Enhancing the Input Representation: From Complexity to Simplicity

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Abstract

We introduce an efficient algorithm for mining informative combinations of attribute-values for a given task. We use informative attribute-values to enhance the input representation of data. We apply our approach to coreference resolution using a simple set of attributes like syntactic roles and string match. With the enhanced representation, a simple coreference model outperforms more complex state-of-the-art models by a large margin. The use of the enhanced representation results in robust improvements in both in-domain and out-of-domain evaluations.

1 Introduction

In this paper, we introduce an efficient pattern mining approach for enhancing the input representation of data in NLP tasks.

Assume the data is described by a set of attributes. Let a pattern be a conjunction of different attribute-values. An informative pattern is a pattern that correlates with target labels. Exploring informative patterns of data attributes is a way to come up with new features for improving the data representation.

Previously, most efforts in machine learning projects were targeted at feature engineering. The use of automatic approaches that find useful combinatorial features or attribute-values can partially take over the manual feature engineering process. However, current state-of-the-art NLP approaches mainly use deep neural networks. Now, the common practice is to find a proper representation using word embeddings and various kinds of neural networks. As a result, extracting useful combinatorial features, either manually or automatically, does not seem to be required anymore.

In this paper, we show that feature engineering, even in a very basic form of finding informative features by combining the existing attribute-values, can still result in significant improvements in a state-of-the-art deep neural model.

There is a large number of attributes that can be used for describing a given chunk of text. For instance, each text chunk can be simply described by the part of speech (POS) tags of the individual words. The description can be improved by computing the syntactic structure of sentences. Named entities of the text can be specified along their types. Similarly, one can apply all types of different text processing modules to the given text to enrich the text description. However, depending on the target task, many of these attribute-values are not informative or necessary. The incorporation of a large non-informative source of information might only confuse the classifier.

We introduce an efficient pattern mining approach for finding informative attribute-values for the given task. Neural networks have their own way of finding an optimized combination of input attribute-values. Therefore, we do not use our informative pattern mining approach to extend the input representation with additional combinatorial features. Instead, we use our algorithm to choose informative values of the existing attributes. In order to enhance the input representation, we first mine an informative set of combinatorial features. Then, instead of incorpor-
We use the following notations and definitions throughout this section:

- \( D = \{X_i, c(X_i)\}_{i=1}^n \): set of training samples. \( X_i \) is the set of attribute-value pairs that describes the \( i \)th sample. \( c(X_i) \in C \) is the label of \( X_i \).

- \( A = \{a_1, \ldots, a_l\} \): set of all attribute-values present in \( D \). We call each \( a_i \in A \) an item.

- \( p \): pattern \( p = a_{i_1} \land \cdots \land a_{i_k} \) is a conjunction of items.

- \( D_p = \{X_i|p \in X_i\} \): the set of samples that is matched by pattern \( p \), referred to as cover \( p \).

- \( \text{support}(p, c_i) \): the number of samples in \( D_p \) that are labeled with \( c_i \), i.e. \( \{|X_i|X_i \in D_p \land c(X_i) = c_i\} \} \).

## 2 Enhancing the Data Representation

In this section, we introduce a new pattern mining approach. Each pattern is a combination of input attribute-values. We first present a large set of possible attribute-values describing different properties of input samples to our algorithm. Our algorithm efficiently mines an informative set of patterns that is useful for distinguishing the target labels. At the end, attribute-values that are included in at least one informative pattern will be used for enhancing the representation of data.

It is worth noting that our algorithm deals with categorical attributes. Other attributes can be incorporated by using a binning method.

### 2.1 Definitions

We use the following notations and definitions throughout this section:

- We use the **FP-Tree** structure (Han et al., 2004) for representing the whole input samples. FP-Tree is an efficient data structure for frequent pattern mining. It provides a structure for representing all existing patterns of data in a compressed form. Using the FP-Tree structure allows efficient enumeration of frequent patterns in data. In the FP-tree structure, items are arranged in descending order of frequency. Frequency of an item corresponds to \( \sum_{c_i \in C} \text{support}(a_i, c_i) \).

  - Except for the root of the tree, which is a null node, each node \( n \) contains an item \( a_i \in A \). It also contains the support values of \( a_i \) in the sub-path of the tree that starts from the root and ends with \( n \). These support values are indicated by \( \text{support}_n(a_i, c_j) \).

  - The FP-Tree construction method is as follows:

    1. Scan \( D \) once to collect \( A \). Compute \( \text{support}(a_i, c_j) \) for each item \( a_i \in A \) and label \( c_j \in C \). Sort \( A \)'s members in descending order according to their frequencies.

    2. Create a null-labeled node as the root.

    3. Scan \( D \) one more time. For each \( (X_i, c(X_i)) \in D \) perform the following steps:

      (a) Order all items \( a_j \in X_i \) according to the order in \( A \).

      (b) Set the current node \( (T) \) to the root.

      (c) Consider \( X_i = [a_k|X_i] \), where \( a_k \) is the first (ordered) item of \( X_i \), and \( X_i = X_i - a_k \). If \( T \) has a child \( n \) that contains \( a_k \) then increment \( \text{support}_n(a_k, c(X_i)) \) by one. Otherwise, create a new node \( n \) that contains \( a_k \) with \( \text{support}_n(a_k, c(X_i)) = 1 \). Add \( n \) to the tree as a child of \( T \).
FP-Tree has a header structure that associates each item \( a_i \) with a list of pointers to all nodes of the tree that contain \( a_i \). From this header structure, one can easily obtain \( \text{support}(a_i, c_j) \) in the whole tree.

From an initial FP-Tree \( (T) \) that represents all existing patterns, we can easily obtain a new FP-Tree in which all patterns include a given sub-pattern \( p \). This can be done by only including sub-paths of \( T \) that contain pattern \( p \). The new tree is called conditional FP-Tree of \( p, T_p \).

### 2.3 Which Pattern is Informative?

Similar to other supervised pattern mining approaches, our goal is to select a set of patterns that is relevant to the class label. We use a \textit{relevance} and an \textit{information novelty} measure in order to determine informative patterns regarding the class label. Similar to other pattern-based feature mining approaches, we also use a \textit{frequency} measure. Frequency can be used to limit the search space in case we are not interested in rare patterns of data. We use the statistical significance of the association of a pattern and the class label as the measure for choosing relevant patterns. We use the binomial test for choosing patterns with novel information.

The \textit{relevance} and \textit{information novelty} measures are partly checked directly during the mining process and also in post-processing. The difference is that the evaluation of the measures in the post-processing step is done in a more stringent way.

**Frequency:** A pattern \( p \) is frequent if one of the following equations holds:

\[
\exists c_i \in C \quad \frac{\text{support}(p, c_i)}{|\{X | c(X) = c_i\}|} \geq \lambda \quad (1)
\]

\[
\exists c_i \in C \quad \text{support}(p, c_i) \geq \lambda \quad (2)
\]

where \( \lambda \) is the minimum support threshold. If \( 0 < \lambda < 1 \), Equation 1 is used. This definition is especially useful in imbalanced datasets. If \( \lambda \geq 1 \), Equation 2 is used for defining frequent patterns.

**Relevance:** We use the \( G^2 \) likelihood ratio statistic (Agresti, 2007) in order to choose patterns whose association with the class variable is statistically significant. \( G^2 \) can be unreliable for expected frequencies of less than 5 (Agresti, 2007). However, since we experiment on large datasets and evaluate the significance measure on patterns satisfying the frequency condition (Equation 1 or 2), this problem does not apply in our case. If one is interested in rare patterns of data, Fisher’s exact test is a better choice. However, Fisher’s exact test is very time consuming in comparison to the \( G^2 \) test for large values. During the mining process, the relevance condition is applied in a more lenient way. A pattern is considered relevant if the p-value returned by the \( G^2 \) test is less than a fixed threshold (i.e. 0.01).

**Information Novelty:** A large number of patterns can be generated by adding irrelevant items to an informative base pattern. This can lead to a large set of redundant patterns conveying similar information regarding the class label. Many of these spurious patterns may also be significant by themselves. However, the information they provide is redundant in comparison to the base pattern. In order to evaluate the information novelty of a pattern we check the following two conditions:

1. For pattern \( p \), assume that \( D_p \) contains \( N \) samples, out of which \( N_c \) samples belong to target class \( c \). Let \( P_c \) be the highest probability achieved by an included item in pattern \( p \), i.e. \( P_c = \max_{a_i \in p} P r(c|D_{a_i}) \). The null hypothesis presumes that \( N_c \) is generated from \( N \) with a binomial distribution with probability \( P_c \). The alternative hypothesis is that the underlying probability that generates \( N_c \) is significantly higher than \( P_c \). The p-value of a one-sided significance test using a binomial distribution should be smaller than a significance level \( \alpha \), i.e. \( Pr_{\text{binomial}}(x \geq N_c | N, P_c) < \alpha \).

   We set \( \alpha = 0.01 \) in our experiments. This condition is checked directly during mining.

2. The second condition is similar to the first one. However, instead of individual items that are included in \( p \), we evaluate \( p \) against its sub-patterns that are relevant (satisfying relevance) and frequent (satisfying frequency). Therefore, for the second condition \( P_r \) is the maximum probability of all the \( p' \subset p \) that are both relevant and frequent. This condition is checked in the post-processing step.
2.4 Mining Algorithm

Our mining algorithm is summarized in Algorithm 1. It takes FP-Tree $T$, pattern $p$ on which $T$ is conditioned, and items ($A_j \subset A$) whose combinations with $p$ will be examined. Initially $p$ is empty and FP-Tree is constructed based on all frequent items of data and $A_j = A$.

For each $a_i \in A_j$, the algorithm builds new pattern $q$ by combining $a_i$ with $p$. frequent($q$) checks whether $q$ meets the frequency condition of Equation 1 or 2. If $q$ is frequent, the algorithm continues the search process. Otherwise, $q$ itself is not qualified as a useful pattern and it is not possible to build any interesting pattern out of $q$.

The relevance and information novelty conditions are then checked for pattern $q$.

Input: $T$: input FP-Tree
Input: $p$: pattern base on which $T$ is conditioned
Input: $A_j$: set of items to be combined with $p$
Output: $P$: set of output patterns

Algorithm mine-feature ($T$, $p$, $A_j$)

foreach $a_i \in A_j$ do
    $q = p \cup a_i$
    if frequent($q$) then
        if Relevant($q$) then
            testCount($|q|$) + = 1
        if Novel($q$) then
            $P = P \cup q$
        end
    end
    if $|q| \geq \Theta_l$ then
        continue
    end
    construct $T_q = q$’s conditional tree
    mine-feature($T_q$, $q$, coItems($a_i$))
end

Algorithm 1: Mining algorithm

If $|q|$ is smaller than $\Theta_l$, conditional FP-Tree $T_q$ is built to represent $q$’s search space. The mining algorithm then continues to recursively search for more specific patterns by combining $q$ with the items included in coItems($a_i$). coItems is built while constructing the original FP-Tree. For each item $a_i$, coItems keeps the list of all ancestors of $a_i$ in the original FP-Tree.

2.5 Post-Processing

The post-processing step checks relevance and information novelty measures in a more stringent way.

When we use a statistical test multiple times, the risk of making false discoveries increases (Webb, 2006). In the post-processing step, we therefore apply the Bonferroni correction for multiple tests in order to reduce search errors. Similar to Bay and Pazzani (2001), we set the p-value threshold for all patterns of length $l$ as follows:

$$\Theta_{pl} = \min\left(\frac{\Theta_{p0}}{2^l \times \text{testCount}(l)}, \Theta_{p_{l-1}}\right),$$

where $\text{testCount}(l)$ is the number of times that the $G^2$ test is applied on a pattern of length $l$ in the mining step.

Now, we have the set of frequent and relevant patterns of data up to length $\Theta_l$. Therefore, we can easily check the second information novelty condition of Section 2.3 on the resulting pattern set.

3 How Does the Enhanced Representation Benefit Coreference Resolution?

We evaluate the effectiveness of our informative pattern mining approach on coreference resolution. A coreference resolver partitions the set of mentions of a text in such a way that each partition represents a real-world entity. Coreference resolution is a challenging task in NLP and far from being solved.

Existing models for coreference resolution are of various complexity. The simplest approach for modeling coreference resolution is a mention-pair approach. Mention-pair approaches consist of two steps. The first step determines how likely it is for individual mention-pairs to be coreferent. Then, a clustering algorithm partitions evaluated mention-pairs into coreference chains.
**Mention-ranking** is a more complex approach for modeling coreference resolution. In mention-ranking models, all candidate antecedents of a given mention are considered together. In this way, the model can capture the competition between candidate antecedents of a single mention. Therefore, mention-ranking models resolve mentions individually. However, for each mention, they consider all antecedents together. Most recent state-of-the-art approaches are mention-ranking models, e.g. Clark and Manning (2016a) and Wiseman et al. (2016).

The loss function of mention-ranking introduced by Wiseman et al. (2015) is as follows:

$$\sum_{i=1}^{N} \max_{a \in A(m_i)} \triangle(a, m_i)(1 + s(a, m_i) - s(\hat{t}_i, m_i)),$$

where $\hat{t}_i = \arg \max_{t \in \tau(m_i)} p(t, m_i)$ and $A(m_i)$ is the set of all candidate antecedents of $m_i$, i.e. all mentions preceding $m_i$ and NA for non-anaphoric mentions. $\triangle(a, m_i)$ is a cost function that assigns different weights to various kinds of errors for creating coreference links.

The **top-pair** model introduced by Clark and Manning (2015) is a middle ground between the mention-pair and mention-ranking models. The top-pair model only processes the highest and lowest scoring antecedents for each mention by a probabilistic loss function:

$$-\sum_{i=1}^{N} \left[ \max_{t \in \tau(m_i)} \log p(t, m_i) + \min_{f \in F(m_i)} \log(1-p(f, m_i)) \right], \quad (3)$$

where $\tau(m_i)$ is the set of true antecedents of $m_i$ and $F(m_i)$ is the set of incorrect antecedents for $m_i$.

**Entity-based** models go beyond individual mentions and operate on the entity-level (e.g. Rahman and Ng (2011), Stoyanov and Eisner (2012), Clark and Manning (2016b)). Despite considerable added complexity, entity-based approaches have not yet resulted in satisfactory improvements over simpler coreference models.

The coreference resolver introduced by Clark and Manning (2016a) is their previous mention-ranking model (Clark and Manning, 2016b) that is directly optimized with reinforcement learning. Their mention-ranking model uses the mention-pair and top-pair models for pretraining.

### 3.1 Consistent Performance Boost Across Various Domains

We show that with an enhanced representation, a simple top-pair model outperforms more complex coreference resolvers by a large margin in both in-domain and out-of-domain evaluations.

We use the top-pair model of deep-coref\(^1\) with the same setting as Clark and Manning (2016b) for pretraining the ranking model. The top-pair model uses a pairwise model for pretraining. The pairwise model is trained for 150 epochs and the top-pair model is trained for 50 epochs.

We describe each mention-pair with the following set of attributes: (a) tokens of one mention is contained in another one, (b) heads of two mentions match, (c) head of one mention is contained in another one, (d) heads of two mentions match and they do not have incompatible pre-modifiers, (e) the nearest candidate antecedent that satisfies (d), (f) three attributes determining whether two mentions are compatible based on number, gender or animacy, (g) two mentions are compatible based on number, gender and animacy, (h) the nearest antecedent that satisfies (g), (i) the nearest antecedent that is a subject and satisfies (g), (j) the nearest antecedent that is an object and satisfies (g), (k) one of the mentions is the acronym of the other, (l) attributes describing the following properties for both anaphor and antecedent: mention type, named entity type of the mention’s head, mention length in words, enhanced dependency relation of the mention’s head to its parent, POS tags of the first, last, head, preceding and following words of a mention.

It is worth noting that for our mining approach we only incorporate attributes that are not originally incorporated in the base coreference resolver. The original feature set of deep-coref includes: speaker features, exact match, refined head match, and relaxed string match. deep-coref also incorporates the embeddings of the head, first, last, two preceding, and two following words of each mention as well as the averaged word embeddings of the five preceding, five following, all mention words, all sentence

\(^1\)Available at https://github.com/clarkkev/deep-coref
words, and all document words. In our experiments, we did not incorporate the averaged word embeddings. The deep-coref performance without these averaged word embeddings is presented in Table 3 as `avg. embeddings`.

We extract all positive and negative mention pairs from the CoNLL 2012 training data and separate them based on the type of the anaphor. Then, we apply our mining algorithm on the extracted pairs and mine separate informative pattern sets for proper names, common nouns and pronouns. Finally, we add the attribute-values that exist in at least one of the mined informative patterns as new binary features to the original feature set of deep-coref. We only mine patterns for the coreferent class, i.e. we only consider the coreferent class in Equation 2. We mine patterns that occur for more than 20 unique anaphora in the training data. We mine patterns up to length five and also add an extra condition in the post-processing step that \( p(\text{coreferent}\mid\text{pattern}) \) should be larger than 60 percent. The mining algorithm takes from two to six hours for mining informative patterns for different types of mentions. It results in 195 new binary features. It is worth noting that among the new features, 107 features are POS related attribute-values. If we remove all these POS related features, the performance drops only around 0.1 to 0.3 percent based on both LEA and the CoNLL score. The pattern mining time on the attribute set without POS tags only takes from four to seven minutes. The best weights of the top-pair model on the development set are selected using the loss value of Equation 3 instead of the LEA score. Therefore, there may be about 0.2 percent difference between the scores of the top-pair model on different experiments.

As the importance of out-of-domain evaluations has been recognized by Moosavi and Strube (2017), we perform both in-domain and out-of-domain evaluations. The results on both CoNLL official test set and the WikiCoref dataset are presented in Table 1. The results are reported using \( MUC \) (Vilain et al., 1995), \( B^3 \) (Bagga and Baldwin, 1998), \( CEAF_e \) (Luo, 2005), the average \( F_1 \) score of these three metrics, i.e. CoNLL score, and \( LEA \) (Moosavi and Strube, 2016). The statistical significance is measured by the approximate randomization test (Noreen, 1989). We consider an improvement statistically significant if \( p < 0.05 \).

\textbf{ranking/base} presents the results of the ranking model of Clark and Manning (2016b) in which the best trained model is selected based on the LEA score on the development set.

\textbf{ranking/reinforce} presents the results of the ranking model with a reward rescaled max-margin objective by Clark and Manning (2016a). As can be seen,

| MUC | \( B^3 \) | CEAF_e | CoNLL | LEA |
|-----|---------|--------|-------|-----|
| R   | P       | F_1    | R    | P   | F_1    | R    | P   | F_1    |
|-----|---------|--------|-------|-----|--------|-------|-----|--------|--------|
| base | rank   |        |       |     |        |       |     |        |        |
| 70.43 | 70.52 | 70.47 | 58.08 | 62.26 | 63.18 | 54.43 | 64.17 | 58.90 | 65.60 |
| reinforce |        |        |       |     |        |       |     |        |        |
| 70.98 | 70.81 | 70.69 | 58.97 | 62.00 | 63.61 | 55.66 | 63.28 | 59.23 | 65.84 |
|       |        |        |       |     |        |       |     |        |        |
| WikiCoref |        |        |       |     |        |       |     |        |        |
| Ghaddar | rank   |        |       |     |        |       |     |        |        |
| 66.06 | 62.80 | 64.16 | 57.73 | 49.53 | 52.78 | 40.76 | 49.54 | 48.11 | 55.11 |
|       |        |        |       |     |        |       |     |        |        |
| base | rank   |        |       |     |        |       |     |        |        |
| 57.48 | 70.55 | 63.35 | 42.12 | 60.13 | 49.54 | 41.40 | 53.08 | 46.52 | 53.14 |
| reinforce |        |        |       |     |        |       |     |        |        |
| 62.11 | 58.97 | 60.50 | 46.98 | 45.78 | 46.37 | 44.28 | 46.34 | 45.29 | 50.72 |
|       |        |        |       |     |        |       |     |        |        |
| top-pair | rank  |        |       |     |        |       |     |        |        |
| 56.30 | 71.73 | 63.09 | 39.77 | 61.85 | 48.41 | 40.79 | 52.84 | 46.04 | 52.51 |
| enhanced |        |        |       |     |        |       |     |        |        |
| 58.23 | 74.05 | 65.19 | 43.33 | 63.89 | 51.64 | 43.44 | 56.32 | 49.05 | 55.29 |

Table 1: Comparison of the results on the CoNLL test set and WikiCoref. The best \( F_1 \) scores for each dataset and metric are boldfaced. \( F_1 \) gains of `top-pair/enhanced` compared to both `top-pair/base` and `ranking/base` are statistically significant for all metrics.
this approach significantly improves the results in an in-domain evaluation. However, this improvement does not apply in an out-of-domain evaluation.

The results of the top-pair model of Clark and Manning (2016b) with the base and our enhanced representations are presented as top-pair/base and top-pair/enhanced, respectively. The use of our enhanced representation improves the performance of the top-pair model about 0.9 percent based on both the CoNLL score and LEA. The top-pair model with an enhanced representation significantly outperforms the examined systems in both datasets. It is worth noting that the CoNLL score of our model, which is trained on the CoNLL training data and tested on WikiCoref, is even higher than those of Ghaddar and Langlais (2016), i.e. Ghaddar in Table 1, which is specifically designed based on the properties of WikiCoref.

We also evaluate the top-pair model with the enhanced representation in in-domain and out-of-domain evaluation settings suggested by Moosavi and Strube (2017) for pt, wb and nw genres. The results are presented in Table 2. The top-pair/enhanced results confirm that the resulting improvements from using an enhanced representation are robust and can be applied to unseen domains.

Similar to Clark and Manning (2016b), we can use the top-pair model for pretraining a ranking model. However, when the enhanced representation is used, the use of the ranking model results in overfitting and decreases the performance on the development set. This shows that a better representation alleviates the need for more complex models.

Is It Due to Additional Attributes or the Enhanced Representation?

As mentioned above, the attributes that are used by our mining algorithm do not exist in the original feature set of deep-coref. In order to verify that the resulting improvements are due to the specific attribute-values that are selected by our mining algorithm, and not the new attributes themselves, we choose ranking/base and top-pair/base as baselines and perform the following experiments: (1) Adding attributes (a)-(c) described in Section 3.1 to the baseline, i.e. +new string matches in Table 3, and (2) adding the enhanced dependency relation of each mention as a new embedding feature, i.e. +dependency rel. The enhanced dependency relation is a lexicalized relation. Therefore, we incorporate it as an embedding feature instead of a binary one.

The addition of dependency relations and the new string match features decreases the performance of ranking/base. On the other hand, they slightly improve the performance of top-pair/base. However,
the results of the improved top-pair model is still not better than that of ranking/base.

Therefore, while the current assumption is that neural networks alleviate the need for fine-tuned feature engineering, our results show that the incorporation of automatic feature engineering in a deep learning architecture is still beneficial.

3.2 Learning More about the Task

Apart from recognizing useful attribute-values for enhancing the representation of data, we can learn more about the properties of the target task by looking at the mined patterns. For example:

1. From the attributes that are described in Section 3.1, we design attributes (d), (e), (g)-(j) after looking at our initial set of patterns. For instance, we observe that attribute-values “antecedent dependency relation=subject”, “compatible gender=true”, “compatible number=true”, and “compatible animacy=true” happen very frequently together and for pairs in which the distance of two mentions is very small. Therefore, we infer new attributes based on these observations. As another example, among the mined patterns for pronouns, there are many patterns in which the POS tag of the preceding word is a quotation mark. Therefore, one feature that can be inferred from this observation is that the mention is quoted.

2. Distance is an important attribute when it comes to resolving pronouns. “nearest compatible antecedent”, i.e. attribute (h) in Section 3.1, is true in around 98% of the informative patterns that are mined for pronouns. However, this ratio is only around 0.01% and 0.07% for proper names and common nouns, respectively. On the other hand, more than 98% of the mined informative patterns for proper names contain one of the (a)-(c) string match features.

3. The syntactic role of an antecedent is a known informative attribute for resolving pronouns. The syntactic role is usually captured by considering the dependency relation of the head of a mention to its parent. The incorporation of POS tags allows us to expand the detection of syntactic roles. For example, there are numerous patterns for pronouns in which the head of an antecedent has other roles like “compound” but the previous or the following word of a mention is tagged as a verb, which in turn implicitly identifies the mention as an object or a subject, respectively.

4 Why Reinvent the Wheel?

In this section, we explain why we introduce a new pattern mining approach for determining informative attribute-values while there are already many approaches available.

Mining a relevant and non-redundant set of patterns from labeled data is a well-established problem that is referred to as supervised pattern set mining. There is a large number of supervised pattern set mining approaches, e.g. Bringmann et al. (2009), Novak et al. (2009), Zimmermann and Nijssen (2014), inter alia, that can be mainly grouped into two categories: (1) post-processing, and (2) iterative approaches. Post-processing approaches first mine a set of patterns satisfying certain constraints, which is usually the frequency constraint. The mining step is then followed by a post-processing step which selects a subset of mined patterns. Iterative approaches mine one or more patterns satisfying certain constraints. Based on the selected pattern(s) they modify the constraints or data and then repeat the mining process. Zimmermann and Nijssen (2014) include a detailed discussion about each of the above categories.

Post-processing approaches are generally faster than iterative ones because they only need one iteration of the mining process. On the other hand, the iterative approaches are more flexible and can potentially lead to higher accuracy.

In natural language processing tasks, it is often the case that the dataset is very large and data is represented with a very large set of attributes. Therefore, efficiency is a main concern for applying a pattern mining approach to NLP tasks.

In this regard, the post-processing approaches are still not efficient enough for larger data sizes or larger search spaces. Enumerating all frequent patterns of data has been proven to be an NP-complete problem (Yang, 2006). Besides, when the search
space is large, the mining step may result in a huge number of patterns, which in turn makes post-processing also a time-consuming step.

In this section, we compare our pattern mining approach in terms of efficiency with two other pattern mining approaches considered to be efficient, namely Minimal Predictive Patterns by Batal and Hauskrecht (2010) and Direct Discriminative Pattern Mining by Cheng et al. (2008). Henceforth, we refer to our mining approach as ESPM, i.e. an Efficient Scalable Pattern Mining approach. We show ESPM is clearly superior to the compared approached in terms of efficiency. Therefore, it is suitable for large scale datasets and large search spaces as those of NLP tasks.

4.1 Compared Feature Mining Approaches

Minimal Predictive Patterns (MPP) and Direct Discriminative Pattern Mining (DDPMine) are two pattern-based feature mining methods that are shown to be more efficient than the post-processing approaches. MPP, introduced by Batal and Hauskrecht (2010), directly mines a compact set of predictive patterns. Therefore, MPP does not have several iterations of the mining algorithm or any post-processing step. MPP explores the search space by an Apriori-like (Agrawal and Srikant, 1994) level wise search. MPP selects patterns that are significantly more predictive than all of their sub-patterns. For each pattern of length $l$, there are $2^l - 1$ sub-patterns to be checked. However, MPP caches the required statistics in an efficient way that does not cost any more computation than that of Apriori itself. The predictive power of pattern $p$ for label $c_i$ is measured by $Pr(c_i|p)$.

DDPMine, introduced by Cheng et al. (2008), is an iterative approach. However, it has a very small number of iterations and it progressively shrinks the search space. As the name implies, DDPMine uses the discriminative power of patterns as pattern selection criterion. At each iteration of the algorithm, the most discriminative pattern that covers the current training samples is found. Then the search space is reduced by removing the samples that are covered by this pattern. DDPMine continues to iterate until all of the samples are covered by at least one discriminative pattern or no more patterns can be mined.

DDPMine evaluates each pattern only on a subset of the dataset. However, MPP and our approach evaluate each pattern against the whole set of examples.

Both DDPMine and our approach use the FP-Tree structure for representing data. On the other hand, the MPP approach is using Apriori in order to generate patterns. Approaches which use the FP-Tree structure are more efficient for large datasets that contain a large number of frequent items. The major advantage of using FP-Tree for generating patterns compared to Apriori is that FP-Tree only uses two scans of data while Apriori requires multiple scans.

4.2 Experimental Setup

For our evaluations, we reimplement DDPMine (Cheng et al., 2008) and MPP (Batal and Hauskrecht, 2010). Approximated MPP that achieves higher efficiency by using a lossy pruning technique is used in our experiments (Batal and Hauskrecht, 2010).

In all of the evaluated feature mining methods, Equation 1 is used as the frequency condition.

We also use threshold $\Theta_l$ for evaluating MPP. All experiments are done using a one core 1.8GHz CPU. We use several real-world datasets from the UCI\textsuperscript{2} and KEEL\textsuperscript{3} machine learning repositories. Table 4 presents a description of the selected datasets. The second column shows the number of

| Dataset   | #Attribute | #FI | #Sample | #Class |
|-----------|------------|-----|---------|--------|
| flare     | (0/0/11)   | 27  | 1066    | 6      |
| nursery   | (0/0/8)    | 27  | 12690   | 5      |
| adult     | (6/0/8)    | 31  | 32561   | 2      |
| sick      | (6/1/22)   | 36  | 2800    | 2      |
| kr-v-k    | (0/0/16)   | 40  | 28056   | 17     |
| marketing | (0/13/0)   | 49  | 6876    | 9      |
| german    | (0/7/13)   | 51  | 1000    | 2      |
| census    | (1/12/28)  | 76  | 299284  | 3      |
| letter    | (0/16/0)   | 159 | 20000   | 26     |
| poker     | (0/10/0)   | 85  | 1025010 | 10     |
| connect-4 | (0/0/42)   | 107 | 67557   | 3      |
| fars      | (5/0/24)   | 226 | 100968  | 8      |
| kddcup99  | (26/0/15)  | 988 | 4898431 | 23     |

Table 4: Data descriptions.

\textsuperscript{2}https://archive.ics.uci.edu/ml/datasets.html
\textsuperscript{3}http://sci2s.ugr.es/keel/datasets.php
(real/integer/nominal) attributes. The third column shows the number of frequent items based on our used frequency threshold. The number of frequent items is an indicator for the search space complexity. The forth and the fifth columns show the number of samples and the number of classes in each dataset. We do not use any binning method in the experiments of this section.

4.3 Efficiency Evaluation

Figure 1 shows the running time (in seconds) of our approach, i.e. ESPM, on the test datasets with different parameters. ESPM(3) shows the running time when $\Theta_l = 3$ and $\lambda = 0.1$. ESPM(4) uses the same $\lambda$, but $\Theta_l$ is set to four. The $\lambda = 0.01$ and $\Theta = 3$ parameters are used for ESPM(0.01). All reported times for ESPM include the post-processing time.

As can be seen in Figure 1, increasing $\Theta_l$, or decreasing $\lambda$ does not notably affect the running time of ESPM on the datasets with smaller search space. However, on the datasets with a larger number of frequent items, decreasing $\lambda$ affects the processing time more than increasing $\Theta_l$.

Figure 2 shows the running time of ESPM(3) in comparison to those of DDPMine and MPP. $\lambda$ is set to 0.1 for all approaches. Because of the significant differences in the running times of ESPM and other approaches (especially MPP), the running times are reported in logarithmic scale. MPP(3) and MPP(4) show the results of the approximated MPP approach when $\Theta_l = 3$ and $\Theta_l = 4$, respectively. When the running time exceeds more than two days, the experiments are not included in the plot.

ESPM is remarkably more efficient in comparison to the other two approaches. For the datasets in the lower part of Table 4, ESPM is the only practical feature miner that mines the feature set in a reasonable amount of time. It is worth noting that the large datasets of Table 4 are still much simpler and smaller than the ones used for NLP applications.

5 Conclusions

We introduce an efficient pattern mining approach that is scalable to large datasets. We use our pattern mining approach for enhancing the input representation in coreference resolution. The following points are worth emphasizing: (1) we use a very basic set of attribute-values. Yet, the enhanced representation improves the results of the base deep neural coreference resolver around one percent in in-domain evaluations and three percent in out-of-domain evaluations. Incorporating other sources of information for enhancing the input representation, or in general incorporating more structure in the input, is a promising avenue for future research. (2) Due to the increasing training time of complex models, recent coreference developments become eye-wateringly time consuming while the task is still far from being solved. We show that a better input representation alleviates the need for more complex models.

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