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Research Article

Quantile Regression Machine Learning Techniques to Handle Outliers in Time Series Data

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ABSTRACT

Time series data often exhibit outliers that can significantly distort the results of traditional regression methods, leading to inaccurate forecasts and suboptimal decision-making. Quantile regression offers a robust alternative by estimating the conditional median or other quantiles of the response variable, thus providing a more comprehensive analysis of the underlying data distribution. This review paper explores the integration of quantile regression with advanced machine learning techniques to effectively handle outliers in time series data. By comparing different approaches, we evaluate how well they perform in terms of root mean square error (RMSE) and mean absolute error (MAE). According to the comparison graph, the EMD-QRnet method greatly boosted the MAE and RMSE by 84.3% and 1.00%, which is the highest gain of any method when compared to others.

Keywords: Machine learning, outliers, time series data.

INTRODUCTION

The integration of quantile regression with machine learning techniques presents a powerful approach for handling outliers in time series data, addressing a critical challenge in accurate forecasting and data analysis. Traditional regression methods, which focus on estimating the mean of the response variable, can be significantly skewed by outliers, leading to biased predictions. In contrast, quantile regression provides a more robust framework by estimating various quantiles (e.g., median, quartiles), thus offering a comprehensive view of the data distribution that is less sensitive to outliers. Machine learning provides innovative solutions for several industrial processes, including transportation [1], manufacturing [2], video surveillance, climate change [3], and networking. Anomaly detection is a prominent machine learning approach that is extensively used in the field of industrial informatics [4,5]. Within the field of time series data mining, outlier identification has become a notable subject that has attracted the attention of both practitioners and academics. Many application domains, including industrial failure diagnostics, cybersecurity intrusion detection, and credit card fraud detection, have extensively researched outlier detection. In particular, the study of outliers in time series data seeks to identify and examine abnormal patterns that emerge over a certain period of time. Figure 1 demonstrates that outliers in time series data may be interpreted in two distinct ways, and the choice between these interpretations is mostly determined by the analyst's focus or the particular context under investigation [6,7]. These results have been linked to data that is loud, imprecise, or unwanted, which does not naturally captivate the analyst. In these situations, removing or fixing outliers is essential to improving the data quality and creating a more accurate dataset that can be used with other data mining techniques. Since getting precise forecasts is the major goal, sensor transmission errors are removed to improve prediction accuracy. But in recent times, especially with regard to time series data, a number of researchers have concentrated on locating and analyzing unusual but fascinating occurrences. This idea is best shown by fraud detection, whose main goal is to locate and assess the anomaly itself. These results are sometimes referred to as anomalies.

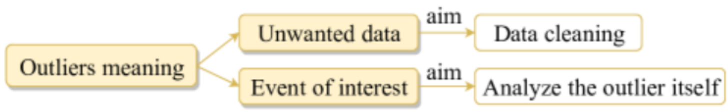

Figure 1: Outlier in time series data depending on the analyst [8]

Labeling and scoring approaches are the two general categories into which the output of anomaly identification methods is divided. Classification-based techniques, also known as labeling techniques, use a trained model to assign class labels (such normal or abnormal) to the test samples. To enable supervised learning, these methods rely on pre-labeled data sets. Large-scale data labeling can be a challenging, expensive, and oftentimes unfinished process because to the resource constraints associated with big data[9]. For unsupervised or semi-supervised learning applications, however, scoring algorithms that calculate anomaly scores based on how much a data instance displays an aberrant profile may be useful [10]. These remedies consist of distance-based and statistical methods [11–13]. The temporal nature of time-series and their vulnerability to noise in the distance computation function pose challenges for the application of distance-based anomaly detection methods. Moreover, these approaches are unsuitable when there is inadequate data that is pertinent to the current goal.

1.2 Outlier

An outlier in time series data refers to a data point or a group of data points that exhibit a substantial deviation from the general pattern or trend seen in the data series. These anomalies may occur as a result of several factors, including inaccuracies in measurements, infrequent occurrences, or changes in the fundamental system being examined. Outliers can distort statistical analyses and predictive models, leading to inaccurate forecasts and misleading interpretations. Identifying and appropriately handling outliers is crucial in time series analysis to ensure the robustness and accuracy of the results.

1.2.1 Taxonomy of Outlier detection techniques in the time series data

The kind of input data, the kind of outlier, and the characteristics of the strategy all influence time series data outlier detection techniques [14]. Hence, a proposed taxonomy that fully incorporates these three characteristics is provided in this section. Figure 2 presents a summary of the resultant taxonomy, and each axis is explained in full below.

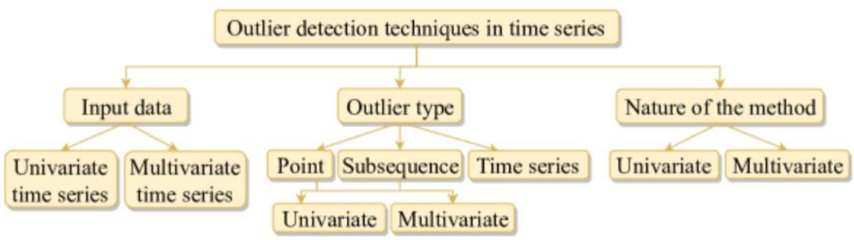

Figure 2: Classification of outlier detection technique [15]

1.2.2 Input data: Univariate vs Multivariate

Outlier identification methods differ depending on the distinct attributes of time series data. Univariate time series analysis is the examination of a single variable over a certain time period. In contrast, multivariate time series analysis entails the simultaneous examination of many variables over a certain time frame. Multivariate detection methods may research many time-dependent variables, whereas univariate detection strategies only study one [16].

1.2.3 Multivariate Time Series

In multivariate time data, multivariate outliers can be found using both univariate and multivariate techniques. Potential interdependencies could be missed when utilizing univariate methods to analyze every variable in a multivariate time series, which could result in knowledge loss. To get past this issue and take use of the advancements in univariate detection techniques, some researchers preprocess multivariate time series to find a new set of uncorrelated variables that may be investigated using univariate techniques. These tactics are predicated on methods for reducing dimensionality. Several studies have shown how to reduce dimensionality in the context of multivariate time series data analysis using a univariate methodology [17–20].

1.2.4 Univariate Time series

This section covers a set of algorithms organized according to the diagram shown in Figure 3, which is intended to help find point anomalies in a univariate time series. Don't forget that these outliers are univariate points that can only be found using univariate detection approaches because these methods only consider one time-dependent variable. Significantly deviating from the predicted value is the most widely used and appropriate definition of a point outlier [21–24].

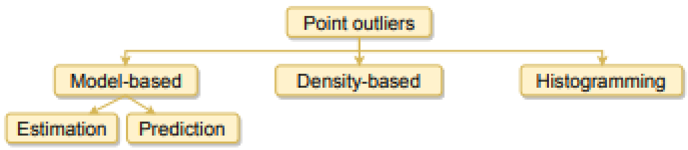

Figure 3: Point outliers in univariate time series[15]

1.3 Outlier type

The selection of outlier identification techniques may vary based on the nature of the outliers:

- Point outlier: A point outlier is a data point that, at a specific moment in time, deviates from the average, either in terms of the surrounding points (local outlier) or the other values in the time series (global outlier).
- Subsequences: This word refers to a sequence of time points that exhibit unexpected behavior when considered together, even if each individual observation may not be considered an outlier.
- Time Series: Outliers may exist across an entire time series, but they can only be identified when the input data is a multivariate time series.

1.4 Nature of the method

Univariate and multivariate detection techniques are examined on the third axis. In multivariate detection, multiple time-dependent variables are analyzed, while in univariate detection, only one is. Even for multivariate time series, a univariate detection technique may be used. It is possible to analyze each time-dependent variable independently, disregarding dependencies. With univariate time series, a multivariate approach cannot be applied. Therefore, this axis will only be used for multivariate time series data.

REVIEW OF LITERATURE

Hu et al., (2024) [25] presented a monotone quantile regression neural network, a time series quantile prediction framework. The suggested approach uses a gradient-based point-wise loss function with quantile information from the input structure to prevent quantile crossover. Time dependence and asymmetric heavy tails are two complex aspects of time series that are captured by a special quantile function. This function accurately depicts data conditional distribution. This model forecasts several quantiles without overlap. Employing, the suggested method is applied to real-world data in numerous disciplines. Evidence suggests that the suggested technique, paired with long short-term memory, may accurately and reliably estimate several quantiles while addressing quantile crossing.

Chronopoulos et al., (2024) [26] conducted a Monte Carlo experiment to analyze the characteristics of the deep quantile estimator and demonstrate its strong performance in limited sample scenarios. Numerous testing methods demonstrate that the deep quantile estimator forecasts value-at-risk better than linear quantile regression and other models. An alternate design for neural networks using mixed frequency data is being investigated. This study compared Shapley Additive Explanation values with partial derivatives to make neural network outputs more understandable.

Chen et al., (2024) [27] introduced a new machine learning approach for detecting outliers and predicting results in combustion diagnostics. The strategy utilizes data correlation to address the limitations and reduce the cost of existing technologies. Cluster analysis was used to produce measurement results for outlier identification. The results indicated that the DBSCAN and suggested GBCN algorithm were effective in detecting and removing the measurement outlier. The outcomes showed that the Artificial Neural Network could successfully learn the flame temperature distribution feature. Even with 70% of the temperature data inside the flame being randomly unmeasured, an artificial neural network (ANN) forecast can still reliably calculate the entire temperature field.

Ambark et al., (2023) [28] Various penalization approaches have been devised to address the issues encountered with conventional least-squares method in quantile regression models. The aim of this study is to create a model that can more accurately fit data and increase forecast accuracy. Additionally, this study looked into the issue of multicollinearity amongst the decomposition components. Both modeling research and empirical applications were conducted. The EnetQR approach achieved the following metrics for the daily closing exchange rates: MAE of 0.8430, RMSE of 1.0083, MASE of 9.1642, and MAPE of 1.211876%. The findings indicate that the suggested EMD-QREnet approach generally surpasses previous methods by enhancing prediction accuracy.

Jensen et al., (2022) [29] introduced ensemble conformalized quantile regression is a novel and cutting-edge method for probabilistic forecasting. Prediction intervals produced by EnCQR are almost marginally valid and distribution-free. These PIs are specifically designed for time series data that is nonstationary and heteroscedastic. Quantile regression is used by the ensemble learners as a machine learning technique in their implementation. By using this method, the ensemble learners can adjust the prediction intervals' size based on the variability in the data that has been observed. According to the results, EnCQR performs better than models that only use QR or conformal prediction and offers prediction intervals that are more reliable, accurate, and instructive.

Yang et al., (2022) [30] presented a novel wind speed forecasting system that utilizes an adaptive robust extreme learning machine (ARELM) model and signal decomposition methods. Firstly, the ARELM is specifically developed to effectively reduce the violation of normalcy assumptions and the influence of outliers. ARELM utilizes an adaptive scaled Huber's loss as its objective function. This loss function effectively reduces the impact of outliers and dynamically determines the optimal combination of normal distribution and Laplace distribution. In addition, our wind-speed forecasting system incorporates the empirical mode decomposition (EMD) technique and its enhanced variants (EEMD, CEEMD, and CEEMDAN). This approach involves modeling the low-frequency sub-series using standard ELM and the high-frequency sub-series using ARELM. This approach allows for the decomposition of complicated wind speed series into several simpler sub-series, hence reducing the complexity of the modeling process. The experimental findings demonstrate that our combined forecasting system, ELM-ARELM, achieves a significant increase of up to 78% in predicting performance compared to approaches that use general Huber's loss and other comparison methods. This clearly indicates the superiority of the adaptive scaled Huber's loss. The error indices (MAE and RMSE) obtained from the suggested system are as follows: (0.25, 0.34) for the 5-minute ahead experiment, (0.32, 0.45) for the 15-minute ahead trial, and (0.38, 0.53) for the 25-minute ahead experiment. These results clearly indicate the efficiency of decomposition techniques in enhancing the accuracy of wind speed prediction.

Jing et al., (2021) [31] presented a new approach for modeling willingness-to-pay curves using logistic functions, which is based on quantile regression (QRLF). The proposed method combines the asymmetric absolute value function from the quantile regression (QR) cost function with logistic functions (LF). This allows for the description of the uncertainty of wind power through fitting curves of different quantiles, without the need to consider the prior distribution of wind power. Three optimization techniques have been chosen for comparative investigations. Furthermore, a novel outlier filtering technique is devised using QRLF, which effectively removes outliers using the symmetrical power distribution relationship. Finally, the performance of the suggested technique is assessed using supervisory control and data acquisition (SCADA) data obtained from wind turbines in three wind farms. Five assessment criteria are used for the purpose of conducting a comparison study. QRLF outperforms common WTPC models in terms of fitting performance for both deterministic and probabilistic power curve modeling.

He et al., (2021) [32] Precise prediction of wind power is crucial for the efficiency and dependability of a power grid. Nevertheless, the presence of non-schedulability and variability in wind power greatly amplifies the unpredictability of power networks. This research suggests doing outlier identification and data reconstruction as a first step to address the uncertainty associated with wind power projection. A wind power probability density forecasting approach, called cubic spline interpolation and support vector quantile regression (CSI-SVQR), is introduced. This method provides a more accurate estimation of the whole wind power probability density curve. Nevertheless, the probability density prediction approach is unable to simultaneously get the ideal point prediction and interval prediction outcomes. The current research examines the uncertainty of wind power by analyzing the prediction outcomes using both probabilistic point prediction and interval prediction approaches. The CSI-SVQR approach is validated using three sets of wind power data obtained from Canada and China. The findings demonstrate that the suggested technique effectively removes wind power outliers and also produces the probability density function, which offers a comprehensive depiction of wind power output fluctuations and attained the MAPE and RMSE is 3.0% and 4.44%. Moreover, superior point prediction and prediction interval (PI) may be achieved in comparison to current approaches. The Wilcoxon signed rank test is used to ascertain if CSI may enhance the efficacy of forecasting techniques.

Tambuwal et. al., (2021)[33] investigated that Time-series anomaly detection receives increasing study interest given the growing number of data-rich application domains. Anomaly detection methods in the research literature have been recently enhanced by the inclusion of deep neural networks. The performance and nature of these algorithms in sequence analysis allow them to learn hierarchical discriminative features and time-series temporal character. Nevertheless, their performance is typically influenced by the assumption of a Gaussian distribution for the prediction error, which is either ranked or specified as a threshold to determine whether data instances are anomalous. The direct relevance of an exact parametric distribution is not always the case in numerous applications. This could result in inaccurate decisions as a result of the high degree of variability in data interpretation, which is caused by false anomaly predictions. Outputs that are confidently produced are anticipated. Therefore, the Prediction Interval (PI) is necessary for implementations, as it quantifies the level of uncertainty associated with the DNN point forecasts. This information is necessary for the purpose of making more informed decisions and preventing false anomaly alarms. An effort has been made to reduce false anomaly alerts by utilizing quantile regression for anomaly identification. However, this approach is restricted to the use of quantile intervals to identify uncertainties in the data. Deep quantile regression anomaly detection (DQR-AD) is described in this paper as an enhanced time-series anomaly detection method. Furthermore, the proposed method employs the quantile interval (QI) as an anomaly score and compares it to a threshold to identify anomalous points in time-series data. The suggested method's effective performance over other methods that presumed a Gaussian distribution on the prediction or reconstruction cost for anomaly detection is demonstrated by the tests conducted on publicly available anomaly benchmark datasets. This indicates that our method may be less susceptible to data distribution than existing methods.

Chakravarty et al., (2020) [34] provided a resilient fuzzy regression functions (FRFN) technique that can effectively handle outliers. The study also assesses the performance of the proposed approach and compares it with several popular machine learning methods in the context of regression problems with outliers. The FRFN technique is based on fuzzy k-means clustering, including a noise cluster.They evaluate the precision of Artificial Neural Networks (ANN), Support Vector Machines (SVM), and the proposed FRFN techniques using various training algorithms/kernel functions on both simulated and actual benchmark datasets. A Monte Carlo simulation setup was used to test and compare the accuracies of 36 implementations of Artificial Neural Networks (ANN), Support Vector Machines (SVM), and FRNF models. These implementations included different training procedures, kernel functions, and loss functions. The evaluation was conducted using data that included outliers. Both Monte Carlo simulations and applications using benchmark datasets have shown that FRFN (Functional Relevance

Fuzzy Neural Network) trained with the Bayes regularization approach and FRFN with SVM (Support Vector Machine) using a Gaussian kernel perform better than traditional implementations of ANN (Artificial Neural Networks) and SVMs (Support Vector Machines) when outliers are present. The suggested noise cluster approach significantly enhances the resilience of fuzzy regression algorithms against outliers and attained the MAE, RMSE of 3.13%, and 2.72%.

Zhang et al., (2019) [35] presented a novel three-level hybrid model, named MF-EMD-CART-AR-EWMA, for outlier detection in sensor data. The model combines the median filter (MF), empirical mode decomposition (EMD), classification and regression tree (CART), auto regression (AR), and exponential weighted moving average (EWMA) methods. The performance of the first-level is compared to that of the Butterworth filter, FIR filter, moving average filter, wavelet filter, and Wiener filter. The experimental results demonstrated that the hybrid model outperformed the other models in terms of generalization ability and accuracy. Additionally, the hybrid model showed exceptional capability in detecting even small deviations in the predicted values.

1.1 Comparison of reviewed techniques

There is a wide range of authors who studied on the Quantile regression machine learning techniques to handle outliers in time series data and give their findings as shown in Table 1.

Table 1: Comparison of reviewed technique

Authors [Ref.]	Year	Technique	Outcome
Hu et al., [25]	2024	MQRNN	The experiments indicate that in combination with LSTM, the recommended technique may accurately anticipate multi-quantiles and reduce quantile crossing.
Chronopoulos et al., [26]	2024	Monte Carlo	The suggested technique compared Shapley Additive Explanation values with partial derivatives to make neural network output more understandable.
Chen et al., [27]	2024	DBSCAN and GBCN	The results indicated that the DBSCAN and suggested GBCN algorithm were effective in detecting and removing the measurement outlier.
Ambark et al., [28]	2023	EMD-QRnet	The findings indicate that the suggested EMD-QREnet approach generally surpasses previous methods by enhancing prediction accuracy.
Jensen et al., [29]	2022	ENCQR	The results show that EnCQR provides more accurate, informative, and consistent prediction intervals than models that only use QR or conformal prediction.
Yang et al., [30]	2022	ELM-ARELM	The experiments conducted indicate that the combined forecasting system, ELM-ARELM, delivers a substantial improvement of up to 78% in predictive accuracy compared to techniques that use general Huber's loss and other comparison methods.
Jing et al., [31]	2021	QRLF	QRLF surpasses typical WTPC models in terms of accuracy in fitting for both determinism and stochastic power curve modeling.
He et al., [32]	2021	CSI-SVQR	The findings demonstrate that the suggested technique effectively removes wind power outliers and also produces the probability density function.

Tambuwal et. al[33]	2021	Deep Quantile Regression Anomaly Detection (DQR-AD)	Less vulnerable to fluctuations in the data distribution, demonstrating superior performance compared to other approaches assuming a Gaussian distribution. Tests on publicly available benchmark datasets indicate improved accuracy and reliability in anomaly detection
Chakravarty et al., [34]	2020	FRFN-SVM	The suggested noise cluster approach significantly enhances the resilience of fuzzy regression algorithms against outliers and attained the MAE, RMSE of 3.13%, and 2.72%.
Zhang et al., [35]	2019	CEEMD-CART-AR	The findings showed that the hybrid model surpassed the other models in terms of its capacity to generalize and its accuracy.

COMPARATIVE ANALYSIS

In this section, several authors provide their results following the Mean absolute error, and Root mean square error parameter, which is described in table 2. According to table 2, Ambark and his fellow students were able to greatly boost the MAE and RMSE in outlier detection in time series data by using the EMD-QRnet approach, which resulted in a 0.843%% and 1.00% increase. By using the ELM-ARELM, Yang and his colleagues were able to improve the outlier in time series data, which ultimately resulted in a MAE of 0.25% and RMSE of 0.34% increase. In comparison to previous methods, the use of CSI-SVQR by He and his fellow students has resulted in a considerable increase in the MAE and RMSE of the outlier detection, which now stands at 0.3% and 0.44%. By using the hybrid model FRFN-SVM, Chakravarty and his fellow students were able to tremendously boost the MAE and RMSE of the outlier in time series data, which ultimately resulted in 0.313% and 0.272%. From this Table, it is clear that the hybrid model (EMD-QRnet) technique that results in the greatest overall improvement in the outliers in time series in comparison to other approaches.

Table 2: Comparison analysis

Author	Techniques	MAE	RMSE
Ambark et al., (2023) [28]	EMD-QRnet	0.843%	1.00%
Yang et al., (2022) [30]	ELM-ARELM	0.25%	0.34%
He et al., (2021) [32]	CSI-SVQR	0.3%	0.44%
Chakravarty et al., (2020) [34]	FRFN-SVM	0.313%	0.272%

The increased parameters MAE and RMSE of the outliers is shown in figure 4, as can be seen in the following graph. The MAE and RMSE has been greatly enhanced due to the EMD-QRnet approaches, which have seen a rise of up to 84.3% and 1.00%, which is the maximum increase seen when compared to other techniques.

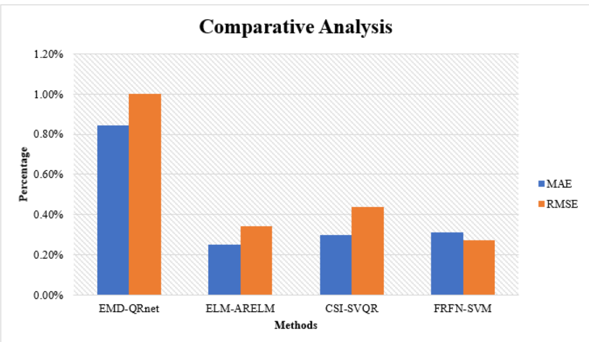

Figure 4: Comparison graph

CONCLUSION

In this study, we have presented a comprehensive studies and methods of quantile regression techniques in providing a comprehensive understanding of the conditional distribution of time series data. Unlike traditional regression methods, quantile regression does not rely on assumptions of normality and is inherently equipped to handle heteroscedasticity and skewness, making it particularly suited for time series data prone to outliers and irregular patterns. Studies have demonstrated the efficacy of integrating quantile regression with machine learning algorithms, such as random forests and neural networks, to improve forecast accuracy and model reliability. We have provided a summary as well as a comparison to the extensive literature review that is included in Table 1. From the Figure 3, it has been concluded that the EMD-QRnet is superior to conventional methods such as FRFN-SVM, and CSI-SVQR in terms of its capacity to increase the MAE and RMSE. When compared to other methods, the MAE and RMSE of EMD-QRnet method is capable of achieving may be enhanced by a maximum of 84.3% and 1.00% as shown in comparison graph. As research progresses, further refinement of these techniques and their integration with other robust statistical methods will continue to enhance their applicability and effectiveness in real-world time series analysis.

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