International Journal of Technology 14(8) 1675-1684 (2023)
Received September 2023 / Revised November 2023 / Accepted December 2023

International Journal of Technology

http://ijtech.eng.ui.ac.id

# Integrating Data Mining Techniques for Fraud Detection in Financial Control Processes

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**Abstract.** Detecting fraud in financial control processes poses significant challenges due to the complex nature of financial transactions and the evolving tactics employed by fraudsters. This paper investigates the integration of data mining techniques, specifically the combination of Benford's Law and machine learning algorithms, to create an enhanced framework for fraud detection. The paper highlights the importance of combating fraudulent activities and the potential of data mining techniques to bolster detection efforts. The literature review explores existing methodologies and their limitations, emphasizing the suitability of Benford's Law for fraud detection. However, shortcomings in practical implementation necessitate improvements for its effective utilization in financial control. Consequently, the article proposes a methodology that combines informative statistical features revealed by Benford's law tests and subsequent clustering to overcome its limitations. The results present findings from a financial audit conducted on a road-construction company, showcasing representations of primary, advanced, and associated Benford's law tests. Additionally, by applying clustering techniques, a distinct class of suspicious transactions is successfully identified, highlighting the efficacy of the integrated approach. This class represents only a small proportion of the entire sample, thereby significantly reducing the labor costs of specialists for manual audit of transactions. In conclusion, this paper underscores the comprehensive understanding that can be achieved through the integration of Benford's Law and other data mining techniques in fraud detection, emphasizing their potential to automate and scale fraud detection efforts in financial control processes.

*Keywords:* Benford's Law; Clustering; Ellipsoidal approximation; Isolation forest; Principal component analysis

## 1. Introduction

In today's digital age, where financial crimes and illicit activities have become increasingly sophisticated, fraud detection is one of the most important functions of financial control entities. As technology advances, fraudsters adapt their methods, making it necessary to integrate advanced data mining techniques to improve fraud detection capabilities.

Despite the large number of data mining techniques studied to date, only a few are most applicable to financial fraud detection. This research aims to address the limitations

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doi: 10.14716/ijtech.v14i8.6830

of existing approaches in applying data mining techniques to fraud detection and propose a comprehensive methodology that can be universally applied to numerical financial data. By combining the power of advanced data mining techniques with Benford's Law, financial control entities can enhance their ability to detect and prevent fraudulent activities, safeguarding their financial integrity and protecting stakeholders' interests.

## 2. Literature Review and Methodology

### *2.1. Literature Review*

The statistical method, commonly referred to as Benford's Law or the Law of Anomalous Numbers, is gaining significant traction in global financial control practices. According to this law, in datasets generated through natural processes and without deliberate human manipulation, the distribution of first digits should conform to a discrete exponential distribution, commonly known as Benford's distribution (Nigrini, 2012).

The use of Benford's Law is justified by the unique characteristics of financial fraud. Fraudulent activities often involve intentional manipulation of financial data, such as falsifying transactions, inflating revenues, or understating expenses. However, they often leave subtle, unintentional traces that go against the expected patterns in naturally occurring data. Fraudulent numbers, often manipulated by humans, tend to deviate from the expected distribution outlined by Benford's Law. This deviation serves as a red flag, alerting financial control entities to the potential presence of fraud.

The greatest contribution to the development of Benford's Law was made by Professor Mark Nigrini, who proposed a methodology for the integrated application of Benford's Law tests to detect financial fraud (Nigrini, 2012; Nigrini, 1993). Validation of the tests proposed by Mark Nigrini on different sets of corporate data proves their effectiveness in terms of identifying anomalies in large sample populations (Pupokusumo *et al.*, 2022; Leonov *et al.*, 2021; Rad *et al.*, 2021; Manuel and Garcia, 2021). The adaptable nature of Benford's law allows it to be combined with other statistical approaches, which has been done in previous research with neural networks, logistic regression, decision trees, and random forests (Bhosale and Troia, 2022; Badal-Valero, Alvarez-Jareño, and Pavía, 2018; Bhattacharya, Xu and Kumar, 2011). In some cases, however, the results obtained by Benford's Law tests may be contradictory and ambiguous (Fernandes and Antunes, 2023; Leonov *et al.*, 2022; Ergin and Erturan, 2020), which points to the need to improve the methodology.

### *2.2. Methodology*

The recognition of the law can be attributed to the publication of a comprehensive study conducted by American engineer Frank Benford in 1938 (Nigrini, 2012). That is why the law is now commonly referred to as Benford's Law, despite it being originally discovered by American astronomer S. Newcomb. Benford's research was supported by extensive analysis of the frequencies of first digits in 20 diverse datasets, encompassing areas such as geography, demographics, physics, mathematics, and other accumulated data. The majority of these examples provided further evidence of the law's validity. Additionally, Benford made a significant contribution by developing formulae for determining the probabilities of the first ($D_1$), second ($D_2$), and the first two ($D_1D_2$) significant digits in any number system ($b$) (formulae 1-3). In practice, problems solved using Benford's law predominantly relate to the decimal number system, hence the utilization of the decimal logarithm in these formulae ($b$ = 10).

$$P(D_1 = d_1) = log_b\left(1 + \frac{1}{d_1}\right) \qquad d_1 \epsilon \{1,2, \dots ,9\} \tag{1}$$

$$P(D_2 = d_2) = \sum_{d_1=1}^{9} log_b\left(1 + \frac{1}{d_1 d_2}\right) \qquad d_2 \epsilon \{0,1, \dots ,9\} \tag{2}$$

$$P(D_1D_2 = d_1d_2) = log_b\left(1 + \frac{1}{d_1d_2}\right) \qquad d_1d_2\epsilon\{10,11,\dots,99\} \qquad (3)$$

American researcher M. Nigrini presented a comprehensive approach for assessing numerical data sets based on Benford's law (Nigrini, 2012). His methodology includes three categories of statistical tests: basic, advanced, and associated. The selection of specific tests from these categories depends on the problem under investigation as well as the quantity of available data. Typically, the tests are conducted in a sequential manner, starting with basic tests and then progressing to advanced and associated tests.

Basic tests, including the first digit test, second digit test, and first two digits test (also known as the first order test) are the fundamental and commonly used tests based on Benford's law. They are conducted separately on positive and negative numbers due to variations in the motives behind their manipulation. For instance, it is observed that management often exaggerates profits but underestimates losses.

Advanced tests, including the summation test and the second-order test, perform a deeper analysis. According to M. Nigrini, these tests can be performed on almost any data set, even if it is assumed that they will not comply with Benford's law (Nigrini, 2012). Preliminary filtering is not required to perform advanced tests.

Associated tests include the number duplication test, the last digits test, and the distortion factor model. These tests are additional and are based not on Benford's law but on other features of the numerical distribution.

The goodness of fit of the actual distribution to Benford's one is estimated not only empirically but also quantitatively. In this regard, statistical characteristics are calculated, each with specific applications and interpretations. One of the most widely utilized is Z-statistics, which entails the comparison of the empirical and theoretical frequencies of a particular digit. The magnitude of deviations directly corresponds to the level of suspicion, with higher deviations indicating a greater degree of anomaly (Nigrini, 2012).

Nevertheless, the methodology proposed by M. Nigrini has several limitations and shortcomings that necessitate improvements for practical implementation in financial control.

Firstly, the application of various methods to test the conformity of the sample distribution to the Benford distribution often yields contradictory results. For instance, the chi-square is rather categorical and frequently indicates non-compliance with the Benford distribution, even when the visual similarity between the sample distribution and the theoretical one suggests otherwise. The mean absolute deviation (MAD) may confirm acceptable or close conformity to the Benford distribution for the same dataset. This discrepancy arises due to the chi-square's dependence on sample size, unlike the mean absolute deviation, making the latter a more preferable and reliable statistic.

Secondly, it is not uncommon for Z-statistics to exceed critical values, while other methods indicate compliance with the Benford distribution when analyzing real data. To address this issue, widening the confidence interval for Z-statistics by increasing the confidence probability is necessary. However, deviating from the standard 95% confidence level is not recommended and should be avoided.

Furthermore, advanced tests, such as the summation and second order tests, are difficult to interpret, and it is challenging to form samples of suspicious transactions based on them. These tests involve complex statistical calculations and may require a deep understanding of mathematical concepts. As a result, it can be difficult for auditors or investigators to accurately identify suspicious transactions based on the results of these tests.

Finally, when dealing with large volumes of data, Nigrini's suspiciousness selection method still leaves significant samples that require further processing. Additional

computational resources and advanced data processing techniques may be necessary to process these results effectively.

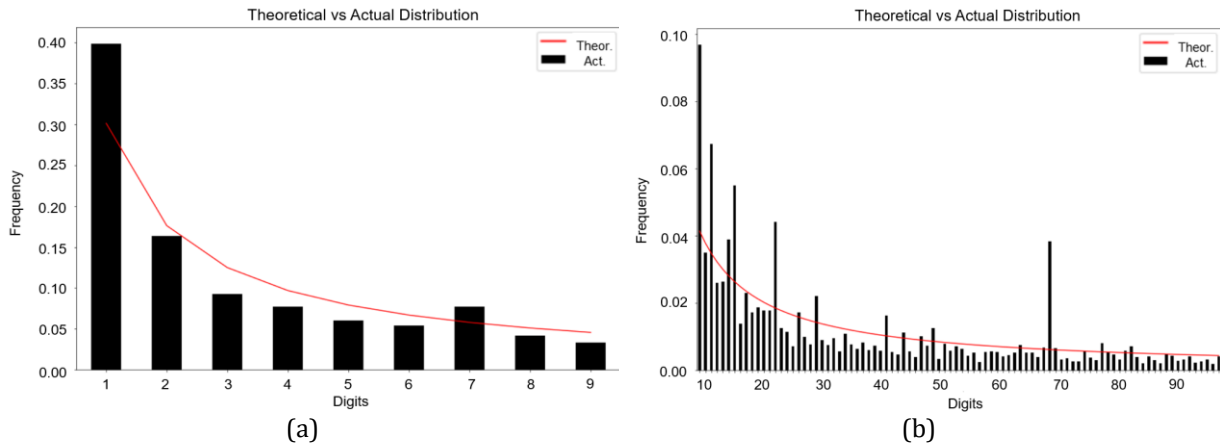
To overcome the aforementioned problems, a potential solution is to combine the most informative statistical features and perform clustering based on them. The proposed methodology begins by implementing basic, advanced, and associated Benford's Law tests and calculating statistical characteristics based on them. Then, clustering algorithms are applied to identify sets of potentially risky transactions that deviate from expected patterns and are more likely to contain fraudulent activity. Additionally, the transactions are clustered based on other fraud indicators such as debit and credit frequency, weekend transactions, and reversal transactions to further narrow down their volume. The result is a subset of high-risk transactions that require manual examination by financial control specialists.

## 3. Results

We validated the improved methodology in a series of financial audits and chose to present the findings from an audit conducted on a road-construction company as it is one of the most representative cases. The data to be analyzed is an array of journal entries for three years, containing 27 attributes and 1,459,270 records. The attributes included the accounts, documents, contents, amounts, and other transaction details. To ensure confidentiality, all names and sensitive information have been changed.

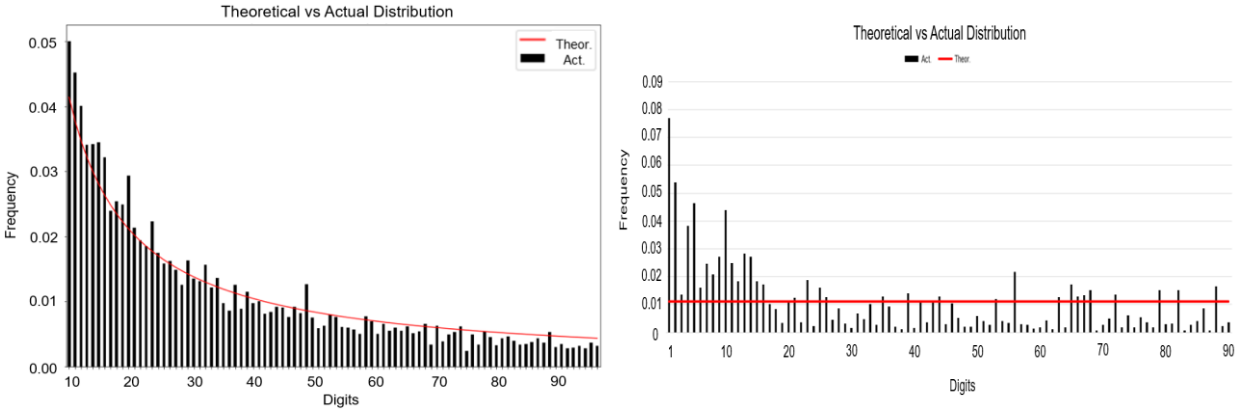
The array was then checked against the requirements that need to be met in order for Benford's Law to be used. These include random formation, sufficient volume, absence of categorical data, no minimum and maximum limits, proximity to an exponential distribution, etc. The array has been verified, and therefore, it was decided to examine the whole set of journal entries over the period, consistently using the primary, advanced, and associated tests. The confidence level at which the tests were conducted is 95%, which is usually used in Benford's Law analysis.

Graphical representations of the results of some primary, advanced, and associated tests are shown in Figures 1, 2 and 3, respectively. From the visual analysis, deviations from the expected theoretical frequencies can already be observed.



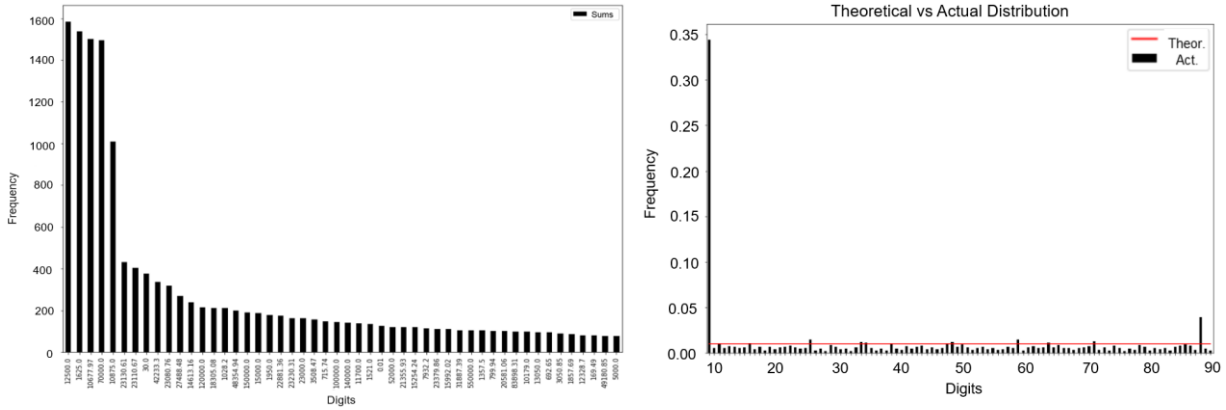

(a) (b)

**Figure 1** Results of the a) First digit test; b) First-order test




(a) (b)

**Figure 2** Results of the a) Second-order test; b) Summation test (for the first pair of digits)




(a) (b)

**Figure 3** Results of the a) Number duplication test; b) Last two digits test

In order to conduct further analysis aimed at detecting potentially fraudulent transactions, it was decided to partition the dataset into distinct classes. The clustering process will be carried out based on the outcomes of Benford's law tests, including:

- Z-statistics for the first digit test;
- Z-statistics for the second digit test;
- Z-statistics for the first-order test;
- Sums of digit frequencies from the summation test;
- Z-statistics for the second-order test;
- Frequency of transaction amounts.

The silhouette method was used to visually estimate the number of clusters into which the sample should be divided (Figure 4). This method helps to evaluate the quality of clustering by measuring how similar an object is to its own cluster compared to other clusters.

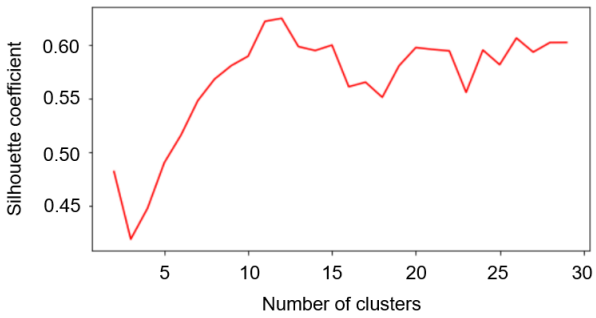



**Figure 4** Silhouette graph

The number of classes is selected by the maximum silhouette value. In this case, it was decided to split the sample into 2 classes. As a result of the division, class 0 included 34,753 objects, and class 1 included 9,030 objects. A plot of means for each cluster is shown in Figure 5. The x-axis represents the features on which clustering was conducted, while the y-axis displays the averaged values within each class.

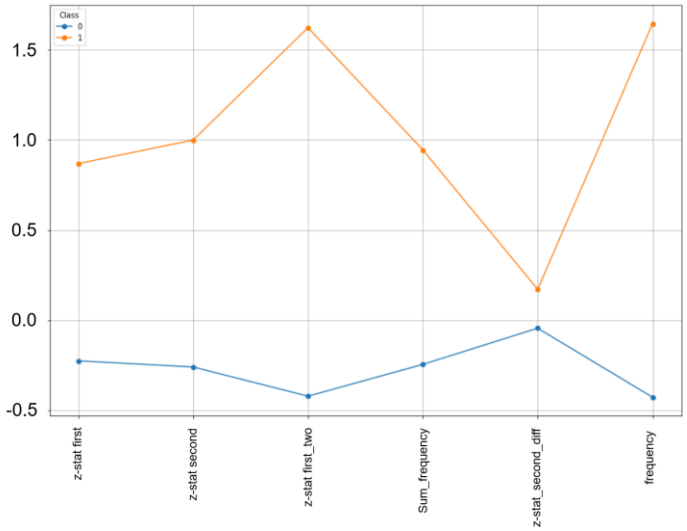



**Figure 5** Plot of means

The figure shows that class 1 is characterized by higher mean values for each feature compared to cluster 0. In addition, class 1 contains a smaller number of objects. Hence, we can assume that suspicious operations were allocated to the 1 cluster.

A visualization in principal components was also constructed for the obtained classes. Principal component analysis is used to show the relationships and patterns among the different classes or groups in the data. Figure 6 shows that the two clusters do not overlap.

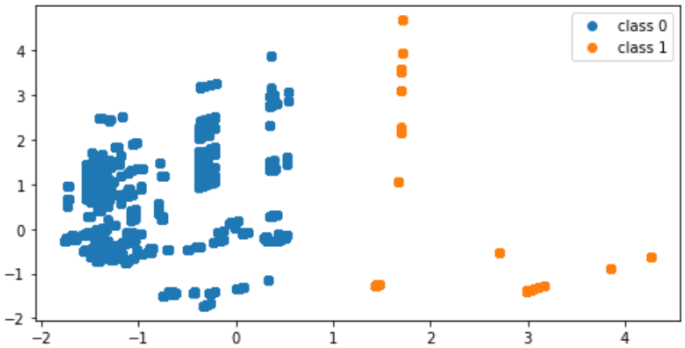



**Figure 6** Visualisation in principal components

In order to identify outliers, two algorithms were utilized – Isolation Forest and Ellipsoidal Approximation. Figures 7 and 8 show the labels assigned by each method based on statistical characteristics.

The isolating forest highlighted most of the Class 1 representatives in the outliers (Figure 7).

| IsoLabels | Class | z-stat first | z-stat second | z-stat first_two | sum_frequency | z_stat_second_diff | Frequency |
|---|---|---|---|---|---|---|---|
| -1 | 0 | 18293 | 18293 | 18293 | 18293 | 18293 | 18293 |
| | 1 | 7492 | 7492 | 7492 | 7492 | 7492 | 7492 |
| 1 | 0 | 16460 | 16460 | 16460 | 16460 | 16460 | 16460 |
| | 1 | 1538 | 1538 | 1538 | 1538 | 1538 | 1538 |

**Figure 7** Result of the isolation forest

The ellipsoidal approximation also highlighted some of the objects in cluster 1 as outliers, but a smaller part of it compared to the previous algorithm (Figure 8).

| ElLabels | Class | z-stat first | z-stat second | z-stat first_two | sum_frequency | z_stat_second_diff | Frequency | IsoLabels |
|---|---|---|---|---|---|---|---|---|
| -1 | 1 | 1706 | 1706 | 1706 | 1706 | 1706 | 1706 | 1706 |
| 1 | 0 | 34753 | 34753 | 34753 | 34753 | 34753 | 34753 | 34753 |
| | 1 | 7324 | 7324 | 7324 | 7324 | 7324 | 7324 | 7324 |

**Figure 8** Result of the ellipsoidal approximation

In Figure 9, the dotted line shows the mean values of the features for the class consisting of objects that were selected as outliers by both algorithms. Cluster 1 is similar to the class consisting of outliers. Hence, we can conclude that class 1 does contain suspicious operations.

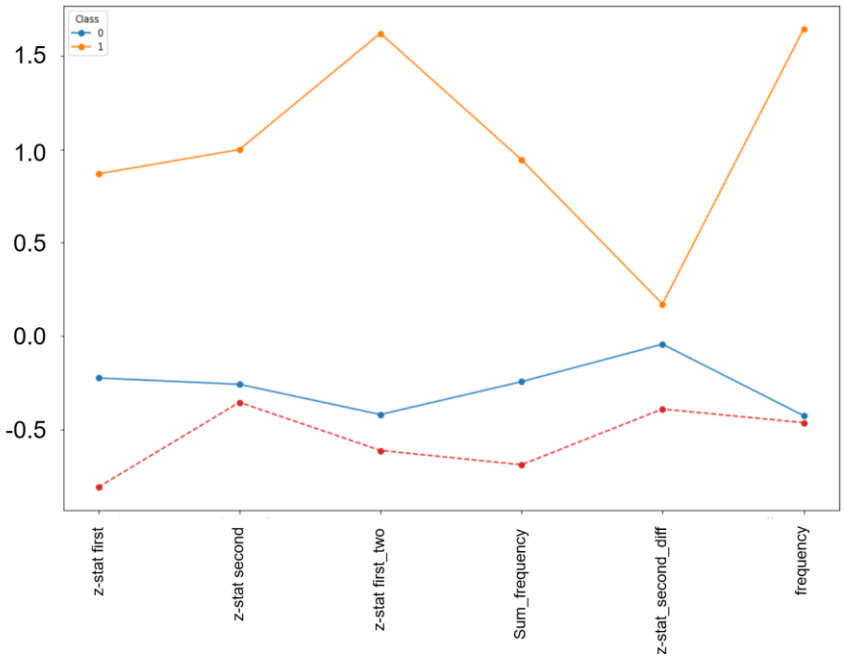



**Figure 9** Plot of means for selected classes and the class of outliers

For the analysis of the suspicious class, we conducted additional clustering based on the following features:

- Debit account frequency;
- Credit account frequency;
- Transaction frequency;
- Author frequency;
- Manual transactions;
- Weekend or weekday transactions;
- Reversal transactions;
- Duplicate count.

The number of classes is also determined by the silhouette method (Figure 10).

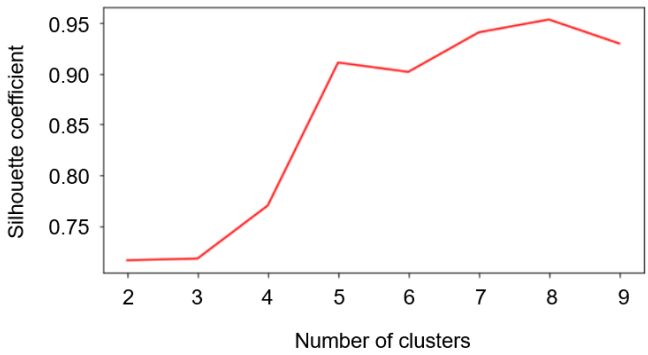



**Figure 10** Silhouette graph for suspicious transactions

Figure 10 shows that the most successful partitioning will be when the number of classes is 5. As a result, class 0 includes 937 objects. The first class includes 69 objects, the second class includes 174 objects, the third class includes 80 objects, and the fourth class includes 446 objects. The mean values for the new clusters are shown in Figure 11.

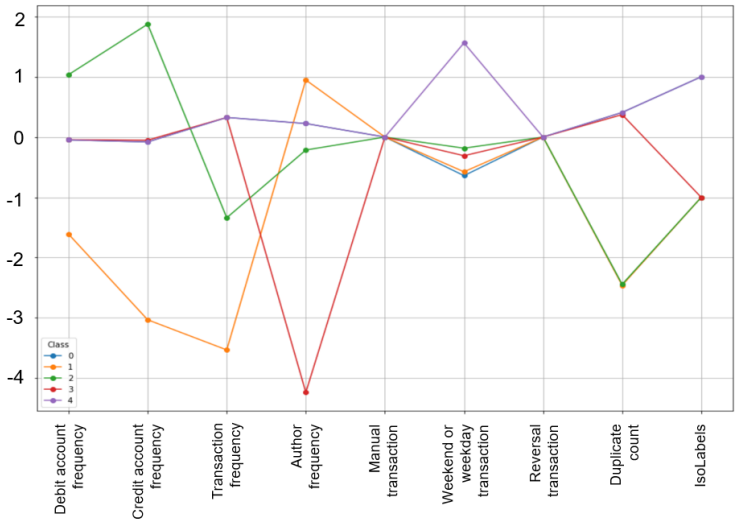



**Figure 11** Plot of means for the new clusters

## 4. Discussion

We proceeded to analyze the outcomes of clustering applied to the suspicious transactions category. This examination is aimed at extracting meaningful insights regarding the underlying patterns and characteristics of the identified clusters.

The analysis reveals that the 0 cluster is the largest in terms of the number of objects. This observation can be attributed to the intermediate mean values observed across all attributes within this cluster. Objects belonging to class 1 exhibit the highest mean value

for the attribute "Author frequency". Class 2 demonstrates the highest mean value for the attribute "Credit account frequency". Class 3 is characterized by a high mean value for the attribute "Transaction frequency" and the lowest mean value for the attribute "Author frequency". Finally, objects in class 4 present the highest mean value for the attribute "Weekend or weekday transaction".

As a result, we successfully identified a class of suspicious transactions that encompassed a total of 52,706 objects, equivalent to 3.61% of the entire sample. This indicates that a small but significant proportion of the transactions exhibited characteristics that warranted further investigation due to their suspicious nature.

In the selected operations, the following signs of potential fraud were identified:

1. Unusual transaction patterns;
2. Misrepresentation of expenses;
3. Unauthorized transactions;
4. Overbilling or double billing;
5. Collusion with vendors or subcontractors;
6. False reporting and documentation;
7. Inadequate internal controls.

While studies in the past two decades have demonstrated the effectiveness of Benford's Law for fraud detection, the current work provides a more comprehensive and efficient approach to financial fraud detection by deepening previous research and combining Benford's Law with other data mining techniques. The universal character of the methodology allows it to be applied to various types of numerical financial data, unlike specific neural networks, logistic regression, and random forest models.

The proposed methodology allows for more efficient and targeted examination of suspicious transactions, minimizing the labor-intensive task of manual auditing for all transactions. Moreover, this study addresses the specific requirements of examining accounting records within the context of financial control measures. By considering the unique characteristics of this domain, the methodology is tailored to accurately identify potential fraudulent activities in financial transactions.

## 5. Conclusions

The application of data mining techniques in financial control activities has indeed been proven to enhance organizational efficiency. By automating routine transaction checks, professionals can allocate their time and resources to more critical operations that require additional scrutiny. This not only improves the overall efficiency of the organization but also ensures that suspicious transactions with significant monetary values are identified promptly. The combination of Benford's Law with other machine learning techniques provides a unique perspective on data analysis for fraud detection. This integration allows for a more comprehensive understanding of patterns and anomalies in financial data. By leveraging the power of machine learning algorithms, the application of Benford's Law can be automated and scaled, making it a valuable tool for large-scale fraud detection efforts. However, while data mining techniques have shown promise in detecting potential fraud, there is always a need to refine and improve the algorithms to reduce false positives and negatives. In addition, this approach relies on historical patterns and may struggle to detect new or evolving forms of fraud. To mitigate these limitations, further research is needed to optimize machine learning algorithms for processing large volumes of journal entries and enhance the accuracy of identifying suspicious transactions. Evaluation and refinement of the models will help achieve better results in identifying signs of fraud.

**Acknowledgments**

The research was funded by the Ministry of Science and Higher Education of the Russian Federation under the strategic academic leadership program "Priority 2030" (Agreement 075-15-2023-380 dated 20.02.2023).

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