Credit Card Fraud Detection as a Classification Problem

Business Problem

Credit card companies can detect fraudulent credit card transactions, preventing customers from being charged for products they did not purchase. Data Science and Machine Learning can be used to solve this type of problems. This project aims to demonstrate the modeling of a data set using machine learning with Credit Card Fraud Detection.

In [1]:
```
# Importing modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import gridspec
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

In [2]:
```
data = pd.read_csv("creditcard.csv")
data.head().append(data.tail())
```

Out[2]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.36378
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.25542
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.51465
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.38702
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.81773
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215	7.305334	1.91442
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330	0.294869	0.58480
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827	0.708417	0.43245
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180	0.679145	0.39208
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006	-0.414650	0.48618

10 rows × 31 columns

In [3]:
```
display(data.info())
display(data.describe())
display(data.shape)
display(data.isnull().sum())
display(data.duplicated().sum())
```

```
<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
 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
None
```

	Time	V1	V2	V3	V4	V5	V6
count	284807.000000	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05
mean	94813.859575	3.918649e-15	5.682686e-16	-8.761736e-15	2.811118e-15	-1.552103e-15	2.040130e-15
std	47488.145955	1.958696e+00	1.651309e+00	1.516255e+00	1.415869e+00	1.380247e+00	1.332271e+00
min	0.000000	-5.640751e+01	-7.271573e+01	-4.832559e+01	-5.683171e+00	-1.137433e+02	-2.616051e+01
25%	54201.500000	-9.203734e-01	-5.985499e-01	-8.903648e-01	-8.486401e-01	-6.915971e-01	-7.682956e-01
50%	84692.000000	1.810880e-02	6.548556e-02	1.798463e-01	-1.984653e-02	-5.433583e-02	-2.741871e-01
75%	139320.500000	1.315642e+00	8.037239e-01	1.027196e+00	7.433413e-01	6.119264e-01	3.985649e-01
max	172792.000000	2.454930e+00	2.205773e+01	9.382558e+00	1.687534e+01	3.480167e+01	7.330163e+01

8 rows × 31 columns

```
(284807, 31)
```

```
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
1081
```

In [4]:

```
# drop duplicated values
data.drop_duplicates(inplace =True)
```

Exploration and Visualization

Now we try to find out the relative proportion of valid and fraudulent credit card transactions.

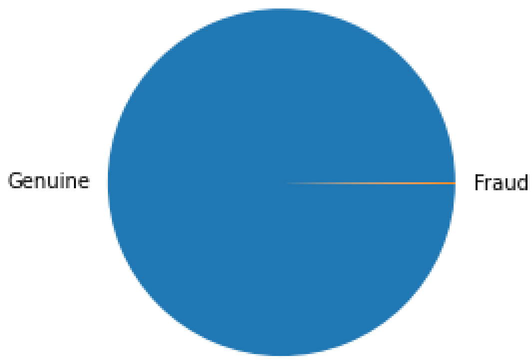
In [5]:

```
print("Fraudulent Cases: " + str(len(data[data["Class"] == 1])))
print("Valid Transactions: " + str(len(data[data["Class"] == 0])))
print("Proportion of Fraudulent Cases: " + str(len(data[data["Class"] == 1])/ data.shape[0]))

# To see how small are the number of Fraud transactions
data_pi = data.copy()
data_pi[" "] = np.where(data_pi["Class"] == 1 ,  "Fraud", "Genuine")

%matplotlib inline
data_pi[" "].value_counts().plot(kind="pie")
```

```
Fraudulent Cases: 473
Valid Transactions: 283253
Proportion of Fraudulent Cases: 0.001667101358352777
```

Out[5]:

```
<AxesSubplot:ylabel=' '>
```



Clearly we can see that there is an imbalance in the data with only 0.17% of the total cases are fraudulent.

Check average Money transaction for the fraudulent and no-fraudulent transations

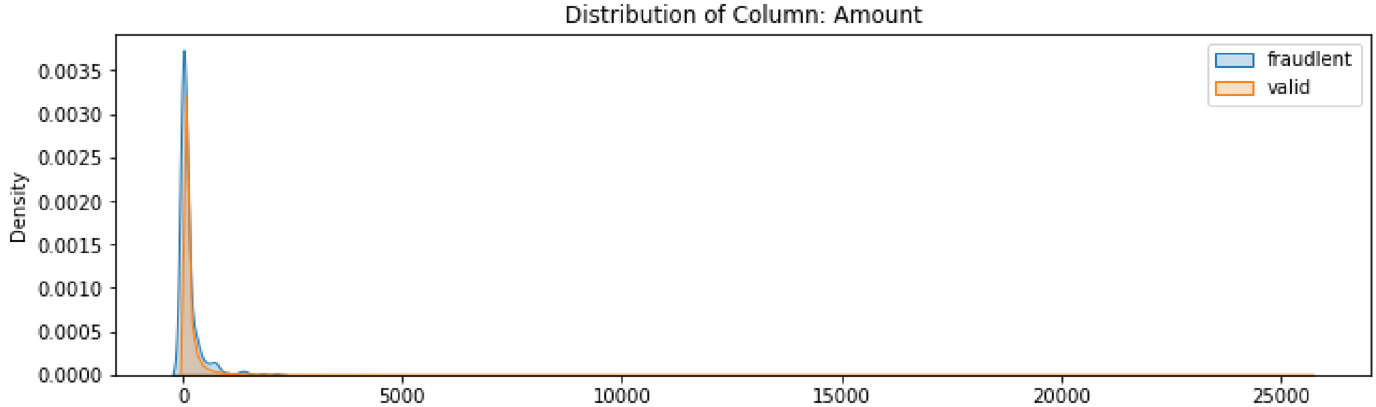
In [6]:
```
print("Average Amount in a Fraudulent Transaction: " + str(data[data["Class"] == 1]["Amount"].mea
print("Average Amount in a Valid Transaction: " + str(data[data["Class"] == 0]["Amount"].mean())
```

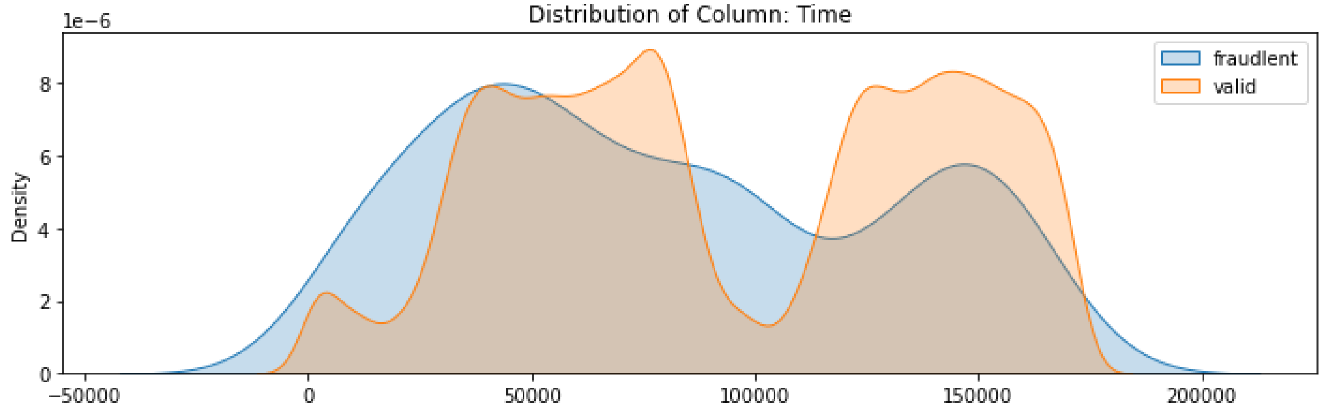
```
Average Amount in a Fraudulent Transaction: 123.87186046511626
Average Amount in a Valid Transaction: 88.41357475466688
```

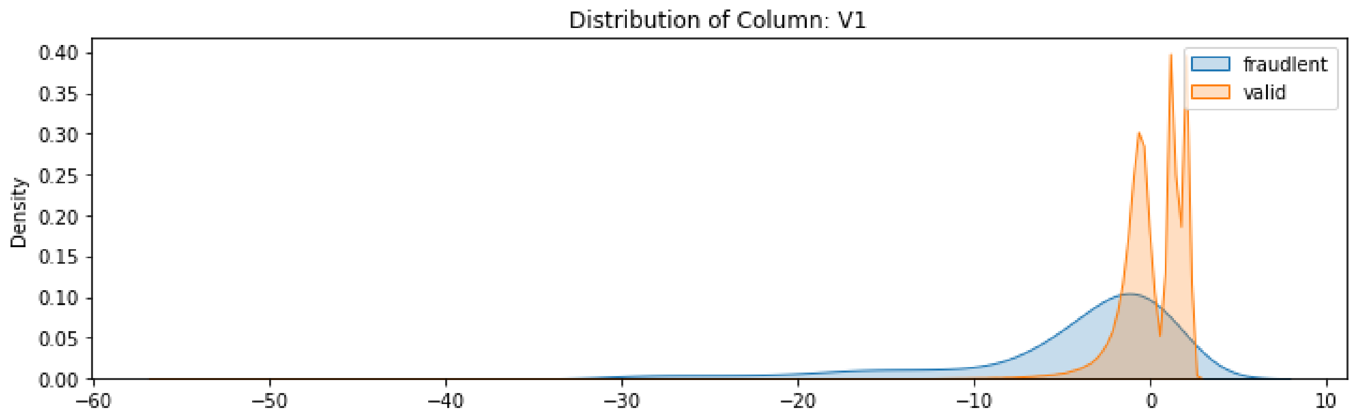
As we can clearly notice from this, the average Money transaction for the fraudulent ones are more.

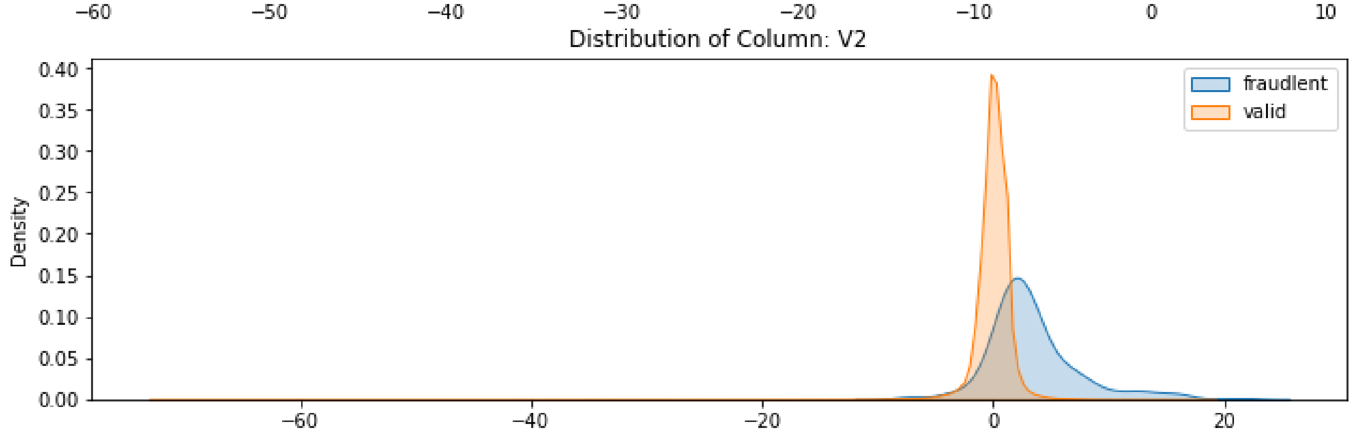
Histograms where values are subgrouped according to Class (valid or fraud)

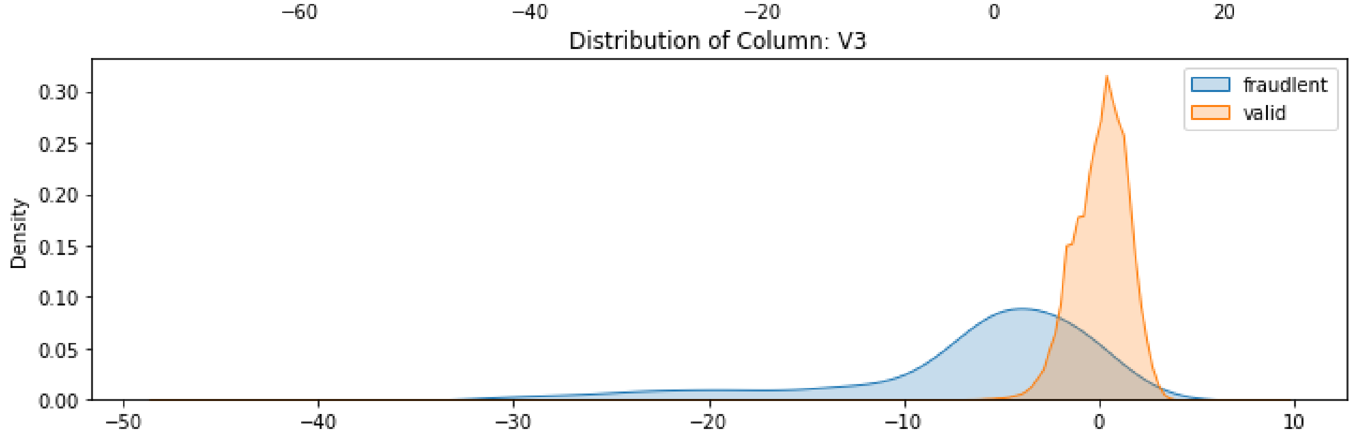
In [7]:
```
# Reorder the columns Amount, Time then the rest
data_plot = data.copy()
amount = data_plot['Amount']
data_plot.drop(labels=['Amount'], axis=1, inplace = True)
data_plot.insert(0, 'Amount', amount)

# Plot the distributions of the features
columns = data_plot.iloc[:,0:30].columns
plt.figure(figsize=(12,30*4))

grids = gridspec.GridSpec(30, 1)
for grid, index in enumerate(data_plot[columns]):
 ax = plt.subplot(grids[grid])
 sns.distplot(data_plot[index][data_plot.Class == 1], hist=False, kde_kws={"shade": True}, bins=
 sns.distplot(data_plot[index][data_plot.Class == 0], hist=False, kde_kws={"shade": True}, bins=
 ax.set_xlabel("")
 ax.set_title("Distribution of Column: "  + str(index))
 ax.legend(labels=['fraudlent','valid'])
plt.show()
```

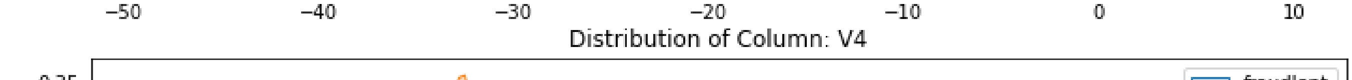

Distribution of Column: Amount
Density
fraudlent
valid
0.0000
0.0005
0.0010
0.0015
0.0020
0.0025
0.0030
0.0035
0
5000
10000
15000
20000
25000

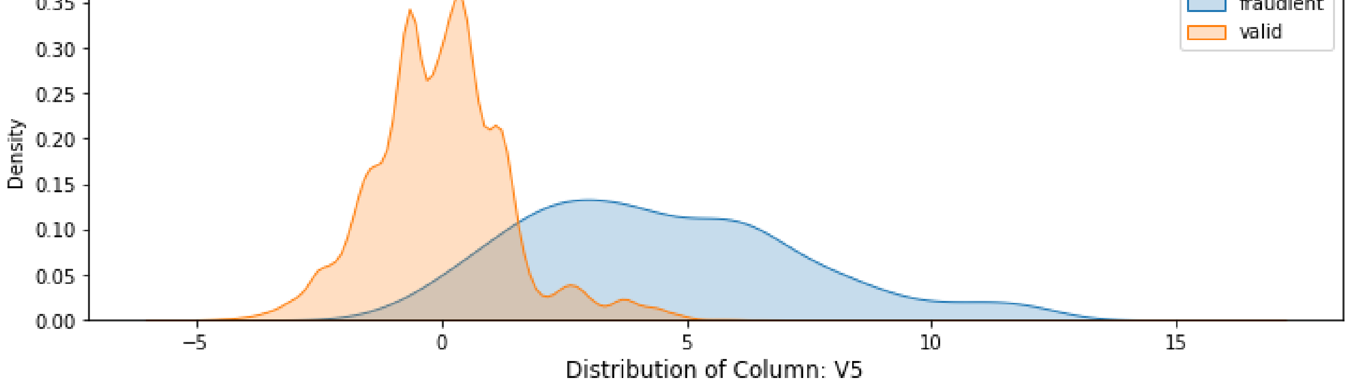

Distribution of Column: Time
1e−6
Density
fraudlent
valid
0
2
4
6
8
−50000
0
50000
100000
150000
200000

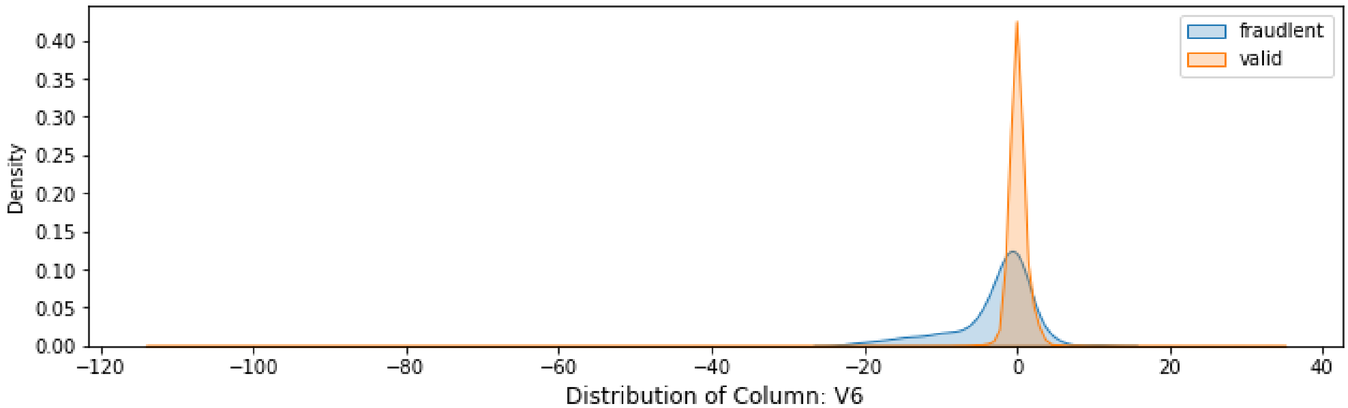

Distribution of Column: V1
Density
fraudlent
valid
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
−60
−50
−40
−30
−20
−10
0
10

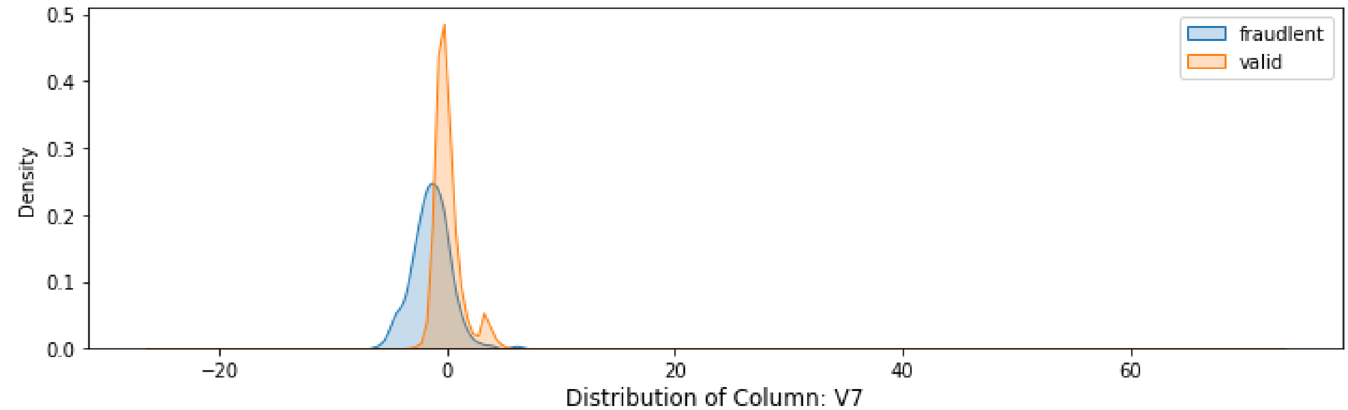

Distribution of Column: V2
Density
fraudlent
valid
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
−60
−40
−20
0
20

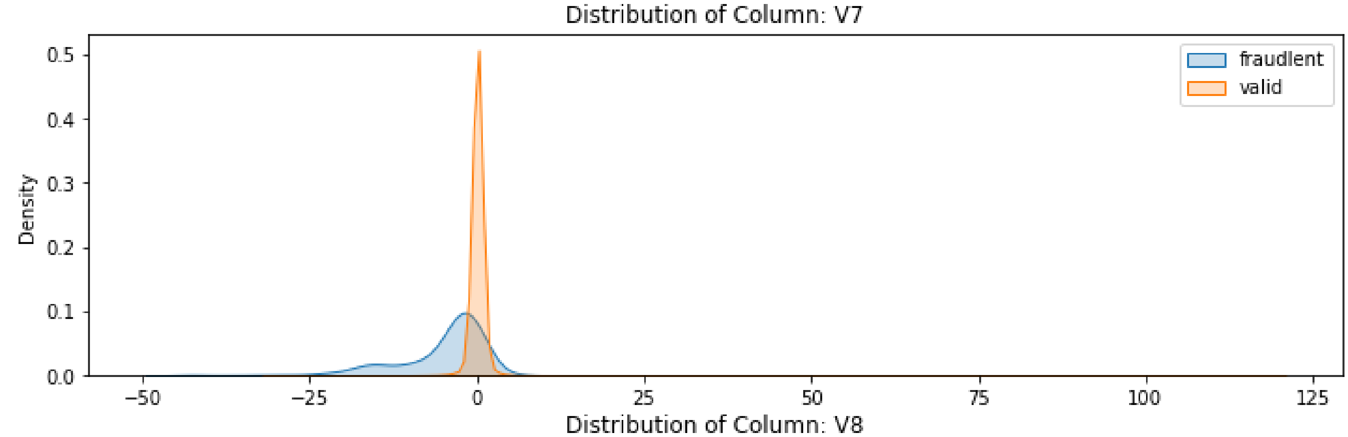

Distribution of Column: V3
Density
fraudlent
valid
0.00
0.05
0.10
0.15
0.20
0.25
0.30
−50
−40
−30
−20
−10
0
10

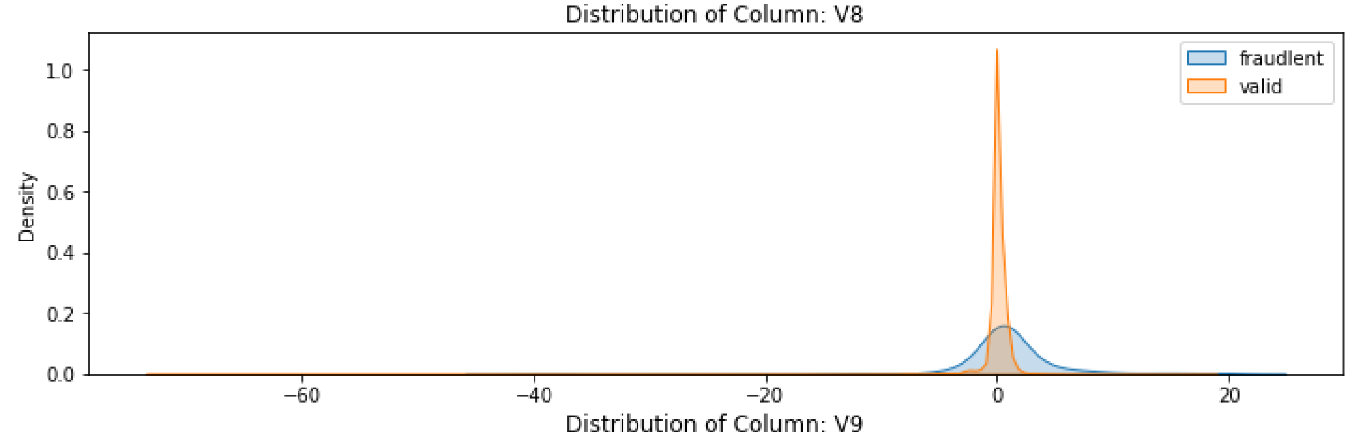

Distribution of Column: V4


fraudlent
valid
Density
Distribution of Column: V5

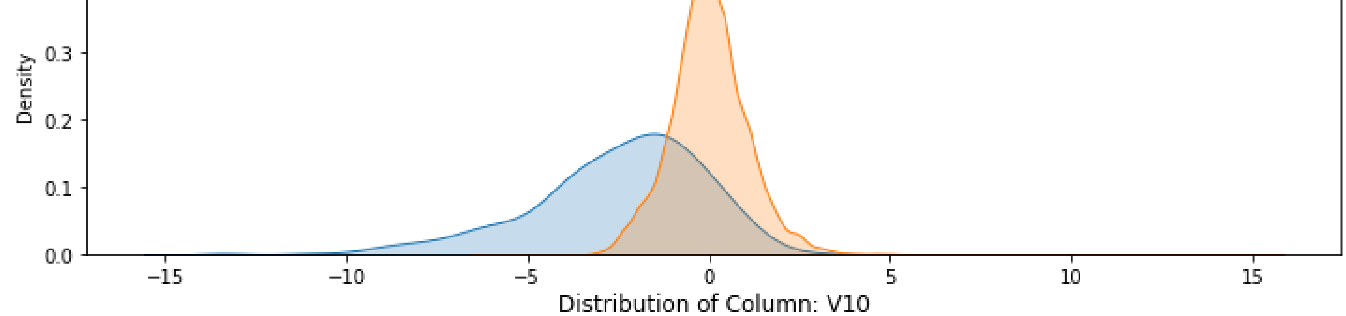

fraudlent
valid
Density
Distribution of Column: V6

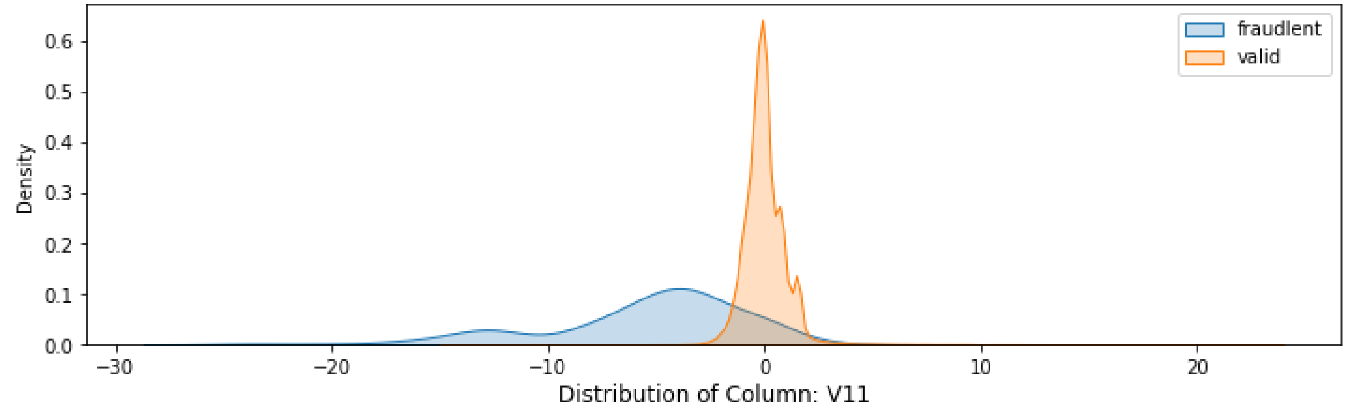

fraudlent
valid
Density
Distribution of Column: V7

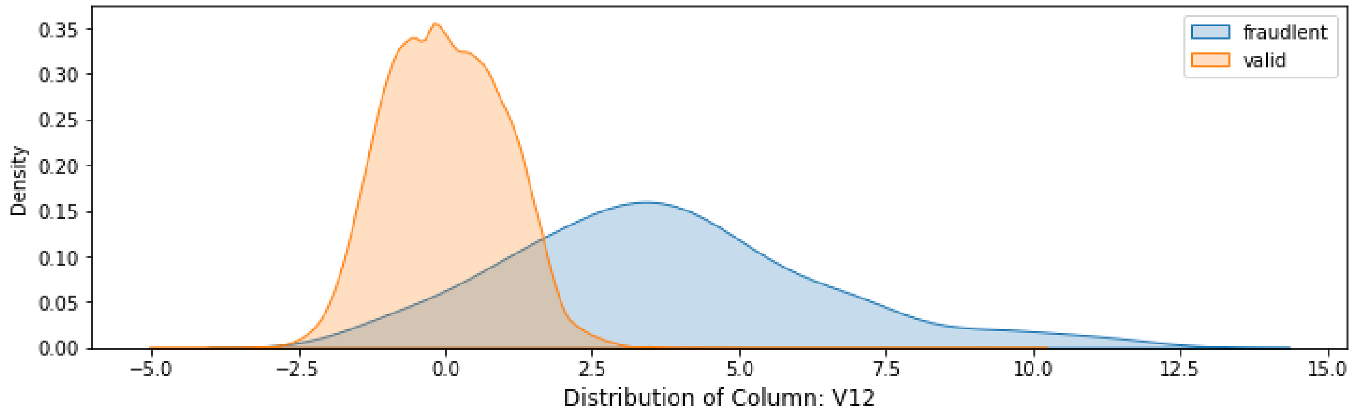

fraudlent
valid
Density
Distribution of Column: V8

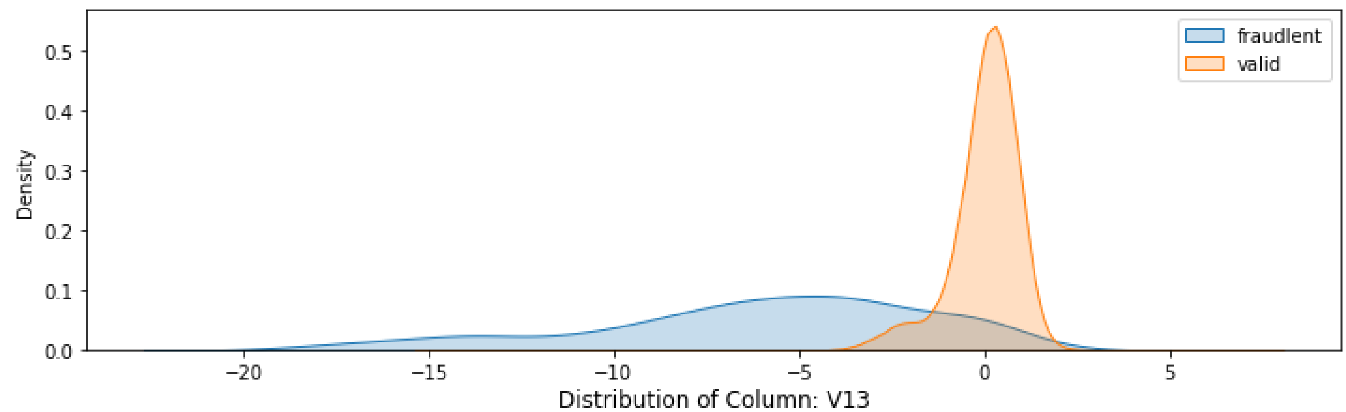

fraudlent
valid
Density
Distribution of Column: V9

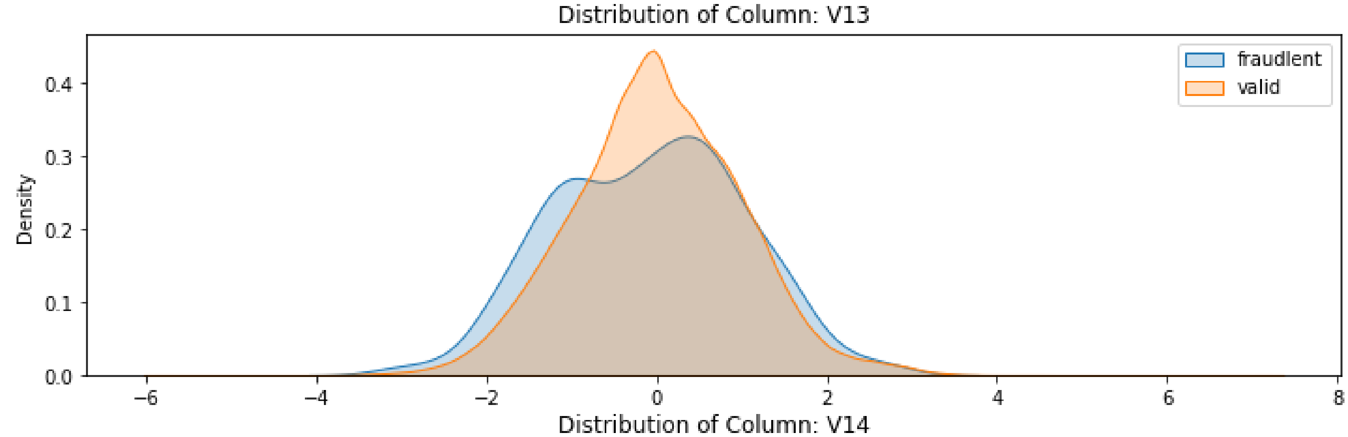

fraudlent
valid

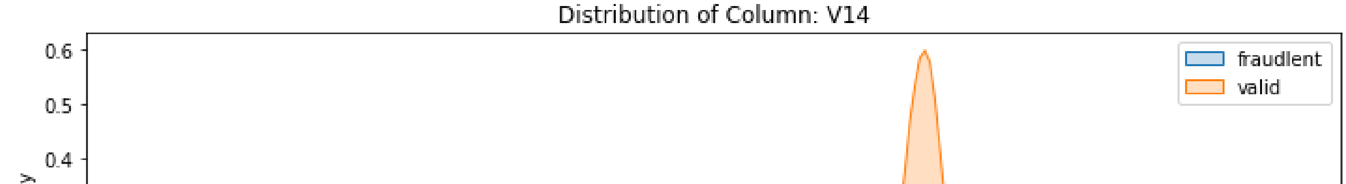

Density
Distribution of Column: V10

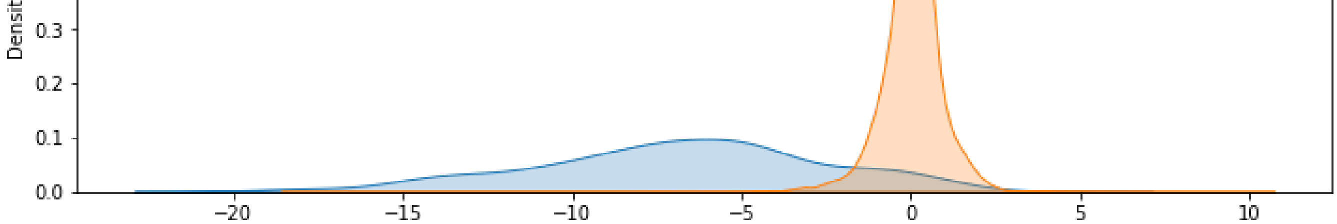

fraudlent
valid
Density
Distribution of Column: V11


fraudlent
valid
Density
Distribution of Column: V12

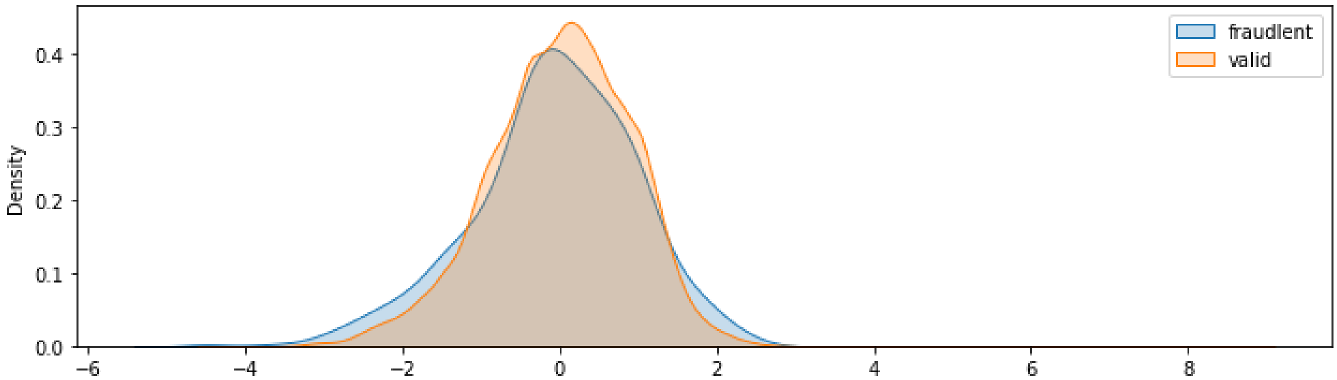

fraudlent
valid
Density
Distribution of Column: V13


fraudlent
valid
Density
Distribution of Column: V14

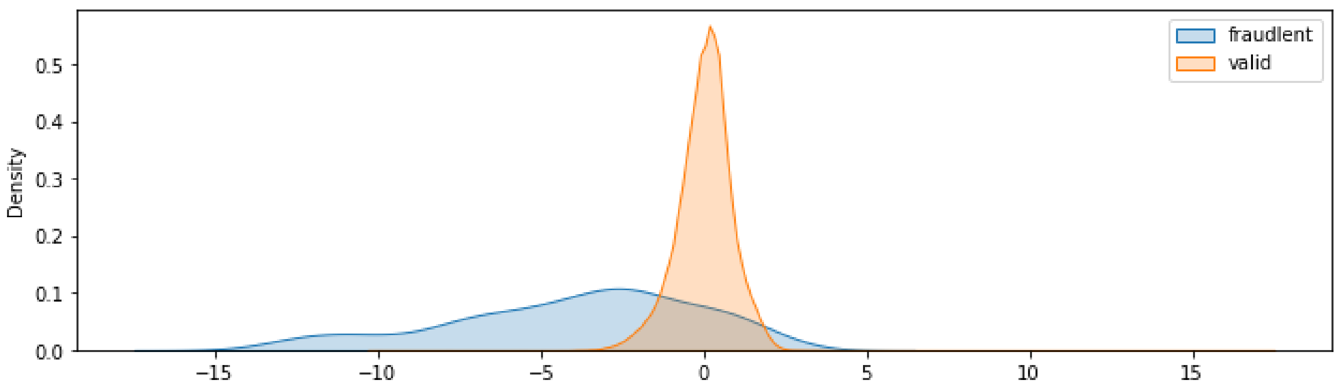

fraudlent
valid



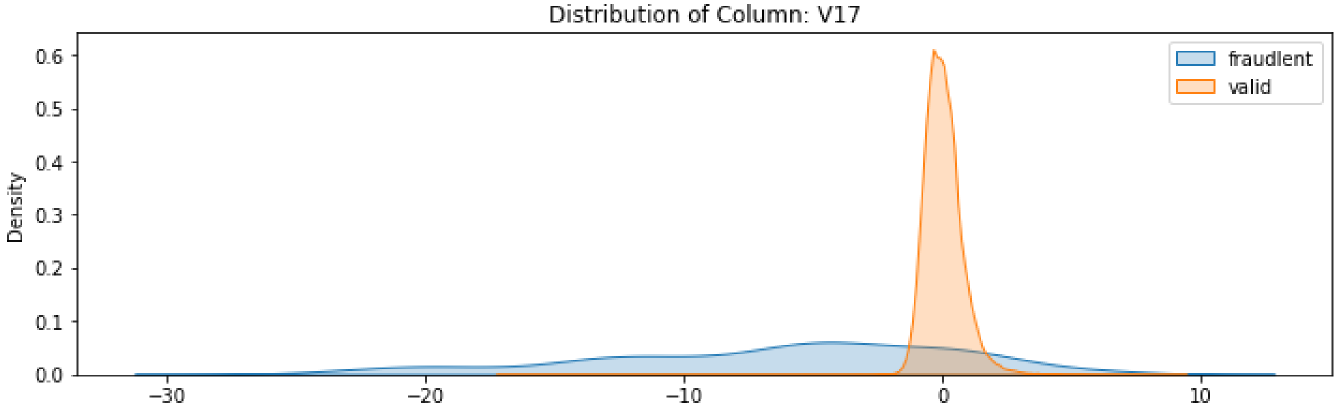
Distribution of Column: V15



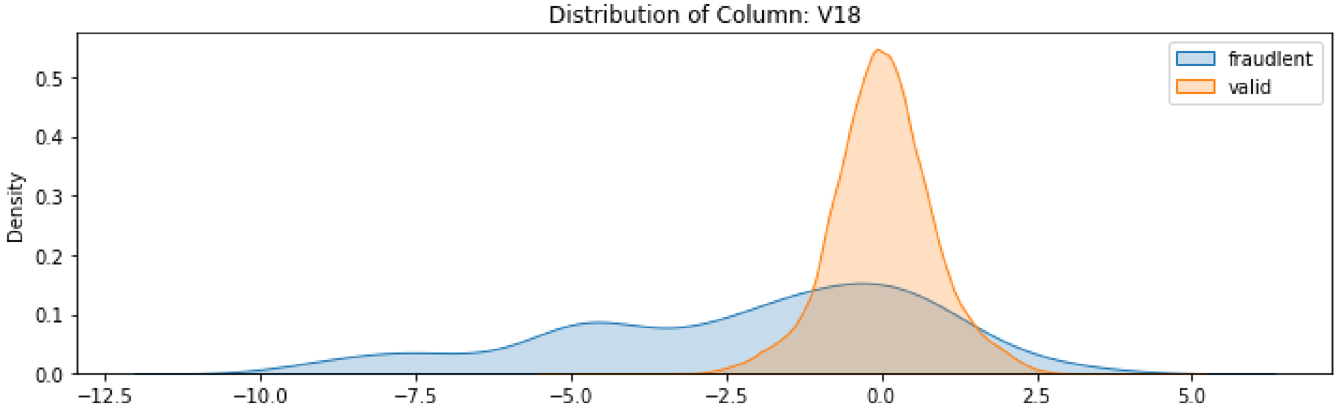
Distribution of Column: V16



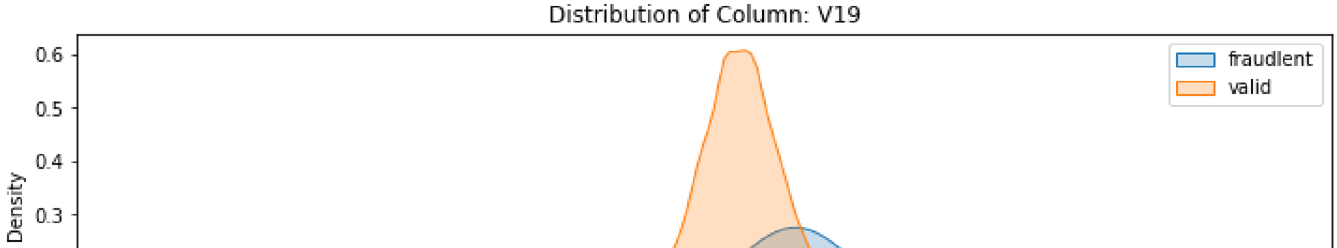
Distribution of Column: V17

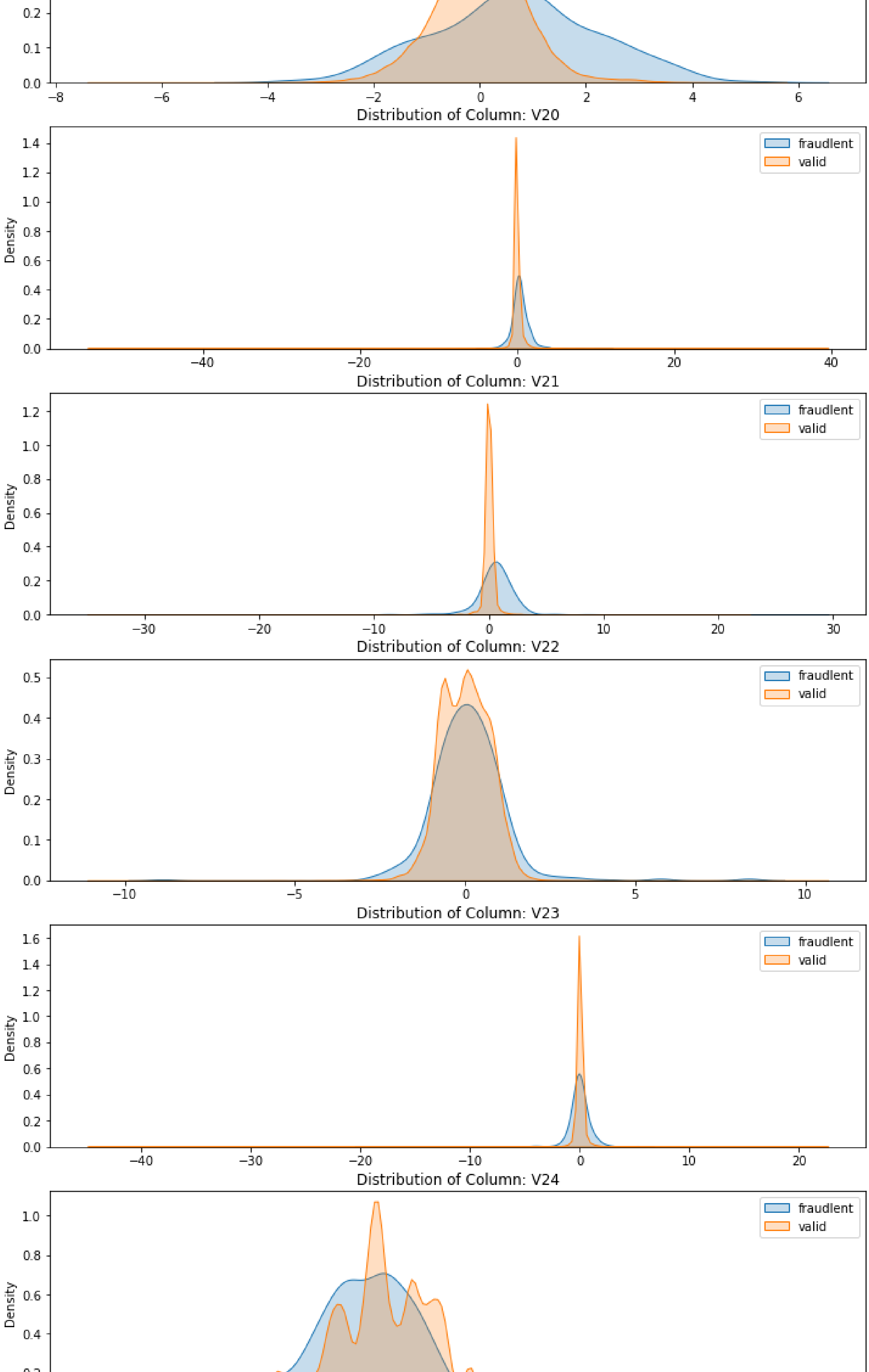


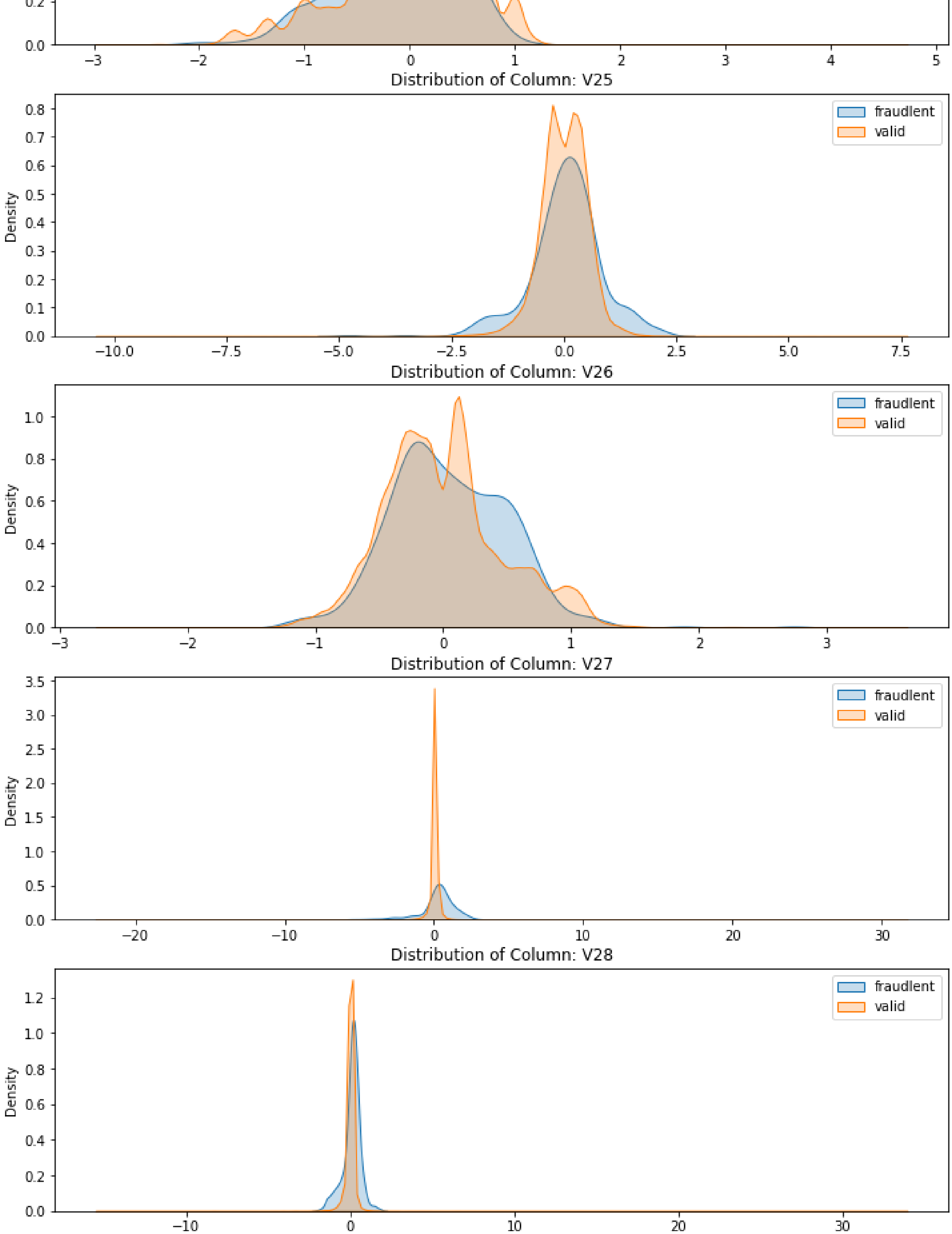
Distribution of Column: V18



Distribution of Column: V19




Distribution of Column: V20
Density
fraudlent
valid
Distribution of Column: V21
Density
fraudlent
valid
Distribution of Column: V22
Density
fraudlent
valid
Distribution of Column: V23
Density
fraudlent
valid
Distribution of Column: V24
Density
fraudlent
valid



Since there are no missing data, standardization is appropriate. We only use RobustScaler to standardize the Time and Amount columns because all other features of the original dataset from v1 to v28 are obtained using PCA, which is already standardized.

In [8]:
```
from sklearn.preprocessing import RobustScaler
scaler = RobustScaler().fit(data[["Time", "Amount"]])
data[["Time", "Amount"]] = scaler.transform(data[["Time", "Amount"]])
```

```
data.head().append(data.tail())
```

Out[8]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	
0	-0.995290	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.3637
1	-0.995290	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.2554
2	-0.995279	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.5146
3	-0.995279	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.3870
4	-0.995267	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.8177
284802	1.035258	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215	7.305334	1.9144
284803	1.035270	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330	0.294869	0.5848
284804	1.035282	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827	0.708417	0.4324
284805	1.035282	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180	0.679145	0.3920
284806	1.035329	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006	-0.414650	0.4861

10 rows × 31 columns

Modelling

First we divide the data into TARGET and features. And also make the train-test split of the data for further modelling and validation.

In [9]:
```
# Separate TARGET and features
y = data["Class"]
X = data.iloc[:,0:30]

# Use SKLEARN for the split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size = 0.2, random_state = 42)
```

Now we describe the flow of the modelling section first and then dive into the sea. As we identified earlier, the dataset is highly imbalanced. Fitting a model on this dataset will result in overfitting towards the majority class. For illustration let's run one model (Random Forest) on the imbalanced data and see the performance.

In [10]:
```
# Using SKLEARN module for random forest
from sklearn.ensemble import RandomForestClassifier

# Fit and predict
naive_rfc = RandomForestClassifier()
naive_rfc.fit(X_train, y_train)
naive_test_preds = naive_rfc.predict(X_test)


# For the performance let's use some metrics from SKLEARN module
from sklearn.metrics import accuracy_score, precision_score, recall_score,f1_score

print("The accuracy is {}".format(accuracy_score(y_test, naive_test_preds) ))
print("The precision is {}".format(precision_score(y_test, naive_test_preds)))
```

```
print("The recall is {}".format(recall_score(y_test, naive_test_preds) ))
print("The f1 score is {}".format(f1_score(y_test, naive_test_preds) ))
```

```
The accuracy is 0.9995418179254926
The precision is 0.9705882352941176
The recall is 0.7333333333333333
The f1 score is 0.8354430379746834
```

One thing to notice here is, we had only 0.17% cases with fraud transactions and a model predicting all trasactions to be valid would have similar accuracy. So we need to train our model in a way that is not overfitted to either of the classes. for this, we introduce Oversampling and Undersampling methods. Oversampling resamples from the minority class to balance the class proportions. And undersampling merges or removes similar observations from the majority to achive the same.

Undersampling

In this section we first describe the structure of the modelling and validations. One trivial point to note is, we will not undersample the test data as we want our model to perform well with skewed class distributions eventually. The steps are as follows (The whole set-up will be structured using the imbalance-learn module):

- Use a 5-fold cross validation on the training set
- On each of the folds use undersampling
- Fit the model on the training folds and validate on the validation fold

In [11]:
```
# Create the cross validation framework
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import GridSearchCV, cross_val_score, RandomizedSearchCV

kf = StratifiedKFold(n_splits=5, random_state = 42, shuffle = True)
```

In [12]:
```
#pip install imblearn
```

In [13]:
```
# Import the imbalance Learn module
from imblearn.pipeline import Pipeline, make_pipeline
from imblearn.under_sampling import NearMiss
from imblearn.over_sampling import SMOTE

# Import the classifiers
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
```

Undersampling - Logistic Regression

In [14]:
```
# Logistic Regression
imba_pipeline = make_pipeline(NearMiss(),
                              LogisticRegression())

log_reg_params = {"penalty": ['l1', 'l2'],
                  'C': [ 0.01, 0.1, 1, 100],
                  'solver' : ['liblinear']}

new_params = {'logisticregression__' + key: log_reg_params[key] for key in log_reg_params}
```

```
grid_imba_log_reg = GridSearchCV(imba_pipeline, param_grid=new_params, cv=kf,
                                  return_train_score=True)

grid_imba_log_reg.fit(X_train, y_train);
logistic_cv_score_us = cross_val_score(grid_imba_log_reg, X_train, y_train, scoring = 'recall', c


y_test_predict = grid_imba_log_reg.best_estimator_.named_steps['logisticregression'].predict(X_te
logistic_recall_us = recall_score(y_test, y_test_predict)
logistic_accuracy_us = accuracy_score(y_test, y_test_predict)

log_reg_us = grid_imba_log_reg.best_estimator_
```

```
C:\Users\user\anaconda3\lib\site-packages\sklearn\svm\_base.py:1225: ConvergenceWarning: Libline
ar failed to converge, increase the number of iterations.
  warnings.warn(
C:\Users\user\anaconda3\lib\site-packages\sklearn\svm\_base.py:1225: ConvergenceWarning: Libline
ar failed to converge, increase the number of iterations.
  warnings.warn(
C:\Users\user\anaconda3\lib\site-packages\sklearn\svm\_base.py:1225: ConvergenceWarning: Libline
ar failed to converge, increase the number of iterations.
  warnings.warn(
```

In [15]:
```
log_reg_us, logistic_cv_score_us
```

Out[15]:
```
(Pipeline(steps=[('nearmiss', NearMiss()),
                 ('logisticregression',
                  LogisticRegression(C=0.1, penalty='l1', solver='liblinear'))]),
 array([0.85526316, 0.89473684, 0.92207792, 0.90909091, 0.92207792]))
```

In [16]:
```
log_reg_us, logistic_cv_score_us, logistic_recall_us, logistic_accuracy_us
```

Out[16]:
```
(Pipeline(steps=[('nearmiss', NearMiss()),
                 ('logisticregression',
                  LogisticRegression(C=0.1, penalty='l1', solver='liblinear'))]),
 array([0.85526316, 0.89473684, 0.92207792, 0.90909091, 0.92207792]),
 0.8777777777777778,
 0.742607408451697)
```

In [17]:
```
f1_socre_log = f1_score(y_test, y_test_predict, average = 'weighted')

recall_log = recall_score(y_test, y_test_predict)

precision_log = precision_score(y_test, y_test_predict)

print(f1_socre_log, recall_log, precision_log)
```

```
0.8507237761700075 0.8777777777777778 0.005383671800463404
```

In [18]:
```
# Cumulatively create a table for the ROC curve
from sklearn.metrics import roc_curve, roc_auc_score

result_table = pd.DataFrame(columns=['classifiers', 'fpr','tpr','auc'])
yproba = grid_imba_log_reg.best_estimator_.named_steps['logisticregression'].predict_proba(X_tes

fpr, tpr, _ = roc_curve(y_test,  yproba)
auc = roc_auc_score(y_test, yproba)

result_table = result_table.append({'classifiers': "Logistic Regression",
                                    'fpr':fpr,
                                    'tpr':tpr,
```

```
                                          'auc':auc}, ignore_index=True)
display(result_table)
```

	classifiers	fpr	tpr	auc
0	Logistic Regression	[0.0, 7.060152499293985e-05, 0.000353007624964...	[0.0, 0.0, 0.0, 0.011111111111111112, 0.011111...	0.921291

Undersampling - Random Forest

In [19]:
```
# Define the pipeline
imba_pipeline = make_pipeline(NearMiss(),
                              RandomForestClassifier())
params = {
    'n_estimators': [50, 100, 200],
    'max_depth': [4, 6, 10, 12],
    'random_state': [13]
}

new_params = {'randomforestclassifier__' + key: params[key] for key in params}


grid_imba_rf = GridSearchCV(imba_pipeline, param_grid=new_params, cv=kf,
                        return_train_score=True)

grid_imba_rf.fit(X_train, y_train);

rfc_cv_score_us = cross_val_score(grid_imba_rf, X_train, y_train, scoring='recall', cv=kf)

y_test_predict = grid_imba_rf.best_estimator_.named_steps['randomforestclassifier'].predict(X_te
rfc_recall_us = recall_score(y_test, y_test_predict)
rfc_accuracy_us = accuracy_score(y_test, y_test_predict)


rfc = grid_imba_rf.best_estimator_
```

In [20]:
```
rfc,rfc_recall_us, rfc_accuracy_us, rfc_cv_score_us
```

Out[20]:
```
(Pipeline(steps=[('nearmiss', NearMiss()),
                 ('randomforestclassifier',
                  RandomForestClassifier(max_depth=4, n_estimators=50,
                                         random_state=13))]),
 0.9555555555555556,
 0.189669756458605,
 array([0.93421053, 0.96052632, 0.94805195, 0.96103896, 1.        ]))
```

In [21]:
```
f1_socre_rfc = f1_score(y_test, y_test_predict, average = 'weighted')

recall_rfc= recall_score(y_test, y_test_predict)

precision_rfc = precision_score(y_test, y_test_predict)

print(f1_socre_rfc, recall_rfc, precision_rfc)
```

```
0.3166242961086456 0.9555555555555556 0.0018669271681319875
```

In [22]:
```
# Cumulatively create a table for the ROC curve
yproba = grid_imba_rf.best_estimator_.named_steps['randomforestclassifier'].predict_proba(X_test

fpr, tpr, _ = roc_curve(y_test,  yproba)
auc = roc_auc_score(y_test, yproba)
```

```python
result_table = result_table.append({'classifiers': "Random Forest",
                                    'fpr':fpr,
                                    'tpr':tpr,
                                    'auc':auc}, ignore_index=True)

display(result_table)
```

	classifiers	fpr	tpr	auc
0	Logistic Regression	[0.0, 7.060152499293985e-05, 0.000353007624964...	[0.0, 0.0, 0.0, 0.011111111111111112, 0.011111...	0.921291
1	Random Forest	[0.0, 8.825190624117481e-05, 8.825190624117481...	[0.0, 0.4444444444444444, 0.5222222222222223, ...	0.873910

Undersampling - Support Vector Classifier

In [23]:
```python
# Define the pipeline
imba_pipeline = make_pipeline(NearMiss(),
                              SVC(probability = True))
svc_params = {'C': [0.5, 0.7, 0.9, 1],
              'kernel': ['rbf', 'poly', 'sigmoid', 'linear']}

new_params = {'svc__' + key: svc_params[key] for key in svc_params}

grid_imba_svc = GridSearchCV(imba_pipeline, param_grid=new_params, cv=kf,
                        return_train_score=True)

grid_imba_svc.fit(X_train, y_train);

svc_cv_score_us = cross_val_score(grid_imba_svc, X_train, y_train, scoring='recall', cv=kf)

y_test_predict = grid_imba_svc.best_estimator_.named_steps['svc'].predict(X_test)
svc_recall_us = recall_score(y_test, y_test_predict)
svc_accuracy_us = accuracy_score(y_test, y_test_predict)


svc = grid_imba_svc.best_estimator_
```

In [24]:
```python
svc, svc_recall_us, svc_accuracy_us, svc_cv_score_us
```

Out[24]:
```
(Pipeline(steps=[('nearmiss', NearMiss()),
                 ('svc', SVC(C=0.5, kernel='poly', probability=True))]),
 0.6,
 0.9916117435590174,
 array([0.63157895, 0.59210526, 0.75324675, 0.71428571, 0.62337662]))
```

In [25]:
```python
f1_socre_svc = f1_score(y_test, y_test_predict, average = 'weighted')

recall_svc = recall_score(y_test, y_test_predict)

precision_svc = precision_score(y_test, y_test_predict)

print(f1_socre_svc, recall_svc, precision_svc)
```

```
0.9944981538721104 0.6 0.10931174089068826
```

In [26]:
```python
# Cumulatively create a table for the ROC curve
yproba = grid_imba_svc.best_estimator_.named_steps['svc'].predict_proba(X_test)[::,1]
```

```
fpr, tpr, _ = roc_curve(y_test,  yproba)
auc = roc_auc_score(y_test, yproba)

result_table = result_table.append({'classifiers': "Support Vector Classifier",
                                    'fpr':fpr,
                                    'tpr':tpr,
                                    'auc':auc}, ignore_index=True)
display(result_table)
```

	classifiers	fpr	tpr	auc
0	Logistic Regression	[0.0, 7.060152499293985e-05, 0.000353007624964...	[0.0, 0.0, 0.0, 0.011111111111111112, 0.011111...	0.921291
1	Random Forest	[0.0, 8.825190624117481e-05, 8.825190624117481...	[0.0, 0.4444444444444444, 0.5222222222222223, ...	0.873910
2	Support Vector Classifier	[0.0, 0.0011825755436317424, 0.001217876306128...	[0.0, 0.2222222222222222, 0.2222222222222222, ...	0.958269

Undersampling - Decision Tree Classifier

In [27]:
```
# DecisionTree Classifier
imba_pipeline = make_pipeline(NearMiss(),
                              DecisionTreeClassifier())

tree_params = {"criterion": ["gini", "entropy"], "max_depth": list(range(2,4,1)),
              "min_samples_leaf": list(range(5,7,1))}
new_params = {'decisiontreeclassifier__' + key: tree_params[key] for key in tree_params}
#grid_imba_tree = GridSearchCV(imba_pipeline, param_grid=new_params, cv=kf, scoring='recall',
#                        return_train_score=True)
grid_imba_tree = GridSearchCV(imba_pipeline, param_grid=new_params, cv=kf,
                        return_train_score=True)


grid_imba_tree.fit(X_train, y_train);
dtree_cv_score_us = cross_val_score(grid_imba_tree, X_train, y_train, scoring='recall', cv=kf)


y_test_predict = grid_imba_tree.best_estimator_.named_steps['decisiontreeclassifier'].predict(X_
dtree_recall_us = recall_score(y_test, y_test_predict)
dtree_accuracy_us = accuracy_score(y_test, y_test_predict)

# print("Cross Validation Score for Decision Tree Classifier: " + str(udtree_cv_score.mean()))
# print("Recall Score for Decision Tree Classifier: " + str(udtree_recall))
tree_clf = grid_imba_tree.best_estimator_
```

In [28]:
```
tree_clf, dtree_accuracy_us, dtree_recall_us, dtree_cv_score_us
```

Out[28]:
```
(Pipeline(steps=[('nearmiss', NearMiss()),
                 ('decisiontreeclassifier',
                  DecisionTreeClassifier(max_depth=2, min_samples_leaf=5))]),
 0.6681704437317167,
 0.8222222222222222,
 array([0.89473684, 0.90789474, 0.94805195, 0.8961039 , 0.83116883]))
```

In [29]:
```
f1_socre_dtree = f1_score(y_test, y_test_predict, average = 'weighted')

recall_dtree = recall_score(y_test, y_test_predict)

precision_dtree = precision_score(y_test, y_test_predict)
```

```
print(f1_socre_dtree, recall_dtree, precision_dtree)
```

```
0.7995125912644028 0.8222222222222222 0.003917831427361288
```

In [30]:
```
# Cumulatively create a table for the ROC curve
yproba = grid_imba_tree.best_estimator_.named_steps['decisiontreeclassifier'].predict_proba(X_te

fpr, tpr, _ = roc_curve(y_test,  yproba)
auc = roc_auc_score(y_test, yproba)

result_table = result_table.append({'classifiers': "Decision Tree",
                                    'fpr':fpr,
                                    'tpr':tpr,
                                    'auc':auc}, ignore_index=True)

display(result_table)
```

	classifiers	fpr	tpr	auc
0	Logistic Regression	[0.0, 7.060152499293985e-05, 0.000353007624964...	[0.0, 0.0, 0.0, 0.011111111111111112, 0.011111...	0.921291
1	Random Forest	[0.0, 8.825190624117481e-05, 8.825190624117481...	[0.0, 0.4444444444444444, 0.5222222222222223, ...	0.873910
2	Support Vector Classifier	[0.0, 0.0011825755436317424, 0.001217876306128...	[0.0, 0.2222222222222222, 0.2222222222222222, ...	0.958269
3	Decision Tree	[0.0, 0.24634637108161536, 0.3243610561988139,...	[0.0, 0.022222222222222223, 0.8222222222222222...	0.650573

Undersampling - k-Nearest Neighbour Classifier

In [31]:
```
# KNeighbors Classifier
imba_pipeline = make_pipeline(NearMiss(),
                              KNeighborsClassifier())

knears_params = {"n_neighbors": list(range(2,5,1)),
                 'algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute']}

new_params = {'kneighborsclassifier__' + key: knears_params[key] for key in knears_params}

grid_imba_knn = GridSearchCV(imba_pipeline, param_grid=new_params, cv=kf,
                        return_train_score=True)

grid_imba_knn.fit(X_train, y_train);
knear_cv_score_us = cross_val_score(grid_imba_knn, X_train, y_train, scoring='recall', cv=kf)


y_test_predict = grid_imba_knn.best_estimator_.named_steps['kneighborsclassifier'].predict(X_tes
knear_recall_us = recall_score(y_test, y_test_predict)
knear_accuracy_us = accuracy_score(y_test, y_test_predict)

knears_neighbors = grid_imba_knn.best_estimator_
```

In [32]:
```
knears_neighbors, knear_accuracy_us, knear_recall_us, knear_cv_score_us
```

```
Out[32]: (Pipeline(steps=[('nearmiss', NearMiss()),
                          ('kneighborsclassifier', KNeighborsClassifier(n_neighbors=4))]),
          0.8127797554012618,
          0.8666666666666667,
          array([0.84210526, 0.93421053, 0.90909091, 0.93506494, 0.8961039 ]))
```

```
In [33]: f1_socre_knears = f1_score(y_test, y_test_predict, average = 'weighted')

         recall_knears= recall_score(y_test, y_test_predict)

         precision_knears= precision_score(y_test, y_test_predict)

         print(f1_socre_knears, recall_knears, precision_knears)
```

```
0.8951661389883894 0.8666666666666667 0.007296538821328344
```

```
In [34]: # Cumulatively create a table for the ROC curve
         yproba = grid_imba_knn.best_estimator_.named_steps['kneighborsclassifier'].predict_proba(X_test)

         fpr, tpr, _ = roc_curve(y_test,  yproba)
         auc = roc_auc_score(y_test, yproba)

         result_table = result_table.append({'classifiers': "k-Nearest Neighbour",
                                             'fpr':fpr,
                                             'tpr':tpr,
                                             'auc':auc}, ignore_index=True)
         display(result_table)
```

	classifiers	fpr	tpr	auc
0	Logistic Regression	[0.0, 7.060152499293985e-05, 0.000353007624964...	[0.0, 0.0, 0.0, 0.011111111111111112, 0.011111...	0.921291
1	Random Forest	[0.0, 8.825190624117481e-05, 8.825190624117481...	[0.0, 0.4444444444444444, 0.5222222222222223, ...	0.873910
2	Support Vector Classifier	[0.0, 0.0011825755436317424, 0.001217876306128...	[0.0, 0.2222222222222222, 0.2222222222222222, ...	0.958269
3	Decision Tree	[0.0, 0.24634637108161536, 0.3243610561988139,...	[0.0, 0.022222222222222223, 0.8222222222222222...	0.650573
4	k-Nearest Neighbour	[0.0, 0.07884425303586558, 0.1873058458062694,...	[0.0, 0.8444444444444444, 0.8666666666666667, ...	0.885104

Summarize the undersampling model performances

```
In [35]: # Gather the scores
         data_score = [['Logistic Regression', logistic_cv_score_us.mean(), logistic_accuracy_us, logisti
                 ['Random Forest', rfc_cv_score_us.mean(), rfc_accuracy_us, rfc_recall_us],
                 ['Support Vector', svc_cv_score_us.mean(), svc_accuracy_us, svc_recall_us],
                 ['Decision Tree', dtree_cv_score_us.mean(), dtree_accuracy_us, dtree_recall_us],
                 ['k-Nearest Neighbour', knear_cv_score_us.mean(), knear_accuracy_us, knear_recall_us]
                      ]

         # Create the dataframe
         data_table = pd.DataFrame(data_score, columns = ['Classifier', 'CV Score', 'Accuracy', 'Recall S
         data_table
```

Out[35]:

	Classifier	CV Score	Accuracy	Recall Score
0	Logistic Regression	0.900649	0.742607	0.877778
1	Random Forest	0.960766	0.189670	0.955556
2	Support Vector	0.662919	0.991612	0.600000
3	Decision Tree	0.895591	0.668170	0.822222
4	k-Nearest Neighbour	0.903315	0.812780	0.866667

In [36]:

```
# Plot the ROC curve for undersampling
result_table.set_index('classifiers', inplace=True)
fig = plt.figure(figsize=(16,6))

for i in result_table.index:
    plt.plot(result_table.loc[i]['fpr'],
             result_table.loc[i]['tpr'],
             label="{}, AUC={:.3f}".format(i, result_table.loc[i]['auc']))

plt.plot([0,1], [0,1], color='orange', linestyle='--')

plt.xticks(np.arange(0.0, 1.1, step=0.1))
plt.xlabel("Flase Positive Rate", fontsize=15)

plt.yticks(np.arange(0.0, 1.1, step=0.1))
plt.ylabel("True Positive Rate", fontsize=15)

plt.title('ROC Curve Analysis for Undersampling', fontweight='bold', fontsize=15)
plt.legend(prop={'size':13}, loc='lower right')

plt.show()
```