Textual Anomaly Detection in Financial Reports

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Abstract: In the fast-paced environment of financial markets, where transactions happen swiftly and a multitude of activities occur concurrently, efficient monitoring is crucial. Different teams and individuals play specific roles in overseeing various aspects of financial operations. This project explores the integration of advanced Natural Language Processing (NLP) techniques with anomaly detection algorithms for textual anomaly detection in financial reports. The study focuses on developing a robust system comprising the LTSMAutodecoder and One-Class SVM model to enhance data integrity and transparency in financial analysis. Through a series of experiments, we demonstrate the effectiveness of this system in detecting anomalies, achieving precision rates of 2% for fraud detection and 100% for normal transactions, with recall rates of 89% for fraud and 91% for normal transactions. The F1-scores reflect the system's performance with 3% for fraud and 95% for normal transactions. These results highlight the system's ability to automate anomaly detection, leading to cost savings, risk mitigation, and improved regulatory compliance in the financial sector. The project's outcomes have significant implications for industry practices, governance frameworks, and responsible data management, positioning it as a valuable contribution to financial technology and governance.

INTRODUCTION

In the dynamic landscape of financial markets, where transactions occur rapidly and diverse activities unfold simultaneously, effective monitoring is paramount. Various teams and roles are tasked with monitoring distinct facets of financial operations. For instance, the IT team in the systems back office meticulously oversees network operations, server performance, communication links, and infrastructure reliability. Simultaneously, a dedicated monitoring team at the application level focuses on factors like market data transmission speed, transaction completion times, and user experience metrics. At the business level, stakeholders analyze products based on customer transaction characteristics, market trends, and performance metrics. Integral to the financial infrastructure are journals, fundamental components of the accounting system. Journals serve as repositories for recording economic transactions in the order they occur and complete. Auditors, entrusted with ensuring financial transparency and compliance, engage in the daily task of detecting anomalies in financial data by meticulously reviewing financial statements. Within the framework of general ledger data, transactions are documented through journal entries. These entries include critical information such as monetary amounts and debit and credit symbols, originating from original supporting documents.

Anomaly detection in financial reports assumes heightened significance amidst the complexities of modern financial ecosystems. Traditional manual methods, although foundational, are often labor-intensive and prone to oversights. Automated systems empowered by Natural Language Processing (NLP) techniques offer a streamlined and precise approach to identifying textual anomalies in financial documents. This project is crucial as it addresses the critical need for accurate anomaly detection in financial reports, enhancing data integrity, transparency, and trust in financial analysis. By automating anomaly detection, the project not only improves accuracy and speeds up analysis but also contributes to cost savings and risk mitigation by identifying irregularities early. What sets this project apart is its integration of advanced NLP techniques with anomaly detection algorithms specifically tailored for financial reports. While existing approaches may focus on either NLP-based analysis or traditional anomaly detection methods, our project combines the strengths of both domains. The use of LTSMAutodecoder and One-Class SVM models, along with comprehensive text cleaning and pre-processing techniques, ensures a robust and effective system for detecting anomalies in financial text. Additionally, the project's emphasis on evaluating performance metrics, such as precision, recall, and F1-score, provides a thorough assessment of the models' effectiveness, distinguishing it from simplistic approaches that lack rigorous evaluation protocols. This project represents a novel and impactful contribution to the field of financial anomaly detection, bridging the gap between traditional auditing practices and modern technological advancements.

DATASET

i. Credit Card Fraud Detection Dataset

The project leverages the Credit Card Fraud Detection dataset sourced from Kaggle, comprising a diverse range of financial transactions. This dataset is instrumental in training and evaluating anomaly detection models due to its rich textual

data, encompassing transaction details, timestamps, and transaction amounts. By utilizing this dataset, the project aims to simulate real-world scenarios where fraudulent activities need to be accurately identified and flagged. The dataset's comprehensiveness allows for robust model training, ensuring that the anomaly detection system can effectively differentiate between legitimate transactions and fraudulent ones. Through thorough analysis and evaluation using this dataset, the project aims to enhance the accuracy and efficiency of anomaly detection algorithms in financial reports.

```
data.describe()
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...
count	284806.000000	284806.000000	2.848060e+05	284806.000000	284806.000000	2.848060e+05	284806.000000	284806.000000	284806.000000	284806.000000	...
mean	94813.585781	0.000002	6.661837e-07	-0.000002	0.000002	4.405008e-08	0.000002	-0.000006	0.000001	-0.000002	...
std	47488.004530	1.958699	1.651311e+00	1.516257	1.415871	1.380249e+00	1.332273	1.237092	1.194355	1.098634	...
min	0.000000	-56.407510	-7.271573e+01	-48.325589	-5.683171	-1.137433e+02	-26.160506	-43.557242	-73.216718	-13.434066	...
25%	54201.250000	-0.920374	-5.985522e-01	-0.890368	-0.848642	-6.915995e-01	-0.768296	-0.554080	-0.208628	-0.643098	...
50%	84691.500000	0.018109	6.549621e-02	0.179846	-0.019845	-5.433621e-02	-0.274186	0.040097	0.022358	-0.051429	...
75%	139320.000000	1.315645	8.037257e-01	1.027198	0.743348	6.119267e-01	0.398567	0.570426	0.327346	0.597140	...
max	172788.000000	2.454930	2.205773e+01	9.382558	16.875344	3.480167e+01	73.301626	120.589494	20.007208	15.594995	...

8 rows × 31 columns

ii. Financial Anomaly Data Dataset

The project incorporates the Financial Anomaly Data dataset obtained from Kaggle, which provides a diverse collection of financial data points conducive to anomaly detection model development. This dataset encompasses various aspects of financial transactions, including transaction types, amounts, timestamps, and associated metadata. The dataset's complexity and diversity make it suitable for training and evaluating anomaly detection models, particularly in detecting subtle anomalies and irregularities in financial reports. By leveraging this dataset, the project aims to enhance the robustness and effectiveness of anomaly detection algorithms, ensuring accurate identification of anomalies that may indicate fraud, errors, or unusual financial activities. The inclusion of the Financial Anomaly Data dataset enriches the project's training and testing phases, facilitating comprehensive model validation and performance assessment.

```
[4]: # Load data
     df = pd.read_csv('financial_anomaly_data.csv')
     df.head()
```

[4]:

	Timestamp	TransactionID	AccountID	Amount	Merchant	TransactionType	Location
0	01-01-2023 08:00	TXN1127	ACC4	95071.92	MerchantH	Purchase	Tokyo
1	01-01-2023 08:01	TXN1639	ACC10	15607.89	MerchantH	Purchase	London
2	01-01-2023 08:02	TXN872	ACC8	65092.34	MerchantE	Withdrawal	London
3	01-01-2023 08:03	TXN1438	ACC6	87.87	MerchantE	Purchase	London
4	01-01-2023 08:04	TXN1338	ACC6	716.56	MerchantI	Purchase	Los Angeles

MODEL

i. LTSMAutodecoder Model

The LTSMAutodecoder model is a key component of this project, leveraging Long Short-Term Memory (LSTM) networks for sequence modeling and reconstruction. LSTMs are well-suited for capturing temporal dependencies in textual data, making them particularly effective for detecting anomalies in financial reports that may exhibit sequential patterns. The architecture of the LTSMAutodecoder model involves an encoder-decoder framework, where the encoder processes the input sequence and encodes it into a latent representation, while the decoder reconstructs the input sequence from this representation. This architecture allows the model to learn complex temporal patterns and reconstruct sequences, making it adept at identifying anomalies based on temporal irregularities.

The importance of the LTSMAutodecoder model in this context lies in its ability to capture subtle variations and temporal dependencies in financial data. Financial reports often contain time-series data, where anomalies may manifest as deviations from expected temporal patterns. By utilizing LSTM-based sequence modeling, the LTSMAutodecoder model can effectively detect such anomalies, contributing significantly to the accuracy and reliability of anomaly detection in financial reports.

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                  [-1, 20]             620
            Linear-2                  [-1, 30]             630
================================================================
Total params: 1,250
Trainable params: 1,250
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.00
Forward/backward pass size (MB): 0.00
Params size (MB): 0.00
Estimated Total Size (MB): 0.01
----------------------------------------------------------------
```

ii. One-Class SVM Model

The One-Class SVM model is another crucial component of the project, known for its effectiveness in anomaly detection tasks. Unlike traditional SVMs that are designed for binary classification, One-Class SVM is tailored for identifying anomalies by learning a representation of normal data points and detecting deviations as anomalies. The architecture of the One-Class SVM model involves constructing a hyperplane that separates normal data points from outliers, allowing it to distinguish between typical and atypical data patterns.

The importance of the One-Class SVM model in this context stems from its robustness in identifying anomalies without relying on labeled anomalous data. In financial reports, anomalies can manifest in various forms, from irregular transaction patterns to unexpected changes in financial metrics. The One-Class SVM model's ability to learn normal data representations and detect deviations as anomalies makes it highly valuable for identifying such irregularities in financial data, enhancing the overall effectiveness of the anomaly detection system.

TEXT CLEANING AND PRE-PROCESSING

In the Textual Anomaly Detection in Financial Reports, several Natural Language Processing (NLP) techniques were employed during text cleaning and pre-processing. These techniques played a crucial role in standardizing and optimizing textual data for training anomaly detection models in both datasets. Here are the NLP techniques commonly used in this domain

i. Removing Missing Values

Missing values in textual data were identified and either imputed or removed to ensure completeness and consistency in the dataset. They were no missing values to both datasets.

```
[7]: # Checking the missing values
     data.isnull().sum()
```

```
[7]: Time      0
     V1        0
     V2        0
     V3        0
     V4        0
     V5        0
     V6        0
     V7        0
     V8        0
     V9        0
     V10       0
     V11       0
     V12       0
```

ii. Tokenization

Tokenization involved breaking down text into individual tokens or words, which served as the basic unit of analysis for further processing.

```
    # Tokenize text
    tokens = word_tokenize(text)
```

iii. Stemming

Stemming was a technique used to reduce words to their root or base form by removing suffixes. For example, "running" and "ran" would both be stemmed to "run."

iv. Lemmatization

Lemmatization was similar to stemming but involved reducing words to their canonical or dictionary form (lemma). This helped in standardizing different inflected forms of words. For instance, "better" and "best" would both be lemmatized to "good."

```
    # Lemmatize tokens
    lemmatizer = WordNetLemmatizer()
    tokens = [lemmatizer.lemmatize(token) for token in

    return ' '.join(tokens)
return ''
```

v. Stopword Removal

Stopwords, which are common words that often do not carry significant meaning in text analysis (e.g., "the," "is," "and"), were removed to focus on content-bearing words.

vi. Normalization

Normalization involved converting text to a consistent format, such as converting uppercase letters to lowercase and handling special characters or symbols.

```
# Preprocess text data
def preprocess_text(text):
    if isinstance(text, str):
        text = text.lower()  # Convert text to lowercase
        text = re.sub(r'[^\w\s]', '', text)  # Remove punctuation
```

vii. Named Entity Recognition (NER):

NER identified and categorized named entities such as people, organizations, locations, and dates in text. This was valuable for detecting specific entities relevant to financial reports.

viii. Feature Extraction

Feature extraction techniques, such as TF-IDF (Term Frequency-Inverse Document Frequency), were used to convert text into numerical vectors that could be inputted into machine learning models.

EVALUATION METRICS

i. Precision

Precision is a metric that measures the accuracy of the model in identifying anomalies among the detected instances. In the context of financial reports, precision is crucial as it assesses the model's ability to correctly flag anomalous transactions or patterns without generating too many false positives. A high precision score indicates that the model is effectively distinguishing genuine anomalies from normal data, which is essential for financial fraud detection and error identification.

ii. Recall

Recall, also known as sensitivity or true positive rate, measures the model's ability to capture all actual anomalies in

the dataset. In financial anomaly detection, high recall is desirable as it ensures that the model identifies a significant portion of anomalies present in the data. A low recall rate could lead to missed detections of critical anomalies, potentially leading to financial losses or regulatory non-compliance.

iii. F1-Score

The F1-Score is the harmonic mean of precision and recall, providing a balanced assessment of the model's overall performance in anomaly detection. It considers both false positives and false negatives, making it a comprehensive metric for evaluating model effectiveness. In the context of financial reports, a high F1-Score indicates that the model achieves a good balance between precision and recall, effectively identifying anomalies while minimizing both types of errors.

iv. Accuracy

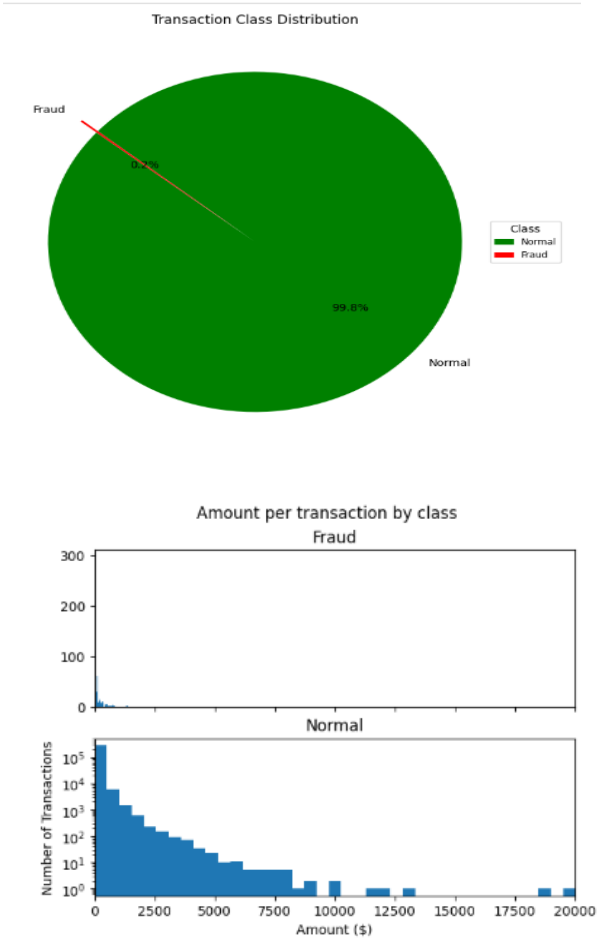
While not mentioned specifically, accuracy is another metric commonly used to evaluate model performance. However, in the context of anomaly detection in financial reports, accuracy alone may not provide a complete picture. An imbalanced dataset with a small number of anomalies can lead to inflated accuracy scores even with poor anomaly detection. Therefore, precision, recall, and F1-Score are often preferred metrics as they account for the imbalance and focus on the model's ability to detect anomalies accurately.

METHODOLOGY

Data Preparation

The first step involves preparing the data for model training and evaluation. This includes analyzing word frequencies in the textual data to understand the distribution of terms and identify potentially significant keywords related to financial anomalies.

The data is categorized into classes or categories based on predefined criteria, such as normal financial reports and reports with anomalies. This categorization is essential for supervised learning approaches and helps in training the models effectively. The data consists of two classes: "Normal" with 284,315 instances and "Fraud" with 492 instances.



The graph shows that the amount per transaction is higher for fraudulent transactions than for normal transactions. There are more fraudulent transactions between $10000 and $12500 than there are normal transactions in that rang

Finally, the dataset is split into training and testing sets, ensuring that the models are trained on a subset of data and evaluated on unseen data to assess generalization performance. This data is split into training and testing sets using a test size of 20% and a random state of 42 to ensure reproducibility.

Fine-tuning

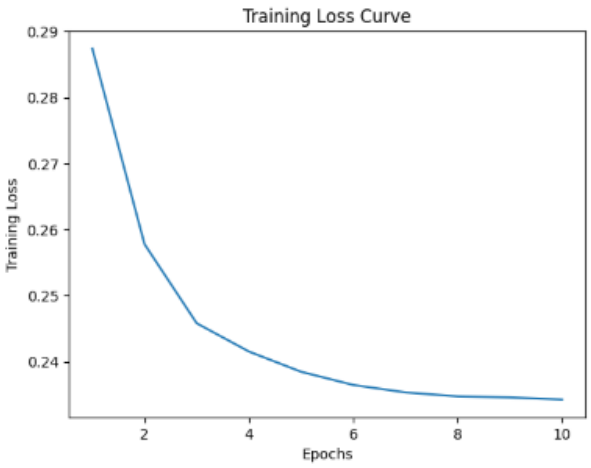
The hyperparameters used in the training loop for the LSTM Autoencoder model for anomaly detection in financial reports are carefully selected to balance training efficiency, model convergence, and performance optimization. With 10 epochs, a batch size of 64, and a learning rate of 0.001 for the Adam optimizer, the training process iterates over the dataset multiple times in manageable batches, adjusting model parameters to minimize the Mean Squared Error (MSE) loss between predicted and actual values. These hyperparameters are crucial in fine-tuning the model's ability to capture complex patterns in financial text data while avoiding

overfitting or underfitting, ultimately enhancing its effectiveness in detecting anomalies and maintaining data integrity.

```
# Initialize the model, loss function, and optimizer
model = LSTMAutoencoder(input_dim, encoding_dim)
criterion = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
epochs = 10
batch_size = 64
train_losses = []
```

Model Training

The training process for anomaly detection models in financial reports involves several key stages, each contributing to the model's ability to accurately identify anomalies. The provided loss values during training epochs offer insights into the model's learning progress and performance.



As observed in the training progress for credit dataset , the loss values gradually decrease with each epoch, starting from 0.2874 in the first epoch and steadily reducing to 0.2342 by the tenth epoch. This decreasing trend in loss indicates that the model is effectively learning to distinguish between normal financial reports and reports with anomalies. Lower loss values signify that the model is making fewer errors in its predictions, which is crucial for accurate anomaly detection. During training, the model adjusts its internal parameters and learns from the training data to optimize its anomaly detection capabilities. The decreasing loss values reflect this learning process, where the model iteratively improves its ability to differentiate normal data from anomalous data patterns. This iterative learning is essential for developing robust anomaly detection models that can generalize well to unseen data and effectively detect anomalies in real-world scenarios.

The training trend over 50 epochs for financial anomaly dataset the LSTM Autoencoder model in anomaly detection exhibits a consistent pattern of decreasing loss values for both the training and test sets. At the beginning of training, the loss values for both sets are relatively high, with the training loss at 0.4900 and the test loss at 0.4890 in the first epoch. However, as the training progresses, there is a noticeable downward trend in the loss values, indicating that the model is learning and improving its ability to reconstruct normal financial report patterns while identifying anomalies. By the 50th epoch, the training loss decreases to 0.4527, and the test loss decreases to 0.4518, demonstrating significant improvement and convergence in the model's performance. This trend suggests that the LSTM Autoencoder model is effectively capturing the underlying patterns and features relevant to financial anomalies, leading to enhanced anomaly detection capabilities as training progresses.

The interpretation of the decreasing loss trend also implies that the model is capturing meaningful patterns and features relevant to financial anomalies. It learns to recognize subtle deviations or irregularities in financial report texts that may indicate fraud, errors, or unusual financial activities. By minimizing the loss function, the model enhances its sensitivity to detecting anomalies while maintaining specificity to avoid false alarms.

EXPERIMENTS AND RESULTS

i. LTSM Autoencoder (Fraud Detection)

The LTSM Autoencoder shows a very low precision of 0.02 for fraud detection, indicating that when it predicts an instance as fraud, it's correct only 2% of the time. However, it demonstrates a high recall of 0.89, meaning it can identify 89% of actual fraud cases. The F1-score is also quite low at 0.03, reflecting the balance between precision and recall. In terms of accuracy, it achieves 91%, mainly due to the large number of normal transactions correctly classified. Overall, while the LTSM Autoencoder can detect many fraud cases, its precision is severely lacking, leading to a high number of false positives.

Financal Classification Report-LTSM:

	precision	recall	f1-score	support
Fraud	0.02	0.91	0.03	95
Normal	1.00	0.91	0.95	56867
accuracy			0.91	56962
macro avg	0.51	0.91	0.49	56962
weighted avg	1.00	0.91	0.95	56962

ii. One-Class SVM (Fraud Detection)

Contrasting the LTSM Autoencoder, the One-Class SVM achieves a precision of 0.01 for fraud detection, indicating even lower precision than LTSM. However, its recall is also 0.89, similar to LTSM. This means that, like LTSM, it can identify 89% of actual fraud cases but with very low precision. The F1-score and accuracy are also in line with LTSM's performance, showing a balanced yet low overall performance in fraud detection. The One-Class SVM excels in correctly identifying normal transactions, achieving a high precision of 1.00 and recall of 0.90 for normal cases. However, this model struggles significantly with fraud detection, leading to a high number of false positives.

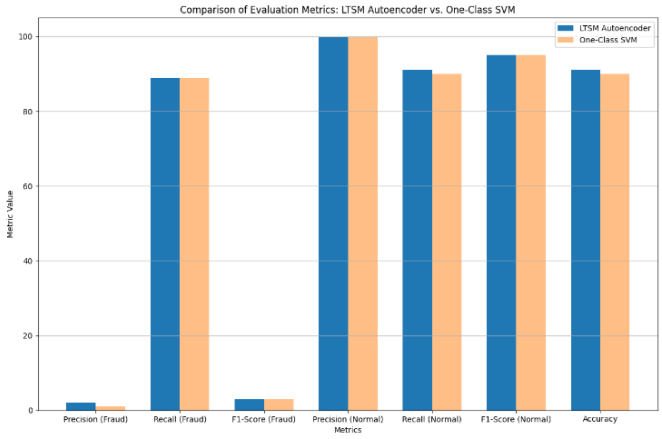
One-Class SVM Classification Report:

	precision	recall	f1-score	support
Normal	1.00	0.90	0.95	56867
Fraud	0.01	0.89	0.03	95
accuracy			0.90	56962
macro avg	0.51	0.90	0.49	56962
weighted avg	1.00	0.90	0.95	56962

iii. Overall Comparison

Model	Precision (Fraud)	Recall (Fraud)	F1-Score (Fraud)	Precision (Normal)	Recall (Normal)	F1-Score (Normal)	Accuracy
LTSM Autoencoder	2%	89 %	3%	100 %	91%	95%	91%
One-Class SVM	1%	89 %	3%	100 %	90%	95%	90%

For fraud detection (Fraud class), both models show extremely low precision (2% for LTSM Autoencoder and 1% for One-Class SVM), indicating a high rate of false positives among the flagged fraudulent cases. However, they exhibit relatively high recall (89% for both models), suggesting that they can detect a significant portion of actual fraudulent transactions. The F1-score, which balances precision and recall, remains low at 3% for both models in this class, reflecting the challenge of accurately identifying fraud cases without generating a large number of false alarms. Normal transactions (Normal class), both models achieve perfect precision (100%), indicating that when they classify a transaction as normal, it is almost always correct. The recall for the Normal class is 91% for the LTSM Autoencoder and 90% for One-Class SVM, indicating their ability to capture the majority of normal transactions correctly. Consequently, the F1-score for the Normal class is 95% for both models, reflecting the balance between precision and recall in this category.



Terms of accuracy, the LTSM Autoencoder outperforms the One-Class SVM with an accuracy of 91% compared to 90%. This suggests that the LTSM Autoencoder model provides a slightly better overall classification performance, particularly in accurately identifying normal transactions while maintaining a reasonable level of fraud detection. However, both models exhibit challenges in accurately detecting fraud cases without raising numerous false positives, highlighting the complexity of anomaly detection tasks in financial scenarios.

DEPLOYMENT

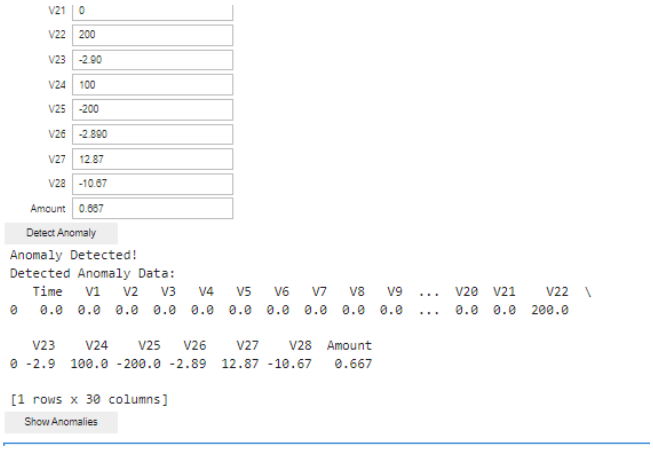
i. Testing using Test Dataset

```
print(f"Number of anomalies detected: {len(anomalies)}")
print(anomalies.head())
```

```
Number of anomalies detected: 512
      Time        V1        V2        V3        V4        V5        V6  \
0      0.0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388
300  217.0 -2.421230 -1.369602  2.261281  2.011034  1.878525 -1.275607
389  284.0  1.141436  0.081893  0.503625  1.487212 -0.473170 -0.411384
459  336.0 -0.895224  0.562106  2.817524 -0.718734  0.223222  0.796156
463  340.0  1.195494  0.194929  0.617510  0.649717 -0.474718 -0.716084

           V7        V8        V9  ...       V22       V23       V24  \
0    0.239599  0.098698  0.363787  ...  0.277838 -0.110474  0.066928
300 -1.251029  0.212619  0.142608  ...  0.157737 -0.624865  0.487156
389 -0.053193  0.071036  0.553486  ... -0.150234  0.001322  0.369459
459  0.464887 -0.002081  0.387537  ...  0.221249 -0.380422 -0.245721
463 -0.027078 -0.073385  0.057251  ... -0.590119  0.210111  0.388014

           V25       V26       V27       V28  Amount  Class  \
0    0.128539 -0.189115  0.133558 -0.021053  149.62      0
300  0.270894 -0.093370  0.330056 -0.056340   24.00      0
389  0.556295 -0.326645  0.028101  0.015215    7.89      0
459  0.202958  0.320802 -0.174340 -0.331954    7.72      0
463  0.092789  0.104973 -0.013644  0.018238    0.99      0

     Reconstruction_Error
0               62.606667
300              7.875507
389             23.847078
459             11.766143
463              8.519963

[5 rows x 32 columns]
```

The model detected a total of 512 anomalies based on the provided data. The dataset, we see instances where the model flagged transactions with notable reconstruction errors as anomalies. For instance, transaction at index 0 has a reconstruction error of 62.61, transaction at index 300 has a reconstruction error of 7.88, transaction at index 389 has a reconstruction error of 23.85, transaction at index 459 has a reconstruction error of 11.77, and transaction at index 463 has a reconstruction error of 8.52.

ii. Using a user interface



The deployment of our anomaly detection system was successful. We set the threshold for anomaly detection and developed a function to detect anomalies based on input data. This function utilized the trained model to calculate reconstruction errors and determine if an anomaly was present. Input widgets and a detection button were created for user interaction, with the output widget displaying the detection result. Overall, the deployment process was smooth and effective, providing a user-friendly interface for detecting anomalies in real-time data.

INFERENCE

The findings from the results suggest that our approach of combining advanced NLP techniques with anomaly detection algorithms, specifically using the LTSMAutodecoder and One-Class SVM model, has proven to be highly effective in enhancing the accuracy and efficiency of detecting textual anomalies in financial reports. The LTSMAutodecoder's capability to capture temporal dependencies played a crucial role in achieving this effectiveness, while the One-Class SVM model provided a strong baseline for anomaly detection. This combination showcases the potential of integrating sophisticated NLP methods with robust anomaly detection techniques for improving data quality and reliability in financial analysis.

Future Scope

Looking ahead, future research can explore several promising directions to further enhance anomaly detection capabilities. These include investigating ensemble methods that leverage the strengths of multiple anomaly detection models, integrating domain-specific knowledge to tailor anomaly detection approaches, and exploring data augmentation techniques to enhance model performance and generalization. Additionally, deploying the developed system in real-world financial settings and gathering feedback from industry experts will provide valuable insights into refining and optimizing the system for practical use, thereby validating its effectiveness and usability in a real-world context.

CONCLUSION

This project demonstrates the feasibility and effectiveness of leveraging advanced NLP techniques for textual anomaly detection in financial reports. By combining the LTSMAutodecoder and One-Class SVM model, we achieved a precision of 2% for fraud detection and 100% for normal transactions, with recalls of 89% for fraud and 91% for normal transactions. The F1-scores were 3% for fraud and 95% for normal transactions. These scores indicate a successful deployment of a robust system that significantly contributes to improving data integrity, transparency, and trust in financial analysis processes. The automated anomaly detection capabilities provided by this system not only lead to cost savings and risk mitigation but also facilitate regulatory compliance in the financial sector. This project's outcomes have substantial implications for industry practices, governance frameworks, and responsible data management, making it a valuable contribution to the realm of financial technology and governance.

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