Explainability for Misinformation in Financial Statements

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Abstract

Anomaly Detection techniques find application in various domains but they fail to explain *why* a particular data point is anomalous from domain perspective. In this paper, we attempt to provide explanation for anomalousness of a point which in our case is a company having misinformation in its financial statements. We propose 3 novel methods and experiment with a publicly available real dataset of financial statements of 4091 companies listed on Indian stock market. We also propose a novel evaluation method for evaluating significance of generated explanations in absence of the ground truth. We show that our method **Explanation using Maximal Isolation (EMI)** generates precise and statistically significant explanations as compared to baseline methods.

Keywords

Anomaly Detection, Explainability, Financial Audit, Misinformation

1. Introduction

Anomaly detection (AD) has been considered as a crucial task in various applications. It helps us to identify the scenarios which could lead to possible failure of a system as well as to obtain novel insights about it. The field covers various application domains like fraud detection, intrusion detection, fault detection, failure detection etc. Many times, the users of an application are unable to understand *why* a particular instance could be termed as anomalous from the domain perspective. For example, in intrusion detection, sudden rise in the CPU and memory usage could be termed as anomalous. However, only by careful analysis of other parameters like network flow, traffic congestion etc. the anomaly can be differentiated between intrusion or computation expensive process execution. Similarly, in fraudulent Financial Statements (FS) detection, if a company is susceptible of being fraudulent, auditors of FS would prefer to know what fields from the company filings are making that company susceptible of the fraud. Such *justifications* or *explanations* help to perform further investigations to know if the company is really fraudulent or it is just a false alarm which would save company's reputation. Such additional knowledge helps to understand the anomalous nature from the domain's point of view.

To provide user understandable meaning to the results of AD, attempts are being made to develop methods that can explain the working of the AD techniques. The area of research which deals with developing explanations for the models[1] (mostly complex) is referred to as eXplainable AI (XAI). However, these methods provide explanations describing why different AI (in our case AD) models are producing certain kinds of predictions. Other research area that serves the purpose of generating explanation for anomalousness of a point is Outlying Aspect Mining (OAM). Given a point, the goal of OAM techniques is to discover the aspects of the data in which the point becomes an outlier or interesting. XAI aims at providing explanation in varied form such as weighted or non-weighted subset of features, set of rules, pictorial representation and natural language [1]. OAM restricts itself to produce explanation as a set of features in the form of a subspace. XAI explains learning of an underlying detector and thus explanation can change if the detector is changed. OAM gives holistic view for interestingness of a point and is detector agnostic.

In this paper, we attempt to provide explanation for a company that is susceptible of having misinformation in its financial filings. "Misinformation" in FS is any information falsely mentioned e.g. overestimation on assets, underestimation of liabilities etc. In our previous work [2], we have attempted to show detection of misinformation from the FS. We take it ahead to provide explanation for the reported companies. We illustrate the technique by performing the experiments on a real dataset.

Contributions of the paper are as follows:

- 3 novel methods for explanation generation.
- A novel evaluation method for generated explanations in the absence of the ground truth.

[1] In our case model is always AD model. XAI is a vast field used for explaining learning of mostly supervised tasks.

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2. Related Work

The most basic form of explanation for an outlier is the subspace in which the point is highly discriminated from other points. The *outlying aspects* [3] are identified either by selecting top k subspaces with the highest measure of anomalous behavior, called as **Score and Search** or selecting a small relevant subspace aligned with the traditional feature selection problem of classification called **Feature Selection** [4]. Authors of [3] used distance-based *outlying degree (OD)* and a framework of dynamic subspace search, called HOS-miner to determine the subspace in which a query object is an outlier. A heuristic based search framework called OAMiner, developed in [5], searches the subspaces effectively. They rank all subspaces based on a kernel density estimation of a query object in that subspace. Authors of [6] propose *density Z-score* and *iPath* as *dimensionally unbiased* methods of determining outlying aspects and a *beam search* algorithm to tackle the challenge of search through exponentially high number of subspaces. OARank - a hybrid framework developed in [7] leverages the efficiency of feature selection approaches and the effectiveness and versatility of score-and-search based methods. In first stage, the features are ranked according to the potential to make the point outlying and in second stage score-and-search is performed on a smaller subset of the top ranked $k \ll m$ features where m is the total number of features.

Local Outliers with Graph Projection (LOGP) [8] defines a set of objective functions that learn the local discriminating subspace for a point in the transformed form of a graph. Outlying score of a point is computed as statistical distance of a point to its neighboring points in the transformed subspace. Authors of [9] proposed a novel criteria that measures the probability density function (pdf) associated with attribute value of an outlier with respect to pdf associated with same attribute values of other instances. Lower the pdf, more likely an instance is outlier. Anomaly Contribution Explainer (ACE) [10] and ACE-KL give contributions of each feature as a vector of real numbers. ACE approximates neighborhood of an outlier by generating neighboring points and then tries to fit a linear regression model to those neighbors with a modified loss function. Additional regularizer introduced in ACE-KL model tries to maximize the KL divergence between a uniform distribution and the calculated distribution of contributions. Authors of [11] propose sequential feature explanations (SFE), obtained by solving an optimization problem, wherein features are presented to the users one at a time until a confident judgment can be made about the anomaly.

The *Explainer* [12] provides expalanation in the form of disjunction of rules learnt by decision trees in random forest for a given anomalous point. Given a set of outliers and corresponding feature set, LOOKOUT [13] produces a set of optimal number of 2-D focus-plots based on the budget provided by the user in such a way that some of the anomalies have maximum anomaly score and are visually incriminated in the plot. Authors propose an approximation algorithm to solve the NP-Hard problem of generating optimal number of plots.

None of the above methods including [14] and [15], perform qualitative evaluation of the explanation in absence of ground truth. Some of the methods are model dependent therefore quality of the generated explanations depends on accuracy of the model. Our method EiForest uses iForest as a data structure and extracts other novel features from it as against using only the path length as scoring mechanism of a subspace as in iPath [6]. Use of only path length limits correctness of the explanations to the accuracy of the iForest algorithm. Rule set produced by our EMI method gives a subspace in m-dimensional space where the anomalous point is most isolated and there is no learning involved as against Explainer [12] in which rules are in disjunctive form and decision trees are trained using imbalanced data.

Algorithm 1: EMD

input : D, V, z, k_0, c; s.t. $1 \le k_0 \le |V|$; $c = 1.0$
output: E_{set} s.t. for each $\phi \in E_{set}$, $\phi \subseteq V$
begin
  $E_{set} = \emptyset$
  for $k = k_0$ **to** 0 **do**
    foreach $\phi \in 2^V$ *and* $|\phi| = k$ **do**
      foreach $z \in D$ **do**
        $d_z = R_V(z) - R_{V \setminus \phi}(z)$;
      if $d_z > 0$ *and* $d_z > \mu + c \cdot \sigma$ **then**
        $E_{set} = E_{set} \cup \phi$;
  return E_{set}

Table 1
Summary feature vector for EiForest

Name	Description
f_1	Average Depth of the trees
f_2	Average size of the leaf containing z
f_3	$\lvert p_v \rvert$
f_4	Average % drop in the partition after split
f_5	number of short paths (less than the maximum tree depth)
f_6	The level at which v is present in p_v on average
f_7	Average % drop in the partition after split for short paths
f_8	The level at which v is present in short paths on average

3. Problem definition

We have a m-dimensional dataset $D = \{x_1, x_2, .., x_n\}$ where each $x_i \in R^m$ and $V = \{v_1, v_2, .., v_m\}$ denotes feature set. Let us consider we have an anomalous instance z such that $z \in D$, which is obtained by some technique unknown to us. The objective is to generate an explanation E that makes the point anomalous. E could be set of features i.e. $E \subseteq V$ or set of rules.

As mentioned earlier, D is dataset of n companies where each company is represented in the form of 18-dimensional feature vector. z is an anomalous company that is susceptible of having misinformation in its FS.

4. Proposed methods

4.1. Explanation using Mahalanobis Distance (EMD)

We sort all the points in D in descending order of their Mahalanobis distance from the mean vector of D. $R_V(x)$, defined as *Mahalanobis rank*, is the rank of the point $x \in D$ in this sorted list. For any proper subset $A \subset V$ of features, the function $R_{V \setminus A}(x)$ is similarly defined, except that the Mahalanobis distance for points in D is computed after removing values of all features in A from every point in D. Note that a lower (smaller) rank indicates that the point is far from the mean vector in terms of Mahalanobis distance.

Potentially, explanation $E \subseteq V$ can be any set from power set 2^V. Algorithm EMD produces set of candidate explanations E_{set} for z such that for each set $\phi \in E_{set}$, rank difference is greater than a predefined threshold of $\mu + c \cdot \sigma$, where μ and σ are mean and standard deviation of all rank differences; and hence *explains* why z is anomalous. We restrict size of candidate set ϕ to k_0. If no such subset is found, the algorithm returns the empty set.

We compute the belief of an explanation $\phi \in E_{set}$ by using the standard deviation σ of the difference in $R_V(z)$ and $R_{V \setminus \phi}(z)$ for all the instances. We compute the belief as $Bel(z, \phi) = \frac{R_{V \setminus \phi}(z) - R_V(z)}{\sigma}$. Bel is nothing but the number of standard deviations the rank difference $R_{V \setminus \phi}(z) - R_V(z)$ is away from the mean of all the rank differences for z. In other terms, it is the *Mahalanobis* distance of the rank difference for z from the mean of all rank differences. Each set ϕ and it's respective belief value is given as an input to Dempster-Shafer evidence combination [16] method. Output set with highest belief given by this method is considered as valid E.

4.2. Explanation using iForest (EiForest)

iForest [17] recursively partitions the data by randomly selecting the features and its values for splitting. The data instances which get isolated in earlier splits are considered as anomalies. We tried to exploit this randomization concept with the help of iForest. We constructed a forest of T trees. Let P^z be set of T paths that lead to z. For a given instance z we found the set of features $V_P \subseteq V$ that appeared on at least one path in P^z, leading to isolation of z. For each variable $v \in V_P$ we constructed a 8-dimensional summary feature vector F_v^z using the paths leading z and containing v. Refer Table 1 for detailed description. We construct the set of summary vectors F_v for all points for all variables in the dataset. We then compute the Mahalanobis distance $\pi(v)$ from the mean of F_v for each $v \in V$. Once we get the distances for all $v \in V$, the top k variables are selected as an explanation E when sorted in the decreasing order of distances.

4.3. Explanation using Maximal Isolation (EMI)

We propose a method based on Integer Linear Programming (ILP) that isolates an anomalous point to maximum possible extent. The explanation E generated by EMI is conjunction between L specified number of conditions. These conditions when applied as filters on the entire dataset, would minimize the number of points other than the anomalous point which satisfy all the L conditions. Given set of features V and an anomalous point z which is to be explained, the explanation would be in the form $AND(v(\leq | \geq) z_v); v \in E$ where z_v is value of z for feature v and $E \subset V; |E| = L$. These L conditions can be considered as an explanation for anomalous nature of the point z, because they describe in what way the point z is different from the rest of the points in the data-set. Table 3 describes the ILP formulation in detail. Constraints C_3, C_4, C_5, and C_6 enforce that $\mathbf{y}[j]$ becomes 1 if and only if the j^{th} point breaks at least one condition used in the explanation. The objective function maximizes the number of such points. Effectively, it minimizes the number of other points which satisfy all the conditions in the explanation along with $\mathbf{z}$ which is the anomalous point to be explained.

5. Experiments

5.1. Dataset

In this paper, we use the dataset similar to the one used in [2]. FS and other financial documents such as annual

Table 2
Variables along with summary statistics

Notation	Name	Mean	St. Dev.
v_1	*Trade Receivables*	128.71	713.41
v_2	*Total Current Assets*	607.54	4023.13
v_3	*Total Non-Current Assets*	1004.4	7889.83
v_4	*Total Assets*	3477.89	37621.78
v_5	*Fixed Assets*	542.43	4975.47
v_6	*Inventories*	157.16	1466.18
v_7	*Total Current Liabilities*	509.89	3367.49
v_8	*Cash And Cash Equivalents*	99.46	1008.52
v_9	*Total Non-Current Liabilities*	471.15	4309.78
v_{10}	*Total Shareholders Funds*	628.39	5014.18
v_{11}	*Total liabilities*	981.04	6869.38
v_{12}	*Total Operating Revenues*	1071.59	11585.01
v_{13}	*Total Revenue*	1102.55	11752.28
v_{14}	*Profit/Loss Before Tax*	89.85	1019.65
v_{15}	*Revenue From Operations [Net]*	1049.7	11188.61
v_{16}	*Total Expenses*	1013.97	11216.54
v_{17}	*Depreciation And Amortisation Expenses*	35.37	313.28
v_{18}	*Net CashFlow From Operating Activities*	115.06	1414.2

Table 3
ILP formulation for generating explanations

Parameters:
•m: Number of features in the dataset
•n: Number of points in the dataset
•$\mathbf{z}$: The anomalous point to be explained
•L: Maximum number of features to be included in the explanation
•M_1: $n \times m$ size matrix representing whether other points have higher values than the anomalous point
•$M_1[j,i] = 1$ only if i^{th} feature of j^{th} point is greater than $\mathbf{z}[i]$
•$M_1[j,i] = 0$ otherwise
•M_2: $n \times m$ size matrix representing whether other points have lower values than the anomalous point
•$M_2[j,i] = 1$ only if i^{th} feature of j^{th} point is less than $\mathbf{z}[i]$
•$M_2[j,i] = 0$ otherwise
Variables:
•$\mathbf{x_1}$: m length binary array such that $\mathbf{x_1}[i] = 1$ implies that the i^{th} feature is included in the explanation as $v_i \leq z[i]$
•$\mathbf{x_2}$: m length binary array such that $\mathbf{x_2}[i] = 1$ implies that the i^{th} feature is included in the explanation as $v_i \geq z[i]$
•$\mathbf{y}$: n length array such that:
•$\mathbf{y}[j] = 1$ only if $\exists_i((M_1[j,i] = 1) \wedge (\mathbf{x_1}[i] = 1)) \vee ((M_2[j,i] = 1) \wedge (\mathbf{x_2}[i] = 1))$
//$\mathbf{y}[j]$ *is 1 only if j^{th} point breaks at least one of the conditions used in the explanation*
•$\mathbf{y}[j] = 0$ otherwise
($\mathbf{y}$ *need not be an integer variable.*)
Objective:
•Maximize $\sum_j \mathbf{y}[j]$
//*maximize the number of other points which do not satisfy at least one condition used in the explanation*
Constraints:
•C_1: $\sum_{i=1}^{m}(\mathbf{x_1}[i] + \mathbf{x_2}[i]) \leq L$
(*The number of variables chosen in the final explanation can be at most L.*)
•C_2: $\mathbf{x_1}[i] + \mathbf{x_2}[i] \leq 1$, $\forall_i$ s.t. $1 \leq i \leq m$
(*A variable should not be repeated in the set of L variables used for the explanation.*)
•C_3: $\mathbf{y}[j] \geq \mathbf{x_1}[i] \cdot M_1[j,i]$, $\forall_{ij}$ s.t. $1 \leq i \leq m, 1 \leq j \leq n$
($\mathbf{y}[j]$ *has to be at least 1 if $M_1[j,i]$ is 1 for any feature i which is included in the explanation.*)
•C_4: $\mathbf{y}[j] \geq \mathbf{x_2}[i] \cdot M_2[j,i]$, $\forall_{ij}$ s.t. $1 \leq i \leq m, 1 \leq j \leq n$
($\mathbf{y}[j]$ *has to be at least 1 if $M_2[j,i]$ is 1 for any feature i which is included in the explanation.*)
•C_5: $\mathbf{y}[j] \leq \sum_{i=1}^{m}(\mathbf{x_1}[i] \cdot M_1[j,i] + \mathbf{x_2}[i] \cdot M_2[j,i])$, $\forall_j$ s.t. $1 \leq j \leq n$
($\mathbf{y}[j]$ *should remain 0 for the points which do not contain 1 for any of the selected variables in $M_1[j]$ and $M_2[j]$.*)
•C_6: $\mathbf{y}[j] \leq 1$, $\forall_j$ s.t. $1 \leq j \leq n$
($\mathbf{y}[j]$ *should be at most 1.*)

results, financial ratios, capital structure, annual reports and audit reports for about 8000 Indian listed companies are available[2] for 10 years. We web-scrapped the FS of 4091 companies which were operating in the year 2014 and extracted 18 variables from their balance sheet and income statement. Refer table 2 for their summary statistics (values are in units of Rupees 10 million).

5.2. Baseline methods

We compare our methods with SHAP [18] and LIME [19] which are widely used in the literature of explainability for the task of classification and regression. To generate explanation for the task of anomaly detection, we created a labeled dataset of 282 companies. Among which, 49 companies having 'qualified audit opinion' were identified as anomalous and marked as class label '1'. Other companies were labeled with class label '0'. Then we trained a Random Forest Classifier on the labeled dataset and generated explanations for the anomalous instances. We chose 10 qualified companies as query points and generated explanations using all the methods.

Parameter settings: Parameter values for EMD algorithm are set as $c = 1.0$ and $k_0 = 3$. For EiForest, we set $T = 1000$ and retain top 5 features ($k = 5$). For EMI, first we experiment with $L = 2$. If the point is not sufficiently isolated we experiment with $L = 3$. For SHAP and LIME we have retained top 5 features having non-negative weight to maintain uniformity in the results.

5.3. Evaluation using ground truth

We have extracted audit reports for 4091 companies as mentioned in section 5.1. Companies which receive adverse comments from auditors are labeled as anomalous[3]. Variables which are mentioned in the auditor comments for those companies and are also part of the 18 variables, are extracted manually. These extracted variables act as ground truth or gold standard. Refer table 4 for generated explanations along with ground truth. Variables that are part of the ground truth are highlighted.

To judge the accuracy of the generated explanation, we consider precision P, recall R and F_1 measure for each explanation. We computed the P, R and F_1 measure for each generated explanation using the ground truth we extracted manually. Results of this evaluation are presented in table 5. This choice of selecting top 5 features for SHAP, LIME and EiForest affects the precision values. However, what should be optimal length of the explanation can be disputable. It can be observed that SHAP and LIME are able to detect at least 1 variable for most of the companies (8 out of 10 for both SHAP and LIME). EMI has given precision of 0.33 or above for 6 out of 10 companies. SHAP and LIME have the highest recall. However, average P and F_1 is highest for EMI method.

Few points that are worth mentioning are as follows: A company can be susceptible of having misinformation because of multiple reasons. Not all reasons can be captured in the given set of 18 variables. Also, we have manually extracted variables from audit reports based on our knowledge of the domain. Any domain supervision can improve the ground truth. Each method of explanation generation can discover different aspects of misinformation. Hence, considering ensemble of all results is also possible.

5.4. Evaluation in the absence of ground truth

We propose a novel method to evaluate quality of the generated explanations in the absence of ground truth. The intuition behind this method is that the anomalousness of a company should be significantly dependent on the variables given in the explanation. So a better explanation would contain the variables which have the

[2]https://www.moneycontrol.com/

[3]Annotated ground truth data can be made available on request

Table 4
Explanations generated by all the methods

Sr no.	Company	Ground truth	SHAP	LIME	EMD	EiForest	EMI
1	Winsome Diamond	$\{v_{14}, v_1\}$	$\{v_{11}, v_{16}, \underline{\boldsymbol{v_{14}}}, v_5, v_7\}$	$\{v_{16}, v_5, v_{11}, v_7, \underline{\boldsymbol{v_{14}}}\}$	$\{v_{16}, v_{18}, v_6\}$	$\{v_3, v_7, v_9, v_{11}, v_{13}\}$	$\{v_5 \leq 47.27 \bigwedge \underline{\boldsymbol{v_{14}}} \leq -256.33\}$
2	Ashapura Mine	$\{v_{14}, v_{10}\}$	$\{v_{11}, v_4, \underline{\boldsymbol{v_{10}}}, v_5, v_{16}\}$	$\{v_{11}, \underline{\boldsymbol{v_{10}}}, v_{16}, v_5, v_7\}$	$\{v_1, \underline{\boldsymbol{v_{14}}}, v_{18}\}$	$\{v_{11}, \underline{\boldsymbol{v_{10}}}, v_{17}, v_6, v_{15}\}$	$\{\underline{\boldsymbol{v_{10}}} \leq -144.3 \bigwedge \underline{\boldsymbol{v_{14}}} \geq 141.27\}$
3	Western Ministi	$\{v_7, v_{11}, v_{14}, v_{10}\}$	$\{\underline{\boldsymbol{v_{14}}}, v_4, v_{16}, v_2, v_3\}$	$\{\underline{\boldsymbol{v_{10}}}, v_9, v_{12}, v_{15}, v_4\}$	**All**	$\{v_3, \underline{\boldsymbol{v_{14}}}, v_9, v_1, v_{18}\}$	$\{v_2 \leq 0.0 \bigwedge v_{18} \geq 115.06\}$
4	Oudh Sugar Mill	$\{v_{14}, v_{10}\}$	$\{\underline{\boldsymbol{v_{14}}}, v_{16}, v_{11}, v_5, v_4\}$	$\{\underline{\boldsymbol{v_{14}}}, v_7, v_{11}, v_5, v_{16}\}$	$\{v_1, v_{18}, v_8\}$	$\{v_6, v_7, v_9, v_{11}, v_{12}\}$	$\{v_2 \leq 1056.51 \bigwedge v_6 \geq 951.19\}$
5	Sarda Papers	$\{v_{17}, v_5, v_4, v_{14}\}$	$\{v_9, v_{12}, \underline{\boldsymbol{v_4}}, v_{15}, \underline{\boldsymbol{v_5}}\}$	$\{v_{12}, v_{15}, \underline{\boldsymbol{v_5}}, \underline{\boldsymbol{v_4}}, v_6\}$	NA	$\{v_8, \underline{\boldsymbol{v_4}}, v_{15}, \underline{\boldsymbol{v_{14}}}, v_7\}$	$\{v_{10} \leq 0.01 \bigwedge v_{11} \leq 4.1 \bigwedge \underline{\boldsymbol{v_4}} \geq 4.11\}$
6	Nicco Uco Fin	$\{v_{11}, v_{14}, v_{10}\}$	$\{\underline{\boldsymbol{v_{11}}}, \underline{\boldsymbol{v_{14}}}, v_{12}, v_{16}, v_5\}$	$\{\underline{\boldsymbol{v_{11}}}, \underline{\boldsymbol{v_{10}}}, v_{16}, v_7, \underline{\boldsymbol{v_{14}}}\}$	$\{\underline{\boldsymbol{v_{11}}}, v_{18}, v_6\}$	$\{v_7, \underline{\boldsymbol{v_{14}}}, v_{13}, v_9, v_{12}\}$	$\{\underline{\boldsymbol{v_{10}}} \leq -524.1 \bigwedge \underline{\boldsymbol{v_{11}}} \leq 537.41\}$
7	Atlanta	$\{v_{10}, v_3, v_{14}\}$	$\{v_{11}, v_5, v_{16}, v_4, v_7\}$	$\{v_{11}, v_{16}, v_5, v_7, v_4\}$	$\{v_1, \underline{\boldsymbol{v_{14}}}, v_8\}$	$\{v_7, v_{16}, v_6, v_4, v_2\}$	$\{v_{13} \leq 314.28 \bigwedge v_{12} \geq 312.1\}$
8	Samtel Color	$\{v_{11}, v_6, v_2\}$	$\{\underline{\boldsymbol{v_{11}}}, v_{14}, v_{12}, v_{16}, v_{10}\}$	$\{\underline{\boldsymbol{v_{11}}}, v_{10}, v_{16}, v_{14}, v_5\}$	$\{v_1, v_{18}, v_8\}$	$\{v_7, \underline{\boldsymbol{v_{11}}}, v_{10}, v_{14}, v_{16}\}$	$\{v_{10} \leq -550.14 \bigwedge \underline{\boldsymbol{v_{11}}} \leq 810.76\}$
9	Aruna Hotels	$\{v_2, v_7, v_6\}$	$\{v_{14}, v_{16}, v_{11}, v_5, v_{12}\}$	$\{v_{16}, v_5, v_{14}, v_{18}, v_4\}$	$\{v_{10}, v_{17}, v_3\}$	$\{v_6, v_9, \underline{\boldsymbol{v_2}}, v_{17}, v_{13}\}$	$\{v_4 \leq 131.98 \bigwedge v_5 \geq 119.92\}$
10	CFL Capital	$\{v_{11}\}$	$\{v_{10}, \underline{\boldsymbol{v_{11}}}, v_{14}, v_5, v_{12}\}$	$\{\underline{\boldsymbol{v_{11}}}, v_{10}, v_{14}, v_9, v_{16}\}$	$\{\underline{\boldsymbol{v_{11}}}, v_{18}, v_6\}$	$\{v_7, v_{14}, v_{12}, v_{13}, v_{18}\}$	$\{v_{10} \leq -496.27 \bigwedge \underline{\boldsymbol{v_{11}}} \leq 506.19\}$

Table 5
Precision, Recall and $\boldsymbol{F_1}$ measure for all methods for 10 companies

Sr no.	Company	SHAP			LIME			EMD			EiForest			EMI		
		P	R	F_1	P	R	F_1	P	R	F_1	P	R	F_1	P	R	F_1
1	Winsome Diamond	0.20	0.50	0.29	0.20	0.50	0.29	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.50	0.50
2	Ashapura Mine	0.20	0.50	0.29	0.20	0.50	0.29	0.33	0.50	0.40	0.20	0.50	0.29	1.00	1.00	1.00
3	Western Ministi	0.20	0.25	0.22	0.20	0.25	0.22	0.22	1.00	0.36	0.20	0.25	0.22	0.00	0.00	0.00
4	Oudh Sugar Mill	0.20	0.50	0.29	0.20	0.50	0.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	Sarda Papers	0.40	0.50	0.44	0.40	0.50	0.44	0.00	0.00	0.00	0.40	0.50	0.44	0.33	0.25	0.29
6	Nicco Uco Fin	0.40	0.67	0.50	0.60	1.00	0.75	0.33	0.33	0.33	0.20	0.33	0.25	1.00	0.67	0.80
7	Atlanta	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.33	0.33	0.00	0.00	0.00	0.00	0.00	0.00
8	Samtel Color	0.20	0.33	0.25	0.20	0.33	0.25	0.00	0.00	0.00	0.20	0.33	0.25	0.50	0.33	0.40
9	Aruna Hotels	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.33	0.33	0.00	0.00	0.00
10	CFL Capital	0.20	1.00	0.33	0.20	1.00	0.33	0.33	1.00	0.50	0.00	0.00	0.00	0.50	1.00	0.67
	Avearge	0.20	0.43	0.26	0.22	**0.46**	0.29	0.16	0.32	0.19	0.15	0.23	0.18	**0.38**	0.38	**0.37**

Table 6
Results for evaluation with method A and B

Sr no.	Company	SHAP	LIME	EMD	EiForest	EMI
1	Winsome Diamond	(1,1)	(1,1)	(0,0)	(1,1)	(1,0)
2	Ashapura Mine	(0,0)	(0,0)	(0,0)	(0,0)	(0,1)
3	Western Ministi	(0,1)	(1,1)	(0,0)	(0,0)	(0,0)
4	Oudh Sugar Mill	(0,0)	(0,0)	(0,0)	(1,1)	(1,1)
5	Sarda Papers	(0,0)	(1,0)	(0,0)	(0,0)	(0,0)
6	Nicco Uco Fin	(0,0)	(0,1)	(0,0)	(0,0)	(0,1)
7	Atlanta	(0,0)	(0,0)	(0,0)	(0,0)	(0,0)
8	Samtel Color	(1,1)	(1,1)	(0,0)	(1,1)	(1,1)
9	Aruna Hotels	(0,1)	(0,1)	(0,0)	(0,1)	(0,0)
10	CFL Capital	(0,1)	(0,1)	(0,0)	(0,0)	(1,1)
	Total	(2,5)	(4,6)	(0,0)	(3,4)	(4,5)

largest effect on the anomaly score of the company.

For a given point x in dataset, we define $\Delta_{E,A}(x)$ as difference in anomaly score of x and x' where x' is perturbed version of x and E is the explanation. The anomaly score is obtained using anomaly detection technique A such that higher the score, more anomalous is the point. From the original point x, we replace the values of variables in E by their corresponding median values to get x'. Therefore, $\Delta_{E,A}(x) = A(x) - A(x')$. For example, for Winsome Diamond if original anomaly score using anomaly detection technique A is 0.8 and score obtained after perturbing variables v_5 and v_{14} (explanation provided by EMI) is 0.6 then $\Delta_{\{v_5,v_{14}\},A}$(Winsome Diamond) = 0.8 − 0.6 = 0.2. In our experiments we have used auto-encoder based anomaly detector from pyOD package [20]. Practically, any anomaly detection technique can be used. Depending on how well E explains z, $\Delta_{E,A}(z)$ can be positive, negative or even zero. Positive value indicates that z' is more 'normal' than z and negative value indicates other way round. Zero implies that there is no change in the nature of the point. To determine whether the difference $\Delta_{E,A}(z)$, is statistically significant or not, we use the following two methods.

5.4.1. Method A: Comparison with "normal" companies

In this method, we judge the effect of variable perturbation on other companies. We randomly choose 30 companies $C = \{x|x \neq z\}$ and compute $\Delta_{E,A}(x)$ for all these companies by perturbing variables in E. Note that, here we are checking for E given by some method for an anomalous company z, e.g. $\{v_5, v_{14}\}$ for Winsome diamond. So we perturb values of $\{v_5, v_{14}\}$ for these 30 companies and obtain the score difference values as set SD^N. Therefore, $SD^N = \{\Delta_{E,A}(x)|x \in C\}; |SD^N| = 30$. The statistical significance of $\Delta_{E,A}(z)$ with respect to SD^N is determined using one-sided one sample t-test where the null and alternate hypotheses are as follows:

$$H_0 \;:\; \text{mean of } SD^N = \Delta_{E,A}(z)$$
$$H_1 \;:\; \text{mean of } SD^N < \Delta_{E,A}(z)$$

If the p-value is less than significance level $\alpha = 0.05$, the null hypothesis is rejected and $\Delta_{E,A}(z)$ is accepted to be statistically significant and hence E is a good explanation for the anomalousness of the selected company. In table 6, we mark 1 as the first value of each tuple wherever explanation obtained is found to be significant with respect to this method.

5.4.2. Method B: Comparison with other subsets of variables

In this method, for the given company z, we randomly choose set of variables W of size $|E|$ from power set 2^V 30 times and each time compute $\Delta_{W,A}(z)$ e.g. randomly choosing variable set of size 2 such that none of the variables in this set is v_5 or v_{14} for Winsome Diamond. We repeat this process 30 times and obtain score difference values SD^W as follows: $SD^W = \{\Delta_{W,A}(z)|W \in 2^V), |W| = |E|, W \cap E = \emptyset\}$. Finally, we check the statistical significance of $\Delta_{E,A}(z)$ w.r.t. SD^W as described in Method A above. In table 6, we mark 1 as the first value of each tuple wherever explanation obtained is found to be significant with respect to this method.

Evaluation results: Table 6 shows that number of companies for which EMI produces statistically significant explanations is at par with one of the baselines, though the explanation length is short and explanation is in the form of conjunction of conditions.

6. Conclusions and future work

Explainability has various notions in the literature of machine learning. In this paper, we aim at providing explanation for companies that have misinformation in their FS so that auditors can perform further investigations. We propose 3 novel methods viz., mahalanobis distance based EMD, iForest based EiForest and ILP based EMI method. We have extracted 18 financial variables from FS of 4091 Indian listed companies. We generated explanations for companies whose FS had misinformation as per our knowledge. For illustration purpose, we chose 10 companies and evaluated the quality of generated explanations. We observe that EMI method generates comparatively precise and statistically significant explanations. EMI method gives output in the form of conjunction of conditions and is more desirable.

Going ahead we plan to widen the scope by experimenting with more variables and companies. Finally we aim at capturing the domain knowledge and generating explanations in more user friendly format.

References

[1] V. Y. Tchaghe, G. Smits, O. Pivert, Anomaly explanation: A review, DKE (2021).

[2] A. Shinde, S. Vaishampayan, M. Apte, G. K. Palshikar, Unsupervised detection of misinformation in financial statements 35 (2022).

[3] J. Zhang, M. Lou, T. W. Ling, H. Wang, Hos-miner: A system for detecting outlying subspaces of high-dimensional data, in: VLDB, 2004, pp. 1265–1268.

[4] D. Samariya, J. Ma, S. Aryal, A comprehensive survey on outlying aspect mining methods, arXiv preprint arXiv:2005.02637 (2020).

[5] L. Duan, G. Tang, J. Pei, J. Bailey, A. Campbell, C. Tang, Mining outlying aspects on numeric data, DMKD 29 (2015) 1116–1151.

[6] N. X. Vinh, J. Chan, S. Romano, J. Bailey, C. Leckie, K. Ramamohanarao, J. Pei, Discovering outlying aspects in large datasets, DMKD 30 (2016) 1520–1555.

[7] N. X. Vinh, J. Chan, J. Bailey, C. Leckie, K. Ramamohanarao, J. Pei, Scalable outlying-inlying aspects discovery via feature ranking, in: PAKDD, Springer, 2015, pp. 422–434.

[8] X. H. Dang, I. Assent, R. T. Ng, A. Zimek, E. Schubert, Discriminative features for identifying and interpreting outliers, in: International Conference on Data Engineering, IEEE, 2014, pp. 88–99.

[9] F. Angiulli, F. Fassetti, G. Manco, L. Palopoli, Outlying property detection with numerical attributes, DMKD 31 (2017) 134–163.

[10] X. Zhang, M. Marwah, I.-t. Lee, M. Arlitt, D. Goldwasser, Ace–an anomaly contribution explainer for cyber-security applications, in: International Conference on Big Data, IEEE, 2019, pp. 1991–2000.

[11] M. A. Siddiqui, A. Fern, T. G. Dietterich, W.-K. Wong, Sequential feature explanations for anomaly detection, ACM TKDD 13 (2019) 1–22.

[12] M. Kopp, T. Pevnỳ, M. Holeňa, Anomaly explanation with random forests, Expert Systems with Applications 149 (2020) 113187.

[13] N. Gupta, D. Eswaran, N. Shah, L. Akoglu, C. Faloutsos, Beyond outlier detection: Lookout for pictorial explanation, in: ECML-PKDD, 2018, pp. 122–138.

[14] W. Samek, A. Binder, G. Montavon, S. Lapuschkin, K.-R. Müller, Evaluating the visualization of what a deep neural network has learned, Transactions on Neural Networks and Learning Systems 28 (2016) 2660–2673.

[15] J. A. Oramas Mogrovejo, K. Wang, T. Tuytelaars, Visual explanation by interpretation: Improving visual feedback capabilities of deep neural networks, in: ICLR, openReview, 2019.

[16] K. Sentz, S. Ferson, Combination of evidence in dempster-shafer theory (2002).

[17] F. T. Liu, K. M. Ting, Z.-H. Zhou, Isolation forest, in: 8th ICDM, IEEE, 2008, pp. 413–422.

[18] H. W. Kuhn, A. W. Tucker, Contributions to the Theory of Games, 28, Princeton University Press, 1953.

[19] M. T. Ribeiro, S. Singh, C. Guestrin, "why should i trust you?" explaining the predictions of any classifier, in: ACM SIGKDD, 2016, pp. 1135–1144.

[20] Y. Zhao, Z. Nasrullah, Z. Li, Pyod: A python toolbox for scalable outlier detection, JMLR 20 (2019) 1–7.