

Evaluating text classification with explainable artificial intelligence

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Article Info

Article history:

Received Dec 10, 2022

Revised Jan 20, 2023

Accepted Mar 10, 2023

Keywords:

Explainable artificial intelligence

LIME

Model interpretability

Text classification

ABSTRACT

Nowadays, artificial intelligence (AI) in general and machine learning techniques in particular has been widely employed in automated systems. Increasing complexity of these machine learning based systems have consequently given rise to blackbox models that are typically not understandable or explainable by humans. There is a need to understand the logic and reason behind these automated decision-making black box models as they are involved in our day-to-day activities such as driving, facial recognition identity systems, online recruitment. Explainable artificial intelligence (XAI) is an evolving field that makes it possible for humans to evaluate machine learning models for their correctness, fairness, and reliability. We extend our previous research work and perform a detailed analysis of the model created for text classification and sentiment analysis using a popular Explainable AI tool named local interpretable model agnostic explanations (LIME). The results verify that it is essential to evaluate machine learning models using explainable AI tools as accuracy and other related metrics does not ensure the correctness, fairness, and reliability of the model. We also present the comparison of explainability and interpretability of various machine learning algorithms using LIME.

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1. INTRODUCTION

In recent years, machine learning has produced cutting-edge performance in autonomous systems, computer vision, prediction, and classification applications. Various prediction and classification algorithms involving varied data such as images, text, speech, and video have been able to achieve near human or even greater accuracy. As the complexity of these machine learning algorithms grows, the human understandability is compromised. These models are becoming more and more blackbox models leading questions regarding their fairness, reliability, and correctness. Number of cases have been reported in which artificial intelligence-based systems even with high accuracy were found to be biased [1]. Therefore, there is a growing concern regarding how machine learning algorithms are learning from the data and making their decisions. Explainable artificial intelligence (XAI) is the latest buzzword in the machine learning world that targets to justify and comprehend the model behavior [2]. It allows for the creation of more robust models with improved decision-making abilities. The aim of XAI is to create explanation approaches that make machine learning models to be transparent and understandable while maintaining strong learning performance. This research is focused on applying XAI techniques to evaluate text classification model created for restaurant reviews classification and

sentiment analysis. The research is an extension of our previous work [3] in which the dataset was collected from one of the popular Facebook group; SWOT's Guide to KARACHI's Restaurants Cafes Dhabas HBFE & Takeouts and manually labeled with the respective sentiment and four categories.

Text classification typically involves natural language processing (NLP) and machine learning techniques. NLP comprises of different processing methods including tokenization, stop words removal, bag of words, and stemming. Traditional machine learning algorithms include Naïve Bayes, random forest, support vector machine. that can be evaluated on various metrics such as accuracy, F1-score, recall, and precision. These metrics measures the model performance however, none of them can be used to interpret the results produced by the model in human understandable language. Numerous explainable machine learning methods have been developed in order to fulfill the need of providing interpretability power to the machine learning models [2], [3] this research study is using local interpretable model agnostic explanations (LIME) [4] for evaluating the interpretability degree of traditional machine learning algorithms. LIME approximates the model locally by employing a linearly weighted combination of input features to explain the individual prediction.

The major contributions of this research are summarized,

- We provide a detailed interpretation of machine learning algorithms for sentiment analysis using LIME.
- We explain how traditional machine learning algorithms are classifying the data in different categories using LIME.
- We present the comparison of various traditional machine learning algorithms in terms of their interpretability

The remaining paper is organized: Section 2 explains the explainable artificial intelligence (XAI). Section 3 provides the related work; Section 4 discusses the methodology of this research. Results are presented and discussed in section 5 while section 6 concludes the research.

2. EXPLAINABLE ARTIFICIAL INTELLIGENCE

Artificial intelligence (AI) has progressed tremendously in recent years and achieved human-like performance in automated systems such as recognizing objects [5], [6], translating text across languages [7], detecting cancer from x-ray images [8], beating expert players of Go [9] and Poker [10]. However, the AI systems are still limited to what they are trained for and end up with failure even if a small invisible change is encountered in the real-time. On March 18, 2018, Uber self-driving car has produced pedestrian fatality and the reason reported was “the inability of the AI to classify an object as a pedestrian unless that object was near a crosswalk” [11]. Further, Amazon's AI powered recruiting tool was found to be gender biased (selecting men) as it was trained on the resumes submitted to the company over a period of 10 years and the majority of those came from men [12]. Moreover, an assistive software and support tool COMPASS used by the U.S. states to predict the risk that a criminal defendant will re-offend was found to be racist making the predictions largely biased towards white defendants [13]. Therefore, it is prudent for AI systems to provide human understandable explanations that express the rationale about how the AI is drawing conclusions [14], [15]. The defense advanced research projects agency (DARPA) introduced the explainable artificial intelligence (XAI) project endeavors to create AI systems whose models and decisions can be understood and trusted by end users [2]. The research community has produced different explainable machine learning methods and techniques that satisfy the need of interpretability of the machine learning models. Few of these are given mention in next section.

2.1. LIME

LIME stands for local interpretable model-agnostic explanations; is a revolutionary explanation technique that provides an interpretable model locally around a prediction to explain any classifier's predictions in an interpretable and faithful manner [7]. LIME is an open-source python package and provides interpretation of the model. For example: when model predict like or dislike of customer behavior in form of accuracy so lime can explain why model predict this behavior of customer.

2.2. Anchors

A model-agnostic system that uses anchors (high-precision rules based on local, sufficient conditions for prediction), that explains the behavior of complex models [16]. Anchors handle variations in other feature values that do not affect the forecast. Reinforcement learning techniques are used for combining an anchor with a graph search algorithm to optimize the model calls while maintaining the capacity to retrieve from local optima.

2.3. Shapley additive explanations (SHAP)

SHAP is a mathematical framework for explaining machine learning model predictions [17], [18]. It is based on game theory concepts and may be used to explain any machine learning model's predictions by computing the contribution of each attribute to the prediction. The basic idea of SHAP is to treat the prediction

of a machine learning model as a cooperative game between the features of the input. The Shapley value, which is a concept from cooperative game theory, is used to assign an importance score to each feature based on its contribution to the model's output.

2.4. ELI5 (explain like i'm 5)

ELI5 is a Python toolkit that employs a standardized application programming interface (API) to display and debug a variety of machine learning models [19]. All scikit-learn algorithms are supported, including `fit()` and `predict()`. It has built-in support for a variety of machine learning frameworks and can explain both white-box and black-box models (Linear regression, decision trees) (Keras, XGBoost). Both regression and classification models can be used with it.

2.5. Graph lime

Graph LIME [20] is an approach that is based on the LIME concept but is not linear. It is used to describe a certain form of neural network design known as graph neural networks (GNN). Because the data is organized in a network structure, these models can handle non-Euclidean data. Three criteria developers were considered: First is the ability to discover ineffective features, second is the ability to determine whether a prediction is reliable, and the third is the ability to determine which of two GNN classifiers the best model is.

3. RELATED WORK

Text classification and sentiment analysis has been an active area of research since last two decades. Numerous intelligent systems are developed, and many studies have been conducted with high accuracy for text classification and sentiment analysis. However, human understandability and interpretability of these complex systems remained questionable. Very few studies are conducted in which machine learning models and their decisions are presented with XAI tools. Table 1 presents a summary of previous research conducted in this regard.

Kumar *et al.* [17] performed random forest and extreme gradient boosting (XGBoost) model to detect the sarcasm from dialogues, LIME and SHAP were used to interpret the results. Through these interpretability methods, users can easily understand how the model is decided for detecting sarcasm in dialogues [17]. Syarifuddin [21] also performed random forest for text classification using YouTube videos comments and use LIME for explaining the model. Also, Mahajan [22] performed different models for predicting toxic or nontoxic comments to stop cyberbullying and used LIME for explaining the machine learning models. However, Roman *et al.* [18], compare different explainable AI techniques which are search for EviDence counterfactual for image classification (SEDC), LIME, and SHAP by using behavioral and textual data sets. Their result shows that different methods have different strengths. Tran *et al.* [23], performed Sentiment analysis using NLP techniques and following machine learning models which are random forest, decision tree, and gradient boosting trees. Ahmed *et al.* [24], also performed sentiment analysis using Apache spark processing. Three models were tested on Amazon's fine food reviews named as Naïve Bayes, logistic regression, and linear support vector classifier (SVC).

Table 1. Summary of existing studies

Reference	Dataset	Machine Learning Algorithms	Explainable AI Tools
[17]	MUStard	Random forest, XGBoost	LIME and SHAP
[21]	Different YouTube videos	Random forest	LIME
[22]	Hate speech, abusive comments	Logistic Regression, Multinomial Naïve bayes, Random Forest, XG-Boost, Conventional neural network, Gated Recurrent Unit	LIME
[18]	13 Behavioral and textual data	-	Comparison of SEDC, LIME and SHAP
[23]	Amazon fine food	Gradient boosting trees, random forest, decision tree	-
[24]	Amazon fine food	Logistic regression, Naïve Bayes, linear SVC	-
Our Research	Restaurant reviews dataset	Logistic regression, Naïve Bayes, support vector machine, random forest	LIME

4. METHODOLOGY

This research study is the extended version of our previous study of sentiment analysis and category classification of restaurants' reviews [25]. The dataset comprises of three attributes i.e., the content of the

review about the restaurant, the category of the review and the sentiment as shown in Figure 1. The model was trained for sentiment analysis and category classification by incorporating NLP toolkit and traditional machine learning algorithms including logistic regression, Naïve Bayes, support vector machine, and random forest.

The methodology employed in this study is to evaluate the performance attained by each classifier in our prior study by explaining the predictions using LIME to ensure whether the results are fair, reliable and can be trusted. As LIME explains individual local predictions, therefore, we select five reviews each for sentiment and category classification. Table 2 mentions the individual reviews with their actual sentiment and category respectively.

	Review	Category	Sentiment
0	It was worth trying it	Value_of_Money	Positive
1	Pizza was great and satisfied my pizza craving	Value_of_Money	Positive
2	food was amazing and the food was hot and fresh	food_taste	Positive
3	Awsome quality of flavoured Naan	food_taste	Positive
4	It was fresh ,hot and yummy	food_taste	Positive

Figure 1. Dataset records

Table 2. Individual reviews with their actual sentiment

S. No.	Review	Sentiment	Review	Category
1.	Worst customer service	Negative	Everything perfect delicious taste	Food_taste
2.	Quality plus service perfect	Positive	Bread like unfresh	Food_taste
3.	Chocolate desert delicious	Positive	Overall pleasant experience	Service
4.	Area wise delivery time perfect taste	Positive	Pocket friendly price	Value_of_Money
5.	Smelly mash potato arrogant staff half cook chicken	Negative	Poor food quality disappoints	Food_taste

5. RESULTS AND DISCUSSION

The results achieved for sentiment analysis from each classifier are presented in Table 3 which shows that the overall performance of each classifier is significantly good i.e., greater than 90%. However, random forest has outperformed the other algorithms. While the results of category classification are given in Table 4 which clearly marks the supremacy of random forest algorithm with 95% accuracy and 96% F1-Score.

Table 3. Results of sentiment analysis

Algorithm	Sentiment	Precision %	Recall %	F1 Score %	Accuracy %
Naïve Bayes	Positive	92	93	92	92
	Negative	92	92	92	
Logistic regression	Positive	93	91	92	92
	Negative	91	93	92	
Support vector machine	Positive	93	91	92	93
	Negative	91	93	92	
Random forest	Positive	93	91	92	95
	Negative	91	93	92	

Table 4. Results of category classification

Algorithm	Naïve Bayes				Logistic regression				Support vector machine				Random forest			
	P	R	F	Acc.%	P	R	F	Acc.	P	R	F	Acc.	P	R	F	Acc.
Categories	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%	%
Food Taste	82	99	89	84	93	98	96	86	84	99	91	89	95	97	96	
Value for Money	92	51	66		92	91	93		94	61	74		94	91	92	
Ambiance	92	62	73		93	85	89		94	67	78		94	90	92	94
Service	93	62	74		91	87	90		95	68	79		94	90	92	

*Where: P = Precision, R = Recall, F = F1-Score, Acc. = Accuracy

5.1. LIME explanations for Naïve Bayes

The Naïve Bayes classifier classifies the predictions accurately for sentiment analysis task however, in the sentence “quality plus service perfect”, it is observed that the word “service” makes this statement negative with the probability of 0.13 which should not be given as this word cannot be used to show negativity in any sentence. Similarly in the sentence “area wise delivery time perfect taste”; the words “area” and “delivery” have given probabilities in negative terms which may result in wrong predictions for larger sentences. However, the word “arrogant” is completely neglected by the classifier which is considered as a key word for negativity. The probabilities given to those common words that cannot be used to show negativity in any sentence derail the accuracy and truthfulness of the classifier as depicted in Figure 2.

Figure 3 presents the interpretation of category classification results which indicates that the classifier works well in identifying the respective category. However, there are words that are understood wrong. For example, in the sentence “pocket friendly price” the word “friendly” has considered to be belong to the food taste category. This same situation has encountered in the sentiment classification too. This clearly depicts that the model does not take care of the actual meaning of the sentence and has learned arbitrarily.

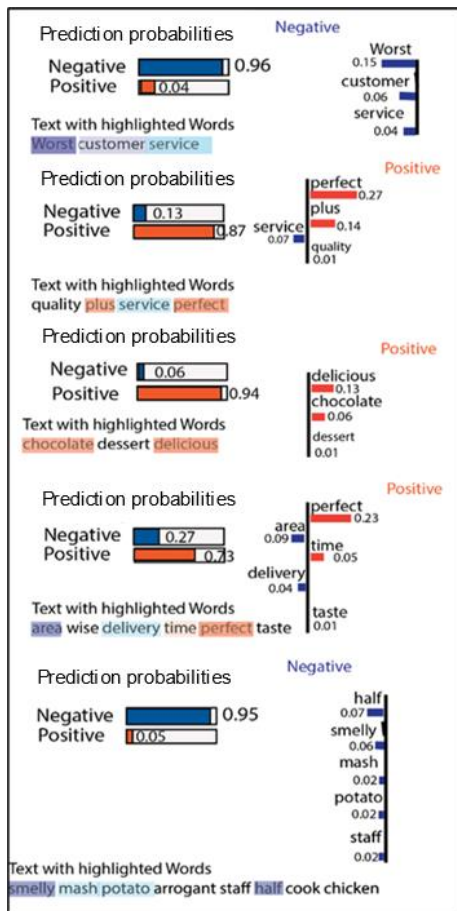


Figure 2. LIME explanations for sentiment analysis of Naive Bayes classifier

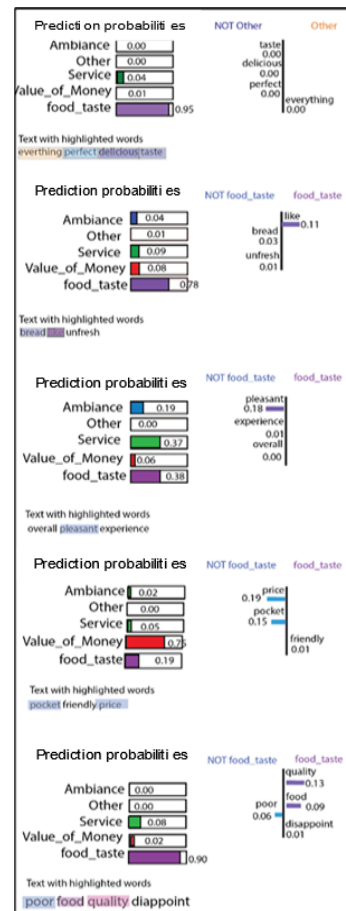


Figure 3. LIME explanations for category classification of Naive Bayes classifier

5.2. LIME explanations for logistic regression

Figure 4 shows the explanations of the specific reviews of the sentiment analysis model made by incorporating logistic regression algorithm. Similar to Naïve Bayes classifier, logistic regression also consider common words i.e., -“service” and “area” as negative and disregard the word “arrogant”; hence this model also does not suit for the sentiment classification. For category classification task, this model achieves accuracy of 86%, and the LIME explanation in Figure 5 indicates there are words that are taken misunderstood by the classifier. For example, “pleasant” and “friendly” are regarded as food taste.

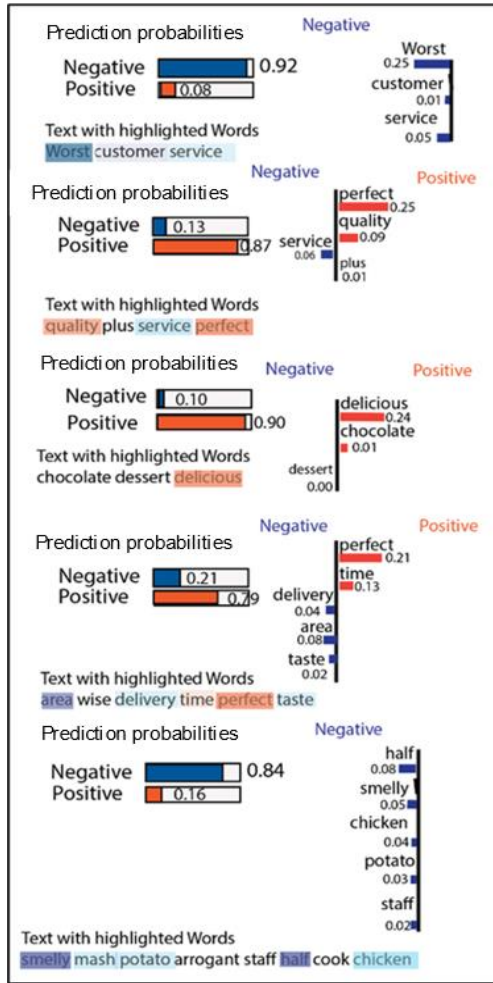


Figure 4. LIME explanations for sentiment analysis of logistic regression classifier

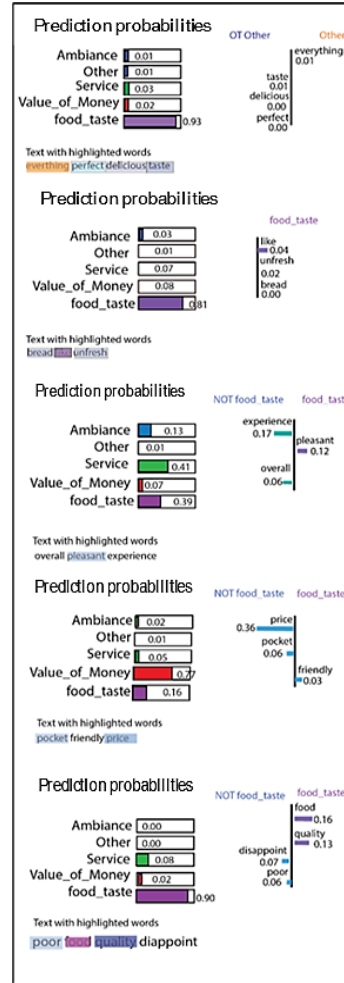


Figure 5. LIME explanations for category classification of logistic regression classifier

5.3. LIME explanations for support vector machine (SVM)

The support vector machine works a little better than previous classifiers for sentiment classification task as presented in Figure 6. But the word “service” is also labeled as the negative word. However, the word “arrogant” is again not considered. This classifier misclassifies one of the sentences selected for LIME explanation; Depicted in Figure 7 in category classification. The sentence “poor food quality disappoint” has been classified as value of money which was actually belongs to food taste category. This misclassification occurs because of the word “disappoint” mainly which clearly indicates that this classifier does not learn the meaning of the whole sentence rather works on individual words irrespective of the context and semantics.

5.4. LIME explanations for random forest

This classifier has got the maximum accuracy and F1-score among all classifiers in both tasks. However, in sentiment analysis, the word “service” is misunderstood by this one too along with other words like “customer”, “chicken”, “staff”. Unlike other classifiers, this classifier does consider the word “arrogant” as the negative one but with very low probability as depicted in Figure 8 in Appendix.

The LIME interpretations of this classifier for category classification are shown in Figure 9 at Appendix. No misclassification occurs in the selected sentences; however, the words nominated for classification are not taken as per their actual meaning. The sentence “bread like unfresh” has been classified as food taste on the basis of the word “like” only. The word “friendly” from the sentence “pocket friendly price” has been regarded as taken from food taste category. Despite being the highest scorer in performance metrics, this classifier does not show different behavior in category classification task from other models i.e., semantics and context of the sentences are overlooked.

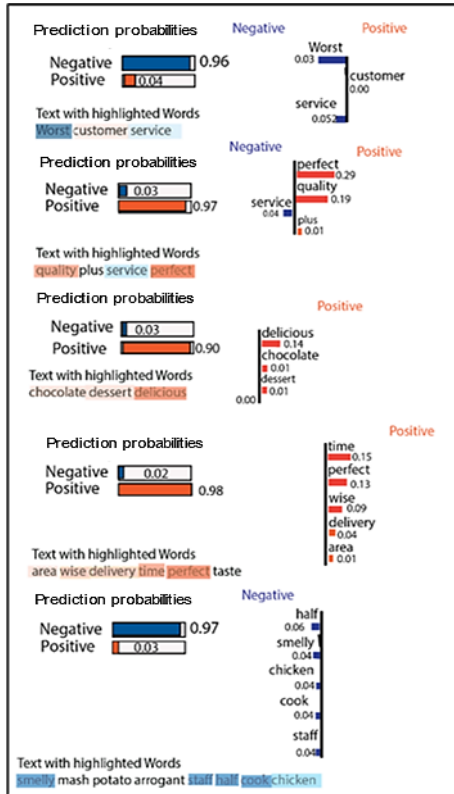


Figure 6. LIME explanations for sentiment analysis of support vector machine

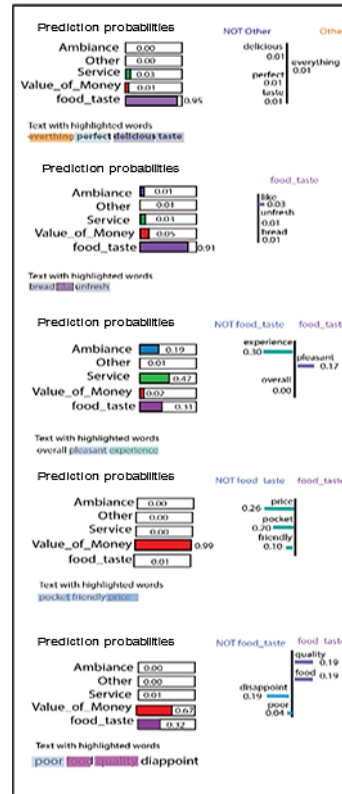


Figure 7. LIME explanations for category classification of support vector machine

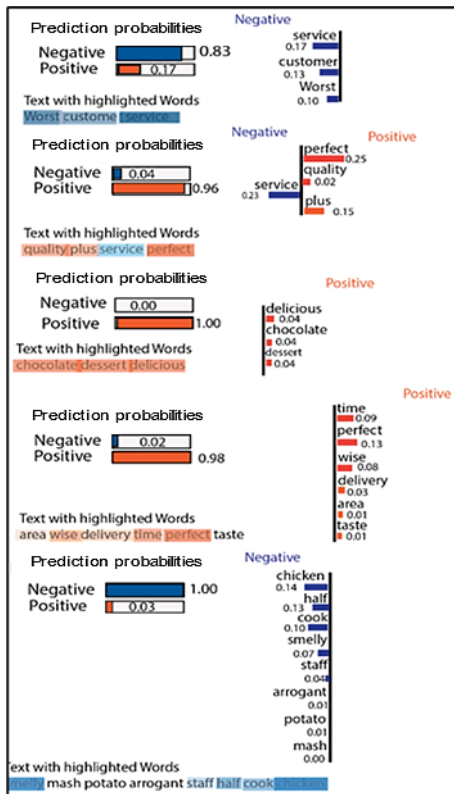


Figure 8. LIME explanations for sentiment analysis of random forest

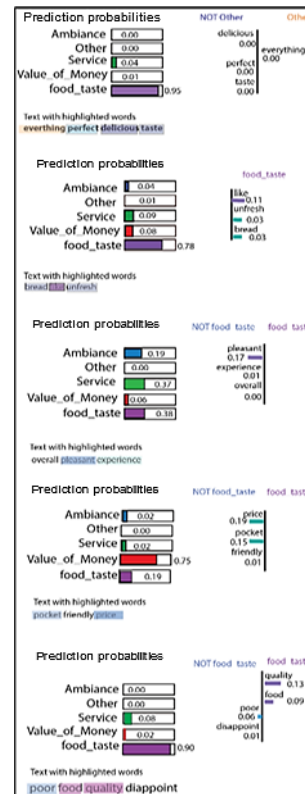


Figure 9. LIME explanations for category classification of random forest

6. DISCUSSION

We have used LIME for interpreting the predictions made by traditional machine learning algorithms for sentiment analysis and category classification tasks. LIME delivers sophisticated explanations to the individual predictions, and it is observed that the classifiers have not understood the words as they are being used in the real world. Although no misclassification happens in the sentences, we selected for sentiment analysis by any classifier. Though, we noticed that the SVM classifier misclassifies one of the sentences in the category classification task and the reason observed by the LIME explanations is the ignorance of the semantics and context of the sentence. Similar behavior of not learning the semantic relation between words and the context of the whole sentence is detected in all classifiers in both tasks. Although, the classifiers for both tasks have achieved the accuracy and related measures of more than 80% but these observations reveals that the models are not faithful to the predictions they made and need improvement. It can be concluded that there were shortcomings in the preprocessing of data; and the models can be optimized by using different preprocessing techniques and then checking their interpretations. Thus, it is crucial to implement explainable AI as it provides logical reasoning of how a model is making certain predictions. Having a clear reason, we can easily improve the model for all the misclassified results and verify its truthfulness.

7. CONCLUSION

We present the interpretation of machine learning models used to perform sentiment analysis and category classification of restaurants' reviews. It is the extension of our previous research work which uses logistic regression, Naïve Bayes, support vector machine, and random forest for the classification tasks. LIME: Local Interpretable Model-agnostic Explanations is used for explaining the predictions in this research. For each classification task, five reviews are selected. It is observed while interpreting the predictions that all models have secured greater scores in the performance evaluation metrics but do not provide valid explanations for the decisions they made. For example, the word "arrogant" was not recognized as the negative key word by three of the classifiers outrightly while random forest considers it as a negative one with very low probability. Thus, questioning the actual accuracy of the models. We conclude that model interpretation is indispensable, and the interpretations provided by LIME are a good source to optimize the model performance as well as establishing trust by providing evidence-based analysis results to users.




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