Anomaly Detection for Fraud in Cryptocurrency Time Series

Eran Kaufman\(^1\) and Andrey Iaremenko\(^3\)

\(^1\) Ben Gurion University of the Negev, Israel
\(^2\) HUB Security, Israel

Abstract. Since the inception of Bitcoin in 2009, the market of cryptocurrencies has grown beyond initial expectations as daily trades exceed $10 billion. As industries become automated, the need for an automated fraud detector becomes very apparent. Detecting anomalies in real time prevents potential accidents and economic losses. Anomaly detection in multivariate time series data poses a particular challenge because it requires simultaneous consideration of temporal dependencies and relationships between variables. Identifying an anomaly in real time is not an easy task specifically because of the exact anomalous behavior they observe. Some points may present pointwise global or local anomalous behavior, while others may be anomalous due to their frequency or seasonal behavior or due to a change in the trend. In this paper we suggested working on real time series of trades of Ethereum from specific accounts and surveyed a large variety of different algorithms traditional and new. We categorized them according to the strategy and the anomalous behavior which they search and showed that when bundling them together to different groups, they can prove to be a good real-time detector with an alarm time of no longer than a few seconds and with very high confidence.

Keywords: Cryptocurrency, Anomaly detection, Machine Learning, Deep nets, Fraud detection

1 Introduction

Blockchain technology has become pervasive today in many industries, such as the financial industry, cloud infrastructure, supply chain management and others. Blockchain is a distributed decentralized ledger with guarantee of immutability of the data stored in the ledger across multiple computational nodes. This cryptography-based technology removes the central authority and enables fast and trusted sharing of data and exchange of value directly between two or more parties. Today there are many kinds of blockchains, customized to specific needs and environments. In the monetary sector there are multiple cryptocurrencies traded on the open markets, just like a regular forex. Moreover, in the US, Japan and Europe cryptocurrency trading is officially regulated. Blockchain based payments with cryptocurrencies (e.g. Bitcoin, Ethereum) provide fast,
cheap, anonymous and secure payments worldwide. However, the immutability of the payment transaction presents a problem when a malicious actor obtains control of the access to the Bitcoin account and moves the tokens to another account on the blockchain. In particular, it is practically impossible to rewind the transaction and retrieve the money. Thus the largest security issue with cryptocurrencies is the access to the private key (a random number of 32 bytes), which represents the entire monetary holdings of a personal account on the blockchain. This risk is exponentially higher in the case of institutions handling large amounts of money and managing third party assets in an automated and round-the-clock manner. Therefore automated malicious activity detection mechanisms are required to keep pace with the organizational use of blockchain. For the financial use of blockchain there are relatively few parameters and data fields to inspect with automated anomaly detection algorithms, similar to regular banking fraud detection. For Bitcoin transactions, the following fields are most relevant for anomaly detection:

1. Payment amount. Each account has relatively unique behavior patterns regarding transaction amounts as stand-alone metric (like groups of values) and also relative to the time scale (time of day, weekly and monthly scales).
2. The destination address. Amount value behavior is coupled to the recipient address field. There may be a small number of addresses that receive similar payments over time, and one-time addresses with a single payment.
3. The Fee value. Fee is a transactional surcharge for the miners (or maintainers) of the blockchain infrastructure. Bitcoin fees are traditionally predefined in the wallet application.

For Ethereum transactions, the following fields are most relevant to anomaly detection:

1. The payment amount value, similar to Bitcoin.
2. The destination address, similar to Bitcoin.
3. Gas limit and Gas price. These two parameters reflect the fee paid to the maintainers of the blockchain infrastructure.

In Ethereum the fee is calculated in real time for each transaction, based on the current network load and on the required speed of transaction approval on the blockchain. In the Ethereum network, a transactional request is an actual computation in a dedicated virtual machine in the network. Gas is the unit of work to execute specific computational operations on the blockchain. Each transaction has a base fee to be included in the blockchain, based on the complexity of the required calculations. The transaction initiator can pay an additional fee to secure faster processing and approval time. Thus the fee component could be an indicator of account fraud. All of the above parameters are trackable per account and per unit of time for use in anomaly detection processes. Each account has a different behavior over time and in between temporal epochs. So the anomaly detection methods should combine training and inference models. The algorithms seek anomalies in the spending behavior of the account over a period of time, for example a comparably large transaction amount or a group of many small transactions.
Our contribution. We focus our attention on the spending behavior of an account over time. Unlike previous work in this field which focused on documented Ponzi schemes, our aim is to find discrepancies in an online working account. We conducted comparative research using multiple anomaly detection algorithms from a vast range of algorithms and models and compared their results in order to find the best suited algorithms for both researchers and practitioners alike.

The algorithms must be both very reliable, and also run in real time, meaning the detection alarm must be raised within a few seconds of its occurrence. Since we work on unsupervised data, we found that 'hand labeling' anomalies rarely works well. This is because the question often posed to an arbiter – when is an anomaly really an anomaly? – is not a simple one to answer. For this reason we ran a large scale of algorithms from different approaches and categorized them into different categories. An anomaly was decided to be an anomaly only when the majority out of multiple algorithms from the same category made the same decision. (We found that deciding anomalies based on different categories led to poor results.) Secondly, in regard to the feature space, out of the many possible features, we identified three features as being the most significant: These are payment amount, Gas price, and gas limit (as explained above). Moreover, we did both a univariate and a multivariate analysis of the data, i.e. we referred to the vector of features both as individual time series as well a combined three-vector. By doing so we mark the fact that while each feature may not be "out of range" individually, the vector as a whole can be anomalous as, for example, the gas price and gas limit should be correlated.

We combined both pointwise anomalies based on representations of the data in the sample space along with contextual and collective anomalies based on the time space representation since for fraud detection not only the value but also the frequency is an important factor. Whilst a certain price may be of regular value in a certain context, it may be the case that a very frequent request implies a D.o.S. (Denial of Service) attack, or conversely, close prices may tend come together in bundles (as this is the current price of the market) where as, a single request followed by long 'silent' periods may be a sign of a fraud.

2 Related Work

2.1 Anomalies in Time-series Data

An anomaly in time-series data is a data point (or points) at a certain time step (or steps) that shows unexpected behaviors differing significantly from the behavior of previous time steps. Anomaly detection can be categorized in the following way [2]:

1. Pointwise anomalies. Also known as global outliers, these points lay outside a user defined sensitivity parameter over the entirety of a data set. This user defined threshold is used to balance between type 1 and type 2 statistical errors.
2. Contextual anomalies. Also referred to as conditional outliers, these anomalies have values that significantly deviate from other data points that exist in the same context (usually a period) but are not significant in the global sense. The value exists within global expectations but may appear anomalous within certain seasonal data patterns.

3. Collective anomalies, when a subset of continuous points within a set is anomalous to the entire dataset. In this category, individual values are not anomalous globally or contextually but only the entire subset. Individual behavior may not deviate from the normal range in a specific section, but when combined with other sections these anomalies become apparent.

2.2 Anomaly Detection Approaches

Another way to categorize anomalies is based on the implementation method:

**Statistical Models.** Statistical models generate statistical measures, such as mean, variance, median, quantile, kurtosis, skewness, and many more. With the generated model, a newly added time-series data can be inspected to determine whether it belongs to the normal boundary [18].

**Predictive Models.** Predictive models are among the common approaches to anomaly detection. These methods forecast future states based on past and current states. We can deduce the anomaly according to the severity of the discrepancy between the predicted value and the real one. For example, autoregressive integrated moving average (ARIMA) [3] is frequently employed to forecast time-series.

The ARIMA model is composed of three parts:

1. An auto-regressive (AR) component which is composed of a weighted sum of lagged values, and can model the value of a random variable $X$ at time step $t$ as:

   \[ AR(P) : X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + \epsilon_t \]  

   where $\{\phi_i\}$ are autocorrelation coefficients and $\epsilon$ is white noise. The parameter $p$ is the order of AR model.

2. A moving-average (MA) component which computes the weighted sum of lagged prediction errors and is formulated as:

   \[ MA(q) : X_t = \epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \ldots - \theta_q \epsilon_{t-q} \]  

   where $\{\theta_i\}$ are moving-average coefficients, $\epsilon_t$ denotes a model prediction error at time step $t$, and $q$ is the order of MA model.

3. An integrated component representing the time-series using differences, and thus a data point at time step $t$ is $\hat{X} = X_t - X_{t-d}$ where $d$ denotes the order of differencing.
The differencing process makes the time-series stationary, resulting in ARIMA being very effective for non-stationary time-series. If the time-series data has a seasonal variation, we can use a variant called seasonal ARIMA (SARIMA) \[30\]. In this case, we introduce the additional parameters: P, D, and Q, which deal with the seasonality. These parameters are used in the same manner as p, d, and q.

The parameters for the S/ARIMA can be learned in a supervised or non-supervised manner. In the non-supervised manner the order of p and q can be determined by using the sample autocorrelation function or via the Akaike information criterion.

In the supervised manner the parameters are learned from a training set using cross-validation. We tested both approaches in our experiments, and saw very similar results.

Another commonly used algorithm is the season-trend decomposition better known as STL. STL is a statistical method for breaking down time-series data into three different uncorrelated components that contain seasonality, trend and residues. The trend analysis of the data shows a general direction of the overall data, while the seasonal analysis presents a pattern which is repeated at a fixed time intervals. The residue (noise) is the random oscillation or unexpected change. The frequency meta parameter for this algorithm can be found either by using the autocorrelation function in the time domain or by calculating the bandwidth of the Fourier transform in the frequency domain.

In the category of predictive models we also include the SVM regressor, the nearest neighbor regressor and neuralnets based regressors. These methods assume a 'natural' trade line to the dataset behavior and exclude points which are out side a certain 'strip' of the predicted line. These are usually global or contextual anomalies.

**Clustering Models.** Clustering based methods are choices for grouping the data into disjoint groups. Once a time-series is mapped into a multidimensional space, clustering algorithms group them close to a cluster depending on their similarities. Here we assume that there is some metric in which closely related points are close to each other and the outliers are far away. They can vary from centroid based clustering like k-means to hierarchical based clustering like BDSCAN and others. These algorithms are usually collective anomalies and are represented in the time (not sample) domain. Popular data clustering methods include the k-means algorithm \[16\], one-class support vector machine (OCSVM) \[17\], or Gaussian mixture model (GMM) \[19\].

OCSVM \[17\] is an unsupervised algorithm based on dividing the points into disjoint spaces with the margin between spaces being as wide as possible.

Instead of working in feature space it is often better to work in the kernel space instead. Working in kernel space provide two principal benefits. The first being that it implicitly induces a non-linear feature map, which allows for a richer space of classifiers. The second is that, when the kernel trick is available, it effectively replaces the dimension of the feature space with the size of the
sample space which allows for faster computations. Among the most popular kernels are linear kernel, polynomial kernel and radial basis kernel (RBF).

**Dimensionality Reduction Models.** Dimensionality reduction models assume that a large scale system can be represented using a few significant factors. Thus, by extracting the main features via dimensional reduction we can reconstruct the data and separate the expected data from noise. Linear algebra based methods include principal component analysis (PCA) and singular value decomposition (SVD) [28].

Tree based methods include isolation forest and neural network based method include the neuralnet AutoEncoder (AE). Isolation forest is an algorithm that detects anomalies by the depth of the tree needed for isolating each point. At the basis of the algorithm there is an assumption that outliers are easier to separate from the rest of the points, compared to ordinary points. In principle, anomalies are further away in the feature space and fewer splits are required than a normal point. Anomalous points will therefore be defined as points where the number of partitions required until they are insulated is low.

**NeuralNet Based Models.** Using deepnets can come in some of aforementioned techniques i.e. either as a predictive model or as a dimensionality reduction model. In time-series applications, the temporal context should be considered when modeling the series. For this reason two general kinds neural net are considered

1. **RNNS.** RNNs have been extended with other variants, such as LSTM [10] and GRU [7]. LSTM and GRU address the vanishing or exploding gradient problem, where the gradient becomes too small or too large as the network goes deeper. There are multiple gates in an LSTM and a GRU cell, and they can learn long-term dependencies by determining the number of previous states to keep or forget at every time step. Meanwhile, the dilated RNN is proposed to extract multiscale features while modeling long-term dependencies by using a skip connection between hidden states. Shen et al. [25] for instance, adopt a three layer dilated RNN and extract features from each layer to jointly consider longterm and short term dependencies. RNN-based approaches are generally used for anomaly detection in two ways. One is to predict future values and compare them to predefined thresholds or the observed values. This strategy is applied in [25,12,21,14]. The other is to construct an autoencoder in order to restore the observed values and evaluate the discrepancy between the reconstructed value and observed one. This strategy is used in [11,15,15,20,9].

2. **CNNs.** Although the RNN is the primary option for modeling time-series data, CNN sometimes shows better performance in several applications that work with short term data. [8,29,31]

   By stacking convolutional layers, each layer learns a higher level of features. In addition, the pooling layers introduce non-linearity to the CNN, allowing
them to capture the complex features in the sequences. Instead of explicitly capturing the temporal context, the CNN models learn patterns in segmented time-series.

In the field of the cryptocurrency anomaly detection many previous works were done on finding anomalies using machine learning techniques. Bartoletti et al. \cite{3}, Chen et al. \cite{5}, \cite{6} and Jung et al. \cite{13} analyzed Ponzi schemes of Ethereum trade developed as smart contracts.

Chen et al. \cite{5} used a regression tree model (XGBoost) to detect Ponzi schemes on Ethereum. A subsequent work of the same authors \cite{6} improved the results by using the Random Forest (RF) classifier. Jung et al. \cite{13} analyzed both behavior and code frequency of contracts to detect Ponzi schemes, and obtained a precision of 99\% and recall of 97\%.

Bartoletti et al. and Toyoda et al. used addresses clustering techniques \cite{22}, \cite{20} to extend their datasets of scam addresses, and both applied supervised machine learning techniques to detect Ponzi schemes. In particular, Toyoda et al. used XGBoost and Random Forest classifiers, and Bartoletti et al. used a cost-sensitive Random Forest classifier.

Schnaubelt \cite{23}, Shahbazi \cite{24} and Tanwar \cite{27} showed the use of deep reinforcement learning to find the optimal placement of cryptocurrency limit orders and Akba et al. \cite{1} used predictive models for detection of a manipulator in the cryptocurrency market.

3 Experiments

For our experiments we ran all the above mentioned algorithms and compared the results for anomalies in the same category. In the category of predictive models we used ARIMA, SARIMA, STL, LSTM based regressors, kernel ridge regression, support vector regressor (SVR) RBF, SVR with a polynomial kernel and nearest neighbor regressor. In the category of dimensionality reduction models we used Isolation forest, LSTM AE and PCA based models. In the category of cluster based models we used the OCSVM, k-means and DBSCAN based model.

The datasets for these experiments are in the public domain, collected from etherscan.io and accessible through public APIs. The name of stock markets and the active accounts are available on our GitHub. Also comprehensive results of the different algorithms with their accuracy can be found on GitHub \cite{3}. Here we present some illustrative results, while the conclusion section summarizes the result from all datasets and algorithms. The algorithms are briefly explained in subsection 2.2.

Processing the Data. The data is given as the dates and amounts of the ethereum transaction for a single account. Dates and time where no transaction

\footnote{https://github.com/erankfmn/anomaly_detection}
took place are not given in the dataset (since this is the common case). While some anomaly algorithms work better in the sample space and even may be confused by a long period of null transactions (essentially, marking every transaction as an anomaly). Other algorithms which search for an anomaly of a point in temporal space need their representation in time domain instead.

When treating the series based on time rather than on samples an issue arises as the data is typically given in the format of value and date, it maybe the case that some exact dates cooccur (at the exact same second). While working in the sample domain these points are regarded as different points however, in the time domain it is unclear as to how they should be treated since there can only be one data point for each sampling time. We decided in these cases to merge these points into a single point. Other possible approaches may include taking the maximum or the average value, but after exhaustive trial and error, we found that merging was more appropriate in the context at hand. An example of such a manipulation is illustrated in figure 1.

Figure 2 shows the raw data in the sample space for the fields of payment amount, gas limit and gas price. It is apparent that the different fields are highly uncorrelated and demonstrate different anomaly behavior.

Figure 3 shows the concurrent result of ARIMA, SARIMA and STL algorithms for the payment amount feature and at the bottom of the graph shows points which more than two algorithms concur.

In order to estimate the parameters for S/ARIMA cross validation was used, the data was split into train and test 70% – 30% and validated over all possible combinations of parameters over the range of 1 – 3. Test values whose difference between the prediction and actual value greater than $3 \cdot RMS$ were detected as an outlier.

We can concluded that the three algorithms identified the same samples quite similarly. For example, for SARIMA accuracy is 97% and recall 96.6% . The ARIMA and SARIMA algorithms identified almost exactly the same anomalies,
Fig. 2: Raw Data of the payment amount gas price and gas limit
Fig. 3: ARIMA SARIMA STL results for anomalies in the payment field
probably due to the fact that the seasonal component did not have significant weight in the sampling classification.

The STL algorithm produced similar results to the two other algorithms.

The points that were identified were usually points at the beginning or end of major trend changes.

The two following graphs in figure 4 are for the gas price and gas limit yielding the same results.

Fig. 4: ARIMA SARIMA STL results for anomalies in the gas fields

(a) Gas Price  
(b) Gas Limit

Figure 5 shows the results of LSTM and regression trees for the payment value. Figure 6 shows the same result for gas price and gas limit. Since predictive models are supervised models they are split to train and test sets. When commerce starts to rise the tendency of predictive models is to keep the tendency line rising and when sudden and abrupt changes occur they are classified as anomalies. The LSTM architecture was constructed by 3 layers of LSTM consisting of 128, 64, 32 units respectively, followed by a dropout layer - this is the encoder part. Afterwards a repeated vector layer followed by the decoder unit of 3 layers of LSTM 32, 64, 128 units respectively.

Figures 7 and 8 were taken from algorithms who look at collective anomalies. For the isolation forest and the OCSVM collective points were prepared as a continuous time-series, the sliding window was set to be 5 continuous minutes and each sampling point can belong to several vectors at the same time in the time domain. These type of algorithms perform online learning, they receive a set of samples of about five minutes and compares them to the previous four.
Fig. 5: Anomalies detected for payment by regression trees and LSTM

Fig. 6: Anomalies detected for the gas fields by regression trees and LSTM

(a) Gas Price

(b) Gas Limit

day database. The database is also updated every four days as detection needs to happen in real time.
Fig. 7: Anomalies detected for payment by isolation forest and OCSVM

Fig. 8: Anomalies detected for gas fields by isolation forest and OCSVM

(a) Gas Price

(b) Gas Limit
We used OCSVM with RBF kernel. The regularization parameter $C$ was 5-fold cross-validated over the set $\{2^5, 2^3, \ldots, 2^{15}\}$, and for the RBF kernel, the $\gamma$ parameter was five-fold cross-validated over the set $\{2^5, 2^3, \ldots, 2^3\}$.\footnote{This is also true for the SVR where also tried both polynomial and RBF kernels}

4 Conclusion and Further Research

In this paper we evaluated the anomalous behavior of Ethereum trade of several accounts for a real-time fraud detector. The detection searched for pointwise as well as contextual and collective anomalies both in the sample domain, the time domain and the frequency domain. We used many well known algorithms traditional and new to try and compare their performances. We categorized the algorithms according to the their strategy of detection. We marked a point as an anomaly when there was a majority vote on that point. In the category of predictive models we found that classical as well as neural based methods have an accuracy of 97\% and a recall of 96.6\%. They work well together and tend to appear when trade line are changes abruptly. Dimensionality reduction methods on the other hand are contextual and collective anomalies and work well both in time or sample representations. Here we found poor results since especially neuralnets AE detected more points than other methods such as isolation forest and PCA and we believe them to be more sensitive due to their complexity. Clustering methods have an accuracy of 96.3\% and a recall of 93.2\%. They are collective anomalies that work well both in the time domain as well as in the sample domain. They also work both as univariate and multivariate models detecting uncorrelated vectors. All model give reliable real time results either pretrained or online learners. The over all conclusion of our research is that for a real-time anomaly detector with unsupervised data the best approach is to have parallel processing divided according to the anomalous behavior: pointwise local or global, contextual, collective, in the sample or time representation. And have them work simultaneously while using a majority vote. Models from the same category traditional and new tend to have a high rate of agreement and are therefore reliable and relatively fast for real-time fraud detection.
References

1. Akba, F., Medeni, I.T., Güzel, M.S., Askerzade, I.N.: Manipulator detection in cryptocurrency markets based on forecasting anomalies. IEEE Access 9, 108819–108831 (2021). https://doi.org/10.1109/ACCESS.2021.3101528

2. Bao, Y., Tang, Z., Li, H., Zhang, Y.: Computer vision and deep learning based data anomaly detection method for structural health monitoring. Structural Health Monitoring: An International Journal 18, 147592171875740 (02 2018). https://doi.org/10.1177/1475921718757405

3. Bartoletti, M., Carta, S., Cimoli, T., Saia, R.: Dissecting ponzi schemes on ethereum: Identification, analysis, and impact. Future Gener. Comput. Syst. 102, 259–277 (2020). https://doi.org/10.1016/j.future.2019.08.014

4. Box, G.E.P., Pierce, D.A.: Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. Journal of the American Statistical Association 65(322), 1509–1526 (1970). https://doi.org/10.1080/01621459.1970.10481180 https://www.tandfonline.com/doi/abs/10.1080/01621459.1970.10481180

5. Chen, W., Zheng, Z., Cui, J., Ngai, E.C.H., Zheng, P., Zhou, Y.: Detecting ponzi schemes on ethereum: Towards healthier blockchain technology. In: Champin, P., Gandon, F., Lalmas, M., Ipeirotis, P.G. (eds.) Proceedings of the 2018 World Wide Web Conference on World Wide Web, WWW 2018, Lyon, France, April 23-27, 2018. pp. 1409–1418. ACM (2018). https://doi.org/10.1145/3178876.3186046

6. Chen, W., Zheng, Z., Ngai, E.C., Zheng, P., Zhou, Y.: Exploiting blockchain data to detect smart ponzi schemes on ethereum. IEEE Access 7, 37575–37586 (2019). https://doi.org/10.1109/ACCESS.2019.2905769

7. Cho, K., van Merrienboer, B., Gülçehre, Ç., Bahdanau, D., Bougares, F., Schwenk, H., Bengio, Y.: Learning phrase representations using RNN encoder-decoder for statistical machine translation. In: Moschitti, A., Pang, B., Daelemans, W. (eds.) Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing, EMNLP 2014, October 25-29, 2014, Doha, Qatar, A meeting of SIGDAT, a Special Interest Group of the ACL. pp. 1724–1734. ACL (2014). https://doi.org/10.3115/v1/d14-1179 https://doi.org/10.3115/v1/d14-1179

8. Choi, Y., Lim, H., Choi, H., Kim, I.: Gan-based anomaly detection and localization of multivariate time series data for power plant. In: Lee, W., Chen, L., Moon, Y., Bourgeois, J., Bennis, M., Li, Y., Ha, Y., Kwon, H., Cuzzocrea, A. (eds.) 2020 IEEE International Conference on Big Data and Smart Computing, BigComp 2020, Busan, Korea (South), February 19-22, 2020. pp. 71–74. IEEE (2020). https://doi.org/10.1109/BigComp48618.2020.00-97 https://doi.org/10.1109/BigComp48618.2020.00-97

9. Guo, Y., Liao, W., Wang, Q., Yu, L., Ji, T., Li, P.: Multidimensional time series anomaly detection: A gru-based gaussian mixture variational autoencoder approach. In: Zhu, J., Takeuchi, I. (eds.) Proceedings of The 10th Asian Conference on Machine Learning, ACML 2018, Beijing, China, November 14-16, 2018. Proceedings of Machine Learning Research, vol. 95, pp. 97–112. PMLR (2018), http://proceedings.mlr.press/v95/guo18a.html
10. Hochreiter, S., Schmidhuber, J.: Long short-term memory. Neural Comput. 9(8), 1735–1780 (1997). https://doi.org/10.1162/neco.1997.9.8.1735

11. Hsieh, R., Chou, J., Ho, C.: Unsupervised online anomaly detection on multivariate sensing time series data for smart manufacturing. In: 12th IEEE Conference on Service-Oriented Computing and Applications, SOCA 2019, Kaohsiung, Taiwan, November 18-21, 2019. pp. 90–97. IEEE (2019). https://doi.org/10.1109/SOCA.2019.00021

12. Hundman, K., Constantiou, V., Laporte, C., Colwell, I., Söderström, T.: Detecting spacecraft anomalies using lstms and nonparametric dynamic thresholding. In: Guo, Y., Farooq, F. (eds.) Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, KDD 2018, London, UK, August 19-23, 2018. pp. 387–395. ACM (2018). https://doi.org/10.1145/3219819.3219845

13. Jung, E., Tilly, M.L., Gehani, A., Ge, Y.: Data mining-based ethereum fraud detection. In: IEEE International Conference on Blockchain, Blockchain 2019, Atlanta, GA, USA, July 14-17, 2019. pp. 266–273. IEEE (2019). https://doi.org/10.1109/Blockchain.2019.00042

14. Kieu, T., Yang, B., Guo, C., Jensen, C.S.: Outlier detection for time series with recurrent autoencoder ensembles. In: Kraus, S. (ed.) Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI 2019, Macao, China, August 10-16, 2019. pp. 2725–2732. ijcai.org (2019). https://doi.org/10.24963/ijcai.2019/378

15. Li, D., Chen, D., Jin, B., Shi, L., Goh, J., Ng, S.: MAD-GAN: multivariate anomaly detection for time series data with generative adversarial networks. In: Tetko, I.V., Kurková, V., Karpov, P., Theis, F.J. (eds.) Artificial Neural Networks and Machine Learning - ICANN 2019: Text and Time Series - 28th International Conference on Artificial Neural Networks, Munich, Germany, September 17-19, 2019, Proceedings, Part IV. Lecture Notes in Computer Science, vol. 11730, pp. 703–716. Springer (2019). https://doi.org/10.1007/978-3-030-30490-4_56

16. MacQueen, J.B.: Some methods for classification and analysis of multivariate observations. In: Cam, L.M.L., Neyman, J. (eds.) Proc. of the fifth Berkeley Symposium on Mathematical Statistics and Probability. vol. 1, pp. 281–297. University of California Press (1967)

17. Manevitz, L.M., Yousef, M.: One-class svms for document classification. J. Mach. Learn. Res. 2, 139–154 (2001). http://jmlr.org/papers/v2/manevitz01a.html

18. Markou, M., Singh, S.: Novelty detection: a review—part I: statistical approaches. Signal Processing 83(12), 2481–2497 (2003). https://doi.org/https://doi.org/10.1016/j.sigpro.2003.07.018

19. McLachlan, G.J., Basford, K.E.: Mixture models: Inference and applications to clustering. Marcel Dekker, New York (1988)

20. Meiklejohn, S., Pomarole, M., Jordan, G., Levchenko, K., McCoy, D., Voelker, G.M., Savage, S.: A fistful of bitcoins: characterizing payments among men with no names. Commun. ACM 59(4), 86–93 (2016). https://doi.org/10.1145/2896384

21. Park, D., Hoshi, Y., Kemp, C.C.: A multimodal anomaly detector for robot-assisted feeding using an lstm-based variational autoencoder. CoRR abs/1711.00614 (2017). http://arxiv.org/abs/1711.00614
22. Reid, F., Harrigan, M.: An analysis of anonymity in the bitcoin system. In: PAS-SAT/SocialCom 2011, Privacy, Security, Risk and Trust (PASSAT), 2011 IEEE Third International Conference on and 2011 IEEE Third International Conference on Social Computing (SocialCom), Boston, MA, USA, 9-11 Oct., 2011. pp. 1318–1326. IEEE Computer Society (2011). https://doi.org/10.1109/PASSAT/SocialCom.2011.79

23. Schnaubelt, M.: Deep reinforcement learning for the optimal placement of cryptocurrency limit orders. Eur. J. Oper. Res. 296(3), 993–1006 (2022). https://doi.org/10.1016/j.ejor.2021.04.050

24. Shahbazi, Z., Byun, Y.: Improving the cryptocurrency price prediction performance based on reinforcement learning. IEEE Access 9, 162651–162659 (2021). https://doi.org/10.1109/ACCESS.2021.3133937

25. Shen, L., Li, Z., Kwok, J.: Timeseries anomaly detection using temporal hierarchical one-class network. In: Larochelle, H., Ranzato, M., Hadsell, R., Balcan, M.F., Lin, H. (eds.) Advances in Neural Information Processing Systems. vol. 33, pp. 13016–13026. Curran Associates, Inc. (2020), https://proceedings.neurips.cc/paper/2020/file/97e401a02082021fd24957f852e0e475-Paper.pdf

26. Su, Y., Zhao, Y., Niu, C., Liu, R., Sun, W., Pei, D.: Robust anomaly detection for multivariate time series through stochastic recurrent neural network. In: Teredesai, A., Kumar, V., Li, Y., Rosales, R., Terzi, E., Karypis, G. (eds.) Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, KDD 2019, Anchorage, AK, USA, August 4-8, 2019. pp. 2828–2837. ACM (2019). https://doi.org/10.1145/3292500.3330672

27. Tanwar, S., Patel, N.P., Patel, S.N., Patel, J.R., Sharma, G., Davidson, I.E.: Deep learning-based cryptocurrency price prediction scheme with inter-dependent relations. IEEE Access 9, 138633–138646 (2021). https://doi.org/10.1109/ACCESS.2021.3117848

28. Wang, X., Miranda-Moreno, L.F., Sun, L.: Hankel-structured tensor robust PCA for multivariate traffic time series anomaly detection. CoRR abs/2110.04352 (2021), https://arxiv.org/abs/2110.04352

29. Wen, T., Keyes, R.: Time series anomaly detection using convolutional neural networks and transfer learning. CoRR abs/1905.13628 (2019), http://arxiv.org/abs/1905.13628

30. Williams, B.M., Hoel, L.A.: Modeling and forecasting vehicular traffic flow as a seasonal arima process: Theoretical basis and empirical results. Journal of Transportation Engineering 129(6), 664–672 (2003). https://doi.org/10.1061/(ASCE)0733-947X(2003)129:6(664)

31. Zhou, B., Liu, S., Hooi, B., Cheng, X., Ye, J.: Beatgan: Anomalous rhythm detection using adversarially generated time series. In: Kraus, S. (ed.) Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI 2019, Macao, China, August 10-16, 2019. pp. 4433–4439. ijcai.org (2019). https://doi.org/10.24963/ijcai.2019/616