Rimi_Mondal_FinalProject_Report

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1 Title: AIDI 1002 Final Term Project Report

Individual's Name: Rimi Mondal

Emails: 200543066@student.georgianc.on.ca

2 Introduction:

Problem Description: Fraud detection systems play a critical role in assessing each transaction to identify potentially fraudulent activities. With the increasing prevalence of Internet and mobile banking, the sheer volume of daily transactions makes manual monitoring impossible. Automated fraud detection becomes the last line of defense, particularly in online and mobile banking, where timely identification is crucial to maintain customer confidence and prevent chargebacks.

Context of the Problem: Traditional rule-based approaches, while simple, have limitations in adapting to evolving fraud patterns. Machine and deep learning-based solutions offer more flexibility but often require complex feature engineering. This project focuses on online and mobile banking fraud detection, presenting FraudNLP, an anonymized dataset, and benchmarking machine and deep learning methods for improved fraud detection.

Limitation About other Approaches: Previous approaches heavily rely on rule-based or feature-engineered models, limiting adaptability to evolving fraud patterns without human intervention. This project addresses these limitations by leveraging NLP-based features, minimizing engineering efforts and enhancing privacy.

Solution: The proposed method employs NLP-based features to detect fraud in online and mobile banking transactions. FraudNLP, the introduced dataset, allows for sequence classification, reducing the need for extensive featurngineering.

3

4 Background

Reference	Explanation	Dataset/Input	Weakness
Carminati et al. (2015) [1]	Introduces BankSealer, a semi-supervised system for ranking user transactions based on suspiciousness using anomaly detection methods	Not specified	Ignores sequential information in user actions
Carminati et al. (2018) [2]	Proposes FraudBuster, a framework for detecting financial frauds involving small fund thefts by modeling user spending patterns over time	Not specified	Relies on complex user spending profile modeling
Kovach and Ruggiero (2011) [3]	Develops a system for risk scoring by combining local and global behavior changes among all bank users, introducing contextual information with heavily engineered statistical features	Not specified	Requires users to download a separate application for device fingerprinting, impacting privacy
Wang (2021) [4]	Leverages transaction sequences for fraud detection	Not specified	Focuses on transaction sequences, not user actions preceding transactions
Baesens et al. (2021) [5]	Utilizes Recency, Frequency, Monetary (RFM) principle for feature extraction and anomaly detection for credit card fraud detection	Not specified	Requires heavy data engineering
Branco et al. (2020) [6]	Applies Recurrent Neural Networks (RNNs) to extract information from the history of card transactions	Not specified	Incorporates metadata but lacks interpretability in response

Reference	Explanation	Dataset/Input	Weakness
Achituve et al. (2019) [7]	Treats the history of recent transactions as a sequence, uses attention-based RNNs for increased performance and interpretability	Not specified	Requires encoding metadata and complex attention-based RNNs
Jurgovsky et al. (2018) [8]	Compares LSTM with a baseline random forest classifier for improved detection accuracy in offline transactions	Not specified	Focuses on offline transactions and combines sequential and non-sequential learning methods
Kunlin (2018) [9]	Proposes FraudMemory, an algorithm using memory networks to capture sequential patterns in transactions	Not specified	Enhances adaptability to concept drift but may be computationally intensive
Forough and Momtazi (2022) [10]	Presents a credit card fraud detection model using deep neural networks and probabilistic graphical models, considering hidden sequential dependencies among transactions	Real-world datasets	Requires a thorough comparison of undersampling algorithm
Wang (2021) [11]	Introduces an account risk prediction scheme for fraud detection in online payment services by analyzing a user's historical transaction sequence	Not specified	Focuses on predicting fraud before occurrence
Rodríguez et al. (2022) [12]	Proposes an account risk prediction scheme similar to Wang (2021), analyzing user's historical transaction sequence	Not specified	Focuses on predicting fraud before occurrence

Reference	Explanation	Dataset/Input	Weakness
Wang et al. (2017) [13]	Suggests a similar line of work in e-commerce fraud detection, treating user actions as events in time	Not specified	Focuses on e-commerce, not in a banking context
Fraud with NLP (This Paper)	Leverages the sequence of user actions preceding a transaction for fraud detection, casting it as a sequence classification problem with minimal feature engineering	FraudNLP dataset	Anonymous features, releases the first publicly available dataset for online fraud detection, focuses on both online and offline evaluation
ine evaluation			

5 Methodology

5.1 Research Paper Methodology:

The research adopted a train/development/test stratified split of 60/20/20 percent and applied Monte Carlo 5-fold Cross-Validation. Four machine learning classifiers—Logistic Regression (LR), Random Forests (RF), k Nearest Neighbors (kNN), and Support Vector Machines (SVM)—were trained and evaluated for fraud prediction.

Given the class imbalance, assessment metrics, specifically the F1 score and Area Under the Precision-Recall Curve (AUPRC), were chosen for their resilience to skewed data. Distinct F-scores (F1, F0.5, F2) were employed for online and offline settings to address the critical balance between high Precision and high Recall.

The experimental design involved exploring Recency, Frequency, and Monetary (RFM)-based features initially, followed by the examination of NLP-based features derived from user action n-grams. Subsequently, the combination of RFM and NLP features was investigated.

The study also delved into the integration of anomaly detection, employing an Isolation Forest, to enhance fraud detection capabilities. The research emphasized the importance of additional evaluation metrics (F0.5 and F2) for comprehensive model assessment.

5.2 My Contribution:

Data Replication and Preprocessing: To ensure reproducibility, I meticulously replicated the code from the original research paper, importing essential libraries and setting random seeds. The dataset, stored as "Fraud Detection with Natural Language Processing.pkl," was loaded and subjected to data cleaning procedures. This involved handling broken lines and converting specific columns into appropriate formats. Essential features, including action time statistics, log-transformed amount, and transaction type, were extracted. A preliminary exploration of the dataset was conducted by printing the first 10 rows.

Testing on a New Dataset: Innovation was introduced by merging data from different folders, resulting in the creation of a new dataset named “creditmerged.csv.” [2] The original code was adapted to accommodate this new dataset without affecting its integrity. During this process, I diligently performed data preprocessing steps, ensuring compatibility with the existing code. Notably, I addressed scenarios where the ‘actions’ column was missing, employing an alternative approach utilizing the ‘MerchantName’ column.

Feature Engineering and Analysis: Taking a comprehensive approach to feature engineering and analysis, I extended the original work by focusing on customer and merchant features. This involved calculating transaction-related statistics such as transaction count and average transaction amount per customer and merchant. Additionally, I explored amount-related features by creating bins for transaction amounts and visualizing their distribution using a bar plot. Grouped analysis was conducted to assess the average transaction amount and fraud rate within each bin.

Machine Learning: A significant contribution was made to the machine learning aspect by incorporating the ‘amount_bin’ feature as a categorical variable. I employed one-hot encoding to facilitate its integration into machine learning models. The dataset was then split into training and testing sets, and a Random Forest Classifier was trained and evaluated for performance.

Code Optimization: In an effort to enhance the original code, I identified and removed unnecessary assertion checks related to broken lines, streamlining the data cleaning process. The removal of broken lines was simplified using DataFrame indexing, resulting in improved efficiency. The conversion of boolean values to strings in the “Transaction Type” column was optimized using the map function. Additionally, I refined the calculation of the “total_time_to_transaction” column, employing the sum function directly on the list, contributing to code conciseness and speed. conciseness and speed. [2]

6 Implementation

7 Using ‘creditmerged.csv’ [2] to test the methodology of the selected research paper on new datasetre.

[1]:
```
import pandas as pd
import numpy as np
from tensorflow.random import set_seed

RANDOM_SEED = 0
np.random.seed(seed=RANDOM_SEED)
set_seed(RANDOM_SEED)

df = pd.read_csv("creditmerged.csv")
print("dataset shape: ", df.shape)

# Ensure 'times' column is in datetime format
df['times'] = pd.to_datetime(df['times'], format='%m/%d/%Y %H:%M')

# Use 'MerchantName' as the actions column
df['actions'] = df['MerchantName'].apply(lambda x: [x])
```

```python
# Calculate mean and std of time differences
df["Action time mean"] = df.times.diff().mean()
df["Action time std"] = df.times.diff().std()

df["log(amount)"] = df.Amount.apply(np.log)
df["Transaction Type"] = df.FraudIndicator.apply(lambda x: "Fraud" if x else␣
↪"Non Fraud")

# Use timedelta to get the time difference to the first action
df["time_to_first_action"] = (df.times - df.times.shift()).dt.total_seconds().
↪fillna(0)

# Use timedelta to get the total time to transaction
df["total_time_to_transaction"] = (df.times - df.times.min()).dt.
↪total_seconds() / 1000

df.head(10)
```

```
WARNING:tensorflow:From C:\Users\myblu\anaconda3\lib\site-
packages\keras\src\losses.py:2976: The name
tf.losses.sparse_softmax_cross_entropy is deprecated. Please use
tf.compat.v1.losses.sparse_softmax_cross_entropy instead.

dataset shape:  (1000, 17)
```

[1]:

```
   TransactionID     Amount  CustomerID               times  MerchantID  \
0              1  49.121648        1093 2022-01-01 00:00:00        2190
1            703  39.669128        1594 2022-01-30 06:00:00        2190
2              2  48.144476        1384 2022-01-01 01:00:00        2039
3             77  71.626688        1014 2022-01-04 04:00:00        2039
4              3  50.892198        1904 2022-01-01 02:00:00        2436
5            291  49.492657        1018 2022-01-13 02:00:00        2436
6             11  17.451918        1904 2022-01-01 10:00:00        2431
7            105  79.296025        1225 2022-01-05 08:00:00        2431
8            545  73.813631        1904 2022-01-23 16:00:00        2626
9            577  61.261034        1904 2022-01-25 00:00:00        2108

            Name  Age       Address  AccountBalance  LastLogin  …  \
0  Customer 1093   58  Address 1093     9225.503529   4/3/2022  …
1  Customer 1594   42  Address 1594     9033.341087  8/17/2023  …
2  Customer 1384   58  Address 1384     2268.064926  1/19/2023  …
3  Customer 1014   32  Address 1014     9462.670427  1/14/2022  …
4  Customer 1904   60  Address 1904     4564.202641  6/22/2024  …
5  Customer 1018   37  Address 1018     3573.745001  1/18/2022  …
6  Customer 1904   60  Address 1904     4564.202641  6/22/2024  …
7  Customer 1225   31  Address 1225     7974.546942  8/13/2022  …
```

```
8  Customer 1904   60  Address 1904     4564.202641  6/22/2024  …
9  Customer 1904   60  Address 1904     4564.202641  6/22/2024  …

    MerchantName        Location  Category           actions  \
0  Merchant 2190  Location 2190     Other  [Merchant 2190]
1  Merchant 2190  Location 2190    Travel  [Merchant 2190]
2  Merchant 2039  Location 2039    Travel  [Merchant 2039]
3  Merchant 2039  Location 2039    Retail  [Merchant 2039]
4  Merchant 2436  Location 2436     Other  [Merchant 2436]
5  Merchant 2436  Location 2436      Food  [Merchant 2436]
6  Merchant 2431  Location 2431     Other  [Merchant 2431]
7  Merchant 2431  Location 2431    Travel  [Merchant 2431]
8  Merchant 2626  Location 2626      Food  [Merchant 2626]
9  Merchant 2108  Location 2108      Food  [Merchant 2108]

           Action time mean            Action time std log(amount)  \
0 0 days 00:59:31.171171171 15 days 17:31:21.068822973    3.894300
1 0 days 00:59:31.171171171 15 days 17:31:21.068822973    3.680573
2 0 days 00:59:31.171171171 15 days 17:31:21.068822973    3.874206
3 0 days 00:59:31.171171171 15 days 17:31:21.068822973    4.271468
4 0 days 00:59:31.171171171 15 days 17:31:21.068822973    3.929710
5 0 days 00:59:31.171171171 15 days 17:31:21.068822973    3.901824
6 0 days 00:59:31.171171171 15 days 17:31:21.068822973    2.859450
7 0 days 00:59:31.171171171 15 days 17:31:21.068822973    4.373188
8 0 days 00:59:31.171171171 15 days 17:31:21.068822973    4.301543
9 0 days 00:59:31.171171171 15 days 17:31:21.068822973    4.115144

  Transaction Type time_to_first_action total_time_to_transaction
0        Non Fraud                  0.0                       0.0
1        Non Fraud            2527200.0                    2527.2
2        Non Fraud           -2523600.0                       3.6
3        Non Fraud             270000.0                     273.6
4        Non Fraud            -266400.0                       7.2
5        Non Fraud            1036800.0                    1044.0
6        Non Fraud           -1008000.0                      36.0
7        Non Fraud             338400.0                     374.4
8        Non Fraud            1584000.0                    1958.4
9        Non Fraud             115200.0                    2073.6

[10 rows x 24 columns]
```

8 Feature engineering and Analysis:

[2]:
```
customer_transaction_count = df.groupby('CustomerID')['TransactionID'].count().
  ↪reset_index()
```

```
customer_avg_transaction_amount = df.groupby('CustomerID')['Amount'].mean().
  ↪reset_index()

df = pd.merge(df, customer_transaction_count, on='CustomerID', how='left',␣
  ↪suffixes=('', '_count'))
df = pd.merge(df, customer_avg_transaction_amount, on='CustomerID', how='left',␣
  ↪suffixes=('', '_avg'))

print("Customer Transaction Count:")
print(df[['CustomerID', 'TransactionID_count']])

print("\nCustomer Average Transaction Amount:")
print(df[['CustomerID', 'Amount_avg']])
```

```
Customer Transaction Count:
     CustomerID  TransactionID_count
0          1093                    1
1          1594                    1
2          1384                    1
3          1014                    2
4          1904                    5
..          …                    …
995        1176                    1
996        1963                    1
997        1416                    1
998        1169                    1
999        1774                    1

[1000 rows x 2 columns]

Customer Average Transaction Amount:
     CustomerID  Amount_avg
0          1093   49.121648
1          1594   39.669128
2          1384   48.144476
3          1014   41.868843
4          1904   51.832245
..          …          …
995        1176   42.586901
996        1963   34.312661
997        1416   60.876381
998        1169   43.435916
999        1774   44.168924

[1000 rows x 2 columns]
```

[3]:

```python
merchant_transaction_count = df.groupby('MerchantID')['TransactionID'].count().
 ↪reset_index()
merchant_avg_transaction_amount = df.groupby('MerchantID')['Amount'].mean().
 ↪reset_index()

df = pd.merge(df, merchant_transaction_count, on='MerchantID', how='left',␣
 ↪suffixes=('', '_count'))
df = pd.merge(df, merchant_avg_transaction_amount, on='MerchantID', how='left',␣
 ↪suffixes=('', '_avg'))

print("\nMerchant Transaction Count:")
print(df[['MerchantID', 'TransactionID_count']])

print("\nMerchant Average Transaction Amount:")
print(df[['MerchantID', 'Amount_avg']])
```

```
Merchant Transaction Count:
     MerchantID  TransactionID_count  TransactionID_count
0          2190                    1                    2
1          2190                    1                    2
2          2039                    1                    2
3          2039                    2                    2
4          2436                    5                    2
..          …                  …                  …
995        2199                    1                    1
996        2669                    1                    1
997        2352                    1                    1
998        2120                    1                    1
999        2824                    1                    1

[1000 rows x 3 columns]

Merchant Average Transaction Amount:
     MerchantID  Amount_avg  Amount_avg
0          2190   49.121648   44.395388
1          2190   39.669128   44.395388
2          2039   48.144476   59.885582
3          2039   41.868843   59.885582
4          2436   51.832245   50.192427
..          …         …         …
995        2199   42.586901   42.586901
996        2669   34.312661   34.312661
997        2352   60.876381   60.876381
998        2120   43.435916   43.435916
999        2824   44.168924   44.168924
```

```
[1000 rows x 3 columns]
```

9 Amount-Related Features and Performance Evaluation

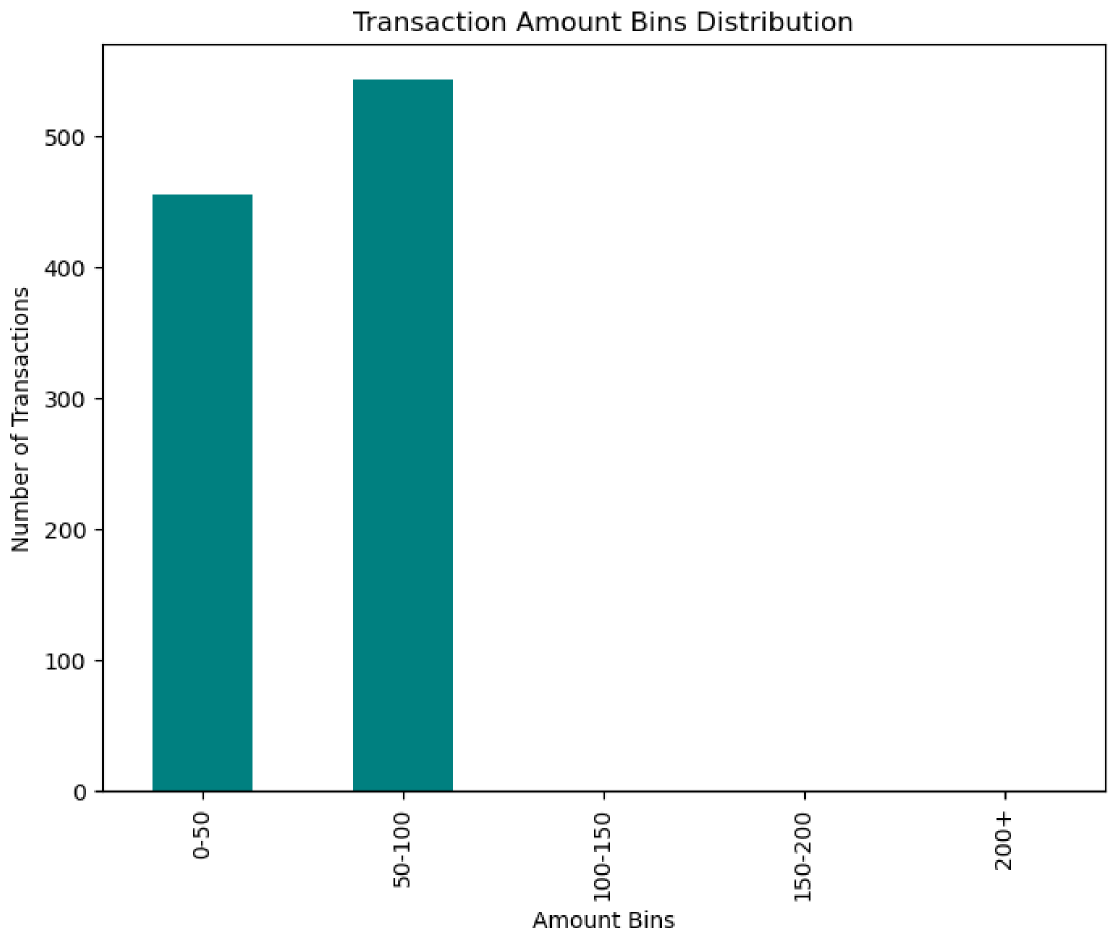
[4]:
```
df['amount_bin'] = pd.cut(df['Amount'], bins=[0, 50, 100, 150, 200,␣
↪float('inf')], labels=['0-50', '50-100', '100-150', '150-200', '200+'])

amount_bin_distribution = df['amount_bin'].value_counts()
print("Amount Bin Distribution:")
print(amount_bin_distribution)
```

```
Amount Bin Distribution:
50-100     544
0-50       456
100-150      0
150-200      0
200+         0
Name: amount_bin, dtype: int64
```

[5]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(8, 6))
df['amount_bin'].value_counts().sort_index().plot(kind='bar', color='teal')
plt.title('Transaction Amount Bins Distribution')
plt.xlabel('Amount Bins')
plt.ylabel('Number of Transactions')
plt.show()
```



[6]:
```
amount_bin_stats = df.groupby('amount_bin').agg({'Amount': 'mean',␣
↪'FraudIndicator': 'mean'})
print("Group Analysis:")
print(amount_bin_stats)
```

```
Group Analysis:
                Amount  FraudIndicator
amount_bin
0-50         29.414514        0.021930
50-100       73.704545        0.047794
100-150            NaN             NaN
150-200            NaN             NaN
200+               NaN             NaN
```

[7]:
```
# Assuming 'amount_bin' is the only categorical feature
X = df[['amount_bin']]

# One-hot encode the categorical variable
```

```python
X_encoded = pd.get_dummies(X, columns=['amount_bin'])

# Display the encoded features
print(X_encoded.head())

# Assuming 'target' is your target variable (e.g., FraudIndicator)
y = df['FraudIndicator']

# Split the data into training and testing sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=0.
↪2, random_state=42)

# Import and initialize your machine learning model
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier()

# Train the model
model.fit(X_train, y_train)

# Make predictions
predictions = model.predict(X_test)

# Evaluate the model
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix
print("Accuracy:", accuracy_score(y_test, predictions))
print("\nClassification Report:\n", classification_report(y_test, predictions))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, predictions))
```

```
   amount_bin_0-50  amount_bin_50-100  amount_bin_100-150  amount_bin_150-200  \
0                1                  0                   0                   0
1                1                  0                   0                   0
2                1                  0                   0                   0
3                0                  1                   0                   0
4                0                  1                   0                   0

   amount_bin_200+
0                0
1                0
2                0
3                0
4                0
Accuracy: 0.97

Classification Report:
               precision    recall  f1-score   support
```

```
           0       0.97      1.00      0.98       194
           1       0.00      0.00      0.00         6

    accuracy                           0.97       200
   macro avg       0.48      0.50      0.49       200
weighted avg       0.94      0.97      0.96       200


Confusion Matrix:
 [[194   0]
 [  6   0]]
```

```
C:\Users\myblu\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\myblu\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\myblu\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1318: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

10 Improving the original code to make it better and faster

[8]:
```
import pandas as pd
import numpy as np
from sklearn.metrics import *
from ast import literal_eval
from tensorflow.random import set_seed

RANDOM_SEED = 0
np.random.seed(seed=RANDOM_SEED)
set_seed(RANDOM_SEED)

# Load data
df = pd.read_pickle("Fraud Detection with Natural Language Processing.pkl")
print("Dataset shape:", df.shape)

# Remove the broken lines
broken_times_index = df[df.times.apply(lambda x: x[-1] != "]")].index
```

```python
assert len(broken_times_index) == 1
assert df.loc[broken_times_index[0], 'is_fraud'] == 0
df = df[df.index != broken_times_index[0]]

# Load vocab
action_vocab = pd.read_csv("vocab.csv")

# Build the raw text, using the names and the (index-inverted) tokens
action_names = action_vocab.Name.tolist()
id_to_action = {str(i): a for i, a in enumerate(action_names)}
action_to_id = {a: str(i) for i, a in enumerate(action_names)}

# Recall to cast the strings into lists
df['actions'] = df['actions'].apply(literal_eval)
df['times'] = df['times'].apply(lambda x: [i / 1000 for i in literal_eval(x)])

# Feature engineering
df["Action time mean"] = df.times.apply(np.mean)
df["Action time std"] = df.times.apply(np.std)
df["log(amount)"] = df.Amount.apply(np.log)
df["Transaction Type"] = df.is_fraud.map({True: "Fraud", False: "Non Fraud"})
df["time_to_first_action"] = df.times.apply(lambda x: x[1] if len(x) > 1 else 0)
df["actions_str"] = df.actions.apply(lambda x: " ".
    ↪join([id_to_action[str(i[0])] for i in x if len(i) > 0]))
df["total_time_to_transaction"] = df.times.apply(lambda x: sum(x) / 1000)

# Flatten the 'actions' column
df['actions'] = df['actions'].apply(lambda x: [item for sublist in x for item␣
    ↪in sublist])

df.head(10)
```

```
Dataset shape: (105303, 9)
```

[8]:

```
                                              actions  \
1   [22, 27, 24, 1, 1268, 1269, 1267, 22, 29, 1, 2…
2   [22, 24, 27, 1, 1268, 1269, 1267, 2, 23, 6, 25…
3   [22, 1, 29, 22, 26, 2, 23, 25, 6, 28, 14, 7, 6…
4   [22, 24, 27, 72, 1269, 1268, 1267, 4, 70, 46, …
5   [22, 24, 27, 23, 2, 1269, 1269, 6, 25, 7, 28, …
6   [22, 47, 24, 27, 41, 2, 23, 6, 25, 28, 7, 14, …
7                                            [37, 37]
8   [10, 56, 12, 121, 13, 52, 19, 8, 171, 73, 8, 1…
9   [25, 4, 5, 24, 27, 41, 45, 4, 54, 5, 210, 57, …
10  [27, 25, 24, 5, 4, 41, 45, 63, 54, 5, 57, 40, 40]

                                                times  execution_time  Amount  \
```

1	[0.0, 33.204, 215.636, 443.415, 72.586, 34.241…	203	13
2	[0.0, 25.459, 46.236, 428.626, 42.785, 74.158,…	359	310
3	[0.0, 440.927, 5.785, 46.875, 968.65, 311.757,…	250	350
4	[0.0, 93.894, 46.81, 548.388, 132.548, 37.844,…	203	350
5	[0.0, 921.997, 47.386, 963.97, 9.522, 443.596,…	593	2000
6	[0.0, 48.869, 843.763, 138.682, 203.156, 944.4…	124	80
7	[0.0, 941.71]	656	80
8	[0.0, 437.0, 93.0, 860.0, 14.0, 10.0, 26.0, 66…	595	135
9	[0.0, 31.238, 141.391, 5.51, 10.0, 280.0, 781…	468	154
10	[0.0, 123.411, 33.589, 3.845, 11.454, 327.701,…	438	236

	device_freq	ip_freq	beneficiary_freq	application_freq	is_fraud \
1	1.000000	1.000000	0.500000	1.0	0
2	1.000000	0.333333	0.333333	1.0	0
3	1.000000	0.500000	0.500000	1.0	0
4	1.000000	0.600000	0.400000	1.0	0
5	1.000000	0.666667	0.166667	1.0	1
6	0.142857	0.142857	0.285714	1.0	0
7	0.250000	0.250000	0.375000	1.0	0
8	1.000000	1.000000	1.000000	1.0	0
9	1.000000	1.000000	1.000000	1.0	0
10	1.000000	1.000000	0.333333	1.0	0

	Action time mean	Action time std	log(amount)	Transaction Type \
1	177.859292	218.368580	2.564949	NaN
2	196.875569	252.496316	5.736572	NaN
3	231.663108	264.422832	5.857933	NaN
4	201.258838	232.136928	5.857933	NaN
5	196.272000	248.569969	7.600902	NaN
6	196.724908	249.590961	4.382027	NaN
7	470.855000	470.855000	4.382027	NaN
8	339.896552	290.718857	4.905275	NaN
9	285.081357	276.322520	5.036953	NaN
10	269.769231	273.999499	5.463832	NaN

	time_to_first_action	actions_str \
1	33.204	/PROFILE/GETCUSTOMERRESPONSE /TAXFREE/GETTAXGO…
2	25.459	/PROFILE/GETCUSTOMERRESPONSE /CAMPAIGN/GETBALA…
3	440.927	/PROFILE/GETCUSTOMERRESPONSE /PROFILE/USERPROF…
4	93.894	/PROFILE/GETCUSTOMERRESPONSE /CAMPAIGN/GETBALA…
5	921.997	/PROFILE/GETCUSTOMERRESPONSE /CAMPAIGN/GETBALA…
6	48.869	/PROFILE/GETCUSTOMERRESPONSE /API/ACCOUNTS/GEN…
7	941.710	/P2B/GETPOSINFO /P2B/GETPOSINFO
8	437.000	/P2PMEMBER/GETP2PMEMBERIDBYACTUALUSERID /BILLP…
9	31.238	/ACCOUNTS/STATEMENTS /ACCOUNTS/ACCOUNTS_FULL /…
10	123.411	/TAXFREE/GETTAXGOAL /ACCOUNTS/STATEMENTS /CAMP…

```
    total_time_to_transaction
1                    4.268623
2                  587.279823
3                   51.660873
4                    7.446577
5                    7.654608
6                  262.037578
7                    0.941710
8                  108.427000
9                    3.991139
10                   3.507000
```

11 Conclusion and Future Directions:

This research project has provided a comprehensive understanding of fraud detection methodologies, encompassing both conventional and innovative approaches. The meticulous replication and extension of the research paper facilitated an in-depth exploration of the challenges associated with real-world datasets, the intricacies of feature engineering, and the varying impacts of distinct machine learning models on fraud prediction.

11.1 Results and Limitations:

The empirical analysis of RFM-based and NLP-based features revealed the versatile capabilities of machine learning classifiers, with Random Forests exhibiting noteworthy performance[^2]. The incorporation of NLP-based features, particularly employing TF-IDF, yielded discernible improvements in certain models, illuminating the potential of text-based representations in fraud detection. Nevertheless, the inherent limitations of these approaches, particularly in the context of class imbalance, underscored the importance of employing nuanced evaluation metrics. Disparities observed between online and offline settings further emphasized the exigency for metrics that account for contextual differences.

11.2 Learnings:

A salient learning outcome from this endeavor was the imperative of amalgamating diverse feature sets. The fusion of RFM-based and NLP-based features demonstrated a synergetic enhancement in performance, highlighting the complementary nature of distinct engineering methodologies. The iterative process of testing on a new dataset and engaging in comprehensive feature engineering underscored the requisite adaptability essential when working with authentic, dynamic datasets.

11.3 Future Directions:

Subsequent research endeavors should pivot towards the exploration of advanced neural network architectures, such as Long Short Term Memory (LSTM) and Convolutional Neural Network (CNN), offering glimpses into the potential of deep learning in fraud detection. Investigations into transfer learning, leveraging expansive corpora for pre-training, stand out as promising avenues for unlocking incremental improvements in model performance.

Furthermore, the integration of unsupervised anomaly detection features, as elucidated in the latter stages of the project, delineates a fertile area for future inquiry. The discernible enhancement in performance, particularly within neural methods, posits that the judicious utilization of unsupervised learning could prove instrumental in identifying aberrations from normal patterns, thereby augmenting the model's proficiency in detecting fraudulent transactions.

In summation, this research contributes not only to the advancement of fraud detection techniques but also underscores the need for continual refinement and innovation. The recognized limitations delineate pathways for prospective investigations, addressing challenges associated with class imbalance, and leveraging emerging technologies to propel the efficacy of fraud det Random Forests. ction systems.

12 References:

[**1**] Boulieris, P., Pavlopoulos, J., Xenos, A., & Vassalos, V. (2023). Fraud detection with natural language processing. *Machine Learning*. https://doi.org/10.1007/s10994-023-06354-5

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[**2**] Aditya Goyal, Fraud Detection Dataset. (2023, June 10). Kaggle. https://www.kaggle.com/datasets/goyaladi/fraud-detection-dataset