ORIE 5741

Anomaly Detection in the U.S. Electricity Grid Data

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1. Overview

This project investigates the application of an ensemble model for anomaly detection in Energy Information Administration hourly electric grid data. Utilizing a comprehensive blend of machine learning algorithms: K-Means, DBSCAN, One-Class SVM, Autoencoder, Random Forest, and Isolation Forest, the study aims to improve the identification of anomalous behavior in power demand data. The results from the algorithmic approach to anomaly screening have shown the potential to efficiently mitigate data quality issues, helping traders to make informed decisions and maximize profits.

2. Problem Definition

Electricity trading is a complex process that involves trading electricity on various markets. Informed decision-making is essential for successful electricity trading, and electricity grid data is a valuable resource that provides insights into market trends, price forecasting, and regulatory compliance. By analyzing this data, traders can identify potential opportunities and risks, allowing them to make informed decisions.

However, anomalies in electricity grid data can have significant consequences for traders. These anomalies can occur due to various reasons, such as data errors, measurement inaccuracies, or equipment malfunctions, and can lead to incorrect price forecasting, improper risk management, and inaccurate regulatory compliance. We aim to identify anomalies in electricity grid data to address this problem. By detecting and replacing these anomalies, we can improve the accuracy in these areas, helping traders to make informed decisions and maximize profits.

3. Data

3.1. Data Characteristics

The Energy Information Administration (EIA) [1] offers access to electricity grid data with a range of features such as demand, demand forecast, net generation, and generation by various energy sources. It also separates the U.S. electricity grid into several regions. Each region, besides an aggregated data source, has several smaller data sources called balancing authorities. Due to the nature of electricity grid data, the raw data is relatively well-maintained. In this project, we chose to analyze data from the Northwest region because it consists of over twenty independent balancing authorities, making it more likely for an anomaly to occur. Our data spans from July 1, 2015 to February 10, 2023 and has over 66000 hourly observations.

3.2. Data visualization

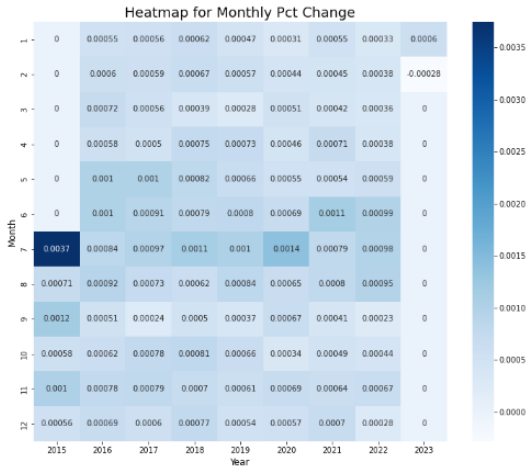


Figure 1 Heatmap Of Demand

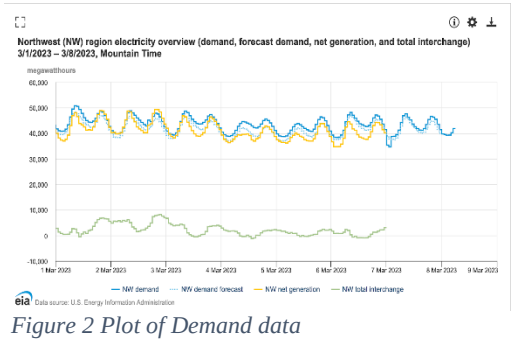


Figure 2 Plot of Demand data

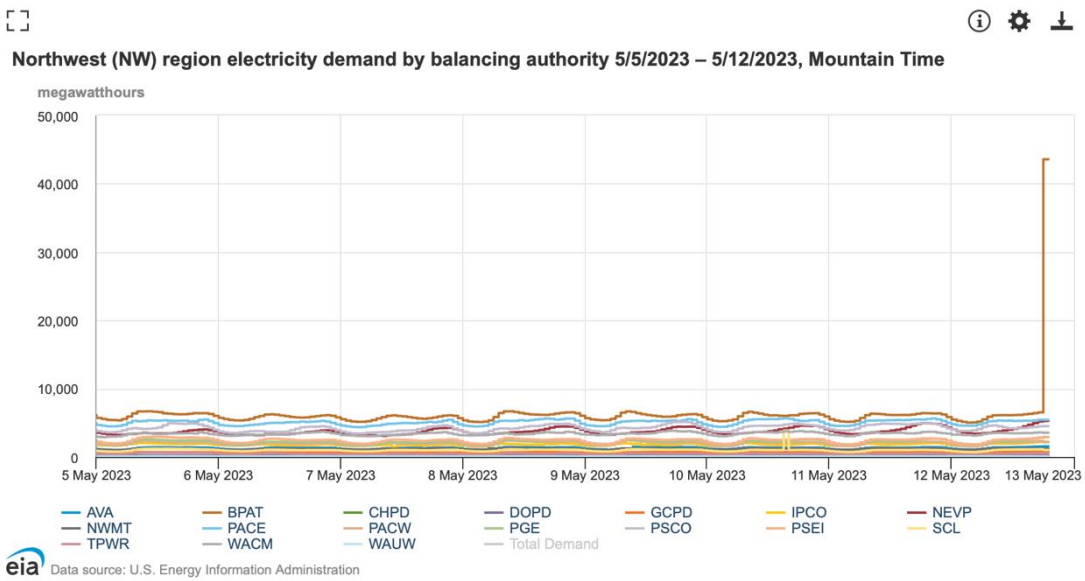


Figure 3 Subregion demand data and an example of an anomaly on 13 May 2023

Figure 1 shows the heatmap of the percentage of monthly demand change, which intuitively shows some larger changes in darker colors. Figure 2 is a visualization of several time series in the NW region. Figure 3 is the demand plot of the subregion and the last data is actually an anomaly because no demand can increase so much in one day.

3.3. Data Preprocessing

To effectively detect anomalies in the aggregated demand in the Northwest region, it is necessary to preprocess the raw data acquired from the EIA. In this study, we identified that not all of the features included in the dataset are essential for anomaly detection. Therefore, we performed feature selection to reduce redundant features and avoid introducing noise to the data. [2] Specifically, we selected the aggregated demand time series for the entire Northwest region, as well as the demand for the seven largest balancing authorities. Additionally, we included the first- and second-degree rate of demand change as features, as these can also serve as indicators of anomalous data. Furthermore, our domain knowledge of electricity data led us to discover that the demand is unlikely to remain unchanged for two consecutive hours. Hence, we created a new binary feature that marks an entry as 1 when this event occurs and as 0 otherwise, to assist machine learning algorithms in identifying these anomalies.

Challenges	Solution
Understanding seasonality, patterns, and obvious anomalies	Extensive exploratory data analysis (EDA)
Missing values	Imputed missing data using linear regression
Difficulty capturing diverse data distributions of power sources within the Northwest (NW) region	Identified, processed, and cleaned datasets for the top 7 (among 21) NW region power sources, creating 7 new features
Feature Engineering	Added first- and second-degree delta of demand
Features of different magnitudes	Standardized the data for each column
Existence of apparent anomalies	Created a new feature that labels those apparent anomalies

Table 1 Challenges from messy data and Solutions

Although the EIA maintains the data well, it still contains missing values, which may negatively impact the performance of machine learning algorithms. We utilized linear regression to impute missing values in time series from balancing authorities based on their high correlation with the Northwest aggregated demand. Additionally, we standardized each column to ensure that different features with varying magnitudes would be treated equally during the modeling process. Overall, these preprocessing steps enabled us to make the data for anomaly detection more robust.

4. Methodology

4.1. K-Means

K-Means is a popular unsupervised machine learning algorithm that can be effectively utilized for anomaly detection. [3] In this context, the algorithm functions by partitioning the input data into distinct clusters based on the similarity of data points, which is typically determined by their Euclidean distance. During the clustering process, K-Means iteratively refines the centroids of each cluster to minimize the within-cluster variation. Once the optimal clustering is achieved, anomalies can be identified by analyzing the distance of each data point from its corresponding cluster centroid. Data points located far from their centroids are considered outliers, as they deviate significantly from the common patterns observed within the cluster. K-Means-based anomaly detection has proven particularly valuable due to its simplicity, scalability, and ability to uncover hidden patterns in large and complex datasets.

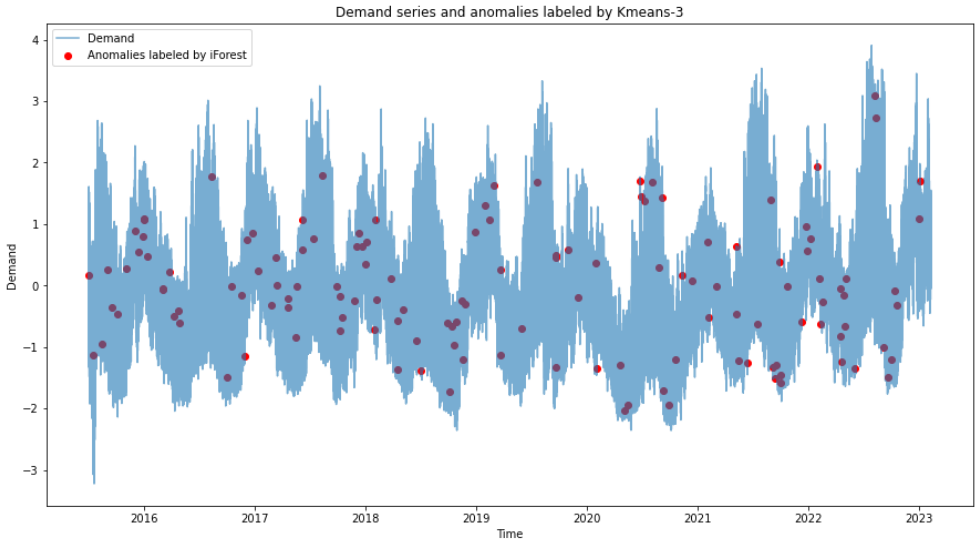


Figure 2 k-means result

4.2. DBSCAN

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is another popular unsupervised machine learning algorithm used for anomaly detection. [4] Unlike K-Means, DBSCAN does not require us to specify the number of clusters upfront and it can discover clusters of arbitrary shapes, making it particularly useful for datasets with complex spatial distributions. It works by defining clusters as high-density regions in the data space separated by areas of lower density. During its operation, DBSCAN classifies data points into three categories: core points, border points, and noise points. In the context of anomaly detection, the noise points, which lie in low-density regions and are far from any cluster, are considered anomalies. Comparatively, while K-Means is simpler and more scalable for large datasets, it may struggle with detecting anomalies when data is not spherical or evenly distributed, as it assumes isotropic clusters. DBSCAN, on the other hand, can handle complex spatial distributions better, and it inherently identifies anomalies as part of its clustering process, but it may struggle with datasets of varying density.

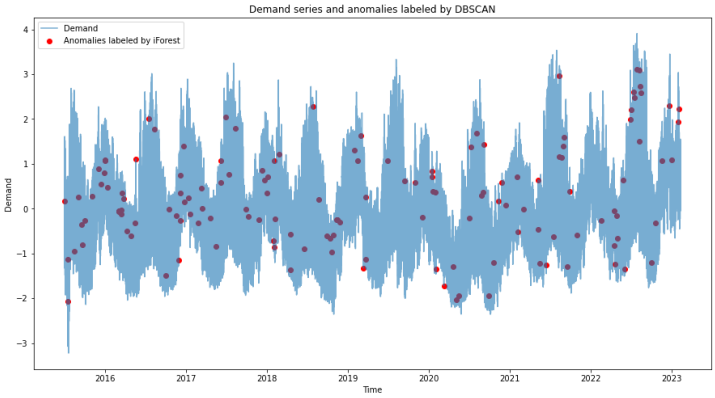


Figure 3 DBSCAN result

4.3. One Class SVM

The conventional SVM is used for classification and identifies a hyperplane with the maximum margin to distinguish positive and negative examples. However, one class SVM operates by minimizing the hypersphere of the single class of examples in the training data and treating all other samples outside of the hypersphere as outliers that fall outside of the training data distribution. [5]

To learn the non-linear relationship among features, we used the "RBF" function to transform the data onto a higher dimension. Then we trained the model on the mapped data, and set a margin around the hyperplane to label data as anomalies or not.

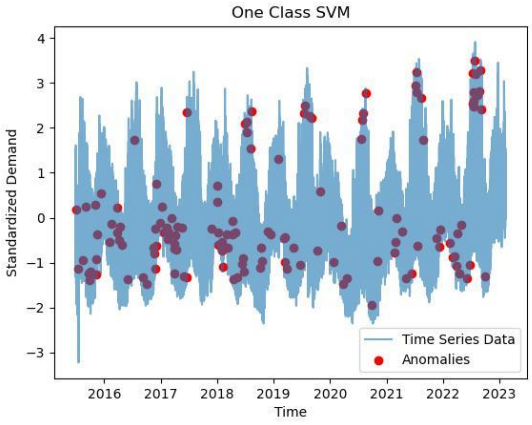


Figure 4 One-class SVM result

4.4. Autoencoder

Autoencoder is a type of neural network that can learn to replicate their inputs as outputs. [6] Unlike PCA, which is a linear method for dimensionality reduction, autoencoders use non-linear transformations that allow them to learn more powerful generalizations. Autoencoder has two layers. The first layer is the encoder layer, it takes in input data with a high dimensionality and converts it into latent data with a lower dimensionality. The second layer is the decoder layer, it takes the output of the encoder as input and aims to reconstruct the original input data. For our project, we used the ReLU function as the encoder function, and tanh function as the decoder function.

When an autoencoder is fed an abnormal input, the reconstruction error is likely to be significant, suggesting a deviation from the normal pattern. Autoencoders can thus be used to detect abnormalities based on the size of the reconstruction error.

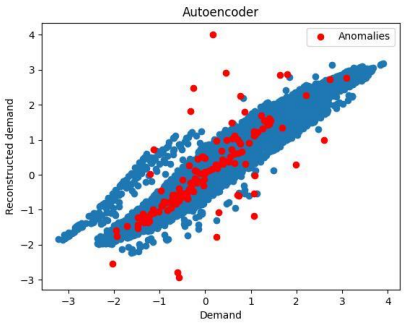


Figure 5 Autoencoder results (reconstructed demand vs original demand)

4.5. Random Forest

Random Forest is an ensemble supervised learning algorithm that utilizes multiple decision trees and bagging to perform classification and regression tasks [7]. Each decision tree is constructed by recursively partitioning the data based on the most informative feature at each node. The split is made based on maximizing a split criterion, such as information gain and Gini impurity.

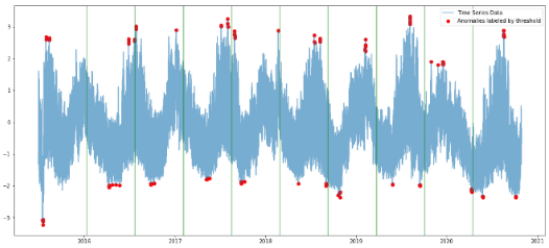


Figure 6 How we use windows and thresholding to label anomalies

To train the random forest model, we had to create labels as the true anomaly labels were unknown. We did this by setting thresholds to identify data points outside the expected range, aiming for a consistent 0.5% identified anomalies across all algorithms. Due to seasonality in demand data, we used half-year windows for a more uniform distribution of anomalies, as shown in figure X. The labeled data was then used to train the random forest model.

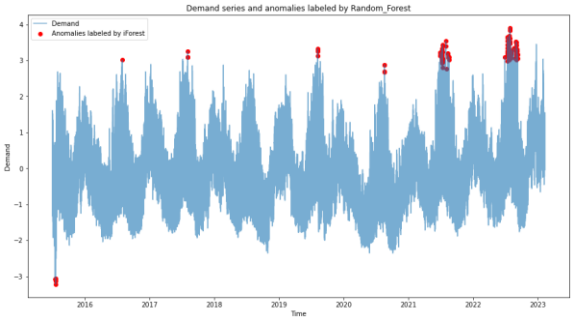


Figure 7 Random Forest result

4.6. Isolation Forest

We also used the isolation forest algorithm for anomaly detection, which efficiently separates anomalous data from normal data. The algorithm randomly selects features and split values to partition the data recursively until each data point is isolated in its own leaf node. The average depth of the tree required to isolate a data point is used to calculate its anomaly score. Anomalous data points have a lower average depth value and therefore a higher anomaly score, as they can be more easily separated from normal data points with fewer splits. Isolation forest is an unsupervised learning algorithm, which makes it suitable for our

task without true anomaly labels. Its *contamination* hyperparameter also allowed us to set the percentage of anomalies in the data.

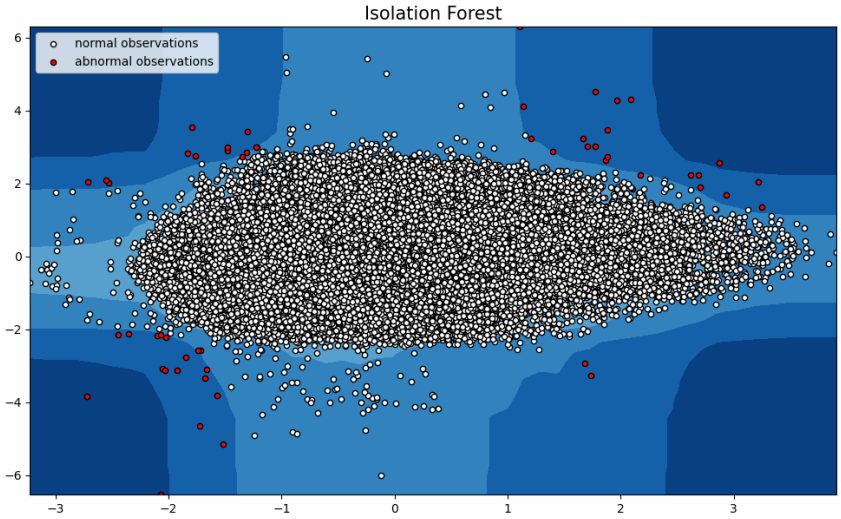


Figure 8 Isolation Forest result heatmap

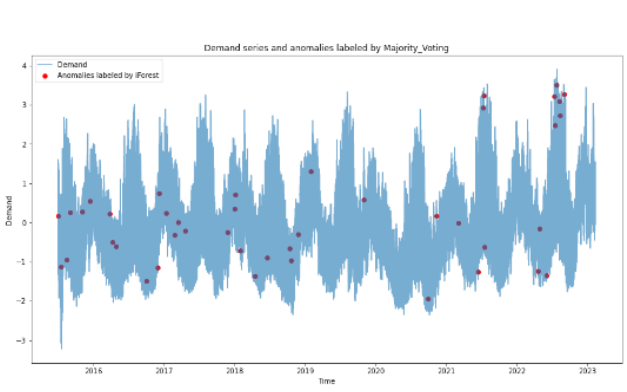
4.7. Ensemble Method - Majority Voting

After running the above six algorithms and generating six sets of anomaly labels, we used majority voting to get the final results. To avoid biases toward a single algorithm because of the number of anomalies it produces, we tweaked hyperparameters to keep the percentage of anomalies in the data around 0.2% for all algorithms.

5. Results

5.1. Anomaly Labels

The results produced by the six anomaly detection algorithms and their majority-voted final results are shown above. Notably, the K-Means and DBSCAN algorithms generated similar anomaly labels that were rather uniformly distributed across the entire time frame. Conversely, the tree-based algorithms, namely random forest, and isolation forest, identified anomalies that were more concentrated around extreme values, particularly towards the end of the time frame. In contrast, the One-class SVM and autoencoder algorithms produced results that were intermediate to the two aforementioned types of algorithms, as the anomalies exhibited a moderately dispersed distribution with some extreme values. These differences in the anomaly detection results highlight the potential benefits of using majority voting to generate final results. By aggregating the outputs of different algorithms, the overall errors are reduced, and the generalizability of the approach is enhanced.



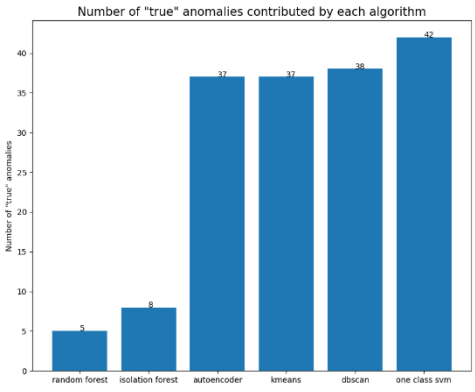


Figure 9 9 Anomaly labels from majority voting *Figure 10 Number of true anomalies from each model*

The majority-voted results are shown above. There are a total of 42 final anomalies. We can see that it gives a more realistic and reasonable set of labels than each individual result, both in terms of the number of anomalies and the distribution of them. Upon closer examination, we checked some of the labeled entries and confirmed that they are actual anomalies. We can also see that one class SVM participated in all of the final anomalies which demonstrated strong accuracy of this model.

In addition, we used the final results from the ensemble method as the "true" anomaly label to calculate metrics such as precision, recall, and AUC. Our results show that one-class SVM outperformed others while tree-based algorithms underperformed. But it is important to note that this is not conclusive as we do not have the actual anomaly labels. Computationally, clustering-based algorithms such as DBSCAN were slower whereas the tree-based algorithms were relatively fast.

	Recall	Precision	F-1 score	AUC-ROC	Space complexity	Time complexity
K-Means [11]	0.9985	0.9999	0.9992	0.9295	O(n * K * d)	O(n * K * I * d)
DBSCAN [12]	0.9984	0.9999	0.9992	0.9411	O(n)	O(n*log(n))
One-Class SVM [13]	0.9986	1.0000	0.9993	0.9877	O(n^2)	O(n * d)
Autoencoder [14]	0.9985	0.9999	0.9992	0.9295	O(n * d)	O(n^2)
Random Forest [15]	0.9983	0.9994	0.9989	0.5573	O(n * t)	O(n * t * log(n) * d)
Isolation Forest [16]	0.9981	0.9995	0.9988	0.5921	O(n)	O(t * n * log(n) * d)

Table 2 Evaluation metrics

In anomaly detection, the majority of instances are "normal" (negative class) and a small minority are "anomalies" (positive class). This is known as an imbalanced classification problem. This would lead to a high number of True Positives (TPs) compared to True Negatives (TN), False Positives (FP), and False Negatives (FN). As a result, we have a high recall, precision and F-1 score. While high precision, recall, and F-1 score are generally desirable, here our goal is to show that **individual models are contributing effectively to the ensemble model**.

5.2. Limitation of Distance-Based Models

All models except random forest and isolation forest are using distance metric for anomaly detection. Even though their ensemble result has been identified good in the view of trader, there are still limitations. First would be diverse error. Because they are using the distance metric, the majority-generated true labels will be biased towards them, that could be one reason why they achieved a higher score than tree-based models.

Furthermore, not all anomalies can be detected solely based on values that are too high or low. Anomalies can also manifest as abnormal patterns, such as consecutive values that are the same. While a new feature has been introduced to account for this behavior, existing models still struggle to distinguish these anomalies from regular data points. Only the k-means method was able to correctly identify all anomalies by clustering them together with the aid of the new feature.

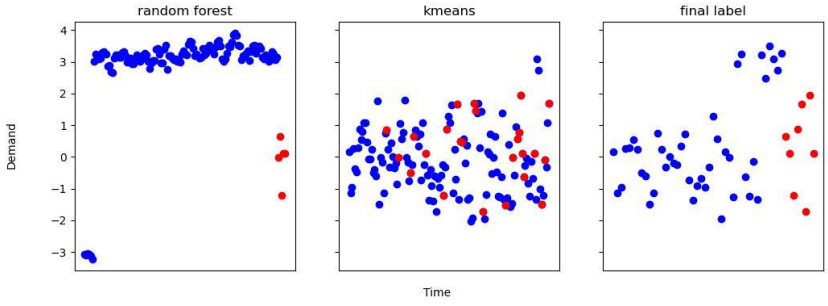


Figure 11 Apparent labels visulization

5.3. Weapon of Math Destruction

"Weapons of Math Destruction" refers to mathematical models or algorithms that, despite their seemingly objective nature, can lead to harmful or destructive outcomes, particularly for the most vulnerable segments of society [9]. Such models are typically characterized by being opaque, scalable, and damaging. For this project, following potential issues could arise:

1. **Opacity**: Machine learning algorithms such as Autoencoder are often black boxes. This could result in unpredictable behavior, such as false positive or false negative detections, which could cause unnecessary panic or missed warnings.

2. **Scale**: If a model with inherent biases or errors is used on a large scale, the negative impact can be widespread. While the project looks at the whole Northwest region, the associated trading volume is relatively low.

3. **Damage**: Our model is an effective way to screen for anomalies but if the model is blindly trusted it could lead to significant trading losses.

It's important to note that the risk of becoming a weapon of math destruction doesn't inherently reside in the algorithms themselves, but in how they are used, the data they are trained on, and the interpretations made from their predictions. Our project is geared towards electricity traders primarily for algorithmic screening of anomalies hence the possibility of our model being used as a weapon of math destruction is very low.

5.4. Fairness

While our project primarily concerns electricity traders and firms, fairness still has potential relevance. This pertains to ensuring the algorithm doesn't generate biases that may unfairly affect specific groups of traders or participants. One main concern is data representation [10]. We're using open-source data from the EIA website, but if some market participants have access to superior non-public data, this could lead to imbalances and potentially breach trading regulations. Thus, it's crucial to ensure the model operates fairly even in this context.

6. Conclusions

Based on our research, there exists a trade-off between algorithm performance and calculation time. The One-class SVM algorithm achieved the highest score across all four metrics, but has a moderate running time. On the other hand, tree-based algorithms had the lowest scores but were the fastest. Our final labels were evaluated by actual traders and were deemed reasonable, thus our approach provides an effective preliminary screening method for traders and experts to identify anomalies with improved efficiency.

While we are confident that our results can have positive practical impacts on traders' workflow, we do think that it can be improved. One possible direction for future work would be to address the issue of diverse errors, where similar weaknesses in models may reduce ensemble benefits. One potential solution would be to use diverse and complementary algorithms to offset individual weaknesses. Additionally, one needs to develop time-series based models to detect anomalies that can't be classified correctly by distance-based models.

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Appendix

Individual team member contributions:

Prabhat Koutha (pk454): Ideation, Problem definition, K-Means, DBSCAN, Score table, Weapon of Math Destruction and Fairness

Lewis Tian (zt89): Data, Random Forest, Isolation Forest, Ensemble, Results

Jiaqi Ding (jd2269): One Class SVM, Autoencoder, Conclusion, Plots