In [1]:
```
pip install tensorflow
```

```
Requirement already satisfied: tensorflow in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (2.17.0)
Requirement already satisfied: tensorflow-intel==2.17.0 in c:\users\brady\onedrive\apps\anaconda\lib\site-packag
es (from tensorflow) (2.17.0)
Requirement already satisfied: absl-py>=1.0.0 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from t
ensorflow-intel==2.17.0->tensorflow) (2.1.0)
Requirement already satisfied: astunparse>=1.6.0 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (fro
m tensorflow-intel==2.17.0->tensorflow) (1.6.3)
Requirement already satisfied: flatbuffers>=24.3.25 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (
from tensorflow-intel==2.17.0->tensorflow) (24.3.25)
Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1 in c:\users\brady\onedrive\apps\anaconda\lib\
site-packages (from tensorflow-intel==2.17.0->tensorflow) (0.6.0)
Requirement already satisfied: google-pasta>=0.1.1 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (f
rom tensorflow-intel==2.17.0->tensorflow) (0.2.0)
Requirement already satisfied: h5py>=3.10.0 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from ten
sorflow-intel==2.17.0->tensorflow) (3.11.0)
Requirement already satisfied: libclang>=13.0.0 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from
tensorflow-intel==2.17.0->tensorflow) (18.1.1)
Requirement already satisfied: ml-dtypes<0.5.0,>=0.3.1 in c:\users\brady\onedrive\apps\anaconda\lib\site-package
s (from tensorflow-intel==2.17.0->tensorflow) (0.4.1)
Requirement already satisfied: opt-einsum>=2.3.2 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (fro
m tensorflow-intel==2.17.0->tensorflow) (3.4.0)
Requirement already satisfied: packaging in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from tensor
flow-intel==2.17.0->tensorflow) (23.2)
Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.4,!=4.21.5,<5.0.0dev,>=3.20.3
in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from tensorflow-intel==2.17.0->tensorflow) (3.20.3)
Requirement already satisfied: requests<3,>=2.21.0 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (f
rom tensorflow-intel==2.17.0->tensorflow) (2.32.2)
Requirement already satisfied: setuptools in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from tenso
rflow-intel==2.17.0->tensorflow) (75.3.0)
Requirement already satisfied: six>=1.12.0 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from tens
orflow-intel==2.17.0->tensorflow) (1.16.0)
Requirement already satisfied: termcolor>=1.1.0 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from
tensorflow-intel==2.17.0->tensorflow) (2.5.0)
Requirement already satisfied: typing-extensions>=3.6.6 in c:\users\brady\onedrive\apps\anaconda\lib\site-packag
es (from tensorflow-intel==2.17.0->tensorflow) (4.11.0)
Requirement already satisfied: wrapt>=1.11.0 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from te
nsorflow-intel==2.17.0->tensorflow) (1.14.1)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (f
rom tensorflow-intel==2.17.0->tensorflow) (1.66.2)
Requirement already satisfied: tensorboard<2.18,>=2.17 in c:\users\brady\onedrive\apps\anaconda\lib\site-package
s (from tensorflow-intel==2.17.0->tensorflow) (2.17.1)
Requirement already satisfied: keras>=3.2.0 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from ten
sorflow-intel==2.17.0->tensorflow) (3.6.0)
Requirement already satisfied: numpy<2.0.0,>=1.26.0 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (
from tensorflow-intel==2.17.0->tensorflow) (1.26.4)
Requirement already satisfied: wheel<1.0,>=0.23.0 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (fr
om astunparse>=1.6.0->tensorflow-intel==2.17.0->tensorflow) (0.44.0)
Requirement already satisfied: rich in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from keras>=3.2.
0->tensorflow-intel==2.17.0->tensorflow) (13.3.5)
Requirement already satisfied: namex in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from keras>=3.2
.0->tensorflow-intel==2.17.0->tensorflow) (0.0.8)
Requirement already satisfied: optree in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from keras>=3.
2.0->tensorflow-intel==2.17.0->tensorflow) (0.13.0)
Requirement already satisfied: charset-normalizer<4,>=2 in c:\users\brady\onedrive\apps\anaconda\lib\site-packag
es (from requests<3,>=2.21.0->tensorflow-intel==2.17.0->tensorflow) (2.0.4)
Requirement already satisfied: idna<4,>=2.5 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from req
uests<3,>=2.21.0->tensorflow-intel==2.17.0->tensorflow) (3.7)
Requirement already satisfied: urllib3<3,>=1.21.1 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (fr
om requests<3,>=2.21.0->tensorflow-intel==2.17.0->tensorflow) (2.2.2)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (fr
om requests<3,>=2.21.0->tensorflow-intel==2.17.0->tensorflow) (2024.8.30)
Requirement already satisfied: markdown>=2.6.8 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from
tensorboard<2.18,>=2.17->tensorflow-intel==2.17.0->tensorflow) (3.4.1)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in c:\users\brady\onedrive\apps\anaconda\li
b\site-packages (from tensorboard<2.18,>=2.17->tensorflow-intel==2.17.0->tensorflow) (0.7.2)
Requirement already satisfied: werkzeug>=1.0.1 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from
tensorboard<2.18,>=2.17->tensorflow-intel==2.17.0->tensorflow) (3.0.3)
Requirement already satisfied: MarkupSafe>=2.1.1 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (fro
m werkzeug>=1.0.1->tensorboard<2.18,>=2.17->tensorflow-intel==2.17.0->tensorflow) (2.1.3)
Requirement already satisfied: markdown-it-py<3.0.0,>=2.2.0 in c:\users\brady\onedrive\apps\anaconda\lib\site-pa
ckages (from rich->keras>=3.2.0->tensorflow-intel==2.17.0->tensorflow) (2.2.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in c:\users\brady\onedrive\apps\anaconda\lib\site-package
s (from rich->keras>=3.2.0->tensorflow-intel==2.17.0->tensorflow) (2.15.1)
Requirement already satisfied: mdurl~=0.1 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from markd
own-it-py<3.0.0,>=2.2.0->rich->keras>=3.2.0->tensorflow-intel==2.17.0->tensorflow) (0.1.0)
Note: you may need to restart the kernel to use updated packages.
```

In [2]:
```
pip install tabulate
```

```
Requirement already satisfied: tabulate in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (0.9.0)
Note: you may need to restart the kernel to use updated packages.
```

In [3]:
```
pip install scikit-learn
```

```
Requirement already satisfied: scikit-learn in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (1.5.2)
Requirement already satisfied: numpy>=1.19.5 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from sc
ikit-learn) (1.26.4)
Requirement already satisfied: scipy>=1.6.0 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from sci
kit-learn) (1.13.1)
Requirement already satisfied: joblib>=1.2.0 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (from sc
ikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in c:\users\brady\onedrive\apps\anaconda\lib\site-packages (
from scikit-learn) (3.5.0)
Note: you may need to restart the kernel to use updated packages.
```

In [4]:
```
#WEEK 2 START
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Embedding, Flatten, Dense, Concatenate
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from scipy.spatial.distance import cdist
```

In [5]:
```
#create pandas DataFrame for financial anomaly data
financial_df = pd.read_csv("~/Analytics-Practicum/data/financial_anomaly_data2.csv")
```

In [6]:
```
#print first 5 columns of DataFrame
financial_df.head(5)
```

Out[6]:

	Timestamp	TransactionID	AccountID	Amount	Merchant	TransactionType	Location
0	1/1/2023 8:00	TXN1127	ACC4	95071.92	MerchantH	Purchase	Tokyo
1	1/1/2023 8:01	TXN1639	ACC10	15607.89	MerchantH	Purchase	London
2	1/1/2023 8:02	TXN872	ACC8	65092.34	MerchantE	Withdrawal	London
3	1/1/2023 8:03	TXN1438	ACC6	87.87	MerchantE	Purchase	London
4	1/1/2023 8:04	TXN1338	ACC6	716.56	MerchantI	Purchase	Los Angeles

In [7]:
```
#print class, RangeIndex, columns, non-null count, data type, and memory usage information
financial_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 216960 entries, 0 to 216959
Data columns (total 7 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   Timestamp        216960 non-null  object 
 1   TransactionID    216960 non-null  object 
 2   AccountID        216960 non-null  object 
 3   Amount           216960 non-null  float64
 4   Merchant         216960 non-null  object 
 5   TransactionType  216960 non-null  object 
 6   Location         216960 non-null  object 
dtypes: float64(1), object(6)
memory usage: 11.6+ MB
```

In [8]:
```
#print shape of DataFrame
financial_df.shape
```

Out[8]:
```
(216960, 7)
```

In [9]:
```
#print sum of null occurrences of each variable in DataFrame
print(financial_df.isnull().sum())
```

```
Timestamp          0
TransactionID      0
AccountID          0
Amount             0
Merchant           0
TransactionType    0
Location           0
dtype: int64
```

In [10]:
```
#create a new DataFrame excluding null occurrences
new_financial_df = financial_df.dropna()
```

In [11]:
```
#print shape of new DataFrame
new_financial_df.shape
```

Out[11]:
```
(216960, 7)
```

In [12]:
```
#verify that null occurrences were handled properly
print(new_financial_df.isnull().sum())
```

```
Timestamp          0
TransactionID      0
AccountID          0
Amount             0
Merchant           0
TransactionType    0
Location           0
dtype: int64
```

In [13]:
```
#print number of unique occurrences of each variable in DataFrame
print(f"Number of unique Timestamp: {new_financial_df['Timestamp'].nunique()}")
print(f"Number of unique TransactionID: {new_financial_df['TransactionID'].nunique()}")
print(f"Number of unique AccountID: {new_financial_df['AccountID'].nunique()}")
print(f"Number of unique Amount: {new_financial_df['Amount'].nunique()}")
print(f"Number of unique Merchant: {new_financial_df['Merchant'].nunique()}")
print(f"Number of unique TransactionType: {new_financial_df['TransactionType'].nunique()}")
print(f"Number of unique Location: {new_financial_df['Location'].nunique()}")
```

```
Number of unique Timestamp: 216960
Number of unique TransactionID: 1999
Number of unique AccountID: 15
Number of unique Amount: 214687
Number of unique Merchant: 10
Number of unique TransactionType: 3
Number of unique Location: 5
```

In [14]:
```
#introduce new variables to DataFrame for analysis of certain variables' interactions
new_financial_df['AccountID/Merchant'] = new_financial_df['AccountID'].astype(str) + '_' + new_financial_df['Me
new_financial_df['AccountID/TransactionID'] = new_financial_df['AccountID'].astype(str) + '_' + new_financial_d
new_financial_df['AccountID/Merchant/TransactionID'] = new_financial_df['AccountID'].astype(str) + '_' + new_fi
new_financial_df['TransactionType/Merchant'] = new_financial_df['TransactionType'].astype(str) + '_' + new_finan
new_financial_df['Location/TransactionType'] = new_financial_df['Location'].astype(str) + '_' + new_financial_d
new_financial_df['Merchant/Location'] = new_financial_df['Merchant'].astype(str) + '_' + new_financial_df['Loca
```

In [15]:
```
#verify that new variables have been created successfully
new_financial_df.head(5)
```

Out[15]:

	Timestamp	TransactionID	AccountID	Amount	Merchant	TransactionType	Location	AccountID/Merchant	AccountID/Transact
0	1/1/2023 8:00	TXN1127	ACC4	95071.92	MerchantH	Purchase	Tokyo	ACC4_MerchantH	ACC4_TXN
1	1/1/2023 8:01	TXN1639	ACC10	15607.89	MerchantH	Purchase	London	ACC10_MerchantH	ACC10_TXN
2	1/1/2023 8:02	TXN872	ACC8	65092.34	MerchantE	Withdrawal	London	ACC8_MerchantE	ACC8_TX
3	1/1/2023 8:03	TXN1438	ACC6	87.87	MerchantE	Purchase	London	ACC6_MerchantE	ACC6_TXN
4	1/1/2023 8:04	TXN1338	ACC6	716.56	MerchantI	Purchase	Los Angeles	ACC6_MerchantI	ACC6_TXN

In [16]:
```
#convert Timestamp variable to a DateTime object
new_financial_df['Timestamp'] = pd.to_datetime(new_financial_df['Timestamp'], format='%d/%m/%Y %H:%M')
```

In [17]:
```
#create distinct features for minute/hour of the day, day of the week, and month
new_financial_df['Minute'] = new_financial_df['Timestamp'].dt.minute
new_financial_df['Hour'] = new_financial_df['Timestamp'].dt.hour
new_financial_df['Day'] = new_financial_df['Timestamp'].dt.dayofweek
new_financial_df['Month'] = new_financial_df['Timestamp'].dt.month
```

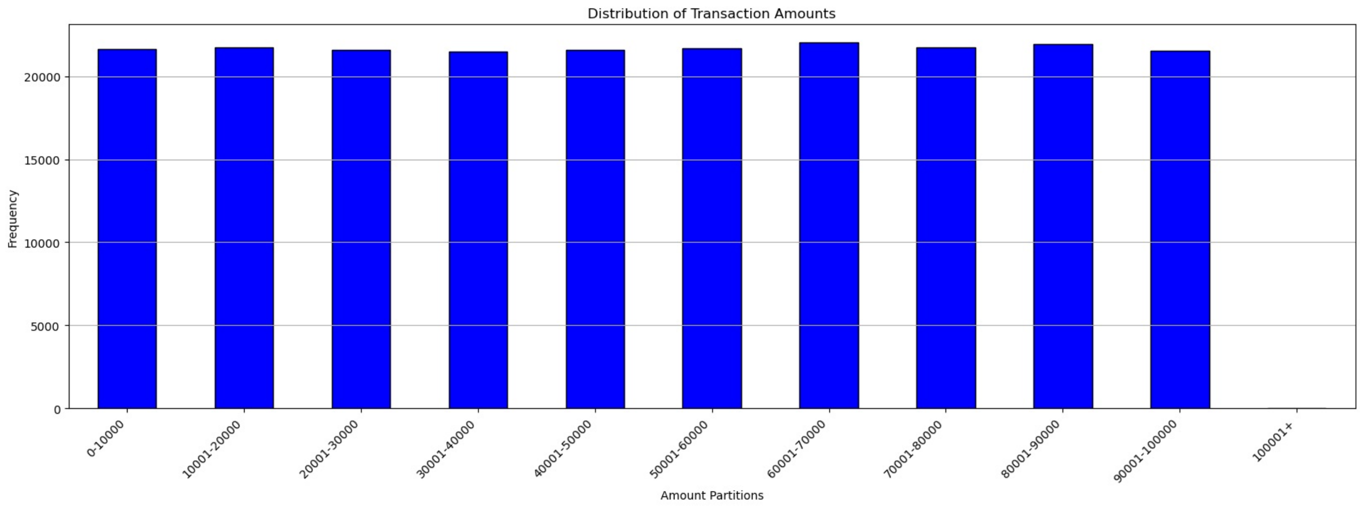
In [18]:
```
#verify again that new variables have been created successfully
new_financial_df.head(5)
```

Out[18]:

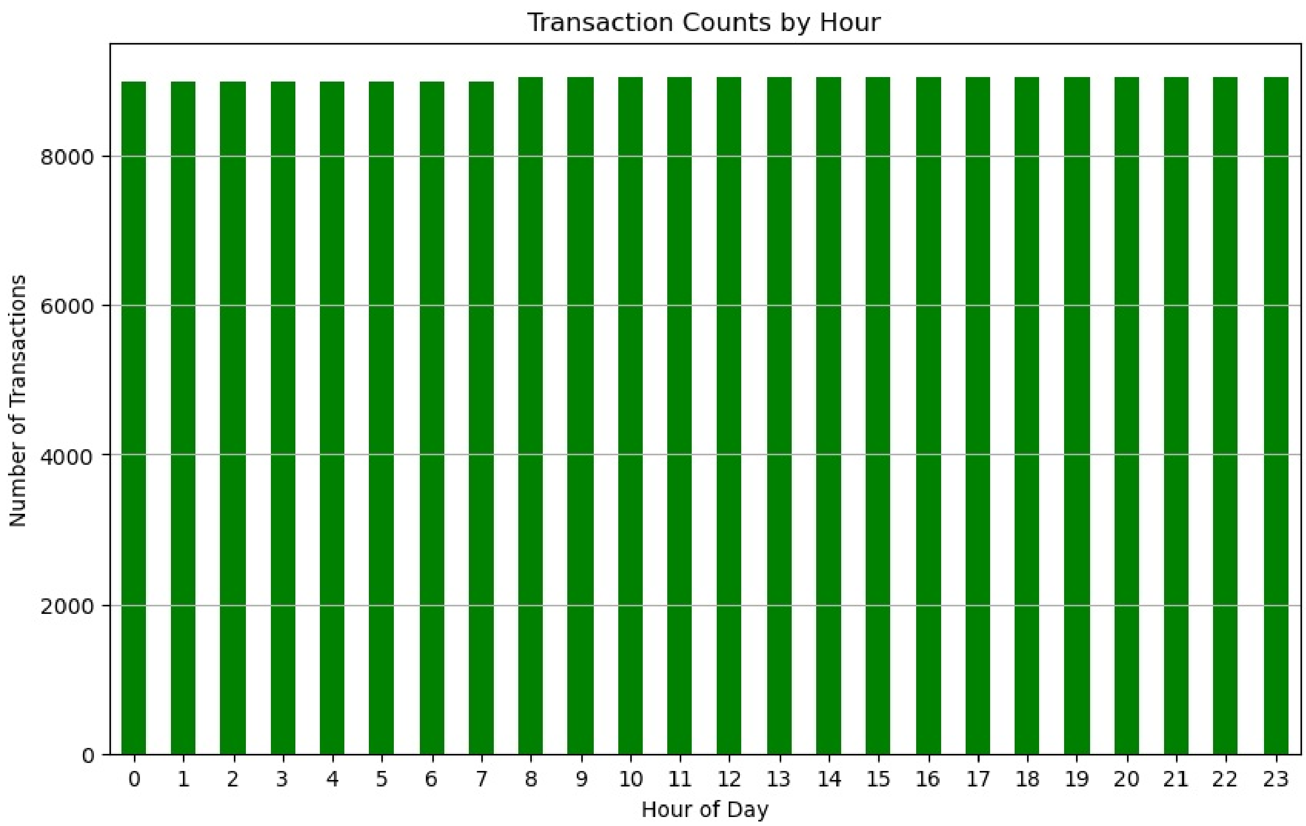
	Timestamp	TransactionID	AccountID	Amount	Merchant	TransactionType	Location	AccountID/Merchant	AccountID/Transact
0	2023-01-01 08:00:00	TXN1127	ACC4	95071.92	MerchantH	Purchase	Tokyo	ACC4_MerchantH	ACC4_TXN
1	2023-01-01 08:01:00	TXN1639	ACC10	15607.89	MerchantH	Purchase	London	ACC10_MerchantH	ACC10_TXN
2	2023-01-01 08:02:00	TXN872	ACC8	65092.34	MerchantE	Withdrawal	London	ACC8_MerchantE	ACC8_TX
3	2023-01-01 08:03:00	TXN1438	ACC6	87.87	MerchantE	Purchase	London	ACC6_MerchantE	ACC6_TXN
4	2023-01-01 08:04:00	TXN1338	ACC6	716.56	MerchantI	Purchase	Los Angeles	ACC6_MerchantI	ACC6_TXN

In [19]:
```
#Divide amount variable into appropriately-sized partitions
bins = [0, 10000, 20000, 30000, 40000, 50000, 60000, 70000, 80000, 90000, 100000, float('inf')]
labels = ['0-10000', '10001-20000', '20001-30000', '30001-40000', '40001-50000', '50001-60000', '60001-70000',
new_financial_df['Amount_Partitions'] = pd.cut(new_financial_df['Amount'], bins=bins, labels=labels)
```

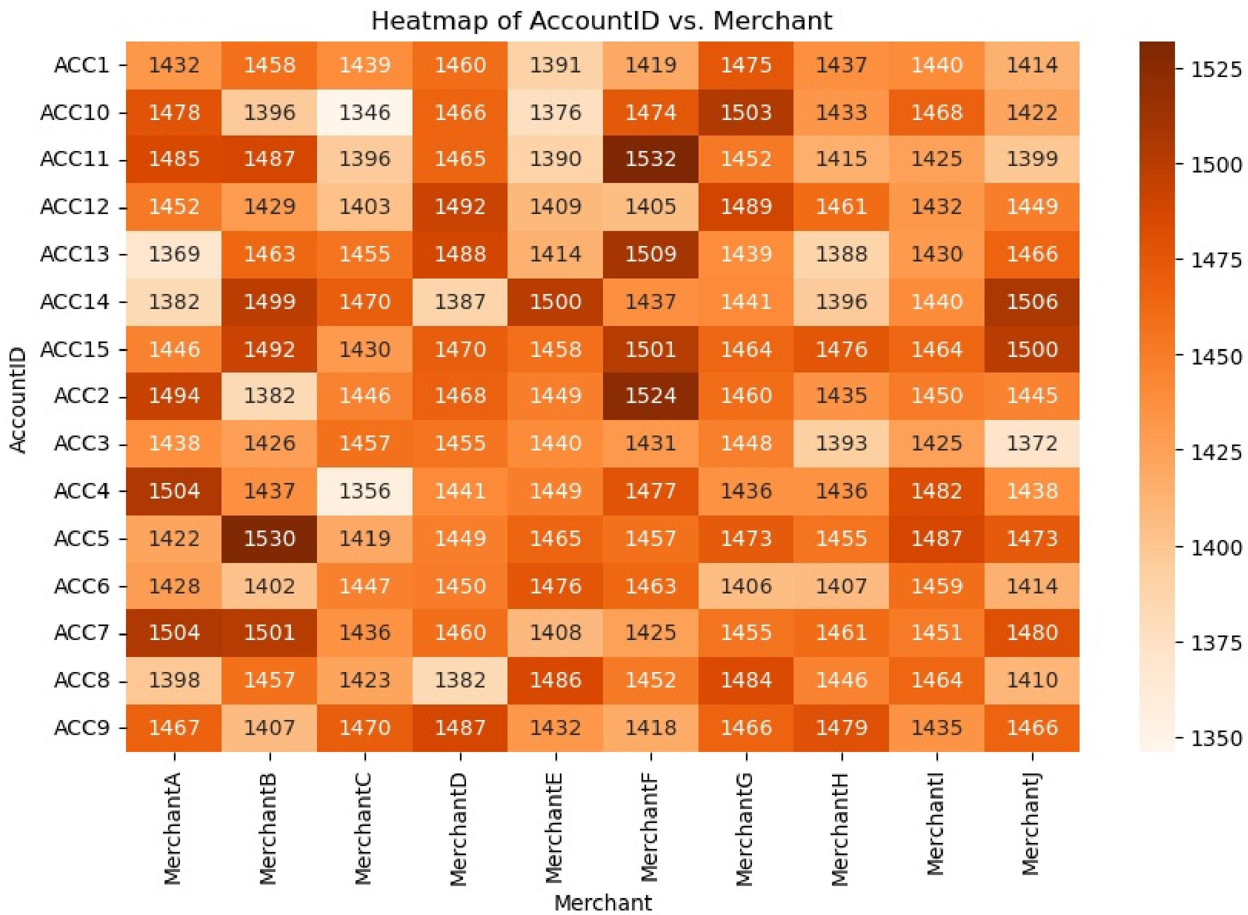
In [20]:
```
#Construct Bar Graph for distribution of transaction in each amount partition
partition_counts = new_financial_df['Amount_Partitions'].value_counts().reindex(labels)

plt.figure(figsize=(20, 6))
partition_counts.plot(kind='bar', color='blue', edgecolor='black')
plt.title('Distribution of Transaction Amounts')
plt.xlabel('Amount Partitions')
plt.ylabel('Frequency')
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y')
plt.show()
```



In [21]:
```
#Construct bar graph for total number of transactions per hour
hour_counts = new_financial_df['Hour'].value_counts().sort_index()

plt.figure(figsize=(10, 6))
hour_counts.plot(kind='bar', color='green')
plt.title('Transaction Counts by Hour')
plt.xlabel('Hour of Day')
plt.ylabel('Number of Transactions')
plt.xticks(rotation=0)
plt.grid(axis='y')
plt.show()
```




```
In [22]: #Construct heat map to visualize total amounts of each combination of AccountID and Merchant (150 combinations)
pivot_table = pd.crosstab(new_financial_df['AccountID'], new_financial_df['Merchant'])

plt.figure(figsize=(10, 6))
sns.heatmap(pivot_table, annot=True, cmap='Oranges', fmt='d')
plt.title('Heatmap of AccountID vs. Merchant')
plt.xlabel('Merchant')
plt.ylabel('AccountID')
plt.show()
```




```
In [23]: #print a sample of the first 10 values of the cleaned dataset with new variables added
new_financial_df.head(10)
```

Out[23]:

	Timestamp	TransactionID	AccountID	Amount	Merchant	TransactionType	Location	AccountID/Merchant	AccountID/Transact
0	2023-01-01 08:00:00	TXN1127	ACC4	95071.92	MerchantH	Purchase	Tokyo	ACC4_MerchantH	ACC4_TXN
1	2023-01-01 08:01:00	TXN1639	ACC10	15607.89	MerchantH	Purchase	London	ACC10_MerchantH	ACC10_TXN
2	2023-01-01 08:02:00	TXN872	ACC8	65092.34	MerchantE	Withdrawal	London	ACC8_MerchantE	ACC8_TX
3	2023-01-01 08:03:00	TXN1438	ACC6	87.87	MerchantE	Purchase	London	ACC6_MerchantE	ACC6_TXN
4	2023-01-01 08:04:00	TXN1338	ACC6	716.56	MerchantI	Purchase	Los Angeles	ACC6_MerchantI	ACC6_TXN
5	2023-01-01 08:05:00	TXN1083	ACC15	13957.99	MerchantC	Transfer	London	ACC15_MerchantC	ACC15_TXN
6	2023-01-01 08:06:00	TXN832	ACC9	4654.58	MerchantC	Transfer	Tokyo	ACC9_MerchantC	ACC9_TX
7	2023-01-01 08:07:00	TXN841	ACC7	1336.36	MerchantI	Withdrawal	San Francisco	ACC7_MerchantI	ACC7_TX
8	2023-01-01 08:08:00	TXN777	ACC10	9776.23	MerchantD	Transfer	London	ACC10_MerchantD	ACC10_TX
9	2023-01-01 08:09:00	TXN1479	ACC12	49522.74	MerchantC	Withdrawal	New York	ACC12_MerchantC	ACC12_TXN

In [24]:

```
#print class, RangeIndex, columns, non-null count, data type, and memory usage information for the updated Data
new_financial_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 216960 entries, 0 to 216959
Data columns (total 18 columns):
 #   Column                              Non-Null Count   Dtype
---  ------                              --------------   -----
 0   Timestamp                           216960 non-null  datetime64[ns]
 1   TransactionID                       216960 non-null  object
 2   AccountID                           216960 non-null  object
 3   Amount                              216960 non-null  float64
 4   Merchant                            216960 non-null  object
 5   TransactionType                     216960 non-null  object
 6   Location                            216960 non-null  object
 7   AccountID/Merchant                  216960 non-null  object
 8   AccountID/TransactionID             216960 non-null  object
 9   AccountID/Merchant/TransactionID    216960 non-null  object
 10  TransactionType/Merchant            216960 non-null  object
 11  Location/TransactionType            216960 non-null  object
 12  Merchant/Location                   216960 non-null  object
 13  Minute                              216960 non-null  int32
 14  Hour                                216960 non-null  int32
 15  Day                                 216960 non-null  int32
 16  Month                               216960 non-null  int32
 17  Amount_Partitions                   216960 non-null  category
dtypes: category(1), datetime64[ns](1), float64(1), int32(4), object(11)
memory usage: 25.0+ MB
```

In [25]:

```
#print number of unique occurrences of newly created variables
print(f"Number of unique AccountID/Merchant: {new_financial_df['AccountID/Merchant'].nunique()}")
print(f"Number of unique AccountID/TransactionID: {new_financial_df['AccountID/TransactionID'].nunique()}")
print(f"Number of unique AccountID/Merchant/TransactionID: {new_financial_df['AccountID/Merchant/TransactionID'
print(f"Number of unique TransactionType/Merchant: {new_financial_df['TransactionType/Merchant'].nunique()}")
print(f"Number of unique Location/TransactionType: {new_financial_df['Location/TransactionType'].nunique()}")
print(f"Number of unique Merchant/Location: {new_financial_df['Merchant/Location'].nunique()}")
print(f"Number of unique Minute: {new_financial_df['Minute'].nunique()}")
print(f"Number of unique Hour: {new_financial_df['Hour'].nunique()}")
print(f"Number of unique Day: {new_financial_df['Day'].nunique()}")
print(f"Number of unique Month: {new_financial_df['Month'].nunique()}")
print(f"Number of unique Amount_Partitions: {new_financial_df['Amount_Partitions'].nunique()}")
```

```
Number of unique AccountID/Merchant: 150
Number of unique AccountID/TransactionID: 29967
Number of unique AccountID/Merchant/TransactionID: 154226
Number of unique TransactionType/Merchant: 30
Number of unique Location/TransactionType: 15
Number of unique Merchant/Location: 50
Number of unique Minute: 60
Number of unique Hour: 24
Number of unique Day: 7
Number of unique Month: 5
Number of unique Amount_Partitions: 11
```

In [26]:

```
new_financial_df.to_csv('Week_2_Data.csv', index=False)
```

In [27]:
```
#WEEK 2 END
```

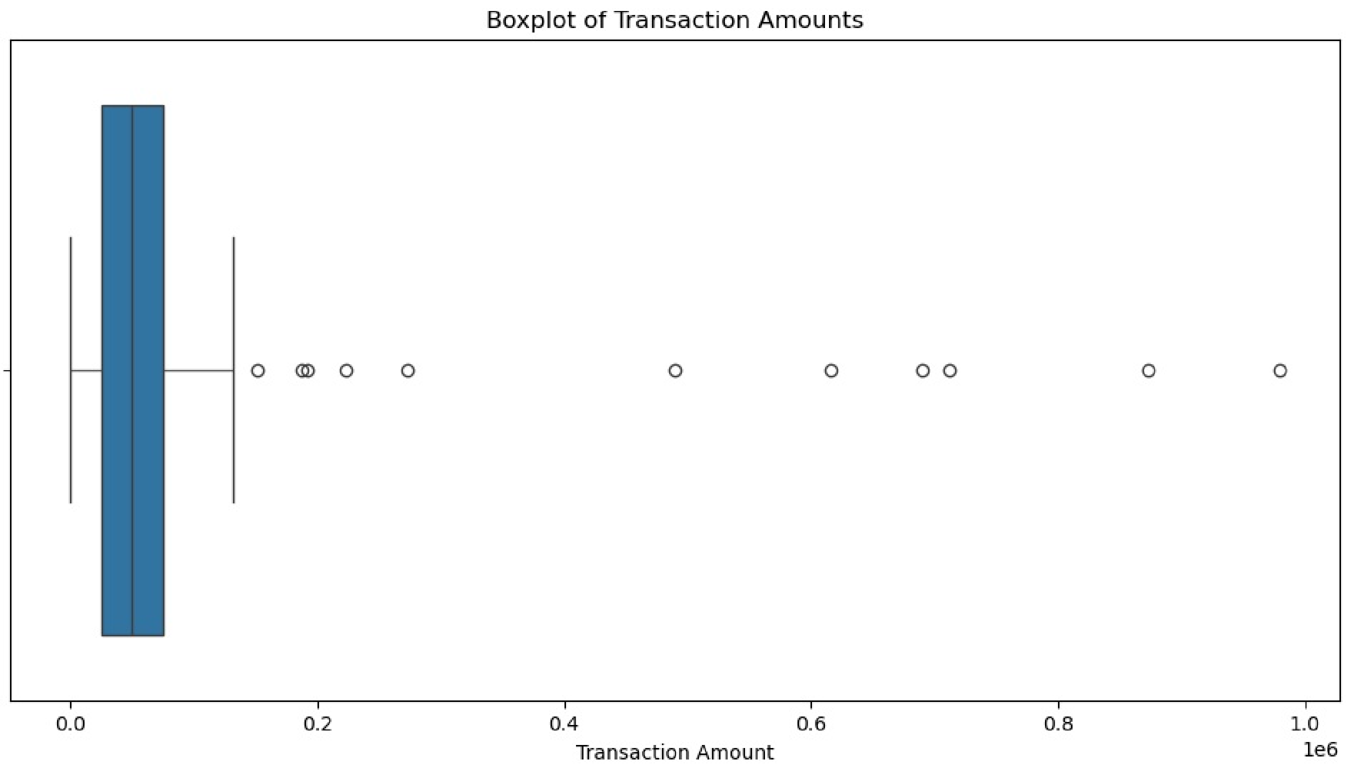
In [28]:
```
#WEEK 3 START
```

In [29]:
```
#describe numerical data to better understand these columns
new_financial_df.describe()
```

Out[29]:

	Timestamp	Amount	Minute	Hour	Day	Month
count	216960	216960.000000	216960.000000	216960.000000	216960.000000	216960.000000
mean	2023-03-17 15:59:30	50090.025108	29.500000	11.517699	2.973451	3.017699
min	2023-01-01 08:00:00	10.510000	0.000000	0.000000	0.000000	1.000000
25%	2023-02-07 23:59:45	25061.242500	14.750000	6.000000	1.000000	2.000000
50%	2023-03-17 15:59:30	50183.980000	29.500000	12.000000	3.000000	3.000000
75%	2023-04-24 07:59:15	75080.460000	44.250000	18.000000	5.000000	4.000000
max	2023-05-31 23:59:00	978942.260000	59.000000	23.000000	6.000000	5.000000
std	NaN	29097.905016	17.318142	6.918770	2.008659	1.421907

In [30]:
```
plt.figure(figsize=(12, 6))
sns.boxplot(x='Amount', data=new_financial_df)
plt.title('Boxplot of Transaction Amounts')
plt.xlabel('Transaction Amount')
plt.show()
```



In [31]:
```
#print counts of each unique value in each column of the DataFrame
for column in new_financial_df.columns:
    column_count = new_financial_df[column].value_counts()
    print(column_count)
```

```
Timestamp
2023-01-01 08:00:00    1
2023-04-11 18:57:00    1
2023-04-11 18:33:00    1
2023-04-11 18:34:00    1
2023-04-11 18:35:00    1
                      ..
2023-02-20 13:23:00    1
2023-02-20 13:24:00    1
2023-02-20 13:25:00    1
2023-02-20 13:26:00    1
2023-05-31 23:59:00    1
Name: count, Length: 216960, dtype: int64
TransactionID
TXN838     139
TXN1768    139
TXN1658    139
```

```
TXN1389    138
TXN340     137
          ...
TXN60       79
TXN891      78
TXN605      78
TXN201      73
TXN799      70
Name: count, Length: 1999, dtype: int64
AccountID
ACC15    14701
ACC5     14630
ACC7     14581
ACC2     14553
ACC9     14527
ACC14    14458
ACC4     14456
ACC11    14446
ACC12    14421
ACC13    14421
ACC8     14402
ACC1     14365
ACC10    14362
ACC6     14352
ACC3     14285
Name: count, dtype: int64
Amount
18010.00    3
34588.69    3
74109.74    3
86099.64    3
7309.50     3
           ..
56652.57    1
36336.36    1
49174.76    1
71557.91    1
65004.99    1
Name: count, Length: 214687, dtype: int64
Merchant
MerchantF    21924
MerchantG    21891
MerchantD    21820
MerchantB    21766
MerchantI    21752
MerchantA    21699
MerchantJ    21654
MerchantE    21543
MerchantH    21518
MerchantC    21393
Name: count, dtype: int64
TransactionType
Transfer      72793
Purchase      72235
Withdrawal    71932
Name: count, dtype: int64
Location
San Francisco    43613
New York         43378
London           43343
Los Angeles      43335
Tokyo            43291
Name: count, dtype: int64
AccountID/Merchant
ACC11_MerchantF    1532
ACC5_MerchantB     1530
ACC2_MerchantF     1524
ACC13_MerchantF    1509
ACC14_MerchantJ    1506
                   ...
ACC10_MerchantE    1376
ACC3_MerchantJ     1372
ACC13_MerchantA    1369
ACC4_MerchantC     1356
ACC10_MerchantC    1346
Name: count, Length: 150, dtype: int64
AccountID/TransactionID
ACC8_TXN239      22
ACC6_TXN154      20
ACC11_TXN1614    19
ACC11_TXN410     19
ACC1_TXN220      19
                 ..
```

```
ACC14_TXN20       1
ACC5_TXN938       1
ACC12_TXN1314     1
ACC3_TXN127       1
ACC2_TXN737       1
Name: count, Length: 29967, dtype: int64
AccountID/Merchant/TransactionID
ACC3_MerchantF_TXN1801     7
ACC11_MerchantJ_TXN1488    6
ACC11_MerchantE_TXN153     6
ACC14_MerchantJ_TXN1389    6
ACC15_MerchantG_TXN220     6
                          ..
ACC10_MerchantH_TXN286     1
ACC7_MerchantF_TXN1587     1
ACC5_MerchantA_TXN1930     1
ACC6_MerchantF_TXN1695     1
ACC3_MerchantG_TXN1807     1
Name: count, Length: 154226, dtype: int64
TransactionType/Merchant
Purchase_MerchantF      7399
Transfer_MerchantG      7354
Transfer_MerchantH      7342
Transfer_MerchantA      7332
Withdrawal_MerchantD    7323
Withdrawal_MerchantI    7308
Transfer_MerchantF      7302
Purchase_MerchantG      7298
Transfer_MerchantB      7291
Transfer_MerchantJ      7286
Purchase_MerchantB      7274
Purchase_MerchantA      7269
Purchase_MerchantD      7250
Transfer_MerchantD      7247
Withdrawal_MerchantG    7239
Transfer_MerchantI      7238
Withdrawal_MerchantF    7223
Purchase_MerchantE      7216
Purchase_MerchantJ      7216
Transfer_MerchantE      7209
Purchase_MerchantI      7206
Withdrawal_MerchantB    7201
Transfer_MerchantC      7192
Withdrawal_MerchantC    7164
Withdrawal_MerchantJ    7152
Withdrawal_MerchantE    7118
Withdrawal_MerchantH    7106
Withdrawal_MerchantA    7098
Purchase_MerchantH      7070
Purchase_MerchantC      7037
Name: count, dtype: int64
Location/TransactionType
London_Transfer            14653
San Francisco_Transfer     14610
Los Angeles_Transfer       14580
San Francisco_Withdrawal   14515
New York_Transfer          14510
Tokyo_Purchase             14506
San Francisco_Purchase     14488
New York_Purchase          14445
Tokyo_Transfer             14440
New York_Withdrawal        14423
Los Angeles_Purchase       14411
London_Purchase            14385
Tokyo_Withdrawal           14345
Los Angeles_Withdrawal     14344
London_Withdrawal          14305
Name: count, dtype: int64
Merchant/Location
MerchantF_Los Angeles      4476
MerchantD_London           4453
MerchantG_London           4446
MerchantI_Tokyo            4445
MerchantG_New York         4432
MerchantE_San Francisco    4424
MerchantB_Los Angeles      4399
MerchantE_New York         4395
MerchantA_Los Angeles      4394
MerchantH_New York         4393
MerchantA_Tokyo            4393
MerchantB_London           4391
MerchantI_San Francisco    4390
MerchantB_San Francisco    4385
```

```
MerchantF_Tokyo            4376
MerchantG_Tokyo            4373
MerchantA_San Francisco    4368
MerchantF_San Francisco    4367
MerchantD_San Francisco    4360
MerchantD_Los Angeles      4360
MerchantF_New York         4356
MerchantJ_Tokyo            4353
MerchantJ_San Francisco    4350
MerchantF_London           4349
MerchantG_San Francisco    4348
MerchantD_Tokyo            4347
MerchantJ_New York         4346
MerchantH_San Francisco    4334
MerchantE_London           4332
MerchantJ_Los Angeles      4332
MerchantB_New York         4332
MerchantA_London           4332
MerchantI_Los Angeles      4330
MerchantH_Tokyo            4311
MerchantC_New York         4310
MerchantI_New York         4302
MerchantD_New York         4300
MerchantC_Tokyo            4296
MerchantG_Los Angeles      4292
MerchantC_San Francisco    4287
MerchantI_London           4285
MerchantC_Los Angeles      4285
MerchantJ_London           4273
MerchantH_London           4267
MerchantB_Tokyo            4259
MerchantE_Los Angeles      4254
MerchantC_London           4215
MerchantH_Los Angeles      4213
MerchantA_New York         4212
MerchantE_Tokyo            4138
Name: count, dtype: int64
Minute
0     3616
1     3616
32    3616
33    3616
34    3616
35    3616
36    3616
37    3616
38    3616
39    3616
40    3616
41    3616
42    3616
43    3616
44    3616
45    3616
46    3616
47    3616
48    3616
49    3616
50    3616
51    3616
52    3616
53    3616
54    3616
55    3616
56    3616
57    3616
58    3616
31    3616
30    3616
29    3616
14    3616
2     3616
3     3616
4     3616
5     3616
6     3616
7     3616
8     3616
9     3616
10    3616
11    3616
12    3616
13    3616
```

```
15    3616
28    3616
16    3616
17    3616
18    3616
19    3616
20    3616
21    3616
22    3616
23    3616
24    3616
25    3616
26    3616
27    3616
59    3616
Name: count, dtype: int64
Hour
8     9060
17    9060
23    9060
22    9060
21    9060
9     9060
19    9060
18    9060
20    9060
16    9060
15    9060
14    9060
13    9060
12    9060
11    9060
10    9060
0     9000
1     9000
2     9000
3     9000
4     9000
5     9000
6     9000
7     9000
Name: count, dtype: int64
Day
0    31680
1    31680
2    31680
6    31200
3    30240
4    30240
5    30240
Name: count, dtype: int64
Month
3    44640
5    44640
1    44160
4    43200
2    40320
Name: count, dtype: int64
Amount_Partitions
60001-70000     22015
80001-90000     21938
10001-20000     21743
70001-80000     21736
50001-60000     21661
0-10000         21651
40001-50000     21605
20001-30000     21601
90001-100000    21530
30001-40000     21466
100001+            14
Name: count, dtype: int64
```

In [32]:

```
#list variables to be one-hot encoded

one_hot_encoding = [
    'AccountID/Merchant',
    'TransactionType',
    'Location',
    'Amount_Partitions'
]

# Apply one-hot encoding
new_financial_df_encoded = pd.get_dummies(new_financial_df, columns=one_hot_encoding)
```

```
# Display the first few rows of the encoded DataFrame
print(new_financial_df_encoded.head())
```

```
            Timestamp TransactionID AccountID    Amount   Merchant  \
0 2023-01-01 08:00:00       TXN1127      ACC4  95071.92  MerchantH
1 2023-01-01 08:01:00       TXN1639     ACC10  15607.89  MerchantH
2 2023-01-01 08:02:00        TXN872      ACC8  65092.34  MerchantE
3 2023-01-01 08:03:00       TXN1438      ACC6     87.87  MerchantE
4 2023-01-01 08:04:00       TXN1338      ACC6    716.56  MerchantI

  AccountID/TransactionID AccountID/Merchant/TransactionID  \
0            ACC4_TXN1127           ACC4_MerchantH_TXN1127
1           ACC10_TXN1639          ACC10_MerchantH_TXN1639
2             ACC8_TXN872            ACC8_MerchantE_TXN872
3            ACC6_TXN1438           ACC6_MerchantE_TXN1438
4            ACC6_TXN1338           ACC6_MerchantI_TXN1338

  TransactionType/Merchant Location/TransactionType      Merchant/Location  \
0       Purchase_MerchantH           Tokyo_Purchase        MerchantH_Tokyo
1       Purchase_MerchantH          London_Purchase       MerchantH_London
2     Withdrawal_MerchantE        London_Withdrawal       MerchantE_London
3       Purchase_MerchantE          London_Purchase       MerchantE_London
4       Purchase_MerchantI     Los Angeles_Purchase  MerchantI_Los Angeles

   ...  Amount_Partitions_10001-20000  Amount_Partitions_20001-30000  \
0  ...                          False                          False
1  ...                           True                          False
2  ...                          False                          False
3  ...                          False                          False
4  ...                          False                          False

   Amount_Partitions_30001-40000  Amount_Partitions_40001-50000  \
0                          False                          False
1                          False                          False
2                          False                          False
3                          False                          False
4                          False                          False

   Amount_Partitions_50001-60000  Amount_Partitions_60001-70000  \
0                          False                          False
1                          False                          False
2                          False                           True
3                          False                          False
4                          False                          False

   Amount_Partitions_70001-80000  Amount_Partitions_80001-90000  \
0                          False                          False
1                          False                          False
2                          False                          False
3                          False                          False
4                          False                          False

   Amount_Partitions_90001-100000  Amount_Partitions_100001+
0                            True                      False
1                           False                      False
2                           False                      False
3                           False                      False
4                           False                      False

[5 rows x 183 columns]
```

In [33]:

```
#print DataFrame info to maintain understanding of DataFrame properties
new_financial_df_encoded.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 216960 entries, 0 to 216959
Columns: 183 entries, Timestamp to Amount_Partitions_100001+
dtypes: bool(169), datetime64[ns](1), float64(1), int32(4), object(8)
memory usage: 54.8+ MB
```

In [34]:

```
#Retrieve one-hot encoded columns
'''
I originally included this correlation analysis although I removed it due to its difficult to read output that 
account_merchant_columns = [col for col in new_financial_df_encoded.columns if 'AccountID/Merchant_' in col]
transaction_type_columns = [col for col in new_financial_df_encoded.columns if 'TransactionType_' in col]
location_columns = [col for col in new_financial_df_encoded.columns if 'Location_' in col]
amount_partitions_columns = [col for col in new_financial_df_encoded.columns if 'Amount_Partitions_' in col]

# Create a dictionary to store correlations
correlation_results = {}

# Iterate through each pair of one-hot encoded columns to compute correlations
for account_merchant in account_merchant_columns:
```

```
    for transaction_type in transaction_type_columns:
        correlation1 = new_financial_df_encoded[account_merchant].corr(new_financial_df_encoded[transaction_type
        correlation_results[(account_merchant, transaction_type)] = correlation1

for account_merchant in account_merchant_columns:
    for location in location_columns:
        correlation2 = new_financial_df_encoded[account_merchant].corr(new_financial_df_encoded[location])
        correlation_results[(account_merchant, location)] = correlation2

for account_merchant in account_merchant_columns:
    for amount_partitions in amount_partitions_columns:
        correlation3 = new_financial_df_encoded[account_merchant].corr(new_financial_df_encoded[amount_partitio
        correlation_results[(account_merchant, amount_partitions)] = correlation3

for transaction_type in transaction_type_columns:
    for location in location_columns:
        correlation4 = new_financial_df_encoded[transaction_type].corr(new_financial_df_encoded[location])
        correlation_results[(transaction_type, location)] = correlation4

for transaction_type in transaction_type_columns:
    for amount_partitions in amount_partitions_columns:
        correlation5 = new_financial_df_encoded[transaction_type].corr(new_financial_df_encoded[amount_partitio
        correlation_results[(transaction_type, amount_partitions)] = correlation5

for location in location_columns:
    for amount_partitions in amount_partitions_columns:
        correlation6 = new_financial_df_encoded[location].corr(new_financial_df_encoded[amount_partitions])
        correlation_results[(location, amount_partitions)] = correlation6

# Display the results
for (account_merchant, transaction_type), correlation1 in correlation_results.items():
    print(f'Correlation between {account_merchant} and {transaction_type}: {correlation1}')

for (account_merchant, location), correlation2 in correlation_results.items():
    print(f'Correlation between {account_merchant} and {location}: {correlation2}')

for (accout_merchant, amount_partitions), correlation3 in correlation_results.items():
    print(f'Correlation between {account_merchant} and {amount_partitions}: {correlation3}')

for (transaction_type, location), correlation4 in correlation_results.items():
    print(f'Correlation between {transaction_type} and {location}: {correlation4}')

for (transaction_type, amount_partitions), correlation5 in correlation_results.items():
    print(f'Correlation between {transaction_type} and {amount_partitions}: {correlation5}')

for (location, amount_partitions), correlation6 in correlation_results.items():
    print(f'Correlation between {location} and {amount_partitions}: {correlation6}')
    '''
```

Out[34]:

```
"\nI originally included this correlation analysis although I removed it due to its difficult to read output th
at took up a significant portion of the project's output (over 200 pages of correlation output)\naccount_mercha
nt_columns = [col for col in new_financial_df_encoded.columns if 'AccountID/Merchant_' in col]\ntransaction_typ
e_columns = [col for col in new_financial_df_encoded.columns if 'TransactionType_' in col]\nlocation_columns =
[col for col in new_financial_df_encoded.columns if 'Location_' in col]\namount_partitions_columns = [col for c
ol in new_financial_df_encoded.columns if 'Amount_Partitions_' in col]\n\n# Create a dictionary to store correl
ations\ncorrelation_results = {}\n\n# Iterate through each pair of one-hot encoded columns to compute correlati
ons\nfor account_merchant in account_merchant_columns:\n    for transaction_type in transaction_type_columns:\n
correlation1 = new_financial_df_encoded[account_merchant].corr(new_financial_df_encoded[transaction_type])\n
correlation_results[(account_merchant, transaction_type)] = correlation1\n\nfor account_merchant in account_mer
chant_columns:\n    for location in location_columns:\n        correlation2 = new_financial_df_encoded[account_
merchant].corr(new_financial_df_encoded[location])\n        correlation_results[(account_merchant, location)] =
correlation2\n\nfor account_merchant in account_merchant_columns:\n    for amount_partitions in amount_partitio
ns_columns:\n        correlation3 = new_financial_df_encoded[account_merchant].corr(new_financial_df_encoded[am
ount_partitions])\n        correlation_results[(account_merchant, amount_partitions)] = correlation3\n\nfor tra
nsaction_type in transaction_type_columns:\n    for location in location_columns:\n        correlation4 = new_f
inancial_df_encoded[transaction_type].corr(new_financial_df_encoded[location])\n        correlation_results[(tr
ansaction_type, location)] = correlation4\n\nfor transaction_type in transaction_type_columns:\n    for amount_
partitions in amount_partitions_columns:\n        correlation5 = new_financial_df_encoded[transaction_type].cor
r(new_financial_df_encoded[amount_partitions])\n        correlation_results[(transaction_type, amount_partition
s)] = correlation5\n\nfor location in location_columns:\n    for amount_partitions in amount_partitions_columns
:\n        correlation6 = new_financial_df_encoded[location].corr(new_financial_df_encoded[amount_partitions])\
n        correlation_results[(location, amount_partitions)] = correlation6\n        \n# Display the results\nfo
r (account_merchant, transaction_type), correlation1 in correlation_results.items():\n    print(f'Correlation b
etween {account_merchant} and {transaction_type}: {correlation1}')\n    \nfor (account_merchant, location), cor
relation2 in correlation_results.items():\n    print(f'Correlation between {account_merchant} and {location}: {
correlation2}')\n    \nfor (accout_merchant, amount_partitions), correlation3 in correlation_results.items():\n
print(f'Correlation between {account_merchant} and {amount_partitions}: {correlation3}')\n    \nfor (transactio
n_type, location), correlation4 in correlation_results.items():\n    print(f'Correlation between {transaction_t
ype} and {location}: {correlation4}')\n    \nfor (transaction_type, amount_partitions), correlation5 in correla
tion_results.items():\n    print(f'Correlation between {transaction_type} and {amount_partitions}: {correlation
5}')\n    \nfor (location, amount_partitions), correlation6 in correlation_results.items():\n    print(f'Correl
ation between {location} and {amount_partitions}: {correlation6}')\n    "
```

In [35]:
```
'''
correlation_matrix = new_financial_df_encoded[account_merchant_columns + transaction_type_columns].corr()

# Create a heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='coolwarm', square=True)
plt.title('Correlation Heatmap between AccountID/Merchant and TransactionType')
plt.show()
'''
```

Out[35]:
```
'\ncorrelation_matrix = new_financial_df_encoded[account_merchant_columns + transaction_type_columns].corr()\n\n# Create a heatmap\nplt.figure(figsize=(12, 8))\nsns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap=\'coolwarm\', square=True)\nplt.title(\'Correlation Heatmap between AccountID/Merchant and TransactionType\')\nplt.show()\n'
```

In [36]:
```
'''
correlation_matrix = new_financial_df_encoded[transaction_type_columns + location_columns].corr()

# Create a heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='coolwarm', square=True)
plt.title('Correlation Heatmap between TransactionType and Location')
plt.show()
'''
```

Out[36]:
```
'\ncorrelation_matrix = new_financial_df_encoded[transaction_type_columns + location_columns].corr()\n\n# Create a heatmap\nplt.figure(figsize=(12, 8))\nsns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap=\'coolwarm\', square=True)\nplt.title(\'Correlation Heatmap between TransactionType and Location\')\nplt.show()\n'
```

In [37]:
```
'''
correlation_matrix = new_financial_df_encoded[transaction_type_columns + amount_partitions_columns].corr()

# Create a heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='coolwarm', square=True)
plt.title('Correlation Heatmap between TransactionType and Amount_Partitions')
plt.show()
'''
```

Out[37]:
```
'\ncorrelation_matrix = new_financial_df_encoded[transaction_type_columns + amount_partitions_columns].corr()\n\n# Create a heatmap\nplt.figure(figsize=(12, 8))\nsns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap=\'coolwarm\', square=True)\nplt.title(\'Correlation Heatmap between TransactionType and Amount_Partitions\')\nplt.show()\n'
```

In [38]:
```
#create train set (70%) and temporary other set (30%)
train_df, temp_df = train_test_split(new_financial_df, test_size=0.30, random_state=1)

#split the leftover temp set into validation and test sets (50% of 30% each- 15% each)
validation_df, test_df = train_test_split(temp_df, test_size=0.50, random_state=42)

#verify shape of train, validation, and test DataFrames
print(f'Training set shape: {train_df.shape}')
print(f'Validation set shape: {validation_df.shape}')
print(f'Test set shape: {test_df.shape}')
```

```
Training set shape: (151872, 18)
Validation set shape: (32544, 18)
Test set shape: (32544, 18)
```

In [39]:
```
'''
# Save the train set
train_df.to_csv('train_data.csv', index=False)

# Save the validation set
validation_df.to_csv('validation_data.csv', index=False)

# Save the test set
test_df.to_csv('test_data.csv', index=False)

print("DataFrames have been saved as CSV files.")
'''
```

Out[39]:
```
'\n# Save the train set\ntrain_df.to_csv(\'train_data.csv\', index=False)\n\n# Save the validation set\nvalidation_df.to_csv(\'validation_data.csv\', index=False)\n\n# Save the test set\ntest_df.to_csv(\'test_data.csv\', index=False)\n\nprint("DataFrames have been saved as CSV files.")\n'
```

In [40]:
```
#END WEEK 3
```

In [41]:
```
#START WEEK 4
```

In [42]:
```
#Apply log transformation to Amount variable
train_df['Amount'] = np.log1p(train_df['Amount'])
```

In [43]:
```
#identify trends in volume of transactions per day per account
train_df['Date'] = train_df['Timestamp'].dt.date
account_activity = train_df.groupby(['Date', 'AccountID']).agg(
    total_transactions=('Amount', 'count'),
    total_amount=('Amount', 'sum'),
    average_amount=('Amount', 'mean'),
    max_transaction=('Amount', 'max'),
    min_transaction=('Amount', 'min'),
).reset_index()

print(account_activity)
```

```
            Date AccountID  total_transactions  total_amount  average_amount  \
0     2023-01-01      ACC1                  45    465.643415       10.347631
1     2023-01-01     ACC10                  39    401.756535       10.301450
2     2023-01-01     ACC11                  45    466.881311       10.375140
3     2023-01-01     ACC12                  48    494.428680       10.300598
4     2023-01-01     ACC13                  51    537.094450       10.531264
...          ...       ...                 ...           ...             ...
2260  2023-05-31      ACC5                  79    829.043252       10.494218
2261  2023-05-31      ACC6                  55    572.603696       10.410976
2262  2023-05-31      ACC7                  61    652.687543       10.699796
2263  2023-05-31      ACC8                  61    636.764154       10.438757
2264  2023-05-31      ACC9                  76    804.576583       10.586534

      max_transaction  min_transaction
0           11.455237         6.655865
1           11.486849         4.735672
2           11.449300         6.820377
3           11.504645         7.298147
4           11.502063         5.600198
...               ...              ...
2260        11.510775         7.355871
2261        11.506599         6.599966
2262        11.506273         8.001646
2263        11.481302         4.934834
2264        11.489540         7.732558

[2265 rows x 7 columns]
```

In [44]:
```
#identify trends in volume of transactions per day per merchant
merchant_activity = train_df.groupby(['Date', 'Merchant']).agg(
    total_transactions=('Amount', 'count'),
    total_amount=('Amount', 'sum'),
    average_amount=('Amount', 'mean'),
    max_transaction=('Amount', 'max'),
    min_transaction=('Amount', 'min'),
).reset_index()

print(merchant_activity)
```

```
            Date   Merchant  total_transactions  total_amount  average_amount  \
0     2023-01-01  MerchantA                  65    693.193900       10.664522
1     2023-01-01  MerchantB                  71    738.537511       10.401937
2     2023-01-01  MerchantC                  83    862.766604       10.394778
3     2023-01-01  MerchantD                  77    807.919846       10.492466
4     2023-01-01  MerchantE                  51    529.932174       10.390827
...          ...        ...                 ...           ...             ...
1505  2023-05-31  MerchantF                  98   1044.751467       10.660729
1506  2023-05-31  MerchantG                 104   1091.297405       10.493244
1507  2023-05-31  MerchantH                 100   1052.697256       10.526973
1508  2023-05-31  MerchantI                  98   1024.712858       10.456254
1509  2023-05-31  MerchantJ                  94   1000.775385       10.646547

      max_transaction  min_transaction
0           11.484058         7.952207
1           11.503438         3.548180
2           11.479025         5.491950
3           11.488507         5.600198
4           11.491695         6.264293
...               ...              ...
1505        11.511874         8.208598
1506        11.511314         4.934834
1507        11.506599         3.700314
1508        11.501197         6.432731
1509        11.505241         8.141434

[1510 rows x 7 columns]
```

In [45]:
```
#identify trends in volume of transactions per day by location
location_activity = train_df.groupby(['Date', 'Location']).agg(
    total_transactions=('Amount', 'count'),
    total_amount=('Amount', 'sum'),
    average_amount=('Amount', 'mean'),
```

```
    max_transaction=('Amount', 'max'),
    min_transaction=('Amount', 'min'),

).reset_index()

print(location_activity)
```

```
           Date       Location  total_transactions  total_amount  \
0    2023-01-01         London                 146   1530.237727
1    2023-01-01    Los Angeles                 139   1454.136479
2    2023-01-01       New York                 135   1402.617642
3    2023-01-01  San Francisco                 138   1445.854505
4    2023-01-01          Tokyo                 133   1410.359817
..          ...            ...                 ...           ...
750  2023-05-31         London                 205   2186.373655
751  2023-05-31    Los Angeles                 191   2004.248091
752  2023-05-31       New York                 213   2215.559017
753  2023-05-31  San Francisco                 187   1982.163977
754  2023-05-31          Tokyo                 197   2080.626500

     average_amount  max_transaction  min_transaction
0         10.481080        11.502063         5.491950
1         10.461414        11.504645         3.548180
2         10.389760        11.507789         5.600198
3         10.477207        11.504023         4.735672
4         10.604209        11.499541         7.197413
..              ...              ...              ...
750       10.665237        11.511553         4.934834
751       10.493446        11.511874         6.505141
752       10.401686        11.511455         3.700314
753       10.599807        11.512224         4.856862
754       10.561556        11.506885         6.397313

[755 rows x 7 columns]
```

In [46]:
```
train_df.head(5)
```

Out[46]:

	Timestamp	TransactionID	AccountID	Amount	Merchant	TransactionType	Location	AccountID/Merchant	AccountID/Tı
9230	2023-01-07 17:50:00	TXN1858	ACC12	9.064231	MerchantB	Withdrawal	London	ACC12_MerchantB	ACC
41764	2023-01-30 08:04:00	TXN76	ACC9	10.757187	MerchantJ	Transfer	London	ACC9_MerchantJ	A
136513	2023-04-06 03:13:00	TXN847	ACC11	10.996651	MerchantD	Transfer	New York	ACC11_MerchantD	AC(
158548	2023-04-21 10:28:00	TXN852	ACC12	11.204528	MerchantI	Withdrawal	Los Angeles	ACC12_MerchantI	AC(
9929	2023-01-08 05:29:00	TXN1822	ACC1	9.295688	MerchantF	Withdrawal	London	ACC1_MerchantF	AC(

In [47]:
```
#drop columns with too many unique values to analyze efficiently
train_df.drop(columns=['TransactionID', 'AccountID/TransactionID', 'AccountID/Merchant/TransactionID', 'Account]
```

In [48]:
```
train_df.head(5)
```

Out[48]:

	Timestamp	AccountID	Amount	Merchant	TransactionType	Location	Minute	Hour	Day	Month	Amount_Partitions
9230	2023-01-07 17:50:00	ACC12	9.064231	MerchantB	Withdrawal	London	50	17	5	1	0-10000
41764	2023-01-30 08:04:00	ACC9	10.757187	MerchantJ	Transfer	London	4	8	0	1	40001-50000
136513	2023-04-06 03:13:00	ACC11	10.996651	MerchantD	Transfer	New York	13	3	3	4	50001-60000
158548	2023-04-21 10:28:00	ACC12	11.204528	MerchantI	Withdrawal	Los Angeles	28	10	4	4	70001-80000
9929	2023-01-08 05:29:00	ACC1	9.295688	MerchantF	Withdrawal	London	29	5	6	1	10001-20000

In [49]:
```
#One hot encode categorical variables
train_encoded_df = pd.get_dummies(train_df, columns=['AccountID', 'Merchant', 'TransactionType', 'Location', 'A
```

In [50]:
```
train_encoded_df.head()
```

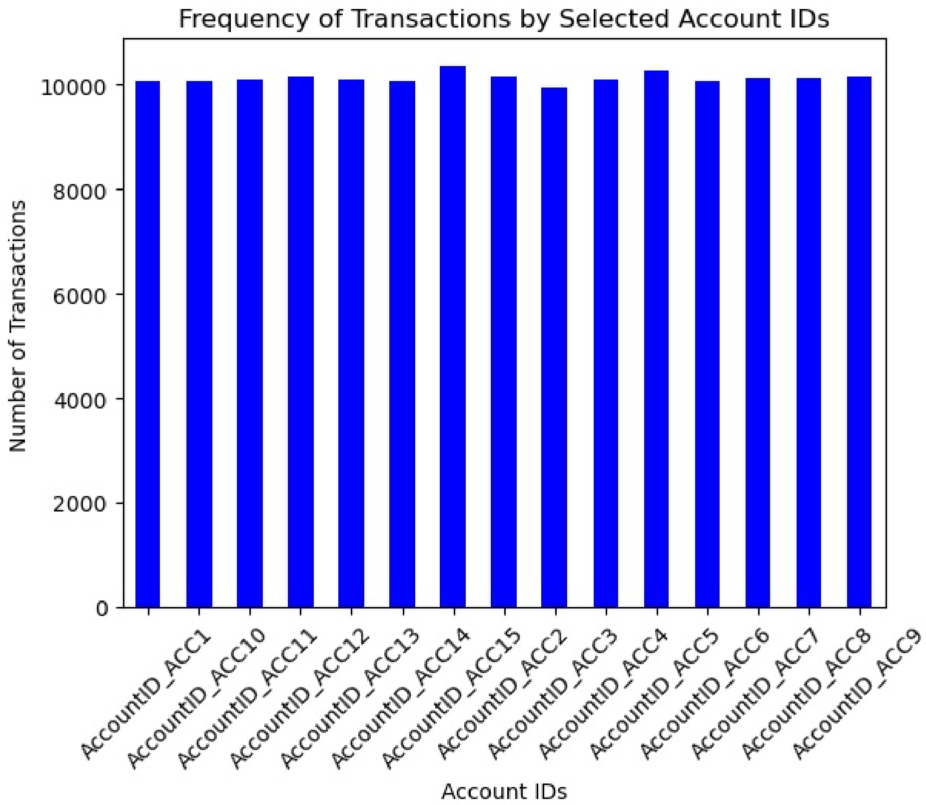
Out[50]:

	Timestamp	Amount	Minute	Hour	Month	Date	AccountID_ACC1	AccountID_ACC10	AccountID_ACC11	AccountID_A(
9230	2023-01-07 17:50:00	9.064231	50	17	1	2023-01-07	False	False	False	
41764	2023-01-30 08:04:00	10.757187	4	8	1	2023-01-30	False	False	False	
136513	2023-04-06 03:13:00	10.996651	13	3	4	2023-04-06	False	False	True	
158548	2023-04-21 10:28:00	11.204528	28	10	4	2023-04-21	False	False	False	
9929	2023-01-08 05:29:00	9.295688	29	5	1	2023-01-08	True	False	False	

5 rows × 57 columns

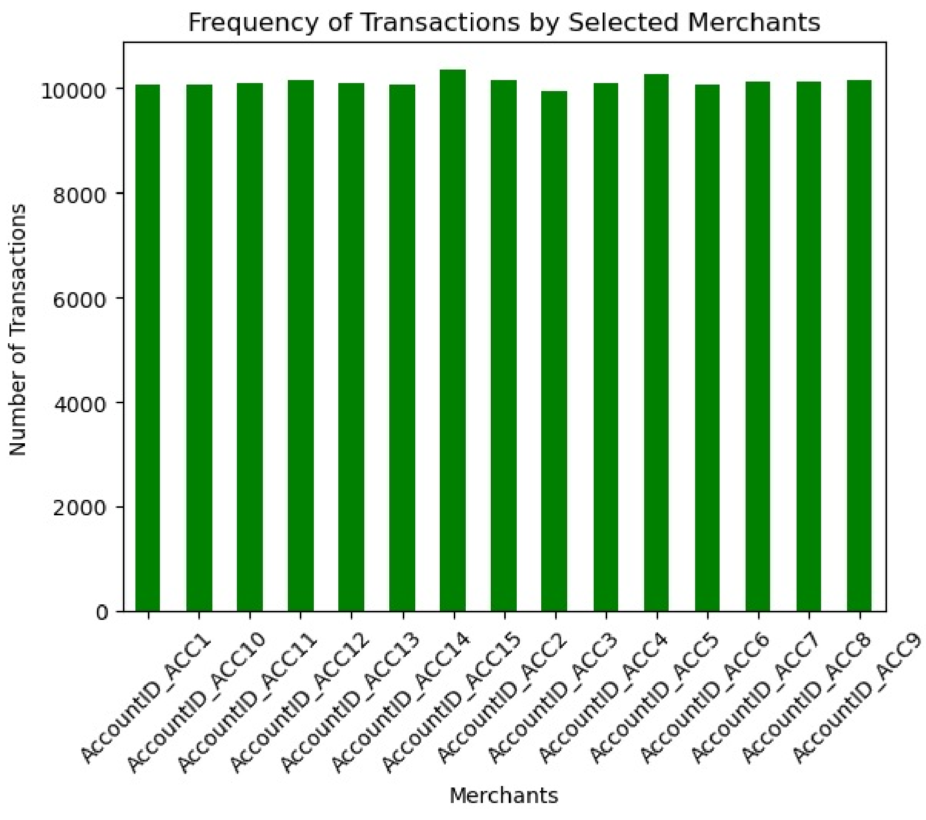
In [51]:

```
#Visualize encoded AccountID Data
account_columns = [col for col in train_encoded_df.columns if col.startswith('AccountID_')]
account_counts = train_encoded_df[account_columns].sum()
account_counts.plot(kind='bar', color='blue')
plt.title('Frequency of Transactions by Selected Account IDs')
plt.xlabel('Account IDs')
plt.ylabel('Number of Transactions')
plt.xticks(rotation=45)
plt.show()
```

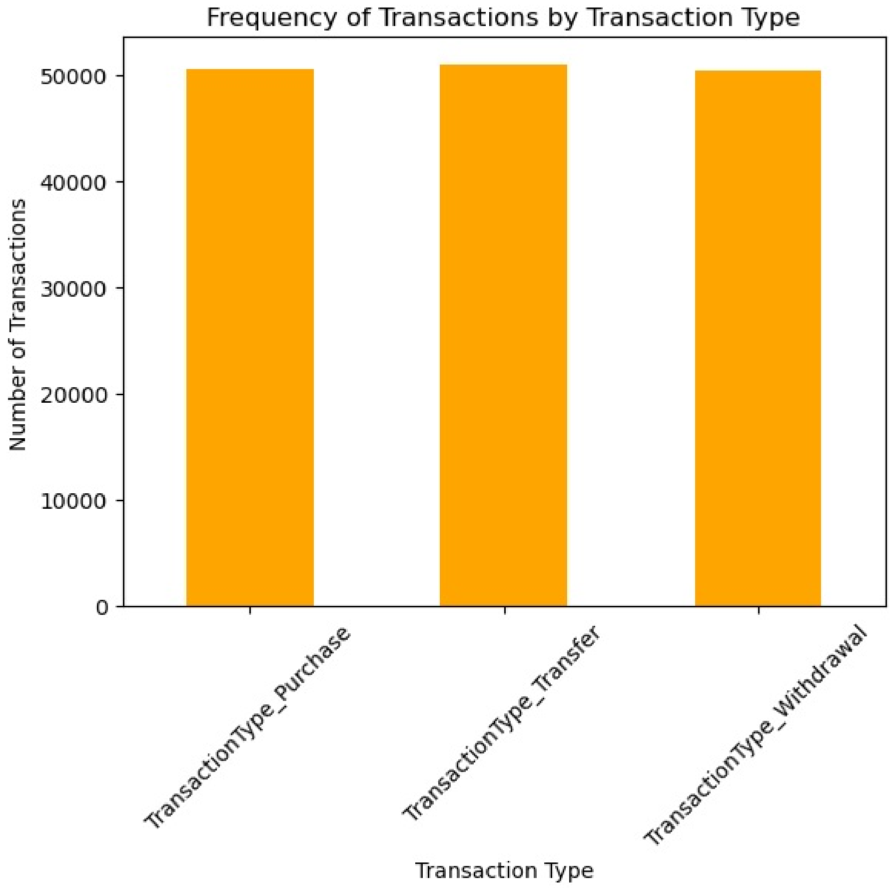


In [52]:

```
#Visualize encoded AccountID Data
merchant_columns = [col for col in train_encoded_df.columns if col.startswith('Merchant_')]
merchant_counts = train_encoded_df[account_columns].sum()
merchant_counts.plot(kind='bar', color='green')
plt.title('Frequency of Transactions by Selected Merchants')
plt.xlabel('Merchants')
plt.ylabel('Number of Transactions')
plt.xticks(rotation=45)
plt.show()
```

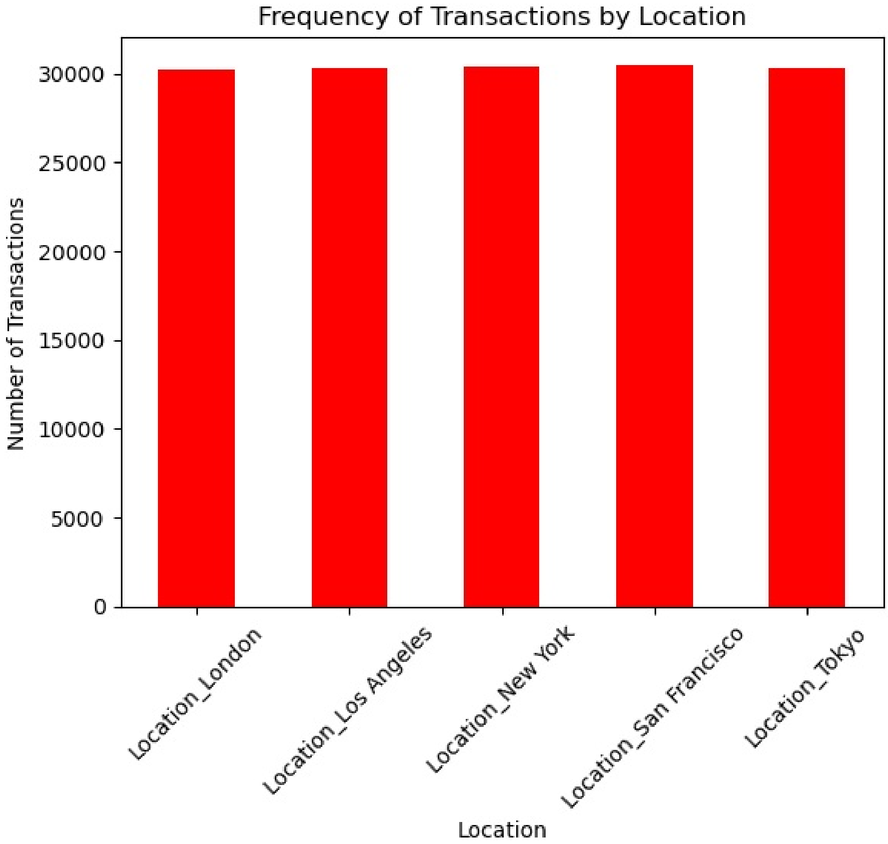


In [53]:
```
#Visualize encoded AccountID Data
TransactionType_columns = [col for col in train_encoded_df.columns if col.startswith('TransactionType_')]
TransactionType_counts = train_encoded_df[TransactionType_columns].sum()
TransactionType_counts.plot(kind='bar', color='orange')
plt.title('Frequency of Transactions by Transaction Type')
plt.xlabel('Transaction Type')
plt.ylabel('Number of Transactions')
plt.xticks(rotation=45)
plt.show()
```



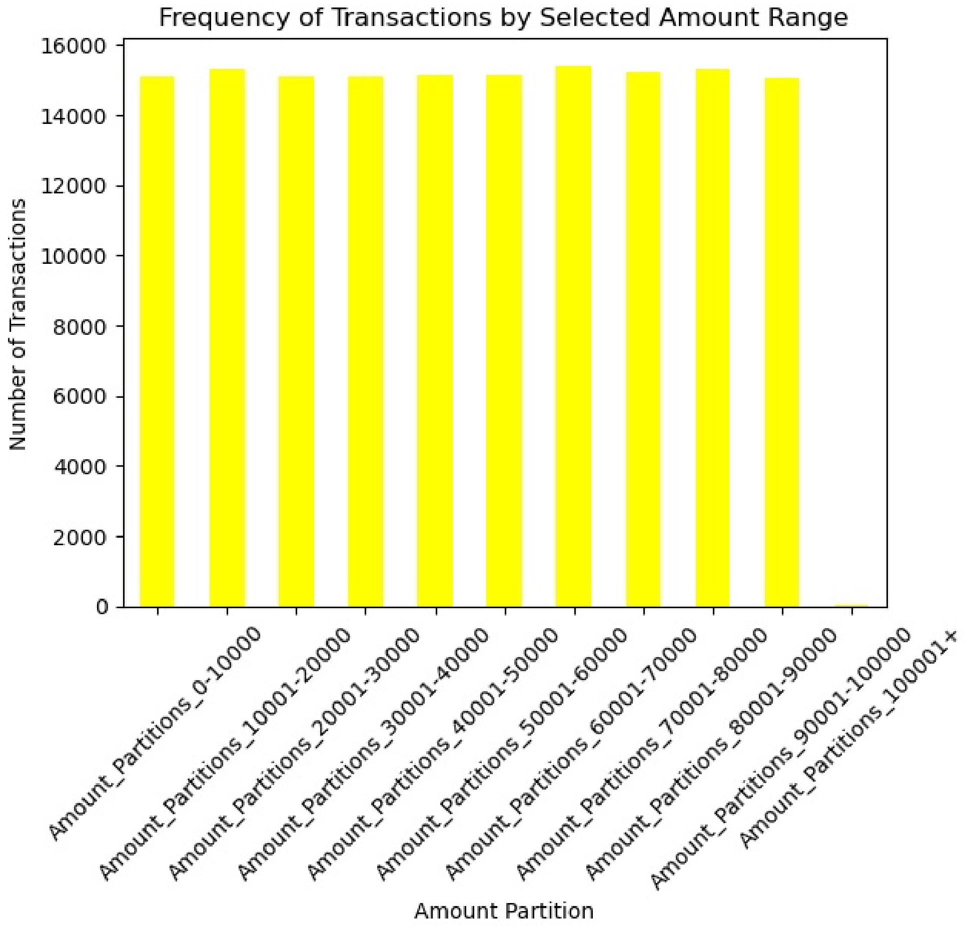
In [54]:
```
#Visualize encoded AccountID Data
location_columns = [col for col in train_encoded_df.columns if col.startswith('Location_')]
location_counts = train_encoded_df[location_columns].sum()
location_counts.plot(kind='bar', color='red')
plt.title('Frequency of Transactions by Location')
```

```
plt.xlabel('Location')
plt.ylabel('Number of Transactions')
plt.xticks(rotation=45)
plt.show()
```



In [55]:

```
#Visualize encoded AccountID Data
amount_partitions_columns = [col for col in train_encoded_df.columns if col.startswith('Amount_Partitions_')]
amount_partitions_counts = train_encoded_df[amount_partitions_columns].sum()
amount_partitions_counts.plot(kind='bar', color='yellow')
plt.title('Frequency of Transactions by Selected Amount Range')
plt.xlabel('Amount Partition')
plt.ylabel('Number of Transactions')
plt.xticks(rotation=45)
plt.show()
```



In [56]:
```
#Perform same preprocessing steps on both Validation and Test Sets
#Apply log transformation to Amount variable
validation_df['Amount'] = np.log1p(validation_df['Amount'])
test_df['Amount'] = np.log1p(test_df['Amount'])
```

In [57]:
```
#identify trends in volume of transactions per day per account (not printing results to reduce potential for bia
validation_df['Date'] = validation_df['Timestamp'].dt.date
val_account_activity = validation_df.groupby(['Date', 'AccountID']).agg(
    total_transactions=('Amount', 'count'),
    total_amount=('Amount', 'sum'),
    average_amount=('Amount', 'mean'),
    max_transaction=('Amount', 'max'),
    min_transaction=('Amount', 'min'),
).reset_index()
```

In [58]:
```
#identify trends in volume of transactions per day per account
test_df['Date'] = test_df['Timestamp'].dt.date
test_account_activity = test_df.groupby(['Date', 'AccountID']).agg(
    total_transactions=('Amount', 'count'),
    total_amount=('Amount', 'sum'),
    average_amount=('Amount', 'mean'),
    max_transaction=('Amount', 'max'),
    min_transaction=('Amount', 'min'),
).reset_index()
```

In [59]:
```
#identify trends in volume of transactions per day per merchant
val_merchant_activity = validation_df.groupby(['Date', 'Merchant']).agg(
    total_transactions=('Amount', 'count'),
    total_amount=('Amount', 'sum'),
    average_amount=('Amount', 'mean'),
    max_transaction=('Amount', 'max'),
    min_transaction=('Amount', 'min'),
).reset_index()
```

In [60]:
```
#identify trends in volume of transactions per day per merchant
test_merchant_activity = test_df.groupby(['Date', 'Merchant']).agg(
    total_transactions=('Amount', 'count'),
    total_amount=('Amount', 'sum'),
    average_amount=('Amount', 'mean'),
    max_transaction=('Amount', 'max'),
    min_transaction=('Amount', 'min'),
).reset_index()
```

In [61]:
```
#identify trends in volume of transactions per day by location
val_location_activity = validation_df.groupby(['Date', 'Location']).agg(
```

```python
    total_transactions=('Amount', 'count'),
    total_amount=('Amount', 'sum'),
    average_amount=('Amount', 'mean'),
    max_transaction=('Amount', 'max'),
    min_transaction=('Amount', 'min'),

).reset_index()
```

In [62]:
```python
#identify trends in volume of transactions per day by location
test_location_activity = test_df.groupby(['Date', 'Location']).agg(
    total_transactions=('Amount', 'count'),
    total_amount=('Amount', 'sum'),
    average_amount=('Amount', 'mean'),
    max_transaction=('Amount', 'max'),
    min_transaction=('Amount', 'min'),

).reset_index()
```

In [63]:
```python
#drop columns with too many unique values to analyze efficiently
validation_df.drop(columns=['TransactionID', 'AccountID/TransactionID', 'AccountID/Merchant/TransactionID', 'Ac
#drop columns with too many unique values to analyze efficiently
test_df.drop(columns=['TransactionID', 'AccountID/TransactionID', 'AccountID/Merchant/TransactionID', 'AccountI
```

In [64]:
```python
#One hot encode categorical variables
validation_encoded_df = pd.get_dummies(validation_df, columns=['AccountID', 'Merchant', 'TransactionType', 'Loca
test_encoded_df = pd.get_dummies(test_df, columns=['AccountID', 'Merchant', 'TransactionType', 'Location', 'Amou
```

In [65]:
```python
'''
# Save the train set
train_encoded_df.to_csv('train_data.csv', index=False)

# Save the validation set
validation_encoded_df.to_csv('validation_data.csv', index=False)

# Save the test set
test_encoded_df.to_csv('test_data.csv', index=False)

print("DataFrames have been saved as CSV files.")
'''
```

Out[65]:
```
'\n# Save the train set\ntrain_encoded_df.to_csv(\'train_data.csv\', index=False)\n\n# Save the validation set\
nvalidation_encoded_df.to_csv(\'validation_data.csv\', index=False)\n\n# Save the test set\ntest_encoded_df.to_
csv(\'test_data.csv\', index=False)\n\nprint("DataFrames have been saved as CSV files.")\n'
```

In [66]:
```python
#END WEEK 4
```

In [67]:
```python
#START WEEK 5
```

In [68]:
```python
# Define bins and labels for groups of hours of the day
bins = [0, 5, 11, 17, 23]
labels = ['0-5', '6-11', '12-17', '18-23']

# Create a new column 'Hour_Group' that bucketizes data into four segments of the day
train_encoded_df['Hour_Group'] = pd.cut(train_encoded_df['Hour'], bins=bins, labels=labels, right=True)
```

In [69]:
```python
# Assign values of Hour_Group to each AccountID
for account in range(1, 15):
    AccountID_column = f'AccountID_ACC{account}'
    if AccountID_column in train_encoded_df.columns:
        train_encoded_df[f'Hour_Group_{account}'] = train_encoded_df.apply(
            lambda row: row['Hour_Group'] if row[AccountID_column] == 1 else None,
            axis=1
        )
```

In [70]:
```python
#Repeat this action to assign values of Hour_Group to each Merchant, TransactionType, and Location
def create_hour_group_columns(train_encoded_df, variable_info, hour_group_column='Hour_Group'):
    for prefix, count in variable_info.items():
        for i in range(1, count + 1):
            column_name = f'{prefix}{i}'
            if column_name in train_encoded_df.columns:
                train_encoded_df[f'{column_name}_{hour_group_column}'] = train_encoded_df.apply(
                    lambda row: row[hour_group_col] if row[column_name] == 1 else None,
                    axis=1
                )

# Define the variable prefixes and their respective counts
variable_info = {
    'Merchant_Merchant': 10,  # Merchants A-J
    'TransactionType_': 3,     # Purchase, Transfer, Withdrawal
    'Location_': 5              # London, Los Angeles, New York, San Francisco, Tokyo
}
```

```python
# Call the function to create the new columns
create_hour_group_columns(train_encoded_df, variable_info)
```

In [71]:
```python
# Define a function to calculate mean and standard deviation for each one-hot encoded account by iterating acro
def calculate_stats(train_encoded_df, account_prefix='AccountID_ACC', num_accounts=15):
    stats = {}

    for i in range(1, num_accounts + 1):
        account_columns = f'{account_prefix}{i}'
        # Only include amounts where the specific account value is true (1 as its binary representation)
        account_data = train_encoded_df[train_encoded_df[account_columns] == 1]['Amount']

        # Perform the mean and standard deviatoin calculations
        mean = account_data.mean()
        std = account_data.std()

        # Store the mean and standard deviation for each account
        stats[f'AccountID_ACC{i}'] = {'mean': mean, 'std': std}

    return stats

# Call the function to calculate mean and standard deviation for AccountID_ACC1 to AccountID_ACC15
account_stats = calculate_stats(train_encoded_df)

# Add mean and standard deviation columns to train_encoded_df
for account, values in account_stats.items():
    train_encoded_df[f'{account}_mean'] = values['mean']
    train_encoded_df[f'{account}_std'] = values['std']
```

In [72]:
```python
# Create a new column for deviation from mean for each transaction
train_encoded_df['Deviation_From_Mean'] = 0.0

# Loop through each account and calculate the deviation
for i in range(1, 15):
    account_columns = f'AccountID_ACC{i}'
    mean_columns = f'AccountID_ACC{i}_mean'
    std_columns = f'AccountID_ACC{i}_std'

    # Calculate the deviation only for transactions in the current account
    condition = train_encoded_df[account_columns] == 1

    # Calculate number of standard deviations of a transaction's Amount value from its Account's Amount mean
    train_encoded_df.loc[condition, 'Deviation_From_Mean'] = (
        (train_encoded_df.loc[condition, 'Amount'] - train_encoded_df.loc[condition, mean_columns]
    ) / train_encoded_df.loc[condition, std_columns])
```

In [73]:
```python
train_encoded_df.head()
```

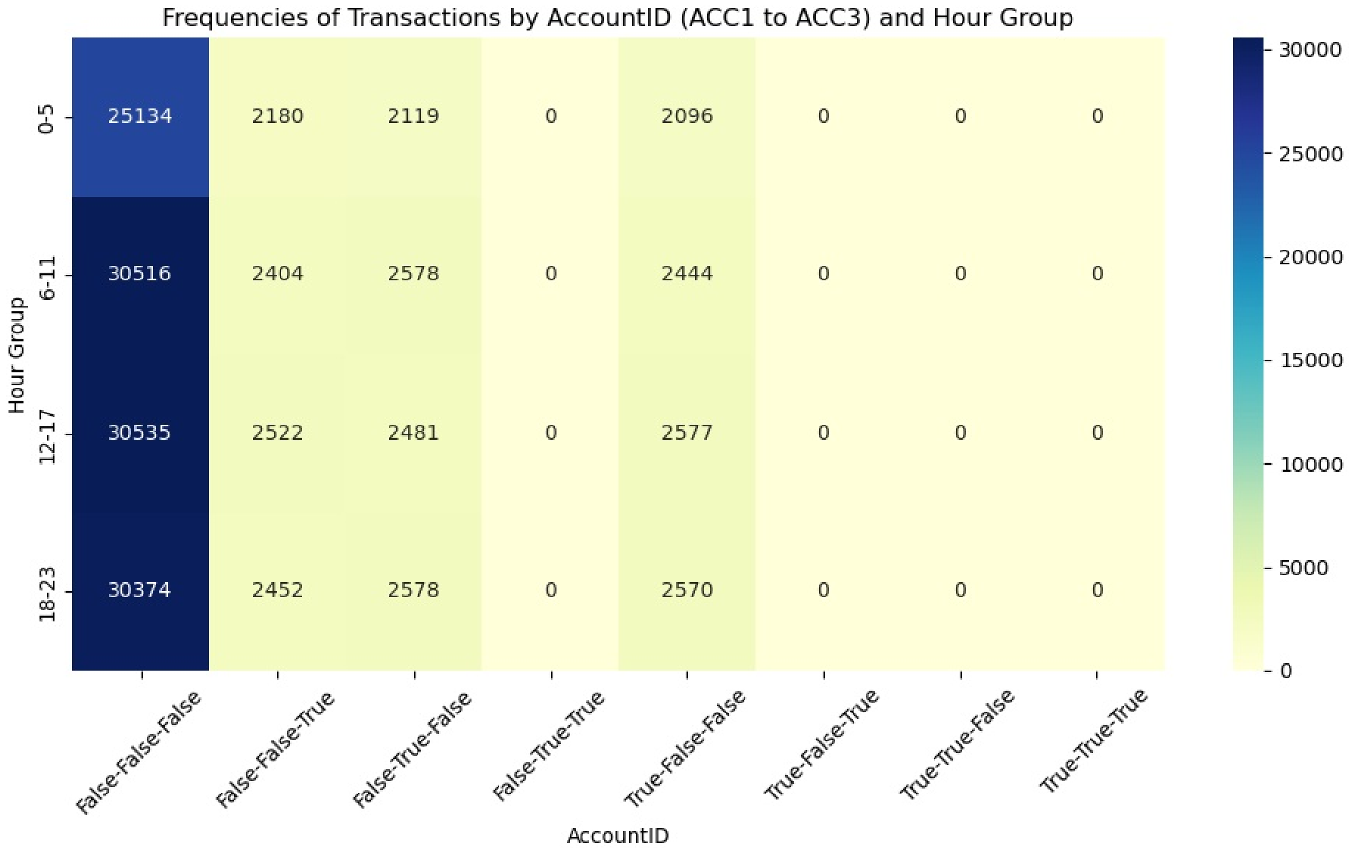
Out[73]:

	Timestamp	Amount	Minute	Hour	Month	Date	AccountID_ACC1	AccountID_ACC10	AccountID_ACC11	AccountID_A(
9230	2023-01-07 17:50:00	9.064231	50	17	1	2023-01-07	False	False	False	
41764	2023-01-30 08:04:00	10.757187	4	8	1	2023-01-30	False	False	False	
136513	2023-04-06 03:13:00	10.996651	13	3	4	2023-04-06	False	False	True	
158548	2023-04-21 10:28:00	11.204528	28	10	4	2023-04-21	False	False	False	
9929	2023-01-08 05:29:00	9.295688	29	5	1	2023-01-08	True	False	False	

5 rows × 103 columns

In [74]:
```python
def plot_interaction_frequencies(df, account_columns, hour_group_column):

    # Create a new DataFrame to hold the frequencies of specific accounts' transactions occurring in certain hou
    interaction_frequencies = df.groupby(account_columns + [hour_group_column], observed=False).size().reset_in

    # Create a pivot table for better visualization
    pivot_table = interaction_frequencies.pivot(index=hour_group_column, columns=account_columns, values='Frequ

    # Plotting
    plt.figure(figsize=(10, 6))
    sns.heatmap(pivot_table, cmap='YlGnBu', annot=True, fmt=".0f")
    plt.title('Frequencies of Transactions by AccountID (ACC1 to ACC3) and Hour Group')
    plt.xlabel('AccountID')
    plt.ylabel('Hour Group')
    plt.xticks(rotation=45)
```

```python
    plt.tight_layout()
    plt.show()

hour_group_column = 'Hour_Group'
account_columns = [f'AccountID_ACC{i}' for i in range(1, 4)]  # Only ACC1 to ACC3 for better visualization purp

# Call the function
plot_interaction_frequencies(train_encoded_df, account_columns, hour_group_column)
```



In [75]:
```python
train_encoded_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 151872 entries, 9230 to 128037
Columns: 103 entries, Timestamp to Deviation_From_Mean
dtypes: bool(51), category(1), datetime64[ns](1), float64(32), int32(3), object(15)
memory usage: 66.0+ MB
```

In [76]:
```python
# Create a list of prefixes for our one-hot columns
one_hot_prefixes = ['AccountID_', 'Merchant_', 'TransactionType_', 'Location_', 'Amount_Partitions_', 'Day']

# Create a variable that stores the columns starting with the respective prefixes from our list
binary = train_encoded_df.columns.str.startswith(tuple(one_hot_prefixes))

# Convert TRUE/FALSE entries to 1/0 entries with exception handling condition
if binary.any():
    try:
        # Check data types of the selected columns
        for col in train_encoded_df.columns[binary]:
            # Get the data type of the column
            column_dtype = train_encoded_df[col].dtype

            if column_dtype != 'int32':
                # Convert directly to int if boolean
                if column_dtype == 'bool':
                    train_encoded_df[col] = train_encoded_df[col].astype(int)
                else:
                    # If it's not bool, you can simply ensure it's int
                    train_encoded_df[col] = train_encoded_df[col].astype('int32')
    except Exception as e:
        print(f"Potential incompatible dtype error during conversion: {e}")
else:
    print("No one-hot encoded columns found with the specified prefixes.")
```

In [77]:
```python
train_encoded_df.head()
```

Out[77]:

	Timestamp	Amount	Minute	Hour	Month	Date	AccountID_ACC1	AccountID_ACC10	AccountID_ACC11	AccountID_A(
9230	2023-01-07 17:50:00	9.064231	50	17	1	2023-01-07	0	0	0	
41764	2023-01-30 08:04:00	10.757187	4	8	1	2023-01-30	0	0	0	
136513	2023-04-06 03:13:00	10.996651	13	3	4	2023-04-06	0	0	1	
158548	2023-04-21 10:28:00	11.204528	28	10	4	2023-04-21	0	0	0	
9929	2023-01-08 05:29:00	9.295688	29	5	1	2023-01-08	1	0	0	

5 rows × 103 columns

In [78]:

```
# Create lists for AccountID, Merchant, TransactionType, Location, and Hour Groups
account_ids = [f'AccountID_ACC{i}' for i in range(1, 15)]  # AccountID's 1 to 15
merchants = [f'Merchant_Merchant{chr(i)}' for i in range(ord('A'), ord('J') + 1)]  # Merchants A to J
transaction_types = ['TransactionType_Purchase', 'TransactionType_Transfer', 'TransactionType_Withdrawal']
locations = ['Location_London', 'Location_Los Angeles', 'Location_New York', 'Location_San Francisco', 'Locatio
hour_groups = [f'Hour_Group_{i}' for i in range(1, 15)]

def encode_columns(df, columns):
    encoder = LabelEncoder()
    encoded_columns = {}

    for column in columns:
        if column in df.columns:
            encoded_columns[column] = encoder.fit_transform(df[column])
        else:
            print(f"Warning: {column} not found in DataFrame.")
    return encoded_columns

# Encode each variable
encoded_account_ids = encode_columns(train_encoded_df, account_ids)
encoded_merchants = encode_columns(train_encoded_df, merchants)
encoded_transaction_types = encode_columns(train_encoded_df, transaction_types)
encoded_locations = encode_columns(train_encoded_df, locations)
encoded_hour_groups = encode_columns(train_encoded_df, hour_groups)

# Assign the encoded values back to the DataFrame
for account_id, encoded_values in encoded_account_ids.items():
    train_encoded_df[account_id] = encoded_values

for merchant, encoded_values in encoded_merchants.items():
    train_encoded_df[merchant] = encoded_values

for transaction_type, encoded_values in encoded_transaction_types.items():
    train_encoded_df[transaction_type] = encoded_values

for location, encoded_values in encoded_locations.items():
    train_encoded_df[location] = encoded_values

for hour_group, encoded_values in encoded_hour_groups.items():
    train_encoded_df[hour_group] = encoded_values

# Prepare Inputs for Embedding
numerical_input = Input(shape=(1,), name='numerical_input')
account_input = Input(shape=(1,), name='account_input')
merchant_input = Input(shape=(1,), name='merchant_input')
transaction_input = Input(shape=(1,), name='transaction_input')
location_input = Input(shape=(1,), name='location_input')
hour_group_input = Input(shape=(1,), name='hour_group_input')

# Create Embedding Layers
embedding_dim = 8
num_accounts = len(account_ids)
num_merchants = len(merchants)
num_transaction_types = len(transaction_types)
num_locations = len(locations)
num_hour_groups = len(hour_groups)

# Embeddings for each one-hot encoded category
account_embedding = Embedding(input_dim=num_accounts, output_dim=embedding_dim)(account_input)
merchant_embedding = Embedding(input_dim=num_merchants, output_dim=embedding_dim)(merchant_input)
transaction_embedding = Embedding(input_dim=num_transaction_types, output_dim=embedding_dim)(transaction_input)
location_embedding = Embedding(input_dim=num_locations, output_dim=embedding_dim)(location_input)
hour_group_embedding = Embedding(input_dim=num_hour_groups, output_dim=embedding_dim)(hour_group_input)
```

```python
# Flatten the embeddings to make a one-dimensional array representation of the variables
flattened_account = Flatten()(account_embedding)
flattened_merchant = Flatten()(merchant_embedding)
flattened_transaction = Flatten()(transaction_embedding)
flattened_location = Flatten()(location_embedding)
flattened_hour_group = Flatten()(hour_group_embedding)

# Concatenate inputs to a single output
concat = Concatenate()([numerical_input, flattened_account, flattened_merchant, flattened_transaction, flattene

# Add Dense Layers to interconnect previous layers
output = Dense(1, activation='sigmoid')(concat)

# Build the Model
model = Model(inputs=[numerical_input, account_input, merchant_input, transaction_input, location_input, hour_g
model.compile(optimizer='adam', loss='mean_squared_error')

# Prepare input data for model training
X_numerical = train_encoded_df[['Amount']].values
X_accounts = train_encoded_df[account_ids].values.argmax(axis=1).reshape(-1, 1)  # Get index for account input
X_merchants = train_encoded_df[merchants].values.argmax(axis=1).reshape(-1, 1)
X_transaction_types = train_encoded_df[transaction_types].values.argmax(axis=1).reshape(-1, 1)
X_locations = train_encoded_df[locations].values.argmax(axis=1).reshape(-1, 1)
X_hour_groups = train_encoded_df[hour_groups].values.argmax(axis=1).reshape(-1, 1)

# Make sure to pass the inputs as a list
model.fit([X_numerical, X_accounts, X_merchants, X_transaction_types, X_locations, X_hour_groups],
          np.zeros(X_numerical.shape[0]),
          epochs=1,
          batch_size=16)

# Create a model to get the embedding outputs
embedding_model = Model(inputs=[account_input, merchant_input, transaction_input, location_input, hour_group_in
                        outputs=[account_embedding, merchant_embedding, transaction_embedding, location_embedd

# Get the embedding outputs
embedding_output = embedding_model.predict([X_accounts, X_merchants, X_transaction_types, X_locations, X_hour_g

# Store the embeddings in a DataFrame
embedding_df = pd.DataFrame({
    'Account_Embeddings': list(embedding_output[0]),
    'Merchant_Embeddings': list(embedding_output[1]),
    'Transaction_Embeddings': list(embedding_output[2]),
    'Location_Embeddings': list(embedding_output[3]),
    'Hour_Group_Embeddings': list(embedding_output[4])
})

# Combine with the original DataFrame if needed
train_embeddings_df = pd.concat([train_encoded_df.reset_index(drop=True), embedding_df.reset_index(drop=True)],
```

```
C:\Users\brady\OneDrive\Apps\Anaconda\Lib\site-packages\keras\src\models\functional.py:225: UserWarning: The str
ucture of `inputs` doesn't match the expected structure: ['numerical_input', 'account_input', 'merchant_input',
'transaction_input', 'location_input', 'hour_group_input']. Received: the structure of inputs=('*', '*', '*', '*
', '*', '*')
  warnings.warn(
9492/9492 ━━━━━━━━━━━━━━━━━━━━ 22s 2ms/step - loss: 0.0077
  85/4746 ━━━━━━━━━━━━━━━━━━━━ 5s 1ms/step
C:\Users\brady\OneDrive\Apps\Anaconda\Lib\site-packages\keras\src\models\functional.py:225: UserWarning: The str
ucture of `inputs` doesn't match the expected structure: ['account_input', 'merchant_input', 'transaction_input'
, 'location_input', 'hour_group_input']. Received: the structure of inputs=('*', '*', '*', '*', '*')
  warnings.warn(
4746/4746 ━━━━━━━━━━━━━━━━━━━━ 9s 2ms/step
```

In [79]:

```python
train_embeddings_df.head()
```

Out[79]:

	Timestamp	Amount	Minute	Hour	Month	Date	AccountID_ACC1	AccountID_ACC10	AccountID_ACC11	AccountID_ACC12
0	2023-01-07 17:50:00	9.064231	50	17	1	2023-01-07	0	0	0	1
1	2023-01-30 08:04:00	10.757187	4	8	1	2023-01-30	0	0	0	0
2	2023-04-06 03:13:00	10.996651	13	3	4	2023-04-06	0	0	1	0
3	2023-04-21 10:28:00	11.204528	28	10	4	2023-04-21	0	0	0	1
4	2023-01-08 05:29:00	9.295688	29	5	1	2023-01-08	1	0	0	0

5 rows × 108 columns

In [80]:

```
print(train_embeddings_df.columns.tolist())
```

```
['Timestamp', 'Amount', 'Minute', 'Hour', 'Month', 'Date', 'AccountID_ACC1', 'AccountID_ACC10', 'AccountID_ACC11
', 'AccountID_ACC12', 'AccountID_ACC13', 'AccountID_ACC14', 'AccountID_ACC15', 'AccountID_ACC2', 'AccountID_ACC3
', 'AccountID_ACC4', 'AccountID_ACC5', 'AccountID_ACC6', 'AccountID_ACC7', 'AccountID_ACC8', 'AccountID_ACC9', '
Merchant_MerchantA', 'Merchant_MerchantB', 'Merchant_MerchantC', 'Merchant_MerchantD', 'Merchant_MerchantE', 'Me
rchant_MerchantF', 'Merchant_MerchantG', 'Merchant_MerchantH', 'Merchant_MerchantI', 'Merchant_MerchantJ', 'Tran
sactionType_Purchase', 'TransactionType_Transfer', 'TransactionType_Withdrawal', 'Location_London', 'Location_Lo
s Angeles', 'Location_New York', 'Location_San Francisco', 'Location_Tokyo', 'Amount_Partitions_0-10000', 'Amoun
t_Partitions_10001-20000', 'Amount_Partitions_20001-30000', 'Amount_Partitions_30001-40000', 'Amount_Partitions_
40001-50000', 'Amount_Partitions_50001-60000', 'Amount_Partitions_60001-70000', 'Amount_Partitions_70001-80000',
'Amount_Partitions_80001-90000', 'Amount_Partitions_90001-100000', 'Amount_Partitions_100001+', 'Day_0', 'Day_1'
, 'Day_2', 'Day_3', 'Day_4', 'Day_5', 'Day_6', 'Hour_Group', 'Hour_Group_1', 'Hour_Group_2', 'Hour_Group_3', 'Ho
ur_Group_4', 'Hour_Group_5', 'Hour_Group_6', 'Hour_Group_7', 'Hour_Group_8', 'Hour_Group_9', 'Hour_Group_10', 'H
our_Group_11', 'Hour_Group_12', 'Hour_Group_13', 'Hour_Group_14', 'AccountID_ACC1_mean', 'AccountID_ACC1_std', '
AccountID_ACC2_mean', 'AccountID_ACC2_std', 'AccountID_ACC3_mean', 'AccountID_ACC3_std', 'AccountID_ACC4_mean',
'AccountID_ACC4_std', 'AccountID_ACC5_mean', 'AccountID_ACC5_std', 'AccountID_ACC6_mean', 'AccountID_ACC6_std',
'AccountID_ACC7_mean', 'AccountID_ACC7_std', 'AccountID_ACC8_mean', 'AccountID_ACC8_std', 'AccountID_ACC9_mean',
'AccountID_ACC9_std', 'AccountID_ACC10_mean', 'AccountID_ACC10_std', 'AccountID_ACC11_mean', 'AccountID_ACC11_st
d', 'AccountID_ACC12_mean', 'AccountID_ACC12_std', 'AccountID_ACC13_mean', 'AccountID_ACC13_std', 'AccountID_ACC
14_mean', 'AccountID_ACC14_std', 'AccountID_ACC15_mean', 'AccountID_ACC15_std', 'Deviation_From_Mean', 'Account_
Embeddings', 'Merchant_Embeddings', 'Transaction_Embeddings', 'Location_Embeddings', 'Hour_Group_Embeddings']
```

In [81]:

```
# List of columns to drop (already converted to one-hot/embeddings or not relevant to problem statement resolve
columns_to_drop = [
    'Minute',
    'Month',
    'Hour',
    'Hour_Group'
] + [f'AccountID_ACC{i}' for i in range(1, 16)] + \
  [f'Merchant_Merchant{chr(i)}' for i in range(ord('A'), ord('J') + 1)] + \
  ['TransactionType_Purchase', 'TransactionType_Transfer', 'TransactionType_Withdrawal'] + \
  ['Location_London', 'Location_Los Angeles', 'Location_New York',
   'Location_San Francisco', 'Location_Tokyo'] + \
  [f'Amount_Partitions_{i}' for i in ['0-10000', '10001-20000', '20001-30000',
                                       '30001-40000', '40001-50000', '50001-60000',
                                       '60001-70000', '70001-80000', '80001-90000',
                                       '90001-100000', '100001+']] + \
  [f'AccountID_ACC{i}_mean' for i in range(1, 16)] + \
  [f'AccountID_ACC{i}_std' for i in range(1, 16)] + \
  [f'Hour_Group_{i}' for i in range(1, 15)]

# Drop the specified columns
train_embeddings_df = train_embeddings_df.drop(columns=columns_to_drop)

# Check the remaining columns
print(train_embeddings_df.columns.tolist())
```

```
['Timestamp', 'Amount', 'Date', 'Day_0', 'Day_1', 'Day_2', 'Day_3', 'Day_4', 'Day_5', 'Day_6', 'Deviation_From_M
ean', 'Account_Embeddings', 'Merchant_Embeddings', 'Transaction_Embeddings', 'Location_Embeddings', 'Hour_Group_
Embeddings']
```

In [82]:

```
# Repeat exact same steps for both validation and test sets

# Create a new column 'Hour_Group' that bucketizes data into four segments of the day
validation_encoded_df['Hour_Group'] = pd.cut(validation_encoded_df['Hour'], bins=bins, labels=labels, right=Tru
```

```
# Assign values of Hour_Group to each AccountID
for account in range(1, 15):
    AccountID_column = f'AccountID_ACC{account}'
    if AccountID_column in validation_encoded_df.columns:
        validation_encoded_df[f'Hour_Group_{account}'] = validation_encoded_df.apply(
            lambda row: row['Hour_Group'] if row[AccountID_column] == 1 else None,
            axis=1
        )

#Repeat this action to assign values of Hour_Group to each Merchant, TransactionType, and Location
def create_hour_group_columns(validation_encoded_df, variable_info, hour_group_column='Hour_Group'):
    for prefix, count in variable_info.items():
        for i in range(1, count + 1):
            column_name = f'{prefix}{i}'
            if column_name in validation_encoded_df.columns:
                validation_encoded_df[f'{column_name}_{hour_group_column}'] = validation_encoded_df.apply(
                    lambda row: row[hour_group_col] if row[column_name] == 1 else None,
                    axis=1
                )

# Define the variable prefixes and their respective counts
variable_info = {
    'Merchant_Merchant': 10,  # Merchants A-J
    'TransactionType_': 3,     # Purchase, Transfer, Withdrawal
    'Location_': 5              # London, Los Angeles, New York, San Francisco, Tokyo
}

# Call the function to create the new columns
create_hour_group_columns(validation_encoded_df, variable_info)

# Define a function to calculate mean and standard deviation for each one-hot encoded account by iterating acro
def calculate_stats(validation_encoded_df, account_prefix='AccountID_ACC', num_accounts=15):
    stats = {}

    for i in range(1, num_accounts + 1):
        account_columns = f'{account_prefix}{i}'
        # Only include amounts where the specific account value is true (1 as its binary representation)
        account_data = validation_encoded_df[validation_encoded_df[account_columns] == 1]['Amount']

        # Perform the mean and standard deviatoin calculations
        mean = account_data.mean()
        std = account_data.std()

        # Store the mean and standard deviation for each account
        stats[f'AccountID_ACC{i}'] = {'mean': mean, 'std': std}

    return stats

# Call the function to calculate mean and standard deviation for AccountID_ACC1 to AccountID_ACC15
account_stats = calculate_stats(validation_encoded_df)

# Add mean and standard deviation columns to validation_encoded_df
for account, values in account_stats.items():
    validation_encoded_df[f'{account}_mean'] = values['mean']
    validation_encoded_df[f'{account}_std'] = values['std']

# Create a new column for deviation from mean for each transaction
validation_encoded_df['Deviation_From_Mean'] = 0.0

# Loop through each account and calculate the deviation
for i in range(1, 15):
    account_columns = f'AccountID_ACC{i}'
    mean_columns = f'AccountID_ACC{i}_mean'
    std_columns = f'AccountID_ACC{i}_std'

 # Calculate the deviation only for transactions in the current account
    condition = validation_encoded_df[account_columns] == 1

    # Calculate number of standard deviations of a transaction's Amount value from its Account's Amount mean
    validation_encoded_df.loc[condition, 'Deviation_From_Mean'] = (
        (validation_encoded_df.loc[condition, 'Amount'] - validation_encoded_df.loc[condition, mean_columns]
    ) / validation_encoded_df.loc[condition, std_columns])

# Create a list of prefixes for our one-hot columns
one_hot_prefixes = ['AccountID_', 'Merchant_', 'TransactionType_', 'Location_', 'Amount_Partitions_', 'Day']

# Create a variable that stores the columns starting with the respective prefixes from our list
binary = validation_encoded_df.columns.str.startswith(tuple(one_hot_prefixes))

# Convert TRUE/FALSE entries to 1/0 entries with exception handling condition
if binary.any():
    try:
        # Check data types of the selected columns
```

```
        for col in validation_encoded_df.columns[binary]:
            # Get the data type of the column
            column_dtype = validation_encoded_df[col].dtype

            if column_dtype != 'int32':
                # Convert directly to int if boolean
                if column_dtype == 'bool':
                    validation_encoded_df[col] = validation_encoded_df[col].astype(int)
                else:
                    # If it's not bool, you can simply ensure it's int
                    validation_encoded_df[col] = validation_encoded_df[col].astype('int32')
    except Exception as e:
        print(f"Potential incompatible dtype error during conversion: {e}")
else:
    print("No one-hot encoded columns found with the specified prefixes.")

# Create lists for AccountID, Merchant, TransactionType, Location, and Hour Groups
account_ids = [f'AccountID_ACC{i}' for i in range(1, 15)]  # AccountID's 1 to 15
merchants = [f'Merchant_Merchant{chr(i)}' for i in range(ord('A'), ord('J') + 1)]  # Merchants A to J
transaction_types = ['TransactionType_Purchase', 'TransactionType_Transfer', 'TransactionType_Withdrawal']
locations = ['Location_London', 'Location_Los Angeles', 'Location_New York', 'Location_San Francisco', 'Location
hour_groups = [f'Hour_Group_{i}' for i in range(1, 15)]

def encode_columns(df, columns):
    encoder = LabelEncoder()
    encoded_columns = {}

    for column in columns:
        if column in df.columns:
            encoded_columns[column] = encoder.fit_transform(df[column])
        else:
            print(f"Warning: {column} not found in DataFrame.")
    return encoded_columns

# Encode each variable
encoded_account_ids = encode_columns(validation_encoded_df, account_ids)
encoded_merchants = encode_columns(validation_encoded_df, merchants)
encoded_transaction_types = encode_columns(validation_encoded_df, transaction_types)
encoded_locations = encode_columns(validation_encoded_df, locations)
encoded_hour_groups = encode_columns(validation_encoded_df, hour_groups)

# Assign the encoded values back to the DataFrame
for account_id, encoded_values in encoded_account_ids.items():
    validation_encoded_df[account_id] = encoded_values

for merchant, encoded_values in encoded_merchants.items():
    validation_encoded_df[merchant] = encoded_values

for transaction_type, encoded_values in encoded_transaction_types.items():
    validation_encoded_df[transaction_type] = encoded_values

for location, encoded_values in encoded_locations.items():
    validation_encoded_df[location] = encoded_values

for hour_group, encoded_values in encoded_hour_groups.items():
    validation_encoded_df[hour_group] = encoded_values

# Prepare Inputs for Embedding
numerical_input = Input(shape=(1,), name='numerical_input')
account_input = Input(shape=(1,), name='account_input')
merchant_input = Input(shape=(1,), name='merchant_input')
transaction_input = Input(shape=(1,), name='transaction_input')
location_input = Input(shape=(1,), name='location_input')
hour_group_input = Input(shape=(1,), name='hour_group_input')

# Create Embedding Layers
embedding_dim = 8
num_accounts = len(account_ids)
num_merchants = len(merchants)
num_transaction_types = len(transaction_types)
num_locations = len(locations)
num_hour_groups = len(hour_groups)

# Embeddings for each one-hot encoded category
account_embedding = Embedding(input_dim=num_accounts, output_dim=embedding_dim)(account_input)
merchant_embedding = Embedding(input_dim=num_merchants, output_dim=embedding_dim)(merchant_input)
transaction_embedding = Embedding(input_dim=num_transaction_types, output_dim=embedding_dim)(transaction_input)
location_embedding = Embedding(input_dim=num_locations, output_dim=embedding_dim)(location_input)
hour_group_embedding = Embedding(input_dim=num_hour_groups, output_dim=embedding_dim)(hour_group_input)

# Flatten the embeddings to make a one-dimensional array representation of the variables
flattened_account = Flatten()(account_embedding)
flattened_merchant = Flatten()(merchant_embedding)
```

```python
flattened_transaction = Flatten()(transaction_embedding)
flattened_location = Flatten()(location_embedding)
flattened_hour_group = Flatten()(hour_group_embedding)

# Concatenate inputs to a single output
concat = Concatenate()([numerical_input, flattened_account, flattened_merchant, flattened_transaction, flattene

# Add Dense Layers to interconnect previous layers
output = Dense(1, activation='sigmoid')(concat)

# Build the Model
model = Model(inputs=[numerical_input, account_input, merchant_input, transaction_input, location_input, hour_g
model.compile(optimizer='adam', loss='mean_squared_error')

# Prepare input data for model training
X_numerical = validation_encoded_df[['Amount']].values
X_accounts = validation_encoded_df[account_ids].values.argmax(axis=1).reshape(-1, 1)  # Get index for account i
X_merchants = validation_encoded_df[merchants].values.argmax(axis=1).reshape(-1, 1)
X_transaction_types = validation_encoded_df[transaction_types].values.argmax(axis=1).reshape(-1, 1)
X_locations = validation_encoded_df[locations].values.argmax(axis=1).reshape(-1, 1)
X_hour_groups = validation_encoded_df[hour_groups].values.argmax(axis=1).reshape(-1, 1)

# Make sure to pass the inputs as a list
model.fit([X_numerical, X_accounts, X_merchants, X_transaction_types, X_locations, X_hour_groups],
          np.zeros(X_numerical.shape[0]),
          epochs=1,
          batch_size=16)

# Create a model to get the embedding outputs
embedding_model = Model(inputs=[account_input, merchant_input, transaction_input, location_input, hour_group_in
                        outputs=[account_embedding, merchant_embedding, transaction_embedding, location_embedd

# Get the embedding outputs
embedding_output = embedding_model.predict([X_accounts, X_merchants, X_transaction_types, X_locations, X_hour_g

# Store the embeddings in a DataFrame
embedding_df = pd.DataFrame({
    'Account_Embeddings': list(embedding_output[0]),
    'Merchant_Embeddings': list(embedding_output[1]),
    'Transaction_Embeddings': list(embedding_output[2]),
    'Location_Embeddings': list(embedding_output[3]),
    'Hour_Group_Embeddings': list(embedding_output[4])
})

# Combine with the original DataFrame if needed
validation_embeddings_df = pd.concat([validation_encoded_df.reset_index(drop=True), embedding_df.reset_index(dr

# List of columns to drop (already converted to one-hot/embeddings or not relevant to problem statement resolve
columns_to_drop = [
    'Minute',
    'Month',
    'Hour',
    'Hour_Group'
] + [f'AccountID_ACC{i}' for i in range(1, 16)] + \
  [f'Merchant_Merchant{chr(i)}' for i in range(ord('A'), ord('J') + 1)] + \
  ['TransactionType_Purchase', 'TransactionType_Transfer', 'TransactionType_Withdrawal'] + \
  ['Location_London', 'Location_Los Angeles', 'Location_New York',
   'Location_San Francisco', 'Location_Tokyo'] + \
  [f'Amount_Partitions_{i}' for i in ['0-10000', '10001-20000', '20001-30000',
                                      '30001-40000', '40001-50000', '50001-60000',
                                      '60001-70000', '70001-80000', '80001-90000',
                                      '90001-100000', '100001+']] + \
  [f'AccountID_ACC{i}_mean' for i in range(1, 16)] + \
  [f'AccountID_ACC{i}_std' for i in range(1, 16)] + \
  [f'Hour_Group_{i}' for i in range(1, 15)]

# Drop the specified columns
validation_embeddings_df = validation_embeddings_df.drop(columns=columns_to_drop)
```

```
C:\Users\brady\OneDrive\Apps\Anaconda\Lib\site-packages\keras\src\models\functional.py:225: UserWarning: The str
ucture of `inputs` doesn't match the expected structure: ['numerical_input', 'account_input', 'merchant_input',
'transaction_input', 'location_input', 'hour_group_input']. Received: the structure of inputs=('*', '*', '*', '*
', '*', '*')
  warnings.warn(
2034/2034 ━━━━━━━━━━━━━━━━━━━━ 6s 2ms/step - loss: 2.2418e-04
  30/1017 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
C:\Users\brady\OneDrive\Apps\Anaconda\Lib\site-packages\keras\src\models\functional.py:225: UserWarning: The str
ucture of `inputs` doesn't match the expected structure: ['account_input', 'merchant_input', 'transaction_input'
, 'location_input', 'hour_group_input']. Received: the structure of inputs=('*', '*', '*', '*', '*')
  warnings.warn(
1017/1017 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step
```

In [83]:

```python
# Create a new column 'Hour_Group' that bucketizes data into four segments of the day
```

```
test_encoded_df['Hour_Group'] = pd.cut(test_encoded_df['Hour'], bins=bins, labels=labels, right=True)

# Assign values of Hour_Group to each AccountID
for account in range(1, 15):
    AccountID_column = f'AccountID_ACC{account}'
    if AccountID_column in test_encoded_df.columns:
        test_encoded_df[f'Hour_Group_{account}'] = test_encoded_df.apply(
            lambda row: row['Hour_Group'] if row[AccountID_column] == 1 else None,
            axis=1
        )

#Repeat this action to assign values of Hour_Group to each Merchant, TransactionType, and Location
def create_hour_group_columns(test_encoded_df, variable_info, hour_group_column='Hour_Group'):
    for prefix, count in variable_info.items():
        for i in range(1, count + 1):
            column_name = f'{prefix}{i}'
            if column_name in test_encoded_df.columns:
                test_encoded_df[f'{column_name}_{hour_group_column}'] = test_encoded_df.apply(
                    lambda row: row[hour_group_col] if row[column_name] == 1 else None,
                    axis=1
                )

# Define the variable prefixes and their respective counts
variable_info = {
    'Merchant_Merchant': 10,  # Merchants A-J
    'TransactionType_': 3,     # Purchase, Transfer, Withdrawal
    'Location_': 5              # London, Los Angeles, New York, San Francisco, Tokyo
}

# Call the function to create the new columns
create_hour_group_columns(test_encoded_df, variable_info)

# Define a function to calculate mean and standard deviation for each one-hot encoded account by iterating acro
def calculate_stats(test_encoded_df, account_prefix='AccountID_ACC', num_accounts=15):
    stats = {}

    for i in range(1, num_accounts + 1):
        account_columns = f'{account_prefix}{i}'
        # Only include amounts where the specific account value is true (1 as its binary representation)
        account_data = test_encoded_df[test_encoded_df[account_columns] == 1]['Amount']

        # Perform the mean and standard deviatoin calculations
        mean = account_data.mean()
        std = account_data.std()

        # Store the mean and standard deviation for each account
        stats[f'AccountID_ACC{i}'] = {'mean': mean, 'std': std}

    return stats

# Call the function to calculate mean and standard deviation for AccountID_ACC1 to AccountID_ACC15
account_stats = calculate_stats(test_encoded_df)

# Add mean and standard deviation columns to test_encoded_df
for account, values in account_stats.items():
    test_encoded_df[f'{account}_mean'] = values['mean']
    test_encoded_df[f'{account}_std'] = values['std']

# Create a new column for deviation from mean for each transaction
test_encoded_df['Deviation_From_Mean'] = 0.0

# Loop through each account and calculate the deviation
for i in range(1, 15):
    account_columns = f'AccountID_ACC{i}'
    mean_columns = f'AccountID_ACC{i}_mean'
    std_columns = f'AccountID_ACC{i}_std'

 # Calculate the deviation only for transactions in the current account
    condition = test_encoded_df[account_columns] == 1

    # Calculate number of standard deviations of a transaction's Amount value from its Account's Amount mean
    test_encoded_df.loc[condition, 'Deviation_From_Mean'] = (
        (test_encoded_df.loc[condition, 'Amount'] - test_encoded_df.loc[condition, mean_columns]
    ) / test_encoded_df.loc[condition, std_columns])

# Create a list of prefixes for our one-hot columns
one_hot_prefixes = ['AccountID_', 'Merchant_', 'TransactionType_', 'Location_', 'Amount_Partitions_', 'Day']

# Create a variable that stores the columns starting with the respective prefixes from our list
binary = test_encoded_df.columns.str.startswith(tuple(one_hot_prefixes))

# Convert TRUE/FALSE entries to 1/0 entries with exception handling condition
if binary.any():
```

```python
    try:
        # Check data types of the selected columns
        for col in test_encoded_df.columns[binary]:
            # Get the data type of the column
            column_dtype = test_encoded_df[col].dtype

            if column_dtype != 'int32':
                # Convert directly to int if boolean
                if column_dtype == 'bool':
                    test_encoded_df[col] = test_encoded_df[col].astype(int)
                else:
                    # If it's not bool, you can simply ensure it's int
                    test_encoded_df[col] = test_encoded_df[col].astype('int32')
    except Exception as e:
        print(f"Potential incompatible dtype error during conversion: {e}")
else:
    print("No one-hot encoded columns found with the specified prefixes.")

# Create lists for AccountID, Merchant, TransactionType, Location, and Hour Groups
account_ids = [f'AccountID_ACC{i}' for i in range(1, 15)]  # AccountID's 1 to 15
merchants = [f'Merchant_Merchant{chr(i)}' for i in range(ord('A'), ord('J') + 1)]  # Merchants A to J
transaction_types = ['TransactionType_Purchase', 'TransactionType_Transfer', 'TransactionType_Withdrawal']
locations = ['Location_London', 'Location_Los Angeles', 'Location_New York', 'Location_San Francisco', 'Locatio
hour_groups = [f'Hour_Group_{i}' for i in range(1, 15)]

def encode_columns(df, columns):
    encoder = LabelEncoder()
    encoded_columns = {}

    for column in columns:
        if column in df.columns:
            encoded_columns[column] = encoder.fit_transform(df[column])
        else:
            print(f"Warning: {column} not found in DataFrame.")
    return encoded_columns

# Encode each variable
encoded_account_ids = encode_columns(test_encoded_df, account_ids)
encoded_merchants = encode_columns(test_encoded_df, merchants)
encoded_transaction_types = encode_columns(test_encoded_df, transaction_types)
encoded_locations = encode_columns(test_encoded_df, locations)
encoded_hour_groups = encode_columns(test_encoded_df, hour_groups)

# Assign the encoded values back to the DataFrame
for account_id, encoded_values in encoded_account_ids.items():
    test_encoded_df[account_id] = encoded_values

for merchant, encoded_values in encoded_merchants.items():
    test_encoded_df[merchant] = encoded_values

for transaction_type, encoded_values in encoded_transaction_types.items():
    test_encoded_df[transaction_type] = encoded_values

for location, encoded_values in encoded_locations.items():
    test_encoded_df[location] = encoded_values

for hour_group, encoded_values in encoded_hour_groups.items():
    test_encoded_df[hour_group] = encoded_values

# Prepare Inputs for Embedding
numerical_input = Input(shape=(1,), name='numerical_input')
account_input = Input(shape=(1,), name='account_input')
merchant_input = Input(shape=(1,), name='merchant_input')
transaction_input = Input(shape=(1,), name='transaction_input')
location_input = Input(shape=(1,), name='location_input')
hour_group_input = Input(shape=(1,), name='hour_group_input')

# Create Embedding Layers
embedding_dim = 8
num_accounts = len(account_ids)
num_merchants = len(merchants)
num_transaction_types = len(transaction_types)
num_locations = len(locations)
num_hour_groups = len(hour_groups)

# Embeddings for each one-hot encoded category
account_embedding = Embedding(input_dim=num_accounts, output_dim=embedding_dim)(account_input)
merchant_embedding = Embedding(input_dim=num_merchants, output_dim=embedding_dim)(merchant_input)
transaction_embedding = Embedding(input_dim=num_transaction_types, output_dim=embedding_dim)(transaction_input)
location_embedding = Embedding(input_dim=num_locations, output_dim=embedding_dim)(location_input)
hour_group_embedding = Embedding(input_dim=num_hour_groups, output_dim=embedding_dim)(hour_group_input)

# Flatten the embeddings to make a one-dimensional array representation of the variables
```

```python
flattened_account = Flatten()(account_embedding)
flattened_merchant = Flatten()(merchant_embedding)
flattened_transaction = Flatten()(transaction_embedding)
flattened_location = Flatten()(location_embedding)
flattened_hour_group = Flatten()(hour_group_embedding)

# Concatenate inputs to a single output
concat = Concatenate()([numerical_input, flattened_account, flattened_merchant, flattened_transaction, flattene

# Add Dense Layers to interconnect previous layers
output = Dense(1, activation='sigmoid')(concat)

# Build the Model
model = Model(inputs=[numerical_input, account_input, merchant_input, transaction_input, location_input, hour_g
model.compile(optimizer='adam', loss='mean_squared_error')

# Prepare input data for model training
X_numerical = test_encoded_df[['Amount']].values
X_accounts = test_encoded_df[account_ids].values.argmax(axis=1).reshape(-1, 1)  # Get index for account input
X_merchants = test_encoded_df[merchants].values.argmax(axis=1).reshape(-1, 1)
X_transaction_types = test_encoded_df[transaction_types].values.argmax(axis=1).reshape(-1, 1)
X_locations = test_encoded_df[locations].values.argmax(axis=1).reshape(-1, 1)
X_hour_groups = test_encoded_df[hour_groups].values.argmax(axis=1).reshape(-1, 1)

# Make sure to pass the inputs as a list
model.fit([X_numerical, X_accounts, X_merchants, X_transaction_types, X_locations, X_hour_groups],
          np.zeros(X_numerical.shape[0]),
          epochs=1,
          batch_size=16)

# Create a model to get the embedding outputs
embedding_model = Model(inputs=[account_input, merchant_input, transaction_input, location_input, hour_group_in
                        outputs=[account_embedding, merchant_embedding, transaction_embedding, location_embedd

# Get the embedding outputs
embedding_output = embedding_model.predict([X_accounts, X_merchants, X_transaction_types, X_locations, X_hour_g

# Store the embeddings in a DataFrame
embedding_df = pd.DataFrame({
    'Account_Embeddings': list(embedding_output[0]),
    'Merchant_Embeddings': list(embedding_output[1]),
    'Transaction_Embeddings': list(embedding_output[2]),
    'Location_Embeddings': list(embedding_output[3]),
    'Hour_Group_Embeddings': list(embedding_output[4])
})

# Combine with the original DataFrame if needed
test_embeddings_df = pd.concat([test_encoded_df.reset_index(drop=True), embedding_df.reset_index(drop=True)], a

# List of columns to drop (already converted to one-hot/embeddings or not relevant to problem statement resolve
columns_to_drop = [
    'Minute',
    'Month',
    'Hour',
    'Hour_Group'
] + [f'AccountID_ACC{i}' for i in range(1, 16)] + \
  [f'Merchant_Merchant{chr(i)}' for i in range(ord('A'), ord('J') + 1)] + \
  ['TransactionType_Purchase', 'TransactionType_Transfer', 'TransactionType_Withdrawal'] + \
  ['Location_London', 'Location_Los Angeles', 'Location_New York',
   'Location_San Francisco', 'Location_Tokyo'] + \
  [f'Amount_Partitions_{i}' for i in ['0-10000', '10001-20000', '20001-30000',
                                      '30001-40000', '40001-50000', '50001-60000',
                                      '60001-70000', '70001-80000', '80001-90000',
                                      '90001-100000', '100001+']] + \
  [f'AccountID_ACC{i}_mean' for i in range(1, 16)] + \
  [f'AccountID_ACC{i}_std' for i in range(1, 16)] + \
  [f'Hour_Group_{i}' for i in range(1, 15)]

# Drop the specified columns
test_embeddings_df = test_embeddings_df.drop(columns=columns_to_drop)
```

```
C:\Users\brady\OneDrive\Apps\Anaconda\Lib\site-packages\keras\src\models\functional.py:225: UserWarning: The str
ucture of `inputs` doesn't match the expected structure: ['numerical_input', 'account_input', 'merchant_input',
'transaction_input', 'location_input', 'hour_group_input']. Received: the structure of inputs=('*', '*', '*', '*
', '*', '*')
  warnings.warn(
2034/2034 ━━━━━━━━━━━━━━━━━━━━ 6s 2ms/step - loss: 2.7502e-04
  26/1017 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step
C:\Users\brady\OneDrive\Apps\Anaconda\Lib\site-packages\keras\src\models\functional.py:225: UserWarning: The str
ucture of `inputs` doesn't match the expected structure: ['account_input', 'merchant_input', 'transaction_input'
, 'location_input', 'hour_group_input']. Received: the structure of inputs=('*', '*', '*', '*', '*')
  warnings.warn(
1017/1017 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step
```

In [84]:
```
'''
# Save the train set
train_embeddings_df.to_csv('train_data.csv', index=False)

# Save the validation set
validation_embeddings_df.to_csv('validation_data.csv', index=False)

# Save the test set
test_embeddings_df.to_csv('test_data.csv', index=False)

print("DataFrames have been saved as CSV files.")
'''
```

Out[84]:
```
'\n# Save the train set\ntrain_embeddings_df.to_csv(\'train_data.csv\', index=False)\n\n# Save the validation s
et\nvalidation_embeddings_df.to_csv(\'validation_data.csv\', index=False)\n\n# Save the test set\ntest_embeddin
gs_df.to_csv(\'test_data.csv\', index=False)\n\nprint("DataFrames have been saved as CSV files.")\n'
```

In [85]:
```
#END WEEK 5
```

In [86]:
```
#WEEK 6 START
```

In [87]:
```
# Print a sample to see the current state of the DataFrame
train_embeddings_df.head()
```

Out[87]:

	Timestamp	Amount	Date	Day_0	Day_1	Day_2	Day_3	Day_4	Day_5	Day_6	Deviation_From_Mean	Account_Embeddings
0	2023-01-07 17:50:00	9.064231	2023-01-07	0	0	0	0	0	1	0	-1.457638	[[-0.19626556, 0.1890982, 0.13639745, 0.199321...
1	2023-01-30 08:04:00	10.757187	2023-01-30	1	0	0	0	0	0	0	0.248660	[[-0.1922804, 0.17092733, 0.117064044, 0.19126...
2	2023-04-06 03:13:00	10.996651	2023-04-06	0	0	0	1	0	0	0	0.498987	[[-0.10577693, 0.14766376, 0.099778645, 0.1798...
3	2023-04-21 10:28:00	11.204528	2023-04-21	0	0	0	0	1	0	0	0.691171	[[-0.19626556, 0.1890982, 0.13639745, 0.199321...
4	2023-01-08 05:29:00	9.295688	2023-01-08	0	0	0	0	0	0	1	-1.204878	[[-0.2237848, 0.30267632, 0.20332241, 0.333834...

In [88]:
```
# Create a features list for modeling purposes
features = [
    'Day_0', 'Day_1', 'Day_2', 'Day_3', 'Day_4', 'Day_5', 'Day_6',
    'Deviation_From_Mean', 'Account_Embeddings', 'Merchant_Embeddings',
    'Transaction_Embeddings', 'Location_Embeddings', 'Hour_Group_Embeddings'
]

# Save feature data in variable X
X_train = train_embeddings_df[features]

# Flatten embeddings to reduce dimensionality
for col in ['Account_Embeddings', 'Merchant_Embeddings', 'Transaction_Embeddings', 'Location_Embeddings', 'Hour_
    if isinstance(X_train[col].iloc[0], np.ndarray):  # Check if the first entry is an ndarray
        embedding_array = pd.DataFrame(X_train[col].apply(lambda x: x.flatten()).tolist())
    else:
        embedding_array = pd.DataFrame(X_train[col].tolist())
#Concatenate newly flattened columns with DataFrame and drop the older, higher dimensional columns
    embedding_array.columns = [f"{col}_{i}" for i in range(embedding_array.shape[1])]
    X_train = pd.concat([X_train, embedding_array], axis=1)
    X_train.drop(columns=[col], inplace=True)

# Ensure all data is numeric
X_train = X_train.apply(pd.to_numeric, errors='coerce')
```

In [89]:
```
'''
# Function to calculate Dunn Index
def dunn_index(X, labels):
    unique_clusters = np.unique(labels)
    intra_distances = []
    inter_distances = []

    # Calculate intra-cluster distances (furthest distance between two points within a cluster)
    for cluster in unique_clusters:
        points = X[labels == cluster]
```

```
        if len(points) > 1:
            intra_distances.append(np.max(cdist(points, points)))

    # Calculate inter-cluster distances (distance between respective clusters)
    for i in range(len(unique_clusters)):
        for j in range(i + 1, len(unique_clusters)):
            points1 = X[labels == unique_clusters[i]]
            points2 = X[labels == unique_clusters[j]]
            inter_distances.append(np.min(cdist(points1, points2)))

    return min(inter_distances) / max(intra_distances) if max(intra_distances) > 0 else 0

# Best k value from previous evaluation (ideally yes, but 5 was simply chosen due to the computational ineffici
best_k_value = 5

# Vary init and n_init
init_values = ['random']
n_init_values = [1]

train_results_variation1 = []

for init in init_values:
    for n_init in n_init_values:
        # Create and fit the KMeans model
        kmeans = KMeans(n_clusters=best_k_value, init=init, n_init=n_init, random_state=42)
        kmeans.fit(X)

        # Get labels and inertia
        labels = kmeans.labels_
        inertia = kmeans.inertia_

        # Calculate Silhouette Score
        silhouette_avg = silhouette_score(X, labels)

        # Calculate Dunn Index
        dunn_idx = dunn_index(X, labels)

        # Store results
        train_results_variation1.append({
            'Init': init,
            'n_init': n_init,
            'Silhouette Score': silhouette_avg,
            'Dunn Index': dunn_idx,
            'Inertia': inertia
        })

# Convert results to DataFrame for better readability
train_results_variation1_df = pd.DataFrame(train_results_variation1)

print(train_results_variation1_df)
'''
```

Out[89]:

```
"\n# Function to calculate Dunn Index\ndef dunn_index(X, labels):\n    unique_clusters = np.unique(labels)\n    intra_distances = []\n    inter_distances = []\n\n    # Calculate intra-cluster distances (furthest distance between two points within a cluster)\n    for cluster in unique_clusters:\n        points = X[labels == cluster]\n        if len(points) > 1:\n            intra_distances.append(np.max(cdist(points, points)))\n\n    # Calculate inter-cluster distances (distance between respective clusters)\n    for i in range(len(unique_clusters)):\n        for j in range(i + 1, len(unique_clusters)):\n            points1 = X[labels == unique_clusters[i]]\n            points2 = X[labels == unique_clusters[j]]\n            inter_distances.append(np.min(cdist(points1, points2)))\n\n    return min(inter_distances) / max(intra_distances) if max(intra_distances) > 0 else 0\n\n# Best k value from previous evaluation (ideally yes, but 5 was simply chosen due to the computational inefficiencies of my dataset and my machine) \nbest_k_value = 5\n\n# Vary init and n_init\ninit_values = ['random']\nn_init_values = [1]\n\ntrain_results_variation1 = []\n\nfor init in init_values:\n    for n_init in n_init_values:\n        # Create and fit the KMeans model\n        kmeans = KMeans(n_clusters=best_k_value, init=init, n_init=n_init, random_state=42)\n        kmeans.fit(X)\n        \n        # Get labels and inertia\n        labels = kmeans.labels_\n        inertia = kmeans.inertia_\n        \n        # Calculate Silhouette Score\n        silhouette_avg = silhouette_score(X, labels)\n        \n        # Calculate Dunn Index\n        dunn_idx = dunn_index(X, labels)\n        \n        # Store results\n        train_results_variation1.append({\n            'Init': init,\n            'n_init': n_init,\n            'Silhouette Score': silhouette_avg,\n            'Dunn Index': dunn_idx,\n            'Inertia': inertia\n        })\n\n# Convert results to DataFrame for better readability\ntrain_results_variation1_df = pd.DataFrame(train_results_variation1)\n\nprint(train_results_variation1_df)\n"
```

In [90]:

```
'''
# Best variation found in the previous step
best_init = 'k-means++'
best_n_init = 1
best_k_value = 5

# Vary max_iter and tol
max_iter_values = [100]
tol_values = [1e-2]

train_results_variation2 = []
```

```
for max_iter in max_iter_values:
    for tol in tol_values:
        # Create and fit the KMeans model
        kmeans = KMeans(n_clusters=best_k_value, init=best_init, n_init=best_n_init,
                        max_iter=max_iter, tol=tol, random_state=42)
        kmeans.fit(X)

        # Get labels and inertia
        labels = kmeans.labels_
        inertia = kmeans.inertia_

        # Calculate Silhouette Score
        silhouette_avg = silhouette_score(X, labels)

        # Calculate Dunn Index
        distances = cdist(X, kmeans.cluster_centers_)
        intra_cluster_distances = np.min(distances, axis=1)
        inter_cluster_distances = np.max(distances)
        dunn_index = np.min(intra_cluster_distances) / inter_cluster_distances

        # Store results
        train_results_variation2.append({
            'max_iter': max_iter,
            'tol': tol,
            'Silhouette Score': silhouette_avg,
            'Dunn Index': dunn_index,
            'Inertia': inertia
        })

# Convert results to DataFrame for better readability
train_results_variation2_df = pd.DataFrame(train_results_variation2)

print(train_results_variation2_df)

# Print train variation 2 results
train_results_variation2 = train_results_variation2_df.loc[train_results_variation2_df['Silhouette Score'].idxma
print(train_results_variation2)
'''
```

Out[90]:

```
"\n# Best variation found in the previous step\nbest_init = 'k-means++'\nbest_n_init = 1\nbest_k_value = 5\n\n#
Vary max_iter and tol\nmax_iter_values = [100]\ntol_values = [1e-2]\n\ntrain_results_variation2 = []\n\nfor max
_iter in max_iter_values:\n    for tol in tol_values:\n        # Create and fit the KMeans model\n        kmean
s = KMeans(n_clusters=best_k_value, init=best_init, n_init=best_n_init,\n                        max_iter=max_i
ter, tol=tol, random_state=42)\n        kmeans.fit(X)\n        \n        # Get labels and inertia\n        labe
ls = kmeans.labels_\n        inertia = kmeans.inertia_\n        \n        # Calculate Silhouette Score\n        
silhouette_avg = silhouette_score(X, labels)\n        \n        # Calculate Dunn Index\n        distances = cdi
st(X, kmeans.cluster_centers_)\n        intra_cluster_distances = np.min(distances, axis=1)\n        inter_clus
ter_distances = np.max(distances)\n        dunn_index = np.min(intra_cluster_distances) / inter_cluster_distanc
es\n        \n        # Store results\n        train_results_variation2.append({\n            'max_iter': max_i
ter,\n            'tol': tol,\n            'Silhouette Score': silhouette_avg,\n            'Dunn Index': dunn_
index,\n            'Inertia': inertia\n        })\n\n# Convert results to DataFrame for better readability\ntr
ain_results_variation2_df = pd.DataFrame(train_results_variation2)\n\nprint(train_results_variation2_df)\n\n# P
rint train variation 2 results\ntrain_results_variation2 = train_results_variation2_df.loc[train_results_variat
ion2_df['Silhouette Score'].idxmax()]\nprint(train_results_variation2)\n"
```

In [91]:

```
'''
# Best variation found in the previous step
best_init = 'k-means++'
best_n_init = 1
best_k_value = 10

# Vary max_iter and tol
max_iter_values = [200]
tol_values = [1e-3]

train_results_variation3 = []

for max_iter in max_iter_values:
    for tol in tol_values:
        # Create and fit the KMeans model
        kmeans = KMeans(n_clusters=best_k_value, init=best_init, n_init=best_n_init,
                        max_iter=max_iter, tol=tol, random_state=42)
        kmeans.fit(X)

        # Get labels and inertia
        labels = kmeans.labels_
        inertia = kmeans.inertia_

        # Calculate Silhouette Score
        silhouette_avg = silhouette_score(X, labels)

        # Calculate Dunn Index
```

```
        distances = cdist(X, kmeans.cluster_centers_)
        intra_cluster_distances = np.min(distances, axis=1)
        inter_cluster_distances = np.max(distances)
        dunn_index = np.min(intra_cluster_distances) / inter_cluster_distances

        # Store results
        train_results_variation3.append({
            'max_iter': max_iter,
            'tol': tol,
            'Silhouette Score': silhouette_avg,
            'Dunn Index': dunn_index,
            'Inertia': inertia
        })

# Convert results to DataFrame for better readability
train_results_variation3_df = pd.DataFrame(train_results_variation3)

print(train_results_variation3_df)

# Identify the best performing final variation
train_results_variation3 = train_results_variation3_df.loc[train_results_variation3_df['Silhouette Score'].idxma
print(train_results_variation3)
'''
```

Out[91]:

```
"\n# Best variation found in the previous step\nbest_init = 'k-means++'\nbest_n_init = 1\nbest_k_value = 10\n\n
# Vary max_iter and tol\nmax_iter_values = [200]\ntol_values = [1e-3]\n\ntrain_results_variation3 = []\n\nfor m
ax_iter in max_iter_values:\n    for tol in tol_values:\n        # Create and fit the KMeans model\n        kme
ans = KMeans(n_clusters=best_k_value, init=best_init, n_init=best_n_init,\n                        max_iter=max
_iter, tol=tol, random_state=42)\n        kmeans.fit(X)\n        \n        # Get labels and inertia\n        la
bels = kmeans.labels_\n        inertia = kmeans.inertia_\n        \n        # Calculate Silhouette Score\n        
silhouette_avg = silhouette_score(X, labels)\n        \n        # Calculate Dunn Index\n        distances = cdi
st(X, kmeans.cluster_centers_)\n        intra_cluster_distances = np.min(distances, axis=1)\n        inter_clus
ter_distances = np.max(distances)\n        dunn_index = np.min(intra_cluster_distances) / inter_cluster_distanc
es\n        \n        # Store results\n        train_results_variation3.append({\n            'max_iter': max_i
ter,\n            'tol': tol,\n            'Silhouette Score': silhouette_avg,\n            'Dunn Index': dunn_
index,\n            'Inertia': inertia\n        })\n\n# Convert results to DataFrame for better readability\ntr
ain_results_variation3_df = pd.DataFrame(train_results_variation3)\n\nprint(train_results_variation3_df)\n\n# I
dentify the best performing final variation\ntrain_results_variation3 = train_results_variation3_df.loc[train_r
esults_variation3_df['Silhouette Score'].idxmax()]\nprint(train_results_variation3)\n"
```

In [92]:

```
#Perform model on validation set
features = [
    'Day_0', 'Day_1', 'Day_2', 'Day_3', 'Day_4', 'Day_5', 'Day_6',
    'Deviation_From_Mean', 'Account_Embeddings', 'Merchant_Embeddings',
    'Transaction_Embeddings', 'Location_Embeddings', 'Hour_Group_Embeddings'
]

# Prepare the feature data
X_val = validation_embeddings_df[features]

# Flatten embeddings
for col in ['Account_Embeddings', 'Merchant_Embeddings', 'Transaction_Embeddings', 'Location_Embeddings', 'Hour_
    if isinstance(X_val[col].iloc[0], np.ndarray):  # Check if the first entry is an ndarray
        embedding_array = pd.DataFrame(X_val[col].apply(lambda x: x.flatten()).tolist())
    else:
        embedding_array = pd.DataFrame(X_val[col].tolist())

    embedding_array.columns = [f"{col}_{i}" for i in range(embedding_array.shape[1])]
    X_val = pd.concat([X_val, embedding_array], axis=1)
    X_val.drop(columns=[col], inplace=True)

# Ensure all data is numeric
X_val = X_val.apply(pd.to_numeric, errors='coerce')
```

In [93]:

```
'''
# Function to calculate Dunn Index
def dunn_index(X, labels):
    unique_clusters = np.unique(labels)
    intra_distances = []
    inter_distances = []

    # Calculate intra-cluster distances
    for cluster in unique_clusters:
        points = X[labels == cluster]
        if len(points) > 1:
            intra_distances.append(np.max(cdist(points, points)))

    # Calculate inter-cluster distances
    for i in range(len(unique_clusters)):
        for j in range(i + 1, len(unique_clusters)):
            points1 = X[labels == unique_clusters[i]]
            points2 = X[labels == unique_clusters[j]]
            inter_distances.append(np.min(cdist(points1, points2)))
```

```
    return min(inter_distances) / max(intra_distances) if max(intra_distances) > 0 else 0

# Best k value from previous evaluation
best_k_value = 5

# Vary init and n_init
init_values = ['random']
n_init_values = [1]

val_results_variation1 = []

for init in init_values:
    for n_init in n_init_values:
        # Create and fit the KMeans model
        kmeans = KMeans(n_clusters=best_k_value, init=init, n_init=n_init, random_state=42)
        kmeans.fit(X)

        # Get labels and inertia
        labels = kmeans.labels_
        inertia = kmeans.inertia_

        # Calculate Silhouette Score
        silhouette_avg = silhouette_score(X, labels)

        # Calculate Dunn Index
        dunn_idx = dunn_index(X, labels)

        # Store results
        val_results_variation1.append({
            'Init': init,
            'n_init': n_init,
            'Silhouette Score': silhouette_avg,
            'Dunn Index': dunn_idx,
            'Inertia': inertia
        })

# Convert results to DataFrame for better readability
val_results_variation1_df = pd.DataFrame(val_results_variation1)

print(val_results_variation1_df)
'''
```

Out[93]:

```
"\n# Function to calculate Dunn Index\ndef dunn_index(X, labels):\n    unique_clusters = np.unique(labels)\n    intra_distances = []\n    inter_distances = []\n\n    # Calculate intra-cluster distances\n    for cluster in unique_clusters:\n        points = X[labels == cluster]\n        if len(points) > 1:\n            intra_distances.append(np.max(cdist(points, points)))\n\n    # Calculate inter-cluster distances\n    for i in range(len(unique_clusters)):\n        for j in range(i + 1, len(unique_clusters)):\n            points1 = X[labels == unique_clusters[i]]\n            points2 = X[labels == unique_clusters[j]]\n            inter_distances.append(np.min(cdist(points1, points2)))\n\n    return min(inter_distances) / max(intra_distances) if max(intra_distances) > 0 else 0\n\n# Best k value from previous evaluation\nbest_k_value = 5\n\n# Vary init and n_init\ninit_values = ['random']\nn_init_values = [1]\n\nval_results_variation1 = []\n\nfor init in init_values:\n    for n_init in n_init_values:\n        # Create and fit the KMeans model\n        kmeans = KMeans(n_clusters=best_k_value, init=init, n_init=n_init, random_state=42)\n        kmeans.fit(X)\n        \n        # Get labels and inertia\n        labels = kmeans.labels_\n        inertia = kmeans.inertia_\n        \n        # Calculate Silhouette Score\n        silhouette_avg = silhouette_score(X, labels)\n        \n        # Calculate Dunn Index\n        dunn_idx = dunn_index(X, labels)\n        \n        # Store results\n        val_results_variation1.append({\n            'Init': init,\n            'n_init': n_init,\n            'Silhouette Score': silhouette_avg,\n            'Dunn Index': dunn_idx,\n            'Inertia': inertia\n        })\n\n# Convert results to DataFrame for better readability\nval_results_variation1_df = pd.DataFrame(val_results_variation1)\n\nprint(val_results_variation1_df)\n"
```

In [94]:

```
'''
# Best variation found in the previous step
best_init = 'k-means++'
best_n_init = 1
best_k_value = 5

# Vary max_iter and tol
max_iter_values = [100]
tol_values = [1e-2]

val_results_variation2 = []

for max_iter in max_iter_values:
    for tol in tol_values:
        # Create and fit the KMeans model
        kmeans = KMeans(n_clusters=best_k_value, init=best_init, n_init=best_n_init,
                        max_iter=max_iter, tol=tol, random_state=42)
        kmeans.fit(X)

        # Get labels and inertia
        labels = kmeans.labels_
        inertia = kmeans.inertia_
```

```
        # Calculate Silhouette Score
        silhouette_avg = silhouette_score(X, labels)

        # Calculate Dunn Index
        distances = cdist(X, kmeans.cluster_centers_)
        intra_cluster_distances = np.min(distances, axis=1)
        inter_cluster_distances = np.max(distances)
        dunn_index = np.min(intra_cluster_distances) / inter_cluster_distances

        # Store results
        val_results_variation2.append({
            'max_iter': max_iter,
            'tol': tol,
            'Silhouette Score': silhouette_avg,
            'Dunn Index': dunn_index,
            'Inertia': inertia
        })

# Convert results to DataFrame for better readability
val_results_variation2_df = pd.DataFrame(val_results_variation2)

print(val_results_variation2_df)

# Identify the best performing final variation
val_results_variation2 = val_results_variation2_df.loc[val_results_variation2_df['Silhouette Score'].idxmax()]
print(val_results_variation2)
'''
```

Out[94]:

```
"\n# Best variation found in the previous step\nbest_init = 'k-means++'\nbest_n_init = 1\nbest_k_value = 5\n\n# Vary max_iter and tol\nmax_iter_values = [100]\ntol_values = [1e-2]\n\nval_results_variation2 = []\n\nfor max_iter in max_iter_values:\n    for tol in tol_values:\n        # Create and fit the KMeans model\n        kmeans = KMeans(n_clusters=best_k_value, init=best_init, n_init=best_n_init,\n                        max_iter=max_iter, tol=tol, random_state=42)\n        kmeans.fit(X)\n        \n        # Get labels and inertia\n        labels = kmeans.labels_\n        inertia = kmeans.inertia_\n        \n        # Calculate Silhouette Score\n        silhouette_avg = silhouette_score(X, labels)\n        \n        # Calculate Dunn Index\n        distances = cdist(X, kmeans.cluster_centers_)\n        intra_cluster_distances = np.min(distances, axis=1)\n        inter_cluster_distances = np.max(distances)\n        dunn_index = np.min(intra_cluster_distances) / inter_cluster_distances\n        \n        # Store results\n        val_results_variation2.append({\n            'max_iter': max_iter,\n            'tol': tol,\n            'Silhouette Score': silhouette_avg,\n            'Dunn Index': dunn_index,\n            'Inertia': inertia\n        })\n\n# Convert results to DataFrame for better readability\nval_results_variation2_df = pd.DataFrame(val_results_variation2)\n\nprint(val_results_variation2_df)\n\n# Identify the best performing final variation\nval_results_variation2 = val_results_variation2_df.loc[val_results_variation2_df['Silhouette Score'].idxmax()]\nprint(val_results_variation2)\n"
```

In [95]:

```
'''
# Best variation found in the previous step
best_init = 'k-means++'
best_n_init = 1
best_k_value = 10

# Vary max_iter and tol
max_iter_values = [200]
tol_values = [1e-3]

val_results_variation3 = []

for max_iter in max_iter_values:
    for tol in tol_values:
        # Create and fit the KMeans model
        kmeans = KMeans(n_clusters=best_k_value, init=best_init, n_init=best_n_init,
                        max_iter=max_iter, tol=tol, random_state=42)
        kmeans.fit(X)

        # Get labels and inertia
        labels = kmeans.labels_
        inertia = kmeans.inertia_

        # Calculate Silhouette Score
        silhouette_avg = silhouette_score(X, labels)

        # Calculate Dunn Index
        distances = cdist(X, kmeans.cluster_centers_)
        intra_cluster_distances = np.min(distances, axis=1)
        inter_cluster_distances = np.max(distances)
        dunn_index = np.min(intra_cluster_distances) / inter_cluster_distances

        # Store results
        val_results_variation3.append({
            'max_iter': max_iter,
            'tol': tol,
            'Silhouette Score': silhouette_avg,
            'Dunn Index': dunn_index,
```

```
            'Inertia': inertia
        })

# Convert results to DataFrame for better readability
val_results_variation3_df = pd.DataFrame(val_results_variation3)

print(val_results_variation3_df)

# Identify the best performing final variation
val_results_variation3 = val_results_variation3_df.loc[val_results_variation3_df['Silhouette Score'].idxmax()]
print(val_results_variation3)
'''
```

Out[95]:

```
"\n# Best variation found in the previous step\nbest_init = 'k-means++'\nbest_n_init = 1\nbest_k_value = 10\n\n
# Vary max_iter and tol\nmax_iter_values = [200]\ntol_values = [1e-3]\n\nval_results_variation3 = []\n\nfor max
_iter in max_iter_values:\n    for tol in tol_values:\n        # Create and fit the KMeans model\n        kmean
s = KMeans(n_clusters=best_k_value, init=best_init, n_init=best_n_init,\n                        max_iter=max_i
ter, tol=tol, random_state=42)\n        kmeans.fit(X)\n        \n        # Get labels and inertia\n        labe
ls = kmeans.labels_\n        inertia = kmeans.inertia_\n        \n        # Calculate Silhouette Score\n        
silhouette_avg = silhouette_score(X, labels)\n        \n        # Calculate Dunn Index\n        distances = cdi
st(X, kmeans.cluster_centers_)\n        intra_cluster_distances = np.min(distances, axis=1)\n        inter_clus
ter_distances = np.max(distances)\n        dunn_index = np.min(intra_cluster_distances) / inter_cluster_distanc
es\n        \n        # Store results\n        val_results_variation3.append({\n            'max_iter': max_ite
r,\n            'tol': tol,\n            'Silhouette Score': silhouette_avg,\n            'Dunn Index': dunn_in
dex,\n            'Inertia': inertia\n        })\n\n# Convert results to DataFrame for better readability\nval_
results_variation3_df = pd.DataFrame(val_results_variation3)\n\nprint(val_results_variation3_df)\n\n# Identify 
the best performing final variation\nval_results_variation3 = val_results_variation3_df.loc[val_results_variati
on3_df['Silhouette Score'].idxmax()]\nprint(val_results_variation3)\n"
```

In [96]:

```
train_inertia_1 = 147040.18201/151872
train_inertia_2 = 143682.817524/151872
train_inertia_3 = 69707.25485/151872
print(train_inertia_1, train_inertia_2, train_inertia_3)
```

```
0.9681849321138853 0.9460783918299621 0.4589868761193637
```

In [97]:

```
val_inertia_1 = 31632.758442/32544
val_inertia_2 = 31714.576743/32544
val_inertia_3 = 16051.701494/32544
print(val_inertia_1, val_inertia_2, val_inertia_3)
```

```
0.9719997063053097 0.9745137888089971 0.4932307489552606
```

In [98]:

```
'''
import pandas as pd
from tabulate import tabulate

# Sample data
data1 = {
    'Variation 1 Silhouette': [0.1814,  0.2434],
    'Variation 1 Dunn Index': [0.0007, 0.0023],
    'Variation 1 Inertia': [0.9682, 0.9720]
}

data2 = {
    'Variation 2 Silhouette': [0.2420,  0.2438],
    'Variation 2 Dunn Index': [0.01740, 0.0190],
    'Variation 2 Inertia': [0.9461, 0.9745]
}

data3 = {
    'Variation 3 Silhouette': [0.4815,  0.4629],
    'Variation 3 Dunn Index': [0.0176, 0.0177],
    'Variation 3 Inertia': [0.4590, 0.4932]
}
# Create a DataFrame
results1_df = pd.DataFrame(data1, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results1_df, headers='keys', tablefmt='pretty'))

# Create a DataFrame
results2_df = pd.DataFrame(data2, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results2_df, headers='keys', tablefmt='pretty'))

# Create a DataFrame
results3_df = pd.DataFrame(data3, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results3_df, headers='keys', tablefmt='pretty'))
'''
```

Out[98]: "\nimport pandas as pd\nfrom tabulate import tabulate\n\n# Sample data\ndata1 = {\n   'Variation 1 Silhouette': [0.1814, 0.2434],\n   'Variation 1 Dunn Index': [0.0007, 0.0023],\n   'Variation 1 Inertia': [0.9682, 0.9720]\n}\n\ndata2 = {\n   'Variation 2 Silhouette': [0.2420, 0.2438],\n   'Variation 2 Dunn Index': [0.01740, 0.0190],\n   'Variation 2 Inertia': [0.9461, 0.9745]\n}\n\ndata3 = {\n   'Variation 3 Silhouette': [0.4815, 0.4629],\n   'Variation 3 Dunn Index': [0.0176, 0.0177],\n   'Variation 3 Inertia': [0.4590, 0.4932]\n}\n# Create a DataFrame\nresults1_df = pd.DataFrame(data1, index=['Training', 'Validation'])\n\n# Print the DataFrame using tabulate for better formatting\nprint(tabulate(results1_df, headers='keys', tablefmt='pretty'))\n\n# Create a DataFrame\nresults2_df = pd.DataFrame(data2, index=['Training', 'Validation'])\n\n# Print the DataFrame using tabulate for better formatting\nprint(tabulate(results2_df, headers='keys', tablefmt='pretty'))\n\n# Create a DataFrame\nresults3_df = pd.DataFrame(data3, index=['Training', 'Validation'])\n\n# Print the DataFrame using tabulate for better formatting\nprint(tabulate(results3_df, headers='keys', tablefmt='pretty'))\n"

In [99]:
```
'''
# Save the train set
train_embeddings_df.to_csv('train_data.csv', index=False)

# Save the validation set
validation_embeddings_df.to_csv('validation_data.csv', index=False)

# Save the test set
test_embeddings_df.to_csv('test_data.csv', index=False)

print("DataFrames have been saved as CSV files.")
'''
```

Out[99]: '\n# Save the train set\ntrain_embeddings_df.to_csv(\'train_data.csv\', index=False)\n\n# Save the validation set\nvalidation_embeddings_df.to_csv(\'validation_data.csv\', index=False)\n\n# Save the test set\ntest_embeddings_df.to_csv(\'test_data.csv\', index=False)\n\nprint("DataFrames have been saved as CSV files.")\n'

In [100…
```
#END WEEK 6
```

In [101…
```
#BEGIN WEEK 7
```

In [102…
```
'''
from sklearn.metrics import silhouette_score, calinski_harabasz_score, davies_bouldin_score
from sklearn.neighbors import LocalOutlierFactor

# Initialize the LOF model
n_neighbors = 2
lof = LocalOutlierFactor(n_neighbors=n_neighbors)

# Fit the model and get the labels for training data
train_labels = lof.fit_predict(X_train)
# LOF returns -1 for outliers and 1 for inliers
train_labels[train_labels == 1] = 0  # Convert inliers to 0
train_labels[train_labels == -1] = 1  # Convert outliers to 1

# Fit the model and get the labels for validation data
val_labels = lof.fit_predict(X_val)
val_labels[val_labels == 1] = 0
val_labels[val_labels == -1] = 1

# Calculate metrics for training data
silhouette_train = silhouette_score(X_train, train_labels)
calinski_train = calinski_harabasz_score(X_train, train_labels)
davies_train = davies_bouldin_score(X_train, train_labels)

# Calculate metrics for validation data
silhouette_val = silhouette_score(X_val, val_labels)
calinski_val = calinski_harabasz_score(X_val, val_labels)
davies_val = davies_bouldin_score(X_val, val_labels)

# Print results
print("Training Data Metrics:")
print(f"Silhouette Score: {silhouette_train:.4f}")
print(f"Calinski-Harabasz Index: {calinski_train:.4f}")
print(f"Davies-Bouldin Index: {davies_train:.4f}")

print("\nValidation Data Metrics:")
print(f"Silhouette Score: {silhouette_val:.4f}")
print(f"Calinski-Harabasz Index: {calinski_val:.4f}")
print(f"Davies-Bouldin Index: {davies_val:.4f}")
'''
```

Out[102… '\nfrom sklearn.metrics import silhouette_score, calinski_harabasz_score, davies_bouldin_score\nfrom sklearn.neighbors import LocalOutlierFactor\n\n# Initialize the LOF model\nn_neighbors = 2\nlof = LocalOutlierFactor(n_neighbors=n_neighbors)\n\n# Fit the model and get the labels for training data\ntrain_labels = lof.fit_predict(X_train)\n# LOF returns -1 for outliers and 1 for inliers\ntrain_labels[train_labels == 1] = 0 # Convert inliers to 0\ntrain_labels[train_labels == -1] = 1 # Convert outliers to 1\n\n# Fit the model and get the labels for validation data\nval_labels = lof.fit_predict(X_val)\nval_labels[val_labels == 1] = 0\nval_labels[val_labels == -1] = 1\n\n# Calculate metrics for training data\nsilhouette_train = silhouette_score(X_train, train_labels)\ncalinski_train = calinski_harabasz_score(X_train, train_labels)\ndavies_train = davies_bouldin_score(X_train, train_labels)\n\n# Calculate metrics for validation data\nsilhouette_val = silhouette_score(X_val, val_labels)\ncalinski_val = calinski_harabasz_score(X_val, val_labels)\ndavies_val = davies_bouldin_score(X_val, val_labels)\n\n# Print results\nprint("Training Data Metrics:")\nprint(f"Silhouette Score: {silhouette_train:.4f}")\nprint(f"Calinski-Harabasz Index: {calinski_train:.4f}")\nprint(f"Davies-Bouldin Index: {davies_train:.4f}")\n\nprint("\nValidation Data Metrics:")\nprint(f"Silhouette Score: {silhouette_val:.4f}")\nprint(f"Calinski-Harabasz Index: {calinski_val:.4f}")\nprint(f"Davies-Bouldin Index: {davies_val:.4f}")\n'

In [103…

```
'''
from sklearn.metrics import silhouette_score, calinski_harabasz_score, davies_bouldin_score
from sklearn.neighbors import LocalOutlierFactor

# Define hyperparameters
# n_neighbors for varying method of evaluating local density (5 nearest points vs 10 nearest points vs 15 neares
n_neighbors_list = [5, 10, 15]  # Different values for n_neighbors
# leaf_size varies search speed (30 is default, 50 is faster)
leaf_size_list = [30, 50]  # Different leaf sizes
# metric considers different scoring methods that yield results tailored towards certain statistics
metric_list = ['euclidean', 'manhattan']

# Store results
results = []

for n_neighbors in n_neighbors_list:
        for leaf_size in leaf_size_list:
            for metric in metric_list:
                # Initialize the LOF model
                lof = LocalOutlierFactor(n_neighbors=n_neighbors,
                                         leaf_size=leaf_size,
                                        metric=metric)

                # Fit the model and get the labels for training data
                train_labels = lof.fit_predict(X_train)
                train_labels[train_labels == 1] = 0  # Convert inliers to 0
                train_labels[train_labels == -1] = 1  # Convert outliers to 1

                # Fit the model and get the labels for validation data
                val_labels = lof.fit_predict(X_val)
                val_labels[val_labels == 1] = 0
                val_labels[val_labels == -1] = 1

                # Calculate metrics for training data
                silhouette_train = silhouette_score(X_train, train_labels)
                calinski_train = calinski_harabasz_score(X_train, train_labels)
                davies_train = davies_bouldin_score(X_train, train_labels)

                # Calculate metrics for validation data
                silhouette_val = silhouette_score(X_val, val_labels)
                calinski_val = calinski_harabasz_score(X_val, val_labels)
                davies_val = davies_bouldin_score(X_val, val_labels)

                # Store results
                results.append({
                    'n_neighbors': n_neighbors,
                    'leaf_size': leaf_size,
                    'metric': ['euclidean', 'manhattan'],
                    'Silhouette Score (Train)': silhouette_train,
                    'Calinski-Harabasz Index (Train)': calinski_train,
                    'Davies-Bouldin Index (Train)': davies_train,
                    'Silhouette Score (Val)': silhouette_val,
                    'Calinski-Harabasz Index (Val)': calinski_val,
                    'Davies-Bouldin Index (Val)': davies_val
                })

# Convert results to DataFrame for better readability
results_df = pd.DataFrame(results)

# Print results
print(results_df)
'''
```

Out[103…

```
"\nfrom sklearn.metrics import silhouette_score, calinski_harabasz_score, davies_bouldin_score\nfrom sklearn.neighbors import LocalOutlierFactor\n\n# Define hyperparameters\n# n_neighbors for varying method of evaluating local density (5 nearest points vs 10 nearest points vs 15 nearest points)\nn_neighbors_list = [5, 10, 15]  # Different values for n_neighbors\n# leaf_size varies search speed (30 is default, 50 is faster)\nleaf_size_list = [30, 50]  # Different leaf sizes\n# metric considers different scoring methods that yield results tailored towards certain statistics\nmetric_list = ['euclidean', 'manhattan']\n\n# Store results\nresults = []\n\nfor n_neighbors in n_neighbors_list:\n        for leaf_size in leaf_size_list:\n            for metric in metric_list:\n                # Initialize the LOF model\n                lof = LocalOutlierFactor(n_neighbors=n_neighbors, \n                                        leaf_size=leaf_size,\n                                        metric=metric)\n\n                # Fit the model and get the labels for training data\n                train_labels = lof.fit_predict(X_train)\n                train_labels[train_labels == 1] = 0  # Convert inliers to 0\n                train_labels[train_labels == -1] = 1  # Convert outliers to 1\n\n                # Fit the model and get the labels for validation data\n                val_labels = lof.fit_predict(X_val)\n                val_labels[val_labels == 1] = 0\n                val_labels[val_labels == -1] = 1\n\n                # Calculate metrics for training data\n                silhouette_train = silhouette_score(X_train, train_labels)\n                calinski_train = calinski_harabasz_score(X_train, train_labels)\n                davies_train = davies_bouldin_score(X_train, train_labels)\n\n                # Calculate metrics for validation data\n                silhouette_val = silhouette_score(X_val, val_labels)\n                calinski_val = calinski_harabasz_score(X_val, val_labels)\n                davies_val = davies_bouldin_score(X_val, val_labels)\n\n                # Store results\n                results.append({\n                    'n_neighbors': n_neighbors,\n                    'leaf_size': leaf_size,\n                    'metric': ['euclidean', 'manhattan'],\n                    'Silhouette Score (Train)': silhouette_train,\n                    'Calinski-Harabasz Index (Train)': calinski_train,\n                    'Davies-Bouldin Index (Train)': davies_train,\n                    'Silhouette Score (Val)': silhouette_val,\n                    'Calinski-Harabasz Index (Val)': calinski_val,\n                    'Davies-Bouldin Index (Val)': davies_val\n                })\n\n# Convert results to DataFrame for better readability\nresults_df = pd.DataFrame(results)\n\n# Print results\nprint(results_df)\n"
```

In [104…

```
'''
from tabulate import tabulate

# n_neighbors=5; euclidean
data1 = {
    'Variation 1.1 Silhouette': [0.0996,  0.2972],
    'Variation 1.1 Calinski-Harabasz Index': [88.1241, 64.4077],
    'Variation 1.1 Davies-Bouldin Index': [4.7576, 3.6680]
}
# n_neighbors=10; euclidean
data2 = {
    'Variation 2.1 Silhouette': [-0.0267,  0.4804],
    'Variation 2.1 Calinski-Harabasz Index': [198.7778, 143.9189],
    'Variation 2.1 Davies-Bouldin Index': [5.5308, 2.0772]
}
# n_neighbors=15; euclidean
data3 = {
    'Variation 3.1 Silhouette': [0.0713,  0.5046],
    'Variation 3.1 Calinski-Harabasz Index': [ 162.3979, 194.8525],
    'Variation 3.1 Davies-Bouldin Index': [4.5217, 1.6319]
}
# n_neighbors=5; manhattan
data4 = {
    'Variation 1.2 Silhouette': [-0.0140,  0.0949],
    'Variation 1.2 Calinski-Harabasz Index': [30.7389, 5.5474],
    'Variation 1.2 Davies-Bouldin Index': [9.3945, 10.6232]
}
# n_neighbors=10; manhattan
data5 = {
    'Variation 2.2 Silhouette': [-0.0595,  0.3006],
    'Variation 2.2 Calinski-Harabasz Index': [182.6127, 21.2976],
    'Variation 2.2 Davies-Bouldin Index': [5.6467, 5.0632]
}
# n_neighbors=15; manhattan
data6 = {
    'Variation 3.2 Silhouette': [0.0234,  0.3937],
    'Variation 3.2 Calinski-Harabasz Index': [113.4173,  51.1523],
    'Variation 3.2 Davies-Bouldin Index': [5.4388, 3.4516]
}
# Create a DataFrame
results1_df = pd.DataFrame(data1, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results1_df, headers='keys', tablefmt='pretty'))

# Create a DataFrame
results2_df = pd.DataFrame(data2, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results2_df, headers='keys', tablefmt='pretty'))

# Create a DataFrame
results3_df = pd.DataFrame(data3, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results3_df, headers='keys', tablefmt='pretty'))
```

```
# Create a DataFrame
results4_df = pd.DataFrame(data4, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results4_df, headers='keys', tablefmt='pretty'))

# Create a DataFrame
results5_df = pd.DataFrame(data5, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results5_df, headers='keys', tablefmt='pretty'))

# Create a DataFrame
results6_df = pd.DataFrame(data6, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results6_df, headers='keys', tablefmt='pretty'))
'''
```

Out[104…

```
"\nfrom tabulate import tabulate\n\n# n_neighbors=5; euclidean\ndata1 = {\n    'Variation 1.1 Silhouette': [0.0996,  0.2972],\n    'Variation 1.1 Calinski-Harabasz Index': [88.1241, 64.4077],\n    'Variation 1.1 Davies-Bouldin Index': [4.7576, 3.6680]\n}\n# n_neighbors=10; euclidean\ndata2 = {\n    'Variation 2.1 Silhouette': [-0.0267,  0.4804],\n    'Variation 2.1 Calinski-Harabasz Index': [198.7778, 143.9189],\n    'Variation 2.1 Davies-Bouldin Index': [5.5308, 2.0772]\n}\n# n_neighbors=15; euclidean\ndata3 = {\n    'Variation 3.1 Silhouette': [0.0713,  0.5046],\n    'Variation 3.1 Calinski-Harabasz Index': [ 162.3979, 194.8525],\n    'Variation 3.1 Davies-Bouldin Index': [4.5217, 1.6319]\n}\n# n_neighbors=5; manhattan\ndata4 = {\n    'Variation 1.2 Silhouette': [-0.0140,  0.0949],\n    'Variation 1.2 Calinski-Harabasz Index': [30.7389, 5.5474],\n    'Variation 1.2 Davies-Bouldin Index': [9.3945, 10.6232]\n}\n# n_neighbors=10; manhattan\ndata5 = {\n    'Variation 2.2 Silhouette': [-0.0595,  0.3006],\n    'Variation 2.2 Calinski-Harabasz Index': [182.6127, 21.2976],\n    'Variation 2.2 Davies-Bouldin Index': [5.6467, 5.0632]\n}\n# n_neighbors=15; manhattan\ndata6 = {\n    'Variation 3.2 Silhouette': [0.0234,  0.3937],\n    'Variation 3.2 Calinski-Harabasz Index': [113.4173,  51.1523],\n    'Variation 3.2 Davies-Bouldin Index': [5.4388, 3.4516]\n}\n# Create a DataFrame\nresults1_df = pd.DataFrame(data1, index=['Training', 'Validation'])\n\n# Print the DataFrame using tabulate for better formatting\nprint(tabulate(results1_df, headers='keys', tablefmt='pretty'))\n\n# Create a DataFrame\nresults2_df = pd.DataFrame(data2, index=['Training', 'Validation'])\n\n# Print the DataFrame using tabulate for better formatting\nprint(tabulate(results2_df, headers='keys', tablefmt='pretty'))\n\n# Create a DataFrame\nresults3_df = pd.DataFrame(data3, index=['Training', 'Validation'])\n\n# Print the DataFrame using tabulate for better formatting\nprint(tabulate(results3_df, headers='keys', tablefmt='pretty'))\n\n# Create a DataFrame\nresults4_df = pd.DataFrame(data4, index=['Training', 'Validation'])\n\n# Print the DataFrame using tabulate for better formatting\nprint(tabulate(results4_df, headers='keys', tablefmt='pretty'))\n\n# Create a DataFrame\nresults5_df = pd.DataFrame(data5, index=['Training', 'Validation'])\n\n# Print the DataFrame using tabulate for better formatting\nprint(tabulate(results5_df, headers='keys', tablefmt='pretty'))\n\n# Create a DataFrame\nresults6_df = pd.DataFrame(data6, index=['Training', 'Validation'])\n\n# Print the DataFrame using tabulate for better formatting\nprint(tabulate(results6_df, headers='keys', tablefmt='pretty'))\n"
```

In [105…

```
train_embeddings_df.head()
```

Out[105…

	Timestamp	Amount	Date	Day_0	Day_1	Day_2	Day_3	Day_4	Day_5	Day_6	Deviation_From_Mean	Account_Embeddings
0	2023-01-07 17:50:00	9.064231	2023-01-07	0	0	0	0	0	1	0	-1.457638	[[-0.19626556, 0.1890982, 0.13639745, 0.199321...
1	2023-01-30 08:04:00	10.757187	2023-01-30	1	0	0	0	0	0	0	0.248660	[[-0.1922804, 0.17092733, 0.117064044, 0.19126...
2	2023-04-06 03:13:00	10.996651	2023-04-06	0	0	0	1	0	0	0	0.498987	[[-0.10577693, 0.14766376, 0.099778645, 0.1798...
3	2023-04-21 10:28:00	11.204528	2023-04-21	0	0	0	0	1	0	0	0.691171	[[-0.19626556, 0.1890982, 0.13639745, 0.199321...
4	2023-01-08 05:29:00	9.295688	2023-01-08	0	0	0	0	0	0	1	-1.204878	[[-0.2237848, 0.30267632, 0.20332241, 0.333834...

In [106…

```
'''
# Save the train set
train_embeddings_df.to_csv('train_data.csv', index=False)

# Save the validation set
validation_embeddings_df.to_csv('validation_data.csv', index=False)

# Save the test set
test_embeddings_df.to_csv('test_data.csv', index=False)

print("DataFrames have been saved as CSV files.")
```

```
'''
```

Out[106…

```
'\n# Save the train set\ntrain_embeddings_df.to_csv(\'train_data.csv\', index=False)\n\n# Save the validation s
et\nvalidation_embeddings_df.to_csv(\'validation_data.csv\', index=False)\n\n# Save the test set\ntest_embeddin
gs_df.to_csv(\'test_data.csv\', index=False)\n\nprint("DataFrames have been saved as CSV files.")\n'
```

In [107…

```
#END WEEK 7
```

In [108…

```
#BEGIN WEEK 8
```

In [109…

```
# Import necessary packages for Density-Based Spatial Clustering of Applications with Noise
from sklearn.metrics import silhouette_score, calinski_harabasz_score, davies_bouldin_score
from sklearn.cluster import DBSCAN
```

In [110…

```
'''
# Define hyperparameters for DBSCAN
eps_list = [0.3, 0.5, 0.7]  # Radius of neighborhood - determines maximum distance allowed between points for tl
#as part of the same neighborhood
min_samples_list = [3, 5, 10]  # Minimum number of samples in a neighborhood to consider a point as a core poin
'''
```

Out[110…

```
'\n# Define hyperparameters for DBSCAN\neps_list = [0.3, 0.5, 0.7]  # Radius of neighborhood - determines maxim
um distance allowed between points for them to be considered\n#as part of the same neighborhood\nmin_samples_li
st = [3, 5, 10]  # Minimum number of samples in a neighborhood to consider a point as a core point - higher val
ues imply more rigid classification decisions\n'
```

In [111…

```
# Store results
# results = []
```

In [112…

```
'''
# Create for loops to iterate through hyperparameter tuning combinations
for eps in eps_list:
    for min_samples in min_samples_list:
        # Initialize the DBSCAN model
        dbscan = DBSCAN(eps=eps, min_samples=min_samples)

        # Fit the model and get the labels for training data - determines anomaly/normal classification based or
        train_labels = dbscan.fit_predict(X_train)
        # Convert core points and noise points
        train_labels[train_labels == -1] = 1  # Convert noise to 1 (anomalies)
        train_labels[train_labels != 1] = 0  # Convert core points to 0 (normal)

        # Fit the model and get the labels for validation data - determines anomaly/normal classification based
        val_labels = dbscan.fit_predict(X_val)
        val_labels[val_labels == -1] = 1  # Convert noise to 1 (anomalies)
        val_labels[val_labels != 1] = 0  # Convert core points to 0 (normal)

        # Calculate metrics for training data (higher silhouette score = better clustering = better anomaly dete
        # higher calinski-harabasz score = better clustering = better anomaly detection;
        # lower davies-bouldin score = better clustering = better anomaly detection)

        silhouette_train = silhouette_score(X_train, train_labels)
        calinski_train = calinski_harabasz_score(X_train, train_labels)
        davies_train = davies_bouldin_score(X_train, train_labels)

        # Calculate metrics for validation data
        silhouette_val = silhouette_score(X_val, val_labels)
        calinski_val = calinski_harabasz_score(X_val, val_labels)
        davies_val = davies_bouldin_score(X_val, val_labels)

        # Store results
        results.append({
            'eps': eps,
            'min_samples': min_samples,
            'Silhouette Score (Train)': silhouette_train,
            'Calinski-Harabasz Index (Train)': calinski_train,
            'Davies-Bouldin Index (Train)': davies_train,
            'Silhouette Score (Val)': silhouette_val,
            'Calinski-Harabasz Index (Val)': calinski_val,
            'Davies-Bouldin Index (Val)': davies_val
        })
        '''
```

Out[112… "\n# Create for loops to iterate through hyperparameter tuning combinations\nfor eps in eps_list:\n   for min_samples in min_samples_list:\n   # Initialize the DBSCAN model\n   dbscan = DBSCAN(eps=eps, min_samples=min_samples)\n\n   # Fit the model and get the labels for training data - determines anomaly/normal classification based on epsilon distance and min_samples\n   train_labels = dbscan.fit_predict(X_train)\n   # Convert core points and noise points\n   train_labels[train_labels == -1] = 1 # Convert noise to 1 (anomalies)\n   train_labels[train_labels != 1] = 0 # Convert core points to 0 (normal)\n\n   # Fit the model and get the labels for validation data - determines anomaly/normal classification based on epsilon distance and min_samples\n   val_labels = dbscan.fit_predict(X_val)\n   val_labels[val_labels == -1] = 1 # Convert noise to 1 (anomalies)\n   val_labels[val_labels != 1] = 0 # Convert core points to 0 (normal)\n\n   # Calculate metrics for training data (higher silhouette score = better clustering = better anomaly detection;\n   # higher calinski-harabasz score = better clustering = better anomaly detection;\n   # lower davies-bouldin score = better clustering = better anomaly detection)\n   \n   silhouette_train = silhouette_score(X_train, train_labels)\n   calinski_train = calinski_harabasz_score(X_train, train_labels)\n   davies_train = davies_bouldin_score(X_train, train_labels)\n\n   # Calculate metrics for validation data\n   silhouette_val = silhouette_score(X_val, val_labels)\n   calinski_val = calinski_harabasz_score(X_val, val_labels)\n   davies_val = davies_bouldin_score(X_val, val_labels)\n\n   # Store results\n   results.append({\n   'eps': eps,\n   'min_samples': min_samples,\n   'Silhouette Score (Train)': silhouette_train,\n   'Calinski-Harabasz Index (Train)': calinski_train,\n   'Davies-Bouldin Index (Train)': davies_train,\n   'Silhouette Score (Val)': silhouette_val,\n   'Calinski-Harabasz Index (Val)': calinski_val,\n   'Davies-Bouldin Index (Val)': davies_val\n   })\n   "

In [113…

```
'''
# Convert results to DataFrame for better readability
results_df = pd.DataFrame(results)

# Print results
print(results_df)
'''
```

Out[113… '\n# Convert results to DataFrame for better readability\nresults_df = pd.DataFrame(results)\n\n# Print results\nprint(results_df)\n'

In [114…

```
from tabulate import tabulate

# eps=0.3; min_samples=3
data1 = {
    'Variation 1.1 Silhouette': [0.1194,  0.1283],
    'Variation 1.1 Calinski-Harabasz Index': [10971.9597, 2266.2809],
    'Variation 1.1 Davies-Bouldin Index': [1.9702, 2.0129]
}
# eps=0.3; min_samples=5
data2 = {
    'Variation 1.2 Silhouette': [0.1319,  0.1464],
    'Variation 1.2 Calinski-Harabasz Index': [10957.8269, 2253.4459],
    'Variation 1.2 Davies-Bouldin Index': [2.0250, 2.1316]
}
# eps=0.3; min_samples=10
data3 = {
    'Variation 1.3 Silhouette': [0.1484,  0.1604],
    'Variation 1.3 Calinski-Harabasz Index': [10993.0411, 2254.2103],
    'Variation 1.3 Davies-Bouldin Index': [2.1291, 2.2791]
}
# eps=0.5; min_samples=3
data4 = {
    'Variation 2.1 Silhouette': [0.1111,  0.1190],
    'Variation 2.1 Calinski-Harabasz Index': [11105.0407, 2304.5240],
    'Variation 2.1 Davies-Bouldin Index': [1.9193, 1.9360]
}
# eps=0.5; min_samples=5
data5 = {
    'Variation 2.2 Silhouette': [0.1137,  0.1284],
    'Variation 2.2 Calinski-Harabasz Index': [11098.1885, 2298.5742],
    'Variation 2.2 Davies-Bouldin Index': [1.9289, 1.9756]
}
# eps=0.5; min_samples=10
data6 = {
    'Variation 2.3 Silhouette': [0.1170,  0.1438],
    'Variation 2.3 Calinski-Harabasz Index': [11080.3622,  2285.6402],
    'Variation 2.3 Davies-Bouldin Index': [1.9422, 2.0631]
}
# eps=0.7; min_samples=3
data7 = {
    'Variation 3.1 Silhouette': [0.1250,  0.1138],
    'Variation 3.1 Calinski-Harabasz Index': [12604.1641, 2310.2167],
    'Variation 3.1 Davies-Bouldin Index': [1.9145, 1.9141]
}
# eps=0.7; min_samples=5
data8 = {
    'Variation 3.2 Silhouette': [0.1257,  0.1208],
    'Variation 3.2 Calinski-Harabasz Index': [12600.0272, 2303.5582],
    'Variation 3.2 Davies-Bouldin Index': [1.9170, 1.9419]
}
```

```python
# eps=0.7; min_samples=10
data9 = {
    'Variation 3.3 Silhouette': [0.1270,  0.1295],
    'Variation 3.3 Calinski-Harabasz Index': [12592.7226,  2299.7924],
    'Variation 3.3 Davies-Bouldin Index': [1.9216, 1.9782]
}
# Create a DataFrame
results1_df = pd.DataFrame(data1, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results1_df, headers='keys', tablefmt='pretty'))

# Create a DataFrame
results2_df = pd.DataFrame(data2, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results2_df, headers='keys', tablefmt='pretty'))

# Create a DataFrame
results3_df = pd.DataFrame(data3, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results3_df, headers='keys', tablefmt='pretty'))

# Create a DataFrame
results4_df = pd.DataFrame(data4, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results4_df, headers='keys', tablefmt='pretty'))

# Create a DataFrame
results5_df = pd.DataFrame(data5, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results5_df, headers='keys', tablefmt='pretty'))

# Create a DataFrame
results6_df = pd.DataFrame(data6, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results6_df, headers='keys', tablefmt='pretty'))

# Create a DataFrame
results7_df = pd.DataFrame(data7, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results7_df, headers='keys', tablefmt='pretty'))

# Create a DataFrame
results8_df = pd.DataFrame(data8, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results8_df, headers='keys', tablefmt='pretty'))

# Create a DataFrame
results9_df = pd.DataFrame(data9, index=['Training', 'Validation'])

# Print the DataFrame using tabulate for better formatting
print(tabulate(results9_df, headers='keys', tablefmt='pretty'))
```

```
+------------+--------------------------+---------------------------------------+------------------------------------+
|            | Variation 1.1 Silhouette | Variation 1.1 Calinski-Harabasz Index | Variation 1.1 Davies-Bouldin Index |
+------------+--------------------------+---------------------------------------+------------------------------------+
|  Training  |          0.1194          |               10971.9597              |               1.9702               |
| Validation |          0.1283          |               2266.2809               |               2.0129               |
+------------+--------------------------+---------------------------------------+------------------------------------+
+------------+--------------------------+---------------------------------------+------------------------------------+
|            | Variation 1.2 Silhouette | Variation 1.2 Calinski-Harabasz Index | Variation 1.2 Davies-Bouldin Index |
+------------+--------------------------+---------------------------------------+------------------------------------+
|  Training  |          0.1319          |               10957.8269              |               2.025                |
| Validation |          0.1464          |               2253.4459               |               2.1316               |
+------------+--------------------------+---------------------------------------+------------------------------------+
```

	Variation 1.3 Silhouette	Variation 1.3 Calinski-Harabasz Index	Variation 1.3 Davies-Bouldin Index
Training	0.1484	10993.0411	2.1291
Validation	0.1604	2254.2103	2.2791

	Variation 2.1 Silhouette	Variation 2.1 Calinski-Harabasz Index	Variation 2.1 Davies-Bouldin Index
Training	0.1111	11105.0407	1.9193
Validation	0.119	2304.524	1.936

	Variation 2.2 Silhouette	Variation 2.2 Calinski-Harabasz Index	Variation 2.2 Davies-Bouldin Index
Training	0.1137	11098.1885	1.9289
Validation	0.1284	2298.5742	1.9756

	Variation 2.3 Silhouette	Variation 2.3 Calinski-Harabasz Index	Variation 2.3 Davies-Bouldin Index
Training	0.117	11080.3622	1.9422
Validation	0.1438	2285.6402	2.0631

	Variation 3.1 Silhouette	Variation 3.1 Calinski-Harabasz Index	Variation 3.1 Davies-Bouldin Index
Training	0.125	12604.1641	1.9145
Validation	0.1138	2310.2167	1.9141

	Variation 3.2 Silhouette	Variation 3.2 Calinski-Harabasz Index	Variation 3.2 Davies-Bouldin Index
Training	0.1257	12600.0272	1.917
Validation	0.1208	2303.5582	1.9419

	Variation 3.3 Silhouette	Variation 3.3 Calinski-Harabasz Index	Variation 3.3 Davies-Bouldin Index
Training	0.127	12592.7226	1.9216
Validation	0.1295	2299.7924	1.9782

-----+

In [115…
```
'''
# Save the train set
train_embeddings_df.to_csv('train_data.csv', index=False)

# Save the validation set
validation_embeddings_df.to_csv('validation_data.csv', index=False)

# Save the test set
test_embeddings_df.to_csv('test_data.csv', index=False)

print("DataFrames have been saved as CSV files.")
'''
```

Out[115…
```
'\n# Save the train set\ntrain_embeddings_df.to_csv(\'train_data.csv\', index=False)\n\n# Save the validation s
et\nvalidation_embeddings_df.to_csv(\'validation_data.csv\', index=False)\n\n# Save the test set\ntest_embeddin
gs_df.to_csv(\'test_data.csv\', index=False)\n\nprint("DataFrames have been saved as CSV files.")\n'
```

In [116…
```
#END WEEK 8
```

In [117…
```
#BEGIN WEEK 9
```

In [118…
```
# Deploy all 9 models (the top 3 performing variations from each of week 6, 7, and 8) on the validation set
# K-Means Models on Validation Set

from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

# Initialize results storage
km_val_results = []

# Variation km_v1: k=5, init='random', n_init=1
k_value_v1 = 5
init_v1 = 'random'
n_init_v1 = 1

# Fit the model for Variation km_v1 using validation data
kmeans_v1 = KMeans(n_clusters=k_value_v1, init=init_v1, n_init=n_init_v1, random_state=42)
kmeans_v1.fit(X_val)
labels_v1 = kmeans_v1.labels_
silhouette_avg_v1 = silhouette_score(X_val, labels_v1)
km_val_results.append({'Variation': 'km_v1', 'Init': init_v1, 'n_init': n_init_v1, 'k': k_value_v1, 'Silhouette

# Variation km_v2: k=5, init='k-means++', n_init=1, max_iter=100, tol=1e-2
k_value_v2 = 5
init_v2 = 'k-means++'
n_init_v2 = 1
max_iter_v2 = 100
tol_v2 = 1e-2

# Fit the model for Variation km_v2 using validation data
kmeans_v2 = KMeans(n_clusters=k_value_v2, init=init_v2, n_init=n_init_v2, max_iter=max_iter_v2, tol=tol_v2, ran
kmeans_v2.fit(X_val)
labels_v2 = kmeans_v2.labels_
silhouette_avg_v2 = silhouette_score(X_val, labels_v2)
km_val_results.append({'Variation': 'km_v2', 'Init': init_v2, 'n_init': n_init_v2, 'k': k_value_v2, 'max_iter':

# Variation km_v3: k=10, init='k-means++', n_init=1, max_iter=200, tol=1e-3 (Ultimately the winning model with
k_value_v3 = 10
init_v3 = 'k-means++'
n_init_v3 = 1
max_iter_v3 = 200
tol_v3 = 1e-3

# Fit the model for Variation km_v3 using validation data
kmeans_v3 = KMeans(n_clusters=k_value_v3, init=init_v3, n_init=n_init_v3, max_iter=max_iter_v3, tol=tol_v3, ran
kmeans_v3.fit(X_val)
labels_v3 = kmeans_v3.labels_
silhouette_avg_v3 = silhouette_score(X_val, labels_v3)
km_val_results.append({'Variation': 'km_v3', 'Init': init_v3, 'n_init': n_init_v3, 'k': k_value_v3, 'max_iter':

# Convert results to DataFrame for better readability
km_val_results_df = pd.DataFrame(km_val_results)

# Print results
print(km_val_results_df)
```

```
  Variation       Init  n_init   k  Silhouette Score  max_iter    tol
0     km_v1     random       1   5          0.244375       NaN    NaN
1     km_v2  k-means++       1   5          0.244305     100.0  0.010
2     km_v3  k-means++       1  10          0.472995     200.0  0.001
```

In [119…

```
# Local Outlier Factor Models on Validation Set

from sklearn.metrics import silhouette_score
from sklearn.neighbors import LocalOutlierFactor

# Initialize results storage
lof_val_results = []

# Variation lof_v1: n_neighbors=15, metric='euclidean'
n_neighbors_v1 = 15
metric_v1 = 'euclidean'

# Fit the model for Variation lof_v1 using validation data
lof_v1 = LocalOutlierFactor(n_neighbors=n_neighbors_v1, metric=metric_v1)
val_labels_v1 = lof_v1.fit_predict(X_val)

silhouette_val_v1 = silhouette_score(X_val, val_labels_v1)
lof_val_results.append({'Variation': 'lof_v1', 'n_neighbors': n_neighbors_v1, 'metric': metric_v1, 'Silhouette S

# Variation lof_v2: n_neighbors=10, metric='euclidean'
n_neighbors_v2 = 10
metric_v2 = 'euclidean'

# Fit the model for Variation lof_v2 using validation data
lof_v2 = LocalOutlierFactor(n_neighbors=n_neighbors_v2, metric=metric_v2)
val_labels_v2 = lof_v2.fit_predict(X_val)

silhouette_val_v2 = silhouette_score(X_val, val_labels_v2)
lof_val_results.append({'Variation': 'lof_v2', 'n_neighbors': n_neighbors_v2, 'metric': metric_v2, 'Silhouette S

# Variation lof_v3: n_neighbors=15, metric='manhattan'
n_neighbors_v3 = 15
metric_v3 = 'manhattan'

# Fit the model for Variation lof_v3 using validation data
lof_v3 = LocalOutlierFactor(n_neighbors=n_neighbors_v3, metric=metric_v3)
val_labels_v3 = lof_v3.fit_predict(X_val)

silhouette_val_v3 = silhouette_score(X_val, val_labels_v3)
lof_val_results.append({'Variation': 'lof_v3', 'n_neighbors': n_neighbors_v3, 'metric': metric_v3, 'Silhouette S

# Convert results to DataFrame for better readability
lof_val_results_df = pd.DataFrame(lof_val_results)

# Print results
print(lof_val_results_df)
```

```
  Variation  n_neighbors     metric  Silhouette Score (Val)
0    lof_v1           15  euclidean                0.278504
1    lof_v2           10  euclidean                0.318406
2    lof_v3           15  manhattan                0.254177
```

In [120…

```
# Density-Based Spatial Clustering of Applications with Noise Models on Validation Set

from sklearn.cluster import DBSCAN
from sklearn.metrics import silhouette_score

# Initialize results storage
dbscan_val_results = []

# Variation db_v1: eps=0.7, min_samples=3
eps_v1 = 0.7
min_samples_v1 = 3

# Fit the model for Variation db_v1 using validation data
dbscan_v1 = DBSCAN(eps=eps_v1, min_samples=min_samples_v1)
val_labels_v1 = dbscan_v1.fit_predict(X_val)
val_labels_v1[val_labels_v1 == -1] = 1  # Convert noise to 1 (anomalies)
val_labels_v1[val_labels_v1 != 1] = 0   # Convert core points to 0 (normal)

# Calculate silhouette score for validation data
silhouette_val_v1 = silhouette_score(X_val, val_labels_v1)
dbscan_val_results.append({'Variation': 'db_v1', 'eps': eps_v1, 'min_samples': min_samples_v1, 'Silhouette Scor

# Variation db_v2: eps=0.3, min_samples=10
eps_v2 = 0.3
min_samples_v2 = 10

# Fit the model for Variation db_v2 using validation data
dbscan_v2 = DBSCAN(eps=eps_v2, min_samples=min_samples_v2)
val_labels_v2 = dbscan_v2.fit_predict(X_val)

# Calculate silhouette score for validation data
silhouette_val_v2 = silhouette_score(X_val, val_labels_v2)
```

```
dbscan_val_results.append({'Variation': 'db_v2', 'eps': eps_v2, 'min_samples': min_samples_v2, 'Silhouette Scor

# Variation db_v3: eps=0.3, min_samples=5
eps_v3 = 0.3
min_samples_v3 = 5

# Fit the model for Variation db_v3 using validation data
dbscan_v3 = DBSCAN(eps=eps_v3, min_samples=min_samples_v3)
val_labels_v3 = dbscan_v3.fit_predict(X_val)
val_labels_v3[val_labels_v3 == -1] = 1  # Convert noise to 1 (anomalies)
val_labels_v3[val_labels_v3 != 1] = 0   # Convert core points to 0 (normal)

# Calculate silhouette score for validation data
silhouette_val_v3 = silhouette_score(X_val, val_labels_v3)
dbscan_val_results.append({'Variation': 'db_v3', 'eps': eps_v3, 'min_samples': min_samples_v3, 'Silhouette Scor

# Convert results to DataFrame for better readability
dbscan_val_results_df = pd.DataFrame(dbscan_val_results)

# Print results
print(dbscan_val_results_df)
```

```
  Variation  eps  min_samples  Silhouette Score (Val)
0     db_v1  0.7            3                0.129129
1     db_v2  0.3           10               -0.066935
2     db_v3  0.3            5                0.160441
```

In [121…

```
#Perform winning model on test set
features = [
    'Day_0', 'Day_1', 'Day_2', 'Day_3', 'Day_4', 'Day_5', 'Day_6',
    'Deviation_From_Mean', 'Account_Embeddings', 'Merchant_Embeddings',
    'Transaction_Embeddings', 'Location_Embeddings', 'Hour_Group_Embeddings'
]

# Prepare the feature data
X_test = test_embeddings_df[features]

# Flatten embeddings
for col in ['Account_Embeddings', 'Merchant_Embeddings', 'Transaction_Embeddings', 'Location_Embeddings', 'Hour_
    if isinstance(X_test[col].iloc[0], np.ndarray):  # Check if the first entry is an ndarray
        embedding_array = pd.DataFrame(X_test[col].apply(lambda x: x.flatten()).tolist())
    else:
        embedding_array = pd.DataFrame(X_test[col].tolist())

    embedding_array.columns = [f"{col}_{i}" for i in range(embedding_array.shape[1])]
    X_test = pd.concat([X_test, embedding_array], axis=1)
    X_test.drop(columns=[col], inplace=True)

# Ensure all data is numeric
X_test = X_test.apply(pd.to_numeric, errors='coerce')
```

In [122…

```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

# Variation km_v3: k=10, init='k-means++', n_init=1, max_iter=200, tol=1e-3
k_value_v3 = 10
init_v3 = 'k-means++'
n_init_v3 = 1
max_iter_v3 = 200
tol_v3 = 1e-3

# Fit the model for Variation km_v3 using test data
kmeans_v3 = KMeans(n_clusters=k_value_v3, init=init_v3, n_init=n_init_v3, max_iter=max_iter_v3, tol=tol_v3, ran
kmeans_v3.fit(X_test)
labels_v3 = kmeans_v3.labels_
silhouette_avg_v3 = silhouette_score(X_test, labels_v3)

# Store results
km_v3_test_results = {
    'Variation': 'km_v3',
    'Init': init_v3,
    'n_init': n_init_v3,
    'k': k_value_v3,
    'max_iter': max_iter_v3,
    'tol': tol_v3,
    'Silhouette Score': silhouette_avg_v3
}

# Print results
print(km_v3_test_results)
```

```
{'Variation': 'km_v3', 'Init': 'k-means++', 'n_init': 1, 'k': 10, 'max_iter': 200, 'tol': 0.001, 'Silhouette Sco
re': 0.4691364773318757}
```

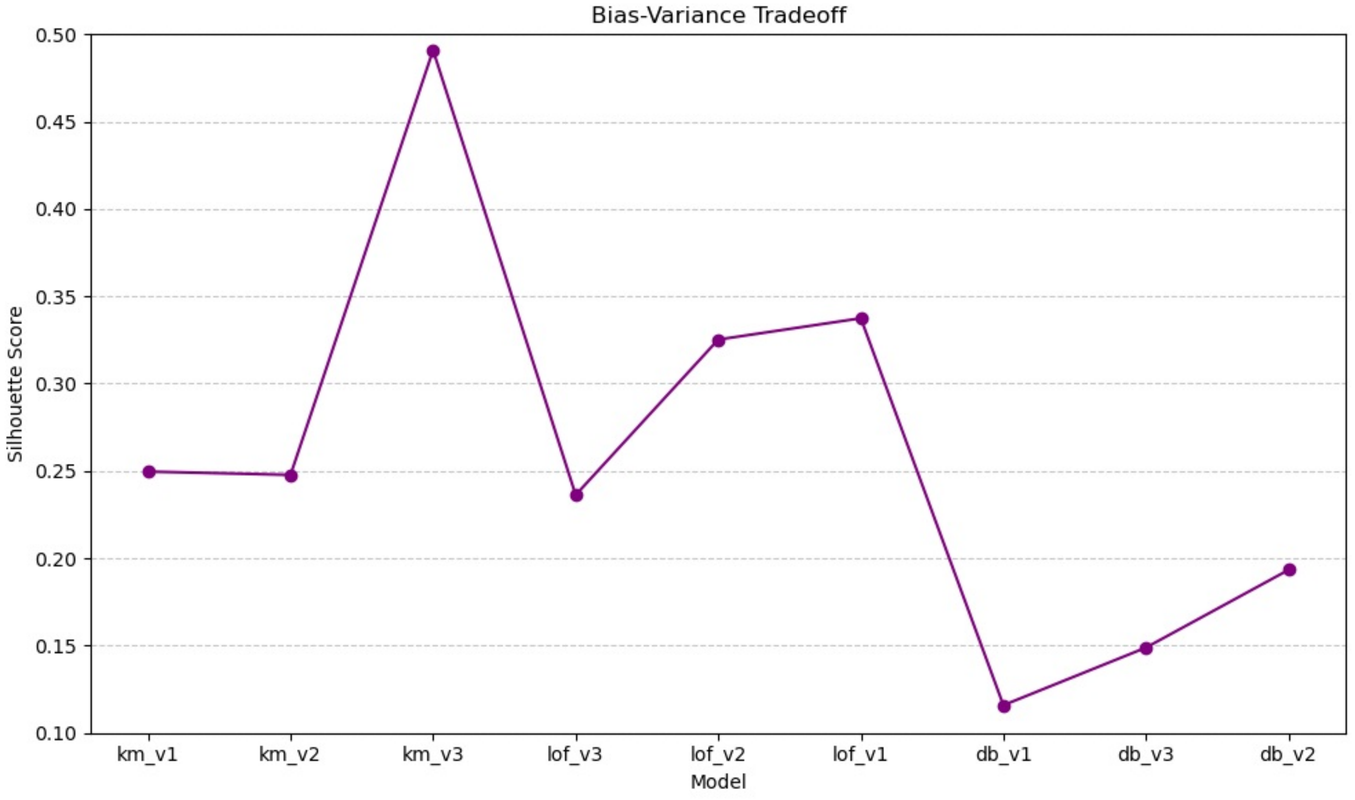
In [123…

```
# Winning Model Train Performance
# Variation km_v3: k=10, init='k-means++', n_init=1, max_iter=200, tol=1e-3
k_value_v3 = 10
init_v3 = 'k-means++'
n_init_v3 = 1
max_iter_v3 = 200
tol_v3 = 1e-3

# Fit the model for Variation km_v3 using validation data
kmeans_v3 = KMeans(n_clusters=k_value_v3, init=init_v3, n_init=n_init_v3, max_iter=max_iter_v3, tol=tol_v3, ran
kmeans_v3.fit(X_train)
labels_v3 = kmeans_v3.labels_
silhouette_avg_v3 = silhouette_score(X_train, labels_v3)

# Store results
km_v3_train_results = {
    'Variation': 'km_v3',
    'Init': init_v3,
    'n_init': n_init_v3,
    'k': k_value_v3,
    'max_iter': max_iter_v3,
    'tol': tol_v3,
    'Silhouette Score': silhouette_avg_v3
}

# Print results
print(km_v3_train_results)
```

```
{'Variation': 'km_v3', 'Init': 'k-means++', 'n_init': 1, 'k': 10, 'max_iter': 200, 'tol': 0.001, 'Silhouette Sco
re': 0.49550755742650765}
```

In [124…

```
# Bias Variance Tradeoff Plot
import matplotlib.pyplot as plt

# 9 model variations to plot (High Variance, Low Bias: K-Means; Middle Variance, Middle Bias: LOF; Low Variance,
models = ['km_v1', 'km_v2', 'km_v3', 'lof_v3', 'lof_v2', 'lof_v1', 'db_v1', 'db_v3', 'db_v2']
# corresponding silhouette scores to analyze bias-variance tradeoff for unsupervised learning task
silhouette_scores = [0.2496, 0.2477, 0.4909, 0.2362, 0.3252, 0.3374, 0.1158, 0.1488, 0.1933]

# Create the plot
plt.figure(figsize=(10, 6))
plt.plot(models, silhouette_scores, marker='o', color='purple', linestyle='-')
plt.xlabel('Model')
plt.ylabel('Silhouette Score')
plt.title('Bias-Variance Tradeoff')
plt.ylim(0.1, 0.5)
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Show the plot
plt.tight_layout()
plt.show()
```



In [125…
```python
from tabulate import tabulate

# Create a dictionary with the performance metrics
kmeans_v3_scores = {
    "Model Stage": ["Train", "Validation", "Test"],
    "Silhouette Score": [0.4638, 0.4909, 0.4865]
}

# Create a DataFrame
performance_metrics = pd.DataFrame(kmeans_v3_scores)

# Print the title and the table using tabulate
table_title = "Winning Model Performance Metrics by Stage"
print(table_title)
print(tabulate(performance_metrics, headers='keys', tablefmt='pretty'))
```

```
Winning Model Performance Metrics by Stage
+---+-------------+------------------+
|   | Model Stage | Silhouette Score |
+---+-------------+------------------+
| 0 |    Train    |      0.4638      |
| 1 | Validation  |      0.4909      |
| 2 |    Test     |      0.4865      |
+---+-------------+------------------+
```

In [126…
```python
'''
# Save the train set
train_embeddings_df.to_csv('train_data.csv', index=False)

# Save the validation set
validation_embeddings_df.to_csv('validation_data.csv', index=False)

# Save the test set
test_embeddings_df.to_csv('test_data.csv', index=False)

print("DataFrames have been saved as CSV files.")
'''
```

Out[126…
```
'\n# Save the train set\ntrain_embeddings_df.to_csv(\'train_data.csv\', index=False)\n\n# Save the validation s
et\nvalidation_embeddings_df.to_csv(\'validation_data.csv\', index=False)\n\n# Save the test set\ntest_embeddin
gs_df.to_csv(\'test_data.csv\', index=False)\n\nprint("DataFrames have been saved as CSV files.")\n'
```

In [127…
```python
# END WEEK 9
```

In [128…
```python
# BEGIN WEEK 10
```

In [129…
```python
'''
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from imblearn.over_sampling import SMOTE
from sklearn.preprocessing import StandardScaler

# Identify small clusters as anomalies based on k-means clustering of winning model from Week 9
# This will be used to create labeled data, which enables SMOTE to be used
def get_anomaly_clusters(X, n_clusters=10, percentile_threshold=10):
    kmeans = KMeans(n_clusters=n_clusters, init='k-means++', n_init=1, max_iter=200, tol=1e-3, random_state=42)
    kmeans_labels = kmeans.fit_predict(X)

    # Calculate the size of each cluster
    cluster_sizes = np.bincount(kmeans_labels)

    # Define threshold size based on the given percentile
    threshold_size = np.percentile(cluster_sizes, percentile_threshold)

    # Identify small clusters based on the threshold
    small_clusters = np.where(cluster_sizes <= threshold_size)[0]

    return small_clusters, kmeans_labels
    '''
```

Out[129…
```
"\nfrom sklearn.decomposition import PCA\nfrom sklearn.cluster import KMeans\nfrom sklearn.metrics import silho
uette_score\nfrom imblearn.over_sampling import SMOTE\nfrom sklearn.preprocessing import StandardScaler\n\n# Id
entify small clusters as anomalies based on k-means clustering of winning model from Week 9\n# This will be use
d to create labeled data, which enables SMOTE to be used\ndef get_anomaly_clusters(X, n_clusters=10, percentile
_threshold=10):\n    kmeans = KMeans(n_clusters=n_clusters, init='k-means++', n_init=1, max_iter=200, tol=1e-3,
random_state=42)\n    kmeans_labels = kmeans.fit_predict(X)\n    \n    # Calculate the size of each cluster\n
cluster_sizes = np.bincount(kmeans_labels)\n    \n    # Define threshold size based on the given percentile\n
threshold_size = np.percentile(cluster_sizes, percentile_threshold)\n    \n    # Identify small clusters based
on the threshold\n    small_clusters = np.where(cluster_sizes <= threshold_size)[0]\n    \n    return small_clu
sters, kmeans_labels\n    "
```

In [130…
```python
'''
```

```
# Data-Centric AI 1: Apply SMOTE to the train data only (on small clusters (smallest 10th percentile of cluster
def apply_smote(X_train, kmeans_labels, small_clusters):
    smote = SMOTE(random_state=42)
    X_train_resampled = X_train.copy()

    # Create a new DataFrame for the small clusters
    X_small_clusters = pd.DataFrame()
    y_small_clusters = []

    # Labels array: `0` for small clusters and `1` for normal clusters
    y_train_labels = np.ones(X_train.shape[0])  # Default to normal (1) for all points
    for cluster in small_clusters:
        # Get the indices of the points in the small cluster
        cluster_indices = np.where(kmeans_labels == cluster)[0]

        # Assign label `0` to points in small clusters
        y_train_labels[cluster_indices] = 0

        # Extract the points in that small cluster
        X_cluster = X_train.iloc[cluster_indices]

        # Only apply SMOTE if the cluster has more than 1 sample
        if X_cluster.shape[0] > 1:
            # Create pseudo-labels for SMOTE: assign a unique label for each small cluster
            y_cluster = np.full(X_cluster.shape[0], cluster)  # Each small cluster gets a unique label

            # Append to the small clusters dataset
            X_small_clusters = pd.concat([X_small_clusters, X_cluster], ignore_index=True)
            y_small_clusters.extend(y_cluster)

    # Apply SMOTE on the combined small clusters with labels
    X_resampled, y_resampled = smote.fit_resample(X_train, y_train_labels)

    return X_resampled
    '''
```

Out[130…

```
'\n# Data-Centric AI 1: Apply SMOTE to the train data only (on small clusters (smallest 10th percentile of clus
ters))\ndef apply_smote(X_train, kmeans_labels, small_clusters):\n    smote = SMOTE(random_state=42)\n    X_tra
in_resampled = X_train.copy()\n    \n    # Create a new DataFrame for the small clusters\n    X_small_clusters
= pd.DataFrame()\n    y_small_clusters = []\n\n    # Labels array: `0` for small clusters and `1` for normal cl
usters\n    y_train_labels = np.ones(X_train.shape[0])  # Default to normal (1) for all points\n    for cluster
in small_clusters:\n        # Get the indices of the points in the small cluster\n        cluster_indices = np.
where(kmeans_labels == cluster)[0]\n        \n        # Assign label `0` to points in small clusters\n        y
_train_labels[cluster_indices] = 0\n        \n        # Extract the points in that small cluster\n        X_clu
ster = X_train.iloc[cluster_indices]\n        \n        # Only apply SMOTE if the cluster has more than 1 sampl
e\n        if X_cluster.shape[0] > 1:\n            # Create pseudo-labels for SMOTE: assign a unique label for
each small cluster\n            y_cluster = np.full(X_cluster.shape[0], cluster)  # Each small cluster gets a u
nique label\n            \n            # Append to the small clusters dataset\n            X_small_clusters = p
d.concat([X_small_clusters, X_cluster], ignore_index=True)\n            y_small_clusters.extend(y_cluster)\n\n
# Apply SMOTE on the combined small clusters with labels\n    X_resampled, y_resampled = smote.fit_resample(X_t
rain, y_train_labels)\n\n    return X_resampled\n    '
```

In [131…

```
'''
# Data-Centric AI 2: Apply PCA to reduce dimensionality while retaining 95% of the dataset's variance (train, va
def apply_pca(X_train, X_val, X_test, n_components=0.95):
    pca = PCA(n_components=n_components)
    X_train_pca = pca.fit_transform(X_train)
    X_val_pca = pca.transform(X_val)
    X_test_pca = pca.transform(X_test)

    return X_train_pca, X_val_pca, X_test_pca
    '''
```

Out[131…

```
"\n# Data-Centric AI 2: Apply PCA to reduce dimensionality while retaining 95% of the dataset's variance (train
, validation, test)\ndef apply_pca(X_train, X_val, X_test, n_components=0.95):\n    pca = PCA(n_components=n_co
mponents)\n    X_train_pca = pca.fit_transform(X_train)\n    X_val_pca = pca.transform(X_val)\n    X_test_pca =
pca.transform(X_test)\n    \n    return X_train_pca, X_val_pca, X_test_pca\n    "
```

In [132…

```
'''
# Data-Centric AI 3: Inject Gaussian noise into the data (train, validation, test)
def inject_noise(X_train, X_val, X_test, noise_factor=0.1):
    noise_train = np.random.normal(loc=0, scale=noise_factor, size=X_train.shape)
    noise_val = np.random.normal(loc=0, scale=noise_factor, size=X_val.shape)
    noise_test = np.random.normal(loc=0, scale=noise_factor, size=X_test.shape)

    X_train_noisy = X_train + noise_train
    X_val_noisy = X_val + noise_val
    X_test_noisy = X_test + noise_test

    return X_train_noisy, X_val_noisy, X_test_noisy
    '''
```

Out[132… '\n# Data-Centric AI 3: Inject Gaussian noise into the data (train, validation, test)\ndef inject_noise(X_train, X_val, X_test, noise_factor=0.1):\n   noise_train = np.random.normal(loc=0, scale=noise_factor, size=X_train.shape)\n   noise_val = np.random.normal(loc=0, scale=noise_factor, size=X_val.shape)\n   noise_test = np.random.normal(loc=0, scale=noise_factor, size=X_test.shape)\n   \n   X_train_noisy = X_train + noise_train\n   X_val_noisy = X_val + noise_val\n   X_test_noisy = X_test + noise_test\n   \n   return X_train_noisy, X_val_noisy, X_test_noisy\n   '

In [133…
```
'''
# Function to apply all Data-Centric AI Techniques
def apply_data_centric_ai(X_train, X_val, X_test, n_clusters=10, percentile_threshold=10, noise_factor=0.1, pca_
    # Identify small clusters using k-means
    small_clusters, kmeans_labels = get_anomaly_clusters(X_train, n_clusters=n_clusters, percentile_threshold=p

    # Apply SMOTE to the train set based on small clusters
    X_train_smote = apply_smote(X_train, kmeans_labels, small_clusters)

    # Apply PCA to reduce dimensionality for train, validation, and test sets
    X_train_pca, X_val_pca, X_test_pca = apply_pca(X_train_smote, X_val, X_test, n_components=pca_n_components)

    # Inject Gaussian noise to the data
    X_train_noisy, X_val_noisy, X_test_noisy = inject_noise(X_train_pca, X_val_pca, X_test_pca, noise_factor=no

    return X_train_noisy, X_val_noisy, X_test_noisy, small_clusters, kmeans_labels
    '''
```

Out[133… '\n# Function to apply all Data-Centric AI Techniques\ndef apply_data_centric_ai(X_train, X_val, X_test, n_clusters=10, percentile_threshold=10, noise_factor=0.1, pca_n_components=0.95):\n   # Identify small clusters using k-means\n   small_clusters, kmeans_labels = get_anomaly_clusters(X_train, n_clusters=n_clusters, percentile_threshold=percentile_threshold)\n   \n   # Apply SMOTE to the train set based on small clusters\n   X_train_smote = apply_smote(X_train, kmeans_labels, small_clusters)\n   \n   # Apply PCA to reduce dimensionality for train, validation, and test sets\n   X_train_pca, X_val_pca, X_test_pca = apply_pca(X_train_smote, X_val, X_test, n_components=pca_n_components)\n   \n   # Inject Gaussian noise to the data\n   X_train_noisy, X_val_noisy, X_test_noisy = inject_noise(X_train_pca, X_val_pca, X_test_pca, noise_factor=noise_factor)\n   \n   return X_train_noisy, X_val_noisy, X_test_noisy, small_clusters, kmeans_labels\n   '

In [134…
```
'''
# Apply the data-centric AI techniques (SMOTE, PCA, Noise Injection)
X_train_final, X_val_final, X_test_final, small_clusters, kmeans_labels = apply_data_centric_ai(
    X_train, X_val, X_test, n_clusters=10, percentile_threshold=10, noise_factor=0.1, pca_n_components=0.95)
    '''
```

Out[134… '\n# Apply the data-centric AI techniques (SMOTE, PCA, Noise Injection)\nX_train_final, X_val_final, X_test_final, small_clusters, kmeans_labels = apply_data_centric_ai(\n   X_train, X_val, X_test, n_clusters=10, percentile_threshold=10, noise_factor=0.1, pca_n_components=0.95)\n   '

In [135…
```
'''
# Fit the k-means model again on the final data
kmeans = KMeans(n_clusters=10, init='k-means++', n_init=1, max_iter=200, tol=1e-3, random_state=42)
kmeans.fit(X_train_final)  # Fit on the final transformed train data
labels_train_final = kmeans.labels_
silhouette_avg_train = silhouette_score(X_train_final, labels_train_final)

labels_val_final = kmeans.predict(X_val_final)  # Predict the labels for the validation set
silhouette_avg_val = silhouette_score(X_val_final, labels_val_final)  # Compute silhouette score for validation

labels_test_final = kmeans.predict(X_test_final)  # Predict the labels for the test set
silhouette_avg_test = silhouette_score(X_test_final, labels_test_final)  # Compute silhouette score for test
'''
```

Out[135… "\n# Fit the k-means model again on the final data\nkmeans = KMeans(n_clusters=10, init='k-means++', n_init=1, max_iter=200, tol=1e-3, random_state=42)\nkmeans.fit(X_train_final) # Fit on the final transformed train data\nlabels_train_final = kmeans.labels_\nsilhouette_avg_train = silhouette_score(X_train_final, labels_train_final)\n\nlabels_val_final = kmeans.predict(X_val_final) # Predict the labels for the validation set\nsilhouette_avg_val = silhouette_score(X_val_final, labels_val_final) # Compute silhouette score for validation\n\nlabels_test_final = kmeans.predict(X_test_final) # Predict the labels for the test set\nsilhouette_avg_test = silhouette_score(X_test_final, labels_test_final) # Compute silhouette score for test\n"

In [136…
```
'''
# Print results of model on data-centric AI-transformed datasets
print(f"Final Silhouette Score on Transformed Train Data: {silhouette_avg_train}")
print(f"Final Silhouette Score on Transformed Validation Data: {silhouette_avg_val}")
print(f"Final Silhouette Score on Transformed Test Data: {silhouette_avg_test}")
'''
```

Out[136… '\n# Print results of model on data-centric AI-transformed datasets\nprint(f"Final Silhouette Score on Transformed Train Data: {silhouette_avg_train}")\nprint(f"Final Silhouette Score on Transformed Validation Data: {silhouette_avg_val}")\nprint(f"Final Silhouette Score on Transformed Test Data: {silhouette_avg_test}")\n'

In [137…
```
'''
from tabulate import tabulate

# Create a dictionary with the performance metrics
data_centric_ai_kmeans_scores = {
```

```
    "Model Stage": ["Train", "Validation", "Test"],
    "Silhouette Score": [0.2975, 0.3100, 0.3083]
}

# Create a DataFrame
performance_metrics = pd.DataFrame(data_centric_ai_kmeans_scores)

# Print the title and the table using tabulate
table_title = "Winning Model Performance Metrics by Stage on Data-Centric AI-Transformed Data"
print(table_title)
print(tabulate(performance_metrics, headers='keys', tablefmt='pretty'))
'''
```

Out[137… '\nfrom tabulate import tabulate\n\n# Create a dictionary with the performance metrics\ndata_centric_ai_kmeans_scores = {\n   "Model Stage": ["Train", "Validation", "Test"],\n   "Silhouette Score": [0.2975, 0.3100, 0.3083]\n}\n\n# Create a DataFrame\nperformance_metrics = pd.DataFrame(data_centric_ai_kmeans_scores)\n\n# Print the title and the table using tabulate\ntable_title = "Winning Model Performance Metrics by Stage on Data-Centric AI-Transformed Data"\nprint(table_title)\nprint(tabulate(performance_metrics, headers=\'keys\', tablefmt=\'pretty\'))\n'

In [138…
```
'''
# Save the train set
X_train_final_df = pd.DataFrame(X_train_final)
X_train_final_df.to_csv('train_data.csv', index=False)

# Save the validation set
X_val_final_df = pd.DataFrame(X_val_final)
X_val_final_df.to_csv('validation_data.csv', index=False)

# Save the test set
X_test_final_df = pd.DataFrame(X_test_final)
X_test_final_df.to_csv('test_data.csv', index=False)

print("DataFrames have been saved as CSV files.")
'''
```

Out[138… '\n# Save the train set\nX_train_final_df = pd.DataFrame(X_train_final)\nX_train_final_df.to_csv(\'train_data.csv\', index=False)\n\n# Save the validation set\nX_val_final_df = pd.DataFrame(X_val_final)\nX_val_final_df.to_csv(\'validation_data.csv\', index=False)\n\n# Save the test set\nX_test_final_df = pd.DataFrame(X_test_final)\nX_test_final_df.to_csv(\'test_data.csv\', index=False)\n\nprint("DataFrames have been saved as CSV files.")\n'

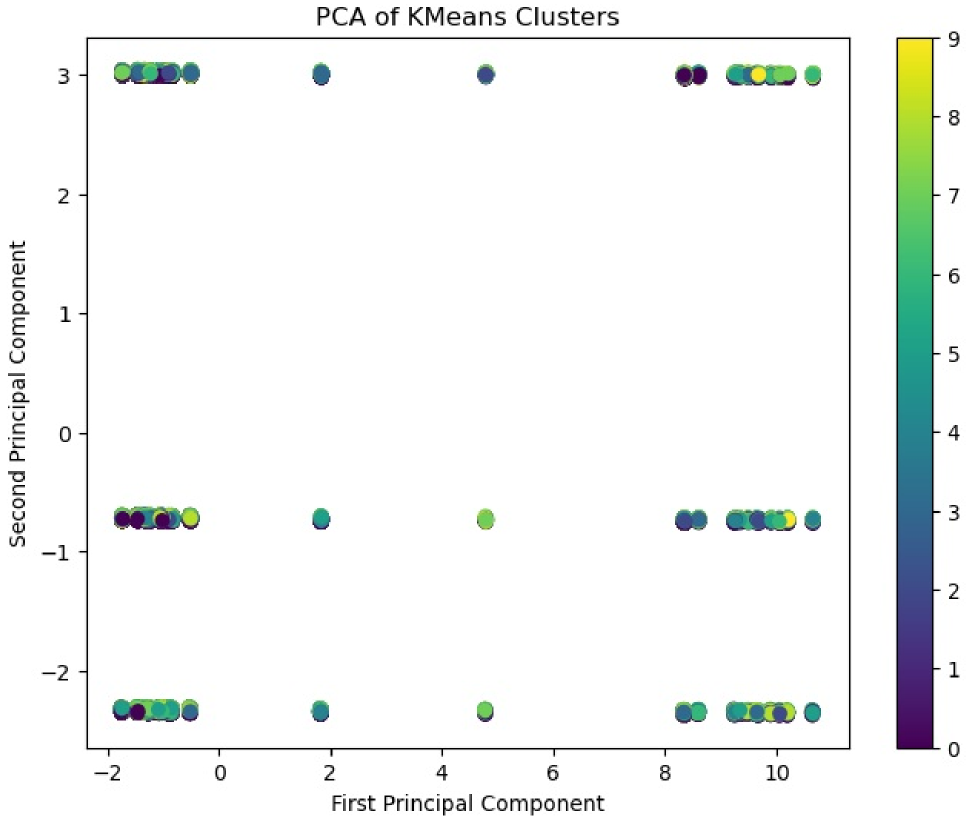
In [139…
```
# END WEEK 10
```

In [140…
```
# BEGIN WEEK 11
```

In [142…
```
# We will use the Week 9 dataset and model for this section as this model performed
# better than the Week 10 model.

# Ensure that embeddings are flattened
embedding_columns = ['Account_Embeddings', 'Merchant_Embeddings', 'Transaction_Embeddings', 'Location_Embedding

for col in embedding_columns:
    # Check if the column contains lists or arrays and flatten them
    if isinstance(X_train[col].iloc[0], (list, np.ndarray)):  # Check if the first entry is a sequence
        embedding_array = pd.DataFrame(X_train[col].apply(lambda x: np.array(x).flatten()).tolist())
        embedding_array.columns = [f"{col}_{i}" for i in range(embedding_array.shape[1])]
        X_train = pd.concat([X_train, embedding_array], axis=1)
        X_train.drop(columns=[col], inplace=True)  # Drop the original embedding column
    else:
        # If already flattened, ensure it's a numeric type
        X_train[col] = pd.to_numeric(X_train[col], errors='coerce')
```

In [144…
```
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

# Perform PCA to aid in identifying most relevant predictors in the dataset
# Scale the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)

# Perform PCA
pca = PCA(n_components=4)
X_pca = pca.fit_transform(X_train_scaled)

# Plot the first two principal components
plt.figure(figsize=(8,6))
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=kmeans_v3.labels_, cmap='viridis')
plt.colorbar()
plt.title('PCA of KMeans Clusters')
plt.xlabel('First Principal Component')
plt.ylabel('Second Principal Component')
plt.show()
```

```python
# Explained variance ratio tells us how much of the variance is captured by each component
print("Explained variance ratio by component:", pca.explained_variance_ratio_)

# You can also examine which features contribute most to the first principal component
features_pca = pd.DataFrame(pca.components_, columns=X_train.columns, index=[f'PC{i+1}' for i in range(len(pca.
print(features_pca)
```




```
Explained variance ratio by component: [0.19020647 0.10468724 0.08504371 0.07977474]
        Day_0     Day_1     Day_2     Day_3     Day_4     Day_5     Day_6  \
PC1  0.000575  0.000389 -0.000180  0.000472 -0.000474 -0.000569 -0.000226
PC2  0.000439 -0.000143 -0.001818 -0.000041 -0.003743  0.003181  0.002124
PC3 -0.000265  0.000363  0.000695  0.001840 -0.002963 -0.001518  0.001801
PC4  0.000878 -0.002022  0.000025  0.001042 -0.002720  0.001845  0.000962

     Deviation_From_Mean  Account_Embeddings_0  Account_Embeddings_1  ...  \
PC1             0.001187             -0.150118              0.194155  ...
PC2            -0.000670              0.000155             -0.000670  ...
PC3            -0.000117              0.018243             -0.020908  ...
PC4            -0.001908             -0.298962              0.344653  ...

     Location_Embeddings_6  Location_Embeddings_7  Hour_Group_Embeddings_0  \
PC1              -0.001343               0.000792                -0.303949
PC2               0.001167               0.001420                 0.000512
PC3               0.435362              -0.327671                -0.012739
PC4               0.026551              -0.018549                 0.194603

     Hour_Group_Embeddings_1  Hour_Group_Embeddings_2  \
PC1                -0.315726                 0.302050
PC2                 0.000615                -0.000250
PC3                -0.009493                 0.012889
PC4                 0.143728                -0.199596

     Hour_Group_Embeddings_3  Hour_Group_Embeddings_4  \
PC1                -0.309024                 0.306405
PC2                 0.000361                -0.000446
PC3                -0.011734                 0.012085
PC4                 0.179452                -0.188488

     Hour_Group_Embeddings_5  Hour_Group_Embeddings_6  Hour_Group_Embeddings_7
PC1                 0.316504                 0.316502                 0.310031
PC2                -0.000607                -0.000636                -0.000493
PC3                 0.008985                 0.008839                 0.011558
PC4                -0.136774                -0.134734                -0.176185

[4 rows x 48 columns]
```

In [152…

```python
# Store the original feature names before scaling
original_feature_names = X_train.columns  # This stores the original feature names

# Fit model with scaled data
kmeans = KMeans(n_clusters=10, init='k-means++', n_init=1, max_iter=200, tol=1e-3, random_state=42)
```

```python
kmeans.fit(X_train_scaled)

# Get the cluster centroids
centroids = kmeans.cluster_centers_

# Assign clusters to each data point
assigned_centroids = kmeans.predict(X_train_scaled)

# Identify random points farthest from their centroids (anomalies)
# Calculate distances from each point to its assigned centroid
distances = np.linalg.norm(X_train_scaled - centroids[assigned_centroids], axis=1)

# Sort the indices of the points based on the distance to centroid (farthest first)
farthest_indices = np.argsort(distances)[::-1]

# Select 5 random points from those farthest from the centroid
random_furthest_points = farthest_indices[:5]

# Calculate the feature-wise contribution to the distance from the centroid for each point
feature_contributions = []

for idx in random_furthest_points:
    point = X_train_scaled[idx]  # Use array indexing to select the point
    assigned_cluster = assigned_centroids[idx]
    centroid = centroids[assigned_cluster]

    # Calculate the squared difference for each feature (contribution to distance)
    feature_contrib = (point - centroid) ** 2
    feature_contributions.append(feature_contrib)

# Manually generate column names based on the original dataset columns
# Since X_train_scaled is a NumPy array, we need to manually use the feature names from the original dataset
columns = original_feature_names

# Convert the contributions to a DataFrame for better readability
# Manually create a DataFrame and match it with the original feature names
feature_contributions_df = pd.DataFrame(feature_contributions, columns=columns)
print("Feature-wise contributions to distance from centroid for selected points:")
print(feature_contributions_df)

# Simulate adjusting the features of a randomly selected point to move 10% closer to its centroid
adjusted_points = []

for idx in random_furthest_points:
    point = X_train_scaled[idx]  # Use array indexing to select the point
    assigned_cluster = assigned_centroids[idx]
    centroid = centroids[assigned_cluster]

    # Calculate the difference for each feature
    feature_differences = point - centroid

    # Calculate how much to adjust each feature (reduce by 10% of the difference)
    adjustment = 0.1 * feature_differences  # 10% adjustment

    # Apply the adjustment to the features
    new_point = point - adjustment  # Move the point closer to the centroid
    adjusted_points.append(new_point)

# Convert the adjusted points into a DataFrame for better readability
# Again, manually assigning feature names
adjusted_points_df = pd.DataFrame(adjusted_points, columns=columns)
print("\nAdjusted feature values for points moved closer to centroids (10% adjustment):")
print(adjusted_points_df)

# Calculate the new distance after the adjustment to see how much the point moved
new_distances = np.linalg.norm(np.array(adjusted_points_df) - centroids[assigned_centroids[random_furthest_poin
print("\nNew distances to centroid after adjustment:")
print(new_distances)
```

```
Feature-wise contributions to distance from centroid for selected points:
      Day_0     Day_1     Day_2     Day_3     Day_4     Day_5     Day_6  \
0  0.172981  0.172447  0.173179  0.163272  0.162168  6.234886  0.167943
1  0.170637  0.164565  0.172248  6.156493  0.172364  0.162026  0.161660
2  0.174762  0.179575  5.821240  0.159325  0.170867  0.152382  0.154537
3  5.865028  0.174708  0.163556  0.161403  0.154641  0.173756  0.168029
4  0.174762  0.179575  0.176124  6.182390  0.170867  0.152382  0.154537

   Deviation_From_Mean  Account_Embeddings_0  Account_Embeddings_1  ...  \
0            70.459024              2.339557              0.381855  ...
1            68.323767              1.139947              0.060031  ...
2            32.048874              0.000049              0.001941  ...
3            68.550852              0.518583              0.383460  ...
4            55.089934              0.721595              1.055179  ...
```

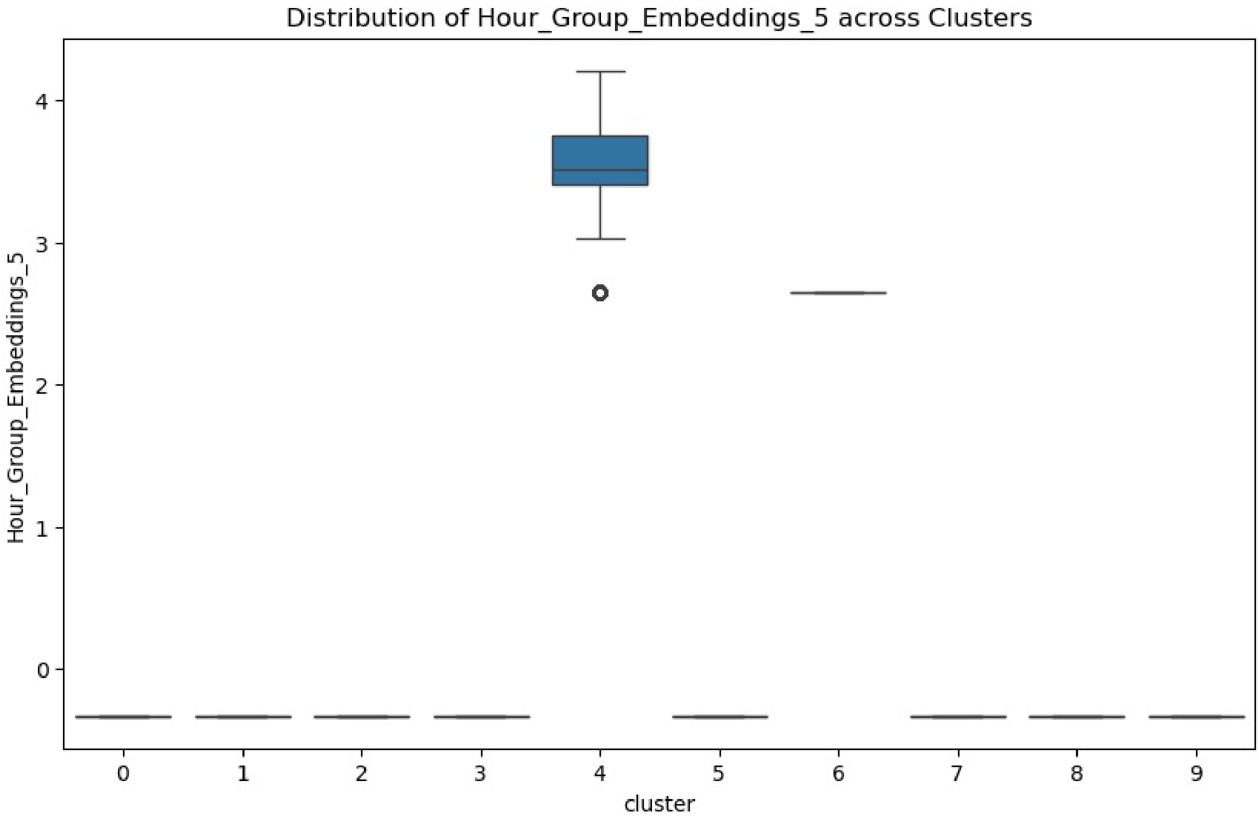
```
   Location_Embeddings_6  Location_Embeddings_7  Hour_Group_Embeddings_0  \
0               0.252400               0.006409             7.499109e-29   
1               0.002823               3.066500             3.462360e-29   
2               0.653537               3.687054             4.727678e+00   
3               0.223810               0.902671             3.865418e-29   
4               2.346223               0.332543             3.899476e-01   

   Hour_Group_Embeddings_1  Hour_Group_Embeddings_2  Hour_Group_Embeddings_3  \
0             2.899372e-29             9.222585e-29             1.701752e-28   
1             7.595560e-29             1.159749e-28             3.038224e-28   
2             1.053798e+00             5.283089e+00             3.366768e+00   
3             7.595560e-29             1.159749e-28             3.057606e-28   
4             4.913953e-03             4.730771e-01             2.682538e-03   

   Hour_Group_Embeddings_4  Hour_Group_Embeddings_5  Hour_Group_Embeddings_6  \
0             4.738096e-29             7.888609e-31             4.930381e-32   
1             1.020712e-28             7.888609e-31             2.829083e-28   
2             4.111301e+00             7.395323e-01             6.868740e-01   
3             1.100738e-28             6.933348e-31             2.961310e-28   
4             7.773590e-01             1.356645e-01             1.636402e-01   

   Hour_Group_Embeddings_7  
0             5.127904e-29  
1             1.100738e-28  
2             3.042660e+00  
3             1.112417e-28  
4             8.748556e-02  

[5 rows x 48 columns]

Adjusted feature values for points moved closer to centroids (10% adjustment):
      Day_0     Day_1     Day_2     Day_3     Day_4     Day_5     Day_6  \
0 -0.371191 -0.372631 -0.371779 -0.362359 -0.361778  2.239072 -0.369701   
1 -0.371474 -0.373591 -0.371891  2.234708 -0.360531 -0.361552 -0.370475   
2 -0.370977 -0.371781  2.177730 -0.362850 -0.360712 -0.362769 -0.371371   
3  2.180409 -0.372359 -0.372951 -0.362591 -0.362724 -0.360121 -0.369691   
4 -0.370977 -0.371781 -0.371426  2.234187 -0.360712 -0.362769 -0.371371   

   Deviation_From_Mean  Account_Embeddings_0  Account_Embeddings_1  ...  \
0            -7.558157              1.633973             -0.906967  ...   
1            -7.439646             -0.710725             -0.129331  ...   
2            -5.069675              0.230465             -0.305022  ...   
3            -7.457654              0.890389              0.209219  ...   
4            -6.654653              1.001293             -1.269169  ...   

   Location_Embeddings_6  Location_Embeddings_7  Hour_Group_Embeddings_0  \
0              -1.164619              -0.771620                 0.311277   
1              -0.789408               1.739231                 0.311277   
2              -0.713879               1.722328                -2.235387   
3              -1.167550              -0.684617                 0.311277   
4               1.392260              -0.524824                -4.754290   

   Hour_Group_Embeddings_1  Hour_Group_Embeddings_2  Hour_Group_Embeddings_3  \
0                 0.327891                -0.308537                 0.317453   
1                 0.327891                -0.308537                 0.317453   
2                -2.685324                 2.178219                -2.379826   
3                 0.327891                -0.308537                 0.317453   
4                -3.546126                 4.865892                -4.077828   

   Hour_Group_Embeddings_4  Hour_Group_Embeddings_5  Hour_Group_Embeddings_6  \
0                -0.314228                -0.329445                -0.329433   
1                -0.314228                -0.329445                -0.329433   
2                 2.300350                 2.742903                 2.750950   
3                -0.314228                -0.329445                -0.329433   
4                 4.918732                 3.848362                 3.860923   

   Hour_Group_Embeddings_7  
0                -0.319338  
1                -0.319338  
2                 2.420499  
3                -0.319338  
4                 4.256591  

[5 rows x 48 columns]

New distances to centroid after adjustment:
[8.90122005 8.88110523 8.85093814 8.83304565 8.7982284 ]
```

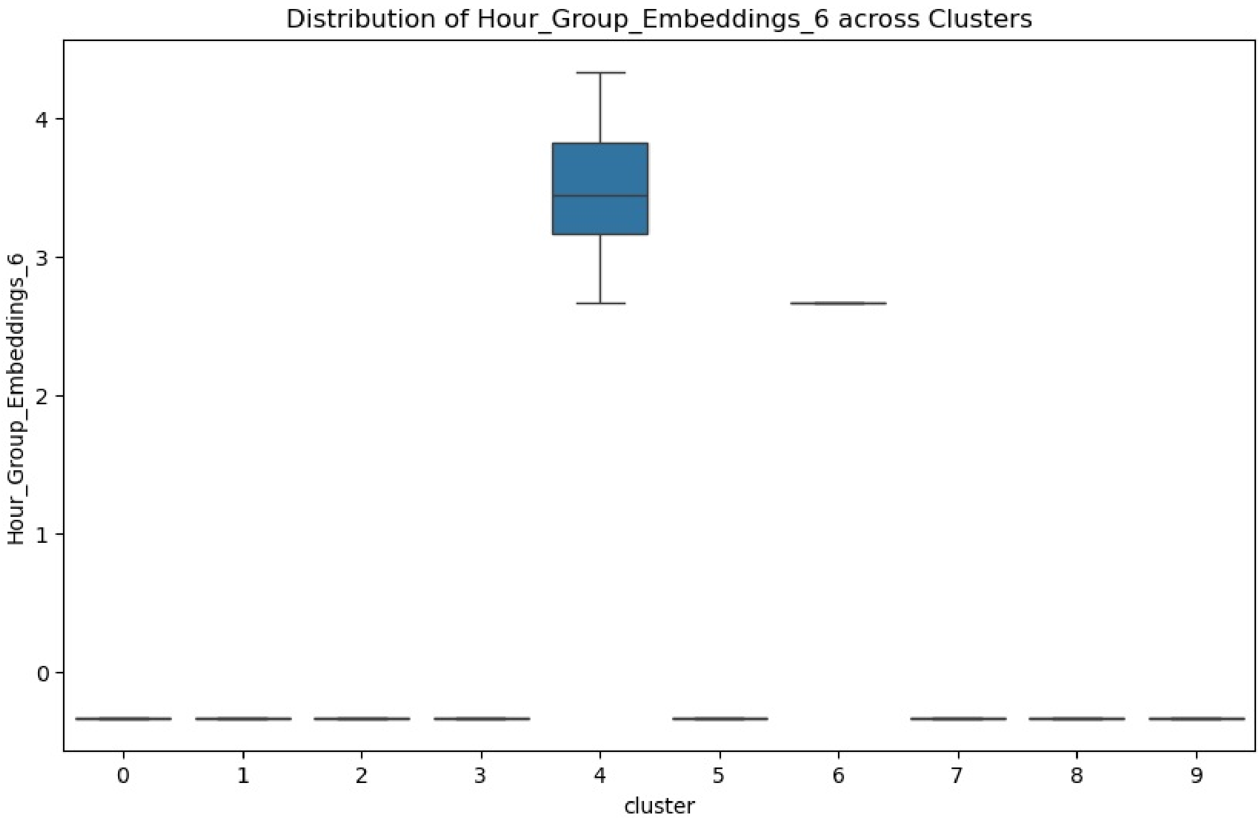
In [154…

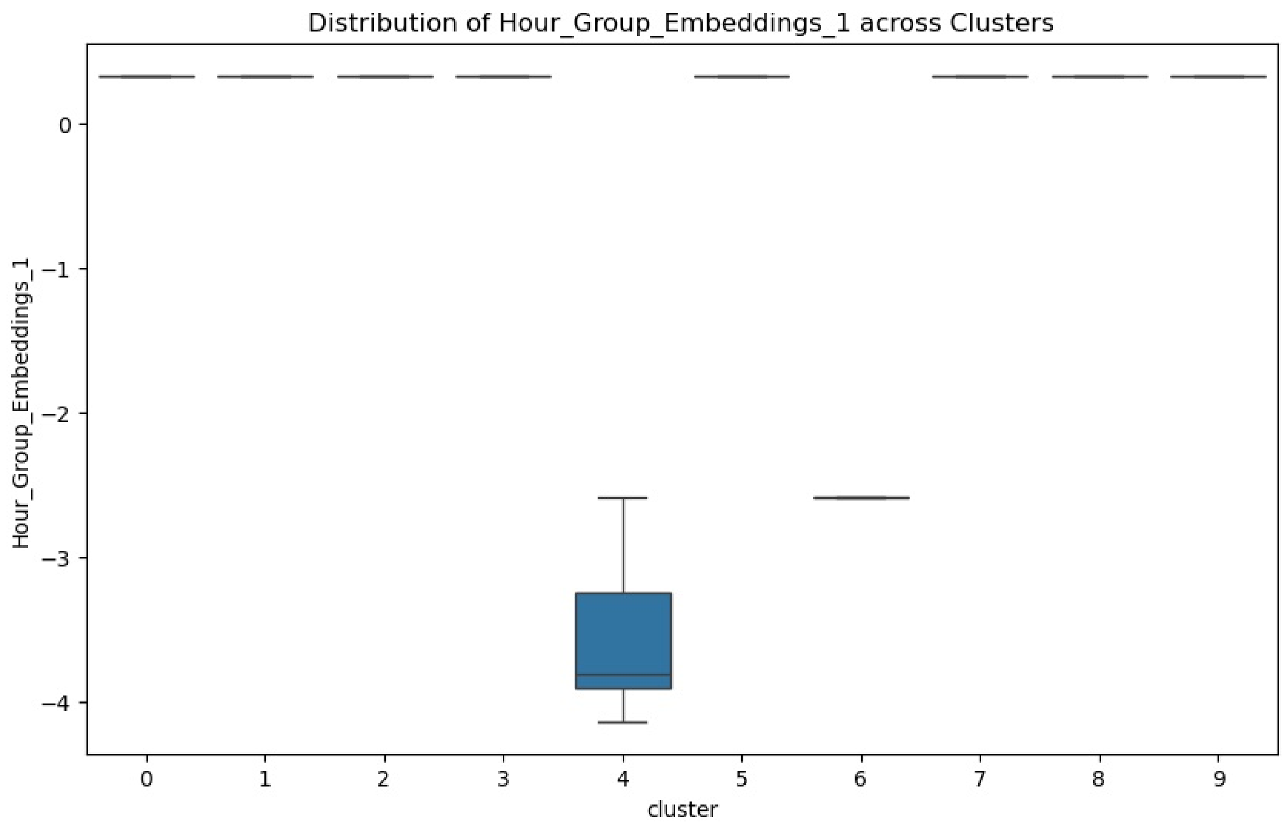
```
# To quantify bias, we will extract the most important contributing features to classification and manually
# determine the likelihood that these features contain inherent bias due to their correlations to
# protected classes that are not explicitly present in our data or model.

# Find the features with the largest loadings (absolute values) for each principal component
```

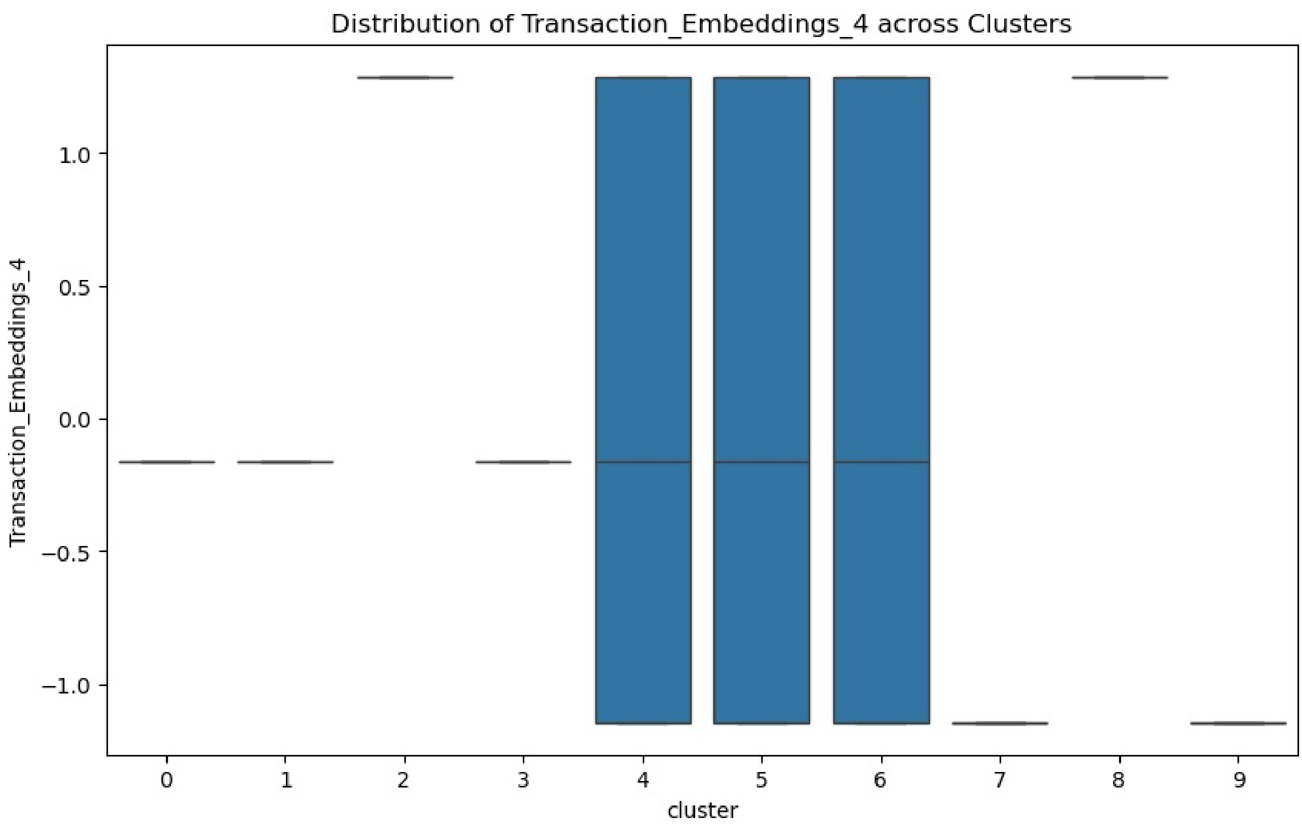
```python
top_features_per_pc = {}

for pc in features_pca.index:
    sorted_features = features_pca.loc[pc].abs().sort_values(ascending=False)
    top_features_per_pc[pc] = sorted_features.head(3)  # Top 3 features for each PC

# Display the most important features for each principal component
print("\nTop features per PC based on their contribution to variance:")
for pc, features in top_features_per_pc.items():
    print(f"{pc}: {features.index.tolist()}")

# Add your clustering results to the dataset from K-Means model for visualization
X_train_scaled_with_clusters = pd.DataFrame(X_train_scaled, columns=X_train.columns)
X_train_scaled_with_clusters['cluster'] = kmeans.labels_

# Visualize how the identified features vary across clusters (for bias detection)
for pc, features in top_features_per_pc.items():
    for feature in features.index:
        plt.figure(figsize=(10, 6))
        sns.boxplot(x='cluster', y=feature, data=X_train_scaled_with_clusters)
        plt.title(f'Distribution of {feature} across Clusters')
        plt.show()
```

```
Top features per PC based on their contribution to variance:
PC1: ['Hour_Group_Embeddings_5', 'Hour_Group_Embeddings_6', 'Hour_Group_Embeddings_1']
PC2: ['Transaction_Embeddings_4', 'Transaction_Embeddings_6', 'Transaction_Embeddings_7']
PC3: ['Location_Embeddings_6', 'Location_Embeddings_4', 'Location_Embeddings_3']
PC4: ['Account_Embeddings_3', 'Account_Embeddings_5', 'Account_Embeddings_4']
```

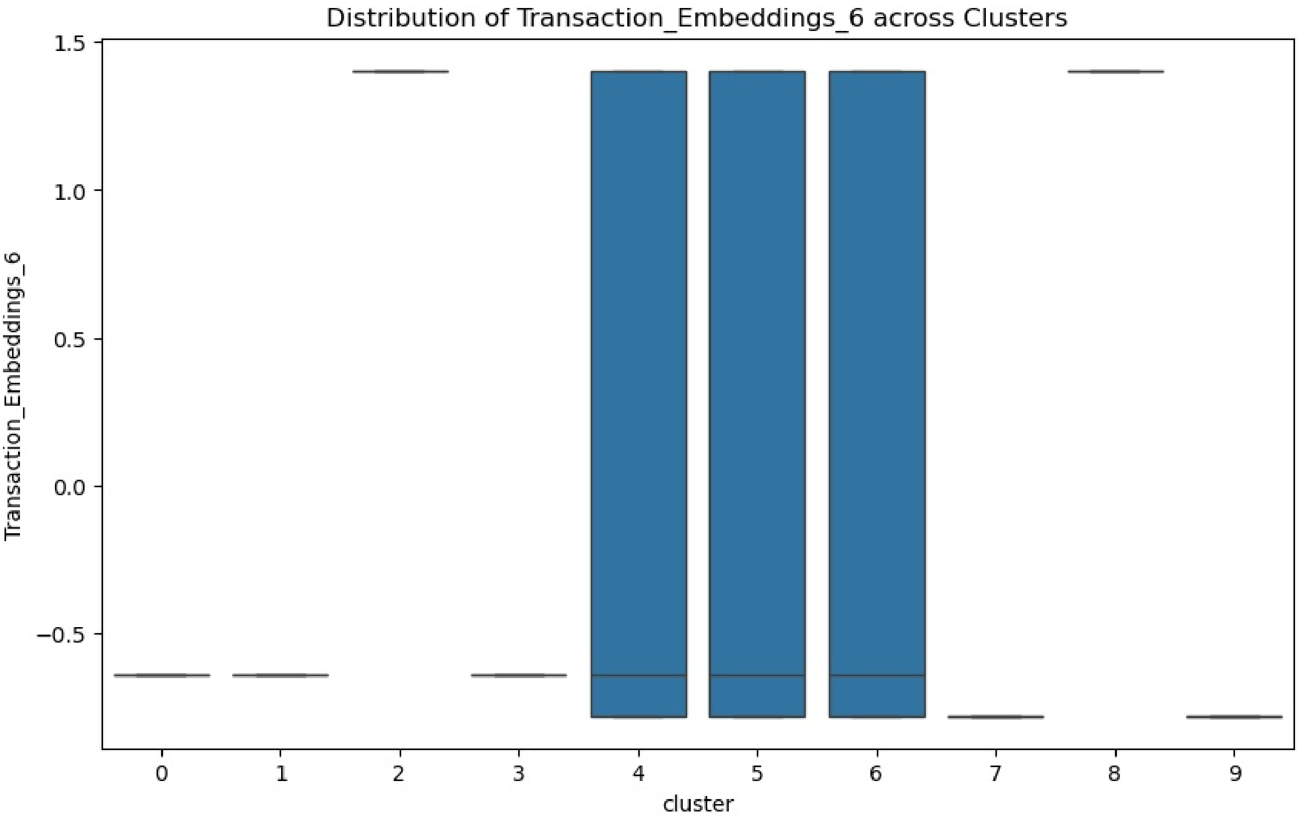



Distribution of Hour_Group_Embeddings_6 across Clusters
Hour_Group_Embeddings_6
0
1
2
3
4
0
1
2
3
4
5
6
7
8
9
cluster

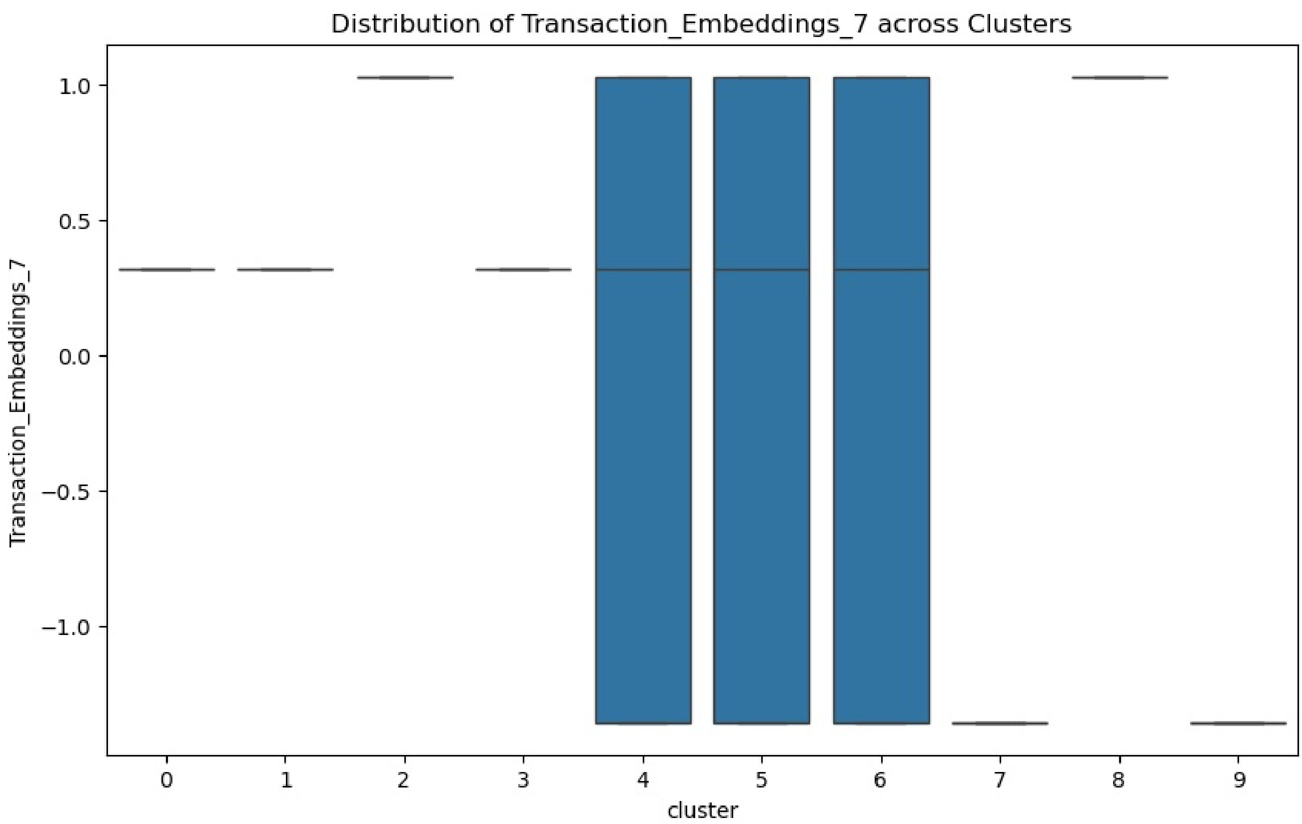

Distribution of Hour_Group_Embeddings_1 across Clusters
Hour_Group_Embeddings_1
0
−1
−2
−3
−4
0
1
2
3
4
5
6
7
8
9
cluster



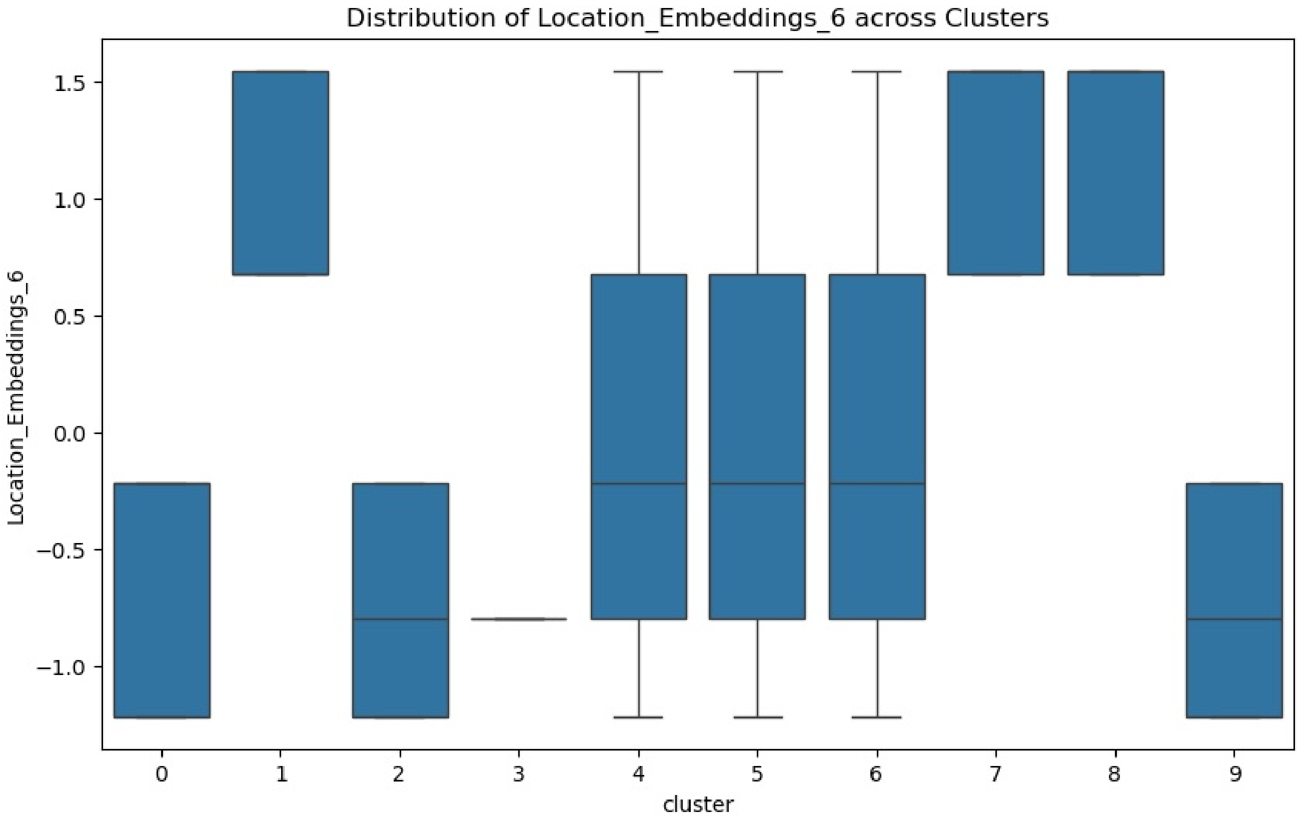
Distribution of Transaction_Embeddings_4 across Clusters
Transaction_Embeddings_4
1.0
0.5
0.0
−0.5
−1.0
0
1
2
3
4
5
6
7
8
9
cluster



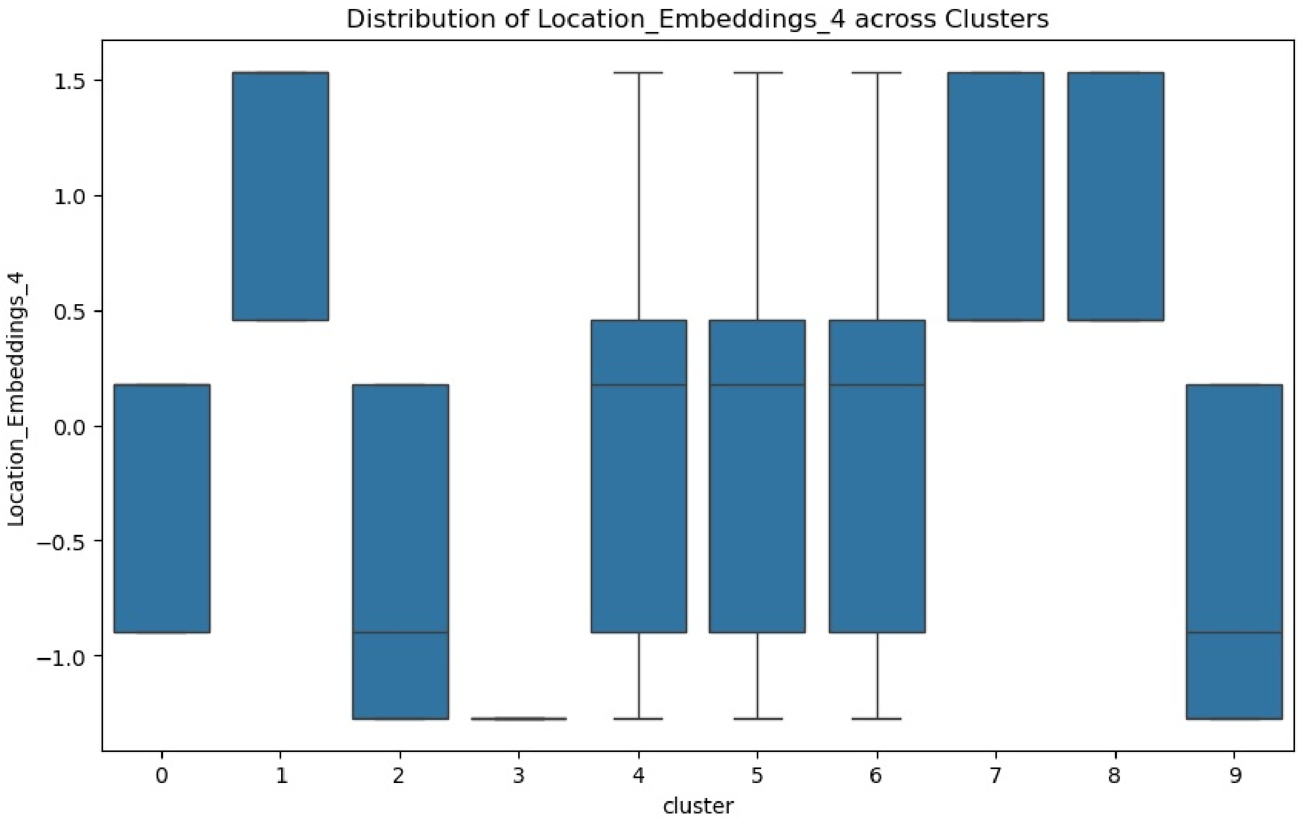
Distribution of Transaction_Embeddings_6 across Clusters
Transaction_Embeddings_6
cluster
1.5
1.0
0.5
0.0
−0.5
0
1
2
3
4
5
6
7
8
9

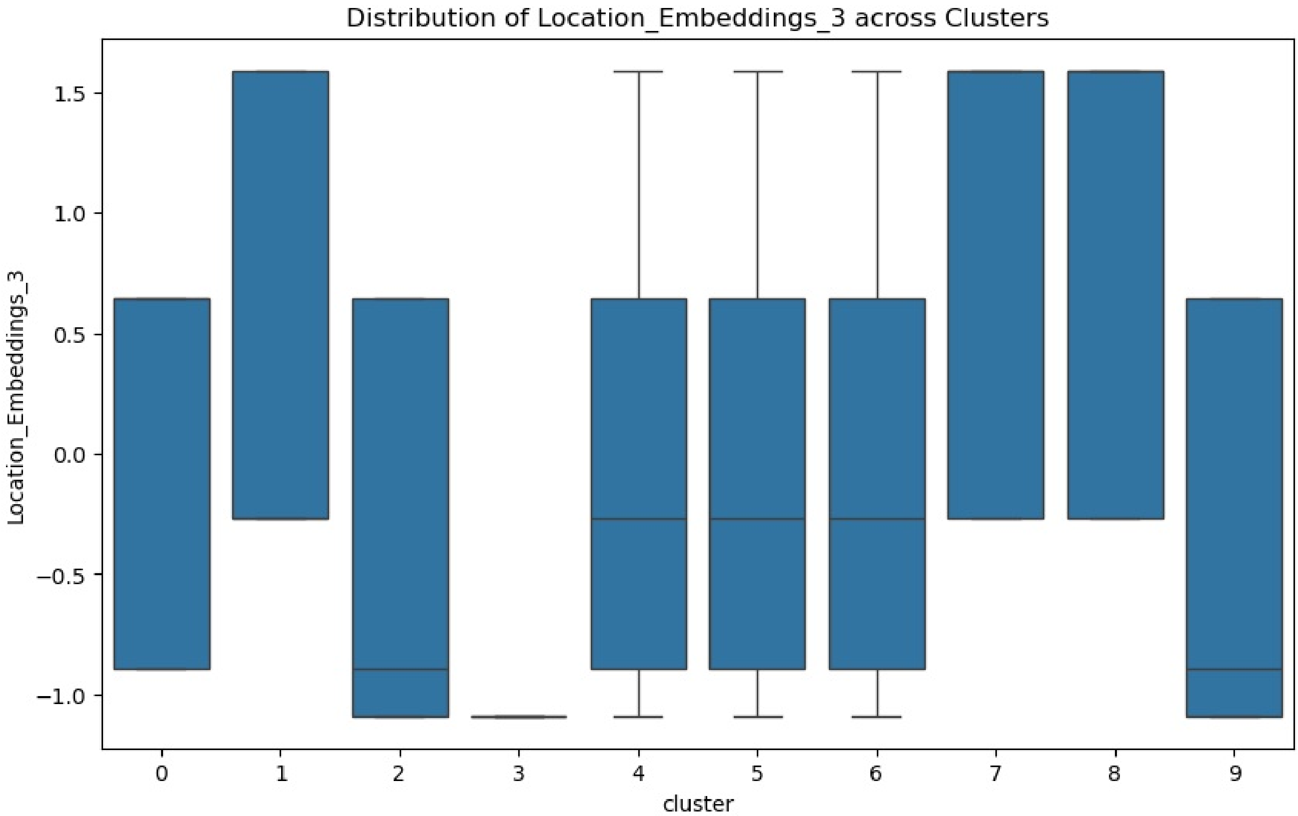


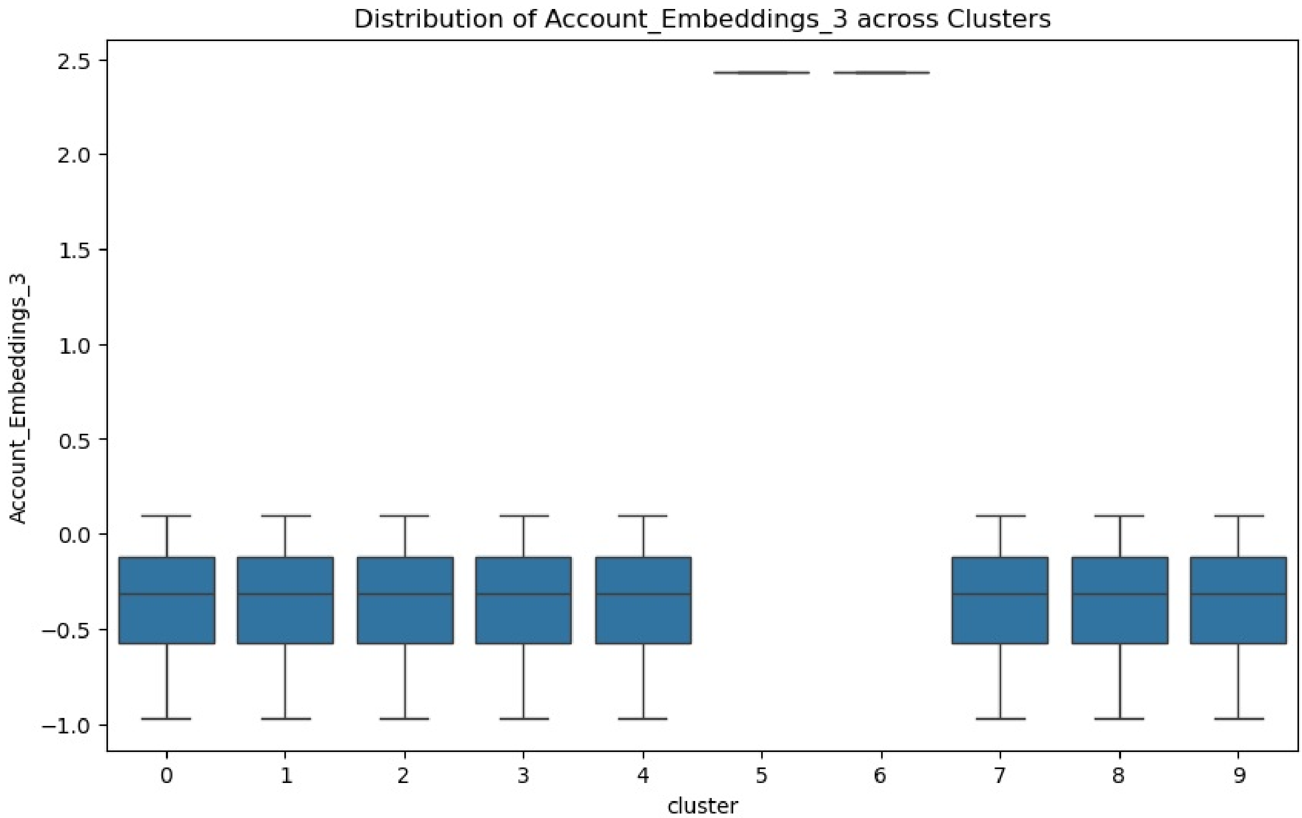
Distribution of Transaction_Embeddings_7 across Clusters
Transaction_Embeddings_7
1.0
0.5
0.0
−0.5
−1.0
0
1
2
3
4
5
6
7
8
9
cluster

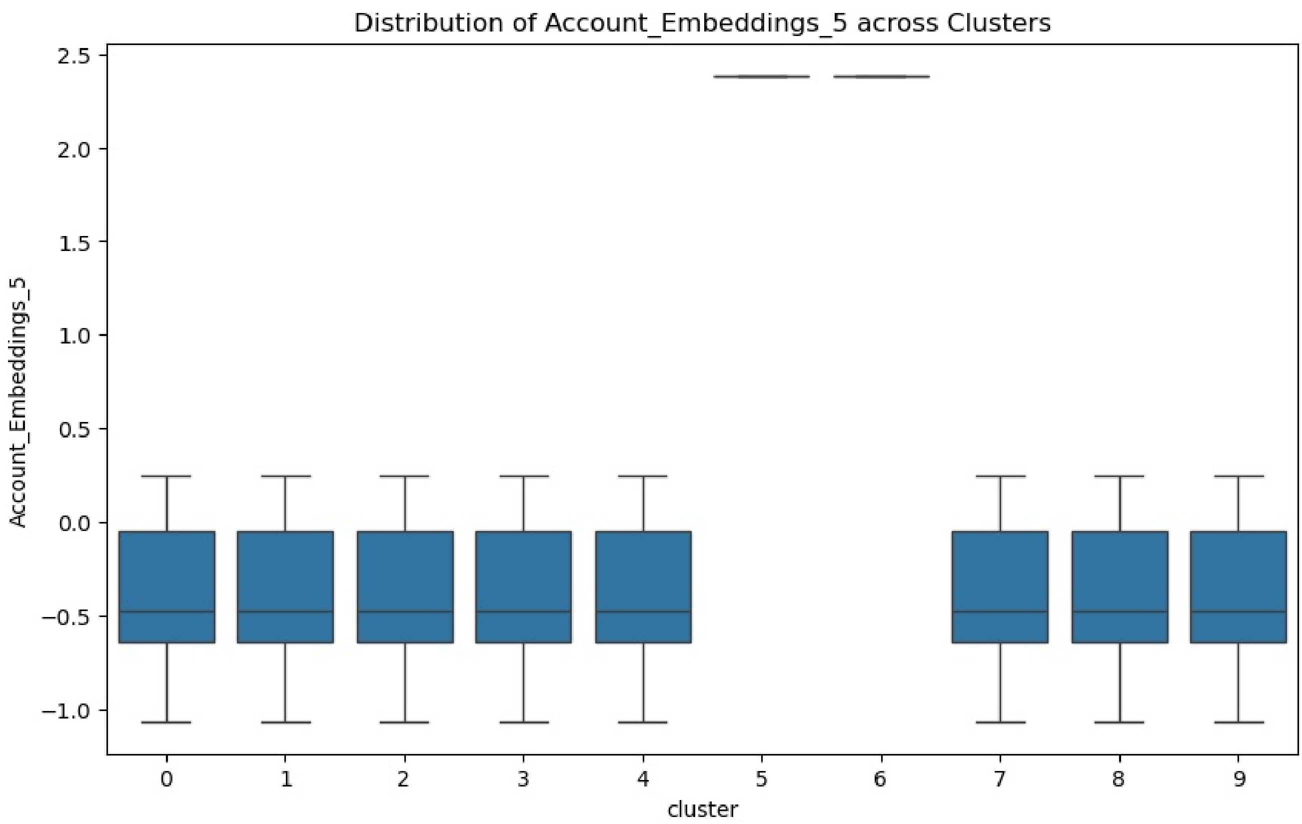


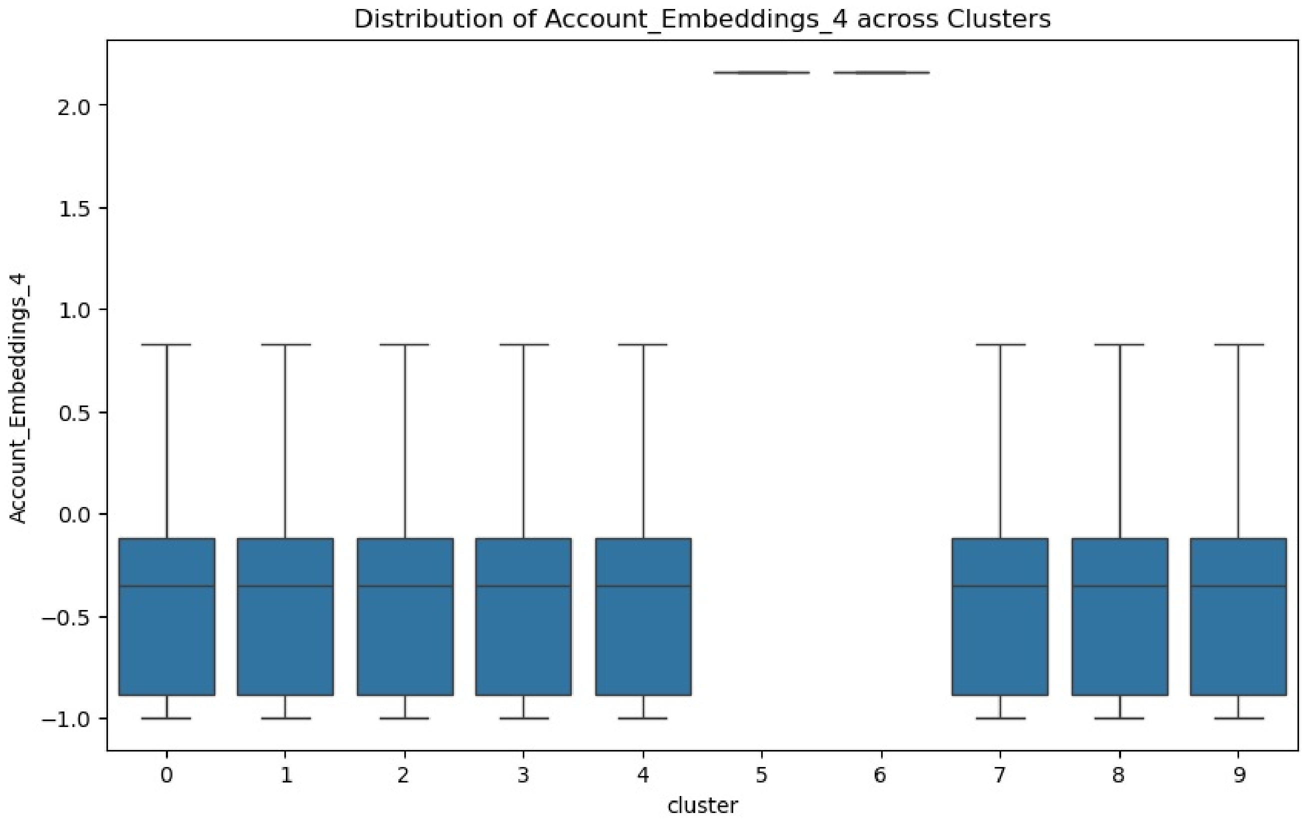
Distribution of Location_Embeddings_6 across Clusters
Location_Embeddings_6
1.5
1.0
0.5
0.0
−0.5
−1.0
0
1
2
3
4
5
6
7
8
9
cluster


Distribution of Location_Embeddings_4 across Clusters
Location_Embeddings_4
1.5
1.0
0.5
0.0
−0.5
−1.0
0
1
2
3
4
5
6
7
8
9
cluster


Distribution of Location_Embeddings_3 across Clusters
Location_Embeddings_3
1.5
1.0
0.5
0.0
−0.5
−1.0
0
1
2
3
4
5
6
7
8
9
cluster


Distribution of Account_Embeddings_3 across Clusters
Account_Embeddings_3
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
0
1
2
3
4
5
6
7
8
9
cluster

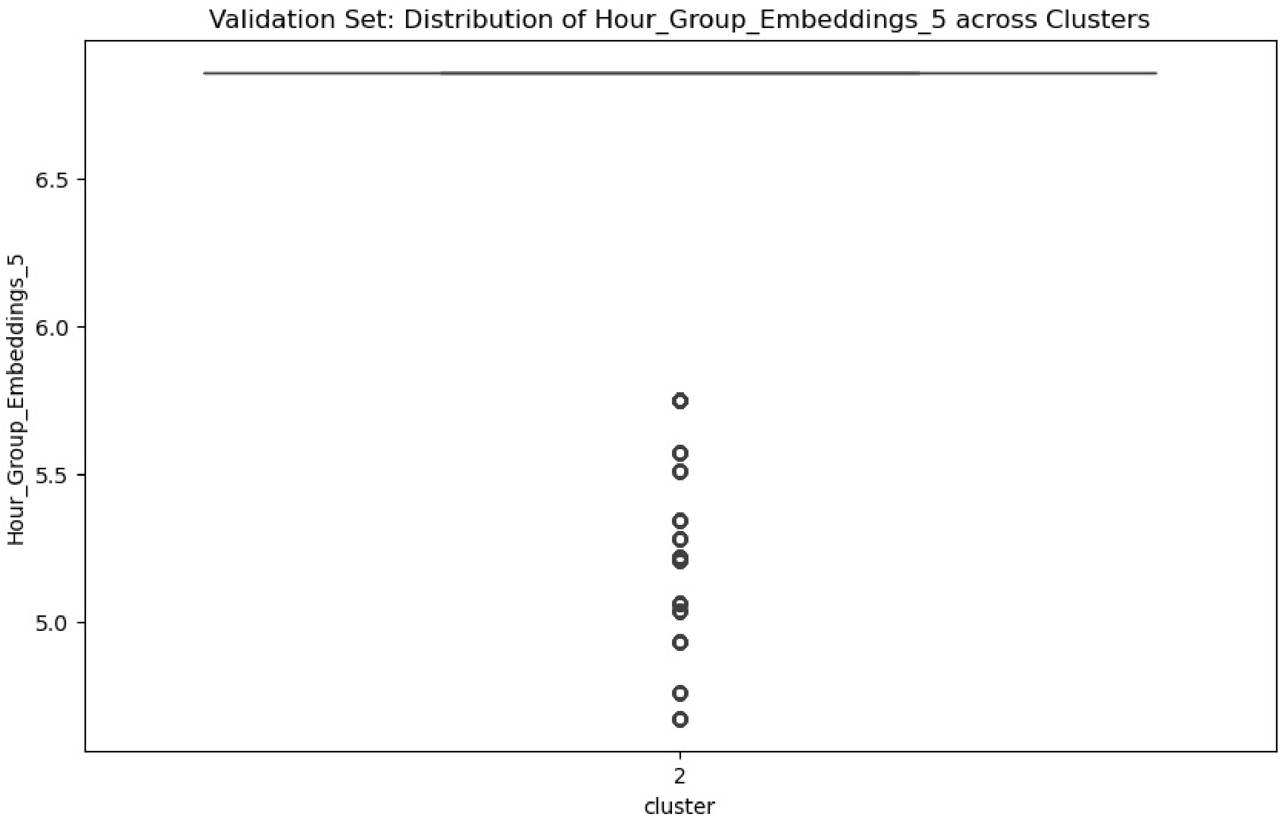

Distribution of Account_Embeddings_5 across Clusters
Account_Embeddings_5
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
0
1
2
3
4
5
6
7
8
9
cluster

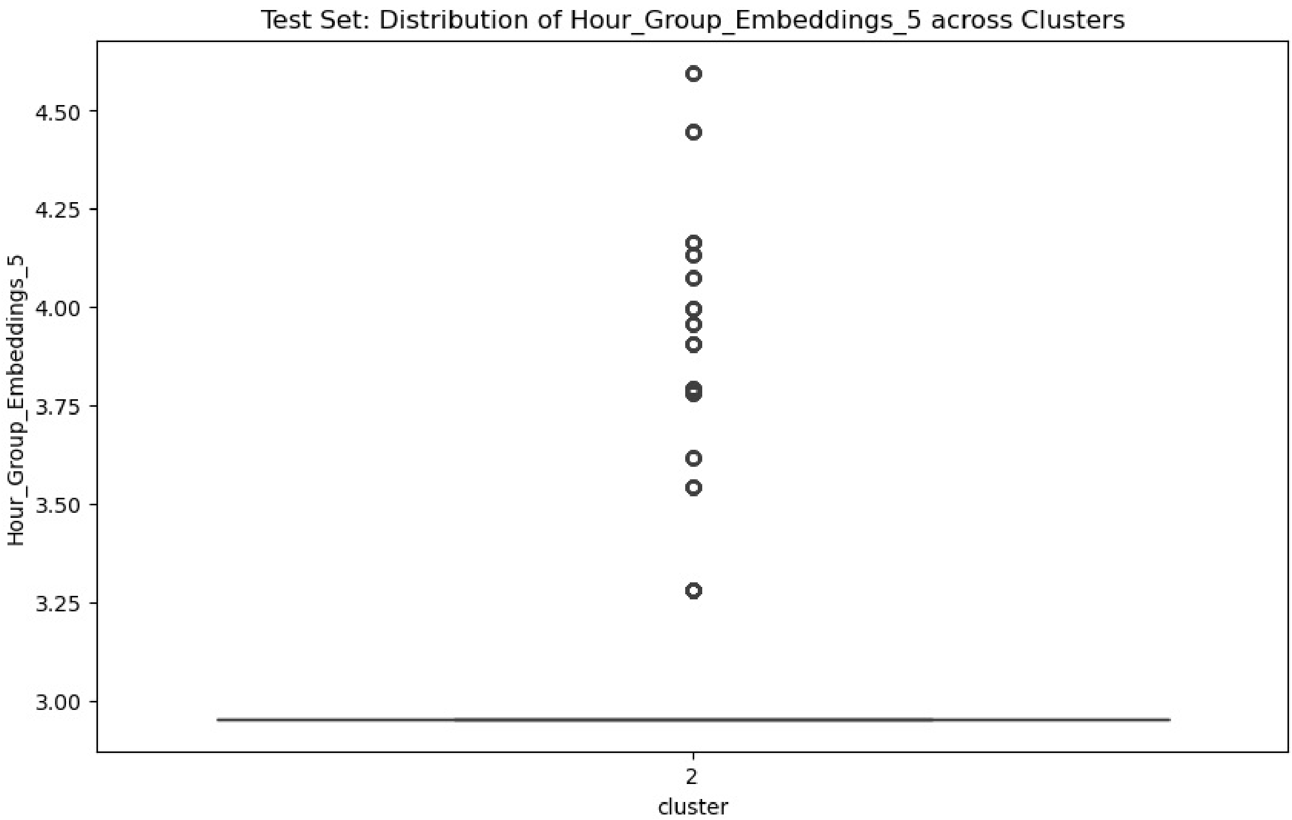


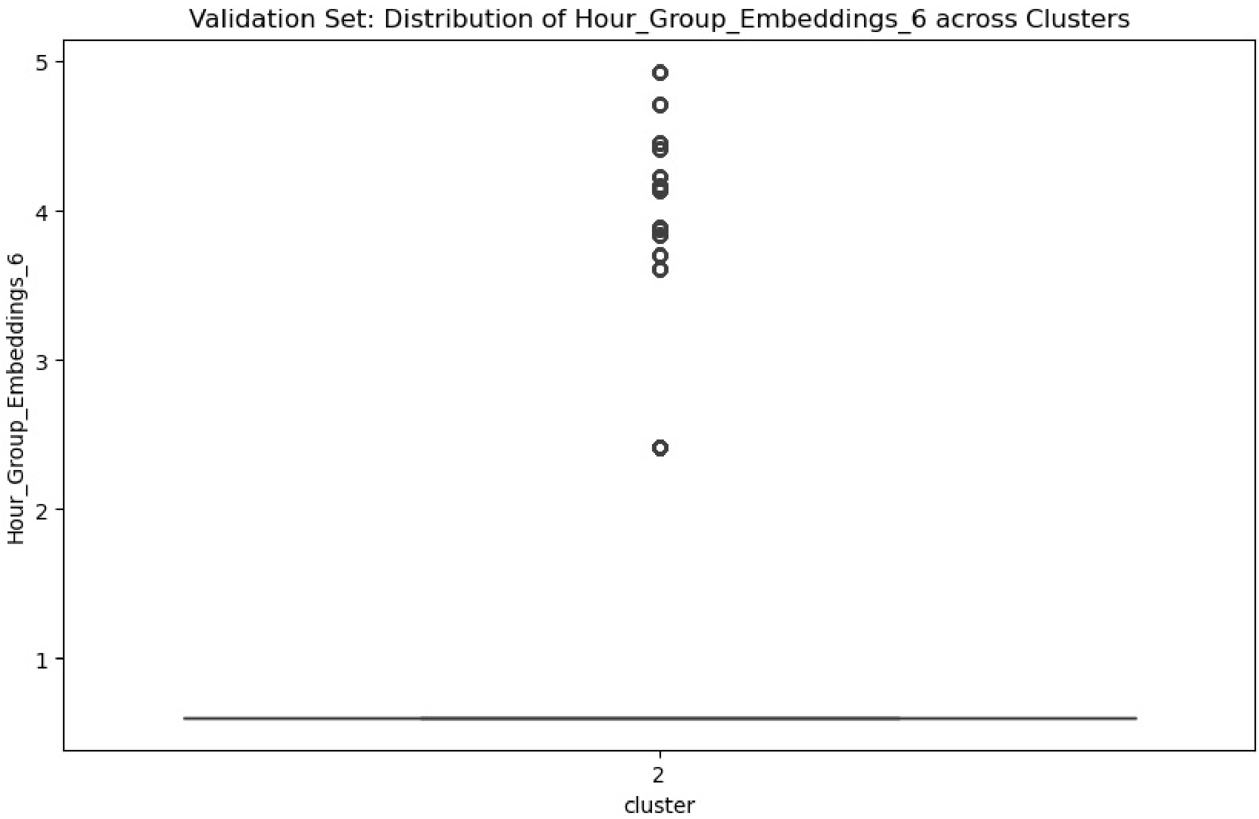
In [156…

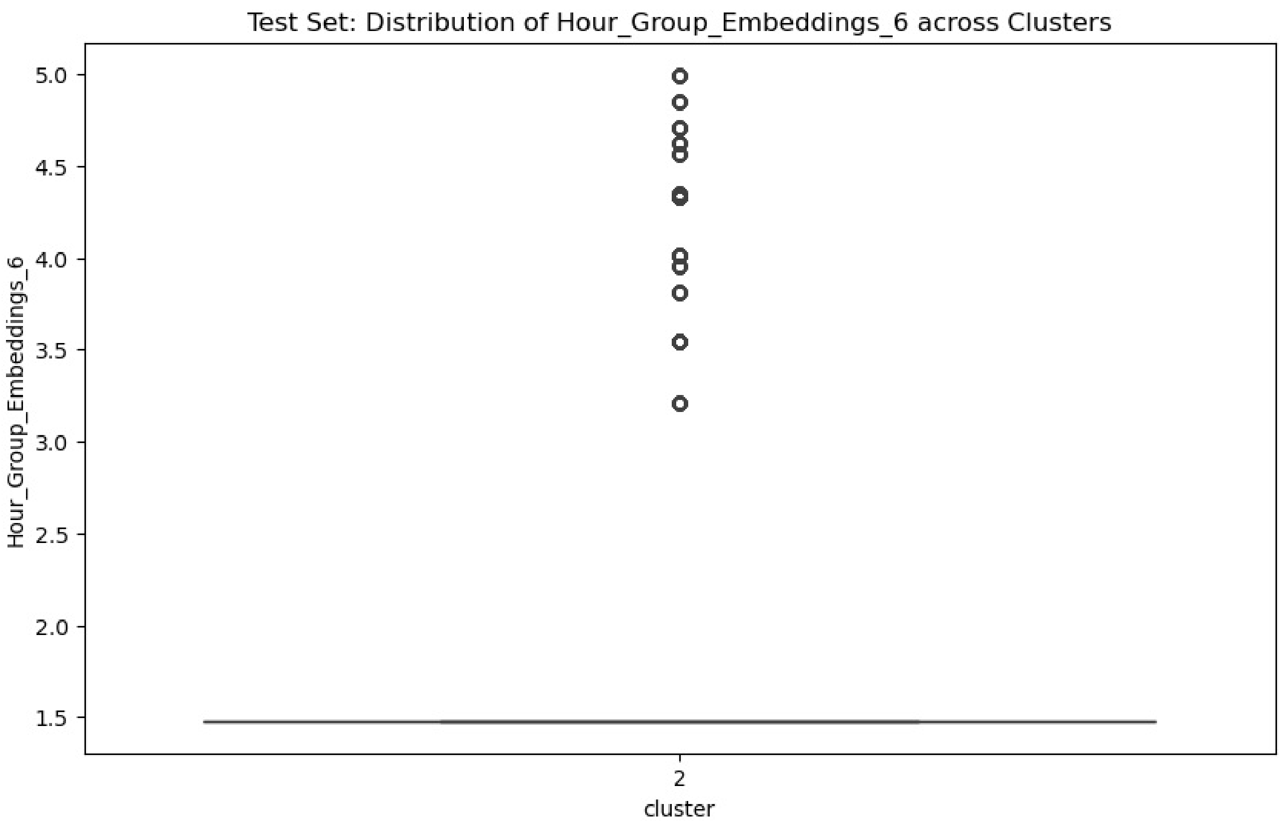
```
# Perform same process on validation and test datasets to analyze
# bias across these datasets as well

# Apply the same scaler used for the training set
X_val_scaled = scaler.transform(X_val)  # Use the same scaler for validation
X_test_scaled = scaler.transform(X_test)  # Use the same scaler for test

# Apply PCA transformation to the validation and test sets
X_val_pca = pca.transform(X_val_scaled)  # Apply PCA to the validation set
X_test_pca = pca.transform(X_test_scaled)  # Apply PCA to the test set

# Predict cluster labels for validation and test sets
val_clusters = kmeans.predict(X_val_scaled)  # Predict clusters for validation
test_clusters = kmeans.predict(X_test_scaled)  # Predict clusters for test

# Step 4: Visualize bias in features based on PCA loadings
# Add clusters to the validation and test sets for visualization
X_val_scaled_with_clusters = pd.DataFrame(X_val_scaled, columns=X_val.columns)
X_val_scaled_with_clusters['cluster'] = val_clusters

X_test_scaled_with_clusters = pd.DataFrame(X_test_scaled, columns=X_test.columns)
X_test_scaled_with_clusters['cluster'] = test_clusters

# Bias Analysis: Visualize key features across clusters
for pc, features in top_features_per_pc.items():
    for feature in features.index:
```

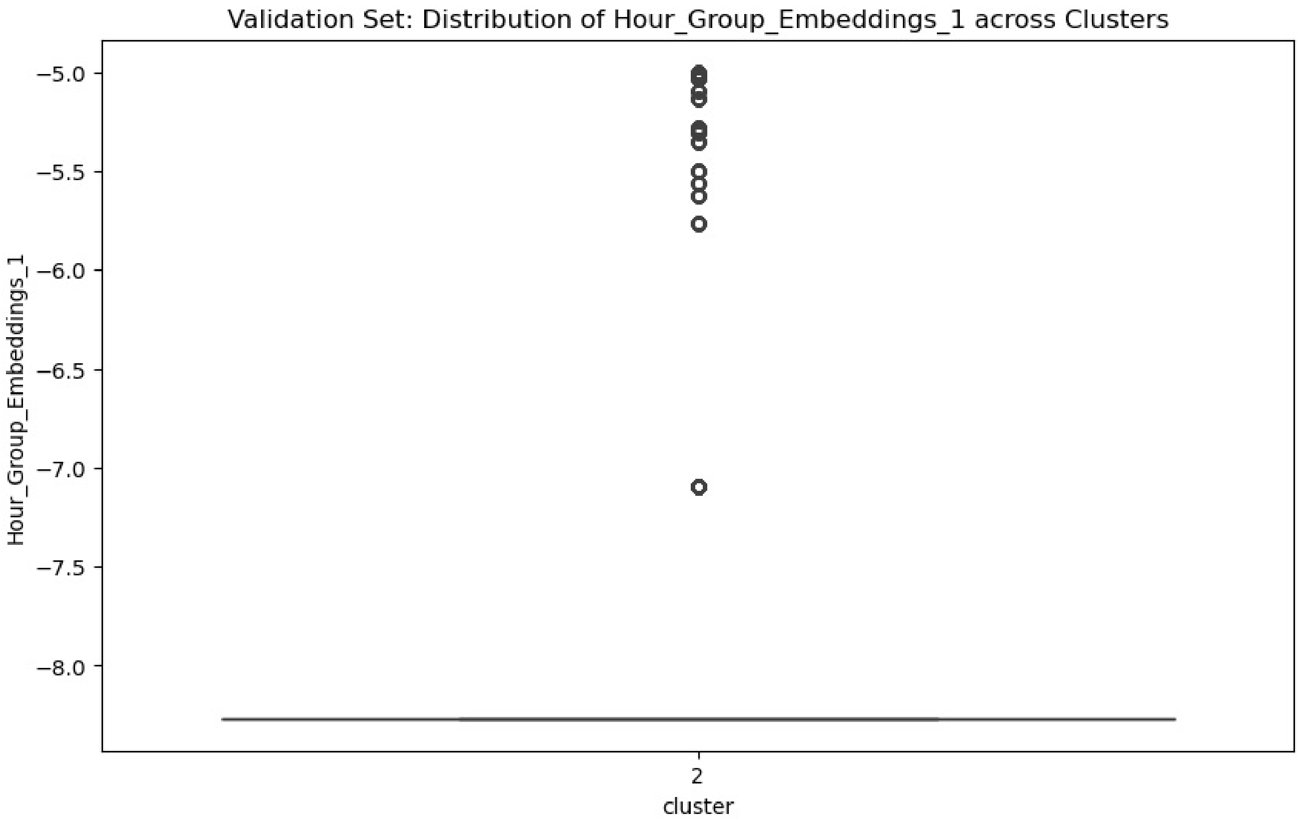
```python
    # Validation Set visualization
    plt.figure(figsize=(10, 6))
    sns.boxplot(x='cluster', y=feature, data=X_val_scaled_with_clusters)
    plt.title(f'Validation Set: Distribution of {feature} across Clusters')
    plt.show()

    # Test Set visualization
    plt.figure(figsize=(10, 6))
    sns.boxplot(x='cluster', y=feature, data=X_test_scaled_with_clusters)
    plt.title(f'Test Set: Distribution of {feature} across Clusters')
    plt.show()
```



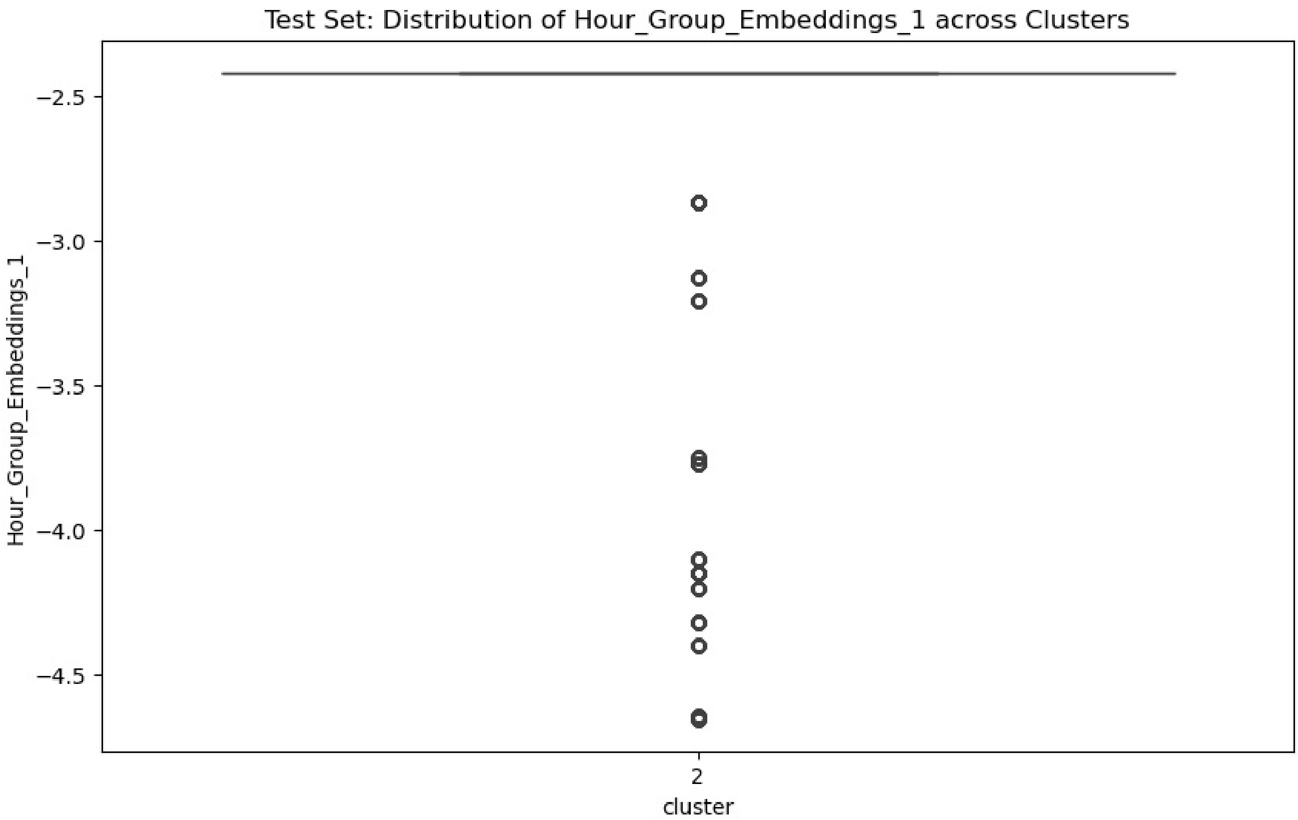



Validation Set: Distribution of Hour_Group_Embeddings_6 across Clusters
Hour_Group_Embeddings_6
5
4
3
2
1
2
cluster

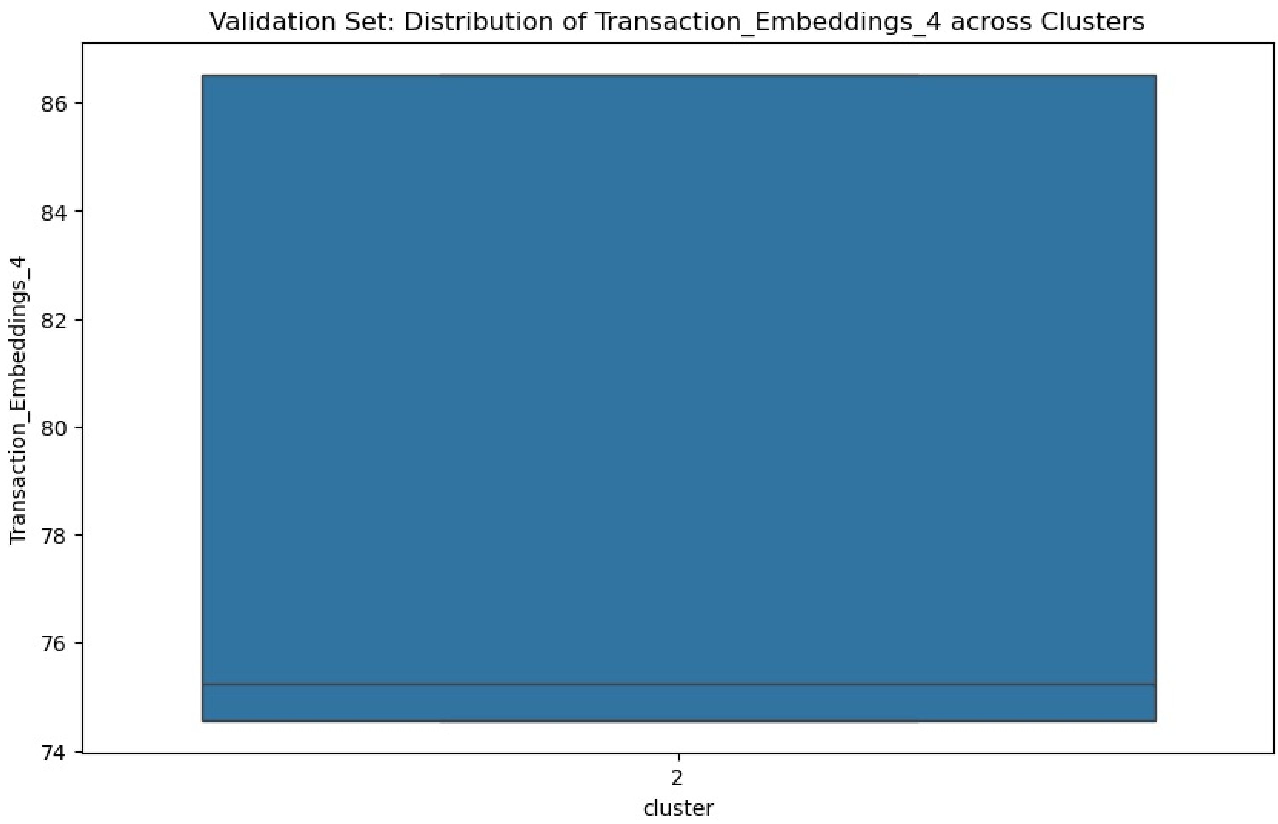

Test Set: Distribution of Hour_Group_Embeddings_6 across Clusters
Hour_Group_Embeddings_6
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
2
cluster

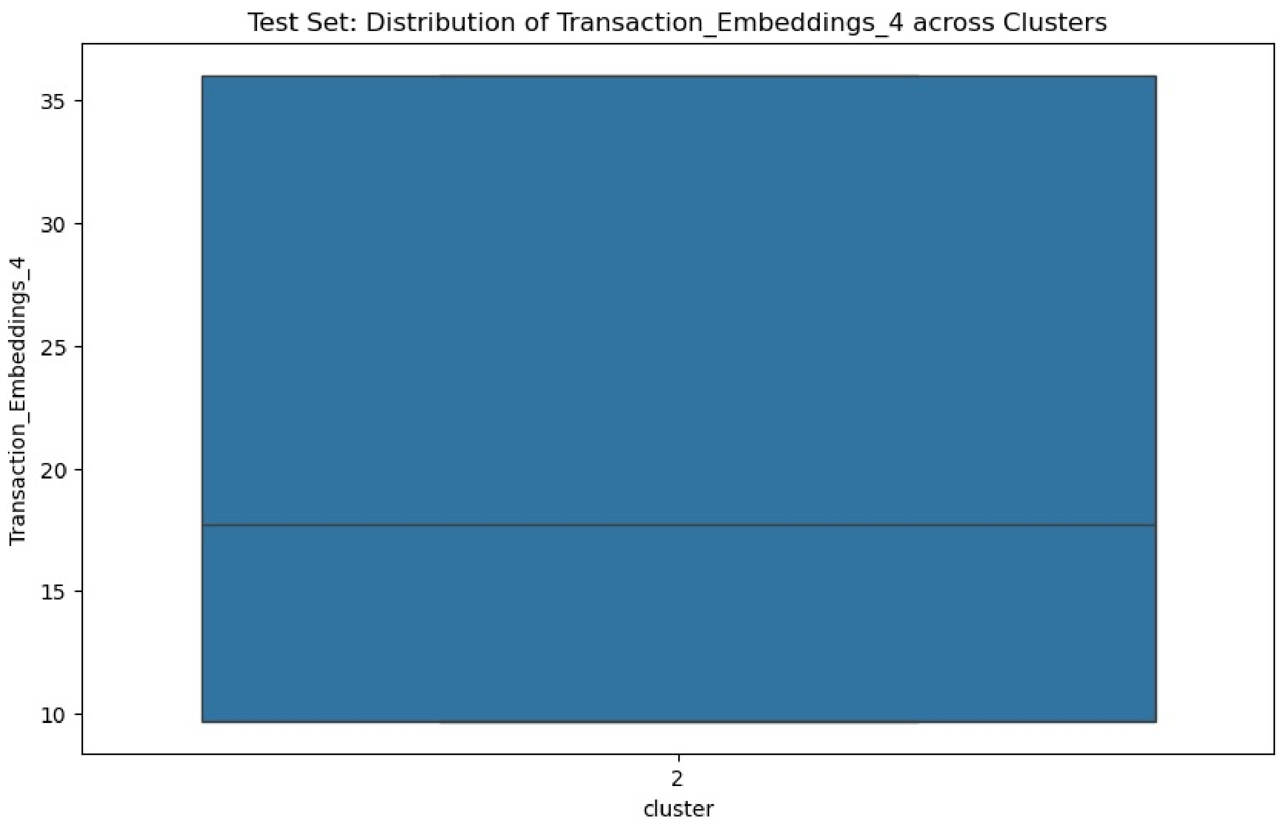


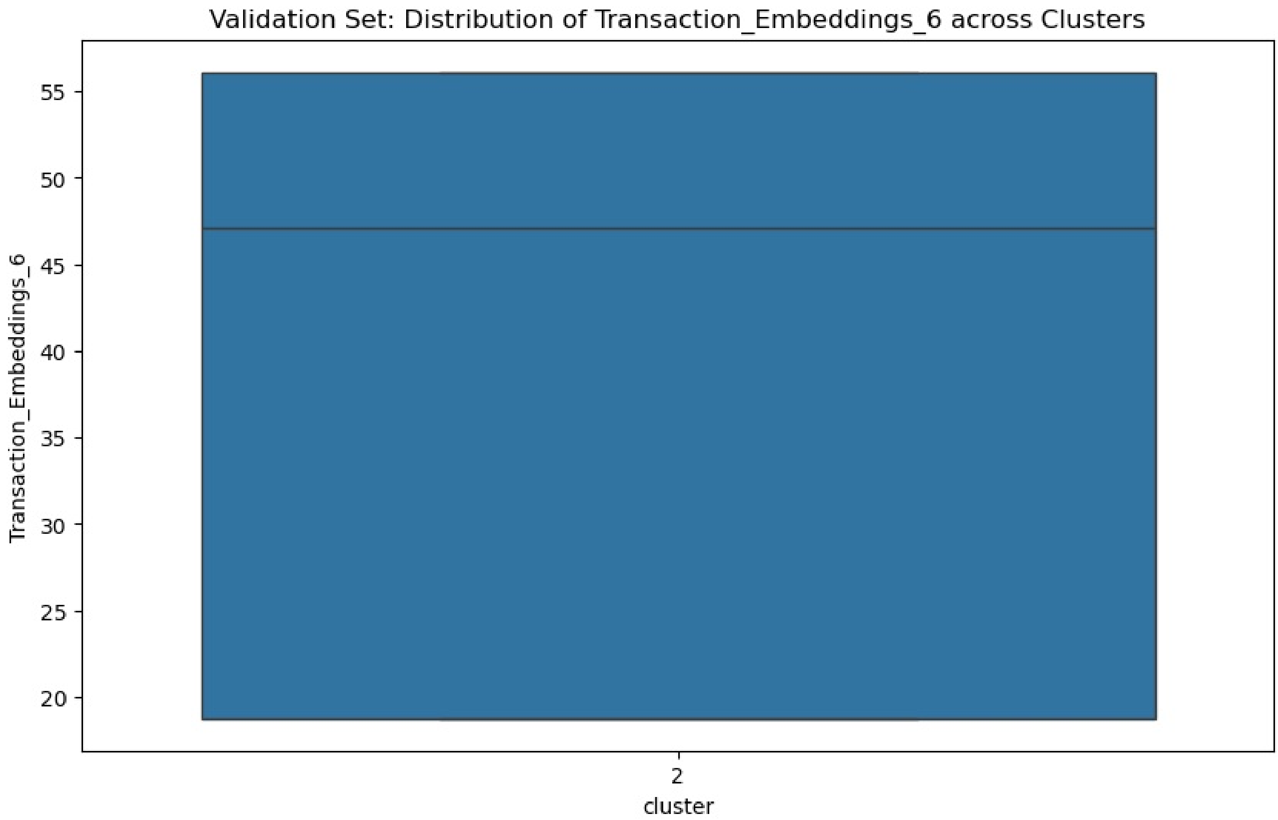
Validation Set: Distribution of Hour_Group_Embeddings_1 across Clusters
−5.0
−5.5
−6.0
−6.5
−7.0
−7.5
−8.0
Hour_Group_Embeddings_1
2
cluster

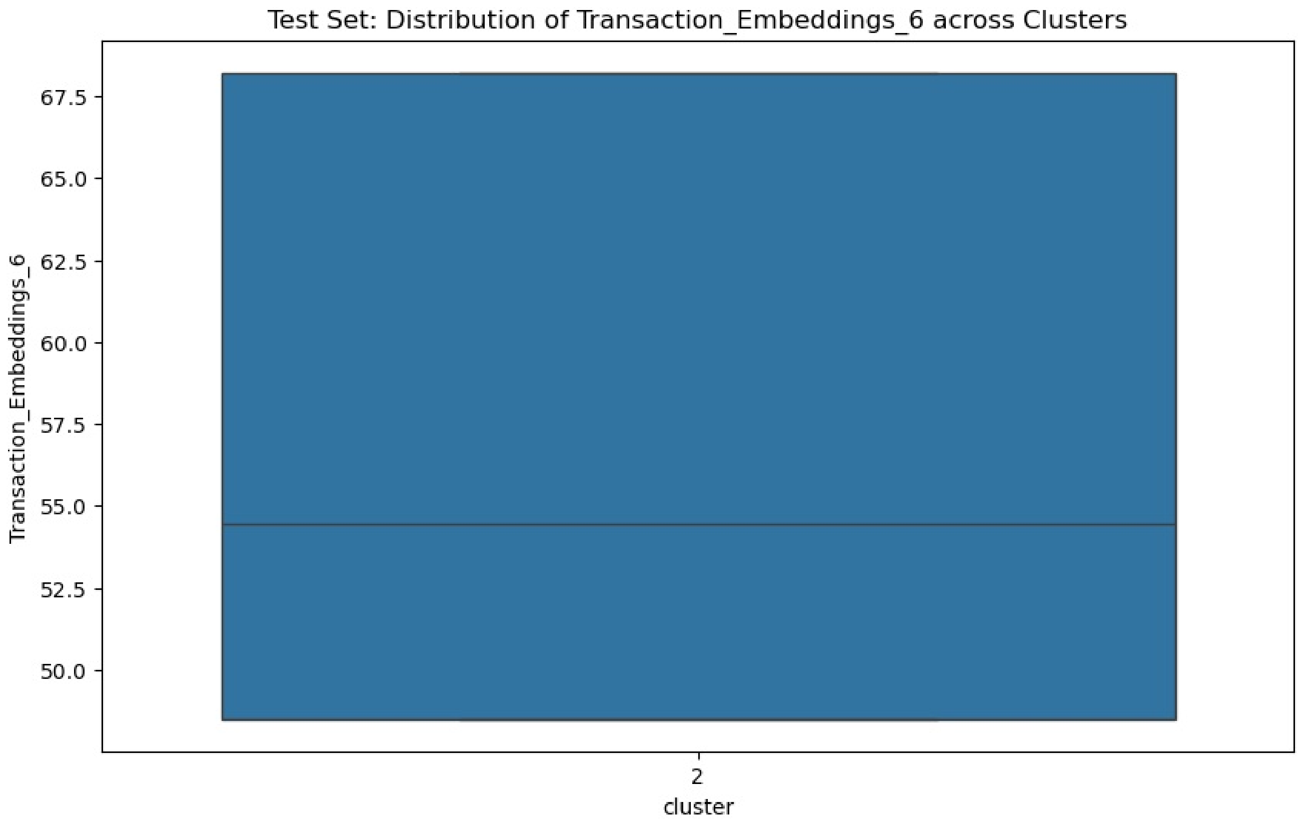


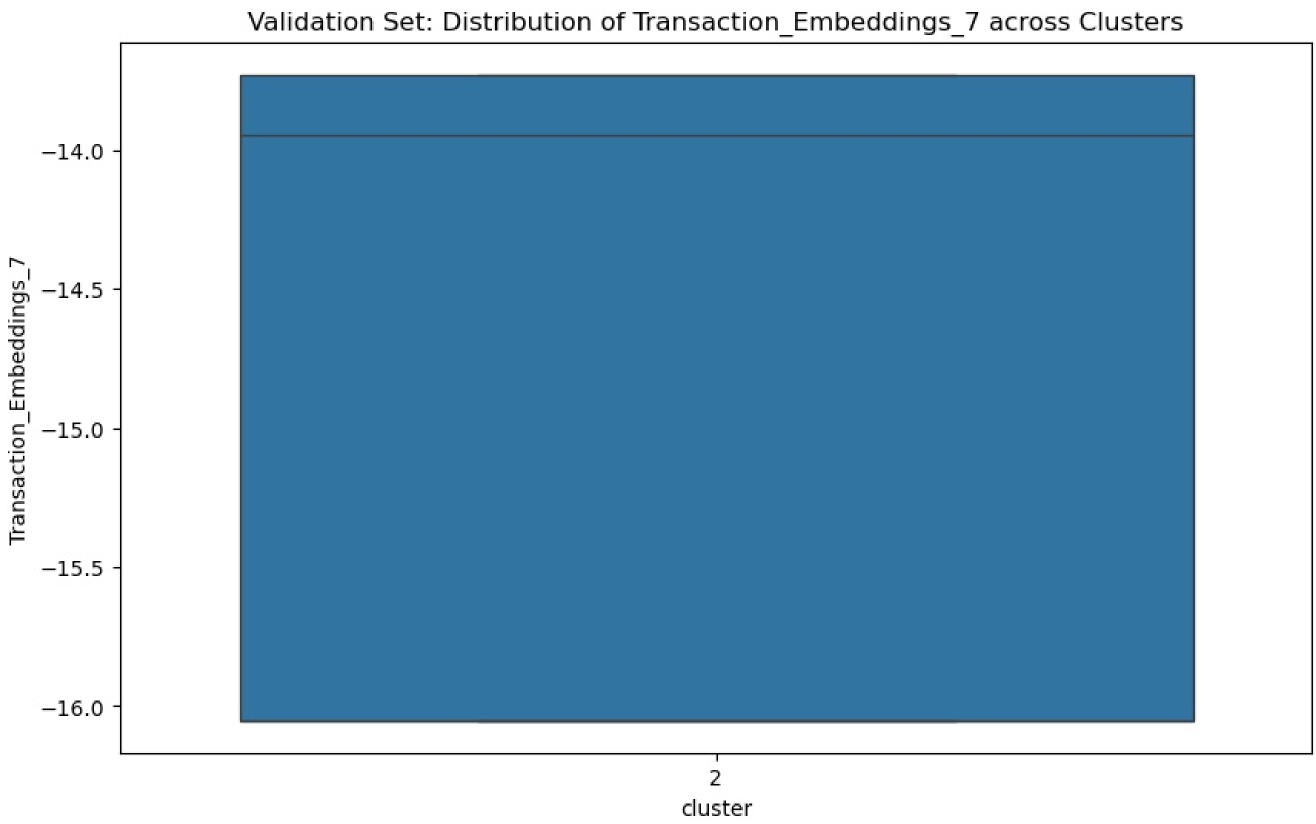
Test Set: Distribution of Hour_Group_Embeddings_1 across Clusters
−2.5
−3.0
−3.5
−4.0
−4.5
Hour_Group_Embeddings_1
2
cluster


Validation Set: Distribution of Transaction_Embeddings_4 across Clusters
Transaction_Embeddings_4
86
84
82
80
78
76
74
2
cluster

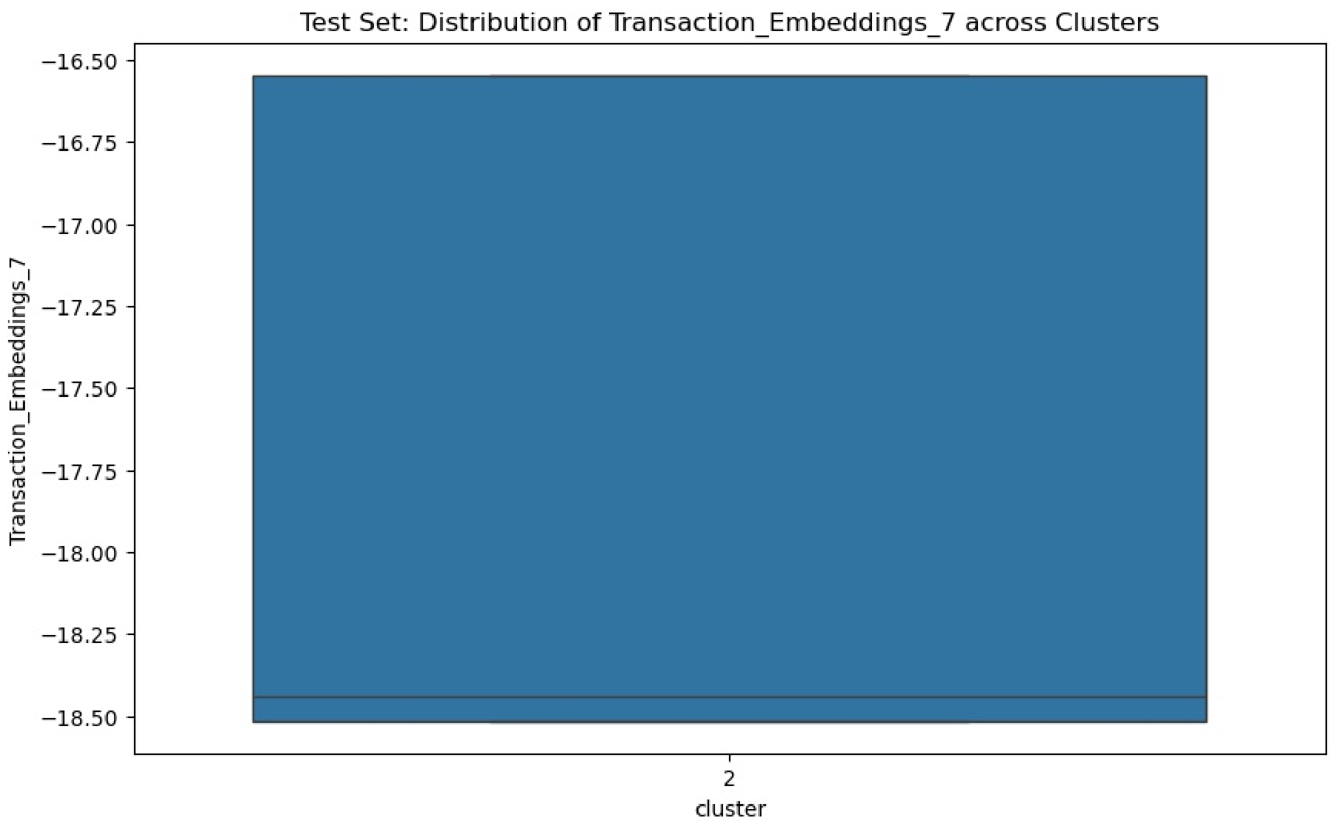

Test Set: Distribution of Transaction_Embeddings_4 across Clusters
Transaction_Embeddings_4
35
30
25
20
15
10
2
cluster


Validation Set: Distribution of Transaction_Embeddings_6 across Clusters
Transaction_Embeddings_6
55
50
45
40
35
30
25
20
2
cluster

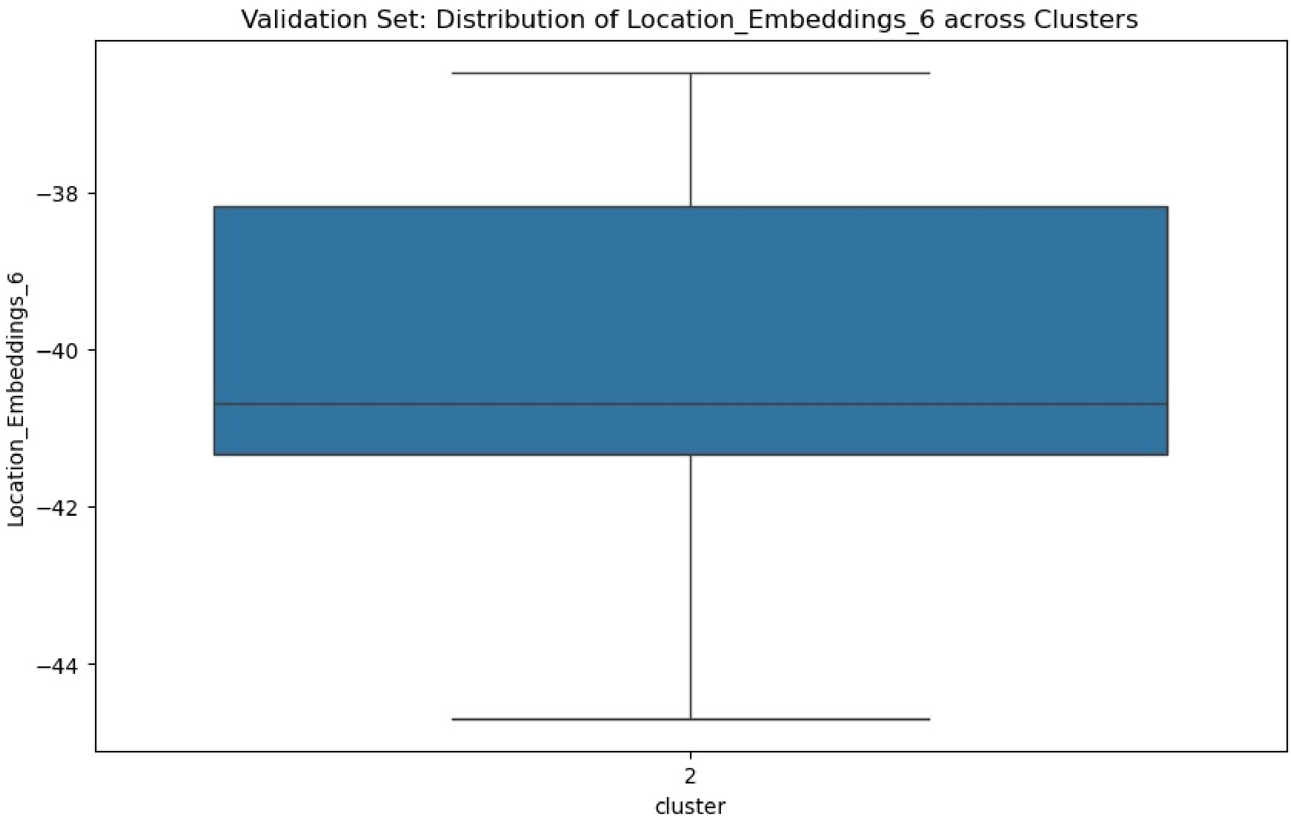

Test Set: Distribution of Transaction_Embeddings_6 across Clusters
Transaction_Embeddings_6
67.5
65.0
62.5
60.0
57.5
55.0
52.5
50.0
2
cluster



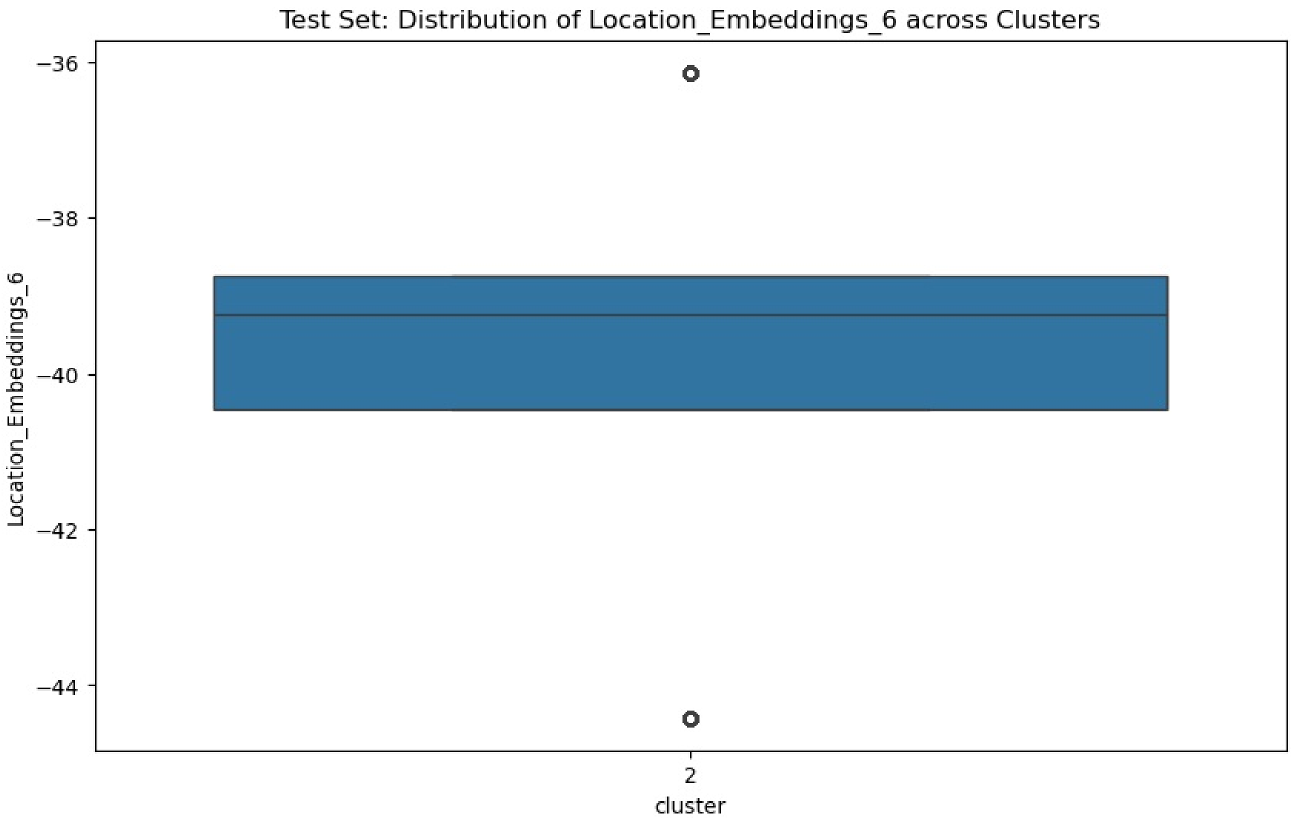
Validation Set: Distribution of Transaction_Embeddings_7 across Clusters
−14.0
−14.5
−15.0
−15.5
−16.0
Transaction_Embeddings_7
2
cluster



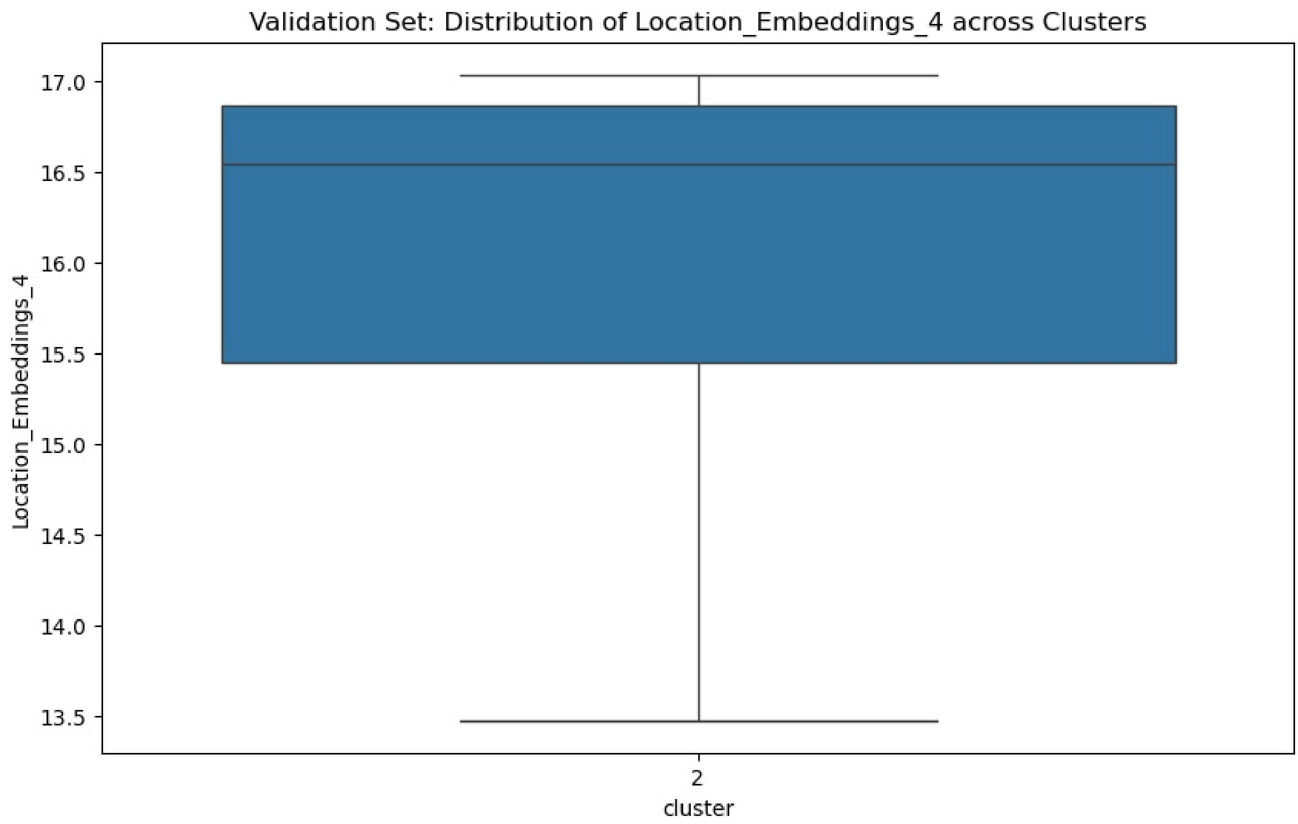
Test Set: Distribution of Transaction_Embeddings_7 across Clusters
−16.50
−16.75
−17.00
−17.25
−17.50
−17.75
−18.00
−18.25
−18.50
Transaction_Embeddings_7
2
cluster



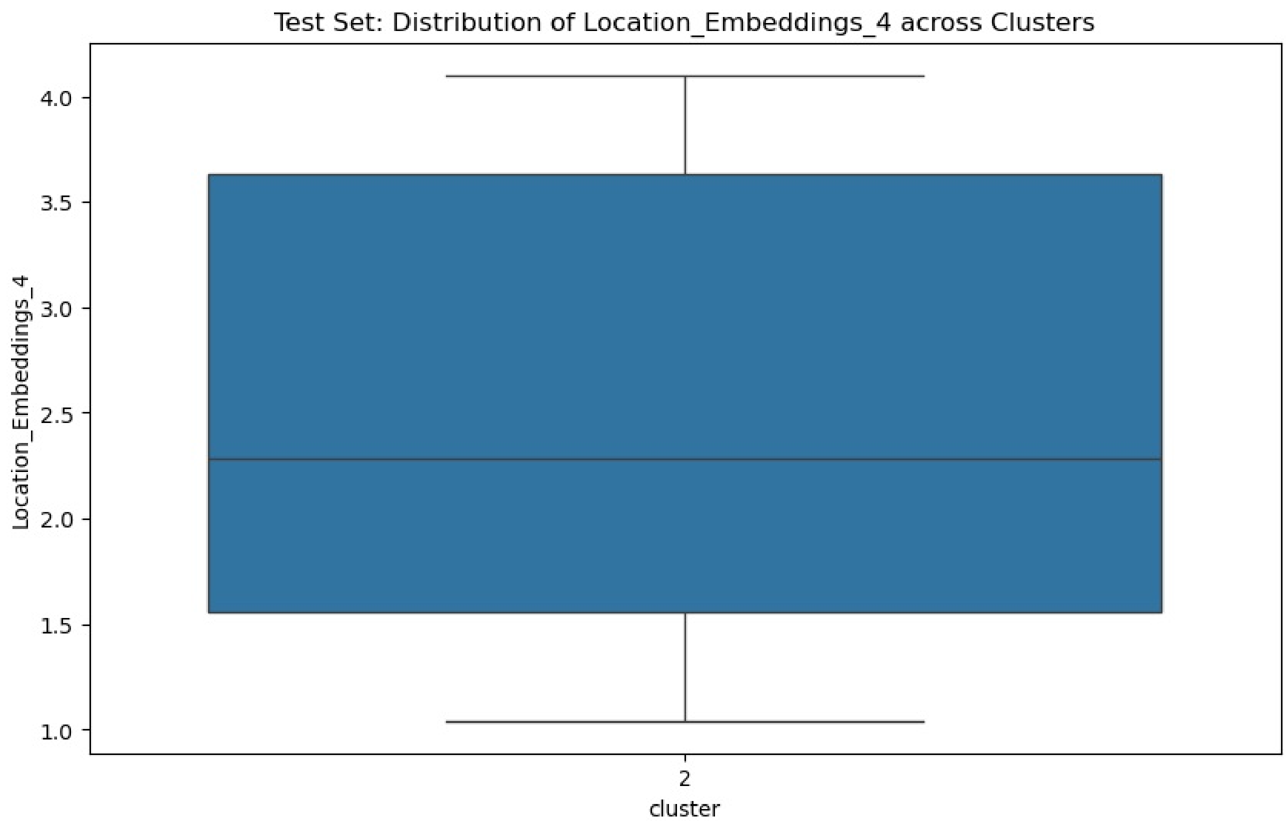
Validation Set: Distribution of Location_Embeddings_6 across Clusters
Location_Embeddings_6
−38
−40
−42
−44
2
cluster



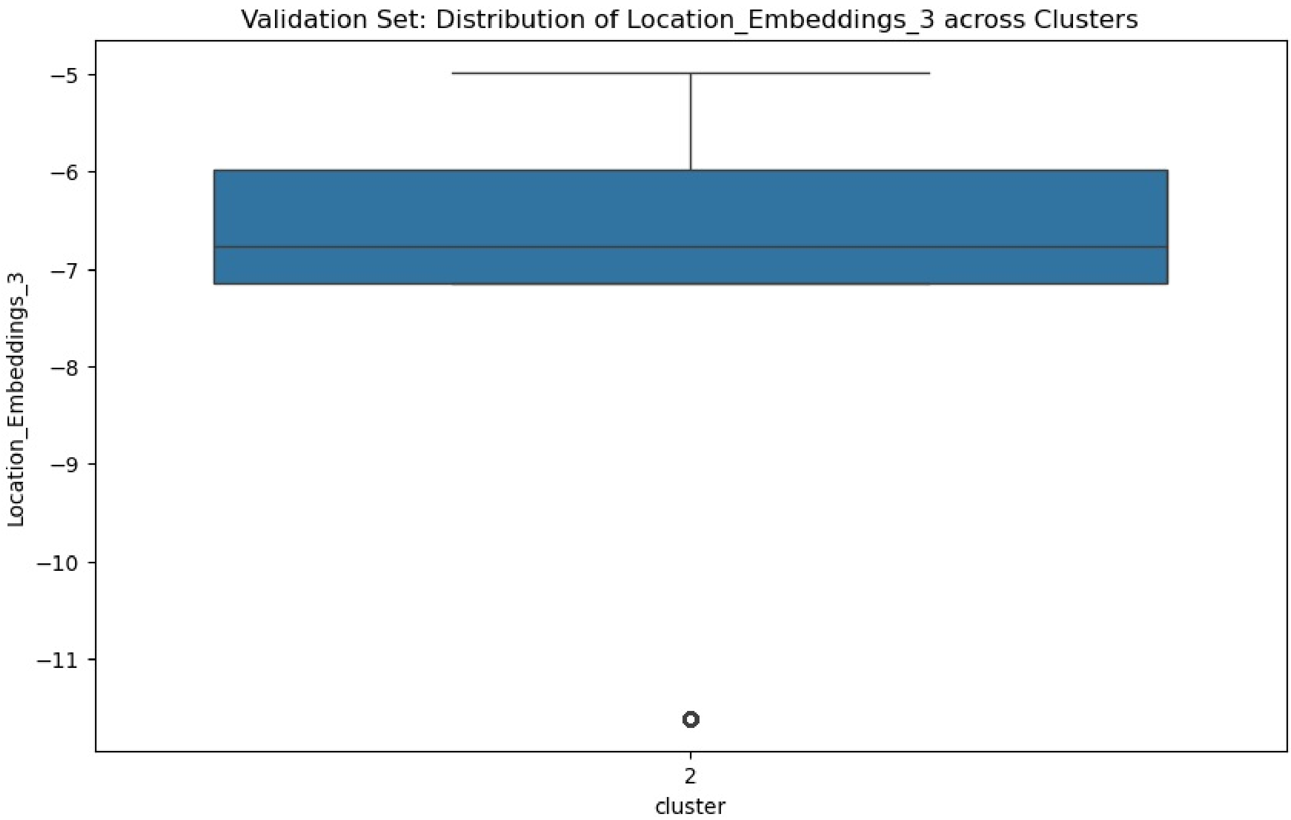
Test Set: Distribution of Location_Embeddings_6 across Clusters
Location_Embeddings_6
−36
−38
−40
−42
−44
2
cluster



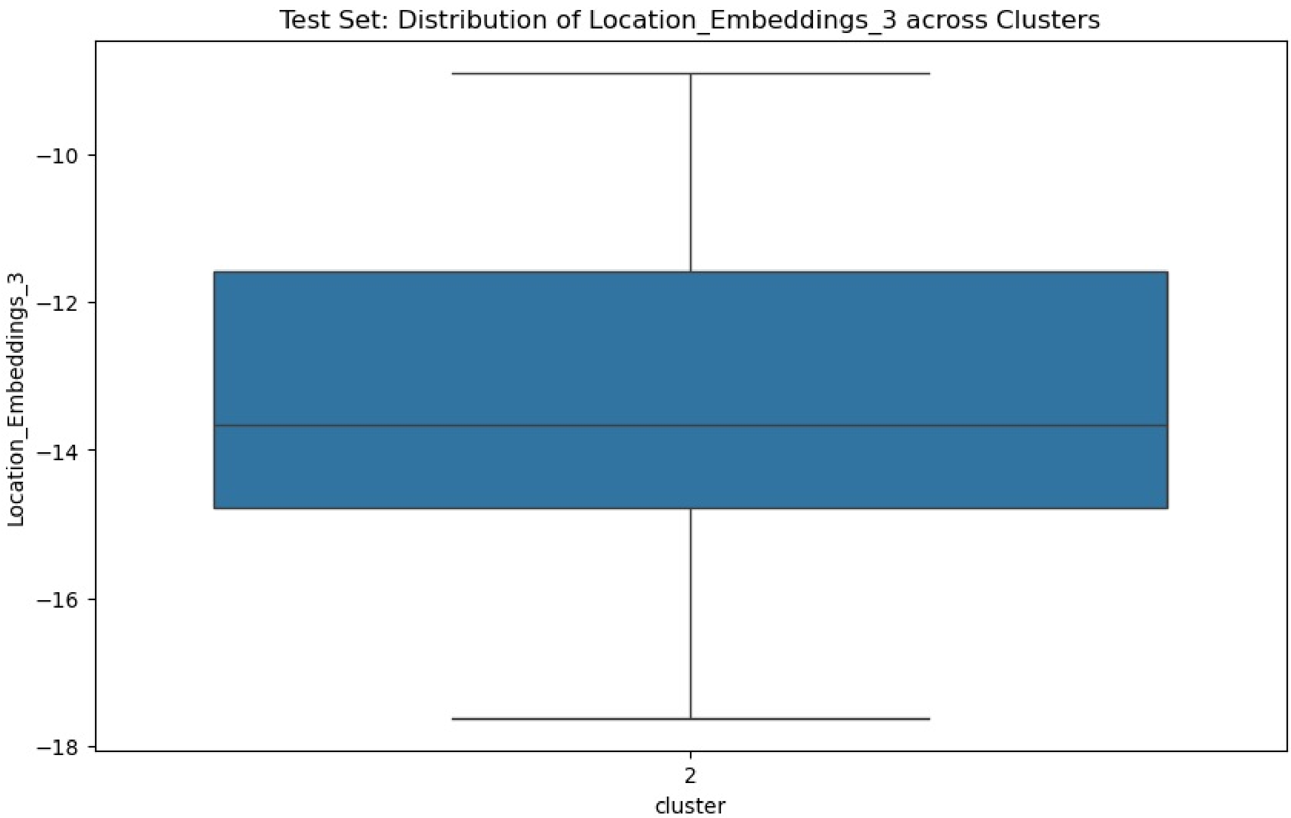
Validation Set: Distribution of Location_Embeddings_4 across Clusters
17.0
16.5
16.0
15.5
15.0
14.5
14.0
13.5
Location_Embeddings_4
2
cluster



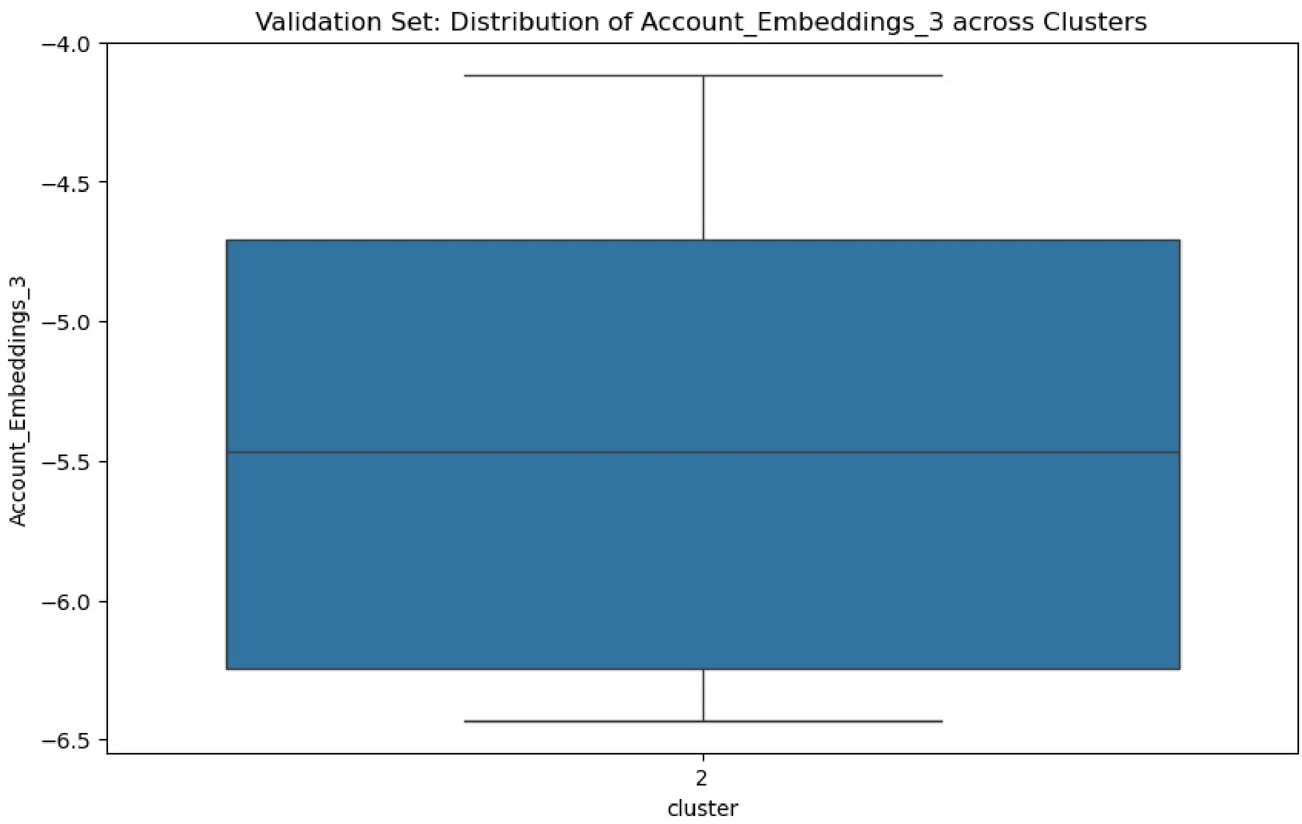
Test Set: Distribution of Location_Embeddings_4 across Clusters
4.0
3.5
3.0
2.5
2.0
1.5
1.0
Location_Embeddings_4
2
cluster

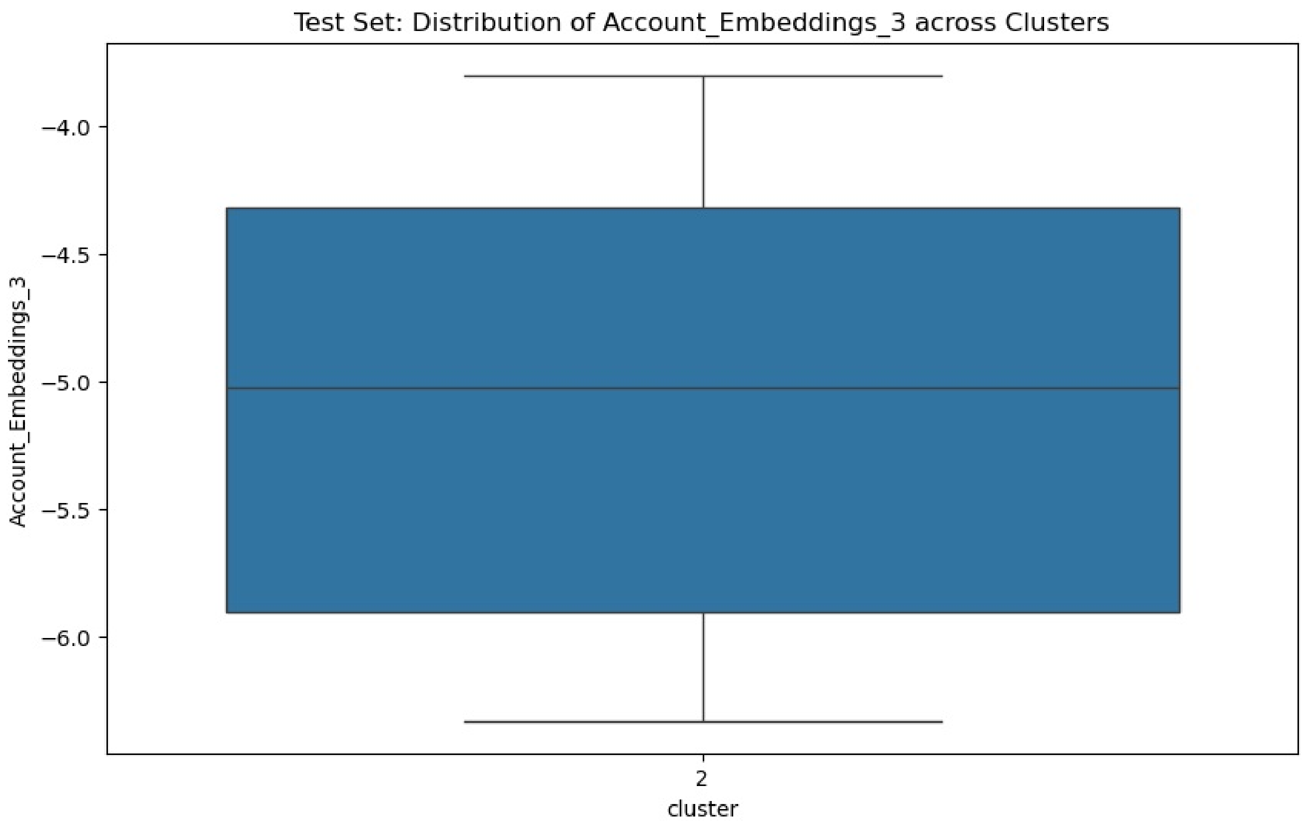


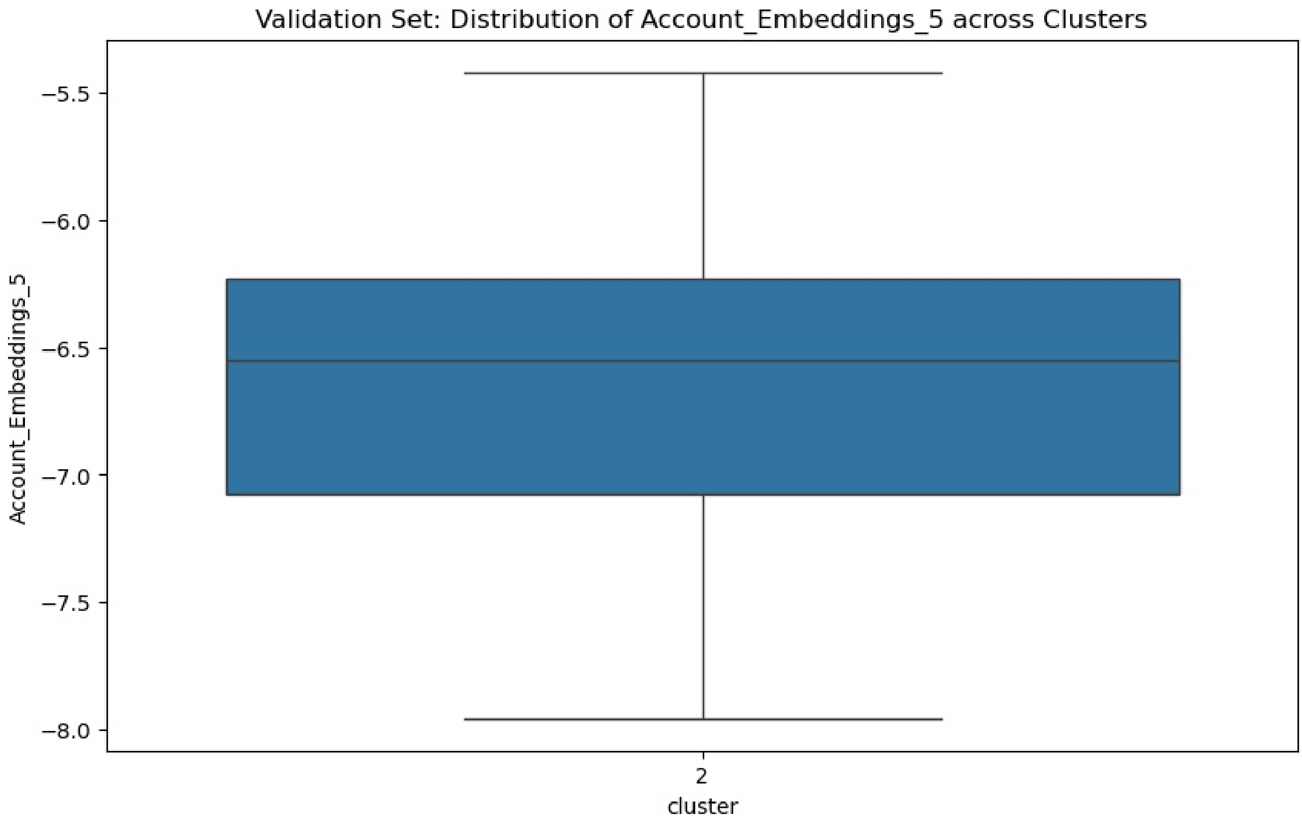
Validation Set: Distribution of Location_Embeddings_3 across Clusters
Location_Embeddings_3
−5
−6
−7
−8
−9
−10
−11
2
cluster

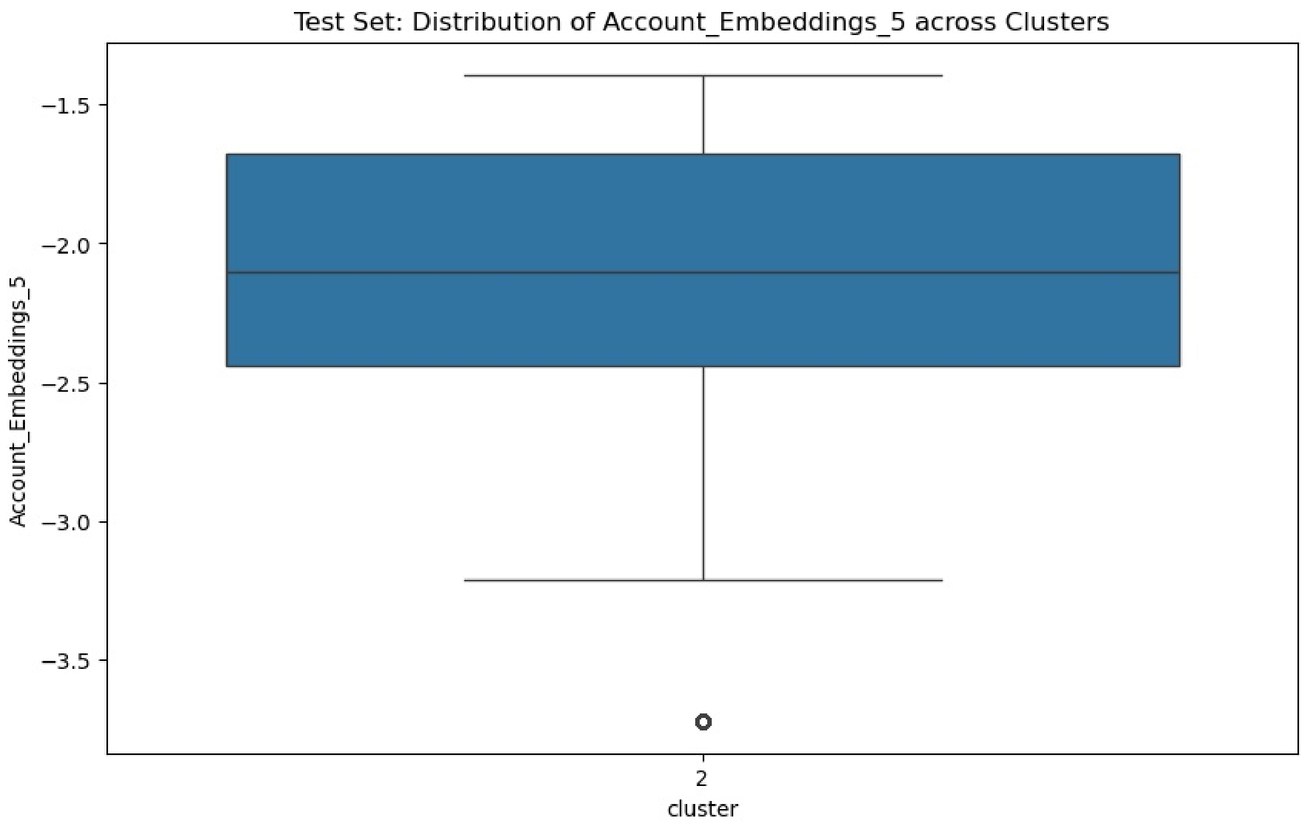


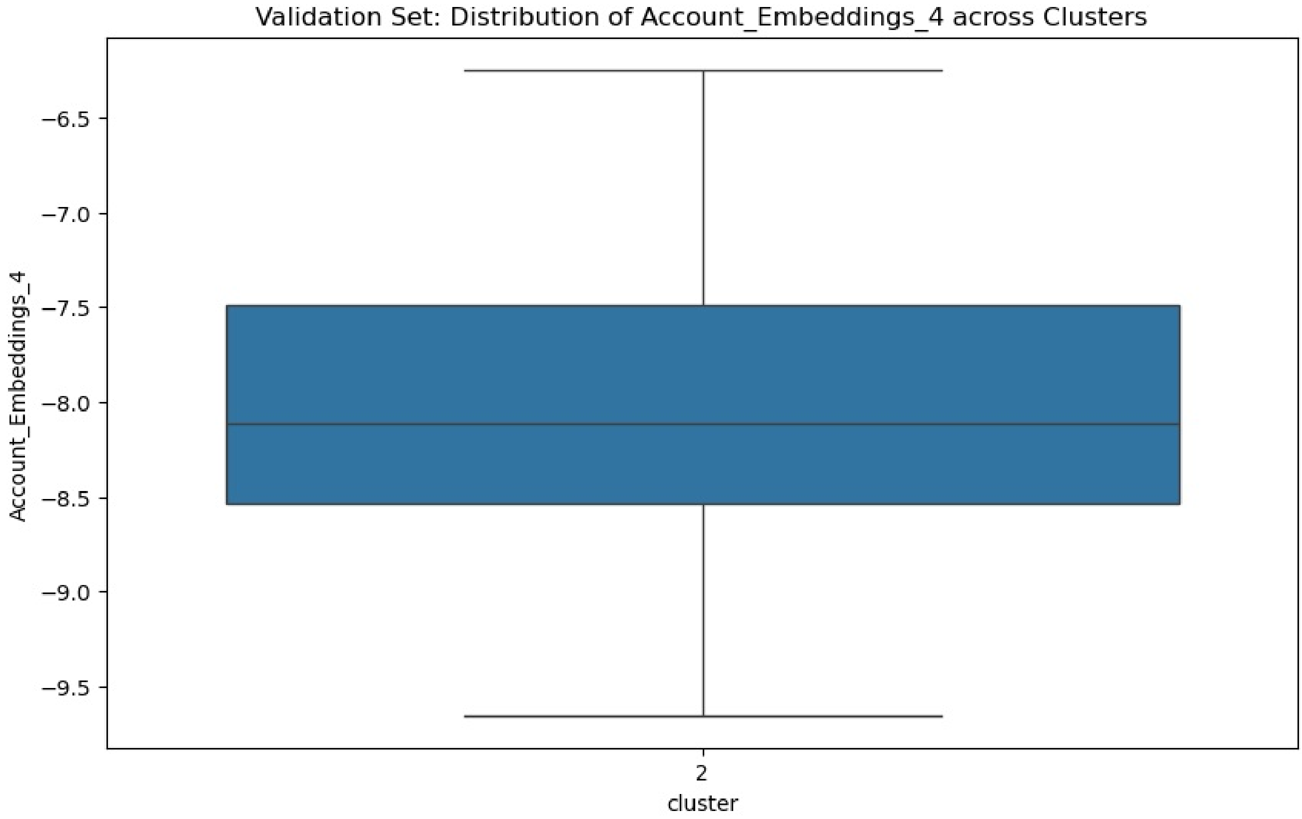
Test Set: Distribution of Location_Embeddings_3 across Clusters
Location_Embeddings_3
−10
−12
−14
−16
−18
2
cluster

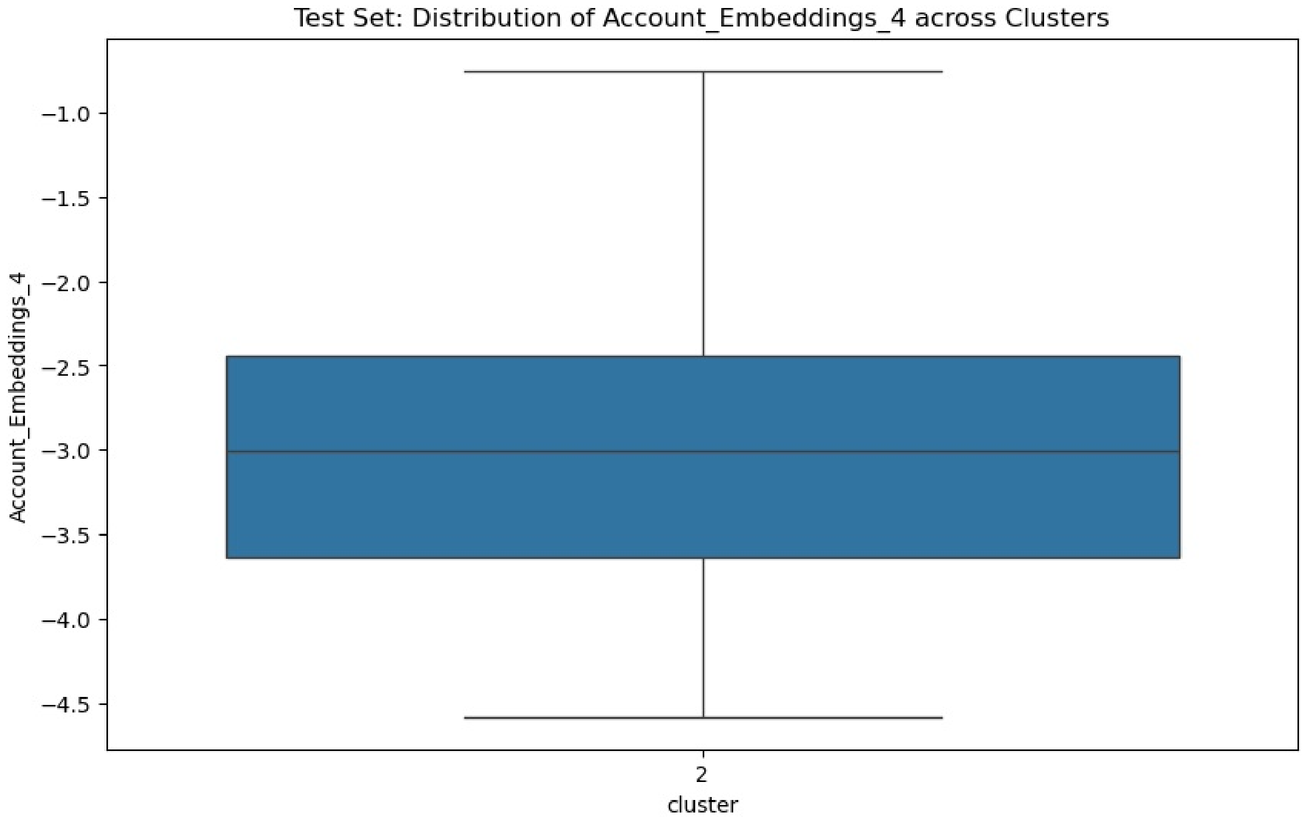

Validation Set: Distribution of Account_Embeddings_3 across Clusters
−4.0
−4.5
−5.0
−5.5
−6.0
−6.5
Account_Embeddings_3
2
cluster


Test Set: Distribution of Account_Embeddings_3 across Clusters
−4.0
−4.5
−5.0
−5.5
−6.0
Account_Embeddings_3
2
cluster


Validation Set: Distribution of Account_Embeddings_5 across Clusters
Account_Embeddings_5
−5.5
−6.0
−6.5
−7.0
−7.5
−8.0
2
cluster


Test Set: Distribution of Account_Embeddings_5 across Clusters
Account_Embeddings_5
−1.5
−2.0
−2.5
−3.0
−3.5
2
cluster





In [157…

```
# Save the train set
train_embeddings_df.to_csv('train_data.csv', index=False)

# Save the validation set
validation_embeddings_df.to_csv('validation_data.csv', index=False)

# Save the test set
test_embeddings_df.to_csv('test_data.csv', index=False)

print("DataFrames have been saved as CSV files.")
```

DataFrames have been saved as CSV files.

In [158…

```
# END WEEK 11
```

In [ ]:

```

```