Credit Fraud Detector

Introduction

In this kernel we will use various predictive models to see how accurate they are in detecting whether a transaction is a normal payment or a fraud. As described in the dataset, the features are scaled and the names of the features are not shown due to privacy reasons. Nevertheless, we can still analyze some important aspects of the dataset. Let's start!

Our Goals:

- Understand the little distribution of the "little" data that was provided to us.
- Create a 50/50 sub-dataframe ratio of "Fraud" and "Non-Fraud" transactions. (NearMiss Algorithm)
- Determine the Classifiers we are going to use and decide which one has a higher accuracy.
- Create a Neural Network and compare the accuracy to our best classifier.
- Understand common mistaked made with imbalanced datasets.

Outline:

I. **Understanding our data**
a) [Gather Sense of our data](#gather)

II. **Preprocessing**
a) Scaling and Distributing
b) Splitting the Data

III. **Testing**
a) Testing with Logistic Regression
b) Neural Networks Testing (Undersampling vs Oversampling)

References:

- Hands on Machine Learning with Scikit-Learn & TensorFlow by Aurélien

Géron (O'Reilly). CopyRight 2017 Aurélien Géron

- Machine Learning - Over-& Undersampling - Python/ Scikit/ Scikit-Imblearn by Coding-Maniac
- auprc, 5-fold c-v, and resampling methods by Jeremy Lane (Kaggle Notebook)

In [1]:
```
# This Python 3 environment comes with many helpful analytics libraries instal
# It is defined by the kaggle/python docker image: https://github.com/kaggle/d
# For example, here's several helpful packages to load in

# Imported Libraries

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import seaborn as sns
import time

# Classifier Libraries
from sklearn.linear_model import LogisticRegression
import collections


# Other Libraries
from sklearn.model_selection import train_test_split
from sklearn.pipeline import make_pipeline
from imblearn.pipeline import make_pipeline as imbalanced_make_pipeline
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import NearMiss
from imblearn.metrics import classification_report_imbalanced
from sklearn.metrics import precision_score, recall_score, f1_score, roc_auc_s
from collections import Counter
from sklearn.model_selection import KFold, StratifiedKFold
import warnings
warnings.filterwarnings("ignore")


df = pd.read_csv('/Users/avijit/Desktop/Himanshu_Project/creditcard.csv')
df.head()
```

Out[1]:

	Time	V1	V2	V3	V4	V5	V6	V7
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.23959
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.07880
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.79146
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.23760
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.59294

5 rows × 31 columns

In [2]:

```
df.describe()
```

Out[2]:

	Time	V1	V2	V3	V
count	284807.000000	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+C
mean	94813.859575	1.168375e-15	3.416908e-16	-1.379537e-15	2.074095e-1
std	47488.145955	1.958696e+00	1.651309e+00	1.516255e+00	1.415869e+C
min	0.000000	-5.640751e+01	-7.271573e+01	-4.832559e+01	-5.683171e+C
25%	54201.500000	-9.203734e-01	-5.985499e-01	-8.903648e-01	-8.486401e-C
50%	84692.000000	1.810880e-02	6.548556e-02	1.798463e-01	-1.984653e-C
75%	139320.500000	1.315642e+00	8.037239e-01	1.027196e+00	7.433413e-C
max	172792.000000	2.454930e+00	2.205773e+01	9.382558e+00	1.687534e+C

8 rows × 31 columns

In [3]:

```
# Good No Null Values!
df.isnull().sum().max()
```

Out[3]:

```
0
```

In [4]:

```
df.columns
```

Out[4]:

```
Index(['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10',
       'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V20',
       'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amount',
       'Class'],
      dtype='object')
```

In [5]:

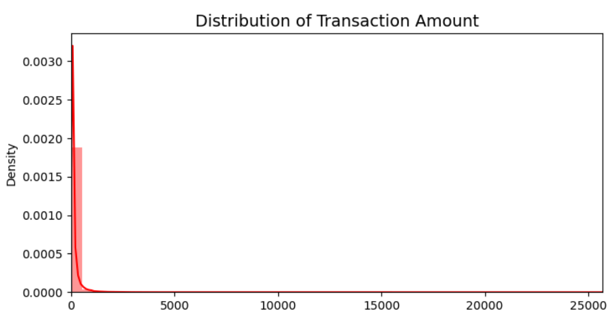
```
# The classes are heavily skewed we need to solve this issue later.
print('No Frauds', round(df['Class'].value_counts()[0]/len(df) * 100,2), '% of
print('Frauds', round(df['Class'].value_counts()[1]/len(df) * 100,2), '% of th
```

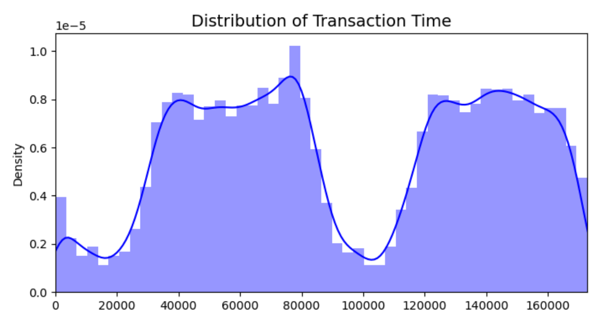
```
No Frauds 99.83 % of the dataset
Frauds 0.17 % of the dataset
```

Note: Notice how imbalanced is our original dataset! Most of the transactions are non-fraud. If we use this dataframe as the base for our predictive models and analysis we might get a lot of errors and our algorithms will probably overfit since it will "assume" that most transactions are not fraud. But we don't want our model to assume, we want our model to detect patterns that give signs of fraud!

Distributions: By seeing the distributions we can have an idea how skewed are these features, we can also see further distributions of the other features. There are techniques that can help the distributions be less skewed which will be implemented in this notebook in the future.

In [7]:
```
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()
```





Scaling and Distributing

In this phase of our kernel, we will first scale the columns comprise of **Time** and **Amount** . Time and amount should be scaled as the other columns. On the other hand, we need to also create a sub sample of the dataframe in order to have an equal amount of Fraud and Non-Fraud cases, helping our algorithms better understand patterns that determines whether a transaction is a fraud or not.

What is a sub-Sample?

In this scenario, our subsample will be a dataframe with a 50/50 ratio of fraud and non-fraud transactions. Meaning our sub-sample will have the same amount of fraud and non fraud transactions.

Why do we create a sub-Sample?

In the beginning of this notebook we saw that the original dataframe was heavily imbalanced! Using the original dataframe will cause the following issues:

- **Overfitting:** Our classification models will assume that in most cases there are no frauds! What we want for our model is to be certain when a fraud occurs.
- **Wrong Correlations:** Although we don't know what the "V" features stand for, it will be useful to understand how each of this features influence the result (Fraud or No Fraud) by having an imbalance dataframe we are not able to see the true correlations between the class and features.

Summary:

- **Scaled amount** and **scaled time** are the columns with scaled values.
- There are **492 cases** of fraud in our dataset so we can randomly get 492 cases of non-fraud to create our new sub dataframe.
- We concat the 492 cases of fraud and non fraud, **creating a new sub-sample.**

In [8]:
```
# Since most of our data has already been scaled we should scale the columns t
from sklearn.preprocessing import StandardScaler, RobustScaler

# RobustScaler is less prone to outliers.

std_scaler = StandardScaler()
rob_scaler = RobustScaler()

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

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

In [9]:
```
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[9]:

	scaled_amount	scaled_time	V1	V2	V3	V4	V
0	1.783274	-0.994983	-1.359807	-0.072781	2.536347	1.378155	-0.3383
1	-0.269825	-0.994983	1.191857	0.266151	0.166480	0.448154	0.0600
2	4.983721	-0.994972	-1.358354	-1.340163	1.773209	0.379780	-0.5031
3	1.418291	-0.994972	-0.966272	-0.185226	1.792993	-0.863291	-0.0103
4	0.670579	-0.994960	-1.158233	0.877737	1.548718	0.403034	-0.4071

5 rows × 31 columns

Splitting the Data (Original DataFrame)

Before proceeding with the **Random UnderSampling technique** we have to separate the orginal dataframe. **Why? for testing purposes, remember although we are splitting the data when implementing Random UnderSampling or OverSampling techniques, we want to test our models on the original testing set not on the testing set created by either of these techniques.** The main goal is to fit the model either with the dataframes that were undersample and oversample (in order for our models to detect the patterns), and test it on the original testing set.

In [10]:

```
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedShuffleSplit

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

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]

# We already have X_train and y_train for undersample data thats why I am usin
# original_Xtrain, original_Xtest, original_ytrain, original_ytest = train_tes
```

```
# Check the Distribution of the labels


# Turn into an array
original_Xtrain = original_Xtrain.values
original_Xtest = original_Xtest.values
original_ytrain = original_ytrain.values
original_ytest = original_ytest.values

# See if both the train and test label distribution are similarly distributed
train_unique_label, train_counts_label = np.unique(original_ytrain, return_cou
test_unique_label, test_counts_label = np.unique(original_ytest, return_counts
print('-' * 100)

print('Label Distributions: \n')
print(train_counts_label/ len(original_ytrain))
print(test_counts_label/ len(original_ytest))
```

```
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  31
002 ... 113964 113965 113966]
Train: [     0      1      2 ... 284804 284805 284806] Test: [ 81609  82400  83
053 ... 170946 170947 170948]
Train: [     0      1      2 ... 284804 284805 284806] Test: [150654 150660 150
661 ... 227866 227867 227868]
Train: [     0      1      2 ... 227866 227867 227868] Test: [212516 212644 213
092 ... 284804 284805 284806]
--------------------------------------------------------------------------------
--------------------
Label Distributions: 

[0.99827076 0.00172924]
[0.99827952 0.00172048]
```

Random Under-Sampling:

In this phase of the project we will implement "*Random Under Sampling*" which basically consists of removing data in order to have a more **balanced dataset** and thus avoiding our models to overfitting.

Steps:

- The first thing we have to do is determine how **imbalanced** is our class (use "value_counts()" on the class column to determine the amount for each label)
- Once we determine how many instances are considered **fraud transactions** (Fraud = "1") , we should bring the **non-fraud**

transactions to the same amount as fraud transactions (assuming we want a 50/50 ratio), this will be equivalent to 492 cases of fraud and 492 cases of non-fraud transactions.
- After implementing this technique, we have a sub-sample of our dataframe with a 50/50 ratio with regards to our classes. Then the next step we will implement is to **shuffle the data** to see if our models can maintain a certain accuracy everytime we run this script.

Note: The main issue with "Random Under-Sampling" is that we run the risk that our classification models will not perform as accurate as we would like to since there is a great deal of **information loss** (bringing 492 non-fraud transaction from 284,315 non-fraud transaction)

In [11]:
```
# Since our classes are highly skewed we should make them equivalent in order

# 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[11]:

	scaled_amount	scaled_time	V1	V2	V3	V4
100193	-0.000279	-0.202610	1.317389	-0.702860	0.728638	-0.734294
215132	9.798225	0.649197	-2.921944	-0.228062	-5.877289	2.201884
226772	-0.281981	0.706129	-0.395931	1.335044	-0.186761	-0.049380
189587	0.641375	0.514327	0.909124	1.337658	-4.484728	3.245358
150660	0.319989	0.107626	-6.185857	7.102985	-13.030455	8.010823

5 rows × 31 columns

Correlation Matrices

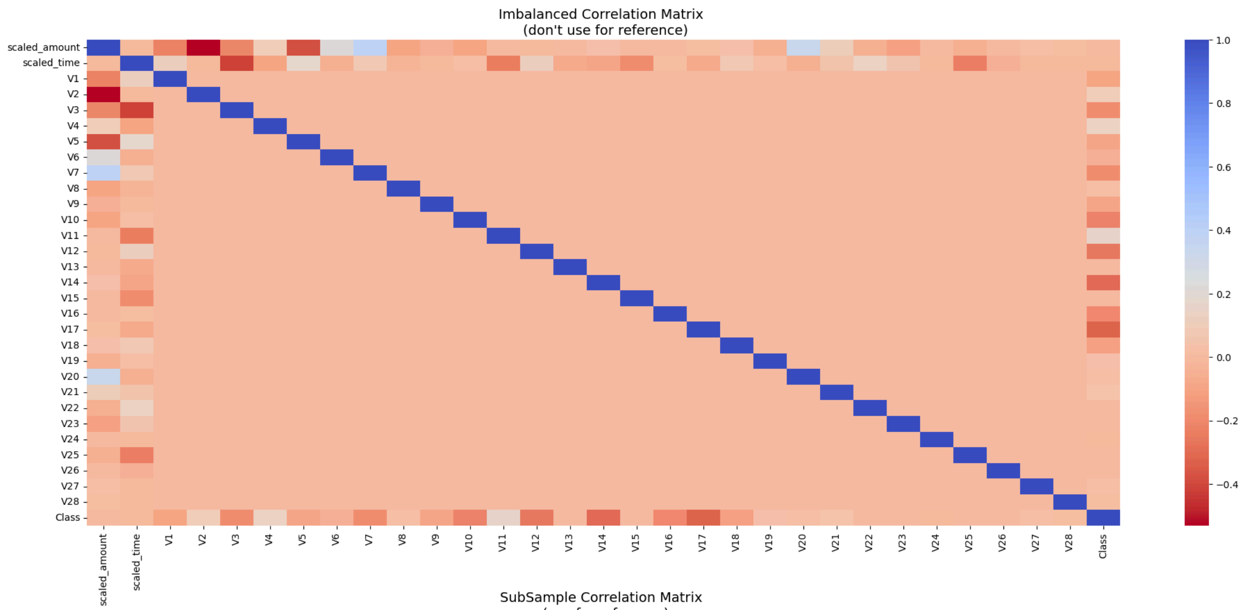
Correlation matrices are the essence of understanding our data. We want to know if there are features that influence heavily in whether a specific transaction is a fraud. However, it is important that we use the correct dataframe (subsample) in order for us to see which features have a high positive or negative correlation with regards to fraud transactions.

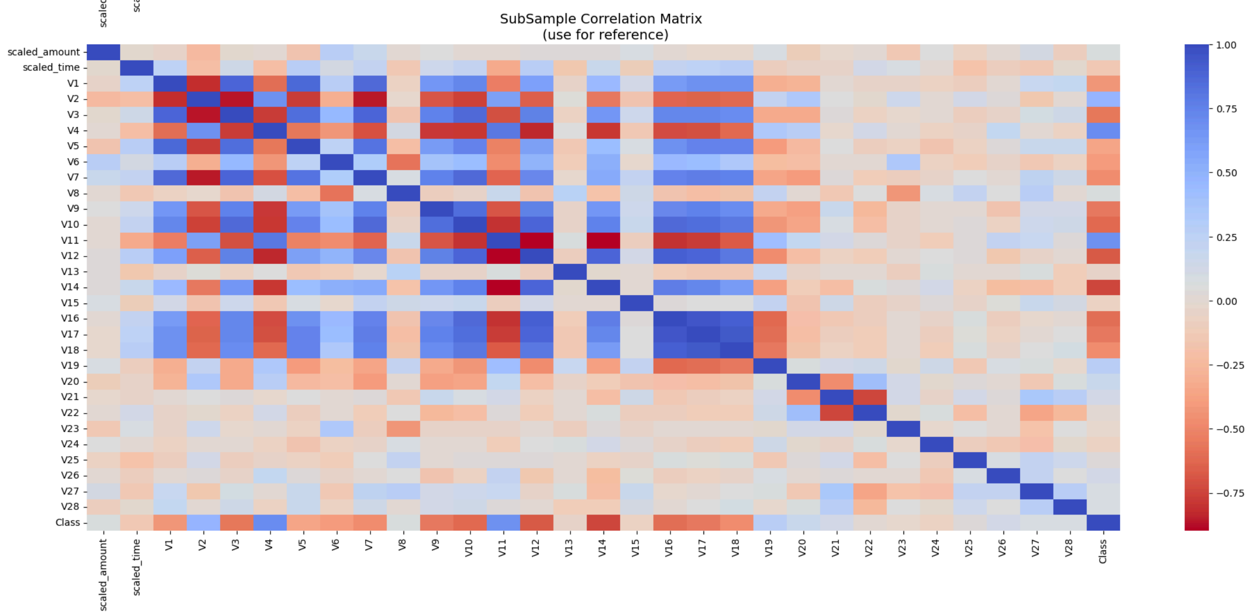
Summary and Explanation:

- **Negative Correlations:** V17, V14, V12 and V10 are negatively correlated. Notice how the lower these values are, the more likely the end result will be a fraud transaction.
- **Positive Correlations:** V2, V4, V11, and V19 are positively correlated. Notice how the higher these values are, the more likely the end result will be a fraud transaction.
- **BoxPlots:** We will use boxplots to have a better understanding of the distribution of these features in fradulent and non fradulent transactions.

**Note: ** We have to make sure we use the subsample in our correlation matrix or else our correlation matrix will be affected by the high imbalance between our classes. This occurs due to the high class imbalance in the original dataframe.

In [13]:
```
# 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)", fo


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=
plt.show()
```

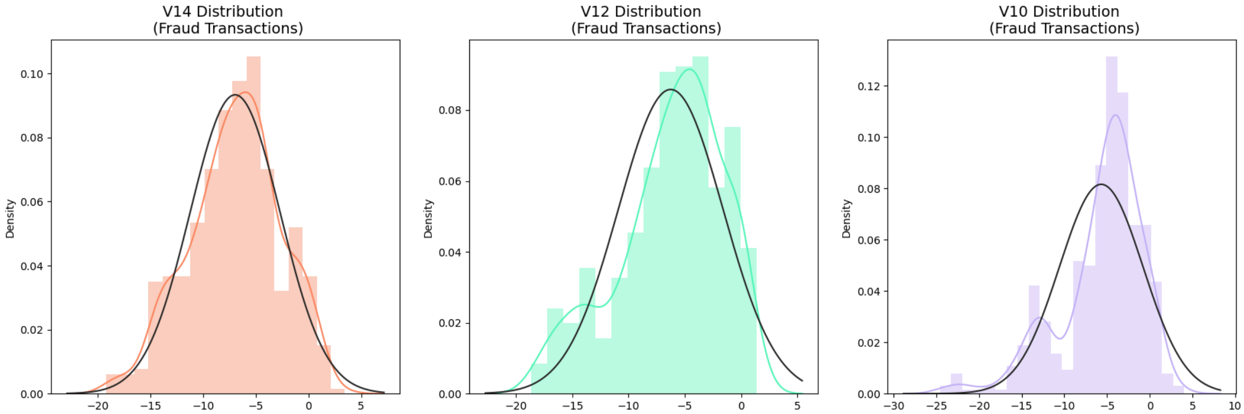




In [14]:

```
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()
```



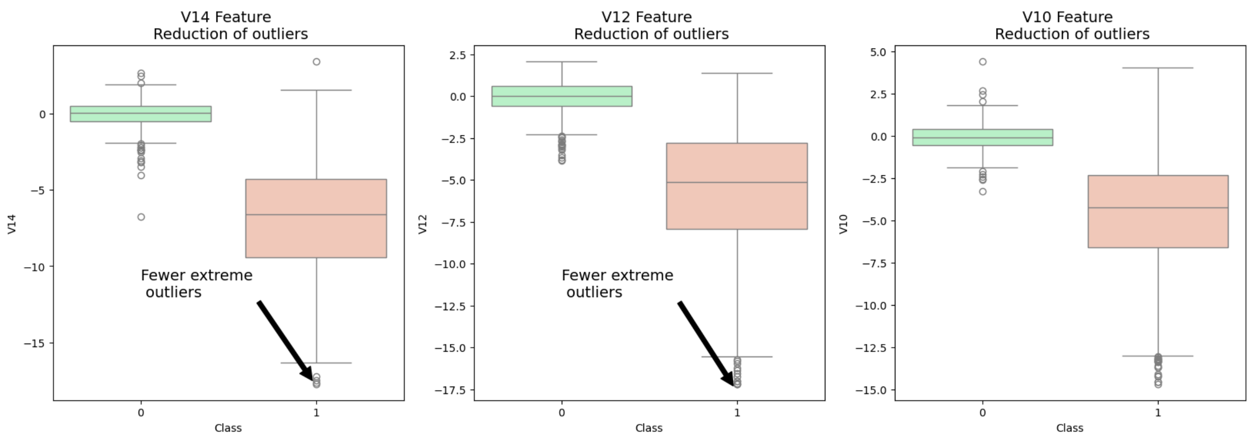
In [15]:
```
# # -----> V14 Removing Outliers (Highest Negative Correlated with Labels)
v14_fraud = new_df['V14'].loc[new_df['Class'] == 1].values
q25, q75 = np.percentile(v14_fraud, 25), np.percentile(v14_fraud, 75)
print('Quartile 25: {} | Quartile 75: {}'.format(q25, q75))
v14_iqr = q75 - q25
print('iqr: {}'.format(v14_iqr))

v14_cut_off = v14_iqr * 1.5
v14_lower, v14_upper = q25 - v14_cut_off, q75 + v14_cut_off
print('Cut Off: {}'.format(v14_cut_off))
print('V14 Lower: {}'.format(v14_lower))
print('V14 Upper: {}'.format(v14_upper))

outliers = [x for x in v14_fraud if x < v14_lower or x > v14_upper]
print('Feature V14 Outliers for Fraud Cases: {}'.format(len(outliers)))
print('V10 outliers:{}'.format(outliers))

new_df = new_df.drop(new_df[(new_df['V14'] > v14_upper) | (new_df['V14'] < v14
print('----' * 44)

# -----> V12 removing outliers from fraud transactions
v12_fraud = new_df['V12'].loc[new_df['Class'] == 1].values
q25, q75 = np.percentile(v12_fraud, 25), np.percentile(v12_fraud, 75)
v12_iqr = q75 - q25

v12_cut_off = v12_iqr * 1.5
v12_lower, v12_upper = q25 - v12_cut_off, q75 + v12_cut_off
print('V12 Lower: {}'.format(v12_lower))
print('V12 Upper: {}'.format(v12_upper))
outliers = [x for x in v12_fraud if x < v12_lower or x > v12_upper]
print('V12 outliers: {}'.format(outliers))
print('Feature V12 Outliers for Fraud Cases: {}'.format(len(outliers)))
new_df = new_df.drop(new_df[(new_df['V12'] > v12_upper) | (new_df['V12'] < v12
print('Number of Instances after outliers removal: {}'.format(len(new_df)))
print('----' * 44)


# Removing outliers V10 Feature
```

```python
v10_fraud = new_df['V10'].loc[new_df['Class'] == 1].values
q25, q75 = np.percentile(v10_fraud, 25), np.percentile(v10_fraud, 75)
v10_iqr = q75 - q25

v10_cut_off = v10_iqr * 1.5
v10_lower, v10_upper = q25 - v10_cut_off, q75 + v10_cut_off
print('V10 Lower: {}'.format(v10_lower))
print('V10 Upper: {}'.format(v10_upper))
outliers = [x for x in v10_fraud if x < v10_lower or x > v10_upper]
print('V10 outliers: {}'.format(outliers))
print('Feature V10 Outliers for Fraud Cases: {}'.format(len(outliers)))
new_df = new_df.drop(new_df[(new_df['V10'] > v10_upper) | (new_df['V10'] < v10
print('Number of Instances after outliers removal: {}'.format(len(new_df)))
```

```
Quartile 25: -9.692722964972386 | Quartile 75: -4.282820849486865
iqr: 5.409902115485521
Cut Off: 8.114853173228282
V14 Lower: -17.807576138200666
V14 Upper: 3.8320323237414167
Feature V14 Outliers for Fraud Cases: 4
V10 outliers:[-18.8220867423816, -19.2143254902614, -18.4937733551053, -18.0499
976898594]
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
------------------
V12 Lower: -17.3430371579634
V12 Upper: 5.776973384895937
V12 outliers: [-18.0475965708216, -18.5536970096458, -18.6837146333443, -18.431
1310279993]
Feature V12 Outliers for Fraud Cases: 4
Number of Instances after outliers removal: 975
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
------------------
V10 Lower: -14.89885463232024
V10 Upper: 4.92033495834214
V10 outliers: [-20.9491915543611, -15.5637913387301, -19.836148851696, -18.2711
681738888, -15.3460988468775, -23.2282548357516, -24.5882624372475, -18.9132433
348732, -16.6011969664137, -14.9246547735487, -16.3035376590131, -24.4031849699
728, -22.1870885620007, -14.9246547735487, -17.1415136412892, -15.123752180345
5, -15.2318333653018, -22.1870885620007, -22.1870885620007, -15.5637913387301,
-16.6496281595399, -16.2556117491401, -15.1241628144947, -15.2399619587112, -2
2.1870885620007, -16.7460441053944, -15.2399619587112]
Feature V10 Outliers for Fraud Cases: 27
Number of Instances after outliers removal: 943
```

In [16]:
```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
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 [17]:
```
# Undersampling before cross validating (prone to overfit)
X = new_df.drop('Class', axis=1)
y = new_df['Class']
```

In [18]:
```
# Our data is already scaled we should split our training and test sets
from sklearn.model_selection import train_test_split

# This is explicitly used for undersampling.
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
```

In [19]:
```
# Turn the values into an array for feeding the classification algorithms.
X_train = X_train.values
X_test = X_test.values
y_train = y_train.values
y_test = y_test.values
```

In [20]:
```
# Let's implement simple classifiers

classifiers = {
```

```
    "LogisiticRegression": LogisticRegression()
}
```

In [21]:
```
# Wow our scores are getting even high scores even when applying cross validat
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 scor
```

```
Classifiers:  LogisticRegression Has a training score of 94.0 % accuracy score
```

In [22]:
```
# Use GridSearchCV to find the best parameters.
from sklearn.model_selection import GridSearchCV


# Logistic Regression
log_reg_params = {"penalty": ['l1', 'l2'], 'C': [0.001, 0.01, 0.1, 1, 10, 100,



grid_log_reg = GridSearchCV(LogisticRegression(), log_reg_params)
grid_log_reg.fit(X_train, y_train)
# We automatically get the logistic regression with the best parameters.
log_reg = grid_log_reg.best_estimator_
```

In [23]:
```
# Overfitting Case

log_reg_score = cross_val_score(log_reg, X_train, y_train, cv=5)
print('Logistic Regression Cross Validation Score: ', round(log_reg_score.mear
```

```
Logistic Regression Cross Validation Score:  94.56%
```

In [24]:
```
# Let's Plot LogisticRegression Learning Curve
from sklearn.model_selection import ShuffleSplit
from sklearn.model_selection import learning_curve

def plot_learning_curve(estimator1, estimator2, estimator3, estimator4, X, y,
                        n_jobs=1, train_sizes=np.linspace(.1, 1.0, 5)):
    f, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2,2, figsize=(20,14), sharey=Tr
    if ylim is not None:
        plt.ylim(*ylim)
    # First Estimator
    train_sizes, train_scores, test_scores = learning_curve(
        estimator1, X, y, cv=cv, n_jobs=n_jobs, train_sizes=train_sizes)
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    ax1.fill_between(train_sizes, train_scores_mean - train_scores_std,
                     train_scores_mean + train_scores_std, alpha=0.1,
                     color="#ff9124")
```

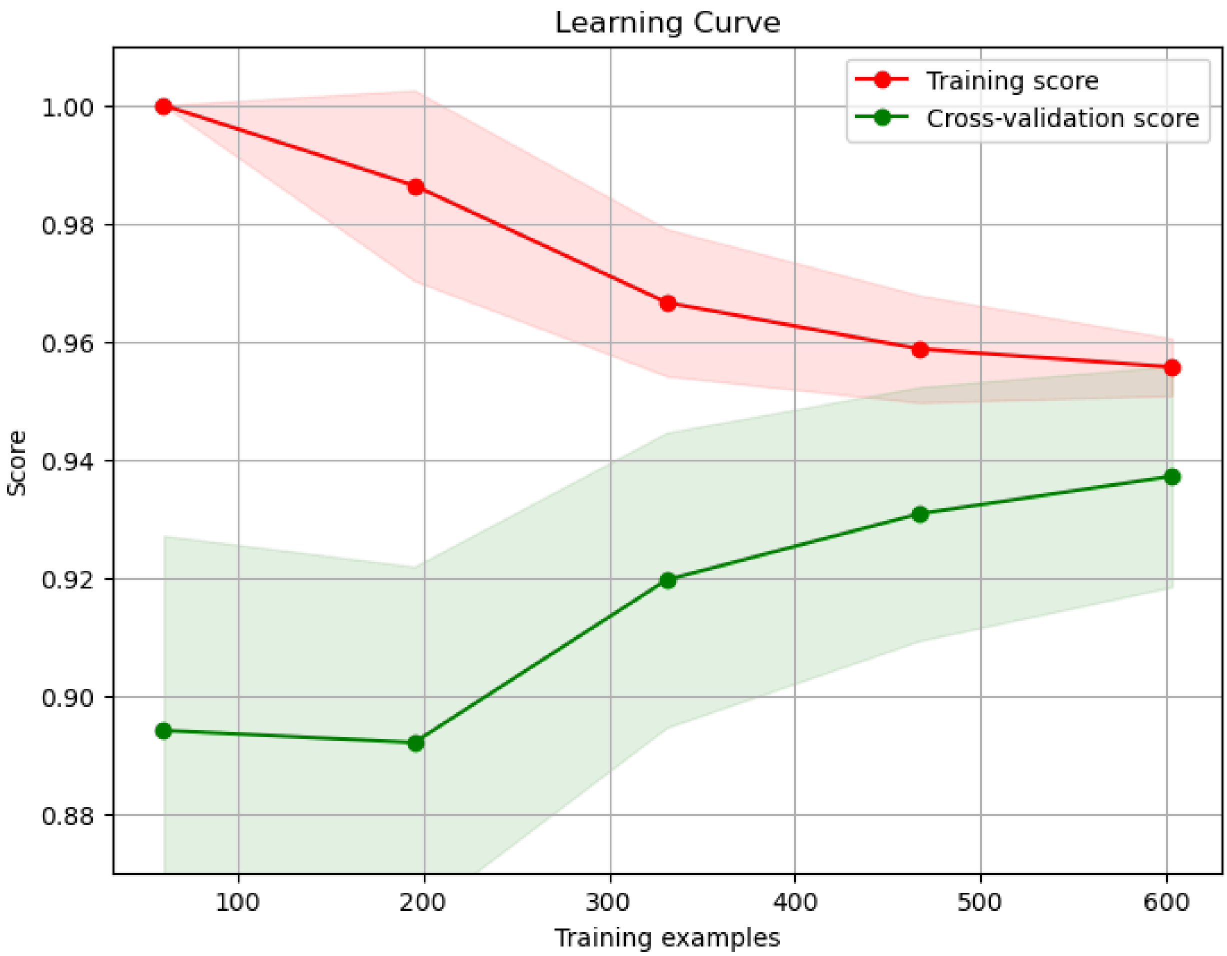
```
    ax1.fill_between(train_sizes, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.1, color="#24
    ax1.plot(train_sizes, train_scores_mean, 'o-', color="#ff9124",
             label="Training score")
    ax1.plot(train_sizes, test_scores_mean, 'o-', color="#2492ff",
             label="Cross-validation score")
    ax1.set_title("Logistic Regression Learning Curve", fontsize=14)
    ax1.set_xlabel('Training size (m)')
    ax1.set_ylabel('Score')
    ax1.grid(True)
    ax1.legend(loc="best")

    # Second Estimator
    train_sizes, train_scores, test_scores = learning_curve(
        estimator2, X, y, cv=cv, n_jobs=n_jobs, train_sizes=train_sizes)
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    ax2.fill_between(train_sizes, train_scores_mean - train_scores_std,
                     train_scores_mean + train_scores_std, alpha=0.1,
                     color="#ff9124")
    ax2.fill_between(train_sizes, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.1, color="#24
    ax2.plot(train_sizes, train_scores_mean, 'o-', color="#ff9124",
             label="Training score")
    ax2.plot(train_sizes, test_scores_mean, 'o-', color="#2492ff",
             label="Cross-validation score")
    ax2.set_title("Knears Neighbors Learning Curve", fontsize=14)
    ax2.set_xlabel('Training size (m)')
    ax2.set_ylabel('Score')
    ax2.grid(True)
    ax2.legend(loc="best")

    # Third Estimator
    train_sizes, train_scores, test_scores = learning_curve(
        estimator3, X, y, cv=cv, n_jobs=n_jobs, train_sizes=train_sizes)
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    ax3.fill_between(train_sizes, train_scores_mean - train_scores_std,
                     train_scores_mean + train_scores_std, alpha=0.1,
                     color="#ff9124")
    ax3.fill_between(train_sizes, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.1, color="#24
    ax3.plot(train_sizes, train_scores_mean, 'o-', color="#ff9124",
             label="Training score")
    ax3.plot(train_sizes, test_scores_mean, 'o-', color="#2492ff",
             label="Cross-validation score")
    ax3.set_title("Support Vector Classifier \n Learning Curve", fontsize=14)
    ax3.set_xlabel('Training size (m)')
    ax3.set_ylabel('Score')
```

```
    ax3.grid(True)
    ax3.legend(loc="best")

    # Fourth Estimator
    train_sizes, train_scores, test_scores = learning_curve(
        estimator4, X, y, cv=cv, n_jobs=n_jobs, train_sizes=train_sizes)
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    ax4.fill_between(train_sizes, train_scores_mean - train_scores_std,
                     train_scores_mean + train_scores_std, alpha=0.1,
                     color="#ff9124")
    ax4.fill_between(train_sizes, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.1, color="#24
    ax4.plot(train_sizes, train_scores_mean, 'o-', color="#ff9124",
             label="Training score")
    ax4.plot(train_sizes, test_scores_mean, 'o-', color="#2492ff",
             label="Cross-validation score")
    ax4.set_title("Decision Tree Classifier \n Learning Curve", fontsize=14)
    ax4.set_xlabel('Training size (m)')
    ax4.set_ylabel('Score')
    ax4.grid(True)
    ax4.legend(loc="best")
    return plt
```

In [26]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import ShuffleSplit, learning_curve

# Create ShuffleSplit cross-validator
cv = ShuffleSplit(n_splits=100, test_size=0.2, random_state=42)

# Plot learning curve function
def plot_learning_curve(estimator, X, y, ylim=None, cv=None, n_jobs=None, trai
    plt.figure(figsize=(8,6))
    if ylim is not None:
        plt.ylim(*ylim)
    plt.xlabel("Training examples")
    plt.ylabel("Score")

    train_sizes, train_scores, test_scores = learning_curve(
        estimator, X, y, cv=cv, n_jobs=n_jobs, train_sizes=train_sizes
    )

    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)

    plt.grid()
    plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                     train_scores_mean + train_scores_std, alpha=0.1, color="r
```

```
    plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.1, color="g")
    plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training
    plt.plot(train_sizes, test_scores_mean, 'o-', color="g", label="Cross-vali

    plt.legend(loc="best")
    plt.title("Learning Curve")
    plt.show()

# Call the function for your Logistic Regression model
plot_learning_curve(
    log_reg,
    X_train,
    y_train,
    ylim=(0.87, 1.01),
    cv=cv,
    n_jobs=4
)
```

```
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on
  n_iter_i = _check_optimize_result(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_logistic.py:4
69: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on
  n_iter_i = _check_optimize_result(
```



In [27]:

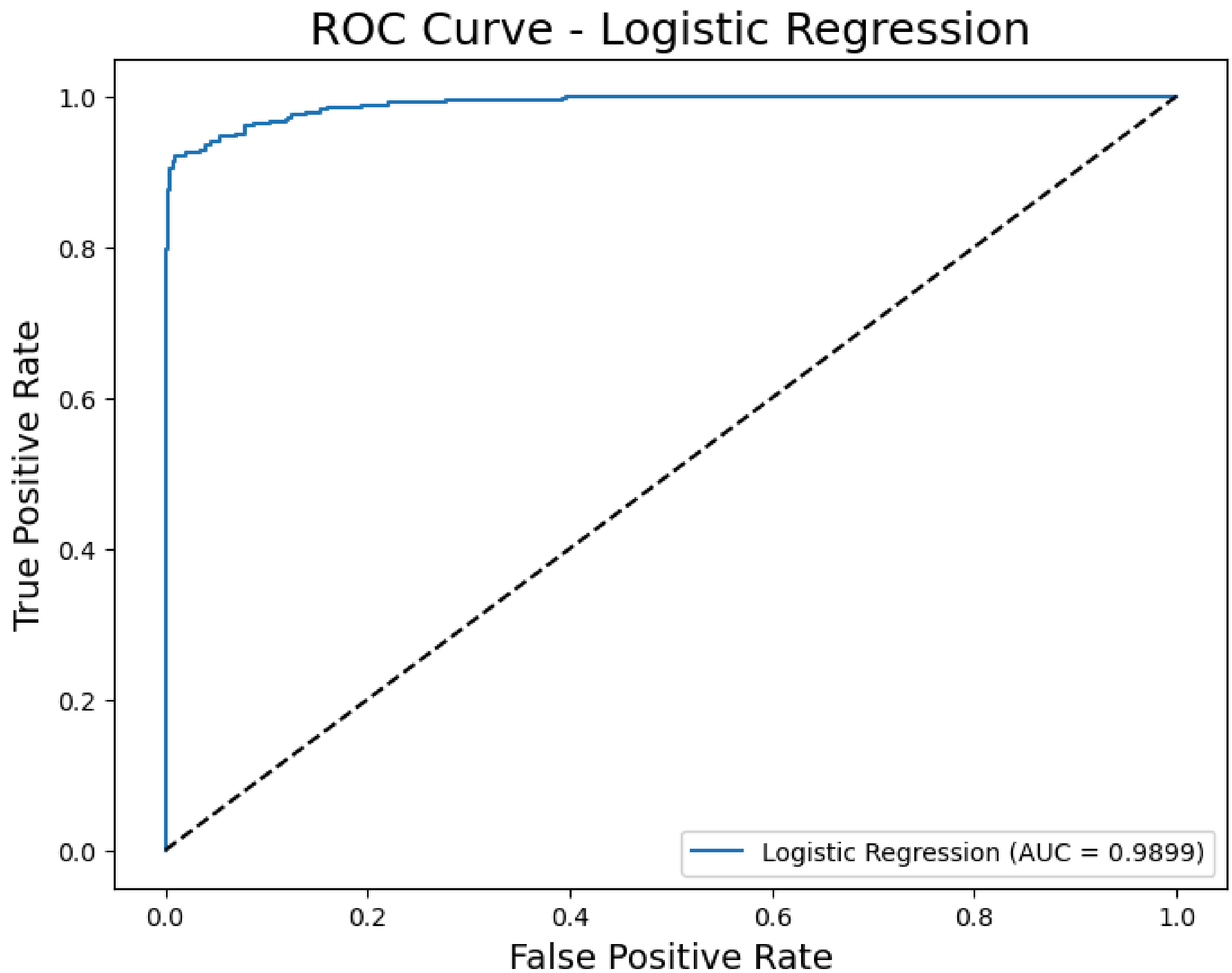
```
from sklearn.metrics import roc_curve
from sklearn.model_selection import cross_val_predict
# Create a DataFrame with all the scores and the classifiers names.

log_reg_pred = cross_val_predict(log_reg, X_train, y_train, cv=5,
```

```
                             method="decision_function")
```

In [28]:
```
from sklearn.metrics import roc_auc_score

print('Logistic Regression: ', roc_auc_score(y_train, log_reg_pred))
```

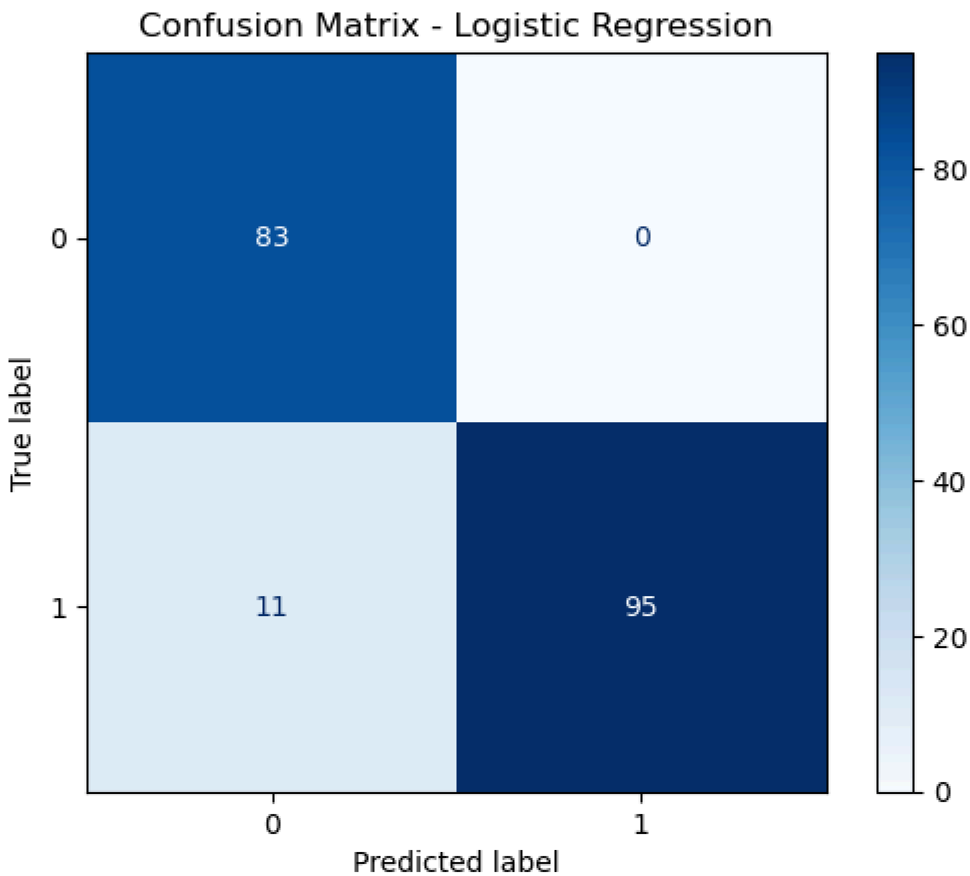
```
Logistic Regression:  0.9669784309982821
```

In [30]:
```
from sklearn.metrics import roc_curve, roc_auc_score

log_reg_pred_prob = log_reg.predict_proba(X_train)[:,1]  # probabilities for R
log_fpr, log_tpr, log_threshold = roc_curve(y_train, log_reg_pred_prob)

def graph_roc_curve_single(log_fpr, log_tpr):
    plt.figure(figsize=(8,6))
    plt.title('ROC Curve - Logistic Regression', fontsize=18)
    plt.plot(log_fpr, log_tpr, label='Logistic Regression (AUC = {:.4f})'.form
        roc_auc_score(y_train, log_reg_pred_prob)))
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlabel('False Positive Rate', fontsize=14)
    plt.ylabel('True Positive Rate', fontsize=14)
    plt.legend(loc="lower right")
    plt.show()

graph_roc_curve_single(log_fpr, log_tpr)
```

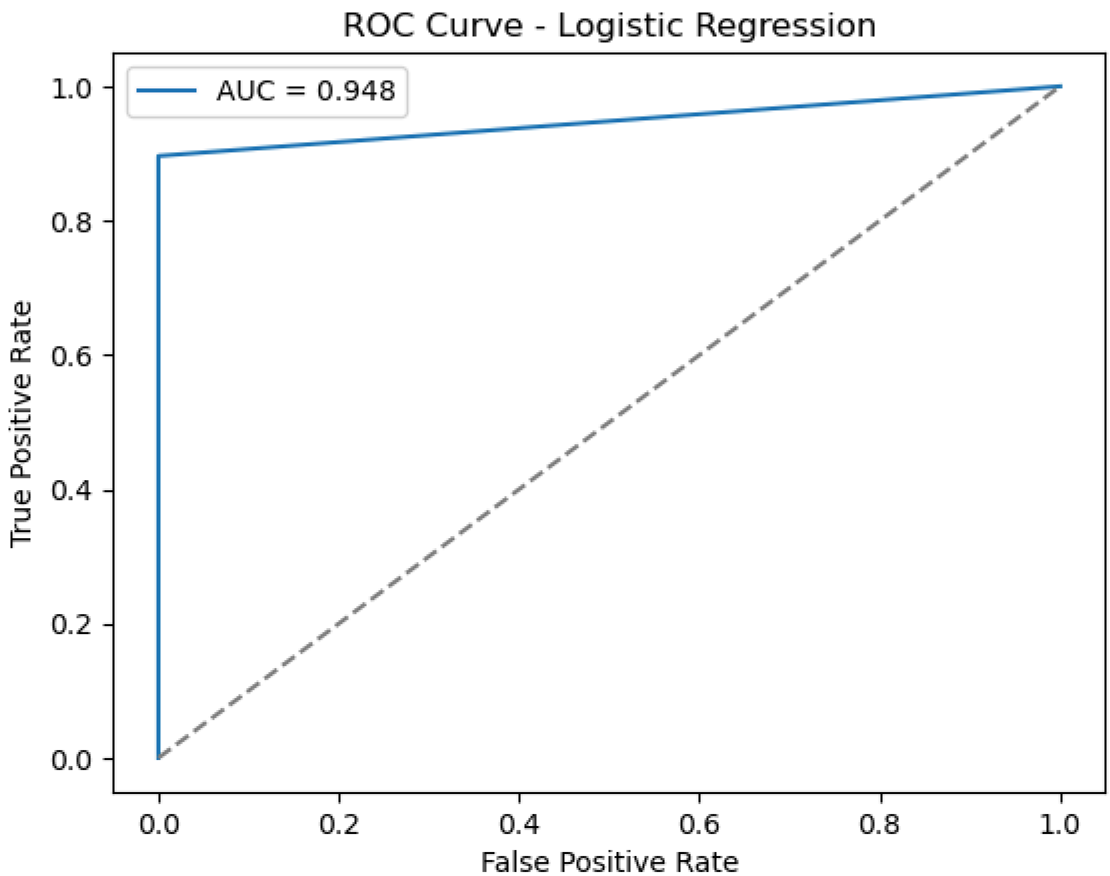


In [32]:
```
# Train the Logistic Regression model
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)

# Predict probabilities and classes
y_pred_proba = log_reg.predict_proba(X_test)[:, 1]  # probabilities for class
y_pred = log_reg.predict(X_test)                      # predicted classes
```

In [33]:
```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt

y_pred_classes = (y_pred > 0.5).astype(int)  # if probabilities
cm = confusion_matrix(y_test, y_pred_classes)

disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=[0, 1])
disp.plot(cmap=plt.cm.Blues, values_format='d')
plt.title("Confusion Matrix - Logistic Regression")
plt.show()
```



In [34]:
```
from sklearn.metrics import roc_curve, roc_auc_score

fpr, tpr, thresholds = roc_curve(y_test, y_pred)
auc_score = roc_auc_score(y_test, y_pred)

plt.plot(fpr, tpr, label=f"AUC = {auc_score:.3f}")
plt.plot([0,1],[0,1],'--', color='gray')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve - Logistic Regression")
plt.legend()
plt.show()
```



Conclusion:

Dataset is highly imbalanced → applied SMOTE/undersampling.

Logistic Regression was trained and evaluated.

Confusion matrix + ROC-AUC showed [insert recall/precision tradeoff].

For fraud detection, recall is more important (catch frauds).