walmart take home ds challenge

April 1, 2022

Outline

- **1. Basic understanding of the data**
- **2. Preprocessing**

a) Scaling and Distributing

b) Splitting the Data

- **3. Random UnderSampling**

a) Equally Distributing and Correlating

b) Anomaly Detection

c) Dimensionality Reduction and Clustering

d) Classifier

e) A Deeper Look Into Logistic Regression

f) OverSampling with SMOTE

- **4. Testing**

a) Test for Logistic Regression.
b) Naive Neural Networks on the Test Set

c) Other Models Testing

- **5. Summary**
- **6. Validation**

1 Basic understanding of the data

[145]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# 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
from sklearn.ensemble import GradientBoostingClassifier
import collections


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_score, accuracy_score, classification_report
from collections import Counter
from sklearn.model_selection import KFold, StratifiedKFold

import keras
from keras import backend as K
from keras.models import Sequential
from keras.layers import Activation
from keras.layers.core import Dense
from tensorflow.keras.optimizers import Adam
from keras.metrics import categorical_crossentropy

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

[2]:
```
data = pd.read_csv('model.csv')
```

[3]:
```
data.head()
```

[3]:
```
      A1     A2       A3        A4     A5     A6    A7      A8     A9    A10  \
0  10.69  86.10  8920.16  19912.85  30.42  31.72  1.18  145.41  2.236  1.786
1  28.50  65.19  6564.00   6716.67  32.50  23.40  2.74   91.11  1.000  1.000
```

```
2  24.87  73.79  4285.47   6463.75  40.50  51.53  2.84   93.90  2.400  1.400
3  13.64  85.82  6887.56   9244.44  49.56  53.44  0.36  171.45  1.875  2.167
4   4.50  95.92  8746.50  19987.50  32.75  37.88  0.92  153.25  2.000  1.500

   …   A22   A23   A24   A25      A26     A27     A28    A29    A30  default
0  …  0.01  0.01  0.01  0.13     0.00    0.00    0.00   0.00   0.00        0
1  …  0.06  0.01  0.00  0.09   285.80    0.00   16.44   1.98  42.26        0
2  …  0.08  0.02  0.02  0.44   494.62  135.41  127.45  46.00  14.92        0
3  …  0.03  0.01  0.00  0.05  1015.19    0.00  210.63  92.58   0.00        0
4  …  0.01  0.00  0.00  0.04     0.00  106.41   79.00   0.00   0.00        0

[5 rows x 31 columns]
```

[4]:

```
data.describe()
```

[4]:

```
                 A1            A2            A3             A4            A5  \
count  94000.000000  94000.000000  94000.000000   94000.000000  94000.000000
mean      12.134211     83.838361   7319.620881   13449.501569     33.507640
std        6.587858      8.672843   2652.539364    8197.452662     11.906865
min        0.000000     20.750000      0.000000       0.000000      0.000000
25%        7.670000     79.000000   5618.627500    8700.000000     26.880000
50%       12.020000     84.360000   7285.590000   11862.650000     32.770000
75%       16.080000     89.670000   8780.870000   15896.575000     39.100000
max       62.710000    100.000000  26333.500000  170300.000000    146.000000

                 A6            A7            A8            A9           A10  \
count  94000.000000  94000.000000  94000.000000  94000.000000  94000.000000
mean      36.983300      1.518232    124.108845      1.697824      1.407075
std       14.209314      1.007398     33.130292      0.776810      0.652138
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%       28.780000      0.820000    103.027500      1.272000      1.000000
50%       35.940000      1.420000    127.240000      1.667000      1.399000
75%       43.830000      2.020000    143.100000      2.064000      1.714000
max      146.000000     18.670000    524.000000     44.000000     44.000000

       …           A22           A23           A24           A25  \
count  …  94000.000000  94000.000000  94000.000000  94000.000000
mean   …      0.074435      0.008550      0.013537      0.133531
std    …      0.138356      0.020052      0.029078      0.156658
min    …     -0.010000     -0.020000     -0.020000      0.000000
25%    …      0.010000      0.000000      0.000000      0.060000
50%    …      0.030000      0.000000      0.010000      0.090000
75%    …      0.080000      0.010000      0.010000      0.140000
max    …      5.300000      0.700000      1.690000      4.080000

                A26           A27           A28           A29           A30  \
count  94000.000000  94000.000000  94000.000000  94000.000000  94000.000000
```

```
mean     290.756534    357.976444    103.482568     28.847016     38.509910
std      471.958770    597.594147    136.248095     62.759062     90.882963
min     -751.260000   -405.370000   -616.230000   -490.160000   -719.720000
25%        0.000000      0.000000     14.970000      0.000000      0.000000
50%      115.140000    102.265000     59.350000     10.500000      0.000000
75%      380.142500    485.880000    140.952500     34.860000     49.862500
max    15288.660000  19503.760000   3265.980000   6561.930000  13487.000000

            default
count  94000.000000
mean       0.042553
std        0.201849
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        1.000000

[8 rows x 31 columns]
```

[5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 94000 entries, 0 to 93999
Data columns (total 31 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   A1       94000 non-null  float64
 1   A2       94000 non-null  float64
 2   A3       94000 non-null  float64
 3   A4       94000 non-null  float64
 4   A5       94000 non-null  float64
 5   A6       94000 non-null  float64
 6   A7       94000 non-null  float64
 7   A8       94000 non-null  float64
 8   A9       94000 non-null  float64
 9   A10      94000 non-null  float64
 10  A11      94000 non-null  float64
 11  A12      94000 non-null  float64
 12  A13      94000 non-null  float64
 13  A14      94000 non-null  float64
 14  A15      94000 non-null  float64
 15  A16      94000 non-null  float64
 16  A17      94000 non-null  float64
 17  A18      94000 non-null  float64
 18  A19      94000 non-null  float64
 19  A20      94000 non-null  float64
 20  A21      94000 non-null  int64
```

```
 21  A22      94000 non-null  float64
 22  A23      94000 non-null  float64
 23  A24      94000 non-null  float64
 24  A25      94000 non-null  float64
 25  A26      94000 non-null  float64
 26  A27      94000 non-null  float64
 27  A28      94000 non-null  float64
 28  A29      94000 non-null  float64
 29  A30      94000 non-null  float64
 30  default  94000 non-null  int64
dtypes: float64(29), int64(2)
memory usage: 22.2 MB
```

[6]:
```
data.isnull().sum().max()
```

[6]:
```
0
```

[7]:
```
data.columns
```

[7]:
```
Index(['A1', 'A2', 'A3', 'A4', 'A5', 'A6', 'A7', 'A8', 'A9', 'A10', 'A11',
       'A12', 'A13', 'A14', 'A15', 'A16', 'A17', 'A18', 'A19', 'A20', 'A21',
       'A22', 'A23', 'A24', 'A25', 'A26', 'A27', 'A28', 'A29', 'A30',
       'default'],
      dtype='object')
```

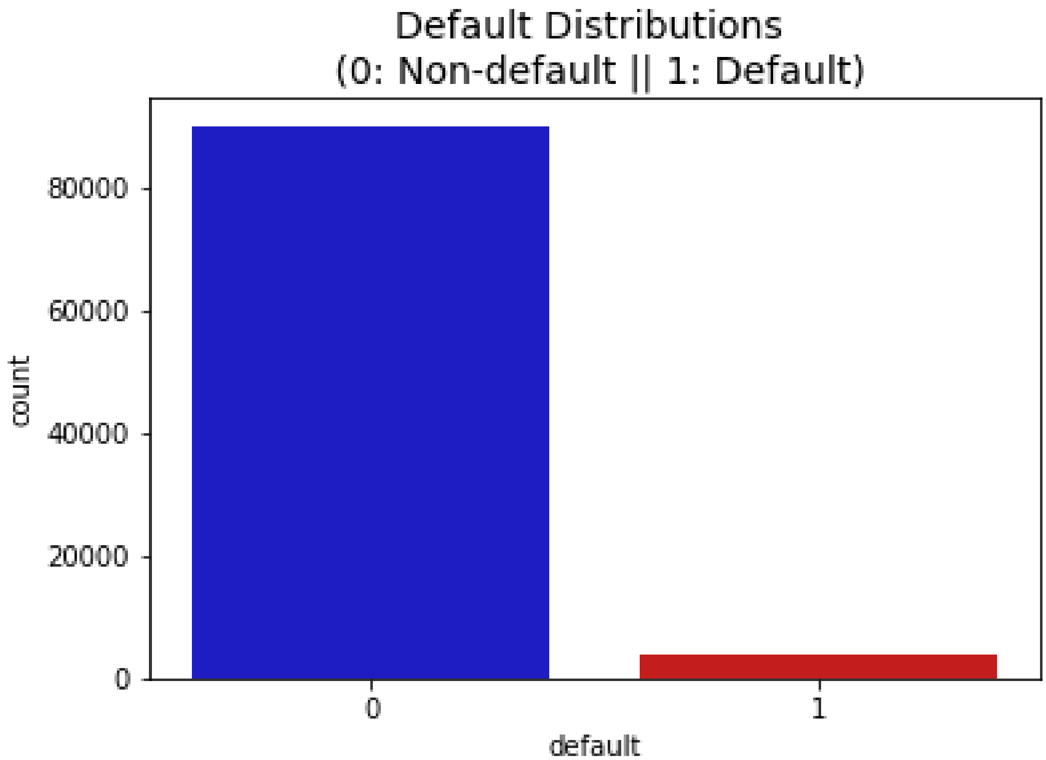
[8]:
```
print('Non-Dault', round(data['default'].value_counts()[0] / len(data) *␣
 ↪100,2), '% of the dataset')
print('Default', round(data['default'].value_counts()[1] / len(data) * 100,2),␣
 ↪'% of the dataset')
```

```
Non-Dault 95.74 % of the dataset
Default 4.26 % of the dataset
```

We can see that there is no missing values in the dataset and this is a quite imbalanced dataset.

[9]:
```
colors = ["#0101DF", "#DF0101"]

sns.countplot('default', data=data, palette=colors)
plt.title('Default Distributions \n (0: Non-default || 1: Default)',␣
 ↪fontsize=14)
```

[9]:
```
Text(0.5, 1.0, 'Default Distributions \n (0: Non-default || 1: Default)')
```



2 Preprocessing

2.1 Scaling and Distributing

As the describe of the data suggests, the mean and standard deviation of each feature (A1 - A30) varies a lot. So we better take some scaling regulation on the original dataset.

Variables that are measured at different scales do not contribute equally to the model fitting & model learned function and might end up creating a bias. Thus, to deal with this potential problem feature-wise standardized (=0, =1) is usually used prior to model fitting.

[10]:
```python
from sklearn.preprocessing import StandardScaler, RobustScaler

# RobustScaler is less prone to outliers

std_scaler = StandardScaler()
rob_scaler = RobustScaler()

features = data.columns[:30]

for feature in features:
    data[feature] = rob_scaler.fit_transform(data[feature].values.reshape(-1,1))
```

```
data.describe()
```

[10]:

	A1	A2	A3	A4	A5	\
count	94000.000000	94000.000000	94000.000000	94000.000000	94000.000000	
mean	0.013580	-0.048888	0.010762	0.220501	0.060363	
std	0.783336	0.812825	0.838816	1.139077	0.974375	
min	-1.429251	-5.961575	-2.303931	-1.648374	-2.681669	
25%	-0.517241	-0.502343	-0.527146	-0.439466	-0.481997	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.482759	0.497657	0.472854	0.560534	0.518003	
max	6.027348	1.465792	6.023545	22.015660	9.265957	

	A6	A7	A8	A9	A10	\
count	94000.000000	94000.000000	94000.000000	94000.000000	94000.000000	
mean	0.069322	0.081860	-0.078137	0.038919	0.011310	
std	0.944140	0.839498	0.826759	0.980820	0.913358	
min	-2.388040	-1.183333	-3.175245	-2.104798	-1.959384	
25%	-0.475748	-0.500000	-0.604217	-0.498737	-0.558824	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.524252	0.500000	0.395783	0.501263	0.441176	
max	7.312957	14.375000	9.901054	53.450758	59.665266	

	…	A22	A23	A24	A25	\
count	…	94000.000000	94000.000000	94000.000000	94000.000000	
mean	…	0.634780	0.855000	0.353681	0.544138	
std	…	1.976520	2.005184	2.907756	1.958220	
min	…	-0.571429	-2.000000	-3.000000	-1.125000	
25%	…	-0.285714	0.000000	-1.000000	-0.375000	
50%	…	0.000000	0.000000	0.000000	0.000000	
75%	…	0.714286	1.000000	0.000000	0.625000	
max	…	75.285714	70.000000	168.000000	49.875000	

	A26	A27	A28	A29	A30	\
count	94000.000000	94000.000000	94000.000000	94000.000000	94000.000000	
mean	0.461976	0.526285	0.350307	0.526306	0.772322	
std	1.241531	1.229921	1.081484	1.800317	1.822672	
min	-2.279145	-1.044774	-5.362491	-14.362020	-14.434094	
25%	-0.302886	-0.210474	-0.352271	-0.301205	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.697114	0.789526	0.647729	0.698795	1.000000	
max	39.915348	39.930631	25.452980	187.935456	270.483831	

	default
count	94000.000000
mean	0.042553
std	0.201849
min	0.000000

```
25%        0.000000
50%        0.000000
75%        0.000000
max        1.000000

[8 rows x 31 columns]
```

2.2 Splitting the Data

Before proceeding with the **Random UnderSampling technique**, I will separate the orginal dataframe.

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 or oversample (in order for our models to detect the pattern of default), and test it on the original testing set.

[11]:
```
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedShuffleSplit

print('Non-Dault', round(data['default'].value_counts()[0] / len(data) *␣
 ↪100,2), '% of the dataset')
print('Default', round(data['default'].value_counts()[1] / len(data) * 100,2),␣
 ↪'% of the dataset')
```

```
Non-Dault 95.74 % of the dataset
Default 4.26 % of the dataset
```

[12]:
```
X = data.drop('default', axis = 1)
y = data['default']

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]

# 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_counts=True)
```

```
test_unique_label, test_counts_label = np.unique(original_ytest,␣
↪return_counts=True)
print('-' * 100)

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

```
Train: [18000 18001 18002 … 93997 93998 93999] Test: [    0     1     2 …
90797 90798 90799]
Train: [    0     1     2 … 93997 93998 93999] Test: [18000 18001 18002 …
91597 91598 91599]
Train: [    0     1     2 … 93997 93998 93999] Test: [36000 36001 36002 …
92397 92398 92399]
Train: [    0     1     2 … 93997 93998 93999] Test: [54000 54001 54002 …
93197 93198 93199]
Train: [    0     1     2 … 93197 93198 93199] Test: [72000 72001 72002 …
93997 93998 93999]
--------------------------------------------------------------------------------
--------------------
Label Distributions:

[0.95744681 0.04255319]
[0.95744681 0.04255319]
```

3 Random UnderSampling

[13]:
```
data['default'].value_counts()
```

[13]:
```
0    90000
1     4000
Name: default, dtype: int64
```

[14]:
```
# Shuffle the data before creating the subsamples

df = data.sample(frac = 1)

# amount of default cases of 4000
default_df = df.loc[df['default'] == 1]
non_default_df = df.loc[df['default'] == 0][:4000]

normal_dist_df = pd.concat([default_df, non_default_df])

#Shuffle again
new_df = normal_dist_df.sample(frac = 1, random_state = 42)

new_df.head()
```

[14]:

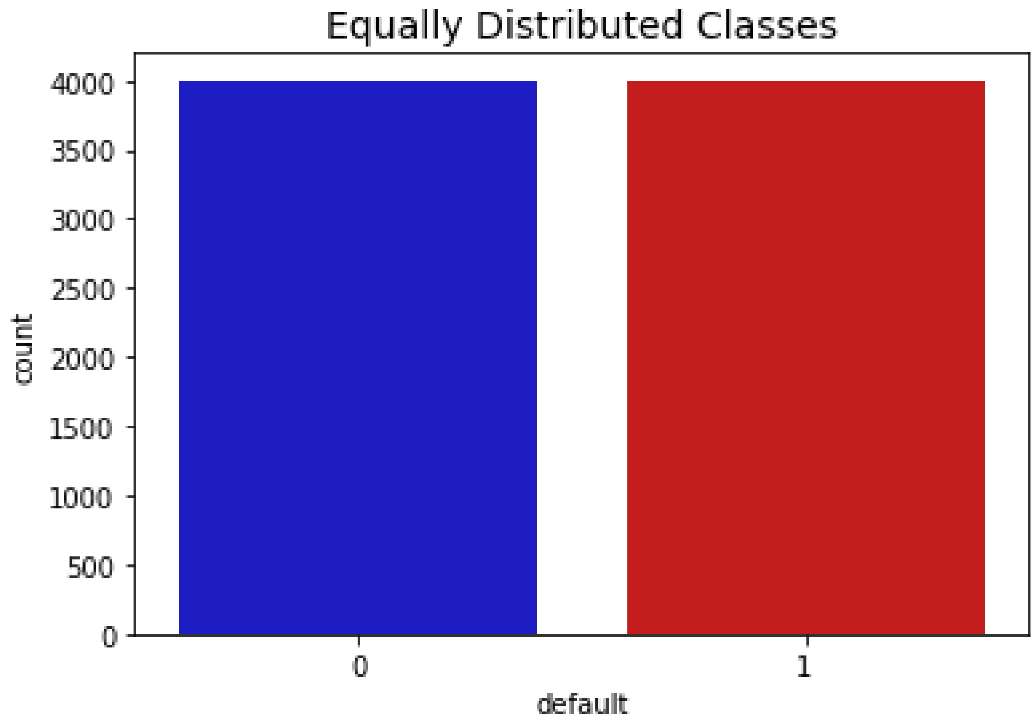
```
              A1        A2        A3        A4        A5        A6        A7  \
90038  0.787158 -0.654171 -1.739089 -1.220016  0.895254  1.410631  0.100000
90094  0.671819 -0.494845 -0.970647 -0.276889  0.734861  0.452492  1.383333
90234  0.995244 -0.080600 -0.864017 -0.530419 -0.479542 -0.177409  0.300000
90738  2.375743 -1.755389 -1.714951 -0.911913  2.621113  1.648505  7.400000
67312  0.562426 -0.402999 -0.454570 -0.461977  0.869885  1.548837 -0.108333

              A8        A9       A10  …        A22  A23   A24    A25  \
90038 -0.827001 -1.473485 -1.259104  …  -0.428571  0.0  -1.0 -0.125
90094 -0.613139 -1.262626 -1.959384  …   0.857143  2.0   1.0  0.500
90234 -0.713706 -0.463384 -0.138655  …   0.285714  2.0   1.0  0.125
90738 -0.545012 -0.842172 -1.959384  …  10.000000  9.0  13.0  1.625
67312  0.474889  0.059343  0.441176  …   0.142857  0.0  -1.0  0.000

             A26       A27       A28       A29       A30  default
90038 -0.180748 -0.210474 -0.347747 -0.301205  0.931161        1
90094  0.321064  0.481261  0.117397  1.429432  0.000000        1
90234  1.228855 -0.210474  0.217252  2.709983  3.782602        1
90738  1.562020 -0.210474  2.829361  0.039300  0.274354        1
67312 -0.108801  0.016002 -0.374496 -0.047619  0.000000        0

[5 rows x 31 columns]
```

3.1 Equally Distributing and Correlating

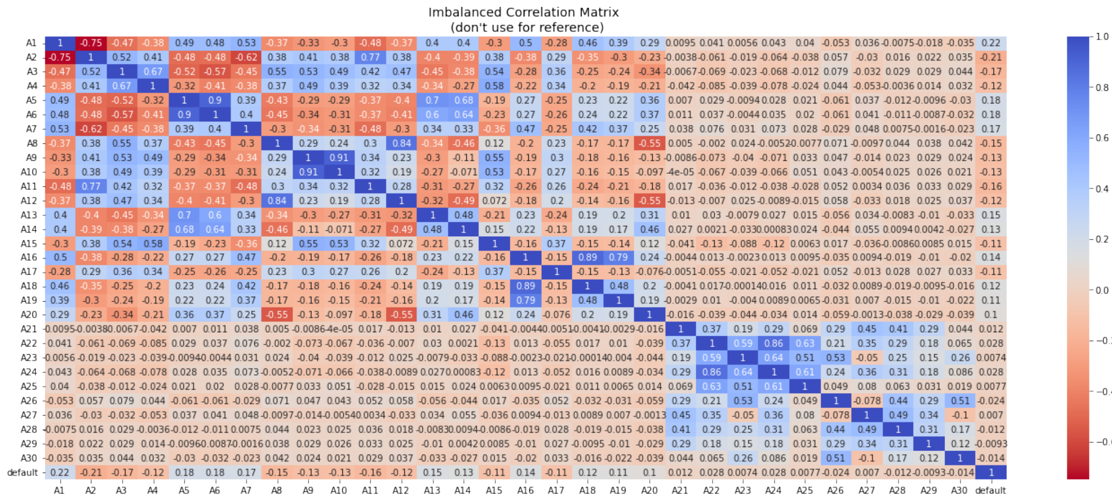
[15]:

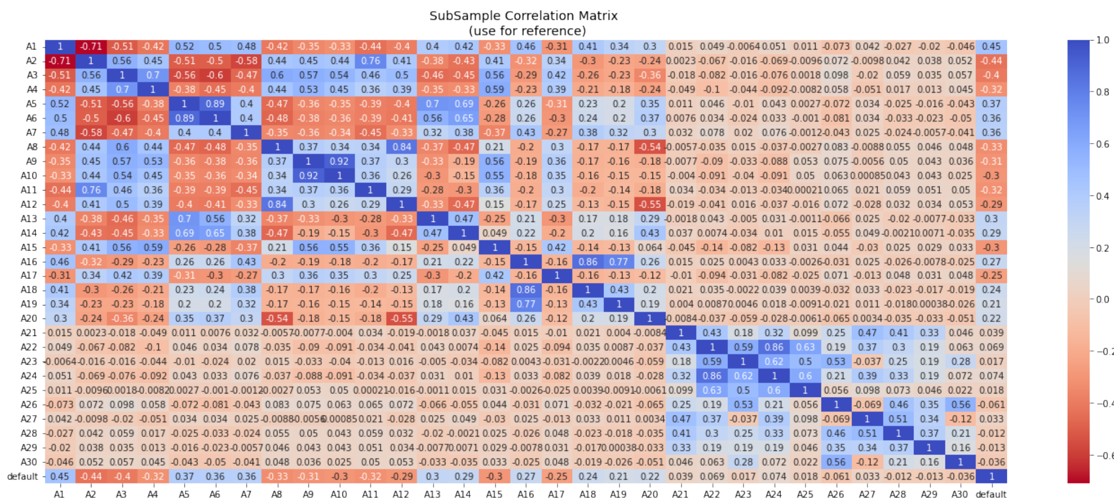
```python
print('Distribution of the Default classes in the subsample dataset')
print(new_df['default'].value_counts() / len(new_df))

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

```
Distribution of the Default classes in the subsample dataset
1    0.5
0    0.5
Name: default, dtype: float64
```



[16]:
```
# Correlation Matrices

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

# Entire DataFrame
corr = data.corr()
sns.heatmap(corr, cmap='coolwarm_r', annot = True, annot_kws={'size':10},␣
  ↪ax=ax1)
ax1.set_title("Imbalanced Correlation Matrix \n (don't use for reference)",␣
  ↪fontsize=14)

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



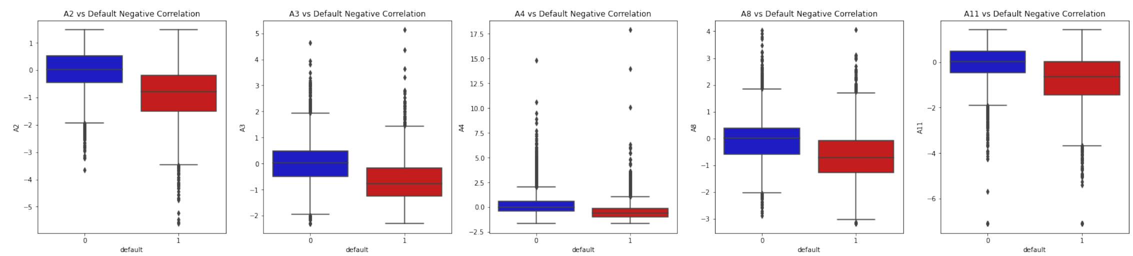


- **Negative Correlation:** A2, A3, A4, A8 and A11 are negatively correlated. The lower these values are, the more likely the result will be a default transaction.
- **Positive Correlation:** A1, A5, A6 and A7 are positively correlated. The higher these values are, the more likely the result will be a default transaction.

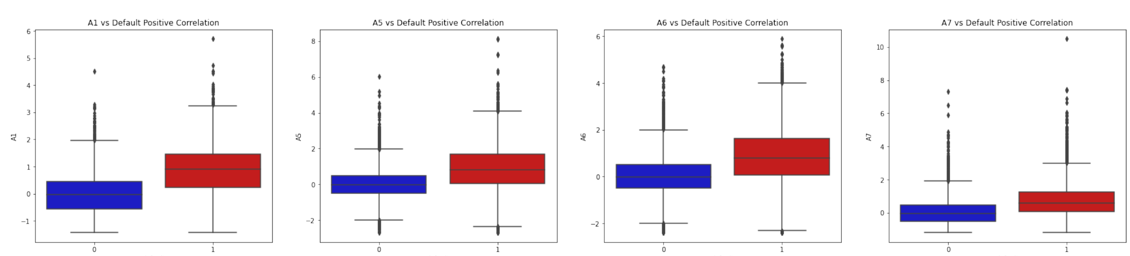
[17]:

```
f, axes = plt.subplots(ncols=5, figsize=(30,6))

# Negative Correlations with our default (The lower our feature value the more likely it will be a default transaction)
sns.boxplot(x="default", y="A2", data=new_df, palette=colors, ax=axes[0])
axes[0].set_title('A2 vs Default Negative Correlation')

sns.boxplot(x="default", y="A3", data=new_df, palette=colors, ax=axes[1])
axes[1].set_title('A3 vs Default Negative Correlation')
```

```
sns.boxplot(x="default", y="A4", data=new_df, palette=colors, ax=axes[2])
axes[2].set_title('A4 vs Default Negative Correlation')

sns.boxplot(x="default", y="A8", data=new_df, palette=colors, ax=axes[3])
axes[3].set_title('A8 vs Default Negative Correlation')

sns.boxplot(x="default", y="A11", data=new_df, palette=colors, ax=axes[4])
axes[4].set_title('A11 vs Default Negative Correlation')

plt.show()
```

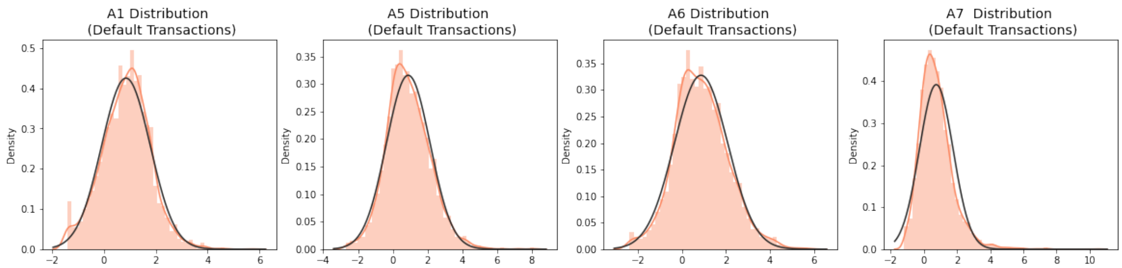


[18]:
```
f, axes = plt.subplots(ncols=4, figsize=(30,6))

# Positive Correlations with our default (The higher our feature value the more likely it will be a default transaction)
sns.boxplot(x="default", y="A1", data=new_df, palette=colors, ax=axes[0])
axes[0].set_title('A1 vs Default Positive Correlation')

sns.boxplot(x="default", y="A5", data=new_df, palette=colors, ax=axes[1])
axes[1].set_title('A5 vs Default Positive Correlation')

sns.boxplot(x="default", y="A6", data=new_df, palette=colors, ax=axes[2])
axes[2].set_title('A6 vs Default Positive Correlation')

sns.boxplot(x="default", y="A7", data=new_df, palette=colors, ax=axes[3])
axes[3].set_title('A7 vs Default Positive Correlation')

plt.show()
```



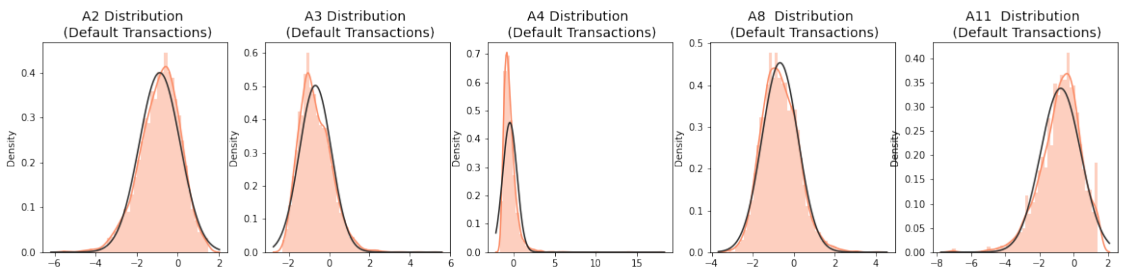
3.2 Anomaly Detection

[19]:
```python
from scipy.stats import norm

f, (ax1, ax2, ax3, ax4) = plt.subplots(1,4, figsize=(20, 4))

a1_default_dist = new_df['A1'].loc[new_df['default'] == 1].values
sns.distplot(a1_default_dist,ax=ax1, fit=norm, color='#FB8861')
ax1.set_title('A1 Distribution \n (Default Transactions)', fontsize=14)

a5_default_dist = new_df['A5'].loc[new_df['default'] == 1].values
sns.distplot(a5_default_dist,ax=ax2, fit=norm, color='#FB8861')
ax2.set_title('A5 Distribution \n (Default Transactions)', fontsize=14)

a6_default_dist = new_df['A6'].loc[new_df['default'] == 1].values
sns.distplot(a6_default_dist,ax=ax3, fit=norm, color='#FB8861')
ax3.set_title('A6 Distribution \n (Default Transactions)', fontsize=14)

a7_default_dist = new_df['A7'].loc[new_df['default'] == 1].values
sns.distplot(a7_default_dist,ax=ax4, fit=norm, color='#FB8861')
ax4.set_title('A7  Distribution \n (Default Transactions)', fontsize=14)

plt.show()
```



[20]:
```python
f, (ax1, ax2, ax3, ax4, ax5) = plt.subplots(1,5, figsize=(20, 4))

a2_default_dist = new_df['A2'].loc[new_df['default'] == 1].values
sns.distplot(a2_default_dist,ax=ax1, fit=norm, color='#FB8861')
ax1.set_title('A2 Distribution \n (Default Transactions)', fontsize=14)

a3_default_dist = new_df['A3'].loc[new_df['default'] == 1].values
sns.distplot(a3_default_dist,ax=ax2, fit=norm, color='#FB8861')
ax2.set_title('A3 Distribution \n (Default Transactions)', fontsize=14)
```

```
a4_default_dist = new_df['A4'].loc[new_df['default'] == 1].values
sns.distplot(a4_default_dist,ax=ax3, fit=norm, color='#FB8861')
ax3.set_title('A4 Distribution \n (Default Transactions)', fontsize=14)

a8_default_dist = new_df['A8'].loc[new_df['default'] == 1].values
sns.distplot(a8_default_dist,ax=ax4, fit=norm, color='#FB8861')
ax4.set_title('A8  Distribution \n (Default Transactions)', fontsize=14)

a11_default_dist = new_df['A11'].loc[new_df['default'] == 1].values
sns.distplot(a11_default_dist,ax=ax5, fit=norm, color='#FB8861')
ax5.set_title('A11  Distribution \n (Default Transactions)', fontsize=14)

plt.show()
```



[21]:
```
# A1 Removing Outliers
print('Removing outliers for A1')
a1_default = new_df['A1'].loc[new_df['default'] == 1].values
q25, q75 = np.percentile(a1_default, 25), np.percentile(a1_default, 75)
print('Quartile 25: {} | Quartile 75: {}'.format(q25, q75))
a1_iqr = q75 - q25
print('iqr: {}'.format(a1_iqr))

a1_cut_off = a1_iqr * 1.5
a1_lower, a1_upper = q25 - a1_cut_off, q75 + a1_cut_off
print('Cut Off: {}'.format(a1_cut_off))
print('A1 Lower: {}'.format(a1_lower))
print('A1 Upper: {}'.format(a1_upper))

outliers = [x for x in a1_default if x < a1_lower or x > a1_upper]
print('Feature A1 Outliers for Default Cases: {}'.format(len(outliers)))

new_df = new_df.drop(new_df[(new_df['A1'] > a1_upper) | (new_df['A1'] <
 ↪a1_lower)].index)
print('Number of Instances after outliers removal: {}'.format(len(new_df)))
print('--' * 50)
```

```
# A5 Removing Outliers
print('Removing outliers for A5')
a5_default = new_df['A5'].loc[new_df['default'] == 1].values
q25, q75 = np.percentile(a5_default, 25), np.percentile(a5_default, 75)
print('Quartile 25: {} | Quartile 75: {}'.format(q25, q75))
a5_iqr = q75 - q25
print('iqr: {}'.format(a5_iqr))

a5_cut_off = a5_iqr * 1.5
a5_lower, a5_upper = q25 - a5_cut_off, q75 + a5_cut_off
print('Cut Off: {}'.format(a5_cut_off))
print('A5 Lower: {}'.format(a5_lower))
print('A5 Upper: {}'.format(a5_upper))

outliers = [x for x in a5_default if x < a5_lower or x > a5_upper]
print('Feature A5 Outliers for Default Cases: {}'.format(len(outliers)))

new_df = new_df.drop(new_df[(new_df['A5'] > a5_upper) | (new_df['A5'] <
  a5_lower)].index)
print('Number of Instances after outliers removal: {}'.format(len(new_df)))
print('--' * 50)

# A6 Removing Outliers
print('Removing outliers for A6')
a6_default = new_df['A6'].loc[new_df['default'] == 1].values
q25, q75 = np.percentile(a6_default, 25), np.percentile(a6_default, 75)
print('Quartile 25: {} | Quartile 75: {}'.format(q25, q75))
a6_iqr = q75 - q25
print('iqr: {}'.format(a6_iqr))

a6_cut_off = a6_iqr * 1.5
a6_lower, a6_upper = q25 - a6_cut_off, q75 + a6_cut_off
print('Cut Off: {}'.format(a6_cut_off))
print('A6 Lower: {}'.format(a6_lower))
print('A6 Upper: {}'.format(a6_upper))

outliers = [x for x in a6_default if x < a6_lower or x > a6_upper]
print('Feature A6 Outliers for Default Cases: {}'.format(len(outliers)))

new_df = new_df.drop(new_df[(new_df['A6'] > a6_upper) | (new_df['A6'] <
  a6_lower)].index)
print('Number of Instances after outliers removal: {}'.format(len(new_df)))
print('--' * 50)

# A7 Removing Outliers
print('Removing outliers for A7')
```

```python
a7_default = new_df['A7'].loc[new_df['default'] == 1].values
q25, q75 = np.percentile(a7_default, 25), np.percentile(a7_default, 75)
print('Quartile 25: {} | Quartile 75: {}'.format(q25, q75))
a7_iqr = q75 - q25
print('iqr: {}'.format(a7_iqr))

a7_cut_off = a7_iqr * 1.5
a7_lower, a7_upper = q25 - a7_cut_off, q75 + a7_cut_off
print('Cut Off: {}'.format(a7_cut_off))
print('A7 Lower: {}'.format(a7_lower))
print('A7 Upper: {}'.format(a7_upper))

outliers = [x for x in a7_default if x < a7_lower or x > a7_upper]
print('Feature A7 Outliers for Default Cases: {}'.format(len(outliers)))

new_df = new_df.drop(new_df[(new_df['A7'] > a7_upper) | (new_df['A7'] <␣
 ↪a7_lower)].index)
print('Number of Instances after outliers removal: {}'.format(len(new_df)))
print('--' * 50)
```

```
Removing outliers for A1
Quartile 25: 0.24227110582639733 | Quartile 75: 1.4482758620689657
iqr: 1.2060047562425684
Cut Off: 1.8090071343638527
A1 Lower: -1.5667360285374554
A1 Upper: 3.2572829964328185
Feature A1 Outliers for Default Cases: 37
Number of Instances after outliers removal: 7961
--------------------------------------------------------------------------------
--------------------
Removing outliers for A5
Quartile 25: 0.05891980360065427 | Quartile 75: 1.6554828150572825
iqr: 1.5965630114566283
Cut Off: 2.3948445171849424
A5 Lower: -2.335924713584288
A5 Upper: 4.050327332242225
Feature A5 Outliers for Default Cases: 75
Number of Instances after outliers removal: 7860
--------------------------------------------------------------------------------
--------------------
Removing outliers for A6
Quartile 25: 0.06162790697674421 | Quartile 75: 1.5931893687707646
iqr: 1.5315614617940203
Cut Off: 2.2973421926910307
A6 Lower: -2.2357142857142867
A6 Upper: 3.8905315614617955
Feature A6 Outliers for Default Cases: 38
Number of Instances after outliers removal: 7812
```

```
----------------------------------------------------------------------------------------------------
Removing outliers for A7
Quartile 25: 0.06666666666666672 | Quartile 75: 1.225
iqr: 1.1583333333333334
Cut Off: 1.7375000000000003
A7 Lower: -1.6708333333333336
A7 Upper: 2.9625000000000004
Feature A7 Outliers for Default Cases: 106
Number of Instances after outliers removal: 7675
----------------------------------------------------------------------------------------------------
```

[22]:
```python
# A2 Removing Outliers
print('Removing outliers for A2')
a2_default = new_df['A2'].loc[new_df['default'] == 1].values
q25, q75 = np.percentile(a2_default, 25), np.percentile(a2_default, 75)
print('Quartile 25: {} | Quartile 75: {}'.format(q25, q75))
a2_iqr = q75 - q25
print('iqr: {}'.format(a2_iqr))

a2_cut_off = a2_iqr * 1.5
a2_lower, a2_upper = q25 - a2_cut_off, q75 + a2_cut_off
print('Cut Off: {}'.format(a2_cut_off))
print('A2 Lower: {}'.format(a2_lower))
print('A2 Upper: {}'.format(a2_upper))

outliers = [x for x in a2_default if x < a2_lower or x > a2_upper]
print('Feature A2 Outliers for Default Cases: {}'.format(len(outliers)))

new_df = new_df.drop(new_df[(new_df['A2'] > a2_upper) | (new_df['A2'] <␣
↪a2_lower)].index)
print('Number of Instances after outliers removal: {}'.format(len(new_df)))
print('--' * 50)

# A3 Removing Outliers
print('Removing outliers for A3')
a3_default = new_df['A3'].loc[new_df['default'] == 1].values
q25, q75 = np.percentile(a3_default, 25), np.percentile(a3_default, 75)
print('Quartile 25: {} | Quartile 75: {}'.format(q25, q75))
a3_iqr = q75 - q25
print('iqr: {}'.format(a3_iqr))

a3_cut_off = a3_iqr * 1.5
a3_lower, a3_upper = q25 - a3_cut_off, q75 + a3_cut_off
print('Cut Off: {}'.format(a3_cut_off))
print('A3 Lower: {}'.format(a3_lower))
```

```
print('A3 Upper: {}'.format(a3_upper))

outliers = [x for x in a3_default if x < a3_lower or x > a3_upper]
print('Feature A3 Outliers for Default Cases: {}'.format(len(outliers)))

new_df = new_df.drop(new_df[(new_df['A3'] > a3_upper) | (new_df['A3'] <␣
 ↪a3_lower)].index)
print('Number of Instances after outliers removal: {}'.format(len(new_df)))
print('--' * 50)

# A4 Removing Outliers
print('Removing outliers for A4')
a4_default = new_df['A4'].loc[new_df['default'] == 1].values
q25, q75 = np.percentile(a4_default, 25), np.percentile(a4_default, 75)
print('Quartile 25: {} | Quartile 75: {}'.format(q25, q75))
a4_iqr = q75 - q25
print('iqr: {}'.format(a4_iqr))

a4_cut_off = a4_iqr * 1.5
a4_lower, a4_upper = q25 - a4_cut_off, q75 + a4_cut_off
print('Cut Off: {}'.format(a4_cut_off))
print('A4 Lower: {}'.format(a4_lower))
print('A4 Upper: {}'.format(a4_upper))

outliers = [x for x in a4_default if x < a4_lower or x > a4_upper]
print('Feature A4 Outliers for Default Cases: {}'.format(len(outliers)))

new_df = new_df.drop(new_df[(new_df['A4'] > a4_upper) | (new_df['A4'] <␣
 ↪a4_lower)].index)
print('Number of Instances after outliers removal: {}'.format(len(new_df)))
print('--' * 50)

# A8 Removing Outliers
print('Removing outliers for A8')
a8_default = new_df['A8'].loc[new_df['default'] == 1].values
q25, q75 = np.percentile(a8_default, 25), np.percentile(a8_default, 75)
print('Quartile 25: {} | Quartile 75: {}'.format(q25, q75))
a8_iqr = q75 - q25
print('iqr: {}'.format(a8_iqr))

a8_cut_off = a8_iqr * 1.5
a8_lower, a8_upper = q25 - a8_cut_off, q75 + a8_cut_off
print('Cut Off: {}'.format(a8_cut_off))
print('A8 Lower: {}'.format(a8_lower))
print('A8 Upper: {}'.format(a8_upper))

outliers = [x for x in a8_default if x < a8_lower or x > a8_upper]
```

```
print('Feature A8 Outliers for Default Cases: {}'.format(len(outliers)))

new_df = new_df.drop(new_df[(new_df['A8'] > a8_upper) | (new_df['A8'] <␣
 ↪a8_lower)].index)
print('Number of Instances after outliers removal: {}'.format(len(new_df)))
print('--' * 50)

# A11 Removing Outliers
print('Removing outliers for A11')
a11_default = new_df['A11'].loc[new_df['default'] == 1].values
q25, q75 = np.percentile(a11_default, 25), np.percentile(a11_default, 75)
print('Quartile 25: {} | Quartile 75: {}'.format(q25, q75))
a11_iqr = q75 - q25
print('iqr: {}'.format(a11_iqr))

a11_cut_off = a11_iqr * 1.5
a11_lower, a11_upper = q25 - a11_cut_off, q75 + a11_cut_off
print('Cut Off: {}'.format(a11_cut_off))
print('A11 Lower: {}'.format(a11_lower))
print('A11 Upper: {}'.format(a11_upper))

outliers = [x for x in a11_default if x < a11_lower or x > a11_upper]
print('Feature A11 Outliers for Default Cases: {}'.format(len(outliers)))

new_df = new_df.drop(new_df[(new_df['A11'] > a11_upper) | (new_df['A11'] <␣
 ↪a11_lower)].index)
print('Number of Instances after outliers removal: {}'.format(len(new_df)))
print('--' * 50)
```

```
Removing outliers for A2
Quartile 25: -1.4299437675726334 | Quartile 75: -0.16119962511715075
iqr: 1.2687441424554826
Cut Off: 1.9031162136832238
A2 Lower: -3.3330599812558575
A2 Upper: 1.741916588566073
Feature A2 Outliers for Default Cases: 32
Number of Instances after outliers removal: 7642
--------------------------------------------------------------------------------
--------------------
Removing outliers for A3
Quartile 25: -1.1987213188109385 | Quartile 75: -0.15276263600909798
iqr: 1.0459586828018406
Cut Off: 1.5689380242027609
A3 Lower: -2.7676593430136993
A3 Upper: 1.416175388193663
Feature A3 Outliers for Default Cases: 39
Number of Instances after outliers removal: 7379
```

```
-----------------------------------------------------------------------------------
--------------------
Removing outliers for A4
Quartile 25: -0.9312888422617701 | Quartile 75: -0.1328965514845603
iqr: 0.7983922907772099
Cut Off: 1.1975884361658147
A4 Lower: -2.1288772784275847
A4 Upper: 1.0646918846812543
Feature A4 Outliers for Default Cases: 146
Number of Instances after outliers removal: 6846
-----------------------------------------------------------------------------------
--------------------
Removing outliers for A8
Quartile 25: -1.2850458543889203 | Quartile 75: -0.11965811965811954
iqr: 1.1653877347308008
Cut Off: 1.7480816020962013
A8 Lower: -3.0331274564851216
A8 Upper: 1.6284234824380819
Feature A8 Outliers for Default Cases: 31
Number of Instances after outliers removal: 6757
-----------------------------------------------------------------------------------
--------------------
Removing outliers for A11
Quartile 25: -1.4199318568994879 | Quartile 75: 0.001064735945484853
iqr: 1.4209965928449728
Cut Off: 2.1314948892674592
A11 Lower: -3.551426746166947
A11 Upper: 2.132559625212944
Feature A11 Outliers for Default Cases: 47
Number of Instances after outliers removal: 6700
-----------------------------------------------------------------------------------
--------------------
```

3.3 Dimensionality Reduction and Clustering

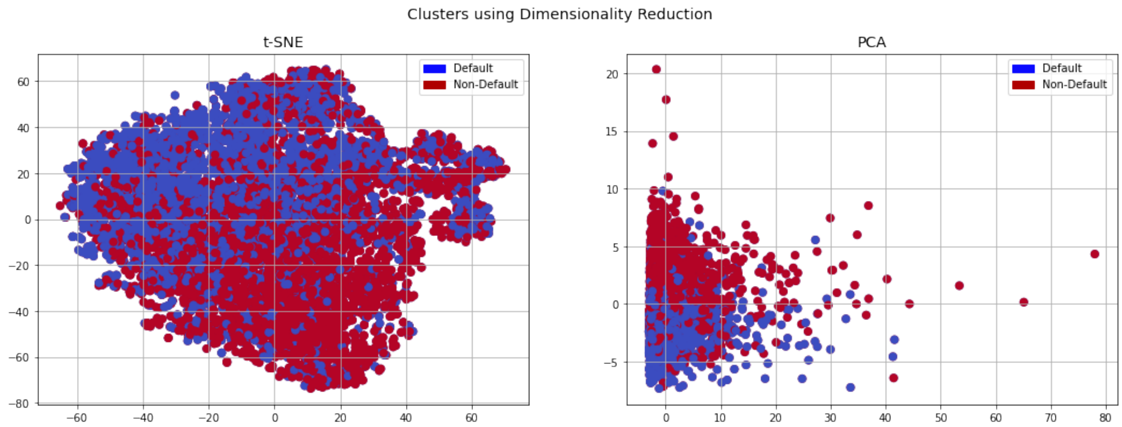
[32]:
```python
# New_df is from the random undersample data (fewer instances)
X = new_df.drop('default', axis=1)
y = new_df['default']


# 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))
```

```
T-SNE took 2.5e+01 s
PCA took 0.014 s
```

[33]:
```
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(18,6))
# labels = ['Default', 'Non-Default']
f.suptitle('Clusters using Dimensionality Reduction', fontsize=14)


blue_patch = mpatches.Patch(color='#0A0AFF', label='Default')
red_patch = mpatches.Patch(color='#AF0000', label='Non-Default')


# t-SNE scatter plot
ax1.scatter(X_reduced_tsne[:,0], X_reduced_tsne[:,1], c=(y == 0),␣
 ↪cmap='coolwarm', label='Non-Default', linewidths=2)
ax1.scatter(X_reduced_tsne[:,0], X_reduced_tsne[:,1], c=(y == 1),␣
 ↪cmap='coolwarm', label='Default', linewidths=2)
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='Non-Default', linewidths=2)
ax2.scatter(X_reduced_pca[:,0], X_reduced_pca[:,1], c=(y == 1),␣
 ↪cmap='coolwarm', label='Default', linewidths=2)
ax2.set_title('PCA', fontsize=14)

ax2.grid(True)

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

[33]:
```
<matplotlib.legend.Legend at 0x7fcabf357b50>
```




```
[34]: new_df.default.value_counts()
```

```
[34]: 1    3449
      0    3251
      Name: default, dtype: int64
```

3.4 Classifers

```
[35]: # Undersampling before cross validation (prone to overfit)
      X = new_df.drop('default',axis=1)
      y = new_df['default']
```

```
[36]: 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)

      X_train = X_train.values
      X_test = X_test.values
      y_train = y_train.values
      y_test = y_test.values
```

```
[38]: classifiers = {
          "LogisiticRegression": LogisticRegression(),
          "KNearest": KNeighborsClassifier(),
          "Support Vector Classifier": SVC(),
          "DecisionTreeClassifier": DecisionTreeClassifier(),
          'GradientBoosting':GradientBoostingClassifier()
      }
```

```
[39]: 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(training_score.mean(), 2) * 100, "% accuracy score")
```

```
Classifiers:  LogisticRegression Has a training score of 74.0 % accuracy score
Classifiers:  KNeighborsClassifier Has a training score of 68.0 % accuracy score
Classifiers:  SVC Has a training score of 74.0 % accuracy score
Classifiers:  DecisionTreeClassifier Has a training score of 64.0 % accuracy
score
Classifiers:  GradientBoostingClassifier Has a training score of 75.0 % accuracy
score
```

[42]:

```
# 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,␣
↪1000]}

grid_log_reg = GridSearchCV(LogisticRegression(), log_reg_params)
grid_log_reg.fit(X_train, y_train)
log_reg = grid_log_reg.best_estimator_

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

grid_knears = GridSearchCV(KNeighborsClassifier(), knears_params)
grid_knears.fit(X_train, y_train)
knears_neighbors = grid_knears.best_estimator_

# Support Vector Classifier
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_

# DecisionTree Classifier
tree_params = {"criterion": ["gini", "entropy"], "max_depth":␣
↪list(range(2,4,1)),
              "min_samples_leaf": list(range(5,7,1))}
```

```python
grid_tree = GridSearchCV(DecisionTreeClassifier(), tree_params)
grid_tree.fit(X_train, y_train)
tree_clf = grid_tree.best_estimator_

# GradientBoosting Classifier
gbt_params = {'learning_rate':[0.01, 0.1, 0.5, 1],
              'n_estimators':[100,200,300,400]}

gbt_tree = GridSearchCV(GradientBoostingClassifier(), gbt_params)
gbt_tree.fit(X_train, y_train)
gbt_clf = gbt_tree.best_estimator_
```

[43]:

```python
# 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.
 ↪mean() * 100, 2).astype(str) + '%')


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(str) + '%')

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(str) + '%')

gbt_score = cross_val_score(gbt_clf, X_train, y_train, cv=5)
print('Gradient Boosting Classifier Cross Validation Score', round(gbt_score.
 ↪mean() * 100, 2).astype(str) + '%')
```

```
Logistic Regression Cross Validation Score:  74.01%
Knears Neighbors Cross Validation Score 67.5%
Support Vector Classifier Cross Validation Score 74.25%
DecisionTree Classifier Cross Validation Score 73.02%
Gradient Boosting Classifier Cross Validation Score 75.09%
```

[47]:

```python
# We will undersample during cross validating
undersample_X = data.drop('default', axis=1)
undersample_y = data['default']

for train_index, test_index in sss.split(undersample_X, undersample_y):
```

```
    print("Train:", train_index, "Test:", test_index)
    undersample_Xtrain, undersample_Xtest = undersample_X.iloc[train_index],␣
 ↪undersample_X.iloc[test_index]
    undersample_ytrain, undersample_ytest = undersample_y.iloc[train_index],␣
 ↪undersample_y.iloc[test_index]

undersample_Xtrain = undersample_Xtrain.values
undersample_Xtest = undersample_Xtest.values
undersample_ytrain = undersample_ytrain.values
undersample_ytest = undersample_ytest.values

undersample_accuracy = []
undersample_precision = []
undersample_recall = []
undersample_f1 = []
undersample_auc = []

# Implementing NearMiss Technique
# Distribution of NearMiss (Just to see how it distributes the labels we won't␣
 ↪use these variables)
X_nearmiss, y_nearmiss = NearMiss().fit_resample(undersample_X.values,␣
 ↪undersample_y.values)
print('NearMiss Label Distribution: {}'.format(Counter(y_nearmiss)))
# Cross Validating the right way

for train, test in sss.split(undersample_Xtrain, undersample_ytrain):
    undersample_pipeline =␣
 ↪imbalanced_make_pipeline(NearMiss(sampling_strategy='majority'), log_reg) #␣
 ↪SMOTE happens during Cross Validation not before..
    undersample_model = undersample_pipeline.fit(undersample_Xtrain[train],␣
 ↪undersample_ytrain[train])
    undersample_prediction = undersample_model.predict(undersample_Xtrain[test])

    undersample_accuracy.append(undersample_pipeline.
 ↪score(original_Xtrain[test], original_ytrain[test]))
    undersample_precision.append(precision_score(original_ytrain[test],␣
 ↪undersample_prediction))
    undersample_recall.append(recall_score(original_ytrain[test],␣
 ↪undersample_prediction))
    undersample_f1.append(f1_score(original_ytrain[test],␣
 ↪undersample_prediction))
    undersample_auc.append(roc_auc_score(original_ytrain[test],␣
 ↪undersample_prediction))
```

```
Train: [18000 18001 18002 … 93997 93998 93999] Test: [    0     1     2 …
90797 90798 90799]
Train: [    0     1     2 … 93997 93998 93999] Test: [18000 18001 18002 …
```

```
91597 91598 91599]
Train: [    0     1     2 … 93997 93998 93999] Test: [36000 36001 36002 …
92397 92398 92399]
Train: [    0     1     2 … 93997 93998 93999] Test: [54000 54001 54002 …
93197 93198 93199]
Train: [    0     1     2 … 93197 93198 93199] Test: [72000 72001 72002 …
93997 93998 93999]
NearMiss Label Distribution: Counter({0: 4000, 1: 4000})
```

[50]:

```python
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")

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)

gbt_pred = cross_val_predict(gbt_clf, X_train, y_train, cv=5)
```

[51]:

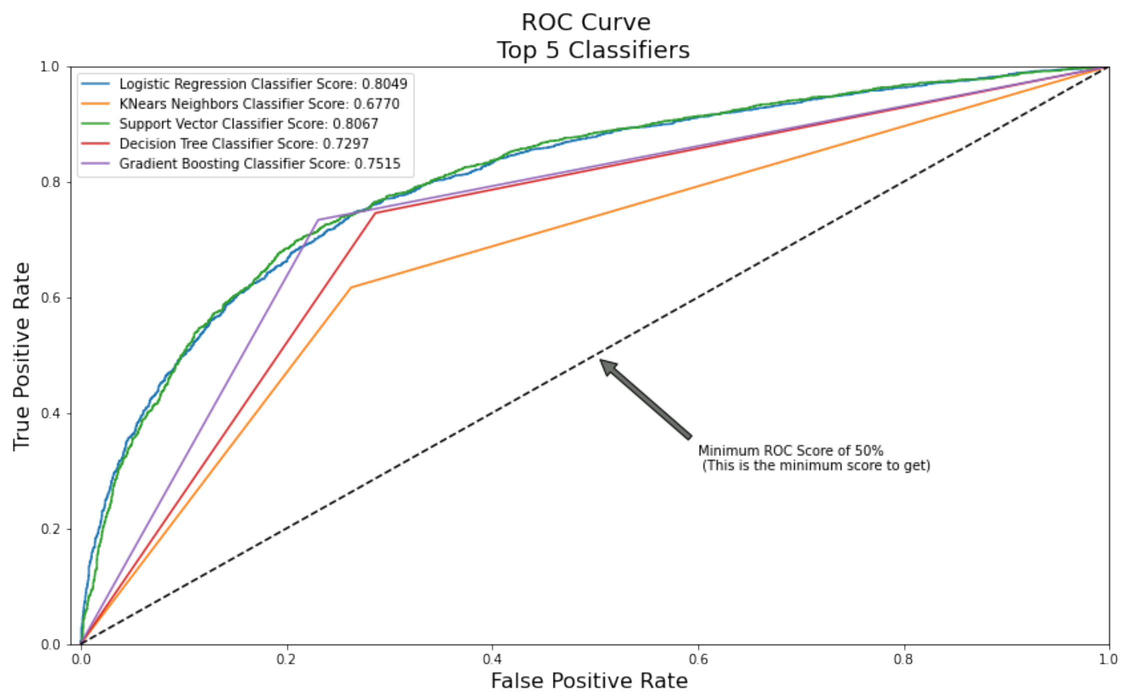
```python
from sklearn.metrics import roc_auc_score

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))
print('Gradient Boosting Classifier: ', roc_auc_score(y_train, gbt_pred))
```

```
Logistic Regression:  0.8048975769707751
KNears Neighbors:  0.6770349083978117
Support Vector Classifier:  0.806697798015338
Decision Tree Classifier:  0.7296714760376848
Gradient Boosting Classifier:  0.7515269122243442
```

[53]:

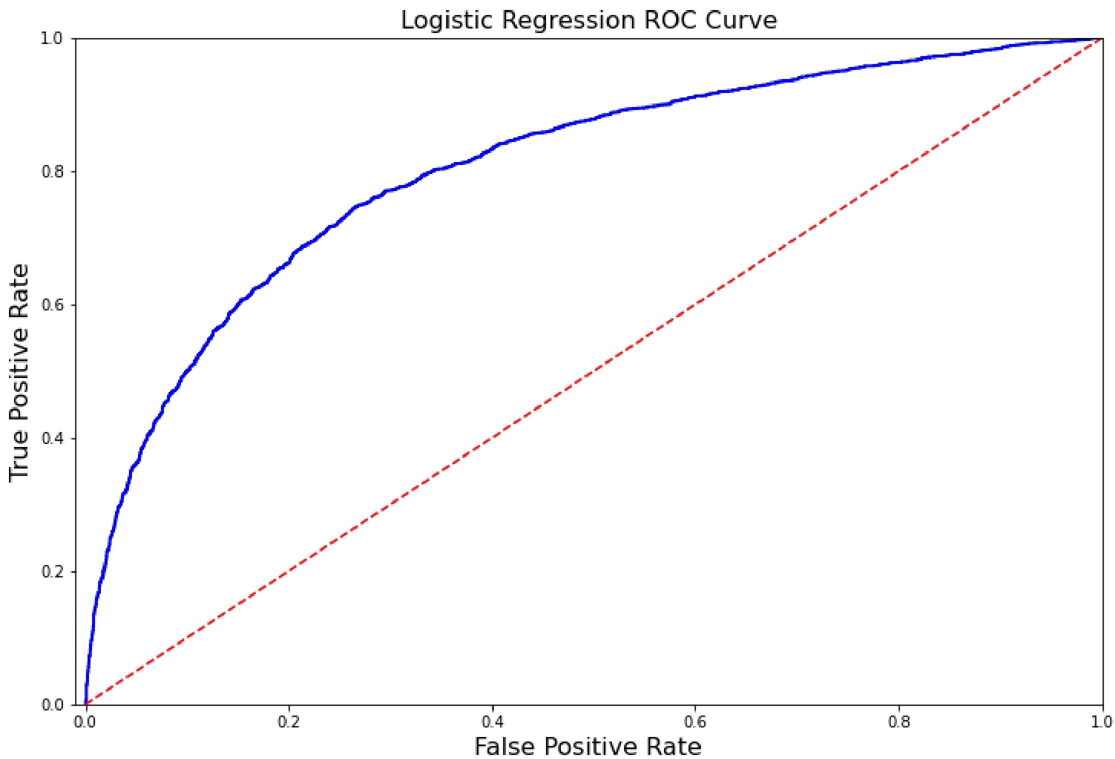
```python
log_fpr, log_tpr, log_thresold = roc_curve(y_train, log_reg_pred)
knear_fpr, knear_tpr, knear_threshold = roc_curve(y_train, knears_pred)
svc_fpr, svc_tpr, svc_threshold = roc_curve(y_train, svc_pred)
tree_fpr, tree_tpr, tree_threshold = roc_curve(y_train, tree_pred)
gbt_fpr, gbt_tpr, gbt_threshold = roc_curve(y_train, gbt_pred)



def graph_roc_curve_multiple(log_fpr, log_tpr, knear_fpr, knear_tpr, svc_fpr,␣
 ↪svc_tpr, tree_fpr, tree_tpr, gbt_fpr, gbt_tpr):
```

```
    plt.figure(figsize=(14,8))
    plt.title('ROC Curve \n Top 5 Classifiers', fontsize=18)
    plt.plot(log_fpr, log_tpr, label='Logistic Regression Classifier Score: {:.
 ↪4f}'.format(roc_auc_score(y_train, log_reg_pred)))
    plt.plot(knear_fpr, knear_tpr, label='KNears Neighbors Classifier Score: {:.
 ↪4f}'.format(roc_auc_score(y_train, knears_pred)))
    plt.plot(svc_fpr, svc_tpr, label='Support Vector Classifier Score: {:.4f}'.
 ↪format(roc_auc_score(y_train, svc_pred)))
    plt.plot(tree_fpr, tree_tpr, label='Decision Tree Classifier Score: {:.4f}'.
 ↪format(roc_auc_score(y_train, tree_pred)))
    plt.plot(gbt_fpr, gbt_tpr, label='Gradient Boosting Classifier Score: {:.
 ↪4f}'.format(roc_auc_score(y_train, gbt_pred)))
    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), xytext=(0.6, 0.3),
                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_tpr, gbt_fpr, gbt_tpr)
plt.show()
```



3.5 A Deeper Look into Logistic Regression

[54]:
```
def logistic_roc_curve(log_fpr, log_tpr):
    plt.figure(figsize=(12,8))
    plt.title('Logistic Regression ROC Curve', fontsize=16)
    plt.plot(log_fpr, log_tpr, 'b-', linewidth=2)
    plt.plot([0, 1], [0, 1], 'r--')
    plt.xlabel('False Positive Rate', fontsize=16)
    plt.ylabel('True Positive Rate', fontsize=16)
    plt.axis([-0.01,1,0,1])


logistic_roc_curve(log_fpr, log_tpr)
plt.show()
```



[55]:
```
from sklearn.metrics import precision_recall_curve

precision, recall, threshold = precision_recall_curve(y_train, log_reg_pred)

from sklearn.metrics import recall_score, precision_score, f1_score,␣
↪accuracy_score
```

```python
y_pred = log_reg.predict(X_train)

# Overfitting Case
print('---' * 45)
print('Overfitting: \n')
print('Recall Score: {:.2f}'.format(recall_score(y_train, y_pred)))
print('Precision Score: {:.2f}'.format(precision_score(y_train, y_pred)))
print('F1 Score: {:.2f}'.format(f1_score(y_train, y_pred)))
print('Accuracy Score: {:.2f}'.format(accuracy_score(y_train, y_pred)))
print('---' * 45)

# How it should look like
print('---' * 45)
print('How it should be:\n')
print("Accuracy Score: {:.2f}".format(np.mean(undersample_accuracy)))
print("Precision Score: {:.2f}".format(np.mean(undersample_precision)))
print("Recall Score: {:.2f}".format(np.mean(undersample_recall)))
print("F1 Score: {:.2f}".format(np.mean(undersample_f1)))
print('---' * 45)
```

```
---------------------------------------------------------------------------------
-------------------------------------------------------
Overfitting:

Recall Score: 0.86
Precision Score: 0.60
F1 Score: 0.71
Accuracy Score: 0.63
---------------------------------------------------------------------------------
-------------------------------------------------------
---------------------------------------------------------------------------------
-------------------------------------------------------
How it should be:

Accuracy Score: 0.42
Precision Score: 0.06
Recall Score: 0.85
F1 Score: 0.11
---------------------------------------------------------------------------------
-------------------------------------------------------
```

3.6 Oversampling with SMOTE

[58]:
```python
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split, RandomizedSearchCV
```

```
print('Length of X (train): {} | Length of y (train): {}'.
 ↪format(len(original_Xtrain), len(original_ytrain)))
print('Length of X (test): {} | Length of y (test): {}'.
 ↪format(len(original_Xtest), len(original_ytest)))

# List to append the score and then find the average
accuracy_lst = []
precision_lst = []
recall_lst = []
f1_lst = []
auc_lst = []

# Classifier with optimal parameters
# log_reg_sm = grid_log_reg.best_estimator_
log_reg_sm = LogisticRegression()




rand_log_reg = RandomizedSearchCV(LogisticRegression(), log_reg_params,␣
 ↪n_iter=4)


# Implementing SMOTE Technique
# Cross Validating the right way
# Parameters
log_reg_params = {"penalty": ['l1', 'l2'], 'C': [0.001, 0.01, 0.1, 1, 10, 100,␣
 ↪1000]}
for train, test in sss.split(original_Xtrain, original_ytrain):
    pipeline = imbalanced_make_pipeline(SMOTE(sampling_strategy='minority'),␣
 ↪rand_log_reg) # SMOTE happens during Cross Validation not before..
    model = pipeline.fit(original_Xtrain[train], original_ytrain[train])
    best_est = rand_log_reg.best_estimator_
    prediction = best_est.predict(original_Xtrain[test])

    accuracy_lst.append(pipeline.score(original_Xtrain[test],␣
 ↪original_ytrain[test]))
    precision_lst.append(precision_score(original_ytrain[test], prediction))
    recall_lst.append(recall_score(original_ytrain[test], prediction))
    f1_lst.append(f1_score(original_ytrain[test], prediction))
    auc_lst.append(roc_auc_score(original_ytrain[test], prediction))

print('---' * 45)
print('')
print("accuracy: {}".format(np.mean(accuracy_lst)))
print("precision: {}".format(np.mean(precision_lst)))
```

```
print("recall: {}".format(np.mean(recall_lst)))
print("f1: {}".format(np.mean(f1_lst)))
print('---' * 45)
```

```
Length of X (train): 75200 | Length of y (train): 75200
Length of X (test): 18800 | Length of y (test): 18800
--------------------------------------------------------------------------------
-------------------------------------------------------


accuracy: 0.7543351063829787
precision: 0.11771099435324268
recall: 0.7346874999999999
f1: 0.20290638291218124
--------------------------------------------------------------------------------
-------------------------------------------------------
```

[59]:
```
labels = ['Non-Default', 'Default']
smote_prediction = best_est.predict(original_Xtest)
print(classification_report(original_ytest, smote_prediction,␣
 ↪target_names=labels))
```

```
              precision    recall  f1-score   support

 Non-Default       0.98      0.76      0.86     18000
     Default       0.12      0.72      0.20       800

    accuracy                           0.75     18800
   macro avg       0.55      0.74      0.53     18800
weighted avg       0.95      0.75      0.83     18800
```

[63]:
```
# SMOTE Technique (OverSampling) After splitting and Cross Validating
sm = SMOTE(sampling_strategy='minority', random_state=42)

Xsm_train, ysm_train = sm.fit_resample(original_Xtrain, original_ytrain)

t0 = time.time()
log_reg_sm = grid_log_reg.best_estimator_
log_reg_sm.fit(Xsm_train, ysm_train)
t1 = time.time()
print("Fitting oversample data took :{} sec".format(t1 - t0))
```

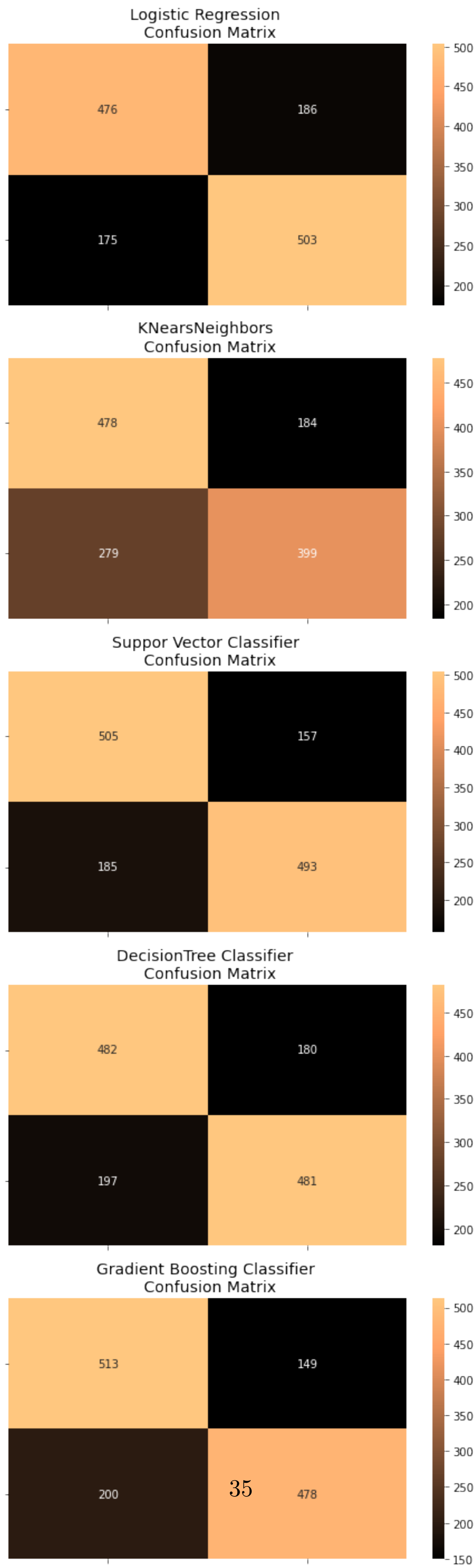
```
Fitting oversample data took :0.4183170795440674 sec
```

4 Testing

4.1 Test for logistic regression

[67]:
```
from sklearn.metrics import confusion_matrix

# Logistic Regression fitted using SMOTE technique
y_pred_log_reg = log_reg_sm.predict(X_test)

# Other models fitted with UnderSampling
y_pred_knear = knears_neighbors.predict(X_test)
y_pred_svc = svc.predict(X_test)
y_pred_tree = tree_clf.predict(X_test)
y_pred_gbt = gbt_clf.predict(X_test)


log_reg_cf = confusion_matrix(y_test, y_pred_log_reg)
kneighbors_cf = confusion_matrix(y_test, y_pred_knear)
svc_cf = confusion_matrix(y_test, y_pred_svc)
tree_cf = confusion_matrix(y_test, y_pred_tree)
gbt_cf = confusion_matrix(y_test, y_pred_gbt)

fig, (ax1, ax2, ax3, ax4, ax5) = plt.subplots(5, 1,figsize=(8,25))


sns.heatmap(log_reg_cf, ax=ax1, annot=True, fmt='g',cmap=plt.cm.copper)
ax1.set_title("Logistic Regression \n Confusion Matrix", fontsize=14)
ax1.set_xticklabels(['', ''], fontsize=14, rotation=90)
ax1.set_yticklabels(['', ''], fontsize=14, rotation=360)

sns.heatmap(kneighbors_cf, ax=ax2, annot=True, fmt='g',cmap=plt.cm.copper)
ax2.set_title("KNearsNeighbors \n Confusion Matrix", fontsize=14)
ax2.set_xticklabels(['', ''], fontsize=14, rotation=90)
ax2.set_yticklabels(['', ''], fontsize=14, rotation=360)

sns.heatmap(svc_cf, ax=ax3, annot=True, fmt='g',cmap=plt.cm.copper)
ax3.set_title("Suppor Vector Classifier \n Confusion Matrix", fontsize=14)
ax3.set_xticklabels(['', ''], fontsize=14, rotation=90)
ax3.set_yticklabels(['', ''], fontsize=14, rotation=360)

sns.heatmap(tree_cf, ax=ax4, annot=True, fmt='g',cmap=plt.cm.copper)
ax4.set_title("DecisionTree Classifier \n Confusion Matrix", fontsize=14)
ax4.set_xticklabels(['', ''], fontsize=14, rotation=90)
ax4.set_yticklabels(['', ''], fontsize=14, rotation=360)

sns.heatmap(gbt_cf, ax=ax5, annot=True, fmt='g',cmap=plt.cm.copper)
ax5.set_title("Gradient Boosting Classifier \n Confusion Matrix", fontsize=14)
ax5.set_xticklabels(['', ''], fontsize=14, rotation=90)
ax5.set_yticklabels(['', ''], fontsize=14, rotation=360)
```

```
plt.show()
```


Logistic Regression
Confusion Matrix
476
186
175
503
500
450
400
350
300
250
200
KNearsNeighbors
Confusion Matrix
478
184
279
399
450
400
350
300
250
200
Suppor Vector Classifier
Confusion Matrix
505
157
185
493
500
450
400
350
300
250
200
DecisionTree Classifier
Confusion Matrix
482
180
197
481
450
400
350
300
250
200
Gradient Boosting Classifier
Confusion Matrix
513
149
200
478
500
450
400
350
300
250
200
150

[69]:
```python
from sklearn.metrics import classification_report


print('Logistic Regression:')
print(classification_report(y_test, y_pred_log_reg))

print('KNears Neighbors:')
print(classification_report(y_test, y_pred_knear))

print('Support Vector Classifier:')
print(classification_report(y_test, y_pred_svc))

print('Decision Tree Classifier:')
print(classification_report(y_test, y_pred_tree))

print('Gradient Boosting Classifier:')
print(classification_report(y_test, y_pred_gbt))
```

```
Logistic Regression:
              precision    recall  f1-score   support

           0       0.73      0.72      0.73       662
           1       0.73      0.74      0.74       678

    accuracy                           0.73      1340
   macro avg       0.73      0.73      0.73      1340
weighted avg       0.73      0.73      0.73      1340

KNears Neighbors:
              precision    recall  f1-score   support

           0       0.63      0.72      0.67       662
           1       0.68      0.59      0.63       678

    accuracy                           0.65      1340
   macro avg       0.66      0.66      0.65      1340
weighted avg       0.66      0.65      0.65      1340

Support Vector Classifier:
              precision    recall  f1-score   support

           0       0.73      0.76      0.75       662
           1       0.76      0.73      0.74       678

    accuracy                           0.74      1340
```

```
   macro avg       0.75      0.74      0.74      1340
weighted avg       0.75      0.74      0.74      1340

Decision Tree Classifier:
              precision    recall  f1-score   support

           0       0.71      0.73      0.72       662
           1       0.73      0.71      0.72       678

    accuracy                           0.72      1340
   macro avg       0.72      0.72      0.72      1340
weighted avg       0.72      0.72      0.72      1340

Gradient Boosting Classifier:
              precision    recall  f1-score   support

           0       0.72      0.77      0.75       662
           1       0.76      0.71      0.73       678

    accuracy                           0.74      1340
   macro avg       0.74      0.74      0.74      1340
weighted avg       0.74      0.74      0.74      1340
```

[74]:

```
# Final Score in the test set of logistic regression
from sklearn.metrics import accuracy_score

# Logistic Regression with Under-Sampling
y_pred = log_reg.predict(X_test)
undersample_score = roc_auc_score(y_test, y_pred)



# Logistic Regression with SMOTE Technique (Better accuracy with SMOTE t)
y_pred_sm = best_est.predict(original_Xtest)
oversample_score = roc_auc_score(original_ytest, y_pred_sm)


d = {'Technique': ['Random UnderSampling', 'Oversampling (SMOTE)'], 'AUC-Score':
 ↪ [undersample_score, oversample_score]}
final_df = pd.DataFrame(data=d)

score = final_df['AUC-Score']
final_df.drop('AUC-Score', axis=1, inplace=True)
final_df.insert(1, 'AUC-Score', score)

final_df
```

[74]:
```
               Technique  AUC-Score
0  Random UnderSampling   0.730461
1  Oversampling (SMOTE)   0.738194
```

4.2 Naive Neural Networks on test set

[142]:
```
n_inputs = X_train.shape[1]

undersample_model = Sequential([
    Dense(n_inputs, input_shape = (n_inputs, ), activation = 'relu'),
    Dense(32, activation = 'relu'),
    Dense(2, activation = 'softmax')
])
```

[143]:
```
undersample_model.summary()
```

```
Model: "sequential_11"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_62 (Dense)            (None, 30)                930

 dense_63 (Dense)            (None, 32)                992

 dense_64 (Dense)            (None, 2)                 66

=================================================================
Total params: 1,988
Trainable params: 1,988
Non-trainable params: 0
_________________________________________________________________
```

[146]:
```
undersample_model.compile(Adam(lr=0.001),␣
 ↪loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

[191]:
```
undersample_model.fit(X_train, y_train, validation_split=0.2, batch_size=25,␣
 ↪epochs=200, shuffle=True, verbose=2)
```

```
Epoch 1/200
172/172 - 0s - loss: 0.4591 - accuracy: 0.7819 - val_loss: 0.5698 -
val_accuracy: 0.7155 - 190ms/epoch - 1ms/step
Epoch 2/200
172/172 - 0s - loss: 0.4579 - accuracy: 0.7857 - val_loss: 0.5685 -
val_accuracy: 0.7155 - 159ms/epoch - 926us/step
Epoch 3/200
172/172 - 0s - loss: 0.4546 - accuracy: 0.7859 - val_loss: 0.5677 -
val_accuracy: 0.7080 - 156ms/epoch - 906us/step
Epoch 4/200
```

```
172/172 - 0s - loss: 0.4515 - accuracy: 0.7885 - val_loss: 0.5839 -
val_accuracy: 0.7192 - 169ms/epoch - 985us/step
Epoch 5/200
172/172 - 0s - loss: 0.4486 - accuracy: 0.7903 - val_loss: 0.5736 -
val_accuracy: 0.7164 - 161ms/epoch - 937us/step
Epoch 6/200
172/172 - 0s - loss: 0.4441 - accuracy: 0.7917 - val_loss: 0.5656 -
val_accuracy: 0.7090 - 165ms/epoch - 958us/step
Epoch 7/200
172/172 - 0s - loss: 0.4410 - accuracy: 0.8011 - val_loss: 0.5806 -
val_accuracy: 0.7108 - 160ms/epoch - 928us/step
Epoch 8/200
172/172 - 0s - loss: 0.4389 - accuracy: 0.7943 - val_loss: 0.5821 -
val_accuracy: 0.7136 - 162ms/epoch - 943us/step
Epoch 9/200
172/172 - 0s - loss: 0.4355 - accuracy: 0.7990 - val_loss: 0.5801 -
val_accuracy: 0.7099 - 157ms/epoch - 910us/step
Epoch 10/200
172/172 - 0s - loss: 0.4338 - accuracy: 0.7959 - val_loss: 0.5923 -
val_accuracy: 0.6978 - 154ms/epoch - 894us/step
Epoch 11/200
172/172 - 0s - loss: 0.4296 - accuracy: 0.8015 - val_loss: 0.5883 -
val_accuracy: 0.7099 - 164ms/epoch - 956us/step
Epoch 12/200
172/172 - 0s - loss: 0.4268 - accuracy: 0.8011 - val_loss: 0.6006 -
val_accuracy: 0.7024 - 150ms/epoch - 873us/step
Epoch 13/200
172/172 - 0s - loss: 0.4260 - accuracy: 0.8018 - val_loss: 0.5946 -
val_accuracy: 0.7052 - 156ms/epoch - 907us/step
Epoch 14/200
172/172 - 0s - loss: 0.4202 - accuracy: 0.8050 - val_loss: 0.5969 -
val_accuracy: 0.6978 - 171ms/epoch - 994us/step
Epoch 15/200
172/172 - 0s - loss: 0.4214 - accuracy: 0.8057 - val_loss: 0.5942 -
val_accuracy: 0.7099 - 166ms/epoch - 968us/step
Epoch 16/200
172/172 - 0s - loss: 0.4152 - accuracy: 0.8109 - val_loss: 0.6016 -
val_accuracy: 0.7071 - 158ms/epoch - 920us/step
Epoch 17/200
172/172 - 0s - loss: 0.4156 - accuracy: 0.8099 - val_loss: 0.6063 -
val_accuracy: 0.7043 - 183ms/epoch - 1ms/step
Epoch 18/200
172/172 - 0s - loss: 0.4108 - accuracy: 0.8099 - val_loss: 0.6147 -
val_accuracy: 0.6922 - 190ms/epoch - 1ms/step
Epoch 19/200
172/172 - 0s - loss: 0.4087 - accuracy: 0.8139 - val_loss: 0.6131 -
val_accuracy: 0.6959 - 151ms/epoch - 878us/step
Epoch 20/200
```

```
172/172 - 0s - loss: 0.4072 - accuracy: 0.8146 - val_loss: 0.6211 -
val_accuracy: 0.6978 - 150ms/epoch - 871us/step
Epoch 21/200
172/172 - 0s - loss: 0.4056 - accuracy: 0.8195 - val_loss: 0.6248 -
val_accuracy: 0.6996 - 149ms/epoch - 866us/step
Epoch 22/200
172/172 - 0s - loss: 0.4021 - accuracy: 0.8186 - val_loss: 0.6260 -
val_accuracy: 0.6931 - 150ms/epoch - 872us/step
Epoch 23/200
172/172 - 0s - loss: 0.3954 - accuracy: 0.8242 - val_loss: 0.6409 -
val_accuracy: 0.6978 - 150ms/epoch - 870us/step
Epoch 24/200
172/172 - 0s - loss: 0.3960 - accuracy: 0.8223 - val_loss: 0.6347 -
val_accuracy: 0.7015 - 150ms/epoch - 870us/step
Epoch 25/200
172/172 - 0s - loss: 0.3929 - accuracy: 0.8209 - val_loss: 0.6356 -
val_accuracy: 0.6922 - 150ms/epoch - 871us/step
Epoch 26/200
172/172 - 0s - loss: 0.3903 - accuracy: 0.8221 - val_loss: 0.6434 -
val_accuracy: 0.6884 - 150ms/epoch - 870us/step
Epoch 27/200
172/172 - 0s - loss: 0.3922 - accuracy: 0.8197 - val_loss: 0.6406 -
val_accuracy: 0.6884 - 150ms/epoch - 874us/step
Epoch 28/200
172/172 - 0s - loss: 0.3904 - accuracy: 0.8258 - val_loss: 0.6634 -
val_accuracy: 0.6884 - 157ms/epoch - 915us/step
Epoch 29/200
172/172 - 0s - loss: 0.3829 - accuracy: 0.8302 - val_loss: 0.6514 -
val_accuracy: 0.6903 - 151ms/epoch - 878us/step
Epoch 30/200
172/172 - 0s - loss: 0.3811 - accuracy: 0.8272 - val_loss: 0.6615 -
val_accuracy: 0.6875 - 151ms/epoch - 880us/step
Epoch 31/200
172/172 - 0s - loss: 0.3813 - accuracy: 0.8295 - val_loss: 0.6637 -
val_accuracy: 0.6847 - 149ms/epoch - 869us/step
Epoch 32/200
172/172 - 0s - loss: 0.3789 - accuracy: 0.8274 - val_loss: 0.6665 -
val_accuracy: 0.6772 - 153ms/epoch - 890us/step
Epoch 33/200
172/172 - 0s - loss: 0.3738 - accuracy: 0.8323 - val_loss: 0.6601 -
val_accuracy: 0.6884 - 152ms/epoch - 883us/step
Epoch 34/200
172/172 - 0s - loss: 0.3705 - accuracy: 0.8298 - val_loss: 0.6844 -
val_accuracy: 0.6866 - 151ms/epoch - 878us/step
Epoch 35/200
172/172 - 0s - loss: 0.3682 - accuracy: 0.8337 - val_loss: 0.6785 -
val_accuracy: 0.6903 - 156ms/epoch - 909us/step
Epoch 36/200
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172/172 - 0s - loss: 0.3678 - accuracy: 0.8382 - val_loss: 0.6761 -
val_accuracy: 0.6884 - 152ms/epoch - 885us/step
Epoch 37/200
172/172 - 0s - loss: 0.3645 - accuracy: 0.8370 - val_loss: 0.6846 -
val_accuracy: 0.6912 - 151ms/epoch - 879us/step
Epoch 38/200
172/172 - 0s - loss: 0.3622 - accuracy: 0.8400 - val_loss: 0.6941 -
val_accuracy: 0.6754 - 150ms/epoch - 869us/step
Epoch 39/200
172/172 - 0s - loss: 0.3618 - accuracy: 0.8428 - val_loss: 0.6980 -
val_accuracy: 0.6838 - 154ms/epoch - 892us/step
Epoch 40/200
172/172 - 0s - loss: 0.3582 - accuracy: 0.8354 - val_loss: 0.6970 -
val_accuracy: 0.6810 - 152ms/epoch - 883us/step
Epoch 41/200
172/172 - 0s - loss: 0.3595 - accuracy: 0.8386 - val_loss: 0.6975 -
val_accuracy: 0.6819 - 152ms/epoch - 884us/step
Epoch 42/200
172/172 - 0s - loss: 0.3550 - accuracy: 0.8438 - val_loss: 0.7033 -
val_accuracy: 0.6950 - 183ms/epoch - 1ms/step
Epoch 43/200
172/172 - 0s - loss: 0.3535 - accuracy: 0.8451 - val_loss: 0.7068 -
val_accuracy: 0.6791 - 150ms/epoch - 872us/step
Epoch 44/200
172/172 - 0s - loss: 0.3501 - accuracy: 0.8489 - val_loss: 0.7043 -
val_accuracy: 0.6800 - 151ms/epoch - 876us/step
Epoch 45/200
172/172 - 0s - loss: 0.3467 - accuracy: 0.8468 - val_loss: 0.7176 -
val_accuracy: 0.6847 - 151ms/epoch - 879us/step
Epoch 46/200
172/172 - 0s - loss: 0.3479 - accuracy: 0.8414 - val_loss: 0.7202 -
val_accuracy: 0.6810 - 156ms/epoch - 907us/step
Epoch 47/200
172/172 - 0s - loss: 0.3461 - accuracy: 0.8447 - val_loss: 0.7206 -
val_accuracy: 0.6866 - 150ms/epoch - 872us/step
Epoch 48/200
172/172 - 0s - loss: 0.3463 - accuracy: 0.8477 - val_loss: 0.7254 -
val_accuracy: 0.6866 - 154ms/epoch - 894us/step
Epoch 49/200
172/172 - 0s - loss: 0.3377 - accuracy: 0.8493 - val_loss: 0.7383 -
val_accuracy: 0.6922 - 156ms/epoch - 907us/step
Epoch 50/200
172/172 - 0s - loss: 0.3371 - accuracy: 0.8514 - val_loss: 0.7348 -
val_accuracy: 0.6828 - 150ms/epoch - 875us/step
Epoch 51/200
172/172 - 0s - loss: 0.3365 - accuracy: 0.8517 - val_loss: 0.7434 -
val_accuracy: 0.6800 - 152ms/epoch - 884us/step
Epoch 52/200
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172/172 - 0s - loss: 0.3332 - accuracy: 0.8514 - val_loss: 0.7506 -
val_accuracy: 0.6800 - 153ms/epoch - 888us/step
Epoch 53/200
172/172 - 0s - loss: 0.3353 - accuracy: 0.8528 - val_loss: 0.7511 -
val_accuracy: 0.6800 - 153ms/epoch - 887us/step
Epoch 54/200
172/172 - 0s - loss: 0.3314 - accuracy: 0.8552 - val_loss: 0.7702 -
val_accuracy: 0.6670 - 154ms/epoch - 893us/step
Epoch 55/200
172/172 - 0s - loss: 0.3289 - accuracy: 0.8587 - val_loss: 0.7611 -
val_accuracy: 0.6819 - 153ms/epoch - 892us/step
Epoch 56/200
172/172 - 0s - loss: 0.3271 - accuracy: 0.8540 - val_loss: 0.7524 -
val_accuracy: 0.6744 - 151ms/epoch - 880us/step
Epoch 57/200
172/172 - 0s - loss: 0.3243 - accuracy: 0.8566 - val_loss: 0.7672 -
val_accuracy: 0.6772 - 154ms/epoch - 898us/step
Epoch 58/200
172/172 - 0s - loss: 0.3248 - accuracy: 0.8549 - val_loss: 0.7677 -
val_accuracy: 0.6735 - 152ms/epoch - 882us/step
Epoch 59/200
172/172 - 0s - loss: 0.3227 - accuracy: 0.8608 - val_loss: 0.7648 -
val_accuracy: 0.6772 - 152ms/epoch - 882us/step
Epoch 60/200
172/172 - 0s - loss: 0.3189 - accuracy: 0.8589 - val_loss: 0.7704 -
val_accuracy: 0.6735 - 159ms/epoch - 926us/step
Epoch 61/200
172/172 - 0s - loss: 0.3188 - accuracy: 0.8629 - val_loss: 0.7878 -
val_accuracy: 0.6819 - 151ms/epoch - 877us/step
Epoch 62/200
172/172 - 0s - loss: 0.3191 - accuracy: 0.8608 - val_loss: 0.7930 -
val_accuracy: 0.6847 - 152ms/epoch - 885us/step
Epoch 63/200
172/172 - 0s - loss: 0.3138 - accuracy: 0.8643 - val_loss: 0.7815 -
val_accuracy: 0.6782 - 153ms/epoch - 888us/step
Epoch 64/200
172/172 - 0s - loss: 0.3112 - accuracy: 0.8647 - val_loss: 0.7888 -
val_accuracy: 0.6707 - 151ms/epoch - 880us/step
Epoch 65/200
172/172 - 0s - loss: 0.3099 - accuracy: 0.8657 - val_loss: 0.7929 -
val_accuracy: 0.6735 - 150ms/epoch - 873us/step
Epoch 66/200
172/172 - 0s - loss: 0.3102 - accuracy: 0.8657 - val_loss: 0.8060 -
val_accuracy: 0.6744 - 150ms/epoch - 872us/step
Epoch 67/200
172/172 - 0s - loss: 0.3052 - accuracy: 0.8654 - val_loss: 0.8165 -
val_accuracy: 0.6632 - 151ms/epoch - 881us/step
Epoch 68/200
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172/172 - 0s - loss: 0.3080 - accuracy: 0.8622 - val_loss: 0.7993 -
val_accuracy: 0.6763 - 166ms/epoch - 965us/step
Epoch 69/200
172/172 - 0s - loss: 0.3011 - accuracy: 0.8713 - val_loss: 0.8045 -
val_accuracy: 0.6707 - 152ms/epoch - 885us/step
Epoch 70/200
172/172 - 0s - loss: 0.3016 - accuracy: 0.8706 - val_loss: 0.8207 -
val_accuracy: 0.6642 - 162ms/epoch - 942us/step
Epoch 71/200
172/172 - 0s - loss: 0.3017 - accuracy: 0.8708 - val_loss: 0.8085 -
val_accuracy: 0.6772 - 162ms/epoch - 940us/step
Epoch 72/200
172/172 - 0s - loss: 0.2983 - accuracy: 0.8678 - val_loss: 0.8176 -
val_accuracy: 0.6679 - 148ms/epoch - 863us/step
Epoch 73/200
172/172 - 0s - loss: 0.2963 - accuracy: 0.8736 - val_loss: 0.8249 -
val_accuracy: 0.6716 - 149ms/epoch - 869us/step
Epoch 74/200
172/172 - 0s - loss: 0.2923 - accuracy: 0.8762 - val_loss: 0.8251 -
val_accuracy: 0.6660 - 150ms/epoch - 872us/step
Epoch 75/200
172/172 - 0s - loss: 0.2930 - accuracy: 0.8731 - val_loss: 0.8285 -
val_accuracy: 0.6651 - 150ms/epoch - 875us/step
Epoch 76/200
172/172 - 0s - loss: 0.2884 - accuracy: 0.8750 - val_loss: 0.8506 -
val_accuracy: 0.6623 - 149ms/epoch - 868us/step
Epoch 77/200
172/172 - 0s - loss: 0.2910 - accuracy: 0.8776 - val_loss: 0.8482 -
val_accuracy: 0.6716 - 153ms/epoch - 892us/step
Epoch 78/200
172/172 - 0s - loss: 0.2867 - accuracy: 0.8778 - val_loss: 0.8540 -
val_accuracy: 0.6698 - 150ms/epoch - 874us/step
Epoch 79/200
172/172 - 0s - loss: 0.2904 - accuracy: 0.8741 - val_loss: 0.8437 -
val_accuracy: 0.6716 - 172ms/epoch - 999us/step
Epoch 80/200
172/172 - 0s - loss: 0.2864 - accuracy: 0.8799 - val_loss: 0.8553 -
val_accuracy: 0.6632 - 150ms/epoch - 871us/step
Epoch 81/200
172/172 - 0s - loss: 0.2829 - accuracy: 0.8815 - val_loss: 0.8528 -
val_accuracy: 0.6735 - 149ms/epoch - 864us/step
Epoch 82/200
172/172 - 0s - loss: 0.2815 - accuracy: 0.8811 - val_loss: 0.8546 -
val_accuracy: 0.6772 - 150ms/epoch - 872us/step
Epoch 83/200
172/172 - 0s - loss: 0.2834 - accuracy: 0.8776 - val_loss: 0.8714 -
val_accuracy: 0.6623 - 149ms/epoch - 866us/step
Epoch 84/200
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172/172 - 0s - loss: 0.2767 - accuracy: 0.8827 - val_loss: 0.8674 -
val_accuracy: 0.6726 - 153ms/epoch - 891us/step
Epoch 85/200
172/172 - 0s - loss: 0.2792 - accuracy: 0.8783 - val_loss: 0.8669 -
val_accuracy: 0.6670 - 150ms/epoch - 873us/step
Epoch 86/200
172/172 - 0s - loss: 0.2794 - accuracy: 0.8771 - val_loss: 0.8774 -
val_accuracy: 0.6735 - 149ms/epoch - 869us/step
Epoch 87/200
172/172 - 0s - loss: 0.2722 - accuracy: 0.8820 - val_loss: 0.8862 -
val_accuracy: 0.6744 - 177ms/epoch - 1ms/step
Epoch 88/200
172/172 - 0s - loss: 0.2722 - accuracy: 0.8815 - val_loss: 0.8906 -
val_accuracy: 0.6576 - 150ms/epoch - 874us/step
Epoch 89/200
172/172 - 0s - loss: 0.2719 - accuracy: 0.8850 - val_loss: 0.9002 -
val_accuracy: 0.6754 - 149ms/epoch - 866us/step
Epoch 90/200
172/172 - 0s - loss: 0.2709 - accuracy: 0.8848 - val_loss: 0.9104 -
val_accuracy: 0.6604 - 151ms/epoch - 875us/step
Epoch 91/200
172/172 - 0s - loss: 0.2692 - accuracy: 0.8878 - val_loss: 0.9028 -
val_accuracy: 0.6614 - 149ms/epoch - 868us/step
Epoch 92/200
172/172 - 0s - loss: 0.2666 - accuracy: 0.8848 - val_loss: 0.9034 -
val_accuracy: 0.6772 - 150ms/epoch - 871us/step
Epoch 93/200
172/172 - 0s - loss: 0.2608 - accuracy: 0.8895 - val_loss: 0.9144 -
val_accuracy: 0.6707 - 150ms/epoch - 872us/step
Epoch 94/200
172/172 - 0s - loss: 0.2660 - accuracy: 0.8867 - val_loss: 0.9079 -
val_accuracy: 0.6735 - 150ms/epoch - 872us/step
Epoch 95/200
172/172 - 0s - loss: 0.2612 - accuracy: 0.8890 - val_loss: 0.9197 -
val_accuracy: 0.6698 - 150ms/epoch - 873us/step
Epoch 96/200
172/172 - 0s - loss: 0.2579 - accuracy: 0.8897 - val_loss: 0.9184 -
val_accuracy: 0.6670 - 148ms/epoch - 859us/step
Epoch 97/200
172/172 - 0s - loss: 0.2571 - accuracy: 0.8876 - val_loss: 0.9231 -
val_accuracy: 0.6744 - 158ms/epoch - 916us/step
Epoch 98/200
172/172 - 0s - loss: 0.2537 - accuracy: 0.8925 - val_loss: 0.9204 -
val_accuracy: 0.6614 - 151ms/epoch - 880us/step
Epoch 99/200
172/172 - 0s - loss: 0.2551 - accuracy: 0.8916 - val_loss: 0.9289 -
val_accuracy: 0.6642 - 148ms/epoch - 861us/step
Epoch 100/200
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172/172 - 0s - loss: 0.2543 - accuracy: 0.8932 - val_loss: 0.9304 -
val_accuracy: 0.6707 - 153ms/epoch - 891us/step
Epoch 101/200
172/172 - 0s - loss: 0.2575 - accuracy: 0.8883 - val_loss: 0.9577 -
val_accuracy: 0.6558 - 150ms/epoch - 873us/step
Epoch 102/200
172/172 - 0s - loss: 0.2549 - accuracy: 0.8906 - val_loss: 0.9487 -
val_accuracy: 0.6670 - 149ms/epoch - 869us/step
Epoch 103/200
172/172 - 0s - loss: 0.2504 - accuracy: 0.8916 - val_loss: 0.9460 -
val_accuracy: 0.6604 - 151ms/epoch - 876us/step
Epoch 104/200
172/172 - 0s - loss: 0.2490 - accuracy: 0.8932 - val_loss: 0.9593 -
val_accuracy: 0.6679 - 186ms/epoch - 1ms/step
Epoch 105/200
172/172 - 0s - loss: 0.2475 - accuracy: 0.8944 - val_loss: 0.9717 -
val_accuracy: 0.6632 - 148ms/epoch - 861us/step
Epoch 106/200
172/172 - 0s - loss: 0.2489 - accuracy: 0.8934 - val_loss: 0.9688 -
val_accuracy: 0.6698 - 150ms/epoch - 873us/step
Epoch 107/200
172/172 - 0s - loss: 0.2452 - accuracy: 0.9004 - val_loss: 0.9837 -
val_accuracy: 0.6670 - 176ms/epoch - 1ms/step
Epoch 108/200
172/172 - 0s - loss: 0.2443 - accuracy: 0.8960 - val_loss: 0.9729 -
val_accuracy: 0.6614 - 157ms/epoch - 914us/step
Epoch 109/200
172/172 - 0s - loss: 0.2405 - accuracy: 0.9004 - val_loss: 0.9875 -
val_accuracy: 0.6707 - 152ms/epoch - 885us/step
Epoch 110/200
172/172 - 0s - loss: 0.2456 - accuracy: 0.8967 - val_loss: 1.0024 -
val_accuracy: 0.6660 - 153ms/epoch - 890us/step
Epoch 111/200
172/172 - 0s - loss: 0.2386 - accuracy: 0.8981 - val_loss: 0.9962 -
val_accuracy: 0.6838 - 159ms/epoch - 922us/step
Epoch 112/200
172/172 - 0s - loss: 0.2427 - accuracy: 0.8997 - val_loss: 0.9991 -
val_accuracy: 0.6623 - 151ms/epoch - 878us/step
Epoch 113/200
172/172 - 0s - loss: 0.2404 - accuracy: 0.8941 - val_loss: 1.0136 -
val_accuracy: 0.6614 - 169ms/epoch - 985us/step
Epoch 114/200
172/172 - 0s - loss: 0.2405 - accuracy: 0.9037 - val_loss: 1.0149 -
val_accuracy: 0.6586 - 187ms/epoch - 1ms/step
Epoch 115/200
172/172 - 0s - loss: 0.2377 - accuracy: 0.9023 - val_loss: 1.0248 -
val_accuracy: 0.6595 - 160ms/epoch - 933us/step
Epoch 116/200
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172/172 - 0s - loss: 0.2380 - accuracy: 0.9030 - val_loss: 1.0395 -
val_accuracy: 0.6716 - 149ms/epoch - 867us/step
Epoch 117/200
172/172 - 0s - loss: 0.2328 - accuracy: 0.9032 - val_loss: 1.0355 -
val_accuracy: 0.6549 - 152ms/epoch - 885us/step
Epoch 118/200
172/172 - 0s - loss: 0.2338 - accuracy: 0.9004 - val_loss: 1.0467 -
val_accuracy: 0.6614 - 155ms/epoch - 904us/step
Epoch 119/200
172/172 - 0s - loss: 0.2343 - accuracy: 0.9053 - val_loss: 1.0537 -
val_accuracy: 0.6595 - 152ms/epoch - 881us/step
Epoch 120/200
172/172 - 0s - loss: 0.2379 - accuracy: 0.8990 - val_loss: 1.0625 -
val_accuracy: 0.6670 - 164ms/epoch - 951us/step
Epoch 121/200
172/172 - 0s - loss: 0.2328 - accuracy: 0.9011 - val_loss: 1.0730 -
val_accuracy: 0.6670 - 151ms/epoch - 876us/step
Epoch 122/200
172/172 - 0s - loss: 0.2338 - accuracy: 0.9044 - val_loss: 1.0569 -
val_accuracy: 0.6670 - 155ms/epoch - 901us/step
Epoch 123/200
172/172 - 0s - loss: 0.2273 - accuracy: 0.9035 - val_loss: 1.0686 -
val_accuracy: 0.6688 - 149ms/epoch - 864us/step
Epoch 124/200
172/172 - 0s - loss: 0.2237 - accuracy: 0.9086 - val_loss: 1.0748 -
val_accuracy: 0.6539 - 154ms/epoch - 894us/step
Epoch 125/200
172/172 - 0s - loss: 0.2251 - accuracy: 0.9086 - val_loss: 1.0771 -
val_accuracy: 0.6763 - 181ms/epoch - 1ms/step
Epoch 126/200
172/172 - 0s - loss: 0.2217 - accuracy: 0.9118 - val_loss: 1.0772 -
val_accuracy: 0.6567 - 178ms/epoch - 1ms/step
Epoch 127/200
172/172 - 0s - loss: 0.2282 - accuracy: 0.9014 - val_loss: 1.0788 -
val_accuracy: 0.6726 - 167ms/epoch - 972us/step
Epoch 128/200
172/172 - 0s - loss: 0.2222 - accuracy: 0.9107 - val_loss: 1.1043 -
val_accuracy: 0.6754 - 150ms/epoch - 874us/step
Epoch 129/200
172/172 - 0s - loss: 0.2223 - accuracy: 0.9086 - val_loss: 1.1025 -
val_accuracy: 0.6632 - 150ms/epoch - 870us/step
Epoch 130/200
172/172 - 0s - loss: 0.2180 - accuracy: 0.9090 - val_loss: 1.1244 -
val_accuracy: 0.6595 - 154ms/epoch - 895us/step
Epoch 131/200
172/172 - 0s - loss: 0.2176 - accuracy: 0.9149 - val_loss: 1.1061 -
val_accuracy: 0.6716 - 149ms/epoch - 865us/step
Epoch 132/200
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172/172 - 0s - loss: 0.2234 - accuracy: 0.9114 - val_loss: 1.1148 -
val_accuracy: 0.6660 - 181ms/epoch - 1ms/step
Epoch 133/200
172/172 - 0s - loss: 0.2140 - accuracy: 0.9123 - val_loss: 1.1193 -
val_accuracy: 0.6567 - 149ms/epoch - 865us/step
Epoch 134/200
172/172 - 0s - loss: 0.2156 - accuracy: 0.9104 - val_loss: 1.1224 -
val_accuracy: 0.6437 - 154ms/epoch - 895us/step
Epoch 135/200
172/172 - 0s - loss: 0.2146 - accuracy: 0.9151 - val_loss: 1.1316 -
val_accuracy: 0.6614 - 150ms/epoch - 870us/step
Epoch 136/200
172/172 - 0s - loss: 0.2151 - accuracy: 0.9114 - val_loss: 1.1355 -
val_accuracy: 0.6707 - 155ms/epoch - 899us/step
Epoch 137/200
172/172 - 0s - loss: 0.2157 - accuracy: 0.9123 - val_loss: 1.1401 -
val_accuracy: 0.6716 - 180ms/epoch - 1ms/step
Epoch 138/200
172/172 - 0s - loss: 0.2199 - accuracy: 0.9076 - val_loss: 1.1563 -
val_accuracy: 0.6521 - 153ms/epoch - 890us/step
Epoch 139/200
172/172 - 0s - loss: 0.2103 - accuracy: 0.9132 - val_loss: 1.1575 -
val_accuracy: 0.6521 - 150ms/epoch - 874us/step
Epoch 140/200
172/172 - 0s - loss: 0.2140 - accuracy: 0.9144 - val_loss: 1.1574 -
val_accuracy: 0.6642 - 151ms/epoch - 877us/step
Epoch 141/200
172/172 - 0s - loss: 0.2045 - accuracy: 0.9172 - val_loss: 1.1525 -
val_accuracy: 0.6642 - 152ms/epoch - 884us/step
Epoch 142/200
172/172 - 0s - loss: 0.2081 - accuracy: 0.9144 - val_loss: 1.1688 -
val_accuracy: 0.6688 - 153ms/epoch - 889us/step
Epoch 143/200
172/172 - 0s - loss: 0.2053 - accuracy: 0.9160 - val_loss: 1.1565 -
val_accuracy: 0.6576 - 161ms/epoch - 937us/step
Epoch 144/200
172/172 - 0s - loss: 0.2091 - accuracy: 0.9139 - val_loss: 1.1735 -
val_accuracy: 0.6698 - 151ms/epoch - 876us/step
Epoch 145/200
172/172 - 0s - loss: 0.2104 - accuracy: 0.9149 - val_loss: 1.1826 -
val_accuracy: 0.6688 - 150ms/epoch - 874us/step
Epoch 146/200
172/172 - 0s - loss: 0.2063 - accuracy: 0.9153 - val_loss: 1.2005 -
val_accuracy: 0.6660 - 150ms/epoch - 872us/step
Epoch 147/200
172/172 - 0s - loss: 0.2046 - accuracy: 0.9163 - val_loss: 1.2201 -
val_accuracy: 0.6642 - 150ms/epoch - 875us/step
Epoch 148/200
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172/172 - 0s - loss: 0.2032 - accuracy: 0.9198 - val_loss: 1.1953 -
val_accuracy: 0.6791 - 159ms/epoch - 924us/step
Epoch 149/200
172/172 - 0s - loss: 0.2013 - accuracy: 0.9181 - val_loss: 1.1996 -
val_accuracy: 0.6586 - 149ms/epoch - 868us/step
Epoch 150/200
172/172 - 0s - loss: 0.2017 - accuracy: 0.9219 - val_loss: 1.2181 -
val_accuracy: 0.6698 - 149ms/epoch - 867us/step
Epoch 151/200
172/172 - 0s - loss: 0.2047 - accuracy: 0.9174 - val_loss: 1.2112 -
val_accuracy: 0.6558 - 149ms/epoch - 866us/step
Epoch 152/200
172/172 - 0s - loss: 0.2025 - accuracy: 0.9179 - val_loss: 1.2091 -
val_accuracy: 0.6716 - 150ms/epoch - 874us/step
Epoch 153/200
172/172 - 0s - loss: 0.2009 - accuracy: 0.9160 - val_loss: 1.2216 -
val_accuracy: 0.6521 - 149ms/epoch - 869us/step
Epoch 154/200
172/172 - 0s - loss: 0.2009 - accuracy: 0.9198 - val_loss: 1.2510 -
val_accuracy: 0.6576 - 150ms/epoch - 874us/step
Epoch 155/200
172/172 - 0s - loss: 0.1951 - accuracy: 0.9223 - val_loss: 1.2683 -
val_accuracy: 0.6595 - 149ms/epoch - 867us/step
Epoch 156/200
172/172 - 0s - loss: 0.1947 - accuracy: 0.9237 - val_loss: 1.2399 -
val_accuracy: 0.6567 - 155ms/epoch - 901us/step
Epoch 157/200
172/172 - 0s - loss: 0.1966 - accuracy: 0.9219 - val_loss: 1.2321 -
val_accuracy: 0.6698 - 148ms/epoch - 859us/step
Epoch 158/200
172/172 - 0s - loss: 0.1917 - accuracy: 0.9235 - val_loss: 1.2639 -
val_accuracy: 0.6614 - 148ms/epoch - 863us/step
Epoch 159/200
172/172 - 0s - loss: 0.1921 - accuracy: 0.9263 - val_loss: 1.2816 -
val_accuracy: 0.6614 - 149ms/epoch - 868us/step
Epoch 160/200
172/172 - 0s - loss: 0.1910 - accuracy: 0.9209 - val_loss: 1.2743 -
val_accuracy: 0.6623 - 155ms/epoch - 902us/step
Epoch 161/200
172/172 - 0s - loss: 0.1931 - accuracy: 0.9216 - val_loss: 1.2856 -
val_accuracy: 0.6558 - 150ms/epoch - 874us/step
Epoch 162/200
172/172 - 0s - loss: 0.1922 - accuracy: 0.9230 - val_loss: 1.3083 -
val_accuracy: 0.6530 - 151ms/epoch - 878us/step
Epoch 163/200
172/172 - 0s - loss: 0.1924 - accuracy: 0.9251 - val_loss: 1.3032 -
val_accuracy: 0.6511 - 150ms/epoch - 872us/step
Epoch 164/200
```

```
172/172 - 0s - loss: 0.1935 - accuracy: 0.9221 - val_loss: 1.2990 -
val_accuracy: 0.6604 - 150ms/epoch - 871us/step
Epoch 165/200
172/172 - 0s - loss: 0.1928 - accuracy: 0.9214 - val_loss: 1.3036 -
val_accuracy: 0.6698 - 150ms/epoch - 872us/step
Epoch 166/200
172/172 - 0s - loss: 0.1892 - accuracy: 0.9230 - val_loss: 1.3306 -
val_accuracy: 0.6651 - 150ms/epoch - 871us/step
Epoch 167/200
172/172 - 0s - loss: 0.1907 - accuracy: 0.9221 - val_loss: 1.3164 -
val_accuracy: 0.6567 - 150ms/epoch - 870us/step
Epoch 168/200
172/172 - 0s - loss: 0.1826 - accuracy: 0.9293 - val_loss: 1.3336 -
val_accuracy: 0.6670 - 155ms/epoch - 902us/step
Epoch 169/200
172/172 - 0s - loss: 0.1988 - accuracy: 0.9181 - val_loss: 1.3298 -
val_accuracy: 0.6688 - 150ms/epoch - 871us/step
Epoch 170/200
172/172 - 0s - loss: 0.1843 - accuracy: 0.9314 - val_loss: 1.3205 -
val_accuracy: 0.6567 - 156ms/epoch - 907us/step
Epoch 171/200
172/172 - 0s - loss: 0.1840 - accuracy: 0.9265 - val_loss: 1.3391 -
val_accuracy: 0.6614 - 178ms/epoch - 1ms/step
Epoch 172/200
172/172 - 0s - loss: 0.1816 - accuracy: 0.9277 - val_loss: 1.3554 -
val_accuracy: 0.6474 - 150ms/epoch - 870us/step
Epoch 173/200
172/172 - 0s - loss: 0.1808 - accuracy: 0.9305 - val_loss: 1.3775 -
val_accuracy: 0.6614 - 150ms/epoch - 874us/step
Epoch 174/200
172/172 - 0s - loss: 0.1826 - accuracy: 0.9258 - val_loss: 1.3623 -
val_accuracy: 0.6455 - 149ms/epoch - 867us/step
Epoch 175/200
172/172 - 0s - loss: 0.1840 - accuracy: 0.9284 - val_loss: 1.3787 -
val_accuracy: 0.6623 - 154ms/epoch - 897us/step
Epoch 176/200
172/172 - 0s - loss: 0.1817 - accuracy: 0.9289 - val_loss: 1.3837 -
val_accuracy: 0.6604 - 150ms/epoch - 872us/step
Epoch 177/200
172/172 - 0s - loss: 0.1804 - accuracy: 0.9305 - val_loss: 1.3716 -
val_accuracy: 0.6642 - 149ms/epoch - 869us/step
Epoch 178/200
172/172 - 0s - loss: 0.1788 - accuracy: 0.9328 - val_loss: 1.4014 -
val_accuracy: 0.6502 - 159ms/epoch - 922us/step
Epoch 179/200
172/172 - 0s - loss: 0.1805 - accuracy: 0.9277 - val_loss: 1.3791 -
val_accuracy: 0.6698 - 150ms/epoch - 871us/step
Epoch 180/200
```

```
172/172 - 0s - loss: 0.1790 - accuracy: 0.9277 - val_loss: 1.4087 -
val_accuracy: 0.6651 - 159ms/epoch - 922us/step
Epoch 181/200
172/172 - 0s - loss: 0.1795 - accuracy: 0.9275 - val_loss: 1.4130 -
val_accuracy: 0.6586 - 151ms/epoch - 876us/step
Epoch 182/200
172/172 - 0s - loss: 0.1790 - accuracy: 0.9321 - val_loss: 1.4236 -
val_accuracy: 0.6660 - 151ms/epoch - 878us/step
Epoch 183/200
172/172 - 0s - loss: 0.1755 - accuracy: 0.9303 - val_loss: 1.4271 -
val_accuracy: 0.6549 - 151ms/epoch - 878us/step
Epoch 184/200
172/172 - 0s - loss: 0.1808 - accuracy: 0.9289 - val_loss: 1.4005 -
val_accuracy: 0.6539 - 148ms/epoch - 863us/step
Epoch 185/200
172/172 - 0s - loss: 0.1764 - accuracy: 0.9289 - val_loss: 1.4225 -
val_accuracy: 0.6642 - 167ms/epoch - 973us/step
Epoch 186/200
172/172 - 0s - loss: 0.1705 - accuracy: 0.9352 - val_loss: 1.4189 -
val_accuracy: 0.6595 - 160ms/epoch - 931us/step
Epoch 187/200
172/172 - 0s - loss: 0.1742 - accuracy: 0.9303 - val_loss: 1.4198 -
val_accuracy: 0.6558 - 167ms/epoch - 972us/step
Epoch 188/200
172/172 - 0s - loss: 0.1707 - accuracy: 0.9319 - val_loss: 1.4340 -
val_accuracy: 0.6698 - 148ms/epoch - 863us/step
Epoch 189/200
172/172 - 0s - loss: 0.1735 - accuracy: 0.9356 - val_loss: 1.4537 -
val_accuracy: 0.6660 - 175ms/epoch - 1ms/step
Epoch 190/200
172/172 - 0s - loss: 0.1727 - accuracy: 0.9317 - val_loss: 1.4759 -
val_accuracy: 0.6595 - 173ms/epoch - 1ms/step
Epoch 191/200
172/172 - 0s - loss: 0.1692 - accuracy: 0.9363 - val_loss: 1.4929 -
val_accuracy: 0.6595 - 161ms/epoch - 936us/step
Epoch 192/200
172/172 - 0s - loss: 0.1722 - accuracy: 0.9305 - val_loss: 1.4784 -
val_accuracy: 0.6660 - 152ms/epoch - 882us/step
Epoch 193/200
172/172 - 0s - loss: 0.1730 - accuracy: 0.9345 - val_loss: 1.4787 -
val_accuracy: 0.6660 - 155ms/epoch - 900us/step
Epoch 194/200
172/172 - 0s - loss: 0.1712 - accuracy: 0.9303 - val_loss: 1.5027 -
val_accuracy: 0.6586 - 148ms/epoch - 863us/step
Epoch 195/200
172/172 - 0s - loss: 0.1711 - accuracy: 0.9305 - val_loss: 1.4937 -
val_accuracy: 0.6651 - 150ms/epoch - 871us/step
Epoch 196/200
```

```
172/172 - 0s - loss: 0.1695 - accuracy: 0.9326 - val_loss: 1.4896 -
val_accuracy: 0.6539 - 150ms/epoch - 872us/step
Epoch 197/200
172/172 - 0s - loss: 0.1675 - accuracy: 0.9373 - val_loss: 1.4910 -
val_accuracy: 0.6604 - 166ms/epoch - 965us/step
Epoch 198/200
172/172 - 0s - loss: 0.1660 - accuracy: 0.9368 - val_loss: 1.5132 -
val_accuracy: 0.6623 - 184ms/epoch - 1ms/step
Epoch 199/200
172/172 - 0s - loss: 0.1746 - accuracy: 0.9303 - val_loss: 1.5593 -
val_accuracy: 0.6539 - 169ms/epoch - 984us/step
Epoch 200/200
172/172 - 0s - loss: 0.1652 - accuracy: 0.9356 - val_loss: 1.5174 -
val_accuracy: 0.6586 - 175ms/epoch - 1ms/step
```

[191]:
```
<keras.callbacks.History at 0x7fcab96e1370>
```

[192]:
```python
undersample_predictions = undersample_model.predict(original_Xtest,␣
↪batch_size=200, verbose=0)
```

[193]:
```python
undersample_default_predictions = np.argmax(undersample_model.
↪predict(original_Xtest), axis = -1)
```

[194]:
```python
import itertools

# Create a confusion matrix
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title, fontsize=14)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)
```

```
    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

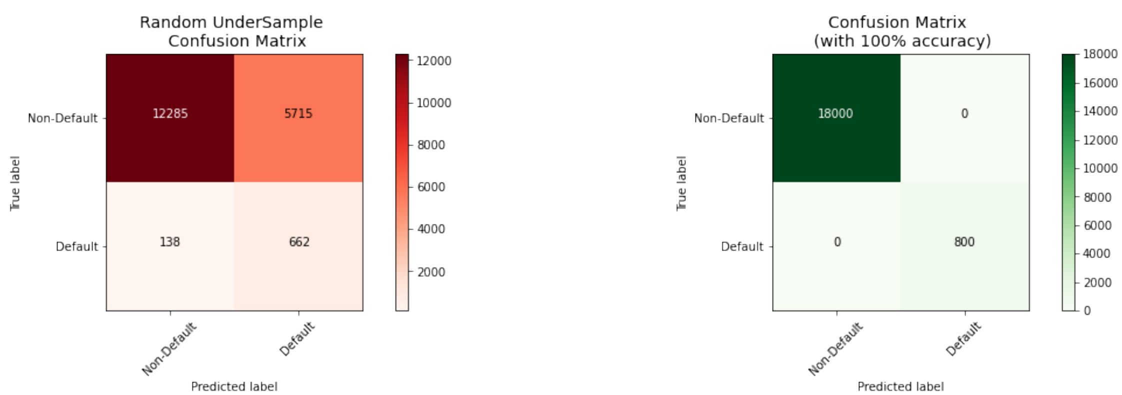
[195]:
```
undersample_cm = confusion_matrix(original_ytest,␣
 ↪undersample_default_predictions)
actual_cm = confusion_matrix(original_ytest, original_ytest)
labels = ['Non-Default', 'Default']

fig = plt.figure(figsize=(16,8))

fig.add_subplot(221)
plot_confusion_matrix(undersample_cm, labels, title="Random UnderSample \n␣
 ↪Confusion Matrix", cmap=plt.cm.Reds)

fig.add_subplot(222)
plot_confusion_matrix(actual_cm, labels, title="Confusion Matrix \n (with 100%␣
 ↪accuracy)", cmap=plt.cm.Greens)
```

```
Confusion matrix, without normalization
[[12285  5715]
 [  138   662]]
Confusion matrix, without normalization
[[18000     0]
 [    0   800]]
```



[173]:
```
n_inputs = Xsm_train.shape[1]

oversample_model = Sequential([
    Dense(n_inputs, input_shape=(n_inputs, ), activation='relu'),
    Dense(32, activation='relu'),
    Dense(2, activation='softmax')
])
```

[174]:
```
oversample_model.compile(Adam(lr=0.001),␣
↪loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

[180]:
```
oversample_model.fit(Xsm_train, ysm_train, validation_split=0.2,␣
↪batch_size=300, epochs=200, shuffle=True, verbose=2)
```

```
Epoch 1/200
384/384 - 0s - loss: 0.3968 - accuracy: 0.8142 - val_loss: 0.5750 -
val_accuracy: 0.7070 - 384ms/epoch - 999us/step
Epoch 2/200
384/384 - 0s - loss: 0.3951 - accuracy: 0.8158 - val_loss: 0.5649 -
val_accuracy: 0.7181 - 338ms/epoch - 880us/step
Epoch 3/200
384/384 - 0s - loss: 0.3936 - accuracy: 0.8168 - val_loss: 0.6070 -
val_accuracy: 0.6881 - 362ms/epoch - 943us/step
Epoch 4/200
384/384 - 0s - loss: 0.3924 - accuracy: 0.8169 - val_loss: 0.5314 -
val_accuracy: 0.7322 - 413ms/epoch - 1ms/step
Epoch 5/200
384/384 - 0s - loss: 0.3902 - accuracy: 0.8189 - val_loss: 0.5424 -
val_accuracy: 0.7287 - 362ms/epoch - 943us/step
Epoch 6/200
384/384 - 0s - loss: 0.3890 - accuracy: 0.8190 - val_loss: 0.4967 -
val_accuracy: 0.7612 - 357ms/epoch - 931us/step
Epoch 7/200
384/384 - 0s - loss: 0.3873 - accuracy: 0.8196 - val_loss: 0.5377 -
val_accuracy: 0.7299 - 356ms/epoch - 927us/step
Epoch 8/200
384/384 - 0s - loss: 0.3864 - accuracy: 0.8208 - val_loss: 0.5912 -
val_accuracy: 0.6956 - 345ms/epoch - 900us/step
Epoch 9/200
384/384 - 0s - loss: 0.3841 - accuracy: 0.8225 - val_loss: 0.5512 -
val_accuracy: 0.7293 - 385ms/epoch - 1ms/step
Epoch 10/200
384/384 - 0s - loss: 0.3829 - accuracy: 0.8233 - val_loss: 0.5066 -
val_accuracy: 0.7557 - 361ms/epoch - 941us/step
Epoch 11/200
384/384 - 0s - loss: 0.3811 - accuracy: 0.8239 - val_loss: 0.5031 -
val_accuracy: 0.7584 - 412ms/epoch - 1ms/step
Epoch 12/200
```

```
384/384 - 0s - loss: 0.3801 - accuracy: 0.8248 - val_loss: 0.4922 -
val_accuracy: 0.7643 - 339ms/epoch - 884us/step
Epoch 13/200
384/384 - 0s - loss: 0.3788 - accuracy: 0.8249 - val_loss: 0.5295 -
val_accuracy: 0.7380 - 397ms/epoch - 1ms/step
Epoch 14/200
384/384 - 0s - loss: 0.3776 - accuracy: 0.8259 - val_loss: 0.5350 -
val_accuracy: 0.7391 - 384ms/epoch - 1ms/step
Epoch 15/200
384/384 - 0s - loss: 0.3761 - accuracy: 0.8267 - val_loss: 0.5045 -
val_accuracy: 0.7551 - 336ms/epoch - 875us/step
Epoch 16/200
384/384 - 0s - loss: 0.3747 - accuracy: 0.8277 - val_loss: 0.5187 -
val_accuracy: 0.7500 - 343ms/epoch - 892us/step
Epoch 17/200
384/384 - 0s - loss: 0.3740 - accuracy: 0.8282 - val_loss: 0.5271 -
val_accuracy: 0.7485 - 359ms/epoch - 934us/step
Epoch 18/200
384/384 - 0s - loss: 0.3725 - accuracy: 0.8286 - val_loss: 0.5009 -
val_accuracy: 0.7593 - 442ms/epoch - 1ms/step
Epoch 19/200
384/384 - 0s - loss: 0.3716 - accuracy: 0.8299 - val_loss: 0.5319 -
val_accuracy: 0.7414 - 339ms/epoch - 882us/step
Epoch 20/200
384/384 - 0s - loss: 0.3709 - accuracy: 0.8292 - val_loss: 0.4754 -
val_accuracy: 0.7751 - 336ms/epoch - 874us/step
Epoch 21/200
384/384 - 0s - loss: 0.3704 - accuracy: 0.8291 - val_loss: 0.5237 -
val_accuracy: 0.7466 - 347ms/epoch - 905us/step
Epoch 22/200
384/384 - 0s - loss: 0.3689 - accuracy: 0.8305 - val_loss: 0.5355 -
val_accuracy: 0.7372 - 340ms/epoch - 885us/step
Epoch 23/200
384/384 - 0s - loss: 0.3682 - accuracy: 0.8312 - val_loss: 0.5556 -
val_accuracy: 0.7291 - 356ms/epoch - 928us/step
Epoch 24/200
384/384 - 0s - loss: 0.3674 - accuracy: 0.8314 - val_loss: 0.5375 -
val_accuracy: 0.7388 - 355ms/epoch - 924us/step
Epoch 25/200
384/384 - 0s - loss: 0.3665 - accuracy: 0.8316 - val_loss: 0.4665 -
val_accuracy: 0.7812 - 387ms/epoch - 1ms/step
Epoch 26/200
384/384 - 0s - loss: 0.3665 - accuracy: 0.8316 - val_loss: 0.5308 -
val_accuracy: 0.7392 - 366ms/epoch - 954us/step
Epoch 27/200
384/384 - 0s - loss: 0.3650 - accuracy: 0.8326 - val_loss: 0.5161 -
val_accuracy: 0.7498 - 337ms/epoch - 878us/step
Epoch 28/200
```

```
384/384 - 0s - loss: 0.3646 - accuracy: 0.8333 - val_loss: 0.4893 -
val_accuracy: 0.7699 - 340ms/epoch - 884us/step
Epoch 29/200
384/384 - 0s - loss: 0.3642 - accuracy: 0.8332 - val_loss: 0.5841 -
val_accuracy: 0.7092 - 340ms/epoch - 885us/step
Epoch 30/200
384/384 - 0s - loss: 0.3632 - accuracy: 0.8334 - val_loss: 0.4762 -
val_accuracy: 0.7730 - 335ms/epoch - 873us/step
Epoch 31/200
384/384 - 0s - loss: 0.3617 - accuracy: 0.8345 - val_loss: 0.4864 -
val_accuracy: 0.7683 - 340ms/epoch - 886us/step
Epoch 32/200
384/384 - 0s - loss: 0.3618 - accuracy: 0.8342 - val_loss: 0.4704 -
val_accuracy: 0.7822 - 335ms/epoch - 872us/step
Epoch 33/200
384/384 - 0s - loss: 0.3607 - accuracy: 0.8359 - val_loss: 0.4936 -
val_accuracy: 0.7605 - 335ms/epoch - 874us/step
Epoch 34/200
384/384 - 0s - loss: 0.3610 - accuracy: 0.8359 - val_loss: 0.5750 -
val_accuracy: 0.7236 - 373ms/epoch - 971us/step
Epoch 35/200
384/384 - 0s - loss: 0.3599 - accuracy: 0.8365 - val_loss: 0.5038 -
val_accuracy: 0.7575 - 338ms/epoch - 879us/step
Epoch 36/200
384/384 - 0s - loss: 0.3596 - accuracy: 0.8369 - val_loss: 0.4876 -
val_accuracy: 0.7684 - 354ms/epoch - 922us/step
Epoch 37/200
384/384 - 0s - loss: 0.3585 - accuracy: 0.8364 - val_loss: 0.4745 -
val_accuracy: 0.7747 - 353ms/epoch - 920us/step
Epoch 38/200
384/384 - 0s - loss: 0.3577 - accuracy: 0.8381 - val_loss: 0.5458 -
val_accuracy: 0.7369 - 354ms/epoch - 923us/step
Epoch 39/200
384/384 - 0s - loss: 0.3574 - accuracy: 0.8370 - val_loss: 0.5437 -
val_accuracy: 0.7355 - 336ms/epoch - 874us/step
Epoch 40/200
384/384 - 0s - loss: 0.3573 - accuracy: 0.8375 - val_loss: 0.4997 -
val_accuracy: 0.7603 - 406ms/epoch - 1ms/step
Epoch 41/200
384/384 - 0s - loss: 0.3561 - accuracy: 0.8381 - val_loss: 0.5546 -
val_accuracy: 0.7278 - 343ms/epoch - 893us/step
Epoch 42/200
384/384 - 0s - loss: 0.3563 - accuracy: 0.8387 - val_loss: 0.5142 -
val_accuracy: 0.7547 - 368ms/epoch - 959us/step
Epoch 43/200
384/384 - 0s - loss: 0.3554 - accuracy: 0.8389 - val_loss: 0.5474 -
val_accuracy: 0.7366 - 343ms/epoch - 892us/step
Epoch 44/200
```

```
384/384 - 0s - loss: 0.3552 - accuracy: 0.8386 - val_loss: 0.5652 -
val_accuracy: 0.7267 - 339ms/epoch - 882us/step
Epoch 45/200
384/384 - 0s - loss: 0.3542 - accuracy: 0.8395 - val_loss: 0.4830 -
val_accuracy: 0.7702 - 342ms/epoch - 891us/step
Epoch 46/200
384/384 - 0s - loss: 0.3542 - accuracy: 0.8400 - val_loss: 0.4646 -
val_accuracy: 0.7854 - 341ms/epoch - 888us/step
Epoch 47/200
384/384 - 0s - loss: 0.3534 - accuracy: 0.8400 - val_loss: 0.4776 -
val_accuracy: 0.7748 - 346ms/epoch - 900us/step
Epoch 48/200
384/384 - 0s - loss: 0.3533 - accuracy: 0.8400 - val_loss: 0.4879 -
val_accuracy: 0.7703 - 338ms/epoch - 879us/step
Epoch 49/200
384/384 - 0s - loss: 0.3531 - accuracy: 0.8405 - val_loss: 0.4210 -
val_accuracy: 0.8078 - 342ms/epoch - 891us/step
Epoch 50/200
384/384 - 0s - loss: 0.3525 - accuracy: 0.8409 - val_loss: 0.4195 -
val_accuracy: 0.8083 - 342ms/epoch - 891us/step
Epoch 51/200
384/384 - 0s - loss: 0.3520 - accuracy: 0.8415 - val_loss: 0.4880 -
val_accuracy: 0.7725 - 343ms/epoch - 894us/step
Epoch 52/200
384/384 - 0s - loss: 0.3518 - accuracy: 0.8414 - val_loss: 0.4506 -
val_accuracy: 0.7953 - 337ms/epoch - 878us/step
Epoch 53/200
384/384 - 0s - loss: 0.3514 - accuracy: 0.8414 - val_loss: 0.5153 -
val_accuracy: 0.7531 - 335ms/epoch - 872us/step
Epoch 54/200
384/384 - 0s - loss: 0.3517 - accuracy: 0.8407 - val_loss: 0.4726 -
val_accuracy: 0.7869 - 337ms/epoch - 878us/step
Epoch 55/200
384/384 - 0s - loss: 0.3507 - accuracy: 0.8412 - val_loss: 0.4949 -
val_accuracy: 0.7691 - 377ms/epoch - 983us/step
Epoch 56/200
384/384 - 0s - loss: 0.3502 - accuracy: 0.8428 - val_loss: 0.5133 -
val_accuracy: 0.7585 - 340ms/epoch - 884us/step
Epoch 57/200
384/384 - 0s - loss: 0.3501 - accuracy: 0.8424 - val_loss: 0.4442 -
val_accuracy: 0.7975 - 345ms/epoch - 898us/step
Epoch 58/200
384/384 - 0s - loss: 0.3501 - accuracy: 0.8424 - val_loss: 0.4997 -
val_accuracy: 0.7631 - 341ms/epoch - 888us/step
Epoch 59/200
384/384 - 0s - loss: 0.3497 - accuracy: 0.8431 - val_loss: 0.5150 -
val_accuracy: 0.7536 - 339ms/epoch - 883us/step
Epoch 60/200
```

```
384/384 - 0s - loss: 0.3491 - accuracy: 0.8425 - val_loss: 0.4495 -
val_accuracy: 0.7928 - 337ms/epoch - 879us/step
Epoch 61/200
384/384 - 0s - loss: 0.3489 - accuracy: 0.8423 - val_loss: 0.4791 -
val_accuracy: 0.7770 - 346ms/epoch - 900us/step
Epoch 62/200
384/384 - 0s - loss: 0.3489 - accuracy: 0.8429 - val_loss: 0.4853 -
val_accuracy: 0.7774 - 354ms/epoch - 921us/step
Epoch 63/200
384/384 - 0s - loss: 0.3482 - accuracy: 0.8431 - val_loss: 0.4195 -
val_accuracy: 0.8131 - 362ms/epoch - 944us/step
Epoch 64/200
384/384 - 0s - loss: 0.3476 - accuracy: 0.8431 - val_loss: 0.4784 -
val_accuracy: 0.7794 - 338ms/epoch - 880us/step
Epoch 65/200
384/384 - 0s - loss: 0.3477 - accuracy: 0.8433 - val_loss: 0.4791 -
val_accuracy: 0.7810 - 332ms/epoch - 864us/step
Epoch 66/200
384/384 - 0s - loss: 0.3474 - accuracy: 0.8435 - val_loss: 0.5266 -
val_accuracy: 0.7500 - 334ms/epoch - 869us/step
Epoch 67/200
384/384 - 0s - loss: 0.3474 - accuracy: 0.8439 - val_loss: 0.4175 -
val_accuracy: 0.8137 - 345ms/epoch - 899us/step
Epoch 68/200
384/384 - 0s - loss: 0.3469 - accuracy: 0.8435 - val_loss: 0.5069 -
val_accuracy: 0.7623 - 336ms/epoch - 875us/step
Epoch 69/200
384/384 - 0s - loss: 0.3465 - accuracy: 0.8441 - val_loss: 0.4018 -
val_accuracy: 0.8230 - 337ms/epoch - 877us/step
Epoch 70/200
384/384 - 0s - loss: 0.3465 - accuracy: 0.8434 - val_loss: 0.4614 -
val_accuracy: 0.7875 - 339ms/epoch - 884us/step
Epoch 71/200
384/384 - 0s - loss: 0.3465 - accuracy: 0.8436 - val_loss: 0.5153 -
val_accuracy: 0.7570 - 364ms/epoch - 948us/step
Epoch 72/200
384/384 - 0s - loss: 0.3453 - accuracy: 0.8438 - val_loss: 0.4870 -
val_accuracy: 0.7738 - 387ms/epoch - 1ms/step
Epoch 73/200
384/384 - 0s - loss: 0.3453 - accuracy: 0.8443 - val_loss: 0.4670 -
val_accuracy: 0.7824 - 349ms/epoch - 908us/step
Epoch 74/200
384/384 - 0s - loss: 0.3455 - accuracy: 0.8440 - val_loss: 0.4609 -
val_accuracy: 0.7885 - 388ms/epoch - 1ms/step
Epoch 75/200
384/384 - 0s - loss: 0.3457 - accuracy: 0.8440 - val_loss: 0.5143 -
val_accuracy: 0.7563 - 336ms/epoch - 874us/step
Epoch 76/200
```

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384/384 - 0s - loss: 0.3452 - accuracy: 0.8447 - val_loss: 0.4846 -
val_accuracy: 0.7755 - 340ms/epoch - 886us/step
Epoch 77/200
384/384 - 0s - loss: 0.3445 - accuracy: 0.8444 - val_loss: 0.4671 -
val_accuracy: 0.7856 - 380ms/epoch - 989us/step
Epoch 78/200
384/384 - 0s - loss: 0.3442 - accuracy: 0.8454 - val_loss: 0.5561 -
val_accuracy: 0.7292 - 340ms/epoch - 885us/step
Epoch 79/200
384/384 - 0s - loss: 0.3445 - accuracy: 0.8449 - val_loss: 0.4177 -
val_accuracy: 0.8119 - 340ms/epoch - 886us/step
Epoch 80/200
384/384 - 0s - loss: 0.3444 - accuracy: 0.8443 - val_loss: 0.3966 -
val_accuracy: 0.8257 - 377ms/epoch - 982us/step
Epoch 81/200
384/384 - 0s - loss: 0.3449 - accuracy: 0.8442 - val_loss: 0.4377 -
val_accuracy: 0.8012 - 334ms/epoch - 871us/step
Epoch 82/200
384/384 - 0s - loss: 0.3440 - accuracy: 0.8452 - val_loss: 0.4828 -
val_accuracy: 0.7764 - 335ms/epoch - 871us/step
Epoch 83/200
384/384 - 0s - loss: 0.3437 - accuracy: 0.8442 - val_loss: 0.5162 -
val_accuracy: 0.7607 - 357ms/epoch - 930us/step
Epoch 84/200
384/384 - 0s - loss: 0.3440 - accuracy: 0.8447 - val_loss: 0.4509 -
val_accuracy: 0.7939 - 342ms/epoch - 890us/step
Epoch 85/200
384/384 - 0s - loss: 0.3432 - accuracy: 0.8453 - val_loss: 0.5173 -
val_accuracy: 0.7588 - 344ms/epoch - 896us/step
Epoch 86/200
384/384 - 0s - loss: 0.3433 - accuracy: 0.8444 - val_loss: 0.4885 -
val_accuracy: 0.7728 - 338ms/epoch - 880us/step
Epoch 87/200
384/384 - 0s - loss: 0.3432 - accuracy: 0.8448 - val_loss: 0.5073 -
val_accuracy: 0.7591 - 333ms/epoch - 867us/step
Epoch 88/200
384/384 - 0s - loss: 0.3424 - accuracy: 0.8452 - val_loss: 0.4736 -
val_accuracy: 0.7793 - 347ms/epoch - 904us/step
Epoch 89/200
384/384 - 0s - loss: 0.3432 - accuracy: 0.8457 - val_loss: 0.4578 -
val_accuracy: 0.7922 - 361ms/epoch - 939us/step
Epoch 90/200
384/384 - 0s - loss: 0.3422 - accuracy: 0.8459 - val_loss: 0.4666 -
val_accuracy: 0.7868 - 336ms/epoch - 875us/step
Epoch 91/200
384/384 - 0s - loss: 0.3429 - accuracy: 0.8459 - val_loss: 0.4699 -
val_accuracy: 0.7859 - 336ms/epoch - 875us/step
Epoch 92/200
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384/384 - 0s - loss: 0.3430 - accuracy: 0.8448 - val_loss: 0.5004 -
val_accuracy: 0.7638 - 348ms/epoch - 905us/step
Epoch 93/200
384/384 - 0s - loss: 0.3420 - accuracy: 0.8454 - val_loss: 0.4437 -
val_accuracy: 0.7985 - 344ms/epoch - 897us/step
Epoch 94/200
384/384 - 0s - loss: 0.3422 - accuracy: 0.8457 - val_loss: 0.3990 -
val_accuracy: 0.8258 - 336ms/epoch - 874us/step
Epoch 95/200
384/384 - 0s - loss: 0.3420 - accuracy: 0.8454 - val_loss: 0.4948 -
val_accuracy: 0.7675 - 336ms/epoch - 874us/step
Epoch 96/200
384/384 - 0s - loss: 0.3418 - accuracy: 0.8463 - val_loss: 0.5522 -
val_accuracy: 0.7334 - 334ms/epoch - 870us/step
Epoch 97/200
384/384 - 0s - loss: 0.3417 - accuracy: 0.8465 - val_loss: 0.4551 -
val_accuracy: 0.7925 - 335ms/epoch - 872us/step
Epoch 98/200
384/384 - 0s - loss: 0.3411 - accuracy: 0.8460 - val_loss: 0.4824 -
val_accuracy: 0.7766 - 340ms/epoch - 886us/step
Epoch 99/200
384/384 - 0s - loss: 0.3409 - accuracy: 0.8456 - val_loss: 0.4475 -
val_accuracy: 0.7961 - 339ms/epoch - 883us/step
Epoch 100/200
384/384 - 0s - loss: 0.3416 - accuracy: 0.8458 - val_loss: 0.4102 -
val_accuracy: 0.8208 - 362ms/epoch - 944us/step
Epoch 101/200
384/384 - 0s - loss: 0.3409 - accuracy: 0.8462 - val_loss: 0.4560 -
val_accuracy: 0.7920 - 337ms/epoch - 878us/step
Epoch 102/200
384/384 - 0s - loss: 0.3408 - accuracy: 0.8465 - val_loss: 0.4806 -
val_accuracy: 0.7791 - 338ms/epoch - 881us/step
Epoch 103/200
384/384 - 0s - loss: 0.3414 - accuracy: 0.8461 - val_loss: 0.4341 -
val_accuracy: 0.8032 - 341ms/epoch - 888us/step
Epoch 104/200
384/384 - 0s - loss: 0.3403 - accuracy: 0.8469 - val_loss: 0.4395 -
val_accuracy: 0.7989 - 339ms/epoch - 882us/step
Epoch 105/200
384/384 - 0s - loss: 0.3400 - accuracy: 0.8460 - val_loss: 0.4862 -
val_accuracy: 0.7751 - 371ms/epoch - 967us/step
Epoch 106/200
384/384 - 0s - loss: 0.3397 - accuracy: 0.8468 - val_loss: 0.4841 -
val_accuracy: 0.7789 - 423ms/epoch - 1ms/step
Epoch 107/200
384/384 - 0s - loss: 0.3407 - accuracy: 0.8468 - val_loss: 0.4593 -
val_accuracy: 0.7887 - 427ms/epoch - 1ms/step
Epoch 108/200
```

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384/384 - 0s - loss: 0.3399 - accuracy: 0.8472 - val_loss: 0.5121 -
val_accuracy: 0.7587 - 400ms/epoch - 1ms/step
Epoch 109/200
384/384 - 0s - loss: 0.3395 - accuracy: 0.8473 - val_loss: 0.4371 -
val_accuracy: 0.8047 - 360ms/epoch - 938us/step
Epoch 110/200
384/384 - 0s - loss: 0.3395 - accuracy: 0.8466 - val_loss: 0.4342 -
val_accuracy: 0.8042 - 342ms/epoch - 890us/step
Epoch 111/200
384/384 - 0s - loss: 0.3396 - accuracy: 0.8467 - val_loss: 0.5007 -
val_accuracy: 0.7658 - 342ms/epoch - 891us/step
Epoch 112/200
384/384 - 0s - loss: 0.3391 - accuracy: 0.8471 - val_loss: 0.5268 -
val_accuracy: 0.7505 - 348ms/epoch - 907us/step
Epoch 113/200
384/384 - 0s - loss: 0.3394 - accuracy: 0.8472 - val_loss: 0.4577 -
val_accuracy: 0.7905 - 339ms/epoch - 882us/step
Epoch 114/200
384/384 - 0s - loss: 0.3390 - accuracy: 0.8471 - val_loss: 0.4951 -
val_accuracy: 0.7672 - 349ms/epoch - 909us/step
Epoch 115/200
384/384 - 0s - loss: 0.3388 - accuracy: 0.8472 - val_loss: 0.4565 -
val_accuracy: 0.7918 - 337ms/epoch - 877us/step
Epoch 116/200
384/384 - 0s - loss: 0.3386 - accuracy: 0.8472 - val_loss: 0.4446 -
val_accuracy: 0.8004 - 340ms/epoch - 886us/step
Epoch 117/200
384/384 - 0s - loss: 0.3388 - accuracy: 0.8483 - val_loss: 0.4126 -
val_accuracy: 0.8193 - 343ms/epoch - 894us/step
Epoch 118/200
384/384 - 0s - loss: 0.3382 - accuracy: 0.8483 - val_loss: 0.4321 -
val_accuracy: 0.8084 - 344ms/epoch - 895us/step
Epoch 119/200
384/384 - 0s - loss: 0.3383 - accuracy: 0.8472 - val_loss: 0.4665 -
val_accuracy: 0.7851 - 343ms/epoch - 892us/step
Epoch 120/200
384/384 - 0s - loss: 0.3385 - accuracy: 0.8473 - val_loss: 0.4608 -
val_accuracy: 0.7922 - 359ms/epoch - 935us/step
Epoch 121/200
384/384 - 0s - loss: 0.3382 - accuracy: 0.8481 - val_loss: 0.4567 -
val_accuracy: 0.7935 - 343ms/epoch - 892us/step
Epoch 122/200
384/384 - 0s - loss: 0.3386 - accuracy: 0.8476 - val_loss: 0.4547 -
val_accuracy: 0.7938 - 337ms/epoch - 879us/step
Epoch 123/200
384/384 - 0s - loss: 0.3384 - accuracy: 0.8484 - val_loss: 0.4297 -
val_accuracy: 0.8068 - 341ms/epoch - 888us/step
Epoch 124/200
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384/384 - 0s - loss: 0.3383 - accuracy: 0.8480 - val_loss: 0.5229 -
val_accuracy: 0.7504 - 335ms/epoch - 871us/step
Epoch 125/200
384/384 - 0s - loss: 0.3384 - accuracy: 0.8484 - val_loss: 0.4698 -
val_accuracy: 0.7798 - 339ms/epoch - 883us/step
Epoch 126/200
384/384 - 0s - loss: 0.3372 - accuracy: 0.8482 - val_loss: 0.4641 -
val_accuracy: 0.7875 - 339ms/epoch - 883us/step
Epoch 127/200
384/384 - 0s - loss: 0.3377 - accuracy: 0.8476 - val_loss: 0.4729 -
val_accuracy: 0.7789 - 336ms/epoch - 876us/step
Epoch 128/200
384/384 - 0s - loss: 0.3382 - accuracy: 0.8478 - val_loss: 0.4362 -
val_accuracy: 0.8071 - 335ms/epoch - 873us/step
Epoch 129/200
384/384 - 0s - loss: 0.3372 - accuracy: 0.8487 - val_loss: 0.4967 -
val_accuracy: 0.7674 - 368ms/epoch - 957us/step
Epoch 130/200
384/384 - 0s - loss: 0.3372 - accuracy: 0.8489 - val_loss: 0.4173 -
val_accuracy: 0.8201 - 337ms/epoch - 878us/step
Epoch 131/200
384/384 - 0s - loss: 0.3384 - accuracy: 0.8483 - val_loss: 0.4603 -
val_accuracy: 0.7877 - 340ms/epoch - 886us/step
Epoch 132/200
384/384 - 0s - loss: 0.3363 - accuracy: 0.8494 - val_loss: 0.5081 -
val_accuracy: 0.7613 - 336ms/epoch - 875us/step
Epoch 133/200
384/384 - 0s - loss: 0.3369 - accuracy: 0.8495 - val_loss: 0.5359 -
val_accuracy: 0.7447 - 334ms/epoch - 870us/step
Epoch 134/200
384/384 - 0s - loss: 0.3372 - accuracy: 0.8489 - val_loss: 0.4527 -
val_accuracy: 0.7912 - 342ms/epoch - 891us/step
Epoch 135/200
384/384 - 0s - loss: 0.3369 - accuracy: 0.8493 - val_loss: 0.4725 -
val_accuracy: 0.7812 - 372ms/epoch - 970us/step
Epoch 136/200
384/384 - 0s - loss: 0.3370 - accuracy: 0.8489 - val_loss: 0.4738 -
val_accuracy: 0.7815 - 343ms/epoch - 893us/step
Epoch 137/200
384/384 - 0s - loss: 0.3369 - accuracy: 0.8495 - val_loss: 0.4220 -
val_accuracy: 0.8135 - 337ms/epoch - 877us/step
Epoch 138/200
384/384 - 0s - loss: 0.3364 - accuracy: 0.8498 - val_loss: 0.5121 -
val_accuracy: 0.7594 - 359ms/epoch - 936us/step
Epoch 139/200
384/384 - 0s - loss: 0.3370 - accuracy: 0.8502 - val_loss: 0.4185 -
val_accuracy: 0.8155 - 339ms/epoch - 883us/step
Epoch 140/200
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384/384 - 0s - loss: 0.3367 - accuracy: 0.8495 - val_loss: 0.4427 -
val_accuracy: 0.7977 - 339ms/epoch - 883us/step
Epoch 141/200
384/384 - 0s - loss: 0.3364 - accuracy: 0.8502 - val_loss: 0.4830 -
val_accuracy: 0.7765 - 337ms/epoch - 878us/step
Epoch 142/200
384/384 - 0s - loss: 0.3367 - accuracy: 0.8488 - val_loss: 0.4198 -
val_accuracy: 0.8122 - 339ms/epoch - 882us/step
Epoch 143/200
384/384 - 0s - loss: 0.3365 - accuracy: 0.8495 - val_loss: 0.4973 -
val_accuracy: 0.7717 - 339ms/epoch - 883us/step
Epoch 144/200
384/384 - 0s - loss: 0.3360 - accuracy: 0.8505 - val_loss: 0.3843 -
val_accuracy: 0.8356 - 340ms/epoch - 884us/step
Epoch 145/200
384/384 - 0s - loss: 0.3358 - accuracy: 0.8497 - val_loss: 0.4362 -
val_accuracy: 0.8056 - 339ms/epoch - 883us/step
Epoch 146/200
384/384 - 0s - loss: 0.3364 - accuracy: 0.8501 - val_loss: 0.4582 -
val_accuracy: 0.7905 - 335ms/epoch - 872us/step
Epoch 147/200
384/384 - 0s - loss: 0.3357 - accuracy: 0.8503 - val_loss: 0.4499 -
val_accuracy: 0.7977 - 355ms/epoch - 923us/step
Epoch 148/200
384/384 - 0s - loss: 0.3363 - accuracy: 0.8490 - val_loss: 0.5482 -
val_accuracy: 0.7411 - 337ms/epoch - 877us/step
Epoch 149/200
384/384 - 0s - loss: 0.3359 - accuracy: 0.8513 - val_loss: 0.4415 -
val_accuracy: 0.8003 - 348ms/epoch - 905us/step
Epoch 150/200
384/384 - 0s - loss: 0.3362 - accuracy: 0.8497 - val_loss: 0.4538 -
val_accuracy: 0.7965 - 347ms/epoch - 904us/step
Epoch 151/200
384/384 - 0s - loss: 0.3358 - accuracy: 0.8499 - val_loss: 0.4091 -
val_accuracy: 0.8227 - 342ms/epoch - 890us/step
Epoch 152/200
384/384 - 0s - loss: 0.3363 - accuracy: 0.8500 - val_loss: 0.4517 -
val_accuracy: 0.7998 - 341ms/epoch - 889us/step
Epoch 153/200
384/384 - 0s - loss: 0.3350 - accuracy: 0.8507 - val_loss: 0.5025 -
val_accuracy: 0.7698 - 335ms/epoch - 872us/step
Epoch 154/200
384/384 - 0s - loss: 0.3354 - accuracy: 0.8510 - val_loss: 0.5269 -
val_accuracy: 0.7484 - 338ms/epoch - 879us/step
Epoch 155/200
384/384 - 0s - loss: 0.3353 - accuracy: 0.8511 - val_loss: 0.5726 -
val_accuracy: 0.7253 - 336ms/epoch - 876us/step
Epoch 156/200
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384/384 - 0s - loss: 0.3350 - accuracy: 0.8514 - val_loss: 0.3951 -
val_accuracy: 0.8322 - 337ms/epoch - 878us/step
Epoch 157/200
384/384 - 0s - loss: 0.3353 - accuracy: 0.8509 - val_loss: 0.4970 -
val_accuracy: 0.7705 - 334ms/epoch - 870us/step
Epoch 158/200
384/384 - 0s - loss: 0.3349 - accuracy: 0.8514 - val_loss: 0.4367 -
val_accuracy: 0.8032 - 381ms/epoch - 992us/step
Epoch 159/200
384/384 - 0s - loss: 0.3359 - accuracy: 0.8503 - val_loss: 0.4719 -
val_accuracy: 0.7860 - 355ms/epoch - 924us/step
Epoch 160/200
384/384 - 0s - loss: 0.3350 - accuracy: 0.8511 - val_loss: 0.4391 -
val_accuracy: 0.8018 - 347ms/epoch - 905us/step
Epoch 161/200
384/384 - 0s - loss: 0.3346 - accuracy: 0.8511 - val_loss: 0.3732 -
val_accuracy: 0.8426 - 338ms/epoch - 880us/step
Epoch 162/200
384/384 - 0s - loss: 0.3345 - accuracy: 0.8512 - val_loss: 0.4926 -
val_accuracy: 0.7687 - 347ms/epoch - 904us/step
Epoch 163/200
384/384 - 0s - loss: 0.3350 - accuracy: 0.8512 - val_loss: 0.4497 -
val_accuracy: 0.8048 - 372ms/epoch - 969us/step
Epoch 164/200
384/384 - 0s - loss: 0.3348 - accuracy: 0.8507 - val_loss: 0.4787 -
val_accuracy: 0.7812 - 349ms/epoch - 908us/step
Epoch 165/200
384/384 - 0s - loss: 0.3343 - accuracy: 0.8521 - val_loss: 0.3971 -
val_accuracy: 0.8280 - 342ms/epoch - 892us/step
Epoch 166/200
384/384 - 0s - loss: 0.3341 - accuracy: 0.8510 - val_loss: 0.4337 -
val_accuracy: 0.8083 - 335ms/epoch - 872us/step
Epoch 167/200
384/384 - 0s - loss: 0.3341 - accuracy: 0.8511 - val_loss: 0.4546 -
val_accuracy: 0.7950 - 352ms/epoch - 917us/step
Epoch 168/200
384/384 - 0s - loss: 0.3340 - accuracy: 0.8511 - val_loss: 0.4351 -
val_accuracy: 0.8066 - 370ms/epoch - 963us/step
Epoch 169/200
384/384 - 0s - loss: 0.3343 - accuracy: 0.8522 - val_loss: 0.4710 -
val_accuracy: 0.7845 - 338ms/epoch - 880us/step
Epoch 170/200
384/384 - 0s - loss: 0.3341 - accuracy: 0.8514 - val_loss: 0.4360 -
val_accuracy: 0.8057 - 336ms/epoch - 875us/step
Epoch 171/200
384/384 - 0s - loss: 0.3337 - accuracy: 0.8522 - val_loss: 0.4600 -
val_accuracy: 0.7915 - 338ms/epoch - 881us/step
Epoch 172/200
```

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384/384 - 0s - loss: 0.3336 - accuracy: 0.8523 - val_loss: 0.4244 -
val_accuracy: 0.8124 - 350ms/epoch - 911us/step
Epoch 173/200
384/384 - 0s - loss: 0.3340 - accuracy: 0.8517 - val_loss: 0.4439 -
val_accuracy: 0.8042 - 360ms/epoch - 937us/step
Epoch 174/200
384/384 - 0s - loss: 0.3342 - accuracy: 0.8516 - val_loss: 0.4923 -
val_accuracy: 0.7756 - 352ms/epoch - 917us/step
Epoch 175/200
384/384 - 0s - loss: 0.3333 - accuracy: 0.8523 - val_loss: 0.4668 -
val_accuracy: 0.7903 - 340ms/epoch - 884us/step
Epoch 176/200
384/384 - 0s - loss: 0.3333 - accuracy: 0.8523 - val_loss: 0.4676 -
val_accuracy: 0.7894 - 341ms/epoch - 888us/step
Epoch 177/200
384/384 - 0s - loss: 0.3343 - accuracy: 0.8520 - val_loss: 0.4796 -
val_accuracy: 0.7834 - 347ms/epoch - 904us/step
Epoch 178/200
384/384 - 0s - loss: 0.3331 - accuracy: 0.8523 - val_loss: 0.4758 -
val_accuracy: 0.7892 - 349ms/epoch - 910us/step
Epoch 179/200
384/384 - 0s - loss: 0.3340 - accuracy: 0.8524 - val_loss: 0.4031 -
val_accuracy: 0.8230 - 353ms/epoch - 918us/step
Epoch 180/200
384/384 - 0s - loss: 0.3331 - accuracy: 0.8523 - val_loss: 0.4222 -
val_accuracy: 0.8146 - 342ms/epoch - 890us/step
Epoch 181/200
384/384 - 0s - loss: 0.3331 - accuracy: 0.8524 - val_loss: 0.4939 -
val_accuracy: 0.7736 - 343ms/epoch - 893us/step
Epoch 182/200
384/384 - 0s - loss: 0.3329 - accuracy: 0.8525 - val_loss: 0.5225 -
val_accuracy: 0.7587 - 343ms/epoch - 894us/step
Epoch 183/200
384/384 - 0s - loss: 0.3336 - accuracy: 0.8529 - val_loss: 0.5288 -
val_accuracy: 0.7527 - 409ms/epoch - 1ms/step
Epoch 184/200
384/384 - 0s - loss: 0.3331 - accuracy: 0.8525 - val_loss: 0.5177 -
val_accuracy: 0.7614 - 387ms/epoch - 1ms/step
Epoch 185/200
384/384 - 0s - loss: 0.3332 - accuracy: 0.8520 - val_loss: 0.4103 -
val_accuracy: 0.8219 - 378ms/epoch - 984us/step
Epoch 186/200
384/384 - 0s - loss: 0.3328 - accuracy: 0.8528 - val_loss: 0.4437 -
val_accuracy: 0.8026 - 415ms/epoch - 1ms/step
Epoch 187/200
384/384 - 0s - loss: 0.3329 - accuracy: 0.8526 - val_loss: 0.4202 -
val_accuracy: 0.8165 - 361ms/epoch - 939us/step
Epoch 188/200
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384/384 - 0s - loss: 0.3327 - accuracy: 0.8534 - val_loss: 0.5034 -
val_accuracy: 0.7722 - 349ms/epoch - 908us/step
Epoch 189/200
384/384 - 0s - loss: 0.3326 - accuracy: 0.8529 - val_loss: 0.4370 -
val_accuracy: 0.8053 - 385ms/epoch - 1ms/step
Epoch 190/200
384/384 - 0s - loss: 0.3327 - accuracy: 0.8523 - val_loss: 0.4524 -
val_accuracy: 0.7988 - 361ms/epoch - 940us/step
Epoch 191/200
384/384 - 0s - loss: 0.3322 - accuracy: 0.8530 - val_loss: 0.4643 -
val_accuracy: 0.7918 - 341ms/epoch - 888us/step
Epoch 192/200
384/384 - 0s - loss: 0.3318 - accuracy: 0.8529 - val_loss: 0.4650 -
val_accuracy: 0.7940 - 362ms/epoch - 942us/step
Epoch 193/200
384/384 - 0s - loss: 0.3331 - accuracy: 0.8533 - val_loss: 0.4616 -
val_accuracy: 0.7969 - 379ms/epoch - 986us/step
Epoch 194/200
384/384 - 0s - loss: 0.3324 - accuracy: 0.8527 - val_loss: 0.4275 -
val_accuracy: 0.8102 - 365ms/epoch - 950us/step
Epoch 195/200
384/384 - 0s - loss: 0.3326 - accuracy: 0.8532 - val_loss: 0.4739 -
val_accuracy: 0.7874 - 355ms/epoch - 925us/step
Epoch 196/200
384/384 - 0s - loss: 0.3321 - accuracy: 0.8533 - val_loss: 0.4592 -
val_accuracy: 0.7939 - 355ms/epoch - 924us/step
Epoch 197/200
384/384 - 0s - loss: 0.3326 - accuracy: 0.8537 - val_loss: 0.4700 -
val_accuracy: 0.7900 - 355ms/epoch - 924us/step
Epoch 198/200
384/384 - 0s - loss: 0.3317 - accuracy: 0.8534 - val_loss: 0.4452 -
val_accuracy: 0.8056 - 368ms/epoch - 957us/step
Epoch 199/200
384/384 - 0s - loss: 0.3316 - accuracy: 0.8530 - val_loss: 0.4899 -
val_accuracy: 0.7747 - 351ms/epoch - 913us/step
Epoch 200/200
384/384 - 0s - loss: 0.3320 - accuracy: 0.8528 - val_loss: 0.3908 -
val_accuracy: 0.8341 - 340ms/epoch - 887us/step
```

[180]:
```
<keras.callbacks.History at 0x7fc998783f70>
```

[181]:
```
oversample_predictions = oversample_model.predict(original_Xtest, batch_size=200, verbose=0)
```

[182]:
```
oversample_default_predictions = np.argmax(oversample_model.predict(original_Xtest), axis = -1)
```

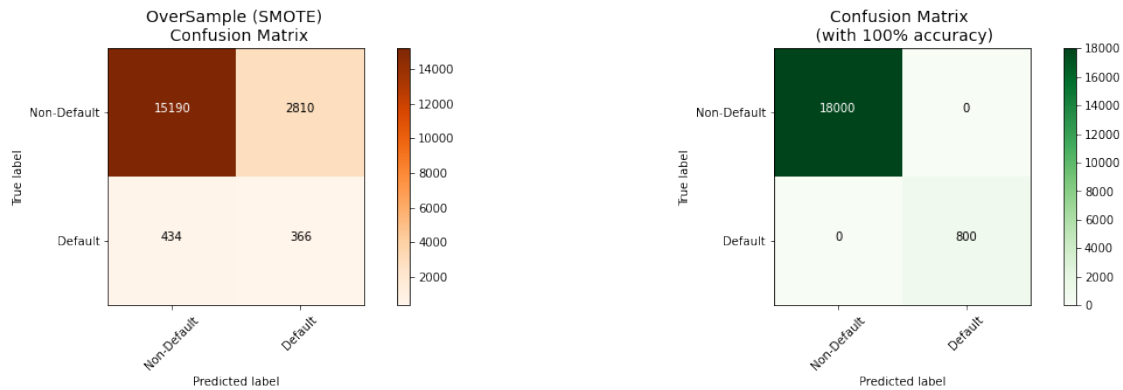
[190]:
```python
oversample_smote = confusion_matrix(original_ytest,␣
 ↪oversample_default_predictions)
actual_cm = confusion_matrix(original_ytest, original_ytest)
labels = ['Non-Default', 'Default']

fig = plt.figure(figsize=(16,8))

fig.add_subplot(221)
plot_confusion_matrix(oversample_smote, labels, title="OverSample (SMOTE) \n␣
 ↪Confusion Matrix", cmap=plt.cm.Oranges)

fig.add_subplot(222)
plot_confusion_matrix(actual_cm, labels, title="Confusion Matrix \n (with 100%␣
 ↪accuracy)", cmap=plt.cm.Greens)
```

```
Confusion matrix, without normalization
[[15190  2810]
 [  434   366]]
Confusion matrix, without normalization
[[18000     0]
 [    0   800]]
```



[196]:
```python
undersample_nn_score = roc_auc_score(original_ytest,␣
 ↪undersample_default_predictions)
oversample_nn_score = roc_auc_score(original_ytest,␣
 ↪oversample_default_predictions)

method = ['UnderSample', 'OverSample']
auc_score = [undersample_nn_score,oversample_nn_score]

nn_table = pd.DataFrame({'Method':method,
                         'AUC':auc_score})
nn_table
```

[196]:
```
        Method       AUC
0  UnderSample  0.755000
1   OverSample  0.650694
```

4.3 Other models Test

[186]:
```
undersample_knn_pred = knears_neighbors.predict(original_Xtest)
undersample_svc_pred = svc.predict(original_Xtest)
undersample_tree_pred = tree_clf.predict(original_Xtest)
undersample_gbt_pred = gbt_clf.predict(original_Xtest)

undersample_knn_score = roc_auc_score(original_ytest,undersample_knn_pred)
undersample_svc_score = roc_auc_score(original_ytest,undersample_svc_pred)
undersample_tree_score = roc_auc_score(original_ytest,undersample_tree_pred)
undersample_gbt_score = roc_auc_score(original_ytest,undersample_gbt_pred)
```

[188]:
```
model = ['KNN','SVM','Decision Tree','GBT']
under_score = [undersample_knn_score, undersample_svc_score,␣
 ↪undersample_tree_score, undersample_gbt_score]

under_table = pd.DataFrame({'Model':model,
                            'AUC':under_score})
under_table
```

[188]:
```
           Model       AUC
0            KNN  0.747667
1            SVM  0.748917
2  Decision Tree  0.733486
3            GBT  0.750958
```

5 Summary

- Faced with such imbalanced dataset, in this notebook, we introduce two methods: UnderSampling by NearMiss and OverSampling by SMOTE. **Undesampling** takes samples of majority class. **Oversampling** copies of the minority class. They treat the dataset by two different ways but they both create a sub dataframe with a 50/50 ratio of default and non-default.
- While facing imbalanced dataset, accuracy may not be a suitable metric, because the model may simply predict the majority class to have a high enough accuracy. As a result, we are going to use the auc score for the model performance in our case.
- There is also a quite common cross validation overfitting mistake. If you are going to perform undersample of oversample the data, you should not do it before cross-validation. The reason is that doing so will directly infulencing the validation set before implementing cross-validation, leading to a data leakage problem.
- In our case, we mainly inplement the undersampling method. And the model I used in this case includes Logistic Regression, K Nearst Neighbors, Support Vector Machine, Decision Tree and Gradient Boosting. And I also implement a naive neural network. We made a

comparison for undersampling method and oversampling method on the logistic regression and neural network.

- Based on the performance dataframe, we can draw the conclusion that, the logistic regression has a higher auc score based on the OverSampling method. And the naive neural network has a higher auc score than the other models based on the UnderSampling method. But since the neural network is quite naive, I am gonna also add the Gradient Boosting Model to validate using val.csv

6 Validation

[198]:
```
val = pd.read_csv('val.csv')
val.head()
```

[198]:
```
      A1     A2        A3        A4     A5     A6    A7      A8     A9    A10  \
0  22.88  75.59   3367.08   6131.31  41.38  43.08  2.13  102.67  0.500  0.500
1  15.94  86.26   5595.00  10867.86  52.29  61.21  3.05  124.94  3.200  2.400
2  25.16  64.20   4758.44   7818.15  46.28  50.72  2.69  110.16  1.124  0.889
3  19.50  77.81   5762.27   6290.00  58.14  76.27  2.44  119.92  1.222  1.000
4  11.11  85.09  11400.50  20936.25  30.00  29.75  0.50  125.89  2.167  1.333

   …   A22   A23   A24   A25     A26      A27     A28    A29    A30  default
0  …  0.08  0.00  0.05  0.17    0.00  1035.14  158.71  13.28   0.00        1
1  …  0.01  0.00  0.00  0.06  438.50     0.00   72.78  44.88  25.39        1
2  …  0.08  0.02  0.02  0.10  622.70   755.52  102.89   6.24   0.00        1
3  …  0.04  0.00  0.01  0.08  197.55   396.27   76.34   8.44   2.00        1
4  …  0.00  0.00  0.00  0.04    0.00     0.00    0.00   0.00   0.00        1

[5 rows x 31 columns]
```

[212]:
```
model = pd.read_csv('model.csv')
model.head()
```

[212]:
```
      A1     A2       A3        A4     A5     A6    A7      A8     A9    A10  \
0  10.69  86.10  8920.16  19912.85  30.42  31.72  1.18  145.41  2.236  1.786
1  28.50  65.19  6564.00   6716.67  32.50  23.40  2.74   91.11  1.000  1.000
2  24.87  73.79  4285.47   6463.75  40.50  51.53  2.84   93.90  2.400  1.400
3  13.64  85.82  6887.56   9244.44  49.56  53.44  0.36  171.45  1.875  2.167
4   4.50  95.92  8746.50  19987.50  32.75  37.88  0.92  153.25  2.000  1.500

   …   A22   A23   A24   A25      A26     A27     A28    A29    A30  default
0  …  0.01  0.01  0.01  0.13     0.00    0.00    0.00   0.00   0.00        0
1  …  0.06  0.01  0.00  0.09   285.80    0.00   16.44   1.98  42.26        0
2  …  0.08  0.02  0.02  0.44   494.62  135.41  127.45  46.00  14.92        0
3  …  0.03  0.01  0.00  0.05  1015.19    0.00  210.63  92.58   0.00        0
4  …  0.01  0.00  0.00  0.04     0.00  106.41   79.00   0.00   0.00        0
```

```
[5 rows x 31 columns]
```

[213]:
```python
X_val = val.drop('default',axis=1)
y_val = val['default']

X_model = model.drop('default',axis=1)
y_model = model.drop('default',axis=1)

# In order to avoid data leakage, we use the statistical data from model.csv to
 ↪scale the valid data
rob_scaler = RobustScaler()
X_scaled_model = rob_scaler.fit_transform(X_model)
X_scaled_val = rob_scaler.transform(X_val)
```

[220]:
```python
# Logistic Regression

y_pred_val_lr = best_est.predict(X_scaled_val)

# Performance
val_auc_lr = round(roc_auc_score(y_val, y_pred_val_lr),3)
```

[221]:
```python
# Neural Network

y_pred_val_nn = np.argmax(undersample_model.predict(X_scaled_val), axis = -1)

# Performance
val_auc_nn = round(roc_auc_score(y_val, y_pred_val_nn),3)
```

[222]:
```python
# Gradient Boosting

y_pred_val_gbt = gbt_clf.predict(X_scaled_val)

# Performance
val_auc_gbt = round(roc_auc_score(y_val, y_pred_val_gbt),3)
```

[223]:
```python
model = ['Logistic Regression', 'Neural Network', 'Gradient Boosting']
auc_score = [val_auc_lr, val_auc_nn, val_auc_gbt]

val_table = pd.DataFrame({'Model':model,
                          'Performance':auc_score})
val_table
```

[223]:

	Model	Performance
0	Logistic Regression	0.745
1	Neural Network	0.673
2	Gradient Boosting	0.757

[227]:

```
pd.DataFrame(y_pred_val_lr).to_csv('results1.csv',index=False,header=False)
```

[228]:

```
pd.DataFrame(y_pred_val_gbt).to_csv('results2.csv',index=False,header=False)
```

[ ]:

```

```