In [2]:

```python
import pandas as pd
import numpy as np
from mpl_toolkits.mplot3d import Axes3D
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import os
```

In [3]:

```python
df = pd.read_csv('creditcard.csv')
df.head()
```

Out[3]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.

5 rows × 31 columns

In [4]:

```python
df.shape
```

Out[4]: (284807, 31)

In [5]:

```python
df.describe()
```

Out[5]:

	Time	V1	V2	V3	V4	V5	V
count	284807.000000	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+0
mean	94813.859575	1.168375e-15	3.416908e-16	-1.379537e-15	2.074095e-15	9.604066e-16	1.487313e-1
std	47488.145955	1.958696e+00	1.651309e+00	1.516255e+00	1.415869e+00	1.380247e+00	1.332271e+0
min	0.000000	-5.640751e+01	-7.271573e+01	-4.832559e+01	-5.683171e+00	-1.137433e+02	-2.616051e+0
25%	54201.500000	-9.203734e-01	-5.985499e-01	-8.903648e-01	-8.486401e-01	-6.915971e-01	-7.682956e-0
50%	84692.000000	1.810880e-02	6.548556e-02	1.798463e-01	-1.984653e-02	-5.433583e-02	-2.741871e-0
75%	139320.500000	1.315642e+00	8.037239e-01	1.027196e+00	7.433413e-01	6.119264e-01	3.985649e-0
max	172792.000000	2.454930e+00	2.205773e+01	9.382558e+00	1.687534e+01	3.480167e+01	7.330163e+0

8 rows × 31 columns

In [6]:

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
```

```
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```

In [7]:

```python
df.isnull().sum()
```

Out[7]:

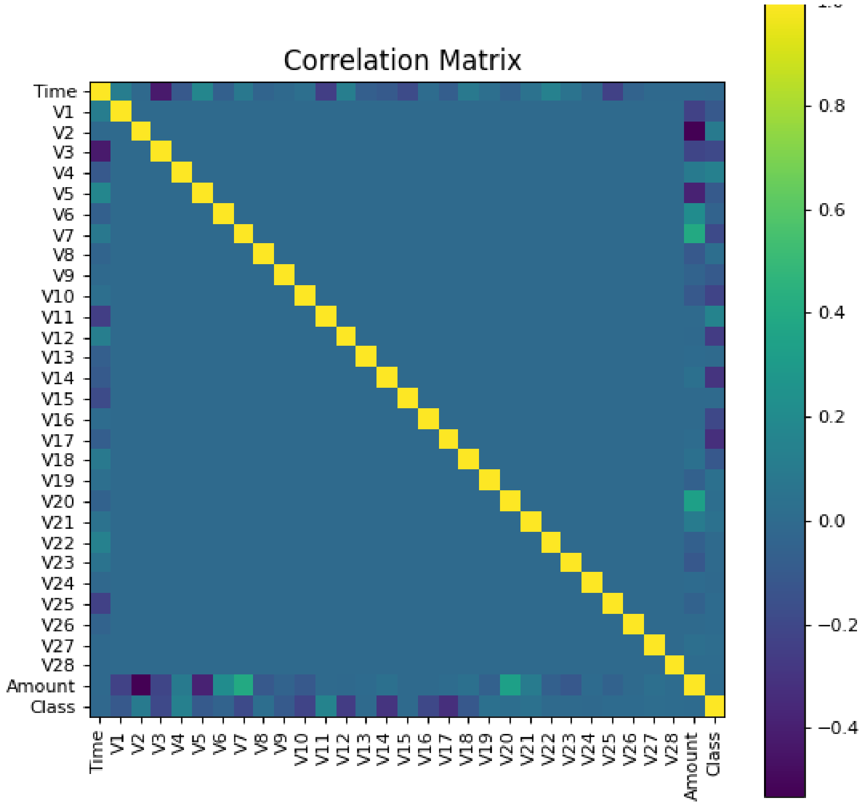
```
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

In [8]:

```python
# Correlation matrix
def plotCorrelationMatrix(df, graphWidth):
    # filename = df.dataframeName
    # df = df.dropna('columns') # drop columns with NaN
    df = df[[col for col in df if df[col].nunique() > 1]] # keep columns where there are more than 1
    if df.shape[1] < 2:
        print(f'No correlation plots shown: The number of non-NaN or constant columns ({df.shape[1]})
        return
    corr = df.corr()
    plt.figure(num=None, figsize=(graphWidth, graphWidth), dpi=80, facecolor='w', edgecolor='k')
    corrMat = plt.matshow(corr, fignum = 1)
    plt.xticks(range(len(corr.columns)), corr.columns, rotation=90)
    plt.yticks(range(len(corr.columns)), corr.columns)
    plt.gca().xaxis.tick_bottom()
    plt.colorbar(corrMat)
    plt.title(f'Correlation Matrix ', fontsize=15)
    plt.show()
```

In [9]:

```python
plotCorrelationMatrix(df, 8)
```



In [10]:

```python
# Count how many times each data type is present in the dataset
pd.value_counts(df.dtypes)
```

Out[10]:

```
float64    30
int64       1
Name: count, dtype: int64
```

In [11]:

```python
df.isna()
```

Out[11]:

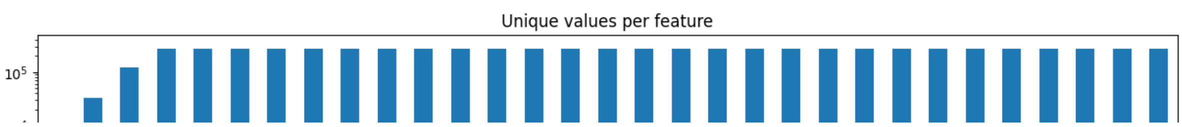
	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26
0	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
284802	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False
284803	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False
284804	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False
284805	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False
284806	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False

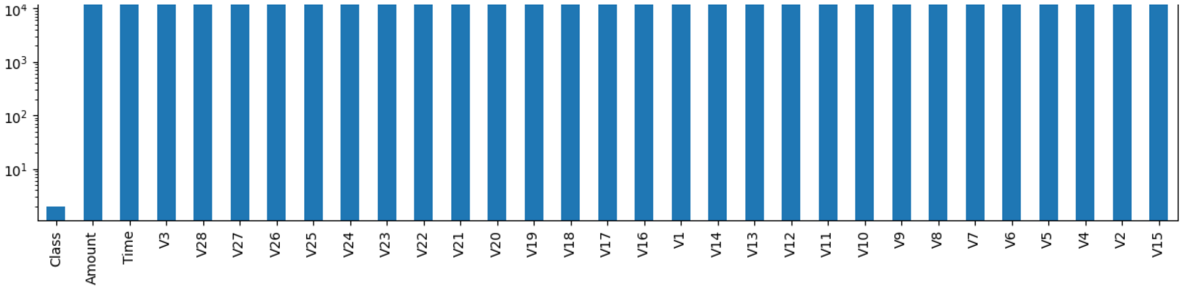
284807 rows × 31 columns

In [12]:

```python
unique_values = df.select_dtypes(include="number").nunique().sort_values()
unique_values.plot.bar(logy=True, figsize=(15, 4), title="Unique values per feature")
```

Out[12]: <Axes: title={'center': 'Unique values per feature'}>

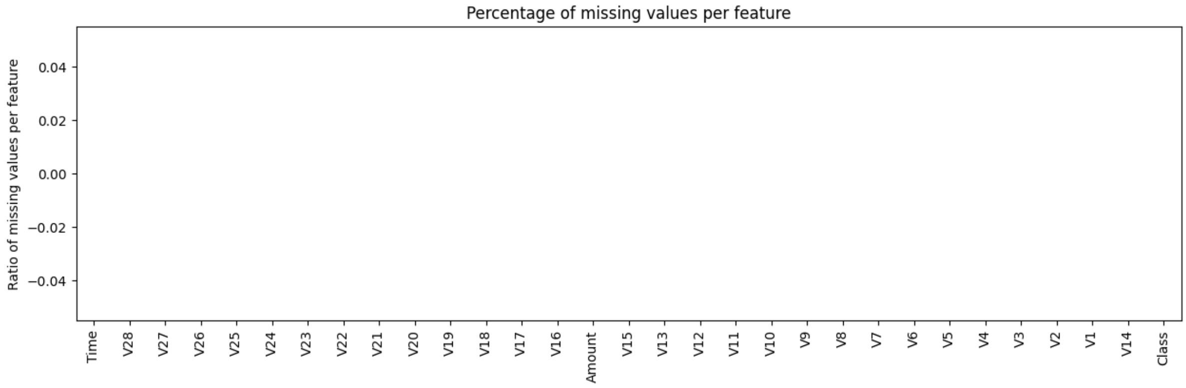




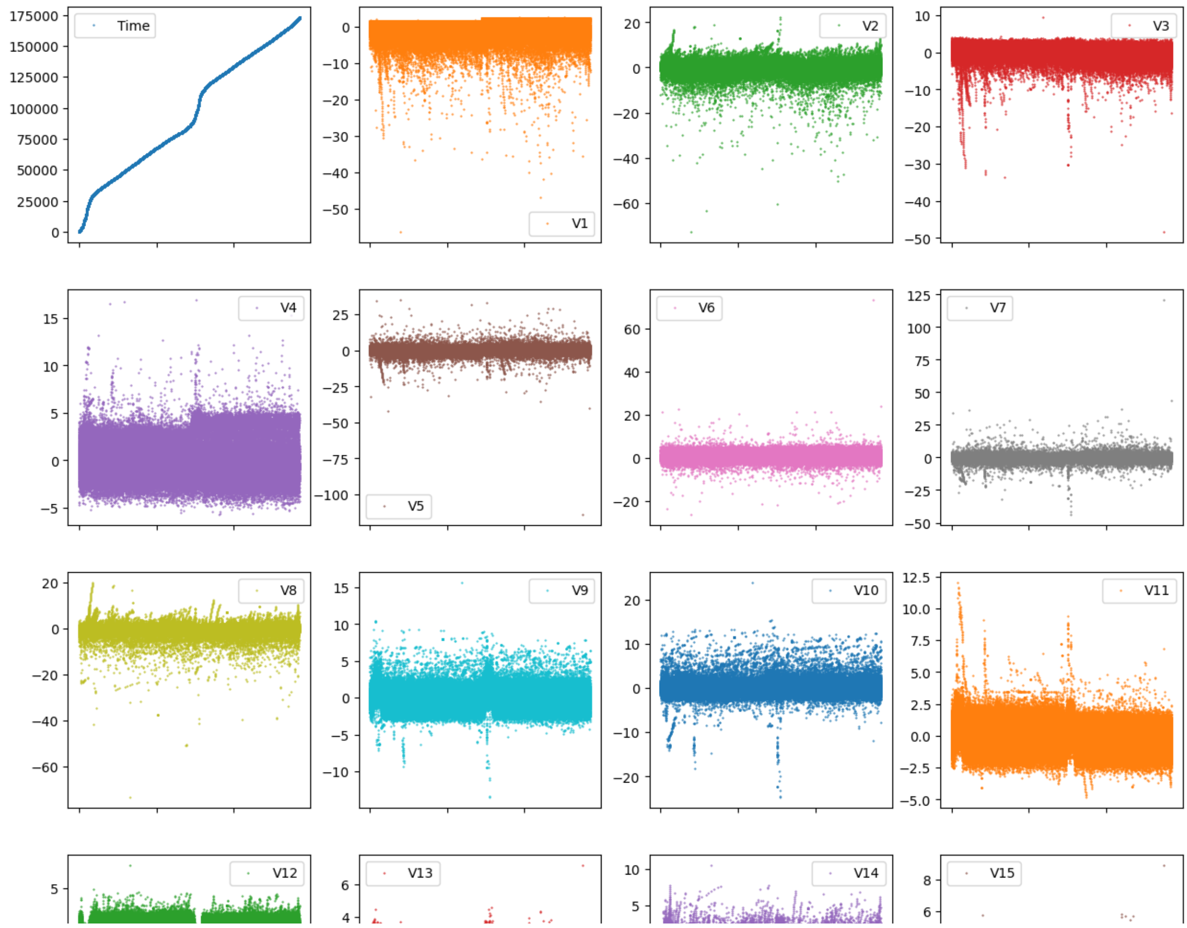
In [15]:
```
n_duplicates = df.drop(labels=["Class"], axis=1).duplicated().sum()
print(f"You seem to have {n_duplicates} duplicates in your database.")
```

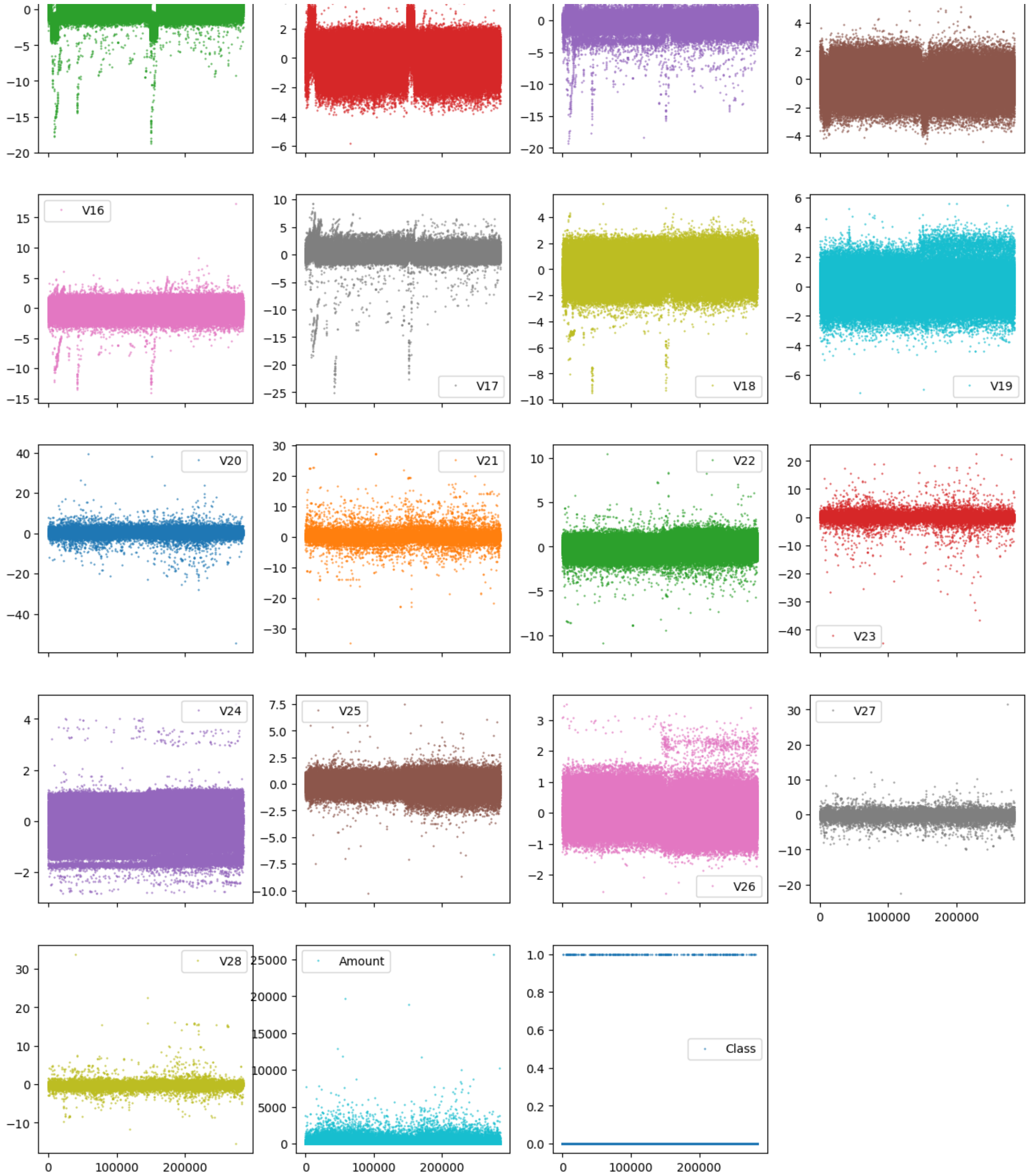
```
You seem to have 1081 duplicates in your database.
```

In [16]:
```
df.isna().mean().sort_values().plot(
    kind="bar", figsize=(15, 4),
    title="Percentage of missing values per feature",
    ylabel="Ratio of missing values per feature");
#that is no missing value
```



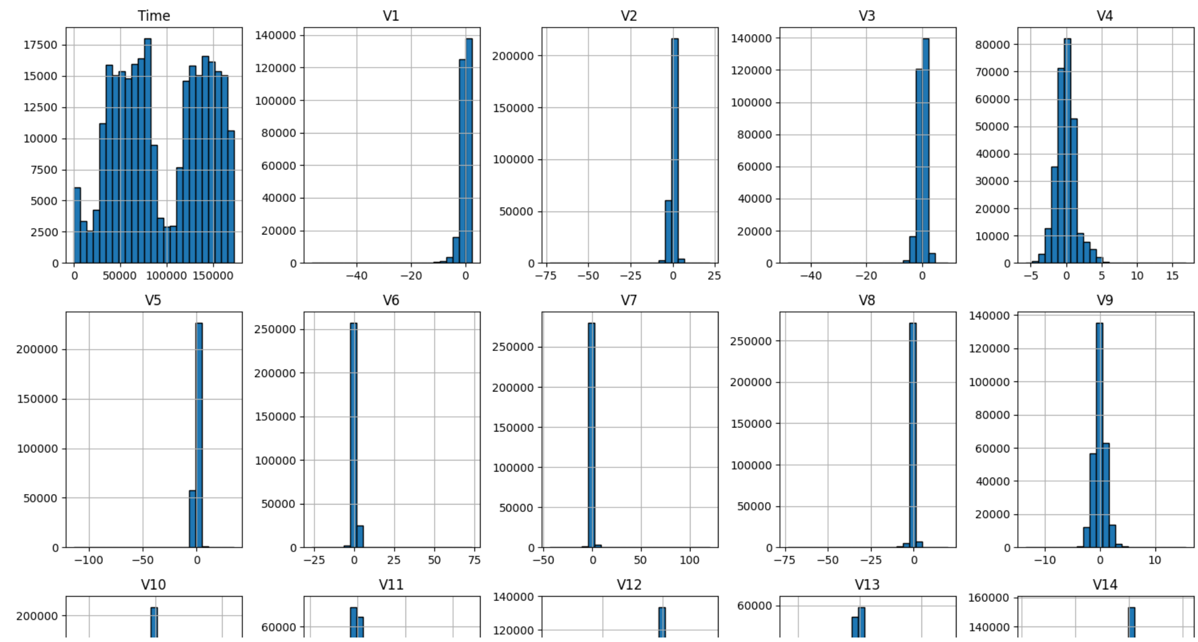
In [17]:
```
df.plot(lw=0, marker=".", subplots=True, layout=(-1, 4),
        figsize=(15, 30), markersize=1);
```

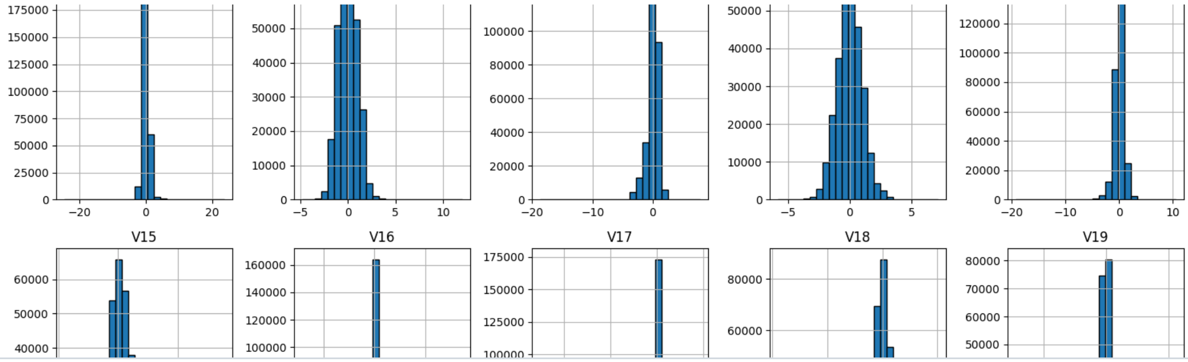




In [21]:

```
df.hist(bins=25, figsize=(15, 25), layout=(-1, 5), edgecolor="black")
plt.tight_layout();
```




V15
V16
V17
V18
V19

In [1]:

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import tensorflow as tf
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.manifold import TSNE
from sklearn.decomposition import PCA, TruncatedSVD
import matplotlib.patches as mpatches
import time

# Classifier Libraries
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
import collections
```

In [ ]:

```
df = pd.read_csv("creditcard.csv")
```

In [ ]:

```
Total_transactions = len(df)
normal = len(df[df.Class == 0])
fraudulent = len(df[df.Class == 1])
fraud_percentage = round(fraudulent/normal*100, 2)

print("total number of transactions: ",Total_transactions)
print("normal transactions: ",normal)
print("fraud transactions: ",fraudulent)
print("percentage: ",fraud_percentage)
```

```
total number of transactions:  284807
normal transactions:  284315
fraud transactions:  492
percentage:  0.17
```

In [ ]:

```
df.head()
```

Out[ ]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.

5 rows × 31 columns

In [ ]:

```
df.isnull().sum()
```

Out[ ]:

```
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
```

```
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

In [ ]:

```
print(df.duplicated().sum())
df.shape
```

```
1081
```

Out[ ]: (284807, 31)

In [ ]:

```
df.drop_duplicates()
```

Out[ ]:

	scaled_amount	scaled_time	V1	V2	V3	V4	V5	V6	V7
110192	0.162230	-0.152434	-0.479760	0.902012	1.678826	0.679300	-0.383552	-0.989120	0.716873
82178	-0.027947	-0.298570	-1.100552	-0.646598	2.384530	-1.618709	-0.307001	0.379083	-0.865919
190623	-0.172990	0.519496	-0.986606	1.030981	0.635763	-1.308280	1.520850	-0.202459	1.226071
48178	0.076853	-0.483617	-1.099733	-0.031313	1.985752	0.380360	-0.885633	0.166664	-0.957074
240411	14.205268	0.774222	0.169344	-3.931869	-3.761457	-0.747751	-0.342344	-0.151290	1.720978
...	...	...	...	...	...	...	...	...	...
85825	-0.293440	-0.278868	-0.989250	0.651069	-0.998413	-1.408951	2.812663	3.547332	-0.818144
169348	0.321246	0.410719	-0.596156	-0.105169	0.846754	-1.464162	0.637215	-0.567283	0.527580
104993	-0.167819	-0.180594	1.155033	-0.192103	0.433161	0.662576	-0.333750	0.358379	-0.389224
66337	-0.294977	-0.384074	0.166544	1.131385	0.144757	0.743303	0.594937	-0.621800	0.917669
115546	-0.234053	-0.126728	-0.801655	1.378684	0.641833	-0.324040	0.691111	0.010191	0.590762

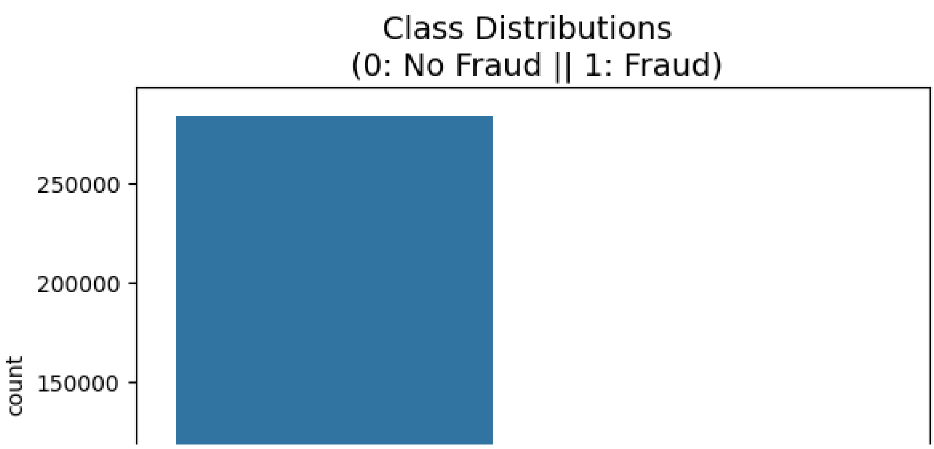
283726 rows × 31 columns

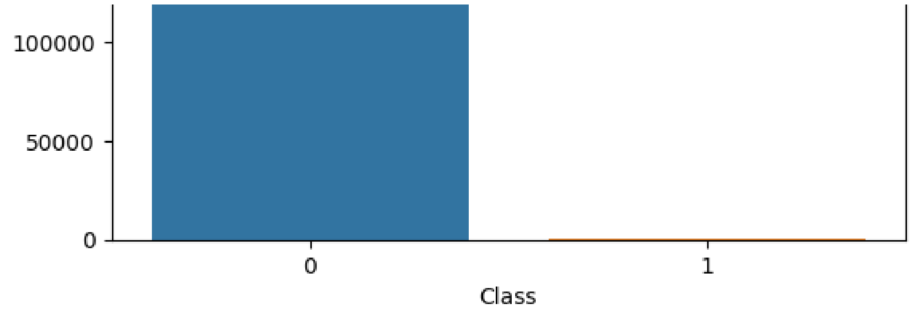
Pre-Processing

In [ ]:

```
import matplotlib.pyplot as plt
colors = ["#0101DF", "#DF0101"]

sns.countplot(x='Class', data=df)
plt.title('Class Distributions \n (0: No Fraud || 1: Fraud)', fontsize=14)
```

Out[ ]: Text(0.5, 1.0, 'Class Distributions \n (0: No Fraud || 1: Fraud)')



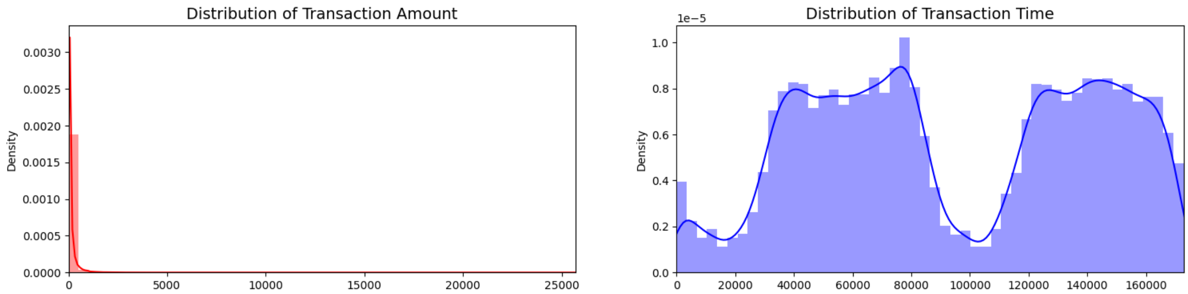


In [ ]:

```python
import warnings
warnings.filterwarnings("ignore")
```

In [ ]:

```python
fig, ax = plt.subplots(1, 2, figsize=(18,4))

amount_val = df['Amount'].values
time_val = df['Time'].values

sns.distplot(amount_val, ax=ax[0], color='r')
ax[0].set_title('Distribution of Transaction Amount', fontsize=14)
ax[0].set_xlim([min(amount_val), max(amount_val)])

sns.distplot(time_val, ax=ax[1], color='b')
ax[1].set_title('Distribution of Transaction Time', fontsize=14)
ax[1].set_xlim([min(time_val), max(time_val)])



plt.show()

#very imbalanced data in amount and time
```



In [ ]:

```python
#scaling colounms amount and time

from sklearn.preprocessing import StandardScaler, RobustScaler

# RobustScaler

std_scaler = StandardScaler()
rob_scaler = RobustScaler()

df['scaled_amount'] = rob_scaler.fit_transform(df['Amount'].values.reshape(-1,1))
df['scaled_time'] = rob_scaler.fit_transform(df['Time'].values.reshape(-1,1))

df.drop(['Time','Amount'], axis=1, inplace=True)
```

In [ ]:

```python
scaled_amount = df['scaled_amount']
scaled_time = df['scaled_time']

df.drop(['scaled_amount', 'scaled_time'], axis=1, inplace=True)
df.insert(0, 'scaled_amount', scaled_amount)
df.insert(1, 'scaled_time', scaled_time)

# Amount and Time are Scaled!

df.head()
```

Out[ ]:

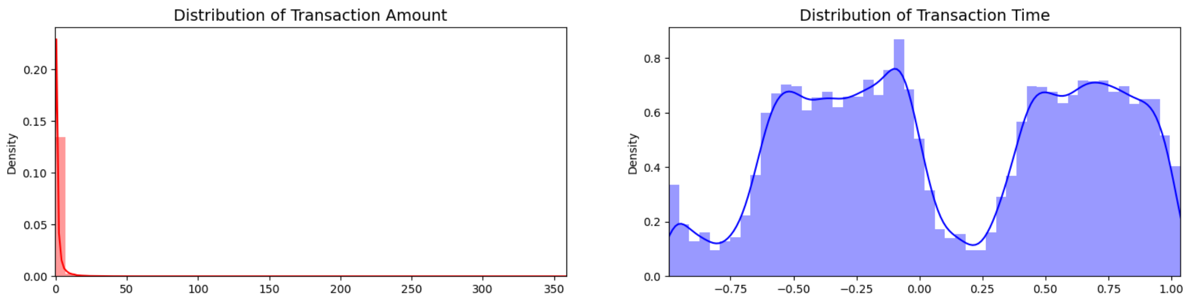
	scaled_amount	scaled_time	V1	V2	V3	V4	V5	V6	V7	
0	1.783274	-0.994983	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098

1	-0.269825	-0.994983	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085
2	4.983721	-0.994972	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247
3	1.418291	-0.994972	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377
4	0.670579	-0.994960	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.27

5 rows × 31 columns

In [ ]:

```
fig, ax = plt.subplots(1, 2, figsize=(18,4))

amount_val = df['scaled_amount'].values
time_val = df['scaled_time'].values

sns.distplot(amount_val, ax=ax[0], color='r')
ax[0].set_title('Distribution of Transaction Amount', fontsize=14)
ax[0].set_xlim([min(amount_val), max(amount_val)])

sns.distplot(time_val, ax=ax[1], color='b')
ax[1].set_title('Distribution of Transaction Time', fontsize=14)
ax[1].set_xlim([min(time_val), max(time_val)])



plt.show()
```



In [ ]:

```
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.model_selection import KFold, StratifiedKFold

print('No Frauds', round(df['Class'].value_counts()[0]/len(df) * 100,2), '% of the dataset')
print('Frauds', round(df['Class'].value_counts()[1]/len(df) * 100,2), '% of the dataset')

X = df.drop('Class', axis=1)
y = df['Class']

sss = StratifiedKFold(n_splits=5, random_state=None, shuffle=False)

for train_index, test_index in sss.split(X, y):
    print("Train:", train_index, "Test:", test_index)
    original_Xtrain, original_Xtest = X.iloc[train_index], X.iloc[test_index]
    original_ytrain, original_ytest = y.iloc[train_index], y.iloc[test_index]
```

```
No Frauds 99.83 % of the dataset
Frauds 0.17 % of the dataset
Train: [ 30473  30496  31002 ... 284804 284805 284806] Test: [     0      1      2 ... 57017 57018 57019]
Train: [     0      1      2 ... 284804 284805 284806] Test: [ 30473  30496  31002 ... 113964 113965 11
3966]
Train: [     0      1      2 ... 284804 284805 284806] Test: [ 81609  82400  83053 ... 170946 170947 17
0948]
Train: [     0      1      2 ... 284804 284805 284806] Test: [150654 150660 150661 ... 227866 227867 22
7868]
Train: [     0      1      2 ... 227866 227867 227868] Test: [212516 212644 213092 ... 284804 284805 28
4806]
```

In [ ]:

```
# Random Under Sampling" which basically consists of removing data in order to have a more balanced d
# Lets shuffle the data before creating the subsamples

df = df.sample(frac=1)

# amount of fraud classes 492 rows.
fraud_df = df.loc[df['Class'] == 1]
```

```
fraud_df = df.loc[df['Class'] == 1]
non_fraud_df = df.loc[df['Class'] == 0][:492]

normal_distributed_df = pd.concat([fraud_df, non_fraud_df])

# Shuffle dataframe rows
new_df = normal_distributed_df.sample(frac=1, random_state=42)

new_df.head()
```

Out[ ]:

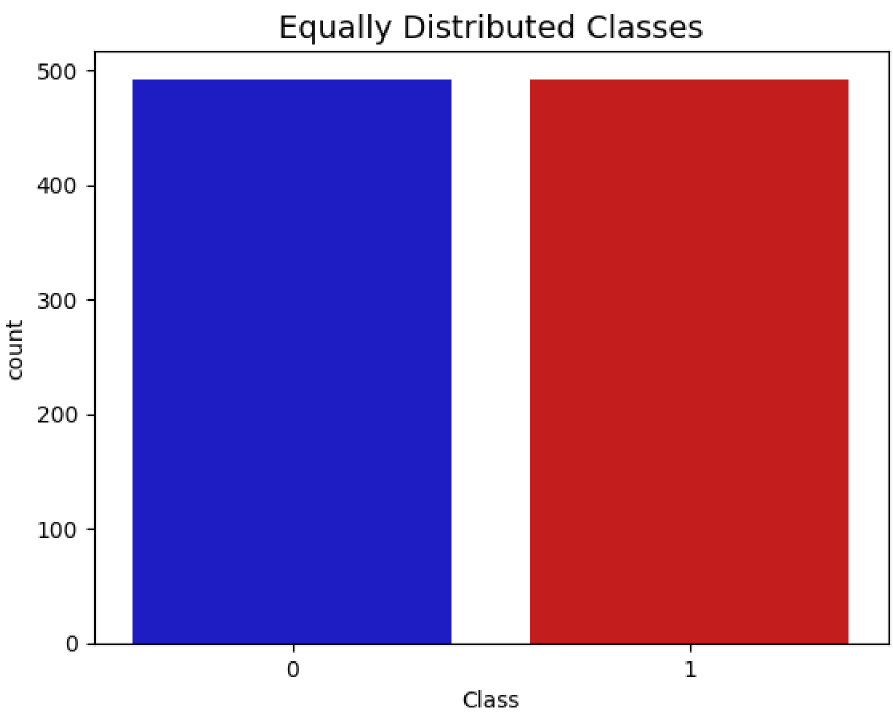
	scaled_amount	scaled_time	V1	V2	V3	V4	V5	V6	V
151906	-0.046112	0.138359	2.057176	0.180285	-1.870319	0.187160	0.523782	-1.505314	0.66731
249963	-0.296653	0.821967	-0.679521	4.672553	-6.814798	7.143500	0.928654	-1.873013	-2.30668
110046	0.314120	-0.153115	1.209445	0.085729	-0.048025	-0.093705	-0.082630	-0.772552	0.31248
150654	-0.307273	0.107403	-3.765680	5.890735	-10.202268	10.259036	-5.611448	-3.235376	-10.63268
154454	1.758821	0.198604	0.913116	1.145381	-4.602878	2.091803	-0.473224	-2.085436	-1.67124

5 rows × 31 columns

In [ ]:

```
print('Distribution of the Classes in the subsample dataset')
print(new_df['Class'].value_counts()/len(new_df))



sns.countplot(x='Class', data=new_df, palette=colors)
plt.title('Equally Distributed Classes', fontsize=14)
plt.show()
```

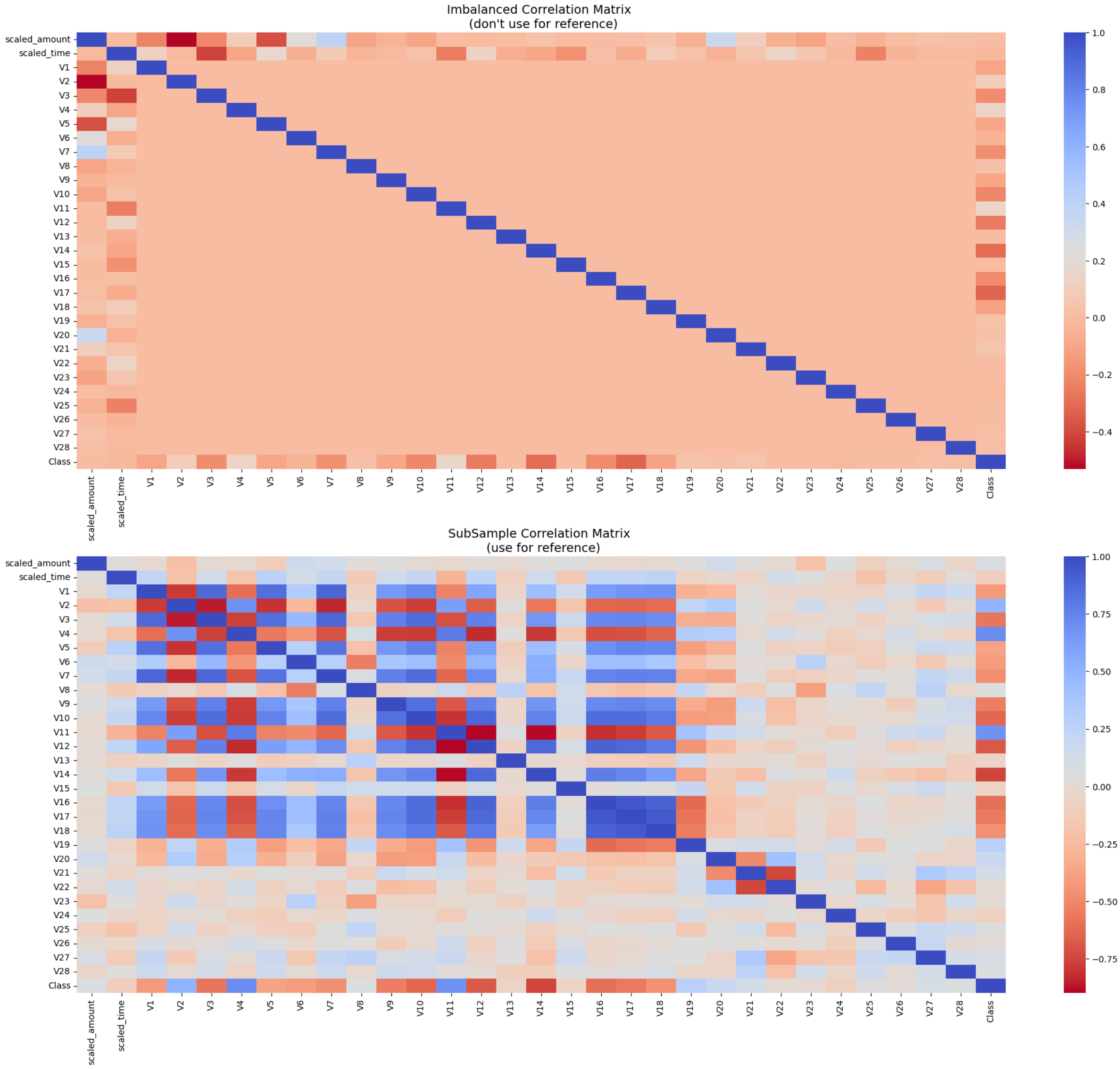
```
Distribution of the Classes in the subsample dataset
Class
0    0.5
1    0.5
Name: count, dtype: float64
```



In [ ]:

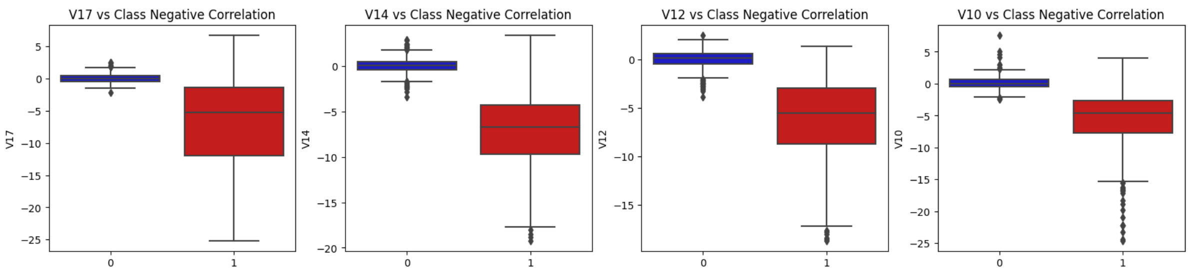
```
# Make sure we use the subsample in our correlation

f, (ax1, ax2) = plt.subplots(2, 1, figsize=(24,20))

# Entire DataFrame
corr = df.corr()
sns.heatmap(corr, cmap='coolwarm_r', annot_kws={'size':20}, ax=ax1)
ax1.set_title("Imbalanced Correlation Matrix \n (don't use for reference)", fontsize=14)
```

```python
sub_sample_corr = new_df.corr()
sns.heatmap(sub_sample_corr, cmap='coolwarm_r', annot_kws={'size':20}, ax=ax2)
ax2.set_title('SubSample Correlation Matrix \n (use for reference)', fontsize=14)
plt.show()
```



In [ ]:

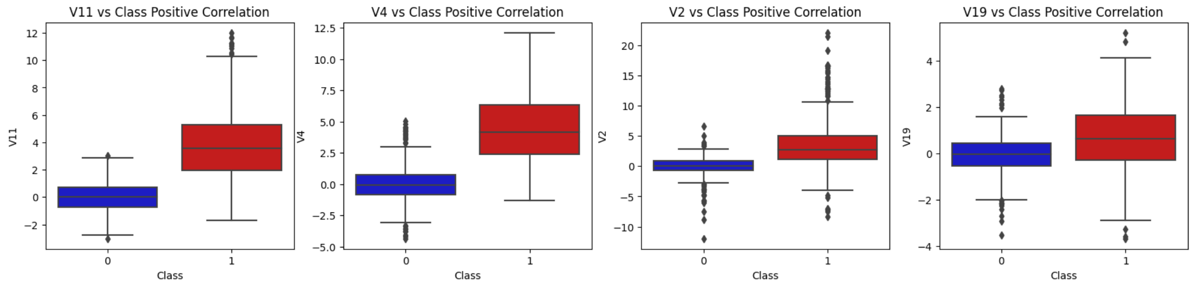
```python
f, axes = plt.subplots(ncols=4, figsize=(20,4))

# Negative Correlations with our Class (The lower our feature value the more likely it will be a frau
sns.boxplot(x="Class", y="V17", data=new_df, palette=colors, ax=axes[0])
axes[0].set_title('V17 vs Class Negative Correlation')

sns.boxplot(x="Class", y="V14", data=new_df, palette=colors, ax=axes[1])
axes[1].set_title('V14 vs Class Negative Correlation')


sns.boxplot(x="Class", y="V12", data=new_df, palette=colors, ax=axes[2])
axes[2].set_title('V12 vs Class Negative Correlation')


sns.boxplot(x="Class", y="V10", data=new_df, palette=colors, ax=axes[3])
axes[3].set_title('V10 vs Class Negative Correlation')

plt.show()
```



Class Class Class Class

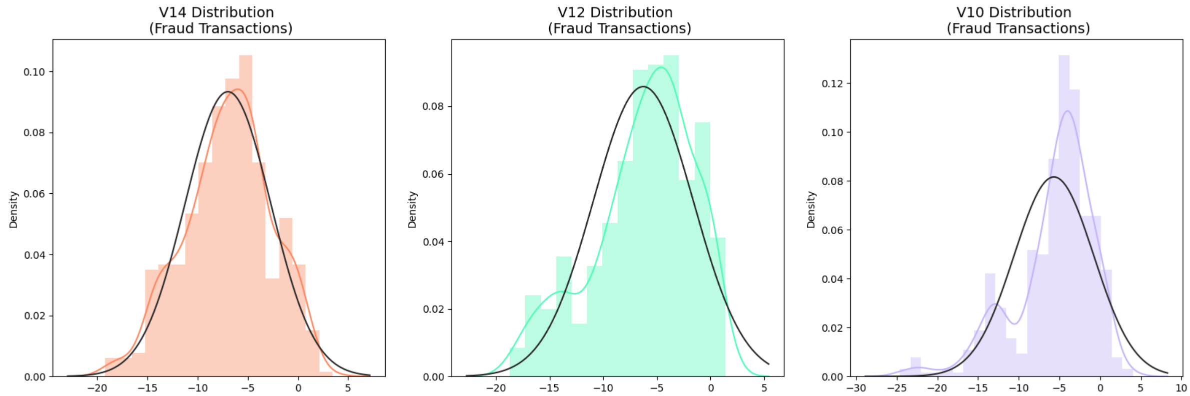
In [ ]:

```
f, axes = plt.subplots(ncols=4, figsize=(20,4))

# Positive correlations (The higher the feature the probability increases that it will be a fraud tra
sns.boxplot(x="Class", y="V11", data=new_df, palette=colors, ax=axes[0])
axes[0].set_title('V11 vs Class Positive Correlation')

sns.boxplot(x="Class", y="V4", data=new_df, palette=colors, ax=axes[1])
axes[1].set_title('V4 vs Class Positive Correlation')


sns.boxplot(x="Class", y="V2", data=new_df, palette=colors, ax=axes[2])
axes[2].set_title('V2 vs Class Positive Correlation')


sns.boxplot(x="Class", y="V19", data=new_df, palette=colors, ax=axes[3])
axes[3].set_title('V19 vs Class Positive Correlation')

plt.show()
```



In [ ]:

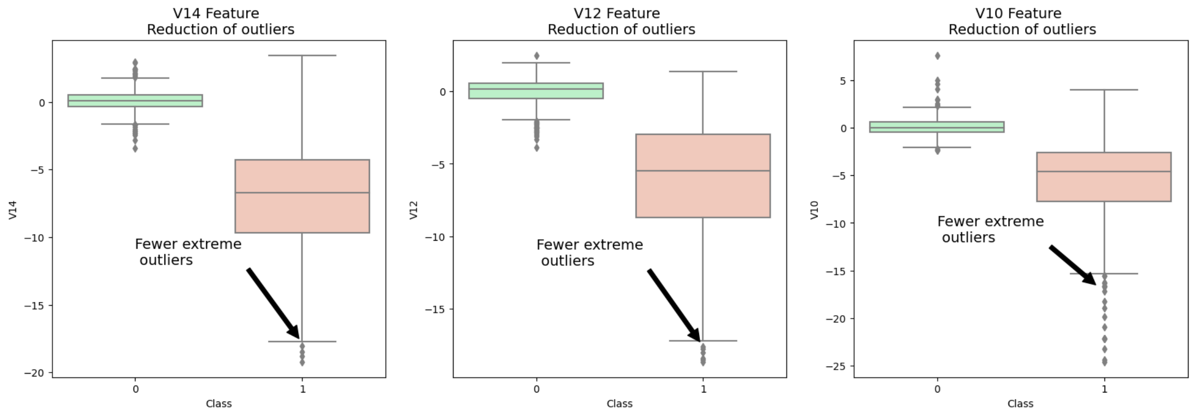
```
# histogram
from scipy.stats import norm

f, (ax1, ax2, ax3) = plt.subplots(1,3, figsize=(20, 6))

v14_fraud_dist = new_df['V14'].loc[new_df['Class'] == 1].values
sns.distplot(v14_fraud_dist,ax=ax1, fit=norm, color='#FB8861')
ax1.set_title('V14 Distribution \n (Fraud Transactions)', fontsize=14)

v12_fraud_dist = new_df['V12'].loc[new_df['Class'] == 1].values
sns.distplot(v12_fraud_dist,ax=ax2, fit=norm, color='#56F9BB')
ax2.set_title('V12 Distribution \n (Fraud Transactions)', fontsize=14)


v10_fraud_dist = new_df['V10'].loc[new_df['Class'] == 1].values
sns.distplot(v10_fraud_dist,ax=ax3, fit=norm, color='#C5B3F9')
ax3.set_title('V10 Distribution \n (Fraud Transactions)', fontsize=14)

plt.show()
```



In [ ]:

```
f,(ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(20,6))

colors = ['#B3F9C5', '#f9c5b3']
# Boxplots with outliers removed
# Feature V14
sns.boxplot(x="Class", y="V14", data=new_df,ax=ax1, palette=colors)
ax1.set_title("V14 Feature \n Reduction of outliers", fontsize=14)
ax1.annotate('Fewer extreme \n outliers', xy=(0.98, -17.5), xytext=(0, -12),
            arrowprops=dict(facecolor='black'),
```

```
            fontsize=14)

# Feature 12
sns.boxplot(x="Class", y="V12", data=new_df, ax=ax2, palette=colors)
ax2.set_title("V12 Feature \n Reduction of outliers", fontsize=14)
ax2.annotate('Fewer extreme \n outliers', xy=(0.98, -17.3), xytext=(0, -12),
            arrowprops=dict(facecolor='black'),
            fontsize=14)

# Feature V10
sns.boxplot(x="Class", y="V10", data=new_df, ax=ax3, palette=colors)
ax3.set_title("V10 Feature \n Reduction of outliers", fontsize=14)
ax3.annotate('Fewer extreme \n outliers', xy=(0.95, -16.5), xytext=(0, -12),
            arrowprops=dict(facecolor='black'),
            fontsize=14)


plt.show()
```



In [ ]:

```
# implementation timings
X = new_df.drop('Class', axis=1)
y = new_df['Class']


# T-SNE Implementation
t0 = time.time()
X_reduced_tsne = TSNE(n_components=2, random_state=42).fit_transform(X.values)
t1 = time.time()
print("T-SNE took {:.2} s".format(t1 - t0))

# PCA Implementation
t0 = time.time()
X_reduced_pca = PCA(n_components=2, random_state=42).fit_transform(X.values)
t1 = time.time()
print("PCA took {:.2} s".format(t1 - t0))

# TruncatedSVD
t0 = time.time()
X_reduced_svd = TruncatedSVD(n_components=2, algorithm='randomized', random_state=42).fit_transform(X
t1 = time.time()
print("Truncated SVD took {:.2} s".format(t1 - t0))
```

```
T-SNE took 3.7 s
PCA took 0.0065 s
Truncated SVD took 0.005 s
```

In [ ]:

```
#clustering
f, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(24,6))
```

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.manifold import TSNE
from sklearn.decomposition import PCA, TruncatedSVD
import matplotlib.patches as mpatches
import time

# Classifier Libraries
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
import collections
```

In [2]:

```
df = pd.read_csv("creditcard.csv")
```

In [3]:

```
Total_transactions = len(df)
normal = len(df[df.Class == 0])
fraudulent = len(df[df.Class == 1])
fraud_percentage = round(fraudulent/normal*100, 2)

print("total number of transactions: ",Total_transactions)
print("normal transactions: ",normal)
print("fraud transactions: ",fraudulent)
print("percentage: ",fraud_percentage)
```

```
total number of transactions:  284807
normal transactions:  284315
fraud transactions:  492
percentage:  0.17
```

In [4]:

```
df.head()
```

Out[4]:

	Time	V1	V2	V3	V4	V5	V
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.4623
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.0823
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.8004
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.2472
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.0959

5 rows × 31 columns

In [5]:

```
df.isnull().sum()
```

Out[5]:

```
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
```

```
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

In [6]:
```
print(df.duplicated().sum())
df.shape
```

```
1081
```

Out[6]:
```
(284807, 31)
```

In [7]:
```
df.drop_duplicates()
```

Out[7]:

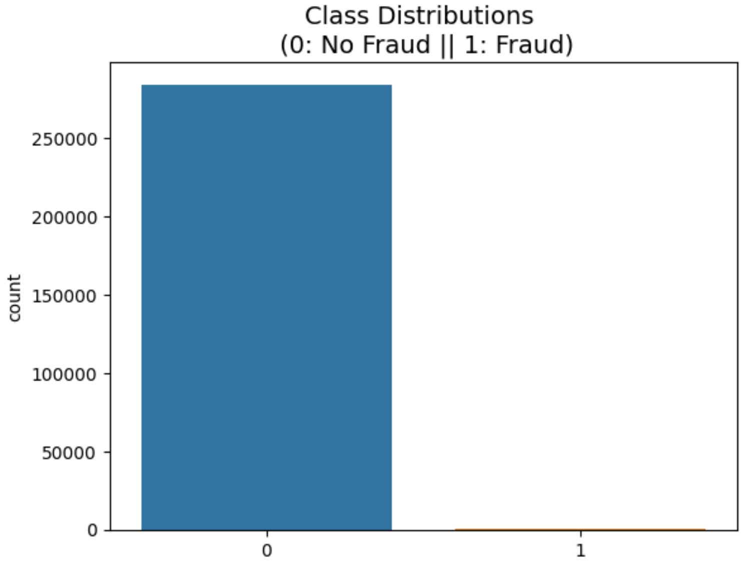
	Time	V1	V2	V3	V4	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.3383
1	0.0	1.191857	0.266151	0.166480	0.448154	0.0600
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.5031
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.0103
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.4071
...	...	...	...	...	...	
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.3644
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.8682
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.6305
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.3779
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.0125

283726 rows × 31 columns

Pre-Processing

In [8]:
```
import matplotlib.pyplot as plt
colors = ["#0101DF", "#DF0101"]

sns.countplot(x='Class', data=df)
plt.title('Class Distributions \n (0: No Fraud || 1: Fraud)', f
```

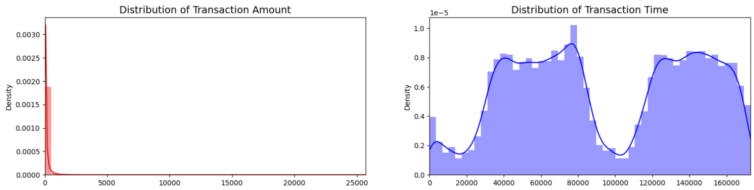
Out[8]:
```
Text(0.5, 1.0, 'Class Distributions \n (0: No Fraud || 1: Frau
d)')
```



Class

In [9]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [10]:
```
fig, ax = plt.subplots(1, 2, figsize=(18,4))

amount_val = df['Amount'].values
time_val = df['Time'].values

sns.distplot(amount_val, ax=ax[0], color='r')
ax[0].set_title('Distribution of Transaction Amount', fontsize=
ax[0].set_xlim([min(amount_val), max(amount_val)])

sns.distplot(time_val, ax=ax[1], color='b')
ax[1].set_title('Distribution of Transaction Time', fontsize=14
ax[1].set_xlim([min(time_val), max(time_val)])



plt.show()

#very imbalanced data in amount and time
```



In [11]:
```
#scaling colounms amount and time

from sklearn.preprocessing import StandardScaler, RobustScaler

# RobustScaler

std_scaler = StandardScaler()
rob_scaler = RobustScaler()

df['scaled_amount'] = rob_scaler.fit_transform(df['Amount'].val
df['scaled_time'] = rob_scaler.fit_transform(df['Time'].values.

df.drop(['Time','Amount'], axis=1, inplace=True)
```

In [12]:
```
scaled_amount = df['scaled_amount']
scaled_time = df['scaled_time']

df.drop(['scaled_amount', 'scaled_time'], axis=1, inplace=True)
df.insert(0, 'scaled_amount', scaled_amount)
df.insert(1, 'scaled_time', scaled_time)

# Amount and Time are Scaled!

df.head()
```

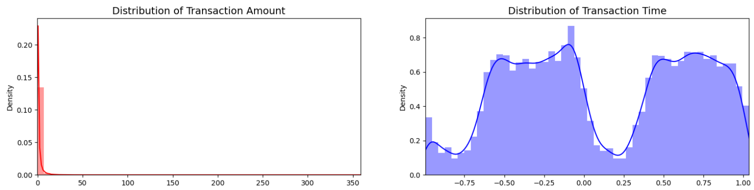
Out[12]:

	scaled_amount	scaled_time	V1	V2	V3	
0	1.783274	-0.994983	-1.359807	-0.072781	2.536347	1.378
1	-0.269825	-0.994983	1.191857	0.266151	0.166480	0.448
2	4.983721	-0.994972	-1.358354	-1.340163	1.773209	0.379
3	1.418291	-0.994972	-0.966272	-0.185226	1.792993	-0.863
4	0.670579	-0.994960	-1.158233	0.877737	1.548718	0.403

5 rows × 31 columns

In [13]:
```
fig, ax = plt.subplots(1, 2, figsize=(18,4))
```

```
amount_val = df['scaled_amount'].values
time_val = df['scaled_time'].values

sns.distplot(amount_val, ax=ax[0], color='r')
ax[0].set_title('Distribution of Transaction Amount', fontsize=
ax[0].set_xlim([min(amount_val), max(amount_val)])

sns.distplot(time_val, ax=ax[1], color='b')
ax[1].set_title('Distribution of Transaction Time', fontsize=14
ax[1].set_xlim([min(time_val), max(time_val)])



plt.show()
```



In [14]:

```
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.model_selection import KFold, StratifiedKFold

print('No Frauds', round(df['Class'].value_counts()[0]/len(df)
print('Frauds', round(df['Class'].value_counts()[1]/len(df) * 1

X = df.drop('Class', axis=1)
y = df['Class']

sss = StratifiedKFold(n_splits=5, random_state=None, shuffle=Fa

for train_index, test_index in sss.split(X, y):
    print("Train:", train_index, "Test:", test_index)
    original_Xtrain, original_Xtest = X.iloc[train_index], X.il
    original_ytrain, original_ytest = y.iloc[train_index], y.il
```

```
No Frauds 99.83 % of the dataset
Frauds 0.17 % of the dataset
Train: [ 30473  30496  31002 ... 284804 284805 284806] Test: [
0      1      2 ... 57017 57018 57019]
Train: [     0      1      2 ... 284804 284805 284806] Test: [ 30
473  30496  31002 ... 113964 113965 113966]
Train: [     0      1      2 ... 284804 284805 284806] Test: [ 81
609  82400  83053 ... 170946 170947 170948]
Train: [     0      1      2 ... 284804 284805 284806] Test: [150
654 150660 150661 ... 227866 227867 227868]
Train: [     0      1      2 ... 227866 227867 227868] Test: [212
516 212644 213092 ... 284804 284805 284806]
```

In [15]:

```
# Random Under Sampling" which basically consists of removing d
# Lets shuffle the data before creating the subsamples

df = df.sample(frac=1)

# amount of fraud classes 492 rows.
fraud_df = df.loc[df['Class'] == 1]
non_fraud_df = df.loc[df['Class'] == 0][:492]

normal_distributed_df = pd.concat([fraud_df, non_fraud_df])

# Shuffle dataframe rows
new_df = normal_distributed_df.sample(frac=1, random_state=42)

new_df.head()
```

Out[15]:

	scaled_amount	scaled_time	V1	V2	V3
153730	-0.027947	0.179114	-2.004446	0.990127	2.55481
63634	1.089779	-0.398078	-9.169790	7.092197	-12.35403
92943	0.070286	-0.240980	1.079165	-0.590200	1.93635
12108	-0.293440	-0.747730	-16.917468	9.669900	-23.73644

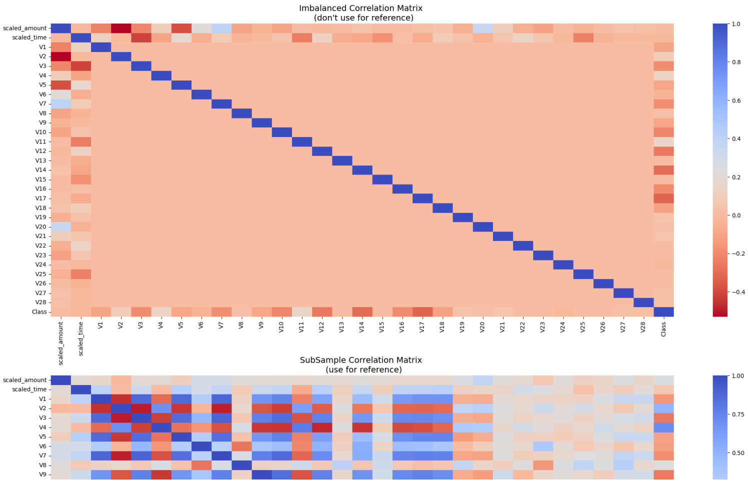
244004	-0.293440	0.792690	-4.673231	4.195976	-8.39242:

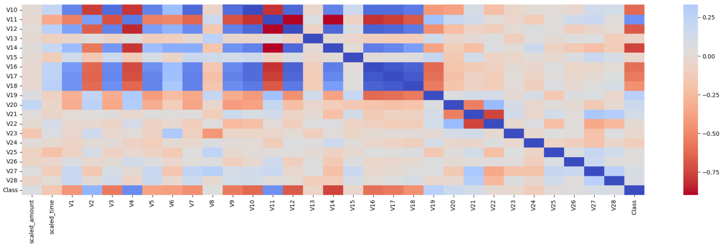
5 rows × 31 columns

In [16]:
```
print('Distribution of the Classes in the subsample dataset')
print(new_df['Class'].value_counts()/len(new_df))



sns.countplot(x='Class', data=new_df, palette=colors)
plt.title('Equally Distributed Classes', fontsize=14)
plt.show()
```

```
Distribution of the Classes in the subsample dataset
Class
0    0.5
1    0.5
Name: count, dtype: float64
```

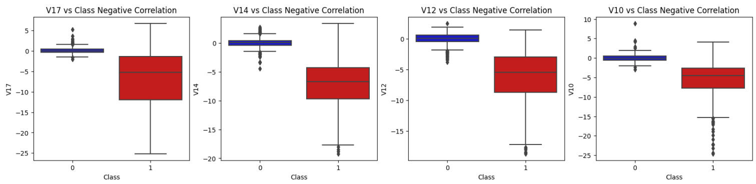
In [17]:
```
# Make sure we use the subsample in our correlation

f, (ax1, ax2) = plt.subplots(2, 1, figsize=(24,20))

# Entire DataFrame
corr = df.corr()
sns.heatmap(corr, cmap='coolwarm_r', annot_kws={'size':20}, ax=
ax1.set_title("Imbalanced Correlation Matrix \n (don't use for


sub_sample_corr = new_df.corr()
sns.heatmap(sub_sample_corr, cmap='coolwarm_r', annot_kws={'siz
ax2.set_title('SubSample Correlation Matrix \n (use for referer
plt.show()
```





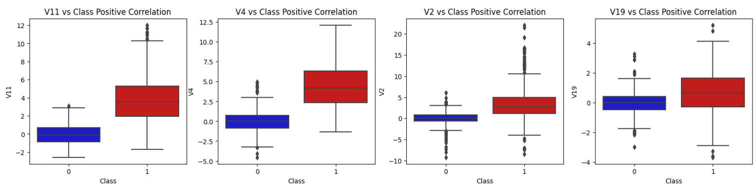
In [18]:

```
f, axes = plt.subplots(ncols=4, figsize=(20,4))

# Negative Correlations with our Class (The lower our feature v
sns.boxplot(x="Class", y="V17", data=new_df, palette=colors, ax
axes[0].set_title('V17 vs Class Negative Correlation')

sns.boxplot(x="Class", y="V14", data=new_df, palette=colors, ax
axes[1].set_title('V14 vs Class Negative Correlation')


sns.boxplot(x="Class", y="V12", data=new_df, palette=colors, ax
axes[2].set_title('V12 vs Class Negative Correlation')


sns.boxplot(x="Class", y="V10", data=new_df, palette=colors, ax
axes[3].set_title('V10 vs Class Negative Correlation')

plt.show()
```



In [19]:

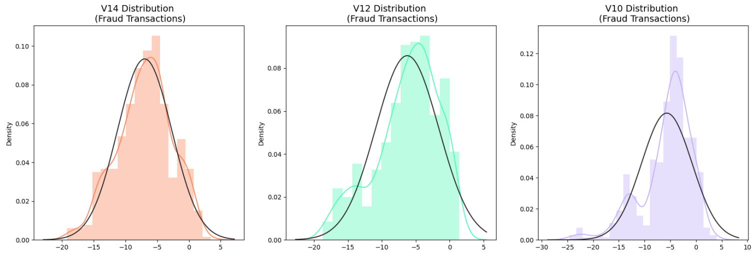
```
f, axes = plt.subplots(ncols=4, figsize=(20,4))

# Positive correlations (The higher the feature the probability
sns.boxplot(x="Class", y="V11", data=new_df, palette=colors, ax
axes[0].set_title('V11 vs Class Positive Correlation')

sns.boxplot(x="Class", y="V4", data=new_df, palette=colors, ax=
axes[1].set_title('V4 vs Class Positive Correlation')


sns.boxplot(x="Class", y="V2", data=new_df, palette=colors, ax=
axes[2].set_title('V2 vs Class Positive Correlation')


sns.boxplot(x="Class", y="V19", data=new_df, palette=colors, ax
axes[3].set_title('V19 vs Class Positive Correlation')

plt.show()
```



In [20]:

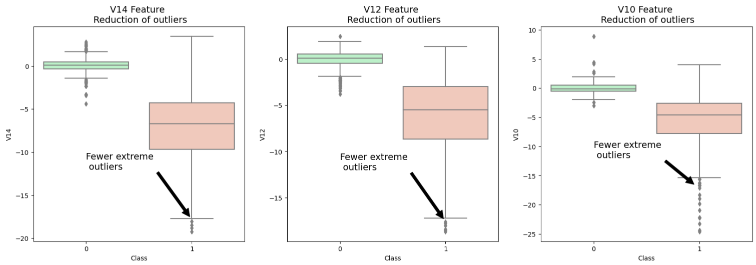
```
from scipy.stats import norm

f, (ax1, ax2, ax3) = plt.subplots(1,3, figsize=(20, 6))

v14_fraud_dist = new_df['V14'].loc[new_df['Class'] == 1].values
sns.distplot(v14_fraud_dist,ax=ax1, fit=norm, color='#FB8861')
ax1.set_title('V14 Distribution \n (Fraud Transactions)', fonts

v12_fraud_dist = new_df['V12'].loc[new_df['Class'] == 1].values
sns.distplot(v12_fraud_dist,ax=ax2, fit=norm, color='#56F9BB')
ax2.set_title('V12 Distribution \n (Fraud Transactions)', fonts


v10_fraud_dist = new_df['V10'].loc[new_df['Class'] == 1].values
```

```
v10_fraud_dist = new_df['V10'].loc[new_df['Class'] == 1].values
sns.distplot(v10_fraud_dist,ax=ax3, fit=norm, color='#C5B3F9')
ax3.set_title('V10 Distribution \n (Fraud Transactions)', fonts

plt.show()
```



In [21]:

```
f,(ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(20,6))

colors = ['#B3F9C5', '#f9c5b3']
# Boxplots with outliers removed
# Feature V14
sns.boxplot(x="Class", y="V14", data=new_df,ax=ax1, palette=col
ax1.set_title("V14 Feature \n Reduction of outliers", fontsize=
ax1.annotate('Fewer extreme \n outliers', xy=(0.98, -17.5), xyt
            arrowprops=dict(facecolor='black'),
            fontsize=14)

# Feature 12
sns.boxplot(x="Class", y="V12", data=new_df, ax=ax2, palette=co
ax2.set_title("V12 Feature \n Reduction of outliers", fontsize=
ax2.annotate('Fewer extreme \n outliers', xy=(0.98, -17.3), xyt
            arrowprops=dict(facecolor='black'),
            fontsize=14)

# Feature V10
sns.boxplot(x="Class", y="V10", data=new_df, ax=ax3, palette=co
ax3.set_title("V10 Feature \n Reduction of outliers", fontsize=
ax3.annotate('Fewer extreme \n outliers', xy=(0.95, -16.5), xyt
            arrowprops=dict(facecolor='black'),
            fontsize=14)


plt.show()
```



In [22]:

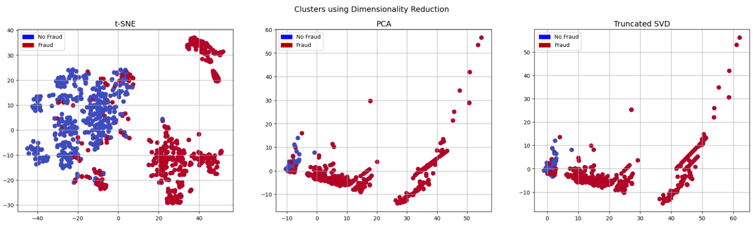
```
X = new_df.drop('Class', axis=1)
y = new_df['Class']


# T-SNE Implementation
t0 = time.time()
X_reduced_tsne = TSNE(n_components=2, random_state=42).fit_tran
t1 = time.time()
print("T-SNE took {:.2} s".format(t1 - t0))

# PCA Implementation
t0 = time.time()
X_reduced_pca = PCA(n_components=2, random_state=42).fit_transf
t1 = time.time()
print("PCA took {:.2} s".format(t1 - t0))

# TruncatedSVD
t0 = time.time()
X_reduced_svd = TruncatedSVD(n_components=2, algorithm='randomi
t1 = time.time()
print("Truncated SVD took {:.2} s".format(t1 - t0))
```

```
T-SNE took 4.6 s
```

```
PCA took 0.0071 s
Truncated SVD took 0.0066 s
```

In [23]:

```python
f, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(24,6))
# labels = ['No Fraud', 'Fraud']
f.suptitle('Clusters using Dimensionality Reduction', fontsize=


blue_patch = mpatches.Patch(color='#0A0AFF', label='No Fraud')
red_patch = mpatches.Patch(color='#AF0000', label='Fraud')


# t-SNE scatter plot
ax1.scatter(X_reduced_tsne[:,0], X_reduced_tsne[:,1], c=(y == 0
ax1.scatter(X_reduced_tsne[:,0], X_reduced_tsne[:,1], c=(y == 1
ax1.set_title('t-SNE', fontsize=14)

ax1.grid(True)

ax1.legend(handles=[blue_patch, red_patch])


# PCA scatter plot
ax2.scatter(X_reduced_pca[:,0], X_reduced_pca[:,1], c=(y == 0),
ax2.scatter(X_reduced_pca[:,0], X_reduced_pca[:,1], c=(y == 1),
ax2.set_title('PCA', fontsize=14)

ax2.grid(True)

ax2.legend(handles=[blue_patch, red_patch])

# TruncatedSVD scatter plot
ax3.scatter(X_reduced_svd[:,0], X_reduced_svd[:,1], c=(y == 0),
ax3.scatter(X_reduced_svd[:,0], X_reduced_svd[:,1], c=(y == 1),
ax3.set_title('Truncated SVD', fontsize=14)

ax3.grid(True)

ax3.legend(handles=[blue_patch, red_patch])

plt.show()
```



Classification Models

In [24]:

```python
# undersampling
X = new_df.drop('Class', axis=1)
y = new_df['Class']
```

In [25]:

```python
from sklearn.model_selection import train_test_split
# splitting
X_train, X_test, y_train, y_test = train_test_split(X, y, test_
X_train = X_train.values
X_test = X_test.values
y_train = y_train.values
y_test = y_test.values
```

In [18]:

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import tensorflow as tf
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.manifold import TSNE
from sklearn.decomposition import PCA, TruncatedSVD
import matplotlib.patches as mpatches
import time

# Classifier Libraries
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
import collections
```

In [19]:

```
df = pd.read_csv("creditcard.csv")
```

In [20]:

```
Total_transactions = len(df)
normal = len(df[df.Class == 0])
fraudulent = len(df[df.Class == 1])
fraud_percentage = round(fraudulent/normal*100, 2)

print("total number of transactions: ",Total_transactions)
print("normal transactions: ",normal)
print("fraud transactions: ",fraudulent)
print("percentage: ",fraud_percentage)
```

```
total number of transactions:  284807
normal transactions:  284315
fraud transactions:  492
percentage:  0.17
```

In [21]:

```
df.head()
```

Out[21]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...

5 rows × 31 columns

In [22]:

```
df.isnull().sum()
```

Out[22]:

```
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
```

```
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

In [23]:
```
print(df.duplicated().sum())
df.shape
```

```
1081
```

Out[23]: `(284807, 31)`

In [24]:
```
df.drop_duplicates()
```

Out[24]:

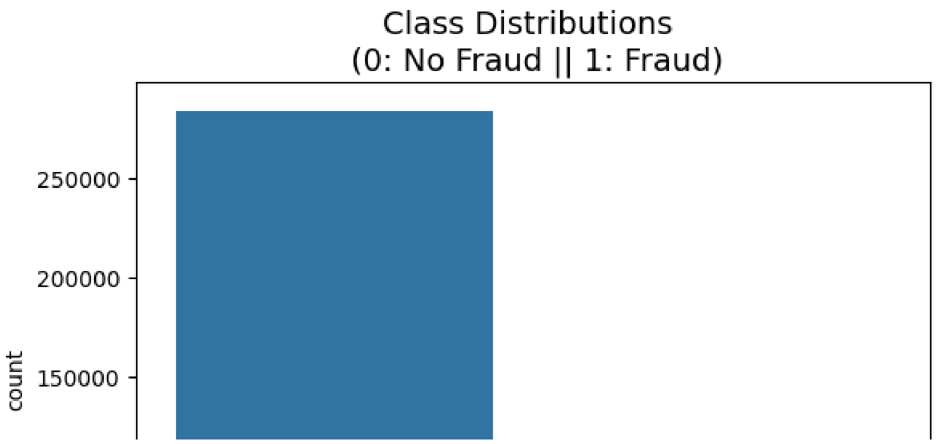
	Time	V1	V2	V3	V4	V5	V6	V7	V8	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.
...	...	...	...	...	...	...	...	...	...	
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215	7.305334	1.
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330	0.294869	0.
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827	0.708417	0.
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180	0.679145	0.
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006	-0.414650	0.

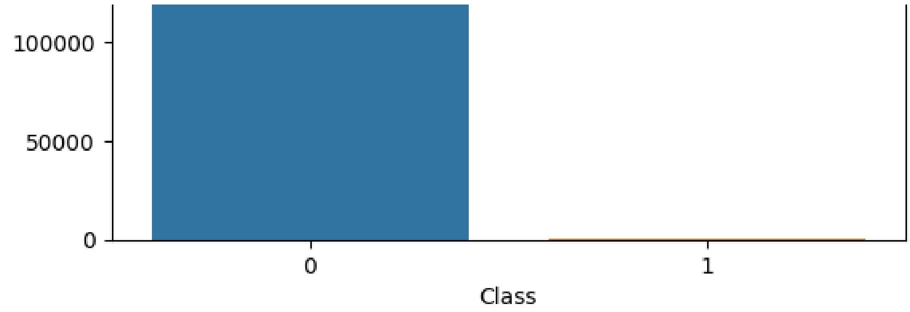
283726 rows × 31 columns

Pre-Processing

In [25]:
```
import matplotlib.pyplot as plt
colors = ["#0101DF", "#DF0101"]

sns.countplot(x='Class', data=df)
plt.title('Class Distributions \n (0: No Fraud || 1: Fraud)', fontsize=14)
```

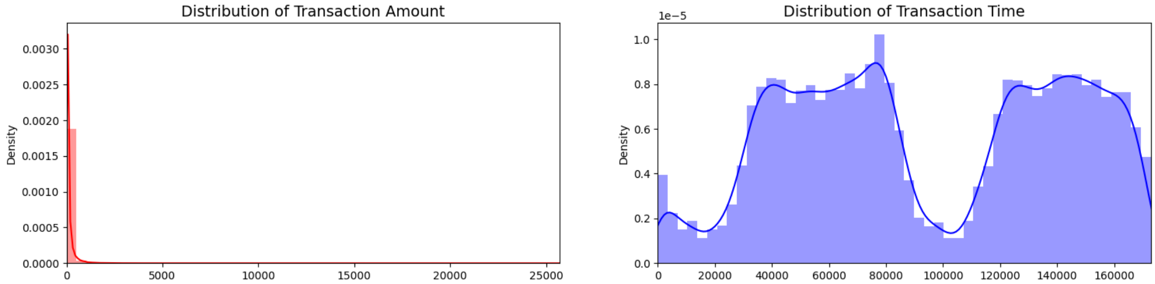
Out[25]: `Text(0.5, 1.0, 'Class Distributions \n (0: No Fraud || 1: Fraud)')`





In [26]:
```python
import warnings
warnings.filterwarnings("ignore")
```

In [27]:
```python
fig, ax = plt.subplots(1, 2, figsize=(18,4))

amount_val = df['Amount'].values
time_val = df['Time'].values

sns.distplot(amount_val, ax=ax[0], color='r')
ax[0].set_title('Distribution of Transaction Amount', fontsize=14)
ax[0].set_xlim([min(amount_val), max(amount_val)])

sns.distplot(time_val, ax=ax[1], color='b')
ax[1].set_title('Distribution of Transaction Time', fontsize=14)
ax[1].set_xlim([min(time_val), max(time_val)])



plt.show()

#very imbalanced data in amount and time
```



In [28]:
```python
#scaling colounms amount and time

from sklearn.preprocessing import StandardScaler, RobustScaler

# RobustScaler

std_scaler = StandardScaler()
rob_scaler = RobustScaler()

df['scaled_amount'] = rob_scaler.fit_transform(df['Amount'].values.reshape(-1,1))
df['scaled_time'] = rob_scaler.fit_transform(df['Time'].values.reshape(-1,1))

df.drop(['Time','Amount'], axis=1, inplace=True)
```

In [29]:
```python
scaled_amount = df['scaled_amount']
scaled_time = df['scaled_time']

df.drop(['scaled_amount', 'scaled_time'], axis=1, inplace=True)
df.insert(0, 'scaled_amount', scaled_amount)
df.insert(1, 'scaled_time', scaled_time)

# Amount and Time are Scaled!

df.head()
```

Out[29]:

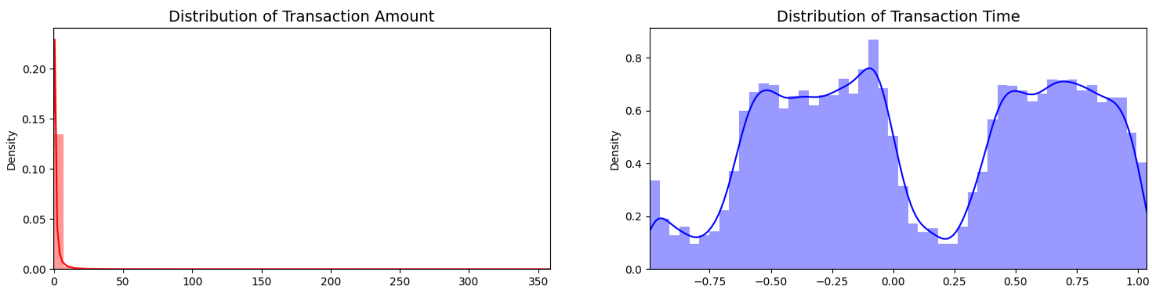
	scaled_amount	scaled_time	V1	V2	V3	V4	V5	V6	V7	
0	1.783274	-0.994983	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0

1	-0.269825	-0.994983	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0
2	4.983721	-0.994972	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0
3	1.418291	-0.994972	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0
4	0.670579	-0.994960	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0

5 rows × 31 columns

In [30]:

```
fig, ax = plt.subplots(1, 2, figsize=(18,4))

amount_val = df['scaled_amount'].values
time_val = df['scaled_time'].values

sns.distplot(amount_val, ax=ax[0], color='r')
ax[0].set_title('Distribution of Transaction Amount', fontsize=14)
ax[0].set_xlim([min(amount_val), max(amount_val)])

sns.distplot(time_val, ax=ax[1], color='b')
ax[1].set_title('Distribution of Transaction Time', fontsize=14)
ax[1].set_xlim([min(time_val), max(time_val)])



plt.show()
```



In [31]:

```
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.model_selection import KFold, StratifiedKFold

print('No Frauds', round(df['Class'].value_counts()[0]/len(df) * 100,2), '% of the dataset')
print('Frauds', round(df['Class'].value_counts()[1]/len(df) * 100,2), '% of the dataset')

X = df.drop('Class', axis=1)
y = df['Class']

sss = StratifiedKFold(n_splits=5, random_state=None, shuffle=False)

for train_index, test_index in sss.split(X, y):
    print("Train:", train_index, "Test:", test_index)
    original_Xtrain, original_Xtest = X.iloc[train_index], X.iloc[test_index]
    original_ytrain, original_ytest = y.iloc[train_index], y.iloc[test_index]
```

```
No Frauds 99.83 % of the dataset
Frauds 0.17 % of the dataset
Train: [ 30473  30496  31002 ... 284804 284805 284806] Test: [    0     1     2 ... 57017 57018 5701
9]
Train: [     0      1      2 ... 284804 284805 284806] Test: [ 30473  30496  31002 ... 113964 113965
113966]
Train: [     0      1      2 ... 284804 284805 284806] Test: [ 81609  82400  83053 ... 170946 170947
170948]
Train: [     0      1      2 ... 284804 284805 284806] Test: [150654 150660 150661 ... 227866 227867
227868]
Train: [     0      1      2 ... 227866 227867 227868] Test: [212516 212644 213092 ... 284804 284805
284806]
```

In [32]:

```
# Random Under Sampling" which basically consists of removing data in order to have a more balance
# Lets shuffle the data before creating the subsamples

df = df.sample(frac=1)

# amount of fraud classes 492 rows.
```

```python
fraud_df = df.loc[df['Class'] == 1]
non_fraud_df = df.loc[df['Class'] == 0][:492]

normal_distributed_df = pd.concat([fraud_df, non_fraud_df])

# Shuffle dataframe rows
new_df = normal_distributed_df.sample(frac=1, random_state=42)

new_df.head()
```

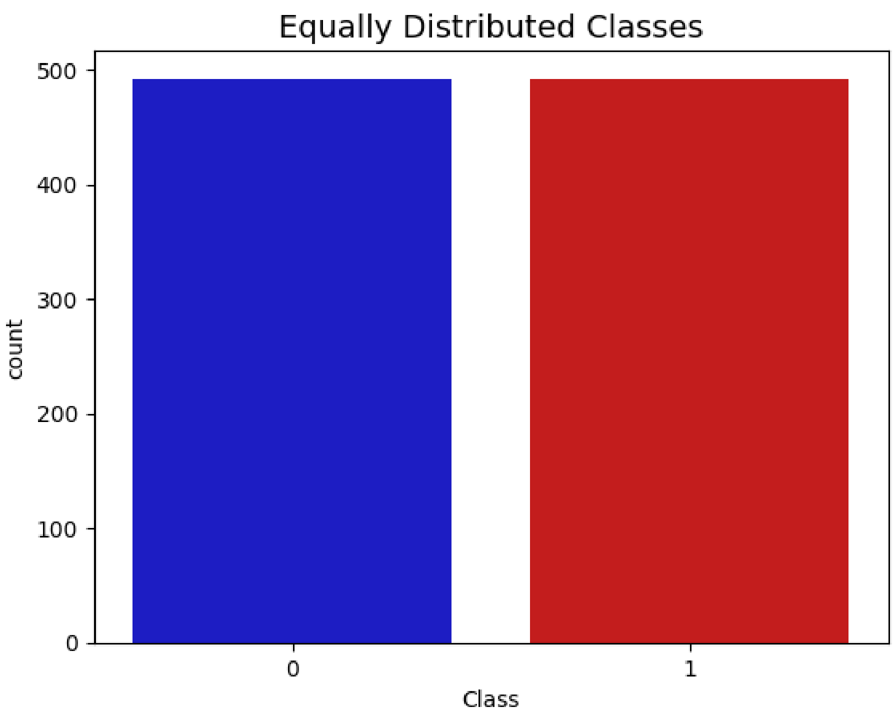
Out[32]:

	scaled_amount	scaled_time	V1	V2	V3	V4	V5	V6	
4774	1.229651	-0.945194	-0.519700	1.087853	1.475829	0.595549	0.135176	0.161461	1.
15166	1.089779	-0.683384	-18.474868	11.586381	-21.402917	6.038515	-14.451158	-4.146524	-14.
42553	-0.237686	-0.511554	1.060336	-0.171373	1.350160	1.229241	-0.906235	0.457292	-0.
157918	8.567037	0.304574	-1.101035	-1.674928	-0.573388	5.617556	0.765556	0.440607	1.
280149	0.780968	0.994596	-0.676143	1.126366	-2.213700	0.468308	-1.120541	-0.003346	-2.

5 rows × 31 columns

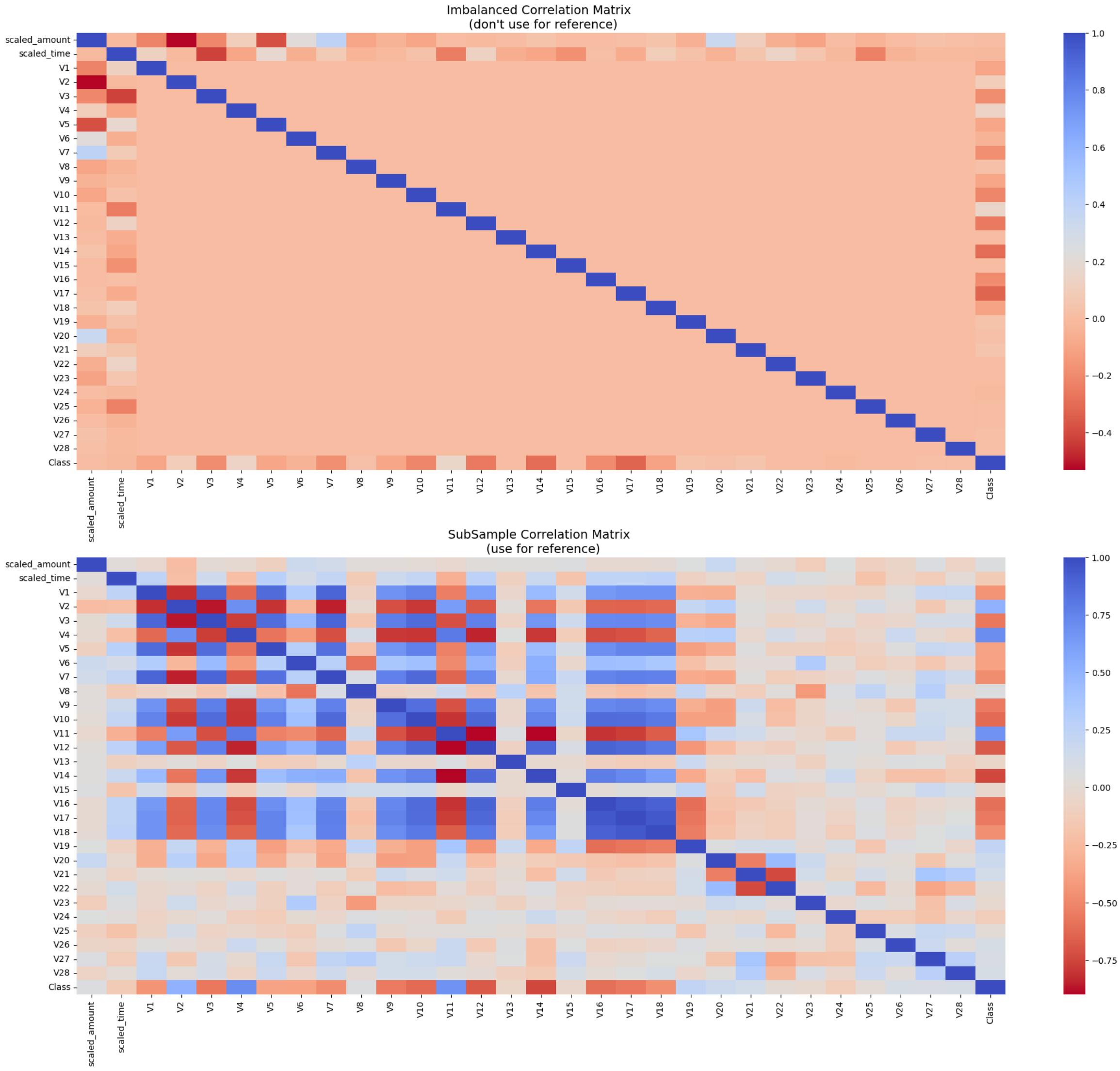
In [33]:
```python
print('Distribution of the Classes in the subsample dataset')
print(new_df['Class'].value_counts()/len(new_df))



sns.countplot(x='Class', data=new_df, palette=colors)
plt.title('Equally Distributed Classes', fontsize=14)
plt.show()
```

```
Distribution of the Classes in the subsample dataset
Class
0    0.5
1    0.5
Name: count, dtype: float64
```



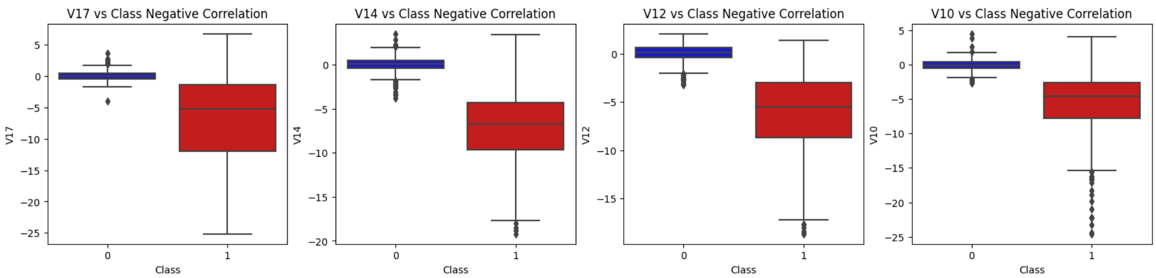
In [34]:
```python
# Make sure we use the subsample in our correlation

f, (ax1, ax2) = plt.subplots(2, 1, figsize=(24,20))

# Entire DataFrame
corr = df.corr()
sns.heatmap(corr, cmap='coolwarm_r', annot_kws={'size':20}, ax=ax1)
ax1.set_title("Imbalanced Correlation Matrix \n (don't use for reference)", fontsize=14)
```

```
sub_sample_corr = new_df.corr()
sns.heatmap(sub_sample_corr, cmap='coolwarm_r', annot_kws={'size':20}, ax=ax2)
ax2.set_title('SubSample Correlation Matrix \n (use for reference)', fontsize=14)
plt.show()
```



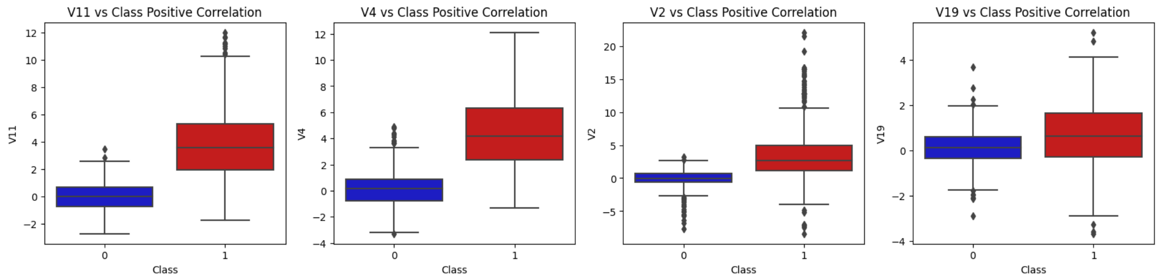
In [35]:

```
f, axes = plt.subplots(ncols=4, figsize=(20,4))

# Negative Correlations with our Class (The lower our feature value the more likely it will be a f
sns.boxplot(x="Class", y="V17", data=new_df, palette=colors, ax=axes[0])
axes[0].set_title('V17 vs Class Negative Correlation')

sns.boxplot(x="Class", y="V14", data=new_df, palette=colors, ax=axes[1])
axes[1].set_title('V14 vs Class Negative Correlation')


sns.boxplot(x="Class", y="V12", data=new_df, palette=colors, ax=axes[2])
axes[2].set_title('V12 vs Class Negative Correlation')


sns.boxplot(x="Class", y="V10", data=new_df, palette=colors, ax=axes[3])
axes[3].set_title('V10 vs Class Negative Correlation')

plt.show()
```



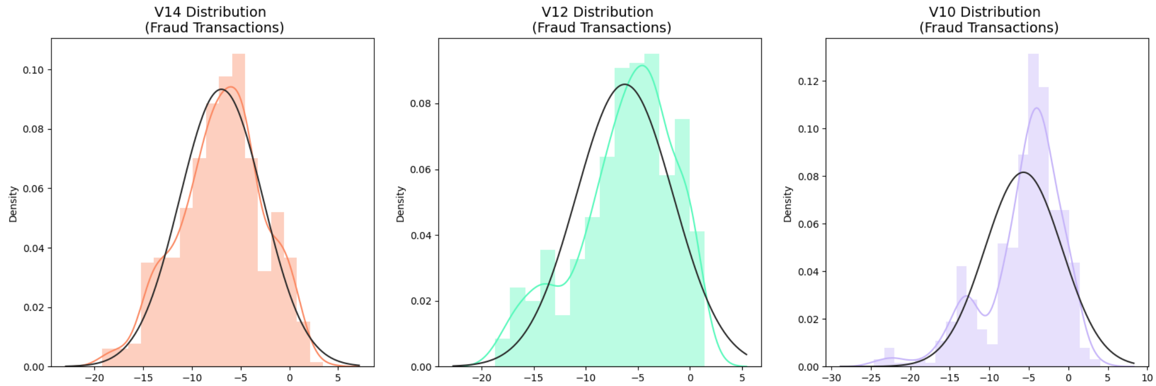
In [36]:

```python
f, axes = plt.subplots(ncols=4, figsize=(20,4))

# Positive correlations (The higher the feature the probability increases that it will be a fraud
sns.boxplot(x="Class", y="V11", data=new_df, palette=colors, ax=axes[0])
axes[0].set_title('V11 vs Class Positive Correlation')

sns.boxplot(x="Class", y="V4", data=new_df, palette=colors, ax=axes[1])
axes[1].set_title('V4 vs Class Positive Correlation')


sns.boxplot(x="Class", y="V2", data=new_df, palette=colors, ax=axes[2])
axes[2].set_title('V2 vs Class Positive Correlation')


sns.boxplot(x="Class", y="V19", data=new_df, palette=colors, ax=axes[3])
axes[3].set_title('V19 vs Class Positive Correlation')

plt.show()
```



In [37]:

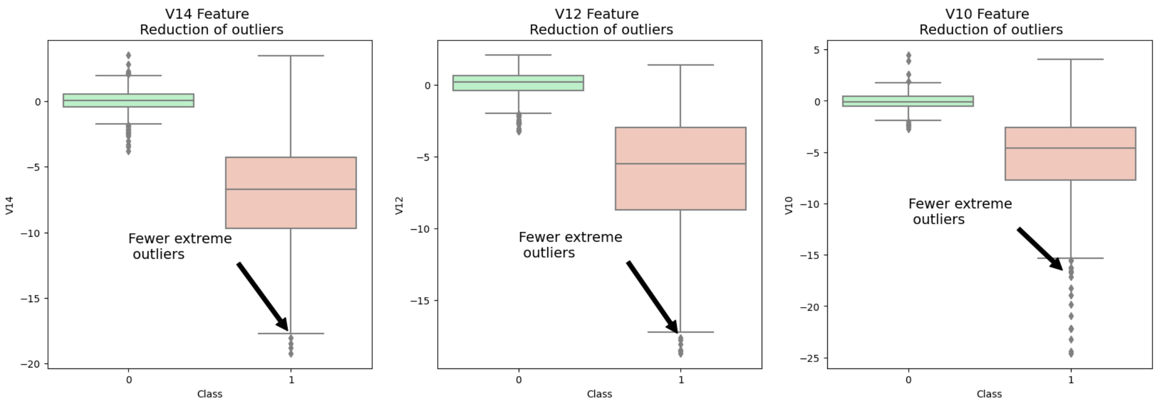
```python
from scipy.stats import norm

f, (ax1, ax2, ax3) = plt.subplots(1,3, figsize=(20, 6))

v14_fraud_dist = new_df['V14'].loc[new_df['Class'] == 1].values
sns.distplot(v14_fraud_dist,ax=ax1, fit=norm, color='#FB8861')
ax1.set_title('V14 Distribution \n (Fraud Transactions)', fontsize=14)

v12_fraud_dist = new_df['V12'].loc[new_df['Class'] == 1].values
sns.distplot(v12_fraud_dist,ax=ax2, fit=norm, color='#56F9BB')
ax2.set_title('V12 Distribution \n (Fraud Transactions)', fontsize=14)


v10_fraud_dist = new_df['V10'].loc[new_df['Class'] == 1].values
sns.distplot(v10_fraud_dist,ax=ax3, fit=norm, color='#C5B3F9')
ax3.set_title('V10 Distribution \n (Fraud Transactions)', fontsize=14)

plt.show()
```



In [38]:

```python
f,(ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(20,6))

colors = ['#B3F9C5', '#f9c5b3']
# Boxplots with outliers removed
# Feature V14
sns.boxplot(x="Class", y="V14", data=new_df,ax=ax1, palette=colors)
ax1.set_title("V14 Feature \n Reduction of outliers", fontsize=14)
ax1.annotate('Fewer extreme \n outliers', xy=(0.98, -17.5), xytext=(0, -12),
            arrowprops=dict(facecolor='black'),
            fontsize=14)

# Feature 12
```

```python
sns.boxplot(x="Class", y="V12", data=new_df, ax=ax2, palette=colors)
ax2.set_title("V12 Feature \n Reduction of outliers", fontsize=14)
ax2.annotate('Fewer extreme \n outliers', xy=(0.98, -17.3), xytext=(0, -12),
            arrowprops=dict(facecolor='black'),
            fontsize=14)

# Feature V10
sns.boxplot(x="Class", y="V10", data=new_df, ax=ax3, palette=colors)
ax3.set_title("V10 Feature \n Reduction of outliers", fontsize=14)
ax3.annotate('Fewer extreme \n outliers', xy=(0.95, -16.5), xytext=(0, -12),
            arrowprops=dict(facecolor='black'),
            fontsize=14)


plt.show()
```



In [39]:

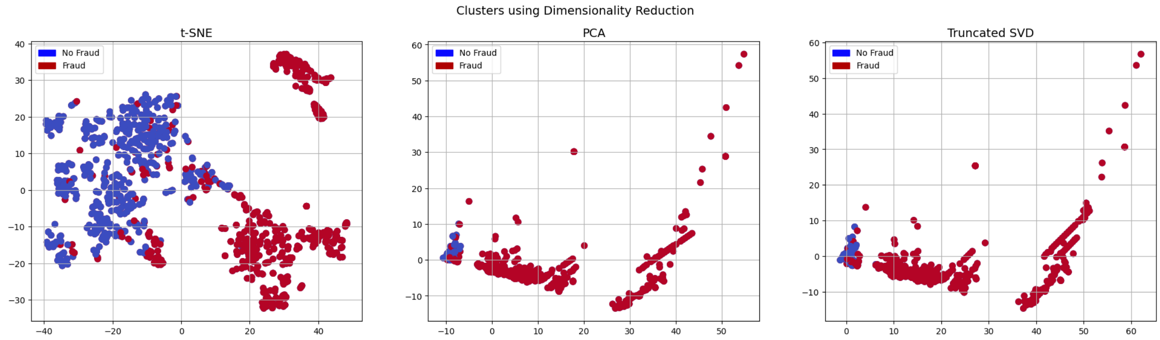
```python
X = new_df.drop('Class', axis=1)
y = new_df['Class']


# T-SNE Implementation
t0 = time.time()
X_reduced_tsne = TSNE(n_components=2, random_state=42).fit_transform(X.values)
t1 = time.time()
print("T-SNE took {:.2} s".format(t1 - t0))

# PCA Implementation
t0 = time.time()
X_reduced_pca = PCA(n_components=2, random_state=42).fit_transform(X.values)
t1 = time.time()
print("PCA took {:.2} s".format(t1 - t0))

# TruncatedSVD
t0 = time.time()
X_reduced_svd = TruncatedSVD(n_components=2, algorithm='randomized', random_state=42).fit_transfor
t1 = time.time()
print("Truncated SVD took {:.2} s".format(t1 - t0))
```

```
T-SNE took 3.2 s
PCA took 0.0 s
Truncated SVD took 0.011 s
```

In [40]:

```python
f, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(24,6))
# labels = ['No Fraud', 'Fraud']
f.suptitle('Clusters using Dimensionality Reduction', fontsize=14)


blue_patch = mpatches.Patch(color='#0A0AFF', label='No Fraud')
red_patch = mpatches.Patch(color='#AF0000', label='Fraud')


# t-SNE scatter plot
ax1.scatter(X_reduced_tsne[:,0], X_reduced_tsne[:,1], c=(y == 0), cmap='coolwarm', label='No Fraud
ax1.scatter(X_reduced_tsne[:,0], X_reduced_tsne[:,1], c=(y == 1), cmap='coolwarm', label='Fraud',
ax1.set_title('t-SNE', fontsize=14)

ax1.grid(True)

ax1.legend(handles=[blue_patch, red_patch])


# PCA scatter plot
```

```
ax2.scatter(X_reduced_pca[:,0], X_reduced_pca[:,1], c=(y == 0), cmap='coolwarm', label='No Fraud',
ax2.scatter(X_reduced_pca[:,0], X_reduced_pca[:,1], c=(y == 1), cmap='coolwarm', label='Fraud', li
ax2.set_title('PCA', fontsize=14)

ax2.grid(True)

ax2.legend(handles=[blue_patch, red_patch])

# TruncatedSVD scatter plot
ax3.scatter(X_reduced_svd[:,0], X_reduced_svd[:,1], c=(y == 0), cmap='coolwarm', label='No Fraud',
ax3.scatter(X_reduced_svd[:,0], X_reduced_svd[:,1], c=(y == 1), cmap='coolwarm', label='Fraud', li
ax3.set_title('Truncated SVD', fontsize=14)

ax3.grid(True)

ax3.legend(handles=[blue_patch, red_patch])

plt.show()
```



Classification Models

In [41]:
```
# undersampling
X = new_df.drop('Class', axis=1)
y = new_df['Class']
```

In [42]:
```
from sklearn.model_selection import train_test_split
# splitting
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
X_train = X_train.values
X_test = X_test.values
y_train = y_train.values
y_test = y_test.values
```

In [43]:
```
classifiers = {
    "LogisiticRegression": LogisticRegression(),
    "KNearest": KNeighborsClassifier(),
    "Support Vector Classifier": SVC(),
    "DecisionTreeClassifier": DecisionTreeClassifier()
}
```

In [44]:
```
from sklearn.model_selection import cross_val_score


for key, classifier in classifiers.items():
    classifier.fit(X_train, y_train)
    training_score = cross_val_score(classifier, X_train, y_train, cv=5)
    print("Classifiers: ", classifier.__class__.__name__, "Has a training score of", round(trainin
```

```
Classifiers:  LogisticRegression Has a training score of 92.0 % accuracy score
Classifiers:  KNeighborsClassifier Has a training score of 92.0 % accuracy score
Classifiers:  SVC Has a training score of 93.0 % accuracy score
Classifiers:  DecisionTreeClassifier Has a training score of 92.0 % accuracy score
```

Cross-Validation

In [45]:
```
from sklearn.model_selection import GridSearchCV

# CV logistic regression
log_reg_params = {"penalty": ['l1', 'l2'], 'C': [0.001, 0.01, 0.1, 1, 10, 100, 1000]}
grid_log_reg = GridSearchCV(LogisticRegression(), log_reg_params)
```

```
grid_log_reg.fit(X_train, y_train)

log_reg = grid_log_reg.best_estimator_
log_reg
```

Out[45]: LogisticRegression(C=0.1)

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook. On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [46]:
```
# CV in KNN
knears_params = {"n_neighbors": list(range(2,5,1)), 'algorithm': ['auto', 'ball_tree', 'kd_tree',
grid_knears = GridSearchCV(KNeighborsClassifier(), knears_params)
grid_knears.fit(X_train, y_train)
knears_neighbors = grid_knears.best_estimator_
```

In [47]:
```
# CV in support vector
svc_params = {'C': [0.5, 0.7, 0.9, 1], 'kernel': ['rbf', 'poly', 'sigmoid', 'linear']}
grid_svc = GridSearchCV(SVC(), svc_params)
grid_svc.fit(X_train, y_train)
svc = grid_svc.best_estimator_
```

In [48]:
```
# CV in DecisionTree

tree_params = {"criterion": ["gini", "entropy"], "max_depth": list(range(2,4,1)),
              "min_samples_leaf": list(range(5,7,1))}
grid_tree = GridSearchCV(DecisionTreeClassifier(), tree_params)
grid_tree.fit(X_train, y_train)
tree_clf = grid_tree.best_estimator_
```

In [49]:
```
log_reg_score = cross_val_score(log_reg, X_train, y_train, cv=5)
print('Logistic Regression Cross Validation Score: ', round(log_reg_score.mean() * 100, 2).astype(


knears_score = cross_val_score(knears_neighbors, X_train, y_train, cv=5)
print('Knears Neighbors Cross Validation Score', round(knears_score.mean() * 100, 2).astype(str) +

svc_score = cross_val_score(svc, X_train, y_train, cv=5)
print('Support Vector Classifier Cross Validation Score', round(svc_score.mean() * 100, 2).astype(

tree_score = cross_val_score(tree_clf, X_train, y_train, cv=5)
print('DecisionTree Classifier Cross Validation Score', round(tree_score.mean() * 100, 2).astype(s
```

```
Logistic Regression Cross Validation Score:  93.13%
Knears Neighbors Cross Validation Score 92.62%
Support Vector Classifier Cross Validation Score 92.63%
DecisionTree Classifier Cross Validation Score 92.12%
```

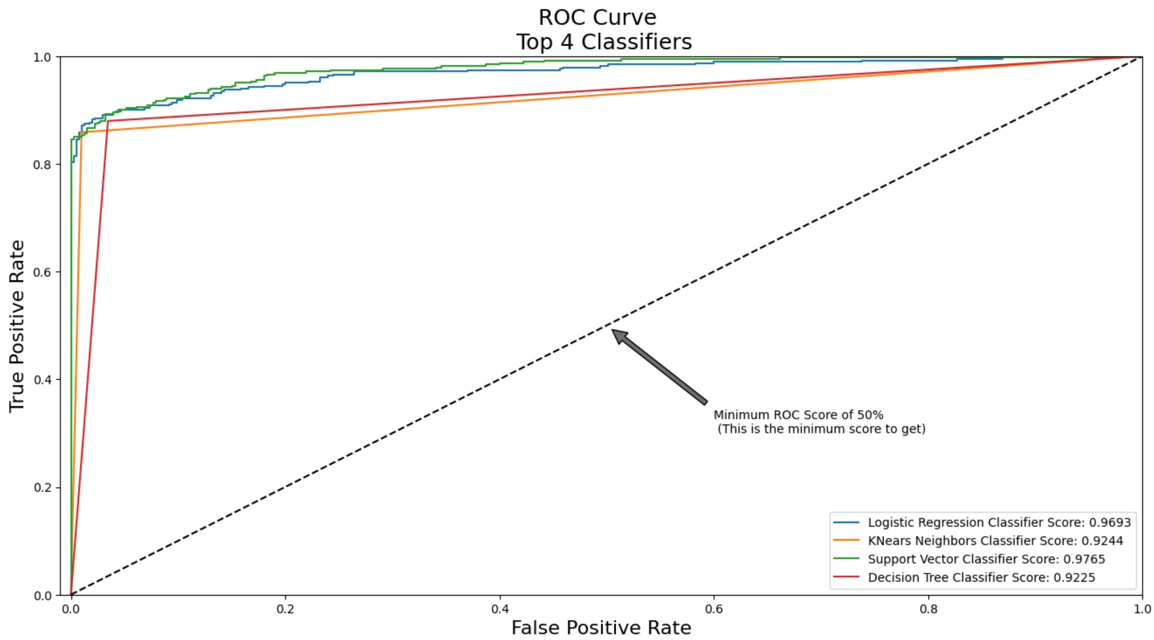
In [50]:
```
from sklearn.metrics import roc_curve
from sklearn.model_selection import cross_val_predict
# DataFrame with all the scores and the classifiers names.

log_reg_pred = cross_val_predict(log_reg, X_train, y_train, cv=5,
                             method="decision_function")

knears_pred = cross_val_predict(knears_neighbors, X_train, y_train, cv=5)

svc_pred = cross_val_predict(svc, X_train, y_train, cv=5,
                             method="decision_function")

tree_pred = cross_val_predict(tree_clf, X_train, y_train, cv=5)
```

In [51]:
```
from sklearn.metrics import roc_auc_score

print('Logistic Regression: ', roc_auc_score(y_train, log_reg_pred))
print('KNears Neighbors: ', roc_auc_score(y_train, knears_pred))
print('Support Vector Classifier: ', roc_auc_score(y_train, svc_pred))
print('Decision Tree Classifier: ', roc_auc_score(y_train, tree_pred))
```

```
Logistic Regression:  0.9693232499515222
KNears Neighbors:  0.9243811001228105
Support Vector Classifier:  0.9764591816947837
Decision Tree Classifier:  0.9225066252989464
```

In [52]:

```
# Receiver Operating Characteristic Curve

log_fpr, log_tpr, log_thresold = roc_curve(y_train, log_reg_pred)
knear_fpr, knear_tpr, knear_threshold = roc_curve(y_train, knears_pred)
svc_fpr, svc_tpr, svc_threshold = roc_curve(y_train, svc_pred)
tree_fpr, tree_tpr, tree_threshold = roc_curve(y_train, tree_pred)


def graph_roc_curve_multiple(log_fpr, log_tpr, knear_fpr, knear_tpr, svc_fpr, svc_tpr, tree_fpr, t
    plt.figure(figsize=(16,8))
    plt.title('ROC Curve \n Top 4 Classifiers', fontsize=18)
    plt.plot(log_fpr, log_tpr, label='Logistic Regression Classifier Score: {:.4f}'.format(roc_auc
    plt.plot(knear_fpr, knear_tpr, label='KNears Neighbors Classifier Score: {:.4f}'.format(roc_au
    plt.plot(svc_fpr, svc_tpr, label='Support Vector Classifier Score: {:.4f}'.format(roc_auc_scor
    plt.plot(tree_fpr, tree_tpr, label='Decision Tree Classifier Score: {:.4f}'.format(roc_auc_sco
    plt.plot([0, 1], [0, 1], 'k--')
    plt.axis([-0.01, 1, 0, 1])
    plt.xlabel('False Positive Rate', fontsize=16)
    plt.ylabel('True Positive Rate', fontsize=16)
    plt.annotate('Minimum ROC Score of 50% \n (This is the minimum score to get)', xy=(0.5, 0.5),
                 arrowprops=dict(facecolor='#6E726D', shrink=0.05),
                 )
    plt.legend()

graph_roc_curve_multiple(log_fpr, log_tpr, knear_fpr, knear_tpr, svc_fpr, svc_tpr, tree_fpr, tree_
plt.show()
```



Ensemble Methods

In [53]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score
```

In [54]:

```
clf1 = LogisticRegression()
clf2 = RandomForestClassifier()
clf3 = KNeighborsClassifier()
```

In [55]:

```
estimators =[('lr',clf1),('rf',clf2),('knn',clf3)]
```

In [69]:

```
X = df.iloc[:,0:-1]
y = df.iloc[:,-1]
```

In [70]:

```
X
```

Out[70]:

	scaled_amount	scaled_time	V1	V2	V3	V4	V5	V6

242358	0.936212	0.784384	1.968663	-1.209091	-0.511551	-0.983898	-0.970887	0.010964	-1.0830
210127	0.521065	0.624537	1.935025	-0.859136	-1.943729	-0.531092	0.504155	0.706313	-0.1899
195950	-0.043038	0.547469	-3.555417	0.451106	-1.261389	-0.614099	0.674008	1.153825	-4.6222
79470	-0.127157	-0.313150	1.179837	0.362327	0.638986	1.373728	-0.577593	-1.178408	0.1749
100920	-0.279466	-0.200038	1.228461	-1.180218	1.627690	-0.335551	-1.785555	0.901651	-1.7863
...	...	...	...	...	...	...	...	...	
94600	-0.230699	-0.231958	1.308012	0.322083	-0.045809	0.501397	0.030490	-0.599270	0.0764
51393	1.313491	-0.467216	1.212028	-1.538757	0.685187	-1.393421	-1.739644	0.018674	-1.3282
149398	-0.279746	0.075941	-0.781961	0.092900	-0.423866	-0.329017	2.583220	-0.975481	0.4761
203919	-0.137777	0.591396	-0.212908	1.552188	-0.430994	1.103847	1.468771	-0.822175	1.6886
165116	7.962831	0.382018	-1.587587	-1.957770	0.378966	-1.343979	0.193843	0.033284	-1.7043

284807 rows × 30 columns

In [71]:

```
y
```