SAGE: Semantic-Aware Global Explanations for Named Entity Recognition

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Abstract

In the last decades, deep learning approaches achieved impressive results in many research fields, such as Computer Vision and Natural Language Processing (NLP). NLP in particular has greatly benefit from unsupervised methods that allow to learn distributed representation of language. On the race for better performances Language Models have reached hundred of billions parameters nowadays. Despite the remarkable results, deep models are still far from being fully exploited in real world applications. Indeed, these approaches are black-boxes, i.e. they are not interpretable by design nor explainable, which is often crucial to make decisions in business. Several task-agnostic methods have been proposed in literature to explain models' decisions. Most techniques rely on the "local" assumption, i.e. explanations are made example-wise. In this paper instead, we present a post-hoc method to produce highly interpretable global rules to explain NLP classifiers. Rules are extracted with a data mining approach on a semantically enriched input representation, instead of using words/wordpieces solely. Semantic information yields more abstract and general rules that are both more explanatory and less complex, while being also better at reflecting the model behaviour. In the experiments we focus on Named Entity Recognition, an NLP task where explainability is under-investigated. We explain the predictions of BERT NER classifiers trained on two popular benchmarks, CoNLL03 and Ontonotes, and compare our model against LIME Ribeiro et al. (2016).

Keywords: *Explainable AI, XAI, Explainable ML, Named Entity Recognition.*

1 Introduction

In recent years, Artificial Intelligence (AI) algorithms, especially deep learning models, are emerging in many applications, reporting state-of-the-art performances in many fields. In NLP, for example, the use of Large Language Models (LLM) based on huge deep neural networks achieved impressive results in many linguistic tasks. However, despite the remarkable results, deep approaches are still far from being fully exploited in real world applications. One major issue is the lack of interpretability and control of the models' predictions. This is often an important requirement for many industrial applications, especially in domains like medicine, defense, finance and law, where it is crucial to understand the decisions and build trust in the algorithms.

The increasing need to address the problem of interpretability and improve model transparency made the "Explainable Artificial Intelligence" a very popular research area in the Computer Science world. Explainable AI (XAI) or Interpretable AI or Explainable Machine Learning (XML) Guidotti et al. (2021) is a broad area of research that studies and proposes AI approaches where humans can understand the causes underlying the decisions and predictions made by the machine Vilone & Longo (2021b). The AI algorithms can be usually grouped into two families Vilone & Longo (2021a): (a) white-box models, which include algorithms whose interpretation is given by design, and (b) black-box approaches where, on the other hand, the decision making process is "opaque" and hard to understand. White-box models such as linear regression, probabilistic classifiers or decision trees are significantly easier to explain and interpret, but, often, provide a low predictive capacity and they are not always capable of modeling the inherent complexity of the task. In black-box models, on the other hand, very little knowledge is available on how the input variables influence the final decision. The relationship between input and output is often the result of a complex composition of

mathematical functions and is not directly interpretable. Although classic ML approaches are still widespread, almost all the modern complex AI techniques, such as deep neural networks, are naturally opaque Lipton (2018). Thus many new methods aimed to make new models more explainable and interpretable have been proposed or are under investigation.

Most explainability techniques rely on the "local" assumption where the descriptions are provided for each example and few approaches exist aiming at provide a interpretable description of the model as whole (glass-box). In this paper, we present SAGE (Semantic-Aware Global Explanations), a method to produce highly interpretable global rules to explain NLP classifiers. Rules are extracted using a data mining algorithm which exploits a semantically enriched input representation. Semantic information yields more abstract and general rules that are both more explanatory and less complex, while being also better at reflecting the model behaviour. In the experiments, we focus on Named Entity Recognition, an NLP task where explainability is under-investigated. In particular, we aimed to explain the predictions of a BERT-based (Devlin et al. (2018)) NER classifier trained and tested on two popular benchmarks, CoNLL03 Tjong Kim Sang & De Meulder (2003) and Ontonotes Pradhan et al. (2013). We compare the proposed model against LIME Ribeiro et al. (2016), which currently is one of the explainability algorithms mostly used in NLP. To evaluate the quality of the explainability algorithm, we measured the ability of the set of rules produced by the algorithms to reproduce the original labels assigned by the model under investigation (BERT-based NER classifier). The results show that the proposed approach infers a set of rules that reproduce the behavior of the model very precisely with respect to LIME.

The paper is organized as follow. In Section 2, we summarize related works, while in Section 3 the proposed algorithm is described in detail. Experiments are reported in Section 4, and finally conclusions and future works are drawn in Section 5.

2 Related Work

As deep learning models have become more complex, many methods have been proposed to yield explanations underlying the output of a model. There are two main groups of XAI techniques: (1) local approaches, which aim to provide an interpretable explanation for each single prediction; (2) global approaches, which try to build a "white-box" version of the black-box model (thus interpretable by design).

Local Explanations. Local algorithms focus on finding an interpretable explanation of the prediction returned by the ML model for a given input example. Those methods rely on the assumption that providing a global interpretation of a model is too complex, whereas it is possible to identify an explanation for a single instance. In Csiszár et al. (2020), the authors propose the use of fuzzy logic to "explain" each unit of an Artificial Neural Network, defining a set of ad-hoc operators. They outline a description of the functioning and signal flow in the network when it is fed with an example. Although showing which connections are involved in the decision-making process of a neural network can lead to insightful intuitions, it does not provide a high-level explanation of the reasons for the choice made by the model. Similar techniques try to identify which features in a particular input vector contribute the most to a neural network's decision. Layer-wise relevance propagation (LRP), for example, exploits a back-propagation similar algorithm to build a heat-map over the input features Binder et al. (2016),Montavon et al. (2019). This method proved to be very effective in computer vision, highlighting which pixels of an image contributed most to the final classification. Other methods such as Lundberg & Lee (2017) and Simonyan et al. (2013) follow the same principles.

Such techniques, however, are strongly related to the ML models' family used and they can be employed only with neural networks. Some model-agnostic approaches were proposed, Ribeiro et al. (2016),Ribeiro et al. (2018).In particular, it was presented in Ribeiro et al. (2016), LIME (Local Interpretable Model-agnostic Explanations). LIME trains a white-box classifier, that has to learn the black-box output distribution on a neighborhood of a given example. Neighbors are obtained perturbing the input features (usually randomly). The explanation can be then constructed by selecting the input features that mostly affects the model prediction. Although this method has become a benchmark for the explainability task, and it has been employed in some NLP classification problems, some significant limitations occur in the NLP field. First of all, we must consider that the

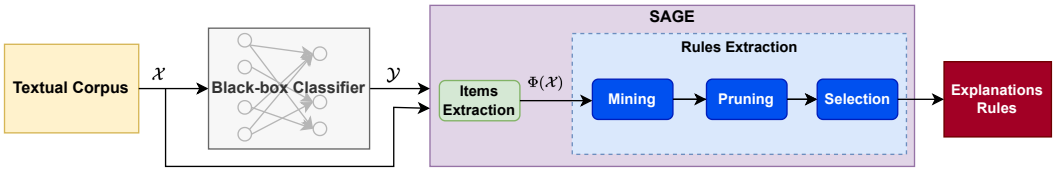

Figure 1: Sketch of Semantic-Aware Global Explanations (SAGE) model.

modern NLP models are based on Large Language Models (LLMs). LLMs tokenize text in subwords, like wordpieces Schuster & Nakajima (2012) in BERT, which requires particular attention in designing the text perturbation step. Masking and perturbation of the input introduce another issue for LLMs, that are contextual. Indeed random masking of tokens can produce artificial and inconsistent contexts, which may invalidate the identification procedure of significant features. Finally, Performing hundreds of input perturbation per sample, can be an expensive process, especially in problems like Named Entity Recognition (NER), where the number of examples corresponds to the number of tokens in a dataset.

Global Explanations While the explanation of a single prediction provides the user with a rationale for the classifier's behavior, it is not sufficient to convey confidence in the model as a whole. Thus, in contrast to local approaches, global explanation algorithms aim to find an interpretable description of the model in the whole input space.

In Ribeiro et al. (2016), authors propose an extension of LIME for global explanation. The resulting SP-LIME algorithm is based on the construction of an explanation matrix which collects the local importance of the interpretable components for each instance in a dataset X. For each component, a global importance in the explanation space is evaluated and the "Submodular pick (SP)" algorithm selects a subset of instances with the highest marginal coverage gain.

Our proposed method (SAGE) falls in this family. Unlike SP-LIME, it is natively global by design and aims to identify the set of semantically-enriched associative rules that best cover the behavior of the model on a reference set. Our algorithm share some of principles behind Bayesian Rule Lists (BRLs) Letham et al. (2015), however, the mining process is specifically designed and optimized to scale in NLP problems, like NER. Furthermore, differently from BRLs, SAGE is not used as an interpretable model per-se, but it is rather an algorithm to explain globally black-box classifier predictions. Finally, to the best of our knowledge, SAGE is the first method which involves semantic knowledge in the generation of the explanations.

3 Semantic-Aware Global Explanations

In this Section, we present SAGE (Semantic-Aware Global Explanations) algorithm, a method to discover globally significant explanation rules. To find relevant rules that provide a global and interpretable description of a black-box classifier, the proposed method follows a data-mining approach. Although it is task agnostic, we present SAGE by exploiting the NER task. Thus, in the following description, firstly we discuss how to formulate NER in the scope of data-mining task. Next, we delineate the data mining algorithm to generate candidate rules and the strategies for pruning and selecting a restricted number of explanations.

3.1 NER as a data mining problem

Named Entity Recognition (NER) is typically addressed as token classification task. Given a corpus of sentences/documents $\mathcal{X}$ and its corresponding annotations $\mathcal{Y}$, the goal is to predict a sequence of labels $\boldsymbol{y} \in \mathcal{Y}$, $\boldsymbol{y} := (y_1, \ldots, y_n)$, from a sequence of tokens $\boldsymbol{x} \in \mathcal{X}, \boldsymbol{x} := (x_1, \ldots, x_n)$. We frame NER into a data mining problem.

In data mining, data is organized in a collection of transactions (aka baskets). Each basket is a set of items. Given a transaction $T := (t_1, \ldots, t_k)$, approaches like apriori Agrawal et al. (1994) aim

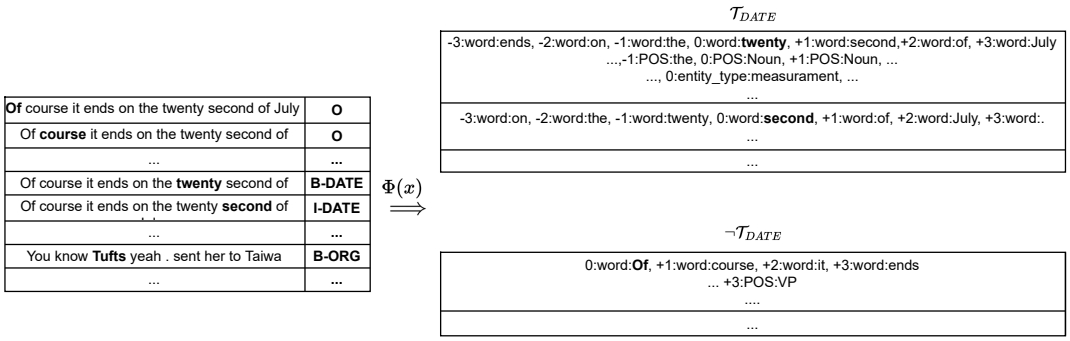

Figure 2: Baskets creation. A function Φ produce a transaction for each token x in the corpus. In the example, Φ considers a $(-3, +3)$ context window and includes semantic/syntactic information for each token in the window.

to retrieve frequent co-occurrence patterns in form of implication rules, e.g. $(t_1, t_6, t_7) \implies t_3$. Retrieved rules establish a causal relation where items in the premise imply the occurrence of the conclusion. In other words, the rule is triggered when the premise is satisfied, i.e. all its items are in the basket.

Tackling NER with data mining requires to arrange textual data into transactions. First of all, we must create a basket for each token in the dataset $\mathcal{X}, \mathcal{Y}$. Moreover, suppose each token x_i is represented with a set of features obtained by a function $\Phi : \boldsymbol{x}, i \rightarrow \boldsymbol{t}$, then each feature can be seen as an item of the token transaction. Beside its representation, also the label y_i is included in the basket. Consequently, we obtain a corpus of transactions $\mathcal{T}$ where each row is associated to its target label $(\Phi(\boldsymbol{x}, i), y_i)$. For the sake of simplicity, from now on we define $\Phi(x_i) := \Phi(\boldsymbol{x}, i)$. In its simplest form, function Φ is the identity, returning the token x_i itself, or x_i and a window of surrounding tokens. In general, it can be any function that returns a sequence of symbols.

Since our goal is to obtain rules to predict NER classes, we are interested only in implication patterns where the conclusion is the target label y_i, i.e. $(\ldots) \implies y_i$ kind. This allows us to divide the problem into independent sub-problems, one per entity class in the corpus, on a reduced set of transactions $\mathcal{T}_{y_i}$. Since each class is treated independently, the generation of frequent patterns is dramatically simplified, which is a crucial aspect for the scalability of apriori-like methods to NER datasets.

Explaining a NER model is an analogous problem, the only difference is that labels $\mathcal{Y}$ are the output predicted by a classifier, instead of being provided by an oracle. When using as explanation method, the In Algorithm 1 the pseudo-code of the algorithm is reported.

Algorithm 1 Semantic-Aware Global Explanations

function SAGE($\mathcal{X}, \mathcal{Y}$)

  for $y_i \in \mathcal{Y}$ **do**
    Given $\tau, mingensup_i, mingenconf_i, maxrulelen_i, maxnrules_i$
    $\mathcal{T}_{y_i}, \mathcal{T}_{\neg y_i} \leftarrow$ GET-TRANSACTIONS($\mathcal{X}, y_i$)
    $R \leftarrow$ CANDIDATES-GEN($\mathcal{T}_{y_i}$,$\mathcal{T}_{\neg y_i}$, τ, $mingensup_i$, $mingenconf_i$, $maxrulelen_i$)
    $R \leftarrow$ PRUNE($\mathcal{T}_{y_i}, \mathcal{T}_{\neg y_i}, R$)
    $E_{y_i} \leftarrow$ SELECTION($R, niters, maxnrules_i$)
  end for
end function

3.2 Semantic Features

Instead of simply using plain words or wordpieces as transaction items, we enrich them with semantic and syntactic positional information, extracted by $\Phi(x_i)$ that is a NLU system as shown in

Figure 2. More abstract information about the structure and the meaning of a text is essential to obtain rules that generalize to more examples. We emphasize the importance of having more general rules because they are more human-readable and reduce the overall number of explanations required to explain a model. We believe that they are essential to make explanations scalable in language, where data is sparse, especially in NER, and information is also positional. We extract semantic information from text with `https://www.expert.ai/` APIs. In particular, we extract POS tagging information, entity types, concepts (like synsets) and classical NER features such as *is_digit, is_upper_case, is_title* that are often important named entities indicators.

3.3 Candidates Generations

We retrieve most frequent patterns with FP-growth Han et al. (2000) algorithm, an efficient variant of apriori Agrawal et al. (1994). Due to the combinatorial nature of the problem and the relatively large amount of items in the transactions, we introduce confidence thresholds, beside the traditional minimun support ($mingensup$), to retain the candidates generation to the most promising frequent patterns only. In particular, we define a minimum confidence $mingenconf$ as in Wang et al. (2002), and we also stop adding items to a rule when confidence improvement is below a specified tolerance threshold τ.

Algorithm 2 Rules pruning

function PRUNE($\mathcal{T}_{y_i}, \mathcal{T}_{\neg y_i}, R$)
  $R_{pruned} \leftarrow \emptyset$
  $R \leftarrow$ SORT-BY-SUPPORT-AND-ABSTRACTION($R, descending$)

  for $r \in R$ **do**
    $\mathcal{T}_r \leftarrow$ SUPPORT-TRANSACTIONS($r, \mathcal{T}_{y_i}, \mathcal{T}_{\neg y_i}$)

    if $\nexists p \in R_{pruned} | \mathcal{T}_r \subseteq$ SUPPORT-TRANSACTIONS($p, \mathcal{T}_{y_i}, \mathcal{T}_{\neg y_i}$) **then**
      $R_{pruned} \leftarrow R_{pruned} \cup r$
    end if
  end for
  return R_{pruned}
end function

3.4 Rules pruning and selection

Rules mining can produce many patterns that are often spurious and/or highly overlapping. The over-generation of rules harms both the quality and the interpretability of the explanations. As a matter of fact, simplicity is crucial to deliver clear explanations that humans can easily understand. Thus, we aim to generate a minimal rule set with limited overlaps and high faithfulness.

We proceed in two steps. First, we start from the observation that most of the rules co-occur in the same subset of baskets, making them pseudo duplicate rules. Hence, among them we prune less generic rules, i.e. the ones having lower support. In case of rules that triggers in the exact same set of transactions, we favor more abstract rules, i.e. the ones having less conditions and/or more high-level concepts as items. Pruning step typically drops the number of relevant patterns by an order of magnitude[1]. Pseudo code is presented in Algorithm 2.

After pruning, a large number of candidates still remains. Most of them have high, but not complete transactions overlap in the corpus. In the second step we aim to keep the optimal subset $S^* \in S$ of rules that provides the best performances. The problem is combinatorial - there are $2^{|S|}$ subsets - thus, we perform a greedy strategy. For a specified number of iterations $niters$, we filter candidates based on their support and confidence and then sub-select at most $maxnrules$ such that they maximize the F1-score. Support and confidence thresholds are sampled with bayesian optimization. Rules sub-selection is performed greedly, search starts from an empty state (no rules solution) and we add one rule at a time, the explanation that provide the greatest F1 score improvement to the

[1]See Appendix A for further details.

state. Despite the approach is heuristic, it improves the quality of the solution, both in terms of performances and complexity reduction. Selection strategy is outlined in Algorithm 3.

Algorithm 3 Explanations selection

```
function SELECTION(R, niters, maxnrules)
    S* ← ∅

    for i = 1, ··· , niters do
        supp, conf ← BAYESIAN-HYPERPARAM-OPTIMIZATION(supprange, confrange)
        R ←FILTER(R, supp, conf)
        S ← ∅

        while |S| < maxnrules and |S| < |R| do
            r ← arg max_{r∈R\S} COMPUTE-F1(S ∪ r)
            if COMPUTE-F1(S ∪ r) ≤ COMPUTE-F1(S) then
                break
            end if
            S ← S ∪ r
        end while

        if COMPUTE-F1(S) > COMPUTE-F1(S*) then
            S* ← S
        end if
    end for
    return S*
end function
```

4 EXPERIMENTS

We evaluate SAGE in two different NER benchmarks, aiming to measure (1) the quality of the explanations, (2) how semantic information is vital to produce generalized rules that are both more effective and easier to understand.

4.1 METRICS

We consider different metrics to evaluate and compare the obtained explanations with different models. To measure the fidelity of explanations with respect to the predictions of the classifier, we report the F1 score (both micro and marco). F1 is the classical metric to assess models in NER task. Another paramount aspect to quantify, is the complexity of explanations. We define it as the number of rules per class.

4.2 DATASETS

Ontonotes. Ontonotes is a dataset containing named entity annotations for multiple languages. There are multiple versions of the dataset, in the experiments we used v12 Pradhan et al. (2013) retrieved from `https://huggingface.co/datasets/conll2012_ontonotesv5/`, English data only. The corpus is composed of texts from various genres. Overall, there are 18 annotated classes.

CoNLL03. CoNLL03[2] Tjong Kim Sang & De Meulder (2003) is a standard Named Entity Recognition (NER) benchmark. The dataset is a collection of news articles from the Reuters corpus. Data is annotated with four entity tags: PERSON, LOCATION, ORGANIZATION and MISC.

[2] `https://huggingface.co/datasets/conll2003`.

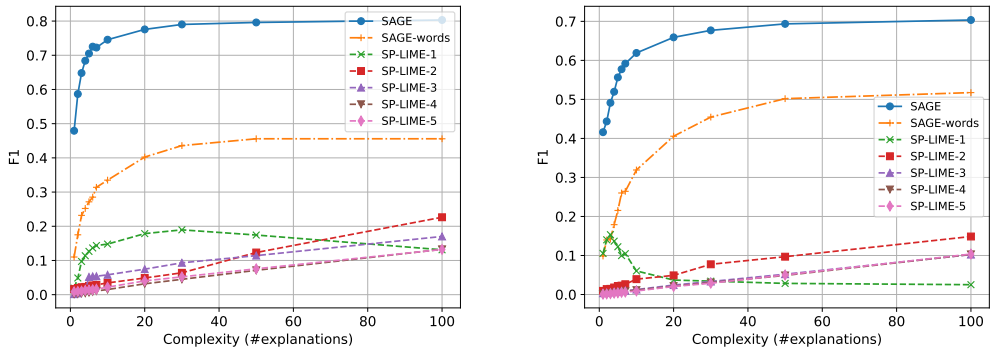

Figure 3: Explanation performances of our method (with and without semantics) and different models built with SP-LIME. We compare all methods in terms of μ-F1 score at the varying of explanation complexity (number of explanations per class) on CoNLL03 (left) and Ontonotes (right).

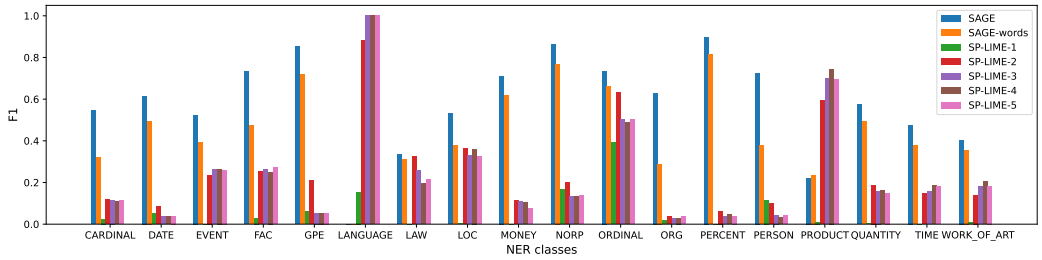

Figure 4: Class-wise F1-scores for each approach in Ontonotes dataset.

4.3 Experimental Setup

Black-box classifiers. We train a BERT Devlin et al. (2018) classifier on each benchmark (CoNLL, Ontonotes) and we explain its predictions on the test set. Predictions are made at word level, i.e. we ignore the output of word sub-tokens as commonly done in NER problems with models based on word-pieces like transformers. Overall, we obtain 4170 and 14227 predicted entities in CoNLL and Ontonotes, respectively.

LIME for NER. LIME is widely used for explaining models in classification problems. However, there are some caveats when applying it in NER. Indeed, predictions are at token-level, while usually the approach is applied for document-level classification problems. Thus, explanations must be positional. Furthermore, current Language Models adopt subword-level tokenizers, while we expect to have word-level explanations. Hence, wordpieces of the same words are perturbed together. For each example, we retrieve the top-k words to build an explanation. Global explanations are then constructed applying submodular-pick (SP-LIME-k). In the experiments, we consider five different SP-LIME models differentiated by the choice of k that varies from 1 up to 5.

SAGE. Baskets are constructed as described in Section 3. Function Φ produces for each token x_i a set of positional features in a $(-3, +3)$ context window, as presented in Section 3.2 and depicted in Figure 2. In the results we also report performances of a variant, called SAGE-words, that exploit a simpler Φ function that yields only words in the $(-3, +3)$ scope, i.e. without any semantic information.

Hyper-parameters of Algorithm 1 could be set differently for each entity. In the experiments, however, most of the hyper-parameters are kept the same for all classes and on both datasets. In particular, we set $\tau = 0.05$, $maxrulelen = 5$, $niters = 100$ and $maxnrules = 100$ everywhere. Only $mingensup$ and $mingenconf$ change depending on the number of occurrences of the class. The

minumum confidence to further explore a rule is set dinamically as follows:

$$mingenconf_i = \frac{|\mathcal{T}_i|}{|\mathcal{T}|},$$

whereas the minimum support is set to 10 for all entities in CoNLL, and varies between $\{2, 5, 15\}$ in Ontonotes depending on the cardinality of $\mathcal{T}_i$ and such that large classes have higher $mingensup$ and, vice versa, underrepresented entities have smaller $mingensup$.

4.4 Results

Explanations. We evaluate the quality of SAGE explanations in terms of F1 score and complexity, as defined in Section 4.1. In particular, we measure how the increase of complexity improves the explanatory capabilities of a model, which may be useful to determine a satisfactory trade-off between the two indicators. Results are reported in Figure 3. SAGE significantly outperforms SP-LIME global explanations. Even a single rule per-class outreaches any SP-LIME setup. Figure 4 shows the F1 scores for each single entity class in Ontonotes. We can see, that SAGE always outperforms SP-LIME explanations, with the exception of LANGUAGE and PRODUCT, two underrepresented classes where SAGE performs poorly because it cannot find rules that are statistically significant enough.

There are several reasons responsible for causing such a gap between SAGE and SP-LIME. First of all, LIME is a local algorithm designed to provide local explanations of predicted examples, and SP-LIME combines them together to provide an overall view of them. However, each explanation is not designed to hold outside the specific example, whereas our approach aim to retrieve statistically relevant rules that trigger a class in the data. Furthermore, token classification tasks, such as NER, introduce additional complexity, because explanation must be positional, and because most of the tokens do not belong to an entity. Lastly, as we will see shortly, semantics is vital to boost performances of our approach.

One could notice however, that SP-LIME-k, $k > 1$ have a linear growth as the number of explanations increases, and it may eventually surpass SAGE performances, $complexity \rightarrow \infty$. As a matter of fact, this will happen, because by construction SP-LIME will retrieve one explanation per example, falling back to providing local explanations. This situation occurs in Ontonotes for class LANGUAGE. Looking at Figure 4, we can see that SP-LIME methods are performing extremely well on such entity, because the number of annotated tokens is only 22, hence SP-LIME extracts one rule per example. However, the number of explanations to reach and surpass SAGE is extremely high, breaking even far from a point where the explanation is easy to understand.

The impact of semantics. Semantic information plays a crucial role in providing better rules. We analyse this aspect comparing SAGE with SAGE-words, a variant where a token x_i is represented only by itself and text in its context, without any external knowledge. Results are outlined in Table 2 and Figure 3. In all the scenarios, semantics provides a significant gain in terms of F1. One explanation per class in SAGE outperforms 100 rules of SAGE-words. Indeed, abstraction is a mean to group less general concepts into a single one. It allows to express rules with higher coverage, and it is particularly important for language, that is characterized by the presence of many discrete symbols (words) combined together. A clear example of how semantics yield more general rules can be seen in Table 1. SAGE rules exploits broader concepts that are valid for much more examples.

5 Conclusions

In this paper, we presented SAGE, a post-hoc method to extract interpretable, global explanations for NLP. A key ingredient of SAGE is the fact that it produces rules based on semantic, more abstract information. We focused on Named Entity Recognition, a particularly challenging NLP problem, which was under-investigated in the scope of explainability. We compared our model against different SP-LIME variants on two BERT models trained in two popular NER benchmarks: CoNLL03 and Ontonotes. Results indicate that our global explanations are more compact (hence more interpretable) and significantly better at mimicking the black-box classifier, although SAGE fails in making explanations of few particularly underrepresented classes. We also prove empirically that semantic and syntactic information bring a major boost to the explanation quality.

SAGE	0:**synset**:Asian $\Longrightarrow$ NORP
	0:**synset**:European $\Longrightarrow$ NORP
SAGE-words	0:word:Chinese $\Longrightarrow$ NORP
	0:word:American $\Longrightarrow$ NORP
SP-LIME-1	0:word:Chinese $\Longrightarrow$ NORP
	0:word:American $\Longrightarrow$ NORP
SP-LIME-2	2:word:. , 0:word:Chinese $\Longrightarrow$ NORP
	3:word:., 0:word:American $\Longrightarrow$ NORP
SP-LIME-3	4:word:., 1:word:North, 2:word:Koreans $\Longrightarrow$ NORP
	-1:word:and, 16:word:., 0:word:American $\Longrightarrow$ NORP
SP-LIME-4	1:word:position, -1:word:the, 2:word:., 0:word:American $\Longrightarrow$ NORP
	-2:word:and, -3:word:television, 3:word:., 0:word:Palestinian $\Longrightarrow$ NORP
SP-LIME-5	8:word:., -1:word:with, 6:word:intransigence, 1:word:North, 2:word:Koreans $\Longrightarrow$ NORP
	-2:word:Russians, -1:word:and, -4:word:Europeans, 2:word:., 0:word:Chinese $\Longrightarrow$ NORP

Table 1: Two examples of generated rules per model for NORP entity in Ontonotes dataset. Only **SAGE** exploits semantics, in this case the **synset** features are important to build rules that are more generic. We can also notice how, the increase of k in **SP-LIME** models makes the explanation more and more wired to the example that generated it.

Explainer	**CoNLL03**		**Ontonotes**	
	μ-F1	**m-F1**	**μ-F1**	**m-F1**
SAGE-words	45.6	40.0	51.5	44.7
SAGE	**80.3**	**78.5**	**70.3**	**57.4**

Table 2: Evaluation of explanations in CoNLL03 and Ontonotes datasets for our approach with and without semantic features.

In the future we plan to investigate possible strategy to guarantee the production of explanations for any class, regardless the amount of predictions of such entity. In particular, we plan to combine local approaches, such as LIME, to SAGE.

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A SCALABILITY

Data mining approaches are combinatorial, therefore the complexity grows non-linearly with the increase of the data. One may wonder how Fp-growth adjustments, rules pruning and selection process of the algorithm contribute in controlling the potential explosion. To shed some light on this, we report in Table 3 the number of elements produced by each step in the Ontonotes dataset (the largest corpus in our experiments).

Entity	#tokens	#generated candidates	#pruning	#selection
EVENT	351	57091	3078	90
WORK_OF_ART	594	304724	7781	**100**
LAW	222	23255	1569	63
LANGUAGE	22	0	0	0
NORP	1411	14216	1926	78
FAC	398	127311	5205	84
LOC	504	36894	2180	30
PRODUCT	236	914	109	7
TIME	668	10184	2327	53
PERCENT	1483	181897	26277	29
MONEY	1109	46497	6871	66
QUANTITY	463	18337	1926	37
ORG	5604	122722	65749	**100**
GPE	4254	411140	24738	53
PERSON	4151	43143	7746	80
DATE	4739	22347	6996	**100**
CARDINAL	1795	14137	1621	**100**
ORDINAL	322	488	91	4
ALL	28326	1435297	166190	1074

Table 3: Number of elements produced by each step. In bold classes were the number of selected explanations was interrupted because the $maxnrules$ was reached.