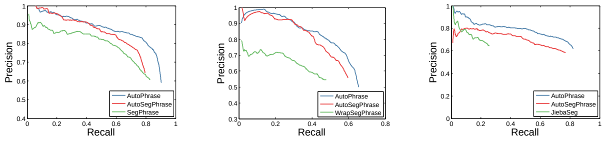
Secondly, we verify that whether the proposed noise reduction mechanism works properly. Compared to EPEN, we evaluate EPDN, which adopts a negative pool of all unknown phrase candidates instead of the well-designed negative pool given by domain experts. Note that the positive pool given by domain experts is shared. In Figure 5, the clear gap between these two methods and their similar trends show that the noisy negative pool is slightly worse than the well-designed negative pool but it still works effectively.

As illustrated in Figure 5, DPDN has the worst performance when positive pools have limited sizes. However, distant training can generate much larger positive pools be-



(a) DBLP (b) Yelp

Figure 6: After we exhaust expert labels.



(a) EN (b) ES (c) CN

Figure 7: AutoPhrase vs. AutoSegPhrase.

yond the ability of domain experts. Consequently, we are interested in that whether the distant training can finally beat domain experts when positive pool sizes become large enough. We call this "enough" number as the ***ideal number***.

We increase positive pool sizes and plot AUC curves of DPEN and DPDN, while EPEN and EPDN are degenerated as lines due to the limited domain expert abilities. As shown in Figure 6, with a large enough positive pool, distant training is able to beat expert labeling. On the *DBLP* dataset, the ideal number is about 700, while on the *Yelp* dataset, it becomes around 1600. Therefore, the ideal number looks proportional to the corpus size. Moreover, compared to the corpus size, the ideal number is relatively small, which means the distant training should be effective in many domains.

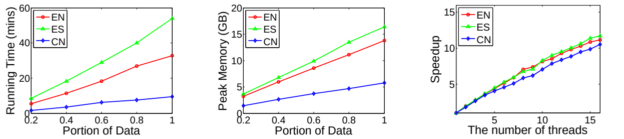
Besides, Figure 6 also shows that when the positive pool size grows, the AUC score always increases but the speed of increasing slows down gradually. Therefore, the performance of distant training will converge after enough number of quality phrases were fed.

5.6 POS-guided Phrasal Segmentation

We are interested in how much advantage we can gain from being aware of POS tags in this segmentation model, especially in different languages. For this purpose, we select Wikipedia article datasets in three different languages: *EN*, *ES*, and *CN*. To make a fair comparison, we propose a variant of AutoPhrase with all components exactly same except for the phrasal segmentation model: **AutoSegPhrase** adopts the length penalty instead of $\delta(t_x, t_y)$.

Figure 7 shows the comparison between AutoPhrase and AutoSegPhrase, with the best baseline methods as references. AutoPhrase outperforms AutoSegPhrase on the English dataset *EN*, even it has been shown the length penalty works well in English datasets [14]. The Spanish dataset *ES* has the similar observation. Moreover, in another very different language, Chinese, the advantage of AutoPhrase becomes more significant on the *CN* dataset. AutoSegPhrase even has a lower precision than JiebaSeg in the beginning .

As the conclusion, due to the extra context information and syntactic information for the particular language, incorporating POS tags during the phrasal segmentation can work better than equally penalizing phrases of the same length.



(a) Running Time (b) Peak Memory (c) Multi-threading

Figure 8: Efficiency of AutoPhrase.

Table 2: Efficiency Comparison between AutoPhrase and SegPhrase/WrapSegPhrase utilizing 10 threads.

	EN		ES		CN	
	Time (mins)	Memory (GB)	Time (mins)	Memory (GB)	Time (mins)	Memory (GB)
AutoPhrase	32.77	13.77	54.05	16.42	9.43	5.74
(Wrap)SegPhrase	369.53	97.72	452.85	92.47	108.58	35.38
Speedup/Saving	11.27	86%	8.37	82%	11.50	83%

Table 3: The results of AutoPhrase on the *EN* and *CN* datasets, with translation and explanations for Chinese. The whitespaces on the *CN* dataset are inserted by the Chinese tokenizer.

	EN	*CN*	
Rank	Phrase	Phrase	Translation (Explanation)
1	Elf Aquitaine	江苏 舜 天	(the name of a soccer team)
2	Arnold Sommerfeld	苦 艾 酒	Absinthe
3	Eugene Wigner	白发 魔 女	(the name of a novel/TV-series)
4	Tarpon Springs	笔记 型 电脑	notebook computer, laptop
5	Sean Astin	党委 书记	Secretary of Party Committee
...	...	...	...
20,001	ECAC Hockey	非洲 国家	African countries
20,002	Sacramento Bee	左翼 党	The Left (German: Die Linke)
20,003	Bering Strait	菲 沙 河谷	Fraser Valley
20,004	Jacknife Lee	海马 体	Hippocampus
20,005	WXYZ-TV	斎 贺光希	Mitsuki Saiga (a voice actress)
...	...	...	...
99,994	John Gregson	计算机 科学技术	Computer Science and Technology
99,995	white-tailed eagle	恒 天然	Fonterra (a company)
99,996	rhombic dodecahedron	中国 作家 协会 副 主席	The Vice President of Writers Association of China
99,997	great spotted woodpecker	维他命 b	Vitamin B
99,998	David Manners	舆论 导向	controlled guidance of the media
...	...	...	...

5.7 Efficiency Evaluation

To study both time and memory efficiency, we choose the three largest datasets: *EN*, *ES*, and *CN*.

Figures 8(a) and 8(b) evaluate the running time and the peak memory usage of AutoPhrase using 10 threads on different proportions of three datasets respectively. Both time and memory are linear to the size of text corpora. Moreover, AutoPhrase can also be parallelized in an almost lock-free way and shows a linear speedup in Figure 9(c).

Besides, compared to the previous state-of-the-art phrase mining method SegPhrase and its variants WrapSegPhrase on three datasets, as shown in Table 2, AutoPhrase achieves about 8 to 11 times speedup and about 5 to 7 times memory usage improvement. These improvements are made by a more efficient indexing and a more thorough parallelization.

5.8 Case Study

We present a case study about the extracted phrases as shown in Table 3. The top ranked phrases are mostly named entities, which make sense for the Wikipedia article datasets. Even in the long tail part, there are still many high-quality phrases. For example, we have the ⌈great spotted woodpecker⌋ (a type of birds) and ⌈计算机 科学技术⌋ (*i.e.*, Computer Science and Technology) ranked about 100,000. In fact, we have more than 345K and 116K phrases with a phrase quality higher than 0.5 on the *EN* and *CN* datasets respectively.

6. SINGLE-WORD PHRASES

AutoPhrase can be extended to model single-word phrases, which can gain about 10% to 30% recall improvements on different datasets. To study the effect of modeling quality single-word phrases, we choose the three Wikipedia article datasets in different languages: *EN*, *ES*, and *CN*.

6.1 Quality Estimation

In *the paper*, the definition of quality phrases and the evaluation only focus on multi-word phrases. In linguistic analysis, however, a phrase is not only a group of multiple words, but also possibly a single word, as long as it functions as a constituent in the syntax of a sentence [8]. As a great portion (ranging from 10% to 30% on different datasets based on our experiments) of high-quality phrases, we should take single-word phrases (*e.g.*, ⌈UIUC⌋, ⌈Illinois⌋, and ⌈USA⌋) into consideration as well as multi-word phrases to achieve a high recall in phrase mining.

Considering the criteria of quality phrases, because single-word phrases cannot be decomposed into two or more parts, the *concordance* and *completeness* are no longer definable. Therefore, we revise the requirements for ***quality single-word phrases*** as below.

- ***Popularity***: Quality phrases should occur with sufficient frequency in the given document collection.
- ***Informativeness***: A phrase is informative if it is indicative of a specific topic or concept.
- ***Independence***: A quality single-word phrase is more likely a complete semantic unit in the given documents.

Only single-word phrases satisfying all *popularity*, *independence*, and *informativeness* requirements are recognized as quality single-word phrases.

Example 6. *"*UIUC*" is a quality single-word phrase. "*this*" is not a quality phrase due to its low informativeness. "*united*", usually occurring within other quality multi-word phrases such as "*United States*", "*United Kingdom*", "*United Airlines*", and "*United Parcel Service*", is not a quality single-word phrase, because its independence is not enough.*

After the phrasal segmentation, in replacement of concordance features, the **independence feature** is added for single-word phrases. Formally, it is the ratio of the rectified frequency of a single-word phrase given the phrasal segmentation over its raw frequency. Quality single-word phrases are expected to have large values. For example, "*united*" is likely to an almost zero ratio.

We use **AutoPhrase+** to denote the extended AutoPhrase with quality single-word phrase estimation.

6.2 Experiments

We have a similar human annotation as that in *the paper*. Differently, we randomly sampled 500 Wiki-uncovered phrases from the returned phrases (*both single-word and multi-word phrases*) of each method in experiments of *the paper*. Therefore, we have *new pools* on the *EN*, *ES*, and *CN* datasets. The intra-class correlations (ICCs) are all more than 0.9, which shows the agreement.

Figure 9 compare all methods based these new pools. Note that all methods except for SegPhrase/WrapSegPhrase extract single-word phrases as well.

Significant recall advantages can be always observed on all *EN*, *ES*, and *CN* datasets. The recall differences between AutoPhrase+ and AutoPhrase, ranging from 10% to 30% sheds light on the importance of modeling single-word phrases. Across two Latin language datasets, *EN* and *ES*, AutoPhrase+ and AutoPhrase overlaps in the beginning, but later, the precision of AutoPhrase drops earlier and has a lower recall due to the lack of single-word phrases. On the *CN* dataset, AutoPhrase+ and AutoPhrase has a clear gap even in the very beginning, which is different from the trends on the *EN* and *ES* datasets, which reflects that single-word phrases are more important in Chinese. The major reason behind is that there are a considerable number of high-quality phrases (*e.g.*, person names) in Chinese have only one token after tokenization.

7. CONCLUSIONS

In this paper, we propose two novel techniques: the robust positive-only distant training and the POS-guided phrasal segmentation incorporating part-of-speech (POS) tags, for the development of an *automated phrase mining* framework AutoPhrase. Our extensive experiments show that AutoPhrase is domain-independent, outperforms other phrase mining methods, and supports multiple languages (*e.g.*, English, Spanish, and Chinese) effectively, with minimal human effort.

For future work, it is interesting to (1) refine quality phrases to entity mentions, (2) apply AutoPhrase to more languages, such as Japanese, and (3) for those languages without general knowledge bases, seek an unsupervised method to generate the positive pool from the corpus, even with some noise.

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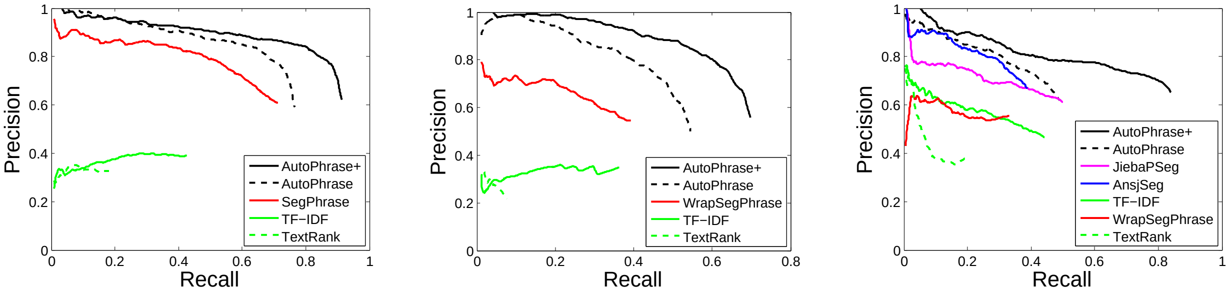

(a) EN (b) ES (c) CN

Figure 9: Precision-recall curves evaluated by human annotation with both single-word and multi-word phrases in pools.

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