Credit Card Transactions or Fraud detection

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Importing libraries

In [3]:

```
import time, psutil, os, gc
import math
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
import seaborn as sns
sns.set_theme()
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
from plotly.offline import init_notebook_mode, iplot
init_notebook_mode(connected=True)
from sklearn.model_selection import train_test_split
```

Runtime and memory usage

In [5]:

```
start = time.time()
process = psutil.Process(os.getpid())
```

In [6]:

```
# Loading the data
data = pd.read_csv('creditcard.csv')
data.head()
```

Out[6]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.066928	0.1285
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638672	0.101288	-0.339846	0.1671
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909412	-0.689281	0.3276
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321	-1.175575	0.6473
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458	0.141267	0.2060

5 rows × 31 columns

In [7]:

```
print(pd.Series({"Memory usage": "{:.2f} MB".format(data.memory_usage().sum()/(1024*1024)),
              "Dataset shape": "{}".format(data.shape)}).to_string())
data.head()
```

```
Memory usage        67.36 MB
Dataset shape    (284807, 31)
```

Out[7]:

Out[7]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.066928	0.1285
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638672	0.101288	-0.339846	0.1671
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909412	-0.689281	-0.3276
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321	-1.175575	0.6473
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458	0.141267	-0.2060

5 rows × 31 columns

Train-Validation-Test Split

In [9]:

```
data_0, data_1 = data[data['Class'] == 0], data[data['Class'] == 1]

X_0, y_0 = data_0.drop('Class', axis = 1), data_0['Class']
X_1, y_1 = data_1.drop('Class', axis = 1), data_1['Class']

X_train, X_test, y_train, y_test = train_test_split(X_0, y_0, test_size = 0.2, random_state = 40)
X_val, X_test, y_val, y_test = train_test_split(X_test, y_test, test_size = 0.5, random_state = 40)
data_val_1, data_test_1 = pd.concat([X_val, y_val], axis = 1), pd.concat([X_test, y_test], axis = 1)

X_val, X_test, y_val, y_test = train_test_split(X_1, y_1, test_size = 0.5, random_state = 40)
data_val_2, data_test_2 = pd.concat([X_val, y_val], axis = 1), pd.concat([X_test, y_test], axis = 1)

data_val, data_test = pd.concat([data_val_1, data_val_2], axis = 0), pd.concat([data_test_1, data_test_2], axis = 0)
X_val, y_val = data_val.drop('Class', axis = 1), data_val['Class']
X_test, y_test = data_test.drop('Class', axis = 1), data_test['Class']
```

In [10]:

```
labels = ['Train', 'Validation', 'Test']
values_0 = [len(y_train[y_train == 0]), len(y_val[y_val == 0]), len(y_test[y_test == 0])]
values_1 = [len(y_train[y_train == 1]), len(y_val[y_val == 1]), len(y_test[y_test == 1])]
fig = make_subplots(rows = 1, cols = 2, specs = [[{'type': 'domain'}, {'type': 'domain'}]])
fig.add_trace(go.Pie(values = values_0, labels = labels, hole = 0.5, textinfo = 'percent', title = "Authentic"),
          row = 1, col = 1)
fig.add_trace(go.Pie(values = values_1, labels = labels, hole = 0.5, textinfo = 'percent', title = "Fraudulent"),
          row = 1, col = 2)
text_title = "Distribution of authentic and fraudulent transactions over training, validation and test set"
fig.update_layout(height = 500, width = 800, showlegend = True, title = dict(text = text_title, x = 0.5, y = 0.95))
fig.show()
```

In [11]:

```
bins_train = math.floor(len(X_train)**(1/3))
```

Feature Engineering

Time

In [14]:

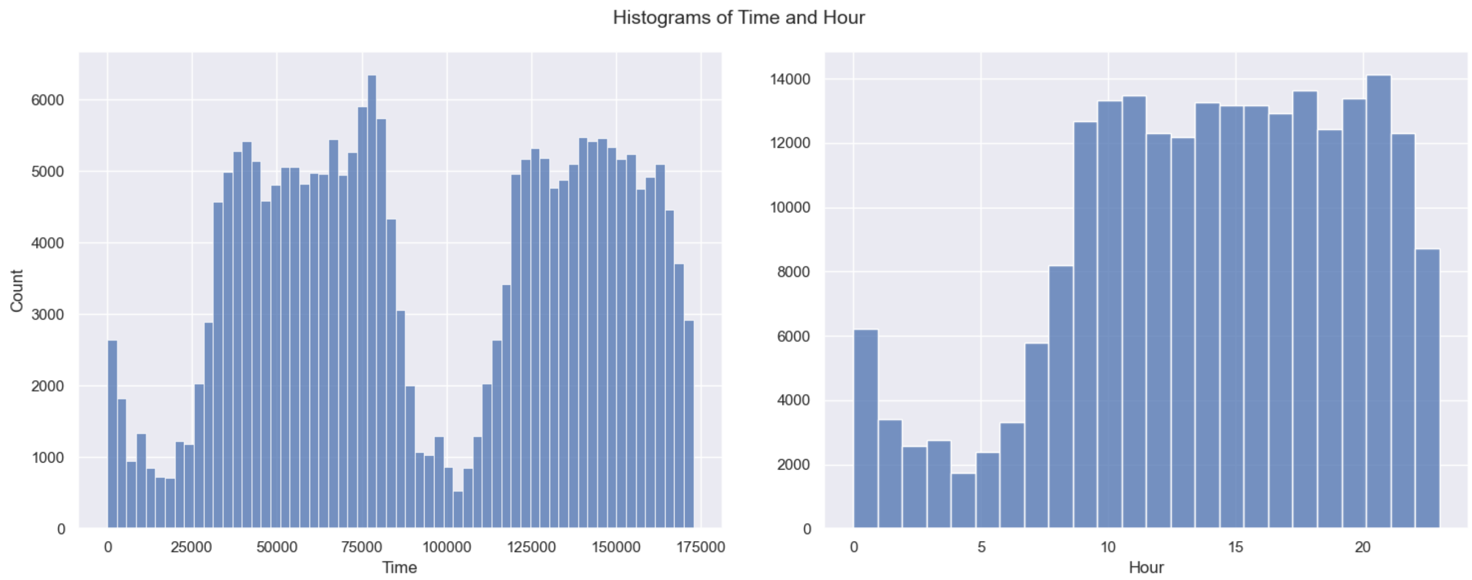
```
for df in [X_train, X_val, X_test]:
    df['Day'], temp = df['Time'] // (24*60*60), df['Time'] % (24*60*60)
    df['Hour'], temp = temp // (60*60), temp % (60*60)
    df['Minute'], df['Second'] = temp // 60, temp % 60
X_train[['Time', 'Day', 'Hour', 'Minute', 'Second']].head()
```

Out[14]:

	Time	Day	Hour	Minute	Second
19594	30401.0	0.0	8.0	26.0	41.0
124712	77397.0	0.0	21.0	29.0	57.0
167920	118964.0	1.0	9.0	2.0	44.0
47377	43191.0	0.0	11.0	59.0	51.0
41731	40804.0	0.0	11.0	20.0	4.0

In [15]:

```
fig, ax = plt.subplots(1, 2, figsize = (15, 6), sharey = False)
sns.histplot(data = X_train, x = 'Time', bins = bins_train, ax = ax[0])
sns.histplot(data = X_train, x = 'Hour', bins = 24, ax = ax[1])
ax[1].set_ylabel(" ")
plt.suptitle("Histograms of Time and Hour", size = 14)
plt.tight_layout()
plt.show()
```



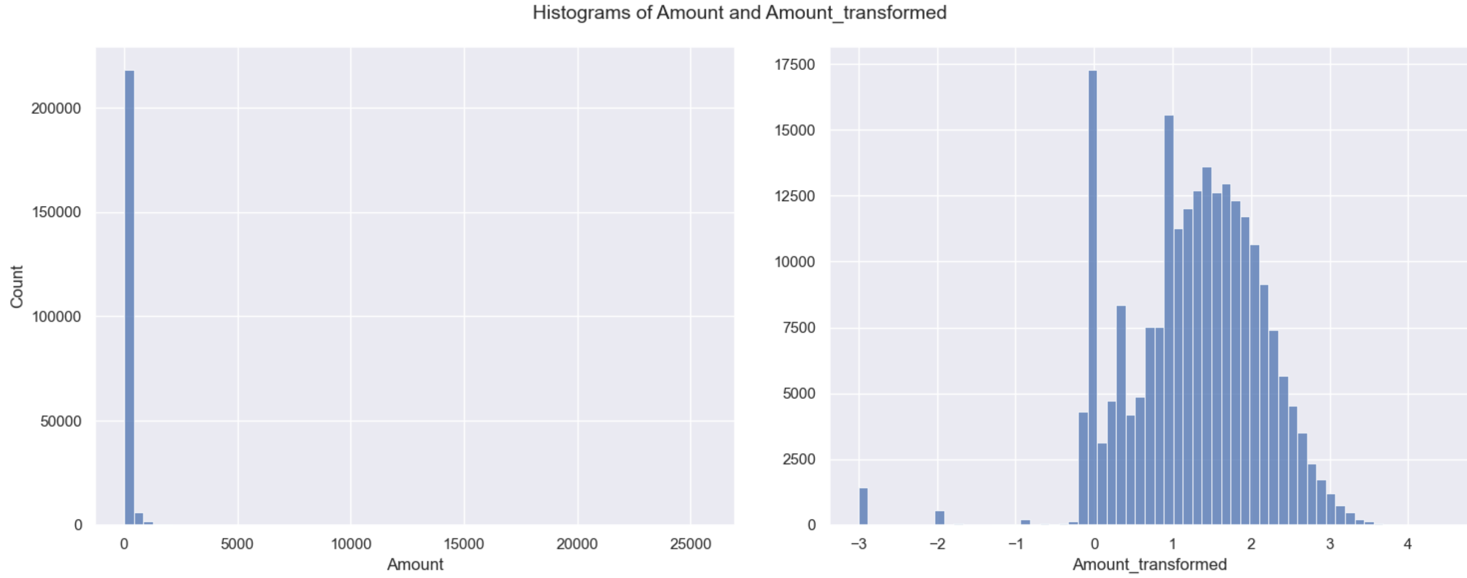
Amount

In [17]:

```
for df in [X_train, X_val, X_test]:
    df['Amount_transformed'] = np.log10(df['Amount'] + 0.001)
```

In [18]:

```
fig, ax = plt.subplots(1, 2, figsize = (15, 6), sharey = False)
sns.histplot(data = X_train, x = 'Amount', bins = bins_train, ax = ax[0])
sns.histplot(data = X_train, x = 'Amount_transformed', bins = bins_train, ax = ax[1])
ax[1].set_ylabel(" ")
plt.suptitle("Histograms of Amount and Amount_transformed", size = 14)
plt.tight_layout()
plt.show()
```



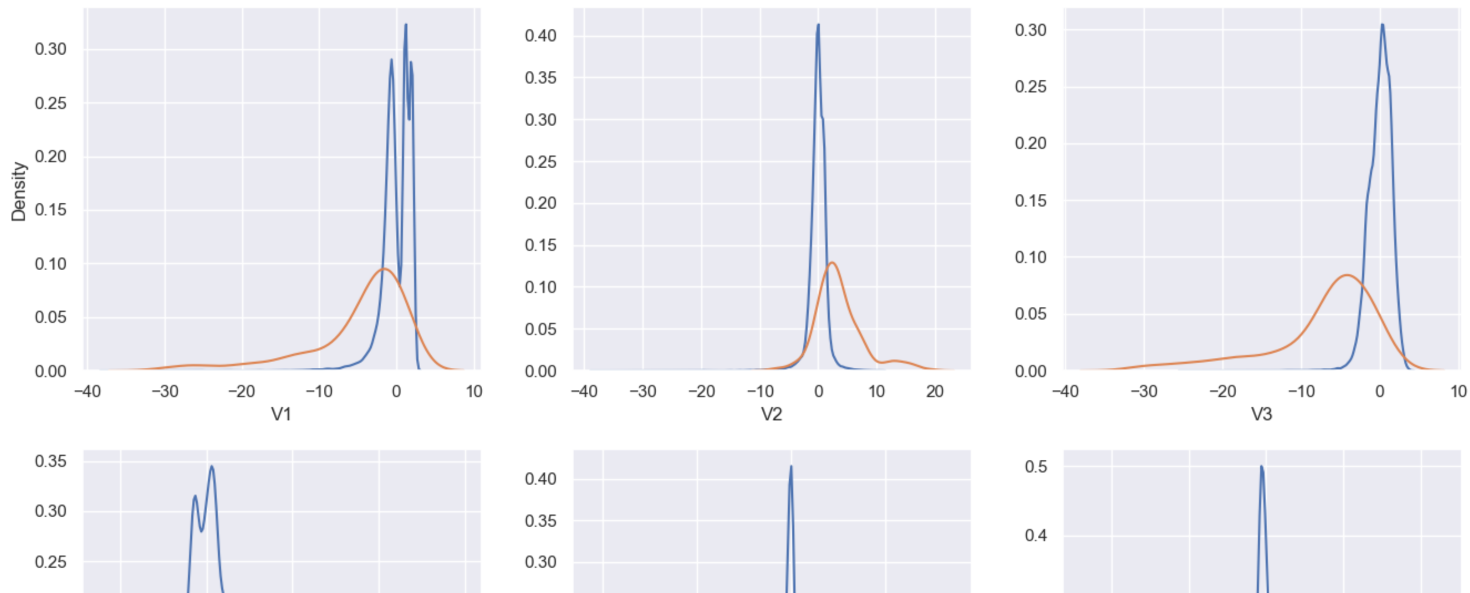
In [19]:

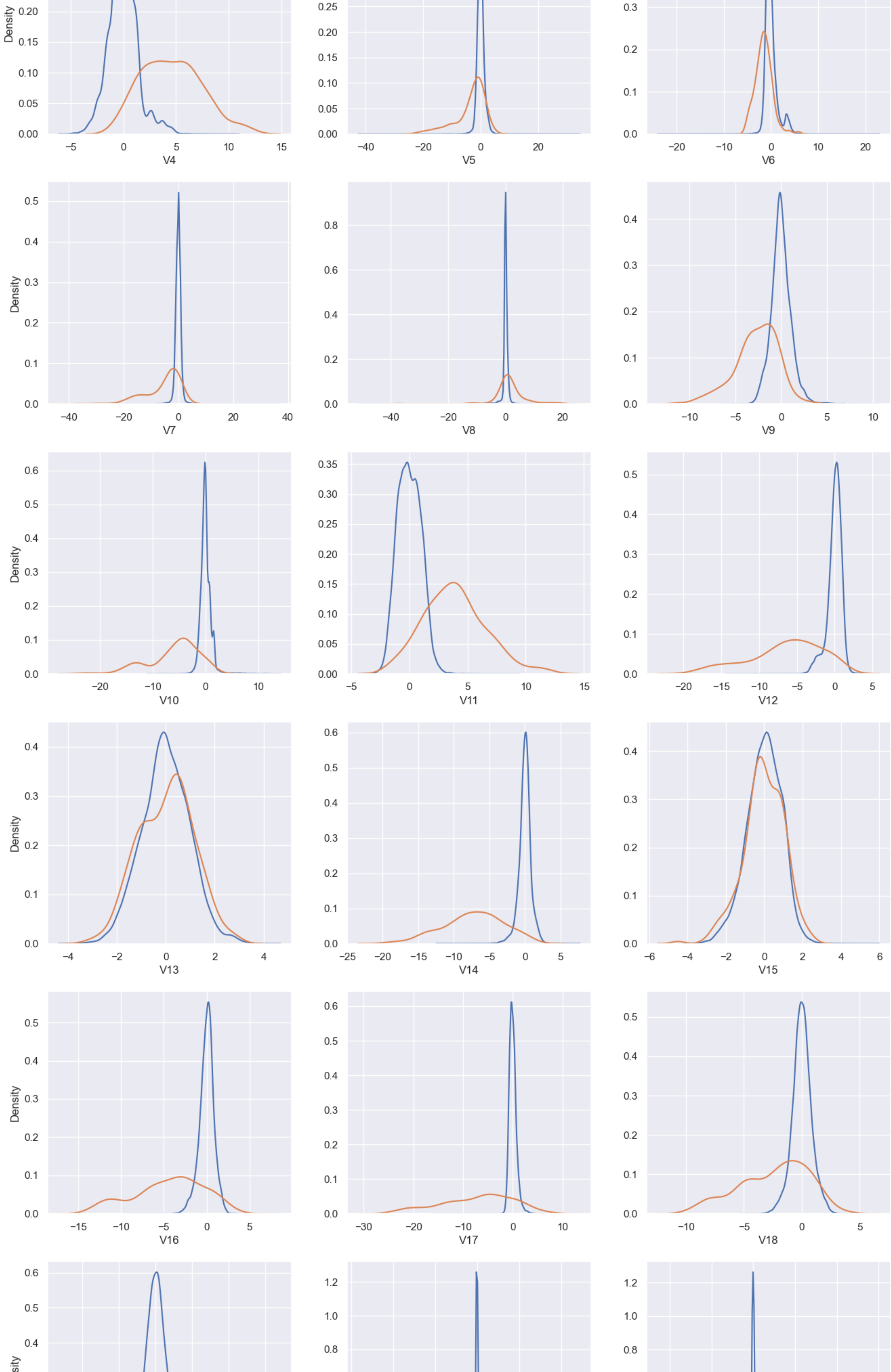
```
for df in [X_train, X_val, X_test]:
    df.drop(['Time', 'Day', 'Minute', 'Second', 'Amount'], axis = 1, inplace = True)
```

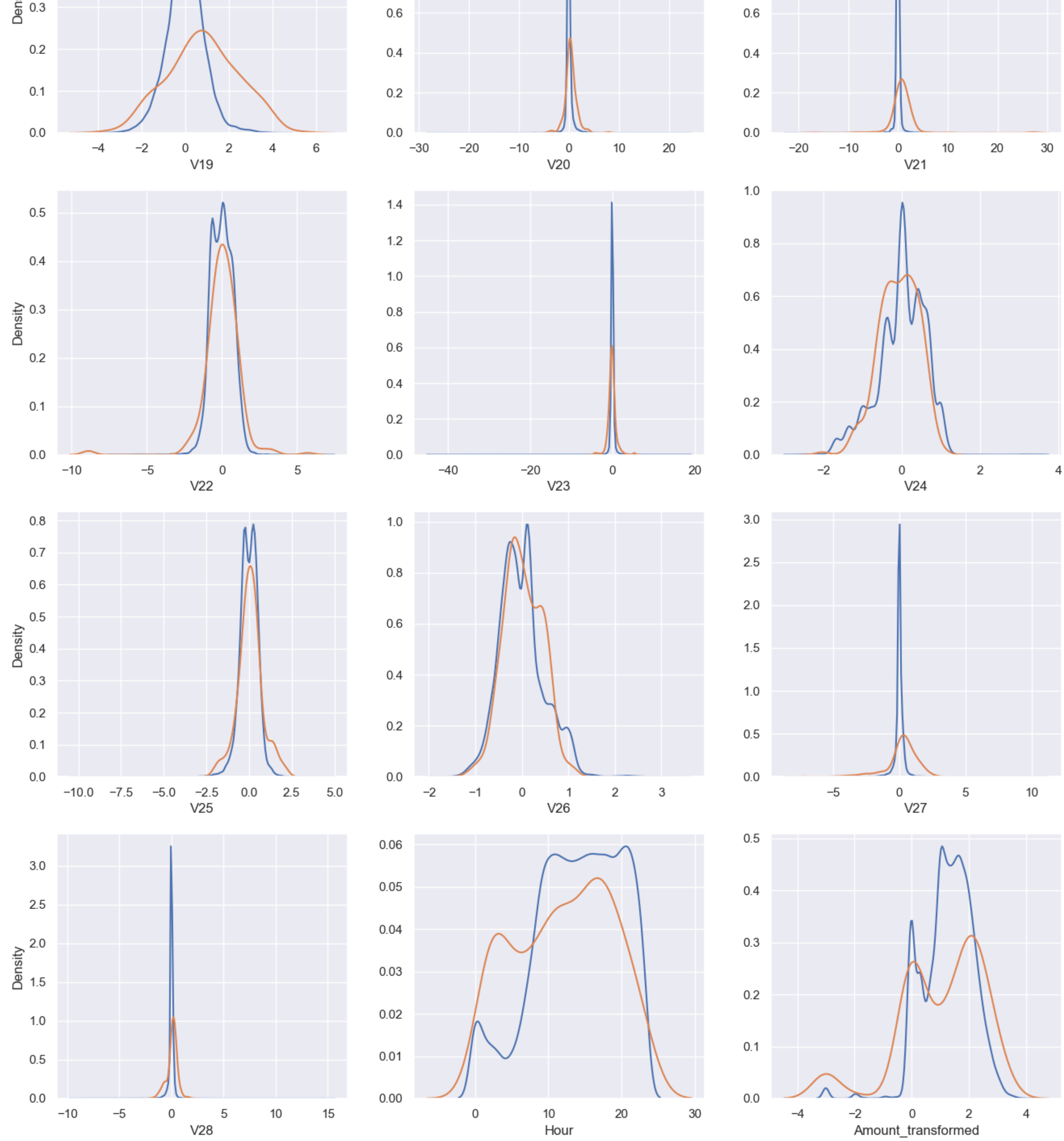
Feature Selection

In [21]:

```
data_val = pd.concat([X_val, y_val], axis = 1)
data_val_0, data_val_1 = data_val[data_val['Class'] == 0], data_val[data_val['Class'] == 1]
cols, ncols = list(X_val.columns), 3
nrows = math.ceil(len(cols) / ncols)
fig, ax = plt.subplots(nrows, ncols, figsize = (4.5 * ncols, 4 * nrows))
for i in range(len(cols)):
    sns.kdeplot(data_val_0[cols[i]], ax = ax[i // ncols, i % ncols])
    sns.kdeplot(data_val_1[cols[i]], ax = ax[i // ncols, i % ncols])
    if i % ncols != 0:
        ax[i // ncols, i % ncols].set_ylabel(" ")
plt.tight_layout()
plt.show()
```




Density
V4
V5
V6
V7
V8
V9
V10
V11
V12
V13
V14
V15
V16
V17
V18



In [22]:

```
cols = ['V4', 'V11', 'V12', 'V14', 'V16', 'V17', 'V18', 'V19', 'Hour']
X_train_fs, X_val_fs, X_test_fs = X_train[cols], X_val[cols], X_test[cols]
X_train_fs.head()
```

Out[22]:

	V4	V11	V12	V14	V16	V17	V18	V19	Hour
19594	-0.706232	2.027925	0.535822	0.250769	0.773615	0.449717	-1.963208	0.613481	8.0
124712	1.474933	-1.154523	0.263527	0.316174	-1.029415	1.030772	-0.438839	0.529080	21.0
167920	4.840766	-2.242431	0.034829	-0.546349	-0.070375	1.033695	0.531801	1.215045	9.0
47377	0.565273	-0.157045	-0.548790	0.419194	0.183518	-0.681323	0.911357	1.318132	11.0
41731	-0.428860	-0.580964	-0.609099	-0.187948	1.226723	0.104368	-0.995711	0.420557	11.0

Implementing Anomaly Detection

In [24]:

```
def normal_density(x, mu, sigma):
    assert sigma > 0, "Standard deviation must be positive"
    f = (1 / (sigma * np.sqrt(2 * np.pi))) * np.exp(- (1 / 2) * ((x - mu) / sigma)**2)
    return f
```

In [25]:

```
def normal_product(x_vec, mu_vec, sigma_vec):
    assert min(sigma_vec) > 0
    assert len(mu_vec) == len(x_vec)
    assert len(sigma_vec) == len(x_vec)

    f = 1
    for i in range(len(x_vec)):
        f = f * normal_density(x_vec[i], mu_vec[i], sigma_vec[i])

    return f
```

In [26]:

```
mu_train, sigma_train = X_train_fs.mean().values, X_train_fs.std().values
```

In [27]:

```
def model_normal(X, epsilon):
    y = []
    for i in X.index:
        prob_density = normal_product(X.loc[i].tolist(), mu_train, sigma_train)
        y.append((prob_density < epsilon).astype(int))
    return y
```

Threshold Tuning on Validation Set

In [29]:

```
def conf_mat(y_test, y_pred):
    y_test, y_pred = list(y_test), list(y_pred)
    count, labels, confusion_mat = len(y_test), [0, 1], np.zeros(shape = (2, 2), dtype = int)
    for i in range(2):
        for j in range(2):
            confusion_mat[i][j] = len([k for k in range(count) if y_test[k] == labels[i] and y_pred[k] == labels[j]])
    return confusion_mat
```

In [30]:

```
def conf_mat_heatmap(y_test, y_pred):
    confusion_mat = conf_mat(y_test, y_pred)
    labels, confusion_mat_df = [0, 1], pd.DataFrame(confusion_mat, range(2), range(2))
    plt.figure(figsize = (6, 4.75))
    sns.heatmap(confusion_mat_df, annot = True, annot_kws = {"size": 16}, fmt = 'd')
    plt.xticks([0.5, 1.5], labels, rotation = 'horizontal')
    plt.yticks([0.5, 1.5], labels, rotation = 'horizontal')
    plt.xlabel("Predicted label", fontsize = 14)
    plt.ylabel("True label", fontsize = 14)
    plt.title("Confusion Matrix", fontsize = 14)
    plt.grid(False)
    plt.show()
```

In [31]:

```
def f2_score(y_test, y_pred):
    confusion_mat = conf_mat(y_test, y_pred)
    tn, fp, fn, tp = confusion_mat[0, 0], confusion_mat[0, 1], confusion_mat[1, 0], confusion_mat[1, 1]
    f2 = (5 * tp) / ((5 * tp) + (4 * fn) + fp)
    return f2
```

In [32]:

```
import numpy as np
from sklearn.metrics import fbeta_score
alpha_list, f2_list, f2_max, alpha_opt, y_val_pred_opt = [], [], 0.0, 0.0, np.zeros(len(y_val))
```

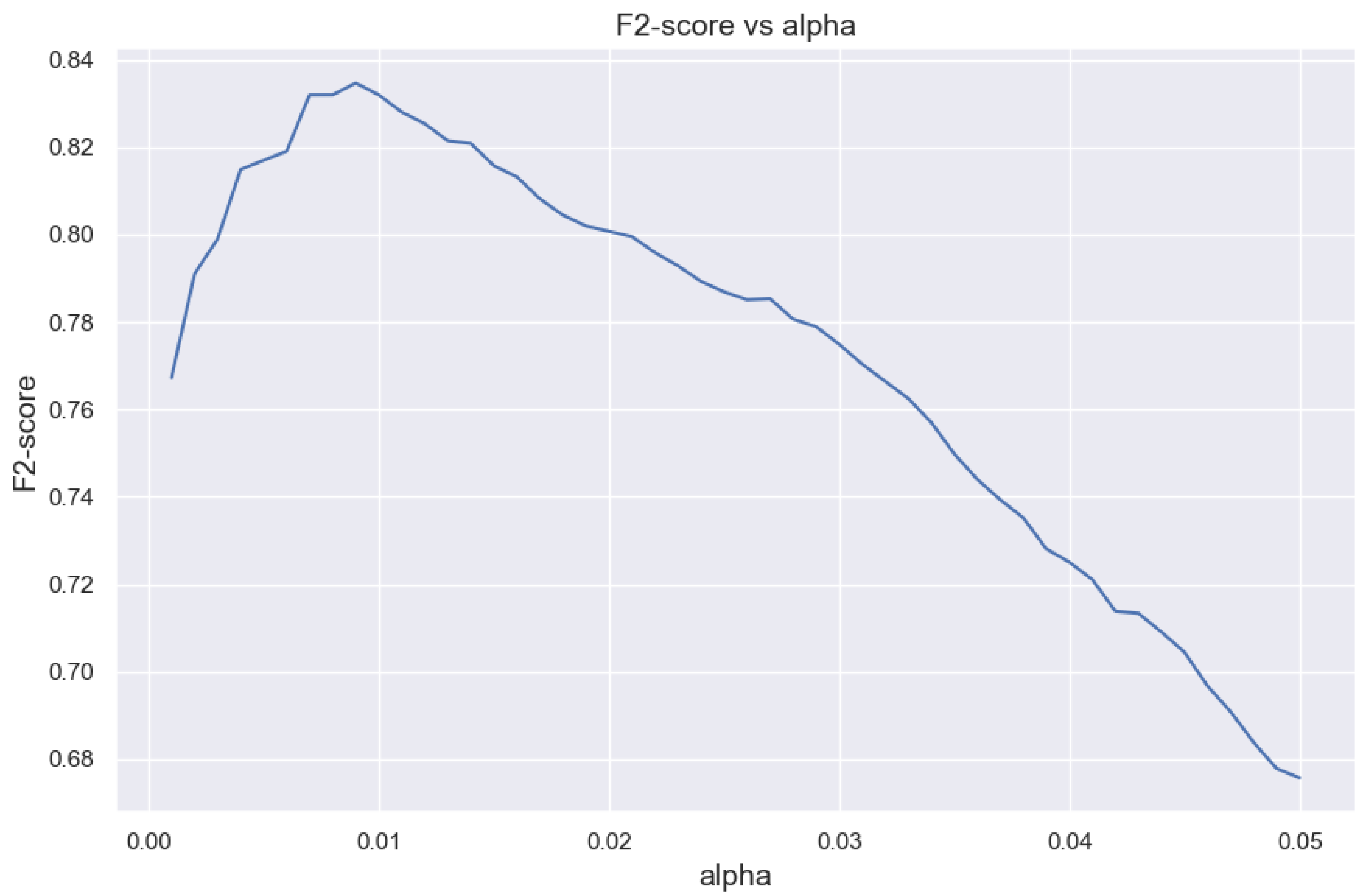
```
alpha_list, f2_list, f2_max, alpha_opt, y_val_pred_opt = [], [], 0.0, 0.0, np.zeros(len(y_val))
for alpha in np.arange(0.001, 0.051, 0.001):
    y_val_pred = model_normal(X_val_fs, epsilon=alpha**X_val_fs.shape[1])  # Adjust as needed
    f2 = fbeta_score(y_val, y_val_pred, beta=2)  # Using f2 score with beta=2

    alpha_list.append(alpha)
    f2_list.append(f2)

    if f2 > f2_max:
        alpha_opt = alpha
        y_val_pred_opt = y_val_pred
        f2_max = f2
```

In [33]:

```
plt.figure(figsize = (9, 6))
plt.plot(alpha_list, f2_list)
plt.xlabel("alpha", fontsize = 14)
plt.ylabel("F2-score", fontsize = 14)
plt.title("F2-score vs alpha", fontsize = 14)
plt.tight_layout()
plt.show()
```



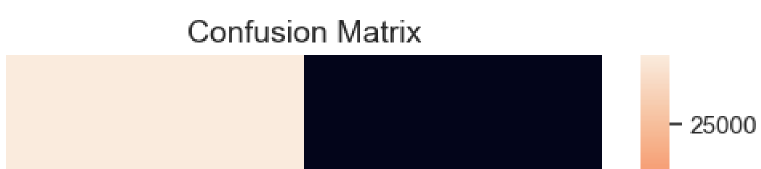
In [34]:

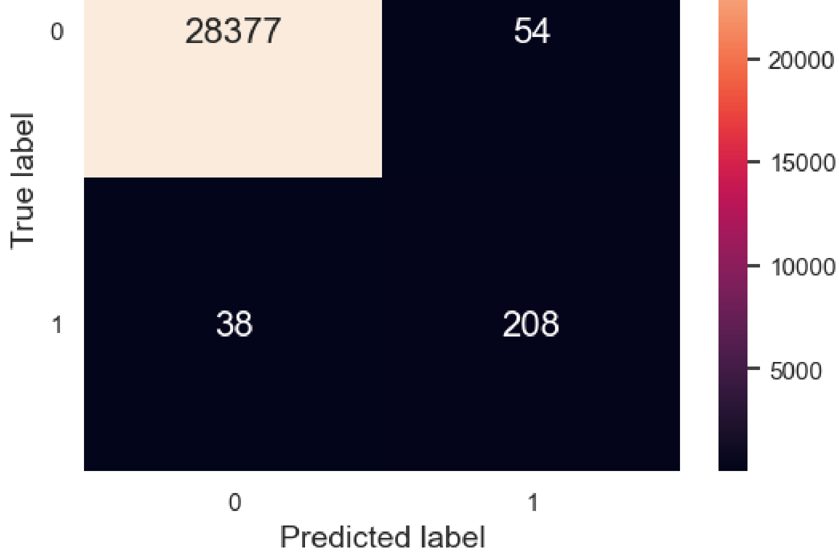
```
print(pd.Series({
    "Optimal alpha": alpha_opt,
    "Optimal F2-score": f2_score(y_val, y_val_pred_opt)
}).to_string())
```

```
Optimal alpha       0.009000
Optimal F2-score    0.834671
```

In [35]:

```
conf_mat_heatmap(y_val, y_val_pred_opt)
```





Prediction and Evaluation on Test Set

In [37]:

```
def evaluation(y_test, y_pred):
    confusion_mat = conf_mat(y_test, y_pred)
    tn, fp, fn, tp = confusion_mat[0, 0], confusion_mat[0, 1], confusion_mat[1, 0], confusion_mat[1, 1]
    print(pd.Series({
        "Accuracy": (tp + tn) / (tn + fp + fn + tp),
        "Precision": tp / (tp + fp),
        "Recall": tp / (tp + fn),
        "F1-score": (2 * tp) / ((2 * tp) + fn + fp),
        "F2-score": (5 * tp) / ((5 * tp) + (4 * fn) + fp),
        "MCC": ((tp * tn) - (fp * fn)) / np.sqrt((tp + fp) * (tp + fn) * (tn + fp) * (tn + fn))
    }).to_string())
```

In [38]:

```
y_test_normal = model_normal(X_test_fs, epsilon = alpha_opt**X_test_fs.shape[1])
evaluation(y_test, y_test_normal)
```

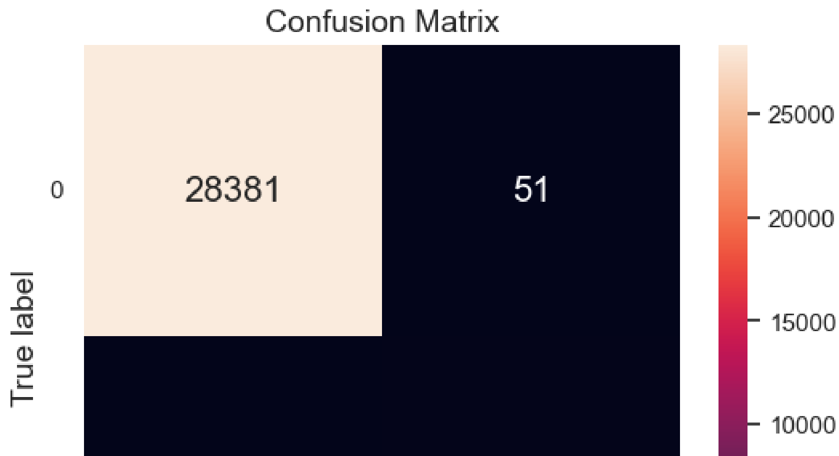
```
Accuracy      0.996687
Precision     0.798419
Recall        0.821138
F1-score      0.809619
F2-score      0.816492
MCC         171.242437
```

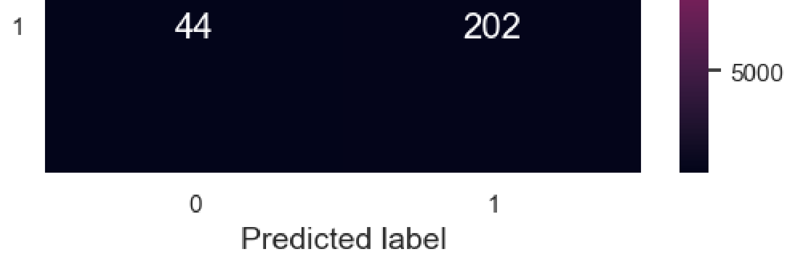
```
C:\Users\GOWTHAM GS PATIL\AppData\Local\Temp\ipykernel_10180\740899491.py:10: RuntimeWarning:

overflow encountered in scalar multiply
```

In [39]:

```
conf_mat_heatmap(y_test, y_test_normal)
```





Conclusion

In [41]:

```
stop = time.time()
print(pd.Series({"Process runtime": "{:.2f} seconds".format(float(stop - start)),
                 "Process memory usage": "{:.2f} MB".format(float(process.memory_info()[0]/(1024*1024)))}).to_string())
```

```
Process runtime         342.84 seconds
Process memory usage       601.33 MB
```