Explaining the Deep Natural Language Processing by Mining Textual Interpretable Features

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Abstract

Despite the high accuracy offered by state-of-the-art deep natural-language models (e.g., LSTM, BERT), their application in real-life settings is still widely limited, as they behave like a black-box to the end-user. Hence, explainability is rapidly becoming a fundamental requirement of future-generation data-driven systems based on deep-learning approaches. Several attempts to fulfill the existing gap between accuracy and interpretability have been done. However, robust and specialized xAI (Explainable Artificial Intelligence) solutions tailored to deep natural-language models are still missing.

We propose a new framework, named T-EBAxO, which provides innovative prediction-local and class-based model-global explanation strategies tailored to black-box deep natural-language models. Given a deep NLP model and the textual input data, T-EBAxO provides an objective, human-readable, domain-specific assessment of the reasons behind the automatic decision-making process. Specifically, the framework extracts sets of interpretable features mining the inner knowledge of the model. Then, it quantifies the influence of each feature during the prediction process by exploiting the novel normalized Perturbation Influence Relation index at the local level and the novel Global Absolute Influence and Global Relative Influence indexes at the global level. The effectiveness and the quality of the local and global explanations obtained with T-EBAxO are proved on (i) a sentiment analysis task performed by a fine-tuned BERT model, and (ii) a toxic comment classification task performed by an LSTM model.

Keywords: Explainable Artificial Intelligence, Natural Language Processing, Text Classification, Black-Box Classifier, Neural Network

1. Introduction

Nowadays more and more deep-learning algorithms such as BERT [1] and LSTM [2] are exploited as the ground basis to build new powerful automatic decision-making systems to solve complex natural language processing (NLP) tasks, e.g., text classification, question answering (QA), and sentiment analysis. These models are often very accurate, even exceeding human performance (e.g., in [3, 4, 5, 6]), but very opaque. They are often defined black-boxes: given an input, they provide an output, without any human-understandable insight about their inner behavior. Moreover, the huge amount of data required to train these black-box models is usually collected from people’s daily lives (e.g., web searches, social networks, e-commerce) increasing the risk of inheriting human prejudices, racism, gender discrimination and other forms of bias [7, 8]. For these reasons, despite the promise of high accuracy, the applicability of these algorithms in our society and in real industrial settings is widely limited. So, the demand for new Explainable Artificial Intelligence (xAI) solutions in future-generation systems is rapidly growing and xAI components will become, in the near future, a design requirement in most data-driven decision-making processes [9].

Table 1 shows a clear example of a misleading prediction provided by an LSTM model. In the example, both sentences are expressing Clean language, however, the predictions are extremely contradictory and the black-box nature of the LSTM model does not allow us to understand why. Thus, the complexity and the opacity of the learning process significantly reduces the adoption of those neural networks in real-life scenarios where a higher level of transparency is needed. The new Explainable Artificial Intelligence (xAI) field of research is currently trying to close the gap between model accuracy and model interpretability, to effectively increase the adoption of those models in real-life settings.

This work proposes T-EBAxO (Text-Explaining Black-Box Models), a novel explanation framework that allows understand-

| Sentence | $P(\text{Toxic})$ |
|----------|------------------|
| Politician-1 is an awesome man | 0.17 |
| Politician-1 is an intellectual | 0.89 |

Table 1: Misleading prediction example of a clean/toxic comment classification. The surname of a well-know politician is anonymized.

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ing the decisions made by black-box neural networks in the context of Natural Language Processing.

Human-readable prediction-local and model-global explanations are offered to users to understand why and how a prediction is made, hence allowing them to consciously trust the model’s outcomes.

T-EBAxO produces prediction-local explanations through a perturbation process applied on different sets of interpretable features, i.e. parts of speech, sentences, and multi-layer word-embedding clusters, which are accurately selected to be meaningful for the model and understandable by humans. Then, T-EBAxO evaluates the performance of the model in presence of the perturbed inputs, quantifying the contribution that each feature had in the prediction process through qualitative and objective indexes. The proposed explanations enable end-users to decide whether a specific local prediction made by a black-box model is reliable and to evaluate the general behavior of the global model across predictions. Prediction-local and model-global explanations are summarized in reports consisting of textual and quantitative contributions, allowing both expert and non-expert users to understand the reasons why a certain decision has been taken by the model under analysis.

As a case study, T-EBAxO has been applied to explain (i) the well-known state-of-the-art language model BERT [11] applied in a sentiment analysis task, and (ii) a custom LSTM [2] model trained to solve a toxic comment binary classification task, i.e. detecting whether a document contains threats, obscenity, insults, or hate speech. Experimental results show the effectiveness of T-EBAxO in providing human-readable, local vs global, interpretations of different model outcomes. The novel contributions of the current work are provided in the following.

• The design and development of a new xAI methodology, named T-EBAxO, tailored to NLP tasks, to produce both prediction-local and model-global explanations, consisting of textual and numerical human-readable reports.

• The design of effective strategies to describe input textual documents through a set of model-wise interpretable features exploiting specific inner-model knowledge (Section 4.1).

• The definition of quantitative and qualitative explanations, measuring the influence of each set of features on the local outcome provided by the black-box model (Section 5.1).

• The definition of an innovative model-global explanation strategy, analyzing the influence of inter- and intra-class concepts, based on two new metrics, the Global Absolute Influence and the Global Relative Influence scores (Section 5.2).

• A thorough experimental evaluation has been performed on two well-known black-box neural-network architectures, BERT and LSTM, on different textual data collections (Section 6).

The paper is organized as follows. Section 2 discusses xAI literature, Section 3 provides an overview of the proposed solution, Section 4 provides the details about the interpretable features compute by our framework, and Section 5 describes how the local and global explanations are computed. Section 6 presents the experimental results and discusses the prediction-local and model-global explanation reports produced by T-EBAxO. Finally, Section 7 concludes this work and presents future research directions.

2. Literature review

Research activities in xAI can be classified based on [10] data-type (e.g. structured data, images, texts), machine learning task (e.g. classification, forecasting, clusterization), and characteristics of the explanations (e.g. local vs global). More generally, explanation frameworks can be grouped in (i) model-agnostic, (ii) domain-specific, and (iii) task-specific approaches.

Up to now, many efforts have been devoted to explain the prediction process in the context of structured data (e.g. measuring quantitative input influence [13], by means of local rules in [14]) and of deep learning models for image classification (e.g. [15], [16], [17]), while less attention has been devoted to domain-specific explanation frameworks for textual data analytics.

Model-agnostic approaches. Tools like [18] or [19] can be applied to explain the decisions made by a black-box model on unstructured inputs (e.g. images or texts) and they provide interesting and human-readable results. LIME [18] is a model-agnostic strategy that allows a local explanation to be generated for any predictive model. It approximates the prediction performed by the model with an interpretable model built locally to the data object to be predicted. SHAP [19], instead, is a unified framework able to interpret predictions produced by any machine learning model, exploiting a game-theoretic approach based on the concept of Shapley Values [20], by iteratively removing possible combinations of input features and measuring the impact that the removal of the features has over the outcome of the prediction task. Since the above-mentioned techniques are model-agnostic, they might not fully exploit the specific characteristics of the data domain and the latent semantic information specifically learned by the predictive models when computing an explanation. Although they can be applied in the context of NLP, they do not provide inner-model awareness, i.e., they are not able to deeply explain what the model has specifically learned, since they do not exploit such information in their explanation process, leading to less specific explanations. Moreover, in the specific case of NLP, model-agnostic techniques analyze the impact of singular words over the prediction, without taking into account the complex semantic relations that exist in textual documents (i.e., semantically correlated portions of text) and that is actually learned by modern neural networks. Also, perturbing singular words can have a very limited impact over the prediction process, in particular
when dealing with long texts, other than being very computationally intensive, compromising the quality of the explanations.

T-EBAxO addresses such limitations and is able to increase the precision of the produced explanations and to limit the feature search space by i) using domain-specific feature extraction techniques and ii) exploiting the inner knowledge of the neural network to identify meaningful inter-word relations learned by the NLP model.

**Domain-specific approaches.** An exhaustive overview of the existing xAI techniques for NLP models, applied in different contexts, such as social networks, medical, and cybersecurity, is presented in [21]. In the explanation process, many works exploit feature-perturbation strategies, analyzing the model reactions to produce prediction-local explanations, like in [22],[17],[19],[18],[23], [24]. This straightforward idea is very powerful but requires a careful selection of the input features to be perturbed. Differently from model-agnostic and domain-agnostic frameworks [18],[19], some strategies have been explored by domain-specific works to determine the information contained in the target model, with the aim to select the most relevant features to be perturbed. The feature extraction process is of utmost importance in the explanation process since the quality of the produced explanations strictly depend on this step. In [22] the authors propose the use of an approximate brute-force strategy to analyze the impact that phrases in the input text have over the predictions made by LSTM models. Also, they define an importance score, that exploits the parameters learned by an LSTM model, to select the phrases which consistently provided a large contribution in the prediction of a specific class. However, this approach has been tailored to LSTM models, making it difficult to generalize the solution. In [22] the authors proposed an explanation strategy tailored to structured and sequential data models with a perturbation strategy that exploits the training of a variational autoencoder to perturb the input data with semantically related variations, introducing controlled perturbations. However, this explanation strategy has been mainly focused on explaining sequence to sequence scenarios (e.g., machine translation), and the perturbation requires the training, in advance, of a variational autoencoder model, introducing a further level of opacity and complexity in the explanation process. The authors in [23] propose to learn how to explain a predictive model jointly with the training of the predictor. To this aim, they introduce an encoder-generator framework able to extract a subset of inputs from the original text as an interpretable summary of the prediction process. Again, the training of a separate model is required to extract the whole explanation, making also this solution equivocal for the end-user. The authors in [24] proposed an explanation process based on a novel strategy to select the minimal set of words to perturb what causes a change in the decision of the model. To this aim, a reinforcement learning approach has been exploited. However, as in previous cases, this method requires the training of an external model to extract features to be perturbed, increasing the complexity and affecting the reliability of the explanation process itself.

Differently than the above-mentioned works, T-EBAxO implements a feature-extraction process that exploits the specific information learned by the predictive model, without the need to train external resources. T-EBAxO exploits the embedding representation of the textual input data, available in the inner layer of the neural network, to identify correlated portions of input text accordingly to the model, which are used in the explanation process. To support this choice, we recall that textual embeddings have interesting interpretable properties, as described in [26]. Following the insights discussed by the authors in [27], modern natural-language models incorporate most of the context-specific information in the latest and innermost layers. T-EBAxO exploits the textual embedding representations as interpretable features to explain model outcomes.

**Task-specific approaches.** Finally, not every task can be explained with model-agnostic or domain-specific approaches. This is why interpretable task-specific solutions are also relevant. In [28] the authors focused their attention on explaining the duplicate question detection task developing a specific model based on the attention mechanism, proposing to interpret the model results by visually analyzing their attention matrix to understand the inter-words relations learned by the model. However, exploiting attention can be performed only for black-box models that are based on this mechanism, and it can be hard to interpret for non-expert users. The authors of [29] developed an explainable tag-based recommendation model that increases the interpretability of its results by proposing an overview of user’s preference correlated with learned topics and predicted tags, but without actually focusing on the reliability of the model or other possible presence of bias. In [30] the authors introduced a specific linguistic explanation approach for fuzzy classifier decisions, which are shown in textual form to users. They focus on a high abstraction level of explanations providing reasons, confidence, coverage, and feature importance. However, their approach does not take into account the complexity of deep learning models. In [31] they propose a framework for recognizing symptoms of cognitive decline that provides natural language explanations of the detected anomalies generated from a trained tree regression algorithm. However, this solution is customized for this specific task and not easily extendable to other contexts.

T-EBAxO proposes a new local and global explanation process for state-of-the-art deep NLP models. T-EBAxO fills in the gap of missing customized solutions for explaining deep NLP models, by introducing a novel architecture and experimental section. Specifically we introduce (i) a novel feature extraction process specifically tailored to textual data and deep natural language models, (ii) new perturbation strategies, and (iii) novel class-based global explanations.

3. **T-EBAxO overview**

T-EBAxO explains the inner functionalities of black-box models in the context of NLP analytics tasks. Its architecture is shown in Figure 1 and includes different building blocks. Both model-agnostic (i.e., part of speech, sentences) and model-aware (i.e., multi-layer word embeddings) features are extracted.
by T-EBAxO.

Given a classification task, an input document is provided to the black-box model ①, and the pre-trained model outputs its predicted class label ②. T-EBAxO extracts a set of interpretable features ③ by exploiting either NLP techniques or the analysis of the knowledge hidden in the model itself (Section 4.1). Then, it performs the perturbation of the set of interpretable features and tests the outcomes of the model on the perturbed inputs ④ (Section 4.3). The perturbation of the interpretable features can influence the model outcome in different ways, as described in the following:

- Case (a): the probability of the class under analysis increases. It means that the analyzed features were negatively impacting on the process;
- Case (b): the predicted probability decreases. It means that the perturbed features were positively impacting the class under analysis;
- Case (c): the predicted probability remains roughly unchanged. It means that the portion of input is irrelevant to the predictive model under analysis.

The significance of the difference in the prediction process before and after the perturbation is evaluated through the nPIR index, a quantitative metric to estimate the effect of the perturbation strategy (Section 4.1). Thus, T-EBAxO generates the local explanation report ⑤, showing the results of the analysis of the perturbations through an informative dashboard.

Finally, aggregating the local explanations produced for a corpus of input documents, T-EBAxO provides model-global explanations highlighting relevant inter- and intra-class semantic concepts that are influencing the black-box decision-making process at a model-global level (details are provided in Section 5.2).

4. Interpretable features

This Section describes the interpretable feature extraction (Section 4.1), with a specific focus on the Multi-layer Word Embedding technique (Section 4.2), and the feature perturbation (Section 4.3) approaches adopted by T-EBAxO.

4.1. Interpretable feature extraction

The interpretable feature extraction block identifies meaningful and correlated sets of words (tokens) having an influence on the outcomes of the NLP model under the exam. It represents the most critical and complex phase in the explanation process workflow. A set of words is meaningful for the model if its perturbation in the input document produces a meaningful change in the prediction outcome. On the other hand, a set of words is meaningful for a user if s/he can easily understand and use it to support the decision-making process.

T-EBAxO considers both word (tokens) and sentence granularity levels to extract the set of interpretable features. Moreover, T-EBAxO records the position of the extracted features in the input text, since the context in which words appear is often very important for NLP models.

T-EBAxO includes three different kinds of interpretable feature extraction techniques:

1. Multi-layer Word Embedding (MLWE) feature extraction. This strategy is the most powerful technique since it exploits the inner knowledge learned by the model to perform the prediction. To access the inner knowledge of the network, this technique needs to know the inner details of the model under analysis. However, the process can be easily adapted to be compliant with different deep architectures (e.g., as reported in [17]) and their hidden layers. A detailed description of the MLWE feature extraction technique is provided in Section 4.2.

2. Part-of-Speech (PoS) feature extraction. This strategy explores the semantic meaning of words by looking to which part-of-speech they belong to (e.g., nouns, adjectives). The intuition behind this type of feature extraction is that the semantic difference corresponding to distinct parts-of-speech can differently influence the model outcome. Firstly, the input text is tokenized, leading to three features: the token itself, its position in the text, and its pos-tag (i.e., part-of-speech tagging). Then, tokens are divided into correlated groups: adjectives, nouns, verbs, adverbs and others. Each group is considered as a separate interpretable feature by T-EBAxO in the perturbation phase.
3. Sentence-based feature extraction. This strategy considers each sentence separately to assess their influence on the model decisions. The straightforward intuition behind this strategy is to verify if the model captures the complete meaning of a sentence and uses it to derive the outcome. The sentence feature extraction characterizes the input text with the position of the sentence and the sentence itself.

Then, separately for each feature extraction method, T-EBASO tests pairwise combinations of features to create larger groups of tokens corresponding to more complex concepts. This allows us to efficiently explore a wider search space of interpretable features allowing us to find even more relevant prediction-local explanations.

4.2. Multi-layer Word Embedding (MLWE) feature extraction

Deep Neural networks are trained to extract knowledge from training data learning a complex numerical model spreading this knowledge on multiple hidden layers. During the prediction process of previously unseen data, all these layers contribute to the outcome. Thus, to get a reliable explanation, it is necessary to mine all the knowledge hidden along with the layers of the model. Thanks to the Multi-layer Word Embedding (MLWE) feature extraction, T-EBASO can achieve this goal.

First, T-EBASO analyzes the outcomes of multiple hidden layers to extract the numerical representation of the input at different levels of the network. The Multi-layer Word Embedding feature extraction process is shown in Figure 2. Firstly, given an input document 1, a tensor containing the numerical embedding representations of different words in different layers is extracted 2. Then, the intermediate embeddings of each layer are aggregated (e.g. through average or sum) and their dimensionalties are further reduced through PCA to obtain an embedded vectorial representation for each input word 3. The outcomes of the aggregation step is the Multi-layer Word Embedding representation of the input document 4. The intuition is that words with a similar MLWE are considered highly correlated by the model and, if grouped together, they represent key input concepts, that most probably are influencing the current prediction. The MLWE feature extraction, and in particular the extraction of the aggregated word embeddings from multiple layers, has to be achieved in different ways depending on the neural network architecture under the exam. Further details about MLWE feature extraction tailored to LSTM and to BERT are provided in Sections 6.2 and 6.2, respectively.

Once the MLWEs are extracted, they are analyzed through an unsupervised clustering analysis 5 to identify sets of correlated words that share common behaviors inside the model under exam. The aim of the unsupervised analysis is to identify the smallest groups of input words that have the highest impact over the model outcome. This allows also to reduce the search space, without affecting the quality of the features. For this purpose, T-EBASO exploits the K-Means 12 clustering algorithm, since it provided good performance in a similar context 17 and represents a good trade-off with computational time. A critical parameter when dealing with K-Means is the setting of the desired number of groups K to correctly model interesting subsets of data. T-EBASO applies K-Means to identify a number of groups ranging in [2, Kmax], where the max number of clusters Kmax is a function of the input size and has been empirically set to:

$$K_{max} = \sqrt{N_{\text{words}}} + 1 \quad (1)$$

On the one hand, using small fixed values of K with large input texts leads to large clusters of words containing both influential and less impacting words, and consequently the explanation provided will be of low interest. On the other hand, the number of words Nwords in a text can be very high and it would not be feasible neither useful to evaluate partitioning that take into account values of K as large as the number of words Nwords. For this reason, evaluating a number of clusters K that is at most equal to the root of the number of words Nwords in a text allows to maintain a good trade-off between partitioning size and performance. T-EBASO produces a quantitative explanation for each K 6, as detailed in Section 5.1. For each value of K ∈ [2, Kmax], K perturbations will be analyzed. In this way, a large number of potentially useful local explanations are produced by T-EBASO.

The objective, however, is to provide only the best explanation to the end-user. T-EBASO selects the most informative local explanations as those extracting the most knowledge from the behavior of the model over a single prediction. To this aim, for each value of K, a score is computed 7 by means of the normalized Perturbation Influence Relation (nPIR) index (introduced in Section 5.1), which is computed as follows:

$$K_{score} = \max_{\kappa \in K} \left( \frac{nPIR_{\kappa}}{|\kappa|} \right) - \min_{\kappa \in K} \left( \frac{nPIR_{\kappa}}{|\kappa|} \right) \quad (2)$$

Where κ is the current cluster, |κ| is the number of words inside the cluster and nPIR_κ is the nPIR value of the current cluster κ, that measures the positive or negative influence of perturbing the tokens in κ (further details are provided in Section 5.1). The selected set of features is the set with max(Kscore). The Kscore tends to assign a high influence to small clusters. The range of Kscore is [0,2], where 2 is the most informative local explanation, obtained when MLWE finds a cluster C1 composed by exactly one word with nPIR_{w=C1} = 1 and another cluster C2 composed exactly by one word with nPIR_{w=C2} = −1. Instead, the least informative local explanation has a score of 0, and it is identified when, for instance, MLWE finds K clusters of words all being neutral for the prediction of the class label, hence having nPIR_κ = 0.

The output of this process is the most informative local explanation 8.

4.3. Interpretable feature perturbation

After the extraction of the interpretable feature sets, a perturbation phase is performed by introducing noise and consequently assessing the impact of the perturbed features on the model outcomes. Adding noise to the model input is a well-known technique adopted by different state-of-the-art approaches
to study the model behavior through the effects on the outcomes. Different input data types require different perturbation strategies. In case of textual data, the perturbation can be performed by feature removal or feature substitution.

In the feature removal approach provided by T-EBAsO, all the interpretable features are iteratively removed from the input text, producing new perturbed variations of the input itself. The perturbed variations of the input are then fed back into the model under analysis and its predictions are collected and analyzed by T-EBAsO to produce the local explanation report (see Section 5.1). Examples of explanations produced by feature removal perturbation are shown in Figures 3b, 3c, and 3d. From the input text in Figure 3a, the model outputs a negative sentiment. So, the user can inspect the highlighted features (in red) in the textual explanation (Figure 3) and the words identified by MLWE in Figure 3e are removed.

The feature substitution is also adopted by T-EBAsO. While the removal perturbation causes an absence of the concept associated with the removed words, the substitution perturbation introduces a new, possibly related, concept that can cause a change in the prediction. The feature substitution perturbation requires an additional step to select new words that will replace the current ones. In T-EBAsO, the substitution of words with their antonyms is exploited. This strategy turned out to be very powerful in some specific cases (e.g. Adjective-POS perturbation), but in general, it has several limitations: (i) some words can have many antonyms and the optimal choice might depend on the context, (ii) antonyms do not exist for some words (e.g. nouns), and (iii) the choice of the new words to be inserted in the substitution of the feature is task-specific (e.g. antonyms work with opposite class labels like Positive and Negative in sentiment analysis, but are not suited with independent class labels as in topic detection). Thus, the effectiveness of this perturbation strategy is affected by these limitations. Figures 3c and 3f show two examples of explanations performed using this technique. For the Adjective-POS features, it is straightforward to find meaningful antonyms. On the contrary, for Verb-POS features, the result is very difficult to evaluate, since verbs like {was, have} are substituted with {differ, lack}. This feature perturbation strategy remains an open task left for further inspection in future works.

5. Explanations

This Section presents the prediction-local (Section 5.1) and the model-global (Section 5.2) explanation processes implemented in T-EBAsO.

5.1. Prediction-local explanations

To produce the local explanations, T-EBAsO exploits the outcomes of the model when fed with the original input and its perturbed versions. A local explanation consists of two main parts: a textual explanation (Figure 5) and a quantitative explanation (Table 2), as detailed in the following.

**Textual explanation.** The textual explanation highlights the most relevant sets of features for the model under analysis also allowing to understand the context in which they appear. Many sets of features can be extracted for each interpretable feature extraction technique. Figure 5 shows a simple example of textual explanations. For this example the BERT model has been trained to detect sentiment the sentiment of a textual document, either positive (P) or negative (N). Given the input document in Figure 5a the model outputs a negative sentiment. So, the user can inspect the highlighted features (in red) in the textual explanations in Figures 5b, 5c, 5d, 5e, and 5f to find out which are the most important sections of the input that have been exploited by the model to make its decision.

**Quantitative explanation.** The quantitative explanation shows the influence of each set of extracted features separately for each prediction by evaluating the newly introduced nPIR index (normalized Perturbation Influence Relation). It assesses
Figure 3: Examples of a textual explanation report. The original text was labeled by BERT as 'Negative' with a probability of 0.99. The most relevant features are highlighted in red. Removed features are in squared brackets.

Table 2: Quantitative explanation for example in Figure 3. Explanation, Feature, L_{o}, L_{f}, nPIR(N), nPIR(O) = 0.998, 0.984, 0.999, and 0.000, respectively.

Information explanations. For instance, if \(-0.5 < nPIR_f < 0.5\), then the difference between the probabilities before and after the perturbation of \(f\) is not informative for a threshold of 0.5. Values of \(nPIR_f < -0.5\) (or \(nPIR_f > 0.5\)) means that the perturbation of feature \(f\) is contributing negatively (or positively) to the prediction, by decreasing (or increasing) significantly the probability of belonging to the class \(c\).

The quantitative explanation is computed by T-EBASO for each feature extraction technique, for each set of features perturbation, and for each class that can be predicted by the model.

Table 2 shows the quantitative explanations for the textual explanations in Figure 3. For each interpretable feature \(f\) the labels assigned by the model before and after their perturbation are reported in columns \(L_{o}\) and \(L_{f}\) respectively along with the \(nPIR\) value calculated for the class-of-interest negative (N). Perturbing the POS adjectives in Figure 3b (EXP1) or the MLWE cluster in Figure 3c (EXP3) the \(nPIR\) is very close to 1. This means that these sets of features are very relevant for the model outcome: removing one of these features will cause completely different outcomes from the model, changing the prediction from negative (N) to positive (P). Instead, the perturbation of the sentence in Figure 3c (EXP2) is not relevant at all for the model, showing a value of \(nPIR\) equal to 0. We can conclude that the feature sets \{'awful', 'bad'\} and \{'was, awful, bad, movie\} are the real reason why the model is predicting the negative class. The information contained in the sentence \{'This film was very awful\} instead does not justify the model outcome alone, like the rest of the text that is also contributing to the prediction.

The quantitative explanations obtained through the substitution perturbation (EXP4 and EXP5) have been also reported in Table 2. Even from these results, it is evident that the substitution perturbation has great potential in expressiveness when it is possible to find suitable antonyms. In the case of Adjective-POS substitution (EXP4), the quantitative explanation shows a \(nPIR\) value close to 1. On the contrary, in the case of EXP5, verbs are replaced with semantically incorrect words (not antonyms) in the context of the phrases, showing no impact in the prediction process with a \(nPIR\) equal to 0.

5.2. Per class model-global explanation

T-EBASO is able to provide per-class model-global explanations of the prediction process. The local explanations computed for a corpus of input documents are aggregated and analyzed together, highlighting possible misleading behaviors of the predictive model.

Two indices have been introduced to measure the global influence of the corpus of input documents: (i) the Global Absolute Influence (GAI) described by Algorithm 1 and (ii) the Global Relative Influence (GRI) defined in Equation 5. The GAI score measures the global importance of all the words impacting on the class-of-interest, without distinction concerning other classes (Figure 4a). On the other hand, the GRI score evaluates the relevance of the words influential only (or mostly) for the class-of-interest, differently from other classes (Figure 4b). Analyzing GAI and GRI scores, the user can extrapolate which are the most relevant inter- and intra-class semantic con-
cepts that are affecting the decision-making process at a model-global level. For example, if a word is influential for all the possible classes, it will have a high GAI score and a GRI score close to 0. On the contrary, a word might show a high GRI score for a specific class, while having a very low GAI, meaning that it is influential and differentiating for that specific class only.

The global explanations are computed for each available class \( c \in C \), analyzing the set of local explanations \( E \). The local explanations \( e_d, f \in E \) are computed for each document \( d \in D \) and for each interpretable feature \( f \).

**Global Absolute Influence.** The Global Absolute Influence value is computed following the process described in Algorithm 1. Given a set of local explanations \( E \) generated for a corpus of documents \( D \), the algorithm computes the global score for each possible class-of-interest and for each lemma (base form of a word) contained in the most informative local explanations. Only MLWE explanations are exploited in the algorithm (line 2) since it is the only feature extraction strategy that exploits inner model knowledge (see Section 4.2). Then, given the MLWE explanations related to a document \( e_d,f \), only the most influential one \( \hat{e}_d \), i.e., the one with the highest \( nPIR \), is selected (line 5) and the lemmas \( L_{\hat{e}_d} \) are extracted from the tokens contained in the corresponding interpretable feature (line 6). The algorithm analyzes lemmas instead of tokens (words) in order to group together their inflected forms, obtaining more significant results. Finally, the GAI score for the corresponding class-of-interest \( c \) and lemma \( l \) is updated (line 8) by summing the \( nPIR \) score of the the explanation \( \hat{e}_d \), only if it is positively impacting the prediction (i.e., \( nPIR > 0 \)). The output of the algorithm is the set of Global Absolute Influence scores.

The GAI score will be 0 for all the lemmas that have always brought a negative influence on class \( c \), and it will grow proportionally to the frequency and to the positive influence of each lemma positively influencing class \( c \). The higher the GAI score, the more positively influential a lemma is for the model under analysis with respect to class \( c \).

**Global Relative Influence.** The Global Relative Influence score highlights the most influential and differentiating lemmas for each class-of-interest, discarding lemmas with multiple impact on other classes. The GRI for a class-of-interest \( c \) and for a specific lemma \( l \) is defined as:

\[
GRI(c, l) = \max[0, GAI(c, l) - \sum_{c' \neq c} GAI(c', l)]
\]

The GRI score is 0 when a lemma is more relevant for other classes than for the one under exam, while \( GRI > 0 \) if its influence is higher for class \( c \) than all the other classes. The higher the GRI value, the more specific the lemma influence is with respect to the class-of-interest.

Section 6.5 provides an experimental analysis of the insights provided by T-EBasO at a model-global level.

**Algorithm 1: Global Absolute Influence.**

| Line | Description |
|------|-------------|
| 1    | Input: Local explanations \( E \), Classes \( C \). |
| 2    | Output: GAI scores for each class label and lemma. |
| 3    | GAI \( \leftarrow \) initHashmap(0); |
| 4    | \( E_{MLWE} \leftarrow \) getExplanationsMLWE(\( E \)); |
| 5    | for \( c \) in \( C \) do |
| 6    | \( \hat{e}_d \leftarrow \) getMax_nPIR_Explanation(\( e_d,c \)); |
| 7    | \( L_{\hat{e}_d} \leftarrow \) lemmatizeTokens(\( \hat{e}_d, \) featureTokens); |
| 8    | for \( l \) in \( L_{\hat{e}_d} \) do |
| 9    | \( GAI(c, l) \leftarrow GAI(c, l) + \max[0, \hat{e}_d.nPIR]; \) |
| 10   | end |
| 11   | end |
| 12   | return \( GAI \); |

6. Experimental results

In this Section we present the experiments performed to assess the ability of T-EBasO to provide useful and human-readable insights on the decisions made by a black-box NLP model.

6.1. Use cases

We applied T-EBasO in two different binary text-classification use cases, as described in the following, intending to address diverse state-of-the-art NLP models, specifically LSTM and BERT, to show the flexibility of T-EBasO independently of the specific black-box model.

**Use case 1.** The first task is a binary toxic comment classification, and it consists of predicting whether the input comment is clean or toxic, i.e., it contains inappropriate content such as obscenity, threat, insult, identity attack, and explicit sexual content. An LSTM model applied to a civil comments dataset has been used. The toxic class label contains several subtypes of toxic comments as identity attacks, insults, explicit sexuality, and threats. The LSTM model is composed by an embedding 300-dimensional layer, two bidirectional LSTM layers (with 256 units for each direction), and finally, a dense layer with 128 hidden units. Transfer learning has been exploited using GloVe (with 300-dimensional vectors) for the embedding layer.
After training, the custom LSTM model reached an accuracy of 90%.

**Use case 2.** The second selected task is *sentiment analysis*, and it consists of predicting if the underlying sentiment of an input text is either positive or negative. The BERT base (uncased) pre-trained model [11] has been chosen as the black-box predictive model, and it has been applied to the IMDB dataset [35], which is a reference set of data for sentiment analysis. We performed a fine-tuning step of the BERT model [11] by adding a classification layer on top of the last encoder transformer’s stack. The BERT model, fine-tuned on the IMDB textual reviews, reached an accuracy of 86%.

### 6.2. Multi-layer word embedding

**LSTM.** RNN with LSTM units are robust architectures that can learn both the time sequence dimension and the feature vector dimension. Multiple LSTM layers usually characterize them, and they can take as input an embedded representation of the text. As highlighted in Section 6.1, the developed LSTM model exploits one embedding layer that works with full tokens and two bidirectional LSTM layers. For these reasons, the MLWE exploits the single embedding layer to extract a tensor of shape \((t \times 300 \times 1)\). Then, a Principal Component Analysis is used to reduce the embedding matrix shape to \((t \times c)\) obtaining the multi-layer word embedding representation for the custom LSTM model.

**BERT.** Figure 5 shows all the steps of the multi-layer word embedding (MLWE) feature extraction process in BERT. The base version of the BERT model [11] is composed by 12 transformer layers [36], each producing an output of shape \((wp \times 768)\), where \(wp\) is the number of word pieces extracted by BERT in its pre-processing phase. The MLWE, in this case, analyzes the word embeddings extracted from the last four transformer layers of the model. It has been motivated in literature [27] that modern natural language models incorporate most of the context-specific information in the last and deepest layers. Thus, the joint analysis of these layers allows the MLWE to extract features more related to the task under exam, avoiding too specific (if analyzing only the last layer) or too general (if analyzing only the first layers) word embeddings.

In the first step of the MLWE feature extraction, the last four transformer layer outputs (i.e. \(L_9\), \(L_{10}\), \(L_{11}\), \(L_{12}\)) are extracted (Figure 5-left), resulting in a tensor of shape \((wp \times 768 \times 4)\). Each row is the embedding representation for each word piece in each layer. Then, the outputs of the four layers are aggregated summing the values of the embeddings over the layer axes in a matrix of shape \(wp \times 768\) (Figure 5-center-left), as suggested by [27].

Since BERT works with word pieces but T-EBaNO objective is to extract full tokens (words), the embedding of word pieces belonging to the same word are aggregated, averaging their values over the word-piece axes, and obtaining a new matrix of tokens embedding of shape \(t \times 768\), where \(t\) is the number of input tokens (Figure 5-center-right). In the end, due to the sparse nature of data, the dimensionality reduction technique, i.e., Principal Component Analysis, is exploited, reducing the final shape of the tokens embeddings matrix to \((t \times c)\), where \(c\) is the number of extracted components (Figure 5-right). This last result is the Multi-layer word embedding representation for the BERT model.

### 6.3. Experiments at a glance

For each input document, the local explanations were computed exploiting all the feature extraction methods described in Section 3 for both use cases.

In the explanation process of the sentiment analysis use case with the BERT model, T-EBaNO has been experimentally evaluated on 400 textual documents, 202 belonging to the class Positive and 198 to the class Negative, for a total of almost 100,000 local explanations, with an average of 250 local explanations for each input document. However, only the most informative local explanations are automatically shown by the engine to the user. A local explanation has been defined to be informative when having a \(nPIR\) value equal to or higher than 0.5. All the rest of the local explanations produced by T-EBaNO are still available to the users, should they liked to investigate further insights into the prediction process. To show the effectiveness of the proposed feature extraction techniques, we analyzed the percentage of documents for which T-EBaNO computed local explanations with at least one informative feature for the class-of-interest. Experiments on the same input texts have been repeated twice, firstly without combining the different features, then including the pairwise combinations for each feature extraction method. Table 3 shows the percentage of documents required to find at least one informative feature (\(nPIR \geq 0.5\)) with and without combinations of pairwise features. The MLWE method leads to abundantly better results than the other methods. The part-of-speech strategy benefits the most from the pairwise combinations, allowing to create features representing more complex concepts. For example, the combination of *adjectives* and *nouns* allows to create features composed by words like \{bad, film\} that, together, can better express a sentiment.

In the explanation process of the toxic comment use case with the custom LSTM model, T-EBaNO has been experimentally evaluated on 2250 documents, 1121 belonging to the class Toxic and 1129 to class Clean, leading to almost 160,000 local explanations in total. Table 4 shows the percentage of input documents for which T-EBaNO has been able to extract at least one informative local explanation (\(nPIR \geq 0.5\)). For the Toxic

| Feature extraction type | No combination | Pairwise combination |
|-------------------------|----------------|---------------------|
| Part-of-speech          | 33%            | 70%                 |
| Sentence                | 22%            | 30%                 |
| MLWE                    | 75%            | 86%                 |
| Overall                 | 80%            | 90%                 |

Table 3: Explanations of the BERT model: percentage of documents for which each feature extraction strategy produces at least one informative local explanation (i.e., with \(nPIR \geq 0.5\)), with and without combination of features. *Overall* is the percentage of documents for which at least one method provided a local explanation with \(nPIR \geq 0.5\).
class. T-EBAsO has been able to identify at least one informative explanation for almost all the documents, with most of the feature extraction strategies. Only the sentence-based feature extraction has a lower percentage of informative explanations w.r.t. the other techniques. This suggests that toxic words tend to be sparse in the input text and not concentrated in a single sentence. Finding informative explanations for the Clean class has proven to be harder. None of the feature extraction techniques can explain more than 15% of the predictions for the Clean class. The nature of the use case under exam can explain possible causes: usually, a document is considered clean; it can become toxic because of the presence of specific words or linguistic expressions. Thus, the hypothesis is that there is no specific pattern of words that represents the Clean class (see Section 6.5 for further details).

### 6.4. Local explanation

The purpose of this Section is to discuss some specific local explanations provided by T-EBAsO in different conditions, to show their relevance and usefulness in explaining the deep NLP model behavior, for both the custom LSTM and the BERT models of the two use cases.

**Local Explanation 1.** In the first example, reported in Figure 5a, the custom LSTM model classifies the input comment in Figure 5a as Toxic. The most influential features identified by T-EBAsO are shown in Figures 5b and 5c. The different feature extraction strategies find that the most positively influential features for the Toxic class labels are \{black man, left, racist, woman, sexist, fool, intolerant\}. In particular, the most informative explanations are extracted with the combination of adjectives and nouns (Table 5 EXP1) and with

| Feature Extraction Type | Clean | Toxic | Clean/Toxic |
|-------------------------|-------|-------|-------------|
| Part-of-speech          | 8%    | 98%   | 53%         |
| Sentence                | 2%    | 76%   | 39%         |
| MLWE                    | 12%   | 98%   | 55%         |
| Overall                 | 15%   | 99%   | 58%         |

Table 4: Explanation of the custom LSTM model: percentage of documents for which each feature extraction strategy produces at least one informative local explanation (i.e. with $nPIR \geq 0.5$), with combination of features, for the class labels Clean and Toxic.

MLWE (Table 5 EXP2). It is interesting to notice that in this case, the combination of adjectives and nouns is very relevant for this model, e.g., it is not just the word black that makes a comment toxic, but the combination black man. Furthermore, the POS feature extraction and the MLWE highlighted very similar sets of words. In this case, the prediction is trustful, and in particular, it is relevant that the model learned features like black man and woman to be influential for the Toxic class.

**Local Explanation 2.** In the second example, the BERT model makes a wrong prediction by classifying the sentiment of the input text in Figure 6a as Negative, while the expected label (ground-truth) is Positive. A user requiring to decide whether to trust such prediction can take advantage of T-EBAsO to understand which are the words influencing the outcome. Figure 6 shows the textual explanations provided by the most influential features. Table 6 contains the corresponding quantitative explanations with the $nPIR$ values. T-EBAsO identified three local explanations for the Negative class with $nPIR$ values higher than 0.5, whose perturbation would cause a change in the predicted label from Negative to Positive. The top informative features were extracted exploiting Adjectives-POS (Figure 7b).
How many movies are there that you can think of when you see a movie like this? I can’t count them but it sure seemed like the movie makers were trying to give me a hint. I was reminded so often of other movies, it became a big distraction. One of the borrowed memorable lines came from a movie from 2003—Day After Tomorrow. One line by itself, is not so bad but this movie borrows so much from so many movies it becomes a bad risk. But... See The Movie! Despite its downfalls there is enough to make it interesting and maybe make it appear clever. While borrowing so much from other movies it never goes overboard. In fact, you’ll probably find yourself harkening down the hatchets and riding the storm out. Why? ...Costner and Kutcher played their characters very well. I have never been a fan of Kutcher’s and I nearly gave up on him in The Guardian, but he surfaced in good fashion. Costner carries the movie swimmingly with the best of Costner’s ability. I don’t think Mrs. Robinson had anything to do with his success. The supporting cast all around played their parts well. I had no problem with any of them in the end. But some of these characters were used too much. From here on out I can only nit-pick so I will save you the wear and tear. Enjoy the movie, the parts that work, work well enough to keep your head above water. Just don’t expect a smooth ride. 7 of 10 but almost a 6.

(a) Original text

(b) EXP1: Adjective-POS feature extraction

(c) EXP2: Sentence feature extraction

(d) EXP3: Multi-layer word embedding feature extraction

Figure 7: Examples of textual explanation report for the input in Figure 7a wrongly labeled by BERT as Negative with a probability of 0.99. The most relevant features are highlighted in red. Sentence (Figure 7c) and MLWE (Figure 7d). Regarding the Adjectives-POS feature extraction, Figure 7b shows that general words like {many, other, big, smooth} have a nPIR value for the class Negative close to 0.88 (Table 6-EXP1). General words with a very strong impact on the final prediction for this specific input text is not a trustful indicator: their absence might lead to entirely different outcomes.

Regarding the sentence-based feature extraction, the negative prediction is triggered by only one specific phrase (Figure 7c), whose absence leads to a Positive prediction with a nPIR value of 0.66 (Table 6-EXP2).

Finally, the MLWE feature extraction strategy identifies a cluster composed by only two instances of a single very general word, {there} (Figure 7d). By removing the two occurrences of the word {there}, the prediction changes from Negative to Positive with a nPIR value of 0.651 (Table 6-EXP3).

Since the output of the prediction model can be drifted (from Negative to Positive) by simply removing occurrences of general words such as {there, many, other, big, smooth, ...} from the input text (actually removing only {there} is enough!), doubts on the predicted class reliability are reasonable. More details related to the global behavior and the robustness of the model are addressed in Section 6.5.

Local Explanation 3. The example is reported in Figure 8 where the BERT model correctly classifies the input text in Figure 8a as Negative. The textual explanations produced by T-EBaXO exploiting different feature extraction strategies are reported as follows: adjective-POS in Figure 8b, verb-POS in Figure 8c, adjective-verb-POS in Figure 8d, sentence in Figure 8e, and multi-layer word embedding in Figure 8f. Their nPIR values are reported in the quantitative explanations of Table 7. We note that only the adjective-verb-POS, sentence, and MLWE techniques provide informative explanations, whereas the adjective-POS and verb-POS yield uninformative explanations, yet we include them in the example for discussion.

The POS feature analysis (Figures 8b, 8c) shows that the different parts-of-speech, taken separately one at a time, are not influential for the prediction of the class Negative. From the quantitative explanation of EXP1 and EXP2 in Table 7 indeed it can be observed that they achieve a nPIR close to 0.003 and 0.137 respectively. A similar result was obtained for all the other POS features considered individually. Consequently, T-EBaXO explores the pairwise combinations (as explained in Section 4.1) of the parts-of-speech to create more sophisticated features and to analyze more complex semantic concepts. In this case, the feature composed by Adjectives and Verbs (Figure 8d) is reported to be impacting for the predicted class label reaching a nPIR value close to 0.915 (EXP3 in Table 7).

The sentence feature extraction strategy, instead, identifies the feature composed by the phrase in Figure 8e as positively influential for the predicted class with a nPIR score of about 0.638 (EXP4 in Table 7).

Finally, the MLWE feature extraction strategy identifies K = 15 as the most influential partitioning of words. Analyzing the 15 different features, composed by clusters of words, emerges that the only one with a significant impact on the output prediction...
Figure 8: (Continued) Examples of textual explanations for the input in Figure 8a, originally labeled by BERT as Negative with a probability of 0.99. Features extracted by T-EBaO are highlighted in red.

| Explanation | Feature | $f$ | $L_p$ | $L_f$ | nPIR $(N)$ |
|-------------|---------|-----|------|------|------------|
| EXP1        | POS-Adjective | N   | N    | N    | 0.003      |
| EXP2        | POS-Verb    | N   | N    |      | 0.137      |
| EXP3        | POS-Adj&Verb | N   | P    |      | 0.915      |
| EXP4        | Sentence    | N   | N    |      | 0.638      |
| EXP5        | MLWE        | N   | P    |      | 0.899      |

Table 7: Quantitative explanations for the example reported in Figure 8a, reaching a nPIR of 0.899 (EXP5 in Table 7).

Analyzing the content of the most informative textual explanations (EXP3, EXP4 and EXP5), it can be observed that, interestingly, all the local explanations with high values of nPIR contain the word trivialized. It might seem that a single word can be the only responsible for the original prediction. However, the explanation EXP2 contains the same word but is not influential for the class label. Therefore, it emerges that the output predictions are not influenced by single words, but is the combination of different words that allows creating more complex concepts which determine the predicted class label. Moreover, it is possible to say that, in this specific prediction, the model is not sensible to the perturbation of adjectives (EXP1 in Figure 8b) or verbs (EXP2 in Figure 8c) separately, highlighting that the proposed prediction has been produced taking into account the whole context of the input text. Only in EXP3 (Figure 8d), it is possible to notice that, when adjectives and verbs are perturbed together, changing the meaning of the input text radically, the predicted class changes. The joint perturbation can be considered a good measure of robustness for the prediction performed by the fine-tuned BERT model under analysis.

However, as for the previous example, it is shown in EXP4 (Figure 8e) that exist a singular phrase more relevant than the others in the decision-making process. The perturbation of the sentence in EXP4 will bring the model to change the prediction from class Negative to Positive. Furthermore, EXP5 (Figure 8f), obtained through the MLWE...
feature extraction technique, shows an apparently random pool of words very relevant in the prediction process. The MLWE feature extraction is able to find the influential feature with higher precision concerning EXP3 (obtained by the combination of all verbs and adjectives), with a very small penalty on the nPIR score. Indeed, the MLWE strategy is able to find a small number of words belonging to different part-of-speeches and different sentences that are affecting the model’s output. So, also the resulting explanations are more understandable and meaningful for the end-user.

As in the previous example, this last experiment shows that the predictive model is particularly sensitive to a few specific variations of, apparently not correlated, input words.

From these examples, it emerges that the different feature extraction strategies should be used in a complementary manner, as they look at different aspects of the input text and provide different kinds of explanations. Furthermore, the proposed examples showed that:

- T-EBANo can be successfully applied to different deep learning models;
- the proposed prediction explanation process can be applied with success to different use cases and NLP tasks;
- T-EBANo can extract meaningful explanations from both long and short text documents without limiting their interpretability;
- the end-user is provided with informative details to analyze critically and judge the quality of the model outcomes, being supported in deciding whether its decision-making process is trustful.

6.5. Model-global explanations

Exploiting the prediction-local explanations computed by T-EBANo for all the input documents, model-global insights can be provided.

Use case 1. For the toxic comment classification, Figure 9 shows the GAI and GRI scores for each influential word under the form of word-clouds for the classes Toxic (Figure 9a and 9c) and Clean (Figure 9b and 9d), respectively. The font size of words is proportional to the GAI or GRI scores obtained for each class separately. The proportion of the font size is relative only to the single word-cloud (i.e., two words with the same size in different word-clouds do not necessarily have the same score, while two words with the same size in the same word-cloud have almost the same score). The same score, while two words with the same size in different word-clouds do not necessarily have the same score, while two words with the same size in the same word-cloud have almost the same score). The GAI word-clouds (Figures 9a and 9b) show that the two classes are influenced by a non-overlapping set of words. This confirms that the model learned that if a word is attributable to toxic language in some context, it is unlikely to be associated to clean language in others. Toxic comments are identified by terms that are strongly related to toxic language, discrimination, or racism. Instead, there is no specific pattern of words that identifies clean comments. Just few concepts like people have an inter-class influence.

Then, the GRI word-clouds (Figures 9c and 9d) determine which are the more differentiating concepts between the two classes, among those selected by the model. The GRI word-cloud highlights even more the impact of words like stupid, idiot and ignorant, but also terms related to minorities and genders like woman, black, white, gay, meaning that the model has learned to recognize racists or sexist comments when these terms are present. Also, the presence of specific politician family names, anonymized as Politician1, Politician2, etc., highlight that those people names are related to toxic comments. These results demonstrate that a black-box model, if not carefully trained, can learn from sensitive content including prejudices and various forms of bias that should be avoided in critical contexts. Finally, associating a specific person’s family name to a class also raises ethical issues.

Use case 2. Analyzing the prediction-local explanations produced for the 400 input texts in the sentiment analysis use case, it is possible to extract global insights regarding the fine-tuned BERT model. Figure 10 shows the GAI and GRI word-clouds for the Positive (Figure 10a and 10c) and Negative (Figure 10b and 10d) class labels.

Differently than the previous example, the GAI word-clouds for the Positive (Figure 10a) and the Negative (Figure 10b) class labels show that several words like story, movie, film, like are impacting on both classes. This means that the model exploits overlapping concepts that do not express directly a sentiment but that, if considered together in their context, can be associated with words that express the mood of the writer (e.g. This film is not as good as expected).

The GRI word-cloud for the Positive class (Figure 10c) shows that words like movie and film are still very relevant for it, while they do not appear anymore for the Negative class (Figure 10d) that is now highly characterized by the concept of book. Exploring the dataset, we noticed that movies inspired by books are used to be associated with negative comments, as typically the original book is more detailed or slightly different, and thus this can be considered a form of bias that the model has learned, in the sense that a movie evaluation might not be based on its comparison with a book. However, the GRI shows also that most of the influential words for positive input texts are concepts strictly related to positive sentiments like good, great, best, love. Similarly, the negative sentiment is associated to words like worst, bad, awful. For these concepts, the model behaves as expected.

Thanks to the model-global explanation process the user can better understand how the predictive model is taking its decisions, identifying the presence of prejudice and/or bias, and allowing to decide if and which corrective actions have to be taken to make the decision-making process more reliable.

7. Conclusion and future research directions

This paper proposed T-EBANo, a new engine able to provide both prediction-local and model-global interpretable explanations in the context of NLP analytics tasks that exploit
black-box deep-learning models. T-EBAxO’s experimental assessment includes two different NLP tasks, i.e., a sentiment analysis task and a toxic document classification, performed through state-of-the-art techniques: a fine-tuned BERT model and a custom LSTM model.

Results showed that T-EBAxO can (i) identify specific features of the textual input data that are predominantly influencing the model’s predictions, (ii) highlight such features to the end-user, and (iii) quantify their impact through novel indexes. The proposed explanations enable end-users to decide whether a specific local prediction made by a black-box model is reliable, and to evaluate the general behavior of the global model across predictions. Besides being useful to general-purpose end users, explanations provided by T-EBAxO are especially useful
for data scientists, artificial intelligence and machine learning experts in need of understanding the behavior of their models, since the extracted features, both textual and numeric, are an efficient way to harness the complex knowledge learned by the models themselves. Future research directions include: (a) Further investigating new strategies for the perturbation of the input features, such as the substitution perturbation; (b) integrating T-EBA into a real-life setting to measure the effectiveness of the proposed textual explanations by human validation, interviewing both expert and non-expert users; (c) generalizing T-EBA to include new analytics goals, such as fine-tuned strategies and concept-drift detection.

References

[1] J. Devlin, M. Chang, K. Lee, K. Toutanova, BERT: pre-training of deep bidirectional transformers for language understanding, CoRR abs/1810.04805. arXiv:1810.04805
[2] S. Hochreiter, J. Schmidhuber, Long short-term memory, Neural computation 9 (1997) 1735–80. doi:10.1162/neco.1997.9.8.1735
[3] A. Wang, A. Singh, J. Michael, F. Hill, O. Levy, S. R. Bowman, Glue: A multi-task benchmark and analysis platform for natural language understanding, arXiv preprint arXiv:1804.07461.
[4] P. Rajpurkar, J. Zhang, K. Lopyrev, P. Liang, Squad: 100,000+ questions for machine comprehension of text (2016). arXiv:1606.05250.
[5] U. Naseem, I. Razzak, K. Mussial, M. Imran, Transformer based deep intelligent contextual embedding for twitter sentiment analysis, Future Generation Computer Systems 113 (2020) 58 – 69. doi:10.1016/j.future.2020.06.050.
[6] M. E. Basiri, S. Nemati, M. Abdar, E. Cambria, U. R. Acharya, Abcdm: An attention-based bidirectional cnn-rnn deep model for sentiment analysis, Future Generation Computer Systems 115 (2021) 279 – 294. doi:10.1016/j.future.2020.08.005.
[7] B. Lepri, J. Stiaiano, D. Sankoyoka, E. Letouze, N. Oliver, The Tyranny of Data? The Bright and Dark Sides of Data-Driven Decision-Making for Social Good, Springer International Publishing, Cham, 2017. pp. 3–24.
[8] T. Bolukbasi, K.-W. Chang, J. Zou, V. Saligrama, A. Kale, Is man to computer programmer as woman is to homemaker? debiasing word embeddings, arXiv.abs/1607.06520.
[9] A. Deeks, The judicial demand for explainable artificial intelligence, Columbia Law Review 119 (7) (2019) 1829–1850.
[10] R. Guidotti, A. Monreale, S. Ruggieri, F. Turini, F. Giannotti, D. Pedreschi, An introduction to methods for explaining black box models, ACM Comput. Surv. 51 (5) (2018) 93:1–93:42. doi:10.1145/3236009.
[11] W. Samek, G. Montavon, A. Vedaldi, L. Hansen, K.-R. Muller, Explainable AI: Interpreting and Visualizing Deep Learning, 2019. doi:10.1007/978-3-030-28564-6.
[12] A. Adadi, M. Berrada, Peeking inside the black-box: A survey on explainable artificial intelligence (xai), IEEE Access 6 (2018) 52138–52160. doi:10.1109/ACCESS.2018.2870052.
[13] A. Datta, S. Sen, Y. Zick, Algorithmic transparency via quantitative input influence: Theory and experiments with learning systems, in: 2016 IEEE Symposium on Security and Privacy (SP), 2016, pp. 598–617. doi:10.1109/SP.2016.62.
[14] E. Pastor, E. Baralis, Explaining black box models by means of local rules, in: Proceedings of the 34th ACM/SIGAPP Symposium on Applied Computing, SAC ’19, ACM, New York, NY, USA, 2019. pp. 510–517. doi:10.1145/3297280.3297328.
[15] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, D. Batra, Grad-cam: Visual explanations from deep networks via gradient-based localization, International Journal of Computer Vision doi:10.1007/s11263-019-01228-7.
[16] R. C. Feng, A. Vedaldi, Interpretable explanations of black boxes by meaningful perturbation, 2017 IEEE International Conference on Computer Vision (ICCV) doi:10.1109/iccv.2017.371.
[17] F. Ventura, T. Criguelli, F. Giacalone, Black-box model explained through an assessment of its interpretable features, in: New Trends in Databases and Information Systems - ADBIS 2018 Short Papers and Workshops, AI*QA, BIPGMPED, CSACDB, M2U, BigDataMAPS, ISTREND, DC, Budapest, Hungary, September, 2-5, 2018, Proceedings, 2018, pp. 138–149. doi:10.1007/978-3-030-00063-9_15.
[18] M. T. Ribeiro, S. Singh, C. Guestrin, "Why should I trust you?": Explaining the predictions of any classifier, CoRR abs/1602.04938. arXiv:1602.04938.
[19] S. M. Lundberg, S.-I. Lee, A unified approach to interpreting model predictions, in: I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, R. Garnett (Eds.), Advances in Neural Information Processing Systems 30, Curran Associates, Inc., 2017, pp. 4765–4774.
[20] L. S. Shapley, A value for n-person games, Contributions to the Theory of Games 2 (28) (1953) 307–317.
[21] S. M. Mathews, Explainable artificial intelligence applications in nlp, biomedical, and malware classification: A literature review, in: K. Arai, R. Bhatia, S. Kapoor (Eds.), Intelligent Computing, Springer International Publishing, Cham, 2019, pp. 1269–1292.
[22] D. Alvarez-Melis, T. S. Jaakkola, A causal framework for explaining the predictions of black-box sequence-to-sequence models, arXiv preprint arXiv:1707.01943.
[23] J. Li, W. Monroe, D. Jurafsky, Understanding neural networks through representation erasure (2016). arXiv:1612.08220.
[24] W. J. Murdoch, A. Szlai, Automatic rule extraction from long short term memory networks (2017). arXiv:1702.02640.
[25] T. Lei, R. Barzilay, T. Jaakkola, Rationalizing neural predictions (2016). arXiv:1606.04155.
[26] V. Trifonov, O.-E. Ganea, A. Potapenko, T. Hofmann, Learning and evaluating sparse interpretable sentence embeddings, in: Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, Association for Computational Linguistics, Brussels, Belgium, 2018, pp. 200–210. doi:10.18653/v1/W18-5422.
[27] K. Ethayarajh, How contextual are contextualized word representations? comparing the geometry of bert, elmo, and gpt-2 embeddings, ArXiv abs/1909.00512.
[28] Q. Zhou, X. Liu, Q. Wang, Interpretable duplicate question detection models based on attention mechanism, Information Sciences.
[29] X. Zheng, M. Wang, C. Chen, Y. Wang, Z. Cheng, Explore: Explainable item-tag co-recommendation, Information Sciences 474 (2019) 170 – 186.
[30] Explaining classifier decisions linguistically for stimulating and improving operators labeling behavior, Information Sciences 420 (2017) 16 – 36.
[31] E. Khodabandeloo, D. Riboni, A. Alimohammadi, Healthiax: Collaborative and explainable ai for supporting early diagnosis of cognitive decline, Future Generation Computer System doi:10.1016/j.future.2020.09.030.
[32] S. Lloyd, Least squares quantization in pcm, IEEE Transactions on Information Theory 28 (2) (1982) 129–137. doi:10.1109/TIT.1982.1056489.
[33] D. Borkan, L. Dixon, J. Sorensen, N. Thain, L. Vasserman, Nuanced metrics for measuring unintended bias with real data for text classification, CoRR abs/1903.04561. arXiv:1903.04561.
[34] J. Pennington, R. Socher, C. D. Manning, Glove: Global vectors for word representation, in: Empirical Methods in Natural Language Processing (EMNLP), 2014, pp. 1532–1543.
[35] A. L. Maas, R. E. Daly, P. T. Pham, D. Huang, A. Y. Ng, C. Potts, Learning vectors for word representation, in: Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, Association for Computational Linguistics, Portland, Oregon, USA, 2011, pp. 142–150.
[36] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, I. Polosukhin, Attention is all you need, CoRR abs/1706.03762. arXiv:1706.03762.
[37] K. Ethayarajh, How contextual are contextualized word representations? comparing the geometry of bert, elmo, and gpt-2 embeddings (2019). arXiv:1909.00512.