Task2

September 28, 2024

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
import plotly.graph_objects as go
import plotly.offline as pyo
pyo.init_notebook_mode()
import duckdb
import warnings
warnings.filterwarnings("ignore")
```

1 Checking Data

[2]:
```
transactions = pd.read_csv('transactions_1.csv')
transactions
```

[2]:
```
        time            status  f0_
0     00h 00          approved    9
1     00h 00            denied    6
2     00h 00          refunded    1
3     00h 01            denied    8
4     00h 01          approved   13
…        …                 …   …
4229  23h 59        processing    4
4230  23h 59            denied    1
4231  23h 59  backend_reversed    5
4232  23h 59          approved   10
4233  23h 59          reversed    6

[4234 rows x 3 columns]
```

[3]:
```
transactions2 = pd.read_csv('transactions_2.csv')
transactions2
```

[3]:
```
        time            status  count
0     00h 00          reversed      7
1     00h 00          approved      9
```

```
2      00h 00        processing     12
3      00h 00            denied      3
4      00h 00  backend_reversed      2
…         …                 …      …
3939   23h 57            denied     11
3940   23h 58            denied      4
3941   23h 58          approved     35
3942   23h 59            denied     10
3943   23h 59          approved     38

[3944 rows x 3 columns]
```

2 Checking for Problems in Data

[4]:
```
print('_ % NaNs  __ First FIle ______')
for col in transactions.columns:
    pct = transactions[f'{col}'].isnull().sum() * 100 / len(transactions.index)
    print(f'{col} - {pct}%')
print('\n_ % NaNs  __ Second FIle ______')
for col in transactions2.columns:
    pct = transactions2[f'{col}'].isnull().sum() * 100 / len(transactions2.
 ↪index)
    print(f'{col} - {pct}%')
```

```
_ % NaNs  __ First FIle ______
time - 0.0%
status - 0.0%
f0_ - 0.0%

_ % NaNs  __ Second FIle ______
time - 0.0%
status - 0.0%
count - 0.0%
```

[5]:
```
print('_ % Zeros  __ First File ______')
for col in transactions.columns:
    pct = len(transactions[transactions[f'{col}']==0].index) * 100 /␣
 ↪len(transactions.index)
    print(f'{col} - {pct}%')
print('\n_ % Zeros  __ Second File ______')
for col in transactions2.columns:
    pct = len(transactions2[transactions2[f'{col}']==0].index) * 100 /␣
 ↪len(transactions2.index)
    print(f'{col} - {pct}%')
```

```
_ % Zeros  __ First File ______
time - 0.0%
```

```
status - 0.0%
f0_ - 0.0%

_ % Zeros  __ Second File ______
time - 0.0%
status - 0.0%
count - 0.0%
```

[6]:

```
print('_ % Duplicates Row Wise __ First FIle ______')
for col in transactions.columns:
    non_duplicates = len(transactions.drop_duplicates(keep='first').index)
    duplicates = len(transactions.index) - non_duplicates
    pct = duplicates * 100 / len(transactions.index)
    print(f'{col} - {pct}%')

print('\n_ % Duplicates Row Wise __ Second FIle ______')
for col in transactions2.columns:
    non_duplicates = len(transactions2.drop_duplicates(keep='first').index)
    duplicates = len(transactions2.index) - non_duplicates
    pct = duplicates * 100 / len(transactions2.index)
    print(f'{col} - {pct}%')
```

```
_ % Duplicates Row Wise __ First FIle ______
time - 0.0%
status - 0.0%
f0_ - 0.0%

_ % Duplicates Row Wise __ Second FIle ______
time - 0.0%
status - 0.0%
count - 0.0%
```

[7]:

```
print('_ % Duplicates Column Wise __ First FIle ______')
for col in transactions.columns:
    non_duplicates = len(transactions.drop_duplicates(col, keep='first').index)
    duplicates = len(transactions.index) - non_duplicates
    pct = duplicates * 100 / len(transactions.index)
    print(f'{col} - {pct}%')

print('\n_ % Duplicates Column Wise __ Second FIle ______')
for col in transactions2.columns:
    non_duplicates = len(transactions2.drop_duplicates(col, keep='first').index)
    duplicates = len(transactions2.index) - non_duplicates
    pct = duplicates * 100 / len(transactions2.index)
    print(f'{col} - {pct}%')
```

```
_ % Duplicates Column Wise __ First FIle ______
time - 68.77657061880019%
status - 99.83467170524327%
```

```
f0_ - 90.3873405762872%

_ % Duplicates Column Wise __ Second FIle ______
time - 66.55679513184585%
status - 99.82251521298174%
count - 88.56490872210954%
```

3 Analysing Data Similarity

3.1 Transforming and preparing data

[8]:
```
transactions.rename(columns={'f0_':'count'}, inplace=True)
```

[9]:
```
transactions = transactions.pivot_table(['count'],'time','status').
 ↪droplevel(0,axis=1)
transactions.columns =␣
 ↪['approved','backend_reversed','denied','failed','processing','refunded','reversed']
transactions.fillna(0, inplace=True)
```

[10]:
```
transactions2 = transactions2.pivot_table(['count'],'time','status').
 ↪droplevel(0,axis=1)
transactions2.columns =␣
 ↪['approved','backend_reversed','denied','failed','processing','refunded','reversed']
transactions2.fillna(0, inplace=True)
```

[11]:
```
transactions
```

[11]:
```
         approved  backend_reversed  denied  failed  processing  refunded  \
time
00h 00        9.0               0.0     6.0     0.0         0.0       1.0
00h 01       13.0               0.0     8.0     0.0         0.0       0.0
00h 02       11.0               0.0     7.0     0.0         0.0       1.0
00h 03       12.0               0.0     3.0     0.0         0.0       0.0
00h 04       11.0               0.0     0.0     0.0         0.0       0.0
…             …                 …       …       …         …           …
23h 55       32.0               0.0     4.0     0.0         0.0       0.0
23h 56       30.0               0.0     3.0     0.0         0.0       0.0
23h 57       21.0               0.0     4.0     0.0         0.0       0.0
23h 58       11.0               4.0     3.0     0.0         3.0       1.0
23h 59       10.0               5.0     1.0     0.0         4.0       0.0

         reversed
time
00h 00        0.0
00h 01        0.0
00h 02        0.0
00h 03        0.0
```

```
00h 04       0.0
…           …
23h 55       0.0
23h 56       0.0
23h 57       1.0
23h 58       2.0
23h 59       6.0

[1322 rows x 7 columns]
```

[12]:
```python
transactions.iloc[800:1000]
```

[12]:
```
        approved  backend_reversed  denied  failed  processing  refunded  \
time
14h 40      17.0               4.0     2.0     0.0         8.0       0.0
14h 41     248.0               1.0    62.0     0.0         7.0       2.0
14h 42     434.0               3.0    87.0     0.0         0.0      13.0
14h 43     782.0               7.0    98.0     0.0         0.0      11.0
14h 44     305.0               6.0    54.0     1.0        14.0       1.0
…           …                …      …      …        …          …
18h 20     227.0              14.0    40.0     0.0         3.0       4.0
18h 22      49.0               5.0    14.0     0.0         3.0       2.0
18h 23     100.0              10.0    16.0     0.0         3.0       3.0
18h 24     306.0              11.0    60.0     0.0         0.0       5.0
18h 25      28.0               4.0     5.0     0.0         1.0       1.0

        reversed
time
14h 40      31.0
14h 41     180.0
14h 42     193.0
14h 43     109.0
14h 44      82.0
…           …
18h 20     101.0
18h 22      18.0
18h 23      35.0
18h 24     103.0
18h 25       7.0

[200 rows x 7 columns]
```

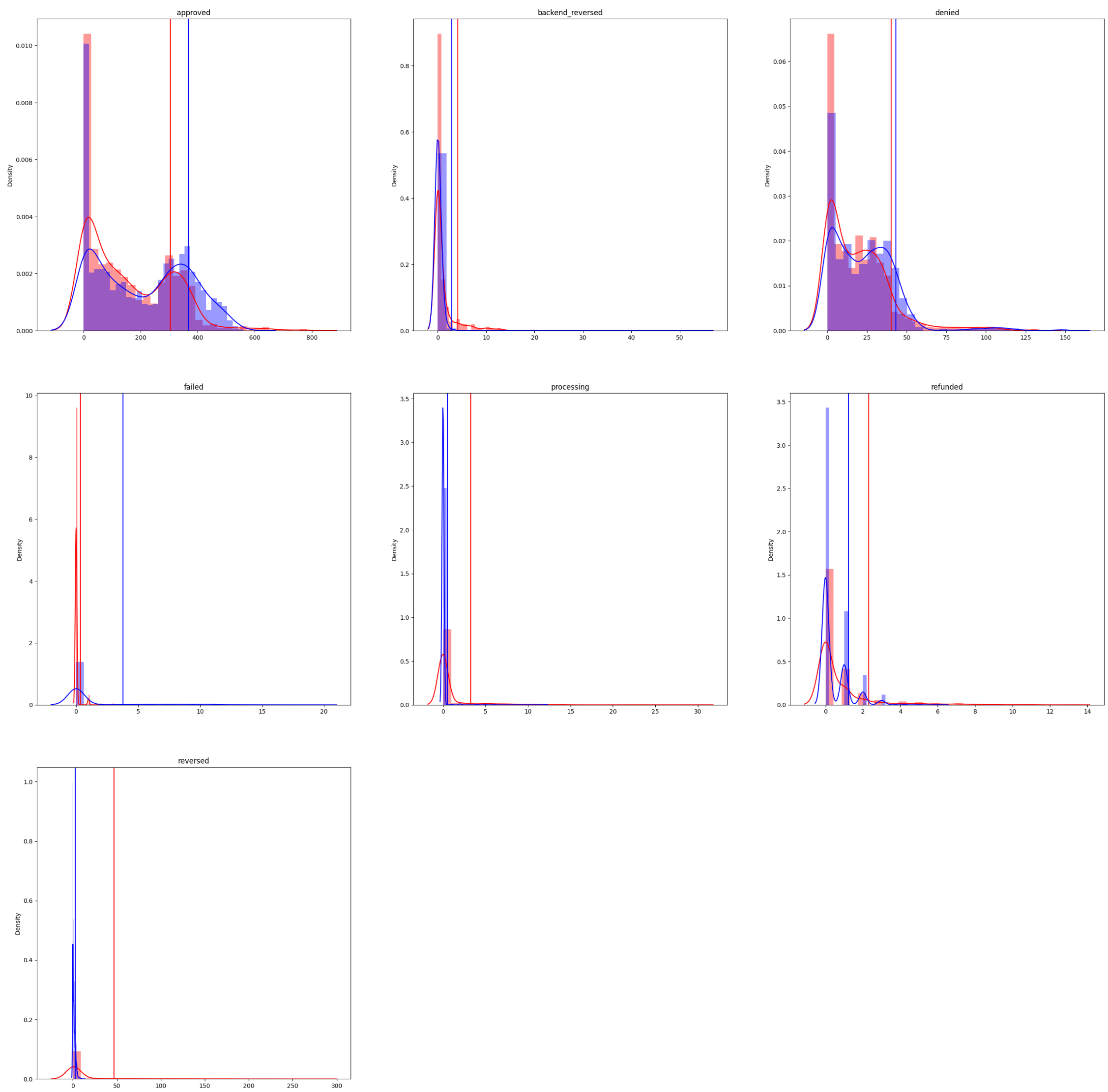
3.2 Kolmogorov–Smirnov test

[13]:
```
from scipy.stats import ks_2samp



for status in transactions.columns:
    first_sample = transactions[status]
    second_sample = transactions2[status]




    print(status, '\t',ks_2samp(first_sample, second_sample)[1], '\t\t\t',␣
 ↪ks_2samp(first_sample, second_sample)[1]>0.05)
```

```
approved         2.749048125448754e-13                        False
backend_reversed         2.8130173420842248e-27                        False
denied    6.314987236267669e-07                        False
failed    1.3325827491135293e-07                        False
processing       8.998373686853123e-10                        False
refunded         0.042507094695754 56                        False
reversed         5.186332038015167e-12                        False
```

3.3 Distributions per Status

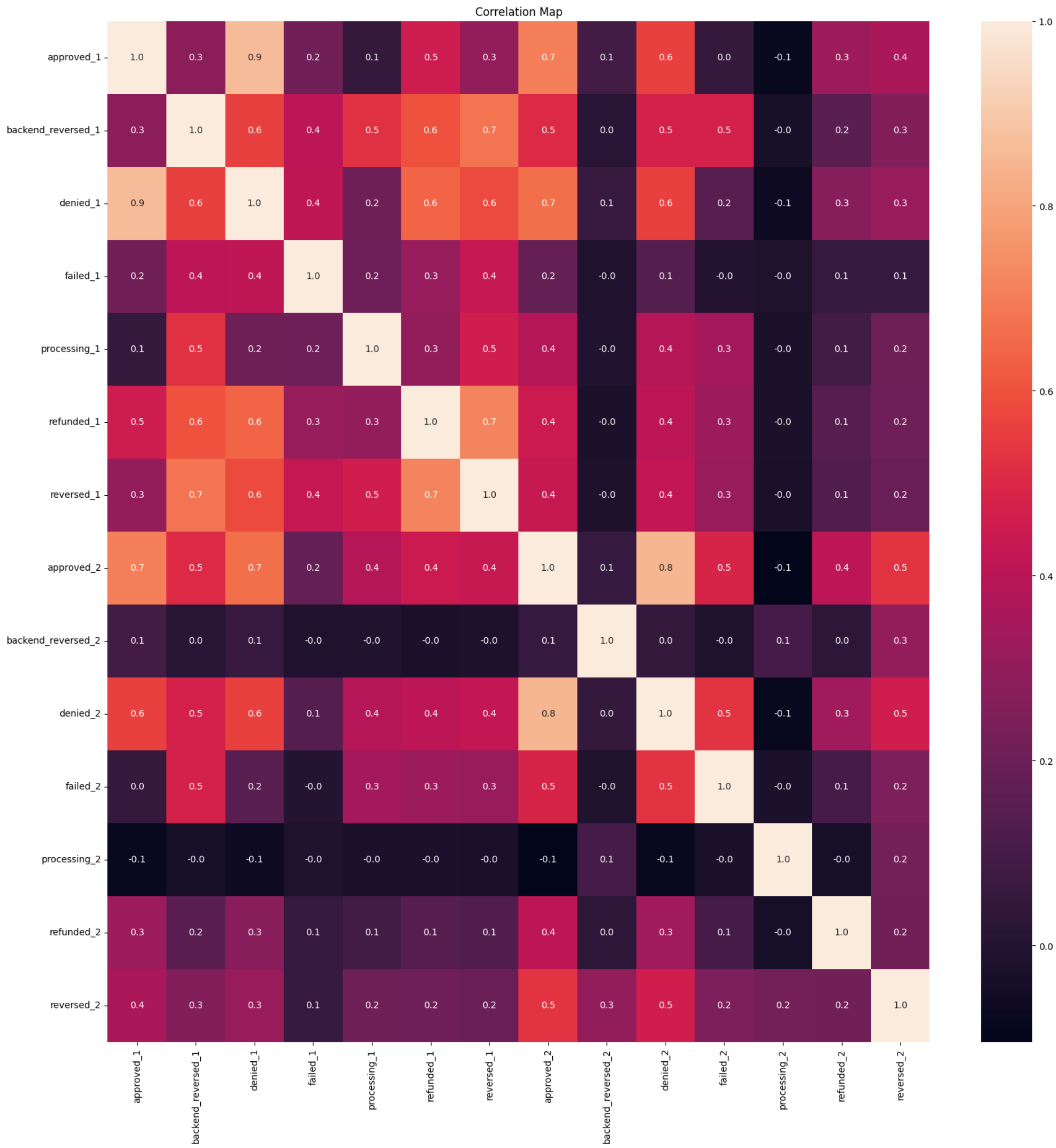
[14]:
```
fig = plt.figure(figsize=(32,32))
fig.subplots_adjust(hspace=0.2, wspace=0.2)

for i, status in enumerate(transactions.columns):

    ax = fig.add_subplot(3, 3, i+1)

    first_sample = transactions[status]
    second_sample = transactions2[status]


    sns.distplot(x=first_sample, kde=True, bins=30, ax=ax, color='red')
    ax.axvline(np.mean(first_sample) + np.std(first_sample), color='red')
    sns.distplot(x=second_sample, kde=True, bins=30, ax=ax, color='blue')
    ax.axvline(np.mean(second_sample) + np.std(second_sample), color='blue')

    ax.set_title(str(status))


plt.show()
```



3.4 Correlation

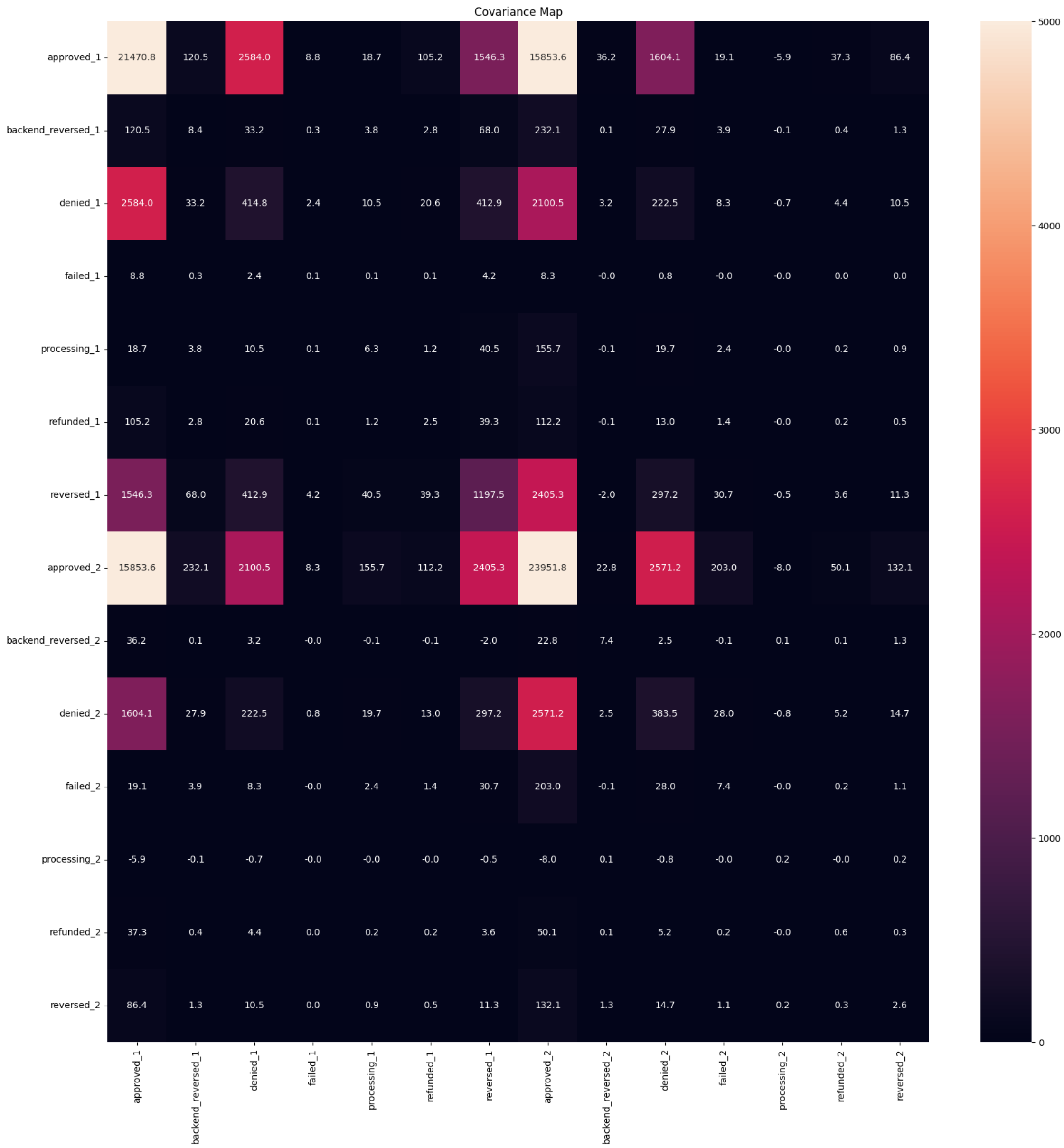
[15]:
```
fig = plt.figure(figsize=(20,20))
corr_df = pd.merge(transactions, transactions2, how='left', on='time',␣
↪suffixes=['_1','_2'])
sns.heatmap(corr_df.corr(), annot=True, fmt='.1f')
plt.title('Correlation Map')
```

[15]:
```
Text(0.5, 1.0, 'Correlation Map')
```



[16]:
```
fig = plt.figure(figsize=(20,20))
corr_df = pd.merge(transactions, transactions2, how='left', on='time',␣
 ↪suffixes=['_1','_2'])
sns.heatmap(corr_df.cov(), annot=True, fmt='.1f', vmin=0, vmax=5*10**3)
plt.title('Covariance Map')
```

[16]: Text(0.5, 1.0, 'Covariance Map')



Considering our context with **the first task**, and what we have analyzed, I think it is fair to assume these are from the same context and POS

Reasons to believe so:

- High correlations between approved 1 and 2, denied 1 and approved 2... basically high correlations between main data features
- High covariance between Approved sales
- With the context that other status are failures or anomalies, it makes sense that there will be divergences between these features
- Similar distributions even though the Kolmogorov test failed, with variances probably being normal and/or explainable

4 Data Augmentation

We will be adding various feature engineering columns to better pronounce the anomalies in the data, but first we will do some necessary basic transformations.

[17]:
```
transactions = pd.concat([transactions.sort_index(ascending=True),␣
 ↪transactions2.sort_index(ascending=True)])
duckdb.query('''
SELECT * FROM transactions
''')
```

[17]:

approved	backend_reversed	denied	failed	processing	refunded	reversed
double	double	double	double	double	double	double
9.0	0.0	6.0	0.0	0.0	1.0	0.0
13.0	0.0	8.0	0.0	0.0	0.0	0.0
11.0	0.0	7.0	0.0	0.0	1.0	0.0
12.0	0.0	3.0	0.0	0.0	0.0	0.0
11.0	0.0	0.0	0.0	0.0	0.0	0.0
9.0	0.0	2.0	0.0	0.0	0.0	0.0
9.0	0.0	2.0	0.0	0.0	0.0	0.0
11.0	0.0	1.0	0.0	0.0	0.0	1.0
7.0	0.0	2.0	0.0	0.0	0.0	0.0
9.0	0.0	0.0	0.0	0.0	0.0	0.0
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
33.0	0.0	11.0	0.0	0.0	0.0	1.0
41.0	0.0	8.0	0.0	0.0	0.0	

```
0.0
      43.0                0.0      9.0      0.0          0.0         0.0
0.0
      33.0                0.0      7.0      0.0          0.0         1.0
0.0
      39.0                0.0      4.0      0.0          0.0         1.0
0.0
      31.0                0.0      8.0      0.0          0.0         0.0
0.0
      34.0                0.0      8.0      0.0          0.0         0.0
0.0
      40.0                0.0     11.0      0.0          0.0         0.0
0.0
      35.0                0.0      4.0      0.0          0.0         0.0
0.0
      38.0                0.0     10.0      0.0          0.0         0.0
0.0


 2641 rows (20 shown)                                                       7
columns
```

```
[18]: transactions.index = pd.to_datetime(transactions.index, format='%Hh %M').
      ↪strftime('%H:%M')
```

```
[19]: transactions = transactions.reset_index()
      transactions['hour'] = pd.to_datetime(transactions.time).dt.hour
```

4.0.1 Creating boolean columns for each hour

This is a demonstration, it will be added after we have added and evaluated our other new features

```
[20]: pd.get_dummies(transactions,columns=['hour'])
```

```
[20]:        time  approved  backend_reversed  denied  failed  processing  refunded  \
      0      00:00       9.0               0.0     6.0     0.0         0.0       1.0
      1      00:01      13.0               0.0     8.0     0.0         0.0       0.0
      2      00:02      11.0               0.0     7.0     0.0         0.0       1.0
      3      00:03      12.0               0.0     3.0     0.0         0.0       0.0
      4      00:04      11.0               0.0     0.0     0.0         0.0       0.0
      …      …       …                 …      …      …        …        …
      2636   23:55      31.0               0.0     8.0     0.0         0.0       0.0
      2637   23:56      34.0               0.0     8.0     0.0         0.0       0.0
      2638   23:57      40.0               0.0    11.0     0.0         0.0       0.0
      2639   23:58      35.0               0.0     4.0     0.0         0.0       0.0
      2640   23:59      38.0               0.0    10.0     0.0         0.0       0.0
```

```
      reversed  hour_0  hour_1  …  hour_14  hour_15  hour_16  hour_17  \
0          0.0    True   False  …    False    False    False    False
1          0.0    True   False  …    False    False    False    False
2          0.0    True   False  …    False    False    False    False
3          0.0    True   False  …    False    False    False    False
4          0.0    True   False  …    False    False    False    False
…          …       …       …    …     …        …        …
2636       0.0   False   False  …    False    False    False    False
2637       0.0   False   False  …    False    False    False    False
2638       0.0   False   False  …    False    False    False    False
2639       0.0   False   False  …    False    False    False    False
2640       0.0   False   False  …    False    False    False    False

      hour_18  hour_19  hour_20  hour_21  hour_22  hour_23
0       False    False    False    False    False    False
1       False    False    False    False    False    False
2       False    False    False    False    False    False
3       False    False    False    False    False    False
4       False    False    False    False    False    False
…       …       …       …       …       …       …
2636    False    False    False    False    False     True
2637    False    False    False    False    False     True
2638    False    False    False    False    False     True
2639    False    False    False    False    False     True
2640    False    False    False    False    False     True

[2641 rows x 32 columns]
```

Denied and *Approved* transactions are very strongly correlated. With this, we can create a Linear Regression model to predict the denied transactions based on the approved ones. If the model makes a prediction of denials, and the reality is too far from the prediction, it should be considered anomalous. The distance will be calculated by the square difference between prediction and reality

[21]:
```python
from sklearn.linear_model import LinearRegression

epsilon = 0.001 # number to avoid infinity in divisions by 0

roll_window = 15 # window for rolling calculations

transactions['total'] = (transactions.approved
                         + transactions.backend_reversed
                         + transactions.denied
                         + transactions.failed
                         + transactions.processing
                         + transactions.refunded
                         + transactions.reversed
```

```
                         )

transactions['denied_approved'] = (transactions.denied / (transactions.
 ↪approved+epsilon)*100)
transactions['denied_pct'] = (transactions.denied / (transactions.total))*100

transactions['reversed_approved'] =  (transactions.reversed / (transactions.
 ↪approved+epsilon))*100
transactions['reversed_pct'] = (transactions.reversed / (transactions.
 ↪total))*100

transactions['failed_approved'] =  (transactions.failed / (transactions.
 ↪approved+epsilon))*100
transactions['failed_pct'] = (transactions.failed / (transactions.total))*100

transactions['processing_approved'] =  (transactions.processing / (transactions.
 ↪approved+epsilon))*100
transactions['processing_pct'] = (transactions.processing / (transactions.
 ↪total))*100

transactions['refunded_approved'] =  (transactions.refunded / (transactions.
 ↪approved+epsilon))*100
transactions['refunded_pct'] = (transactions.refunded / (transactions.
 ↪total))*100

transactions['backend_reversed_approved'] =  (transactions.backend_reversed /␣
 ↪(transactions.approved+epsilon))*100
transactions['backend_reversed_pct'] = (transactions.backend_reversed /␣
 ↪(transactions.total))*100


transactions['denied_sqr'] = transactions.denied**2
transactions['reversed_sqr'] = transactions.reversed**2
transactions['failed_sqr'] = transactions.failed**2
transactions['processing_sqr'] = transactions.processing**2
transactions['refunded_sqr'] = transactions.refunded**2
transactions['backend_reversed_sqr'] = transactions.backend_reversed**2


transactions['denied_sqroot'] = transactions.denied**0.5
transactions['reversed_sqroot'] = transactions.reversed**0.5
transactions['failed_sqroot'] = transactions.failed**0.5
transactions['processing_sqroot'] = transactions.processing**0.5
transactions['refunded_sqroot'] = transactions.refunded**0.5
transactions['backend_reversed_sqroot'] = transactions.backend_reversed**0.5
```

```
transactions['denied_approved_roll30_corr'] = transactions.denied.
 ↪rolling(roll_window).corr(transactions.approved)
transactions['reversed_approved_roll30_corr'] = transactions.reversed.
 ↪rolling(roll_window).corr(transactions.approved)
transactions['failed_approved_roll30_corr'] = transactions.failed.
 ↪rolling(roll_window).corr(transactions.approved)
transactions['processing_approved_roll30_corr'] = transactions.processing.
 ↪rolling(roll_window).corr(transactions.approved)
transactions['refunded_approved_roll30_corr'] = transactions.refunded.
 ↪rolling(roll_window).corr(transactions.approved)
transactions['backend_reversed_approved_roll30_corr'] = transactions.
 ↪backend_reversed.rolling(roll_window).corr(transactions.approved)


transactions['denied_roll30_cumsum'] = transactions.denied.rolling(roll_window).
 ↪sum()
transactions['reversed_roll30_cumsum'] = transactions.reversed.
 ↪rolling(roll_window).sum()
transactions['failed_roll30_cumsum'] = transactions.failed.rolling(roll_window).
 ↪sum()
transactions['processing_roll30_cumsum'] = transactions.processing.
 ↪rolling(roll_window).sum()
transactions['refunded_roll30_cumsum'] = transactions.refunded.
 ↪rolling(roll_window).sum()
transactions['backend_reversed_roll30_cumsum'] = transactions.backend_reversed.
 ↪rolling(roll_window).sum()


transactions['denied_roll30_avg'] = transactions.denied.rolling(roll_window).
 ↪mean()
transactions['reversed_roll30_avg'] = transactions.reversed.
 ↪rolling(roll_window).mean()
transactions['failed_roll30_avg'] = transactions.failed.rolling(roll_window).
 ↪mean()
transactions['processing_roll30_avg'] = transactions.processing.
 ↪rolling(roll_window).mean()
transactions['refunded_roll30_avg'] = transactions.refunded.
 ↪rolling(roll_window).mean()
transactions['backend_reversed_roll30_avg'] = transactions.backend_reversed.
 ↪rolling(roll_window).mean()

transactions['denied_roll30_min'] = transactions.denied.rolling(roll_window).
 ↪min()
transactions['reversed_roll30_min'] = transactions.reversed.
 ↪rolling(roll_window).min()
```

```
transactions['failed_roll30_min'] = transactions.failed.rolling(roll_window).
  ↪mean()
transactions['processing_roll30_min'] = transactions.processing.
  ↪rolling(roll_window).min()
transactions['refunded_roll30_min'] = transactions.refunded.
  ↪rolling(roll_window).min()
transactions['backend_reversed_roll30_min'] = transactions.backend_reversed.
  ↪rolling(roll_window).min()

transactions['denied_roll30_max'] = transactions.denied.rolling(roll_window).
  ↪max()
transactions['reversed_roll30_max'] = transactions.reversed.
  ↪rolling(roll_window).max()
transactions['failed_roll30_max'] = transactions.failed.rolling(roll_window).
  ↪max()
transactions['processing_roll30_max'] = transactions.processing.
  ↪rolling(roll_window).max()
transactions['refunded_roll30_max'] = transactions.refunded.
  ↪rolling(roll_window).max()
transactions['backend_reversed_roll30_max'] = transactions.backend_reversed.
  ↪rolling(roll_window).max()

# For denied transactions, we will use linear regression to measure distance of␣
  ↪data point from hypothesis
X, y = np.array(transactions.approved).reshape(-1, 1), transactions.denied
linearR_denied = LinearRegression().fit(X,y)
score = linearR_denied.score(X,y)
print(f'Linear Regression score: {score}')
predicted_denied = linearR_denied.predict(X)

transactions['denied_sqr_distance'] = (transactions.denied -␣
  ↪predicted_denied)**2


transactions = transactions.replace(np.nan, 0)
```

```
Linear Regression score: 0.7303313244160479
```

4.0.2 Checking for NaNs post feature engineering

[22]:
```
print('\t\t____NaNs______\n')
for col in transactions.columns:
    pct = transactions[f'{col}'].isnull().sum() * 100 / len(transactions.index)
    print(f'{col} - {pct}%')
```

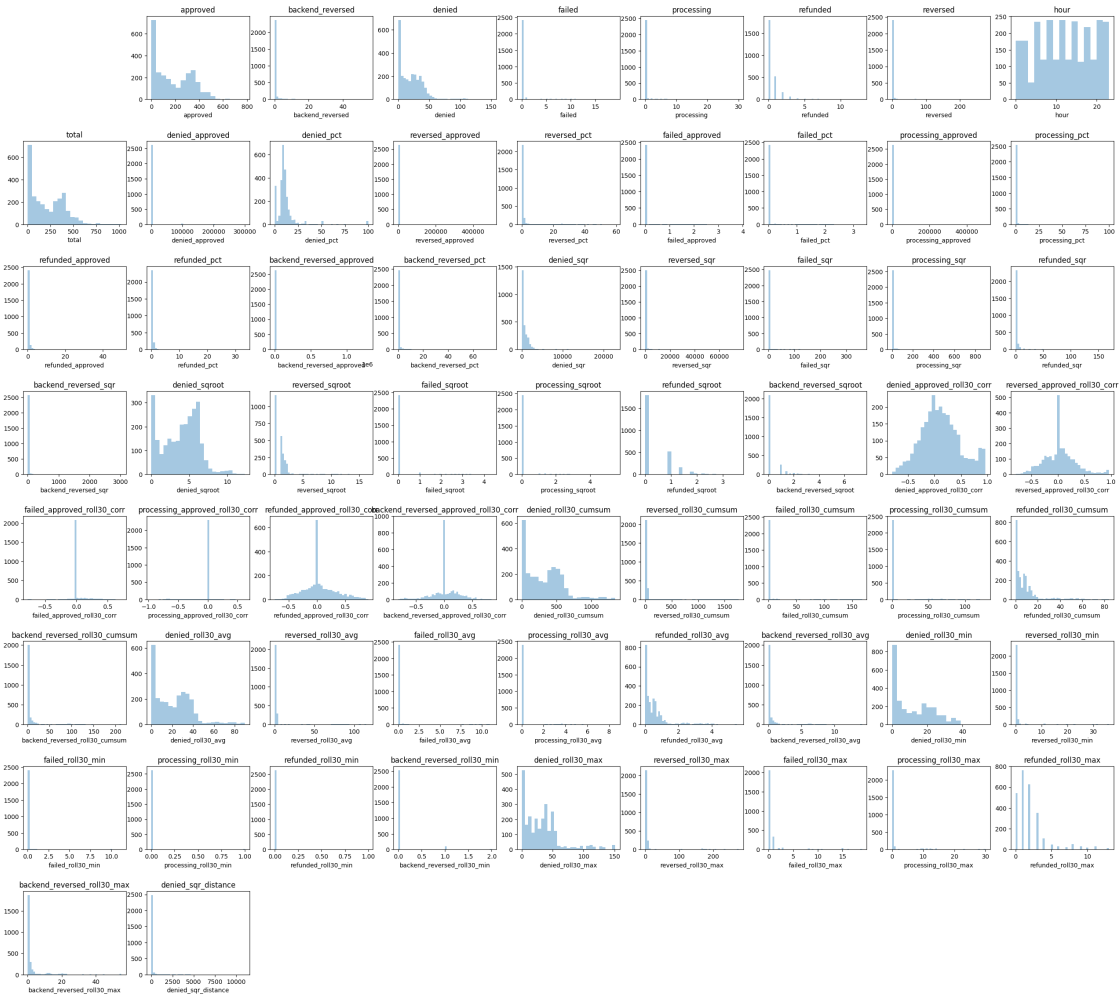
```
                ____NaNs______
```

```
time - 0.0%
approved - 0.0%
backend_reversed - 0.0%
denied - 0.0%
failed - 0.0%
processing - 0.0%
refunded - 0.0%
reversed - 0.0%
hour - 0.0%
total - 0.0%
denied_approved - 0.0%
denied_pct - 0.0%
reversed_approved - 0.0%
reversed_pct - 0.0%
failed_approved - 0.0%
failed_pct - 0.0%
processing_approved - 0.0%
processing_pct - 0.0%
refunded_approved - 0.0%
refunded_pct - 0.0%
backend_reversed_approved - 0.0%
backend_reversed_pct - 0.0%
denied_sqr - 0.0%
reversed_sqr - 0.0%
failed_sqr - 0.0%
processing_sqr - 0.0%
refunded_sqr - 0.0%
backend_reversed_sqr - 0.0%
denied_sqroot - 0.0%
reversed_sqroot - 0.0%
failed_sqroot - 0.0%
processing_sqroot - 0.0%
refunded_sqroot - 0.0%
backend_reversed_sqroot - 0.0%
denied_approved_roll30_corr - 0.0%
reversed_approved_roll30_corr - 0.0%
failed_approved_roll30_corr - 0.0%
processing_approved_roll30_corr - 0.0%
refunded_approved_roll30_corr - 0.0%
backend_reversed_approved_roll30_corr - 0.0%
denied_roll30_cumsum - 0.0%
reversed_roll30_cumsum - 0.0%
failed_roll30_cumsum - 0.0%
processing_roll30_cumsum - 0.0%
refunded_roll30_cumsum - 0.0%
backend_reversed_roll30_cumsum - 0.0%
denied_roll30_avg - 0.0%
reversed_roll30_avg - 0.0%
```

```
failed_roll30_avg - 0.0%
processing_roll30_avg - 0.0%
refunded_roll30_avg - 0.0%
backend_reversed_roll30_avg - 0.0%
denied_roll30_min - 0.0%
reversed_roll30_min - 0.0%
failed_roll30_min - 0.0%
processing_roll30_min - 0.0%
refunded_roll30_min - 0.0%
backend_reversed_roll30_min - 0.0%
denied_roll30_max - 0.0%
reversed_roll30_max - 0.0%
failed_roll30_max - 0.0%
processing_roll30_max - 0.0%
refunded_roll30_max - 0.0%
backend_reversed_roll30_max - 0.0%
denied_sqr_distance - 0.0%
```

4.0.3 Distribution of variables

[23]:
```
fig = plt.figure(figsize=(32,32))
fig.subplots_adjust(hspace=0.5, wspace=0.2)
for i, col in enumerate(transactions.columns):
    if col=='time':continue





    ax = fig.add_subplot(9, 9, i+1)
    sns.distplot(transactions[col], kde=False, ax=ax)

    ax.set_title(col)


plt.show()
```



4.0.4 Final Transformations

Transforming hours to numerical

[24]:
```
transactions['hour'] = transactions.time.str[:2]
transactions.hour
```

[24]:
```
0       00
1       00
2       00
3       00
4       00
        ..
2636    23
2637    23
2638    23
2639    23
```

```
2640    23
Name: hour, Length: 2641, dtype: object
```

[25]:
```python
transactions.drop('time', axis=1, inplace=True)
```

One Hot Encoder for each Hour

[26]:
```python
transactions = pd.get_dummies(transactions, 'hour', dtype=int)
transactions
```

[26]:
```
      approved  backend_reversed  denied  failed  processing  refunded  \
0          9.0               0.0     6.0     0.0         0.0       1.0
1         13.0               0.0     8.0     0.0         0.0       0.0
2         11.0               0.0     7.0     0.0         0.0       1.0
3         12.0               0.0     3.0     0.0         0.0       0.0
4         11.0               0.0     0.0     0.0         0.0       0.0
…         …                  …       …       …        …        …
2636      31.0               0.0     8.0     0.0         0.0       0.0
2637      34.0               0.0     8.0     0.0         0.0       0.0
2638      40.0               0.0    11.0     0.0         0.0       0.0
2639      35.0               0.0     4.0     0.0         0.0       0.0
2640      38.0               0.0    10.0     0.0         0.0       0.0

      reversed  total  denied_approved  denied_pct  …  hour_14  hour_15  \
0          0.0   16.0        66.659260   37.500000  …        0        0
1          0.0   21.0        61.533728   38.095238  …        0        0
2          0.0   19.0        63.630579   36.842105  …        0        0
3          0.0   15.0        24.997917   20.000000  …        0        0
4          0.0   11.0         0.000000    0.000000  …        0        0
…         …     …              …          …  …     …       …
2636       0.0   39.0        25.805619   20.512821  …        0        0
2637       0.0   42.0        23.528720   19.047619  …        0        0
2638       0.0   51.0        27.499313   21.568627  …        0        0
2639       0.0   39.0        11.428245   10.256410  …        0        0
2640       0.0   48.0        26.315097   20.833333  …        0        0

      hour_16  hour_17  hour_18  hour_19  hour_20  hour_21  hour_22  hour_23
0           0        0        0        0        0        0        0        0
1           0        0        0        0        0        0        0        0
2           0        0        0        0        0        0        0        0
3           0        0        0        0        0        0        0        0
4           0        0        0        0        0        0        0        0
…        …      …      …      …      …      …      …      …
2636        0        0        0        0        0        0        0        1
2637        0        0        0        0        0        0        0        1
2638        0        0        0        0        0        0        0        1
2639        0        0        0        0        0        0        0        1
2640        0        0        0        0        0        0        0        1
```

[2641 rows x 87 columns]

[27]:
```
transactions.columns
```

[27]:
```
Index(['approved', 'backend_reversed', 'denied', 'failed', 'processing',
       'refunded', 'reversed', 'total', 'denied_approved', 'denied_pct',
       'reversed_approved', 'reversed_pct', 'failed_approved', 'failed_pct',
       'processing_approved', 'processing_pct', 'refunded_approved',
       'refunded_pct', 'backend_reversed_approved', 'backend_reversed_pct',
       'denied_sqr', 'reversed_sqr', 'failed_sqr', 'processing_sqr',
       'refunded_sqr', 'backend_reversed_sqr', 'denied_sqroot',
       'reversed_sqroot', 'failed_sqroot', 'processing_sqroot',
       'refunded_sqroot', 'backend_reversed_sqroot',
       'denied_approved_roll30_corr', 'reversed_approved_roll30_corr',
       'failed_approved_roll30_corr', 'processing_approved_roll30_corr',
       'refunded_approved_roll30_corr',
       'backend_reversed_approved_roll30_corr', 'denied_roll30_cumsum',
       'reversed_roll30_cumsum', 'failed_roll30_cumsum',
       'processing_roll30_cumsum', 'refunded_roll30_cumsum',
       'backend_reversed_roll30_cumsum', 'denied_roll30_avg',
       'reversed_roll30_avg', 'failed_roll30_avg', 'processing_roll30_avg',
       'refunded_roll30_avg', 'backend_reversed_roll30_avg',
       'denied_roll30_min', 'reversed_roll30_min', 'failed_roll30_min',
       'processing_roll30_min', 'refunded_roll30_min',
       'backend_reversed_roll30_min', 'denied_roll30_max',
       'reversed_roll30_max', 'failed_roll30_max', 'processing_roll30_max',
       'refunded_roll30_max', 'backend_reversed_roll30_max',
       'denied_sqr_distance', 'hour_00', 'hour_01', 'hour_02', 'hour_03',
       'hour_04', 'hour_05', 'hour_06', 'hour_07', 'hour_08', 'hour_09',
       'hour_10', 'hour_11', 'hour_12', 'hour_13', 'hour_14', 'hour_15',
       'hour_16', 'hour_17', 'hour_18', 'hour_19', 'hour_20', 'hour_21',
       'hour_22', 'hour_23'],
      dtype='object')
```

[28]:
```
for col in transactions.columns:
    pct = transactions[f'{col}'].isnull().sum() * 100 / len(transactions.index)
    print(f'{col} - {pct}%')
```

```
approved - 0.0%
backend_reversed - 0.0%
denied - 0.0%
failed - 0.0%
processing - 0.0%
refunded - 0.0%
reversed - 0.0%
total - 0.0%
denied_approved - 0.0%
```

denied_pct - 0.0%
reversed_approved - 0.0%
reversed_pct - 0.0%
failed_approved - 0.0%
failed_pct - 0.0%
processing_approved - 0.0%
processing_pct - 0.0%
refunded_approved - 0.0%
refunded_pct - 0.0%
backend_reversed_approved - 0.0%
backend_reversed_pct - 0.0%
denied_sqr - 0.0%
reversed_sqr - 0.0%
failed_sqr - 0.0%
processing_sqr - 0.0%
refunded_sqr - 0.0%
backend_reversed_sqr - 0.0%
denied_sqroot - 0.0%
reversed_sqroot - 0.0%
failed_sqroot - 0.0%
processing_sqroot - 0.0%
refunded_sqroot - 0.0%
backend_reversed_sqroot - 0.0%
denied_approved_roll30_corr - 0.0%
reversed_approved_roll30_corr - 0.0%
failed_approved_roll30_corr - 0.0%
processing_approved_roll30_corr - 0.0%
refunded_approved_roll30_corr - 0.0%
backend_reversed_approved_roll30_corr - 0.0%
denied_roll30_cumsum - 0.0%
reversed_roll30_cumsum - 0.0%
failed_roll30_cumsum - 0.0%
processing_roll30_cumsum - 0.0%
refunded_roll30_cumsum - 0.0%
backend_reversed_roll30_cumsum - 0.0%
denied_roll30_avg - 0.0%
reversed_roll30_avg - 0.0%
failed_roll30_avg - 0.0%
processing_roll30_avg - 0.0%
refunded_roll30_avg - 0.0%
backend_reversed_roll30_avg - 0.0%
denied_roll30_min - 0.0%
reversed_roll30_min - 0.0%
failed_roll30_min - 0.0%
processing_roll30_min - 0.0%
refunded_roll30_min - 0.0%
backend_reversed_roll30_min - 0.0%
denied_roll30_max - 0.0%

```
reversed_roll30_max - 0.0%
failed_roll30_max - 0.0%
processing_roll30_max - 0.0%
refunded_roll30_max - 0.0%
backend_reversed_roll30_max - 0.0%
denied_sqr_distance - 0.0%
hour_00 - 0.0%
hour_01 - 0.0%
hour_02 - 0.0%
hour_03 - 0.0%
hour_04 - 0.0%
hour_05 - 0.0%
hour_06 - 0.0%
hour_07 - 0.0%
hour_08 - 0.0%
hour_09 - 0.0%
hour_10 - 0.0%
hour_11 - 0.0%
hour_12 - 0.0%
hour_13 - 0.0%
hour_14 - 0.0%
hour_15 - 0.0%
hour_16 - 0.0%
hour_17 - 0.0%
hour_18 - 0.0%
hour_19 - 0.0%
hour_20 - 0.0%
hour_21 - 0.0%
hour_22 - 0.0%
hour_23 - 0.0%
```

5 Principal Component Analysis (PCA)

We will use PCA to analyse the importance of the features we created and reduce them to a smaller number of features. We can also try to detect anomalies with PCA through **reconstruction error** when reconstructing the features after reducing them through PCA.

We will use PCA and keep the features that sum a 95% of variance explained

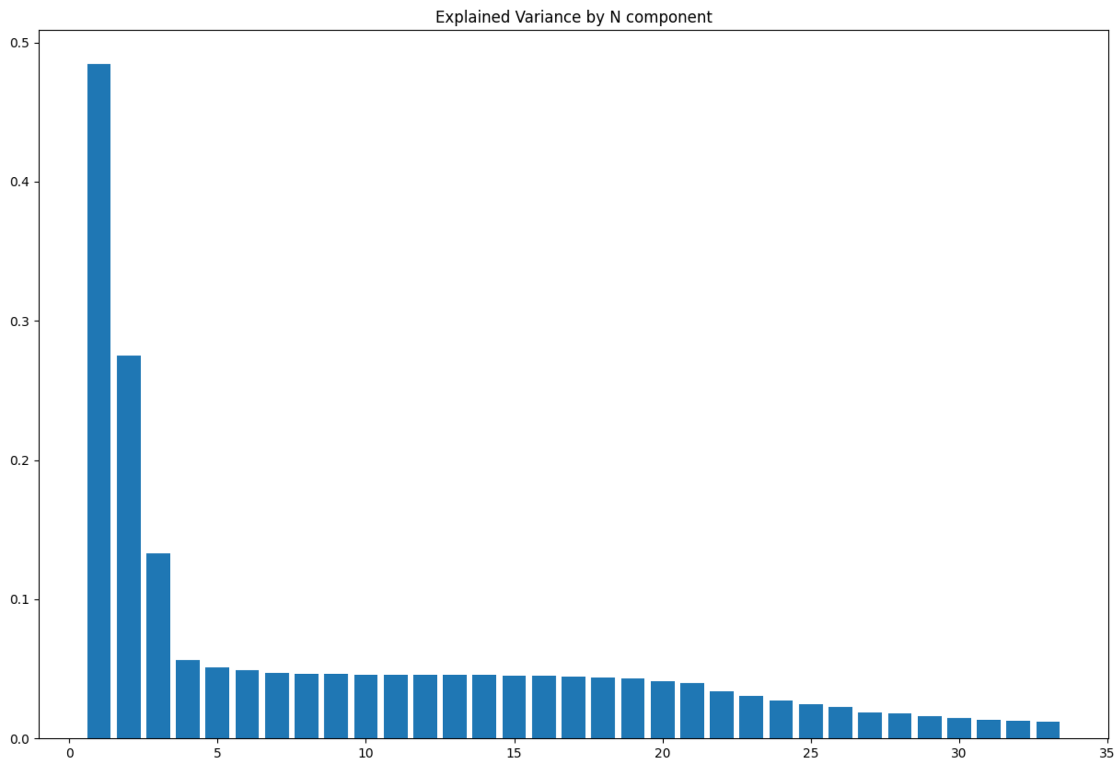
[29]:
```python
from sklearn.decomposition import PCA
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

x = scaler.fit_transform(transactions)

pca = PCA(.95).set_output(transform='pandas')
```

```
reduced = pca.fit_transform(x)

print('Features Before PCA:  ',x.shape[1])
print('Features After PCA:  ',reduced.shape[1])
```

```
Features Before PCA:   87
Features After PCA:   33
```

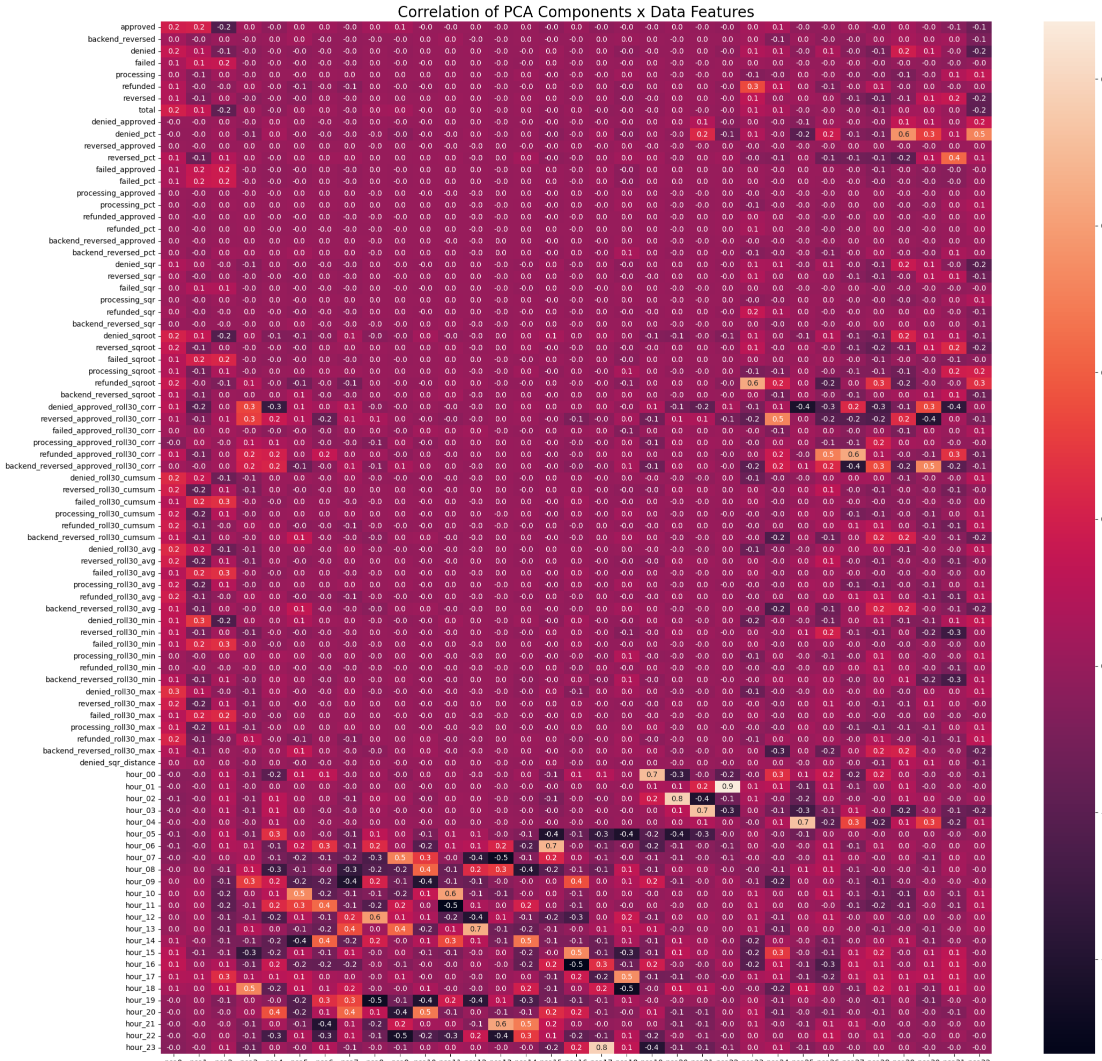
[30]:
```
plt.figure(figsize=(15,10))
plt.bar(range(1, len(pca.explained_variance_) +1), pca.explained_variance_  )
plt.title('Explained Variance by N component')
```

[30]: `Text(0.5, 1.0, 'Explained Variance by N component')`



[31]:
```
fig = plt.figure(figsize=(25,25))
components_df = pd.DataFrame(pca.components_ ,columns=transactions.columns␣
 ↪,index =pca.get_feature_names_out())
sns.heatmap(components_df.T, xticklabels=True, yticklabels=True, annot=True,␣
 ↪fmt='.1f')
plt.title('Correlation of PCA Components x Data Features', fontsize=20)
```

[31]: `Text(0.5, 1.0, 'Correlation of PCA Components x Data Features')`

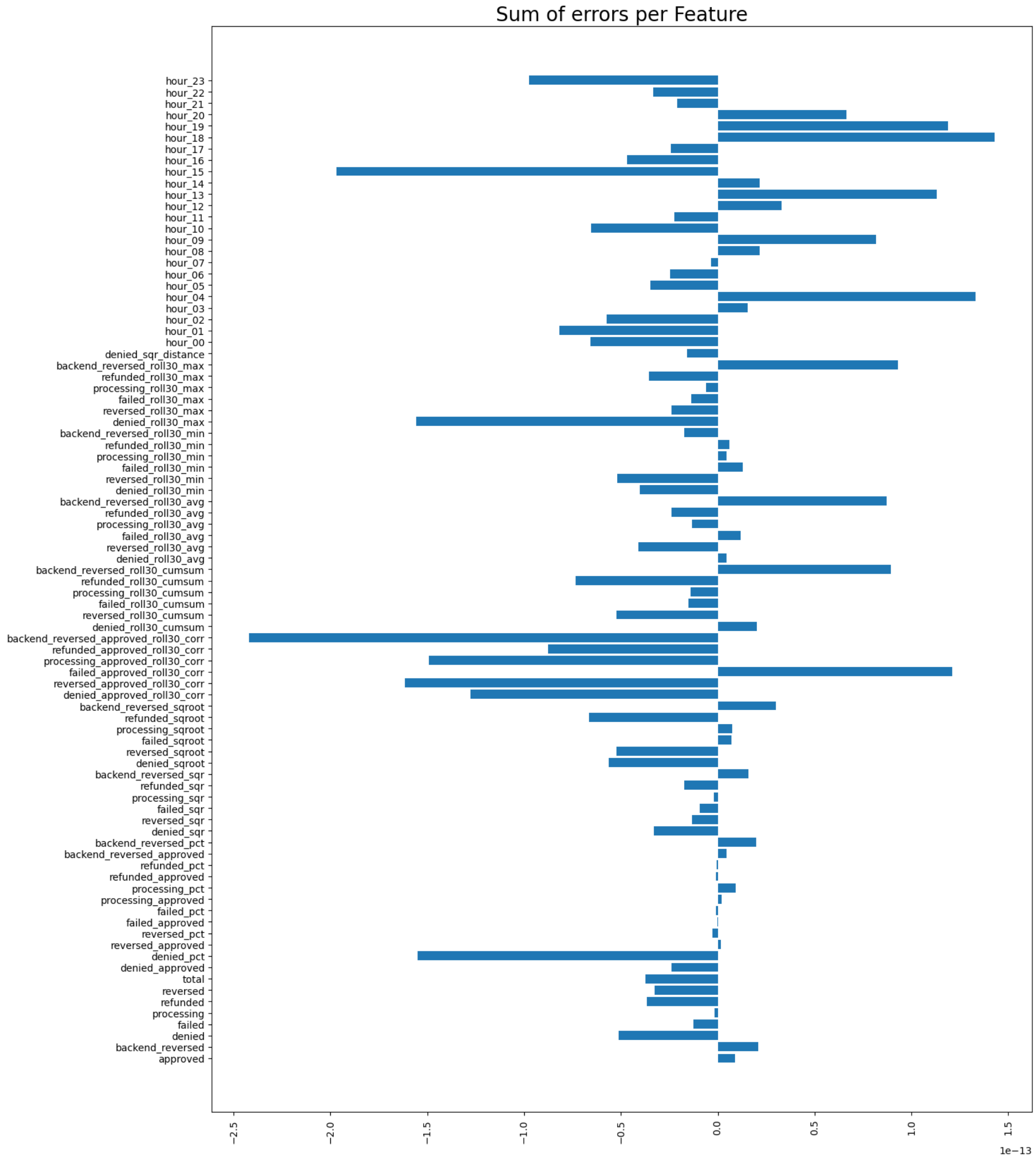


5.1 Reconstruction Error

Now that we reduced the data, we can reconstruct it through PCA and find errors in reconstruction. By subtracting the original scaled data from the reconstructed data we get the reconstruction error.

[32]:
```
reverse_construct = pca.inverse_transform(reduced)
reconstruction_error = (reverse_construct - x)
reconstruction_error.columns = transactions.columns

plt.figure(figsize=(15,20))
plt.barh(reconstruction_error.columns, reconstruction_error.sum()  )
plt.xticks(rotation=90)
plt.title('Sum of errors per Feature', fontsize=20)
```

[32]: Text(0.5, 1.0, 'Sum of errors per Feature')



[33]:
```
plt.figure(figsize=(20,10))
fig = go.Figure()

for col in reconstruction_error.columns:
    fig.add_trace(go.Scatter(x=reconstruction_error.index,␣
↪y=reconstruction_error[col],
                             mode='lines',
```

```
                        name=col))

fig.update_layout(
    autosize=False,
    width=1200,
    height=900,
)

fig.update_layout(
    title=dict(text="Reconstruction Error over time", font=dict(size=30))
)

fig.show()
```

```
<Figure size 2000x1000 with 0 Axes>
```

5.2 Looking Good

Our PCA model has some clear trends and anomalies detected, this is very promising for our anomaly detection and alert system. Let's check the average and the standard deviation of the errors so that maybe we can use the 3-sigma rule to rule out the anomalies

Average of the averages

[34]:
```
reconstruction_error.mean().mean()
```

[34]:
```
np.float64(-6.168952615209917e-18)
```

Standard Deviations

[35]:
```
pd.DataFrame(reconstruction_error.std())
```

[35]:

	0
approved	0.040513
backend_reversed	0.034633
denied	0.032984
failed	0.026389
processing	0.036593
…	…
hour_19	0.008720
hour_20	0.006816
hour_21	0.005729
hour_22	0.006516
hour_23	0.007740

[87 rows x 1 columns]

Average of Standard Deviations

[36]:
```
reconstruction_error.std().mean()
```

[36]: np.float64(0.029273677475230001)

We will square the errors, so we can further seperate normal data from anomalies, this will also make all values positive. Then we take the average and the mean and use the 3-sigma rule to plot the anomalies

[37]:
```
re_squared = reconstruction_error**2

def rule_out(reconstruction_error:pd.Series, re_squared:pd.DataFrame):
    column = reconstruction_error.name
    mean = re_squared[column].mean()
    std = re_squared[column].std()

    sigma3 = mean + 3*std
    sgima3_negative  = mean - 3*std


    return (reconstruction_error >= sigma3) | (reconstruction_error <=␣
 ↪sgima3_negative)
```

[38]:
```
plt.figure(figsize=(20,10))
fig = go.Figure()

for col in re_squared.columns:
    anomalies = re_squared[col].mask( ~rule_out(re_squared[col], re_squared) )
    fig.add_trace(go.Scatter(x=reconstruction_error.index, y=anomalies,
                        mode='markers',
                        name=col))

fig.update_layout(
    autosize=False,
    width=1200,
    height=900,
)

fig.update_layout(
    title=dict(text="Reconstruction Error over time", font=dict(size=30))
)

fig.show()
```

```
<Figure size 2000x1000 with 0 Axes>
```

5.3 Disturbance Readings

We will use **Softmax** to see how much each feature contributes to the total of the reconstruction error, then we will stack the values to create a kind of *seismometer*. Unfortunately we can't put the labels because there are too many of them and it wouldn't help to understand the data, but you will see that it does help to identify anomalous behavior

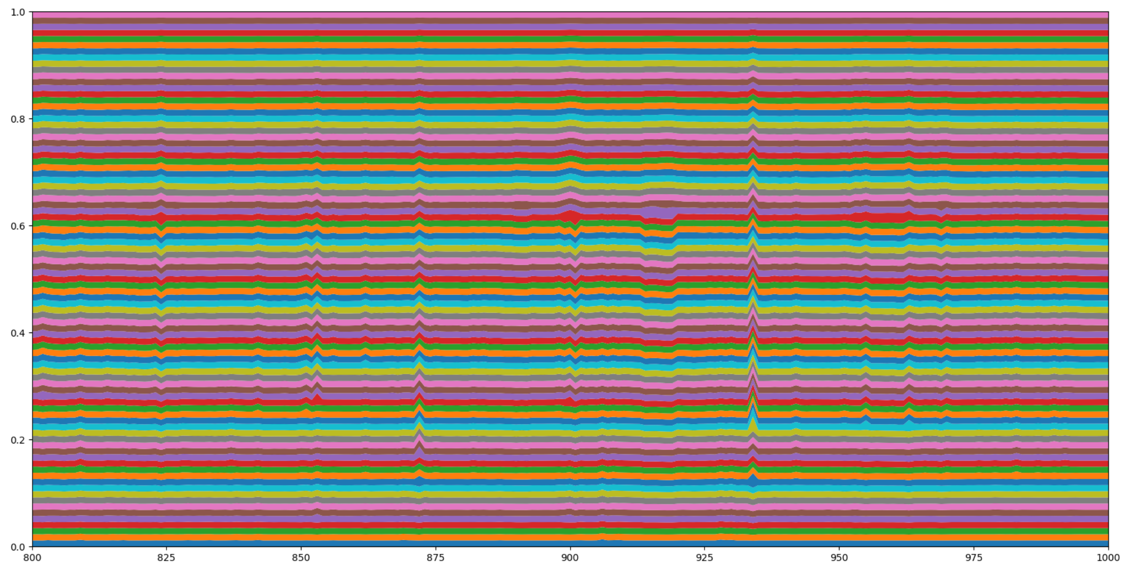
[39]:
```
from scipy.special import softmax
plt.figure(figsize=(20,10))



labels = re_squared.columns

re_squared = pd.DataFrame(softmax(re_squared, axis=1), columns=labels)


plt.stackplot(re_squared.index, *[re_squared[column] for column in labels],
              labels = labels)




plt.ylim(0,1)
```

[39]:
```
(0.0, 1.0)
```

The small *scribbles* you see are from anomalies that bump the other stacks because of it's higher contribution towards the total error. As softmax adds everything up to 1, it's natural that the oter features lose space in the readings. That's why this graph helps a lot in finding anomalies

```
[40]: plt.figure(figsize=(20,10))
      plt.stackplot(re_squared.index, *[re_squared[column] for column in labels],
                    labels = labels)


      plt.xlim(800, 1000)
      plt.ylim(0,1)
```

```
[40]: (0.0, 1.0)
```



It mighte seem small, but remember these are 87 features. With softmax making all the feature errors summing to 1, that leaves about ~1% for each feature to contribute

```
[41]: re_squared.mean()
```

```
[41]: approved            0.011500
      backend_reversed    0.011496
      denied              0.011494
      failed              0.011489
      processing          0.011497
                            …
      hour_19             0.011482
      hour_20             0.011482
      hour_21             0.011482
      hour_22             0.011482
      hour_23             0.011482
      Length: 87, dtype: float64
```

```
[42]: re_squared.max().sort_values(ascending=False)
```

[42]:
```
processing_approved          0.028251
refunded_roll30_min          0.027583
backend_reversed_approved    0.027390
reversed_approved            0.027317
refunded_approved            0.027189
                               …
hour_19                      0.011494
hour_08                      0.011494
hour_20                      0.011494
hour_21                      0.011494
hour_22                      0.011494
Length: 87, dtype: float64
```

As we can see, the average of the error values is around 1.14% which is very small. But the max values i.e. the main anomalous values go up to almost 3% which is a large difference from the normal readings

5.4 Why PCA

The reason we will stick with using PCA for this and not using other alternative models for anomaly detection is the following:

- PCA can handle these smaller datasets, which other models tend to not perform well
- Our PCA approach has a very good "lead" on spotting anomalies
- There is a hand few of other anomaly detection algorithms that could work, but testing each approach would require time we don't have

6 Final Touches

We will do the final touches so we can focus on the API and systems. Creating functions to receive the data, transform and detect anomalies. Saving the models to use later, etc.

Dict to save means and standard deviations for anomaly detection

[43]:
```python
re_squared = reconstruction_error**2


means_dict = {}
for col in re_squared.columns:
    mean = re_squared[col].mean()
    std = re_squared[col].std()
    means_dict.update(
        {col:{'mean':mean,'std':std}}
    )
```

Function to receive raw data in a API and detect anomalies, returning a dictionary

[44]:
```
def detect_anomalies(data:pd.DataFrame):
    anomaly_dict = {}

    columns = data.columns
    data = scaler.transform(data)
    pca_transformed = pca.transform(data)
    pca_inversed = pca.inverse_transform(pca_transformed)
    pca_inversed.columns = data.columns
    data = (data - pca_inversed)**2
    softmax_data = softmax(data)



    for col in data.columns:
        mean = means_dict.get(col).get('mean')
        std = means_dict.get(col).get('std')

        sigma3 = mean + 3*std
        sgima3_negative  = mean - 3*std

        value = data[col].values[0]
        key = col.split('_')[0]
        pct = softmax_data[col].values[0]

        if  value >= sigma3 or value <= sgima3_negative: anomaly = True

        else: anomaly = False


        anomaly_dict.update({key: {'anomaly':anomaly, 'value':value,'pct':pct}})

    return anomaly_dict
```

Saving models and important data in files

[45]:
```
import joblib
import pickle

joblib.dump(scaler, 'scaler.save')
joblib.dump(pca, 'pca.save')
joblib.dump(linearR_denied, 'linearR_denied.save')
```

```python
with open('means_dict.pkl', 'wb') as f:
    pickle.dump(means_dict, f)
```