ABSTRACT
Anomaly detection algorithms are often thought to be limited because they don't facilitate the process of validating results performed by domain experts. In contrast, deep learning algorithms for anomaly detection, such as autoencoders, point out the outliers, saving experts the time-consuming task of examining normal cases in order to find anomalies. Most outlier detection algorithms output a score for each instance in the database. The top-k most intense outliers are returned to the user for further inspection; however, the manual validation of results becomes challenging without additional clues. An explanation of why an instance is anomalous enables the experts to focus their investigation on most important anomalies and may increase their trust in the algorithm. Recently, a game theory-based framework known as SHapley Additive exPlanations (SHAP) has been shown to be effective in explaining various supervised learning models. In this research, we extend SHAP to explain anomalies detected by an autoencoder, an unsupervised model. The proposed method extracts and visually depicts both the features that most contributed to the anomaly and those that offset it. A preliminary experimental study using real world data demonstrates the usefulness of the proposed method in assisting the domain experts to understand the anomaly and filtering out the uninteresting anomalies, aiming at minimizing the false positive rate of detected anomalies.

CCS CONCEPTS
- Computing methodologies → Unsupervised learning; Anomaly detection; Neural networks;

KEYWORDS
Explainable AI, Interpretable AI, Explainability, Interpretability, Autoencoder, Anomaly detection, SHAP, Shapley values, SHapley Additive exPlanations, explaining unsupervised model

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1 INTRODUCTION
Recently, deep learning algorithms have been used for a wide variety of problems including anomaly detection. While anomaly detection algorithms may be effective at saving experts' time, they have a major drawback because their output is hard to explain. This shortcoming can make it challenging to convince experts to trust and adopt such potentially beneficial intelligent systems. The output of such algorithms may contain anomalous instances that the domain expert was previously unaware of, and an explanation of why an instance is anomalous can increase the domain expert's trust in the algorithm.

The need to provide an explanation per instance (as opposed to providing an explanation for the whole model) came to the fore fairly recently, as models have become more complex. In the last decade, a few methods have been developed to explain predictions from supervised models. One way of explaining is using an interpretable approximation of the original model [6]. LIME [8] is an example for a model agnostic method used to explaining a prediction using a local model while DeepLIFT [11] is an example for a model specific method for explaining deep learning models by back propagating the contributions of all neurons in the network to the input features. SHAP (SHapley Additive exPlanation) [6] unifies previous methods for explaining predictions by calculating feature importance using shapley values considering properties from game theory that promise consistency, as opposed to previous methods.

Recently, it is common to use an autoencoder for unsupervised anomaly detection tasks [2, 7, 10]. Autoencoder is an unsupervised algorithm that represents the normal data in lower dimensionality and then reconstruct the data into the original dimensionality; thus, the normal instances are reconstructed properly, and the outliers are not, making the anomalies clear. To the best of our knowledge, no previous research has been performed to explain anomalies revealed by an unsupervised models and specifically by autoencoder. In this paper, we present a new method based on SHAP values, to explain the anomalies found in an autoencoder's output. The contribution to the field is (1) explaining the output of an unsupervised autoencoder model (2) using the explanation to detect interesting anomalies. (3) conduct preliminary experiment with real-world data and domain experts. The method will be beneficial to experts requiring justification and visualization regarding such anomalies. Domain experts involved in a preliminary experiment on real world data, provided positive feedback, claiming that the explanations helped them inspect the anomalies. In addition, the results revealed insights about how to minimize the false positive rate of anomalies.
2 RELATED WORK

2.1 Autoencoder

Autoencoders were first introduced in the 1980s [9] and in the last decade have most commonly been used in deep architectures [1, 4, 5]. An autoencoder is an unsupervised neural network that is trained to produce target values equal to its inputs. [3]. An autoencoder represents the data in lower dimensionality (encoding) and reconstruct the data into the original dimensionality (decoding). Based on the input, the autoencoder learns an identity function so that the autoencoder’s output is similar to the input and the embedded model created in the encoding represents normal instances well. In contrast, anomalies are not reconstructed well and have a high amount of reconstruction error, so in the process of encoding and decoding the instances, the anomalies are discovered.

2.2 SHAP

The SHAP framework [6] (SHapley Additive exPlanation) unifies previous methods such as LIME [8] and DeepLIFT [11] under the class of additive feature attribution methods. Methods in this class are explanation models in the form of a linear function of simplified binary variables, as in \( f(x) = g(z) = \theta_0 + \sum_{i=1}^{m} \theta_i z_i \) where \( f(x) \) is the original model (autoencoder in this paper); \( g(x) \) is the explanation model; \( z \) is the simplified input; \( x = h_{\theta}(z) \) - a mapping function to the original method; and \( \theta_0 = f(h_{\theta}(0)) \) the model output without all of the simplified inputs.

SHAP provides sound theoretic basis which is a benefit in regulated scenarios. It uses shapely values from game theory to explain a specific prediction by assigning an importance value (SHAP value) to each feature that meets the following properties: (1) local accuracy - the explanation model has to at least match the output of original model; (2) missingness - features missing in the original input must have no impact; (3) consistency - if we revise a model such that it depend more on a certain feature, then the importance of that feature should not decrease regardless of other features.

Lundberg and Lee [6] demonstrate that SHAP is better aligned than previous methods with human intuition since it meets those properties. The SHAP framework suggests a model-agnostic approximation for SHAP values, called Kernel SHAP. It uses linear LIME [8] with Shapley values to build a local explanation model. A local model uses a small background set from the data to build an interpretable model that take into account the proximity to the instance to be explained[8]. We use kernel SHAP as it provides more accurate estimates with fewer evaluations of the original model than previous sampling-based estimates.

3 EXPLAINING AUTOENCODER ANOMALIES

Our challenge was to find a method to explain an anomaly where existing explainability methods are used for explaining a prediction (output). We used autoencoder to detect anomalies through the reconstruction error. We explain an anomaly, which is the difference (error) between the input value and the output (reconstructed) value. An anomaly, if exists, resides in the values of the input and the explaining model needs to explain why this instance is not predicted (reconstructed) well. Thus an explanation must be connected to the error. Our method therefore computes the SHAP values of the reconstructed features and relates them to the true (anomalous) values in the input. As previously mentioned, the anomalies are identified because of their high value of reconstruction error.

Given an input instance \( X \) with a set of features \( x_1, x_2, \ldots, x_n \) and their corresponding output \( X' \) and reconstructed values \( x'_{1}, x'_{2}, \ldots, x'_{n} \) using an autoencoder model \( f \), the reconstruction error of the instance is the sum of errors of each feature \( L(X, X') = \sum_{i=1}^{n} (x_i - x'_i)^2 \). Let \( x_{(1)}, \ldots, x_{(n)} \) be a reordering of the features in errorList such that \( |x_{(1)} - x'_{(1)}| \geq \cdots \geq |x_{(m)} - x'_{(m)}| \), top features \( = x_{(1)}, \ldots, x_{(m)} \), contains a minimal set of features that their corresponding errors \( topErrors : |x_{(1)} - x'_{(1)}|, \ldots, |x_{(m)} - x'_{(m)}| \) sum to at least 80 percent (adjustable) of \( L(X, X') \).

Our method explains the reasons (the features and their values) that caused each of the \( topFeatures \) to be reconstructed with a large error. Algorithm 1 presents the pseudo-code for the

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\text{Algorithm 1 Calculate SHAP values for topFeatures}
\]

**Input:** \( X \) - An instance we want to explain, \( X_{1..100} \) - Instances that SHAP uses as background examples, ErrorList - An ordered list of error per feature, \( f \) - Autoencoder model

**Output:** \( shapTopMFeatures \) - SHAP values for each feature within \( topMFeatures \)

1. \( \text{weights} \leftarrow f \cdot \text{getweights} \)
2. \( \text{topMFeatures} \leftarrow \text{top values from ErrorList} \)
3. for each \( i \in \text{topMFeatures} \) do
4. \( \text{weights}(0)[i] \leftarrow 0 \)
5. \( \text{explainer} \leftarrow \text{shap.KernelExplainer}(f, X_{1..100}) \)
6. \( \text{shapTopMFeatures}[i] \leftarrow \text{explainer}\cdot\text{shapvalues}(X, i) \)
7. return \( \text{shapTopMFeatures} \)

process. At first, we refer to the model’s weights in order to eliminate the weights emanating from the inspected feature (in line 4), since we are not interested in knowing the effect of the feature on its reconstruction. Then, we extract the features with the highest reconstruction error from the ErrorList and save them in the \( topMFeatures \) list. Next, for each feature \( x'_i \) in \( topMFeatures \), we use kernel SHAP to obtain the SHAP values, i.e, the importance of each feature \( x_1, x_2, \ldots, x_n \) (except for \( x_i \)) in predicting the examined feature \( x'_i \). kernel SHAP receives \( f \) and a background set with 100 instances for building the local explanation model and calculating the SHAP values. Then \( f \) takes as input \( X \) and \( i \) and predicts \( X' \). The value in the \( i \)’th feature is returned (Algorithm 2), which is a feature in the \( topMFeatures \). The result of this step is a two-dimensional list \( \text{shapTopMFeatures} \), in which each row represents the SHAP values for one feature from the \( topMFeatures \). We divide the SHAP values into values contributing to the anomaly

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\text{Algorithm 2 f(X,i)}
\]

**Input:** \( X \) - An instance we want to explain, \( i \) - The feature we want to get the prediction for (from the output vector of the autoencoder), \( f \) - autoencoder model

**Output:** \( x'_i \) - The value of the \( i \)’th feature in \( X' \)

1. \( x'_i \leftarrow f \cdot \text{predict}(X)[i] \)
2. return \( x'_i \)

- those pushing the predicted (reconstructed) value farther from
the true value and values offsetting the anomaly — those pushing the predicted value towards the true value. The pseudo code in Algorithm 3 presents how the SHAP values are divided. For each feature (line 1), we check if the true (input) feature value is greater than the predicted value (line 2), the contributing features are the features with a negative SHAP value (line 3), and the offsetting features are the positives (line 4). If the predicted feature value is greater than the actual (input) value (line 5), it is the opposite. This algorithm returns two lists shapContributin and shapOffsetting that contain the contributing and offsetting features, along with their SHAP values, for each feature from the topM features. The next step to be applied is the extraction of the most important features in a prediction of each of the features in the topM features list. The most important features are the ones with high SHAP values, so from each row in shapContributin and shapOffsetting we extract the highest values. Since our goal is to help the domain expert understand why an instance is an anomaly, we present the explanation in a form of a table that depicts the contributing and offsetting anomaly features using colors which correspond to the SHAP values (Figure 2b). A higher SHAP value (depicted by a darker color) means that the feature is more important for the prediction. contributing features appear in red and offsetting features appear in blue.

4 EXAMPLE

For demonstration, we assume that we are trying to detect drug abuse, using a prescription database. Each record has ten features that may point to drug abuse. The instance presented in Figure 1a, which has a high reconstruction error, is a prescription for a large amount of painkillers prescribed to a 30-years-old man who has no comorbidities but was recently involved in a car accident.

Extracting top error features. Since the total reconstruction error is calculated from the error of each feature \( |X_i - X'_i| \), we can extract the features with the highest reconstruction error. Let’s assume that features \( X_3 \) (drug amount), \( X_4 \) (days between prescription and purchase date), \( X_5 \) (doctor name), have the highest errors; therefore they are the features that we explain using SHAP.

Calculating SHAP values for a feature with high error. In order to explain the reconstruction error in the drug amount feature \( X_3 \), we use the autoencoder for predicting the value of the drug amount \( X'_3 \), as in Figure 1b and use SHAP to obtain the importance of each feature in the network in predicting \( X'_3 \), relative to a baseline which is calculated using the background set as in Algorithm 1.

Features contributing or offsetting an anomaly. Figure 2a presents a plot with positive (blue in the figure) and negative (red) SHAP values. Assume that the real value of feature \( X_3 \) is 1 and the autoencoder predicted that \( X'_3 \) equals 0.01. To divide the features to contributing and offsetting the anomaly, we use the true (input) value, output (reconstructed) value and the polarity of SHAP values as in Algorithm 3. Only event=car accident \( (X_2) \) pushed the value towards the true value, offsetting the anomaly, while time from last prescription=five days \( (X_5) \), age=30 \( (X_{10}) \) and medical background=no disease \( (X_1) \) pushed the value farther from the true value towards the prediction, contributing to the anomaly. Because the young patient had no disease and requested painkillers five days before, the autoencoder predicted that the amount would be much lower than what was prescribed. Perhaps the event feature \( (X_2) \) offsets the anomaly, because the fact that the patient was involved in a car accident makes this prescription correct.

Depiction of contributing and offsetting anomaly features. Figure 2b demonstrates how we visually depict the features contributing and offsetting the anomaly to the domain expert. For each feature in the topM features \( (X'_3, X'_4, X'_5) \), we show the contributing features in red. For example, \( X_3 \) is the feature that contributed most to the error of feature \( X_3 \). In the third column we show the real value of that feature. Then we present the features that offset the anomaly in blue and in the last column the real value of that feature.

The importance of using SHAP for explaining anomalies. The prescription described in our example may be normal. Painkillers are commonly prescribed, even for young, healthy people. So why is it anomalous? Without using SHAP to provide an explanation for the anomalies revealed by the autoencoder, the domain expert would receive an alert regarding this prescription, and the only clue he/she would have about its anomalous nature is that the autoencoder (wrongly) predicted that another doctor prescribed a much smaller amount of the drug and the patient purchased the
drug later than he did. The reason for the anomaly remains vague. Using SHAP, we are able to explain what caused the errors. When the expert sees the features that most affected the prediction, it is clearer why the autoencoder revealed it as an anomaly. In this example we had only ten features, but in many real-world problems, the number of features is much higher, which makes it much harder to understand the anomaly without a proper explanation.

## 5 Preliminary User Study

As part of a project aimed at developing an anomaly detection method for cost monitoring of warranty claims of a big manufacturer, we developed an autoencoder-based anomaly detector. The detection of fraud or human error is part of an effective cost monitoring process which is extremely important to the company, enabling them to reduce costs, improve their products, and better serve their customers. Until now, the domain experts at the company have produced reports based on pre-defined rules according to KPIs to reveal irregularities in warranty claims. The output of the autoencoder revealed anomalies that the domain experts were unable to detect using the existing process. However, an explanation of the anomalies is needed in order to convince the domain experts regarding the correctness of the anomalies found. In this study we wanted to evaluate our hypotheses that (1) The explanations assist the experts to understand the anomalies (2) In interesting anomalies there is an intersection between features with high reconstruction error and the features that explain them. We used an autoencoder to detect anomalies from 15,000 warranty claims, with 1000 features. 10 field engineers (domain experts) received a list of top anomalies based on the interquartile range of the reconstruction errors $(Q3 - Q1) \cdot 1.5 + Q3$. They were instructed to decide both using their systems and the visual depiction provided by us if the anomaly should be further inspected.

The experts labeled 114 instances; 90 were labeled as ‘should be inspected’ and 24 were ‘uninteresting’. It is unbalanced since the list of anomalies contained the top anomalies so most of them are interesting for the experts. As reported by the domain experts, the explanations provided a clear direction of how to examine the anomalies, bu using first the most important explaining contributing features (darker color) to examine the anomaly. When detecting anomalies one major problem is the false positive rate that may result in wasting expensive time of the domain expert investigating anomalies that occur due to various reasons such as rareness. We checked for each claim if there is at least one feature that contributed to the anomaly which is also a feature with high reconstruction error, both for all the features in shaptopM features and only in the top three features in shaptopM features. The results of the analysis are shown in Table 1. We can see that in 72% of the interesting anomalies, there was an intersection (as in Figure 3b) between the features with high reconstruction error to those explaining them. In contrast, only in 37% of the uninteresting anomalies there was an intersection. In the top three features only in 16% of the uninteresting cases there was an intersection. We will further investigate if we can eliminate instances without intersection (Figure 3a) in the first three features from the anomalies list. Such an insight can assist us to provide the experts an even more precise list of anomalies, save them more time in examining anomalies and raise their trust in the algorithm.

## 6 Conclusion and Future Work

We developed a method that uses SHAP values which are based on game theory, in order to explain anomalies revealed by an autoencoder. The feedback obtained from the domain experts about the explanations to the anomalies was positive. Our preliminary study showed that we can use the connection between the features with high reconstruction error and the explaining features that contribute the anomaly to detect interesting anomalies. We plan to further develop the proposed method by enlisting the assistance of additional domain experts and evaluate the effectiveness of our method with a larger user study. We would like to show that SHAP agrees more strongly with human explanation than LIME or DeepLIFT specifically on autoencoder-based anomaly detection. We will also examine the way we chose to visually depict the results.
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