FinalProject_creditcardfraud

April 19, 2021

1 Import necessary libraries for building models

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
import warnings

warnings.filterwarnings("ignore")

dataset = pd.read_csv('creditcard.csv')
RANDOM_STATE = 0
```

2 Analyzing the dataset to make decision for building model

[2]:
```
# The info show us that there are no null value
# Therefore, we does not have to treat the null value.

dataset.info()
```

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

```
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```

[3]:
```
dataset.describe()
```

[3]:
```
                Time            V1            V2            V3            V4  \
count  284807.000000  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean    94813.859575  1.165980e-15  3.416908e-16 -1.373150e-15  2.086869e-15
std     47488.145955  1.958696e+00  1.651309e+00  1.516255e+00  1.415869e+00
min         0.000000 -5.640751e+01 -7.271573e+01 -4.832559e+01 -5.683171e+00
25%     54201.500000 -9.203734e-01 -5.985499e-01 -8.903648e-01 -8.486401e-01
50%     84692.000000  1.810880e-02  6.548556e-02  1.798463e-01 -1.984653e-02
75%    139320.500000  1.315642e+00  8.037239e-01  1.027196e+00  7.433413e-01
max    172792.000000  2.454930e+00  2.205773e+01  9.382558e+00  1.687534e+01

                 V5            V6            V7            V8            V9  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean   9.604066e-16  1.490107e-15 -5.556467e-16  1.177556e-16 -2.406455e-15
std    1.380247e+00  1.332271e+00  1.237094e+00  1.194353e+00  1.098632e+00
min   -1.137433e+02 -2.616051e+01 -4.355724e+01 -7.321672e+01 -1.343407e+01
25%   -6.915971e-01 -7.682956e-01 -5.540759e-01 -2.086297e-01 -6.430976e-01
50%   -5.433583e-02 -2.741871e-01  4.010308e-02  2.235804e-02 -5.142873e-02
75%    6.119264e-01  3.985649e-01  5.704361e-01  3.273459e-01  5.971390e-01
max    3.480167e+01  7.330163e+01  1.205895e+02  2.000721e+01  1.559499e+01

       …            V21           V22           V23           V24  \
```

```
count  …  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean   …  1.656562e-16 -3.444850e-16  2.578648e-16  4.471968e-15
std    …  7.345240e-01  7.257016e-01  6.244603e-01  6.056471e-01
min    … -3.483038e+01 -1.093314e+01 -4.480774e+01 -2.836627e+00
25%    … -2.283949e-01 -5.423504e-01 -1.618463e-01 -3.545861e-01
50%    … -2.945017e-02  6.781943e-03 -1.119293e-02  4.097606e-02
75%    …  1.863772e-01  5.285536e-01  1.476421e-01  4.395266e-01
max    …  2.720284e+01  1.050309e+01  2.252841e+01  4.584549e+00

                V25           V26           V27           V28         Amount  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  284807.000000
mean   5.340915e-16  1.687098e-15 -3.666453e-16 -1.220404e-16      88.349619
std    5.212781e-01  4.822270e-01  4.036325e-01  3.300833e-01     250.120109
min   -1.029540e+01 -2.604551e+00 -2.256568e+01 -1.543008e+01       0.000000
25%   -3.171451e-01 -3.269839e-01 -7.083953e-02 -5.295979e-02       5.600000
50%    1.659350e-02 -5.213911e-02  1.342146e-03  1.124383e-02      22.000000
75%    3.507156e-01  2.409522e-01  9.104512e-02  7.827995e-02      77.165000
max    7.519589e+00  3.517346e+00  3.161220e+01  3.384781e+01   25691.160000

               Class
count  284807.000000
mean        0.001727
std         0.041527
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         1.000000

[8 rows x 31 columns]
```

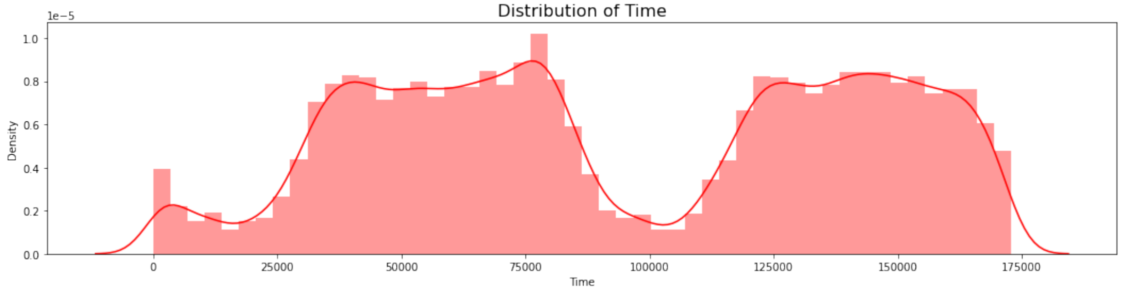
[4]:
```
# Check the percentage of fraud and non-fraud transaction
non_fraud_trans = dataset['Class'].value_counts()[0] # number of non-fraud␣
↪transaction
fraud_trans = dataset['Class'].value_counts()[1] # number of fraud transaction
total_trans = len(dataset) # total number of transactions in the whole datasets
print('No Frauds =', non_fraud_trans, "which equal", round(non_fraud_trans/
↪total_trans * 100, 2), '% of the dataset')
print('Frauds =', fraud_trans, "which equal", round(fraud_trans/total_trans *␣
↪100,2), '% of the dataset')

# The result show us that the dataset for credit card fraud is really␣
↪imbalanced
# because we have 99.83% of the dataset is non-fraudulent
# and only 0.17% of the dataset is fradulent transaction
```

```
No Frauds = 284315 which equal 99.83 % of the dataset
```

```
Frauds = 492 which equal 0.17 % of the dataset
```

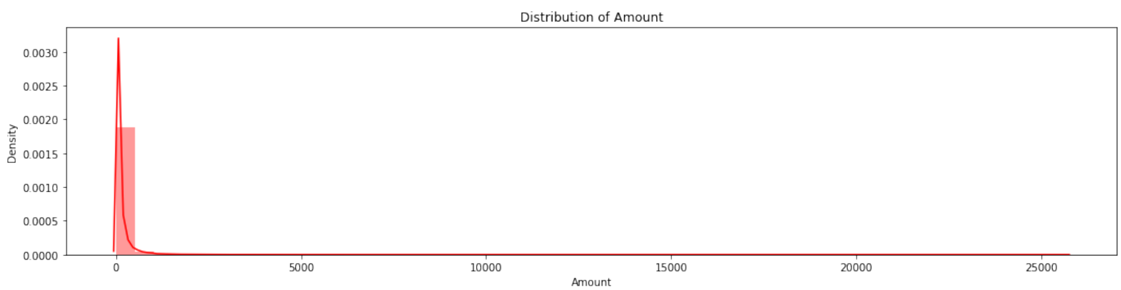
[5]:
```python
plt.figure(figsize=(18,4))
plt.title('Distribution of Time', fontsize = 16)
sns.distplot(dataset.Time, color = 'r')
```

[5]:
```
<AxesSubplot:title={'center':'Distribution of Time'}, xlabel='Time',
ylabel='Density'>
```



[6]:
```python
plt.figure(figsize=(18,4))
plt.title('Distribution of Amount')
sns.distplot(dataset.Amount, color = 'r')
```

[6]:
```
<AxesSubplot:title={'center':'Distribution of Amount'}, xlabel='Amount',
ylabel='Density'>
```



3 Preprocessing Technique

1. Scaling and Distributing
2. Spliting dataset

[7]:
```python
# Scaling and Distributing
# Since the whole dataset is already scaled except for the time and amount
```

```
# thus we have to scale the time and amount columns of the dataset before we␣
↪working on building models

std_scaler = StandardScaler()

dataset.insert(0, 'scaled_amount', std_scaler.fit_transform(dataset['Amount'].
↪values.reshape(-1,1)))
dataset.insert(1, 'scaled_time', std_scaler.fit_transform(dataset['Time'].
↪values.reshape(-1,1)))
```

[8]:
```
dataset.drop(['Amount','Time'], axis = 1, inplace = True)
```

[9]:
```
dataset.head() # Use this to make visualize the datset after the modification␣
↪above
```

[9]:
```
   scaled_amount  scaled_time        V1        V2        V3        V4  \
0       0.244964    -1.996583 -1.359807 -0.072781  2.536347  1.378155
1      -0.342475    -1.996583  1.191857  0.266151  0.166480  0.448154
2       1.160686    -1.996562 -1.358354 -1.340163  1.773209  0.379780
3       0.140534    -1.996562 -0.966272 -0.185226  1.792993 -0.863291
4      -0.073403    -1.996541 -1.158233  0.877737  1.548718  0.403034

         V5        V6        V7        V8  …       V20       V21       V22  \
0 -0.338321  0.462388  0.239599  0.098698  …  0.251412 -0.018307  0.277838
1  0.060018 -0.082361 -0.078803  0.085102  … -0.069083 -0.225775 -0.638672
2 -0.503198  1.800499  0.791461  0.247676  …  0.524980  0.247998  0.771679
3 -0.010309  1.247203  0.237609  0.377436  … -0.208038 -0.108300  0.005274
4 -0.407193  0.095921  0.592941 -0.270533  …  0.408542 -0.009431  0.798278

        V23       V24       V25       V26       V27       V28  Class
0 -0.110474  0.066928  0.128539 -0.189115  0.133558 -0.021053      0
1  0.101288 -0.339846  0.167170  0.125895 -0.008983  0.014724      0
2  0.909412 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752      0
3 -0.190321 -1.175575  0.647376 -0.221929  0.062723  0.061458      0
4 -0.137458  0.141267 -0.206010  0.502292  0.219422  0.215153      0

[5 rows x 31 columns]
```

[10]:
```
X = dataset.iloc[:, dataset.columns != 'Class']
y = dataset['Class']
```

[11]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.4,␣
↪random_state = RANDOM_STATE)

X_test, X_val, y_test, y_val = train_test_split(X_test, y_test, test_size = 0.
↪5, random_state = RANDOM_STATE)
```

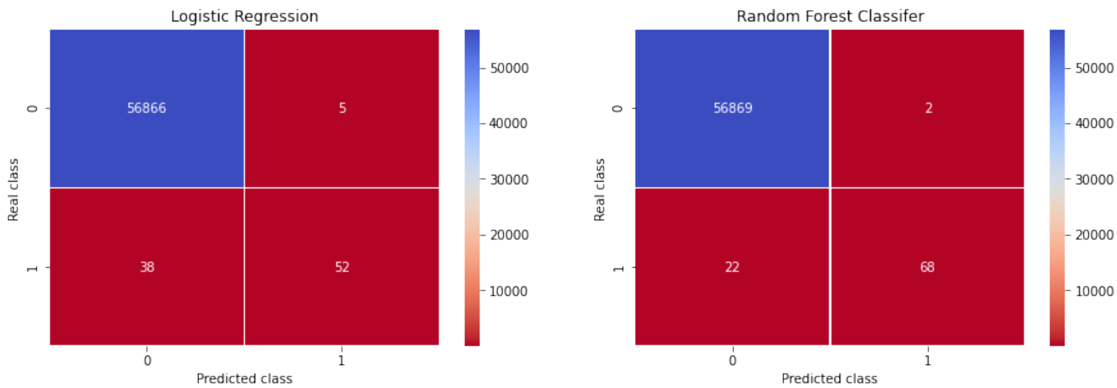
4 Use simple parameter for Learning Algorithm on the imbalance dataset to prove that the model will be overfiting if we don't use the resample training set

[12]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier

# Use Logistic Regression on original dataset
lr = LogisticRegression(random_state = RANDOM_STATE).fit(X_train, y_train)
y_lr_pred = lr.predict(X_test)

# User Random Forest on undersample dataset
rfc = RandomForestClassifier(random_state = RANDOM_STATE).fit(X_train, y_train)
y_rf_pred = rfc.predict(X_test)
```

5 Use confusion matrix to visualize the original dataset

[13]:
```
from sklearn.metrics import confusion_matrix

# Logistic Regression confusion matrix
lr_cm = confusion_matrix(y_test, y_lr_pred)

# Random Forest confusino matrix
rf_cm = confusion_matrix(y_test, y_rf_pred)
```

[14]:
```
fig= plt.figure(figsize=(15,10))

ax1 = fig.add_subplot(2,2,1)
sns.heatmap(lr_cm, cmap="coolwarm_r",annot=True, fmt = "", linewidths=0.5)
plt.title("Logistic Regression")
plt.xlabel("Predicted class")
plt.ylabel("Real class")

ax2 = fig.add_subplot(2,2,2)
sns.heatmap(rf_cm, cmap="coolwarm_r",annot=True, fmt = "", linewidths=0.5)
plt.title("Random Forest Classifier")
plt.xlabel("Predicted class")
plt.ylabel("Real class")

plt.show()

# TN = 0,0 no. of normal transaction which are predited normal
# FP = 0,1 no of normal transaction which are predicted fraud
# FN = 1,0 no of fraud Transaction which are predicted normal
# TP = 1,1 no of fraud transaction which are predicted fraud
```



[15]:
```
from sklearn.metrics import classification_report

print("\t\t Overfitting Log Regression \n\n",classification_report(y_test,␣
↪y_lr_pred))

print("\t\t Overfitting RF \n\n",classification_report(y_test, y_rf_pred))
```

```
                 Overfitting Log Regression

               precision    recall  f1-score   support

           0       1.00      1.00      1.00     56871
           1       0.91      0.58      0.71        90

    accuracy                           1.00     56961
   macro avg       0.96      0.79      0.85     56961
weighted avg       1.00      1.00      1.00     56961

                 Overfitting RF

               precision    recall  f1-score   support

           0       1.00      1.00      1.00     56871
           1       0.97      0.76      0.85        90

    accuracy                           1.00     56961
   macro avg       0.99      0.88      0.92     56961
weighted avg       1.00      1.00      1.00     56961
```

[16]:
```
# This is still preprocessing datatset
from imblearn.under_sampling import RandomUnderSampler
```

```
undersample = RandomUnderSampler(sampling_strategy='majority')
X_train_us, y_train_us= undersample.fit_resample(X_train, y_train)
```

6 Use GridSearchCV to find the best parameters for each classifier on the resample dataset

1. Find the best parameters for Logistic Regression on resampled dataset

[17]:
```
from sklearn.model_selection import GridSearchCV

lr_params = {"penalty": ['l1', 'l2'],
             'C': [0.001, 0.01, 0.1, 1, 10, 100, 1000]}

grid_lr = GridSearchCV(LogisticRegression(), lr_params)

grid_lr.fit(X_train_us, y_train_us)
```

[17]:
```
GridSearchCV(estimator=LogisticRegression(),
             param_grid={'C': [0.001, 0.01, 0.1, 1, 10, 100, 1000],
                         'penalty': ['l1', 'l2']})
```

[18]:
```
grid_lr.best_params_
```

[18]:
```
{'C': 0.01, 'penalty': 'l2'}
```

2. Find the best parameters for Support Vector Machine on original dataset and resampled dataset

[19]:
```
rf_params = {'n_estimators': [8, 16, 64, 200],
             'max_depth': [None,10,50,200,1000]}

grid_rf = GridSearchCV(RandomForestClassifier(), rf_params)

grid_rf.fit(X_train_us, y_train_us)
```

[19]:
```
GridSearchCV(estimator=RandomForestClassifier(),
             param_grid={'max_depth': [None, 10, 50, 200, 1000],
                         'n_estimators': [8, 16, 64, 200]})
```

[20]:
```
grid_rf.best_params_
```

[20]:
```
{'max_depth': 1000, 'n_estimators': 200}
```

7 Fit the dataset with the classifier

1. Fit train dataset on Logistic Regression Classifier

[21]:
```
lr = LogisticRegression(C = 0.01, penalty ='l2', random_state=RANDOM_STATE)
lr.fit(X_train_us, y_train_us)
y_lr_pred = lr.predict(X_test)
```

2. Fit train dataset on Random Forest

[22]:
```
rf = RandomForestClassifier(max_depth = None, n_estimators = 16)
rf.fit(X_train_us, y_train_us)
y_rf_pred = rf.predict(X_test)
```

[40]:
```
from sklearn.model_selection import cross_val_score

lr_cv_score = cross_val_score(lr, X_train_us, y_train_us, cv=5)

print("Logistic Regression has",round(lr_cv_score.mean(), 2) * 100, "% cross␣
 ↪validation score")

rf_cv_score = cross_val_score(rf, X_train_us, y_train_us, cv=5)

print("Random Forest Classifier has",round(rf_cv_score.mean(), 2) * 100, "%␣
 ↪cross validation score")
```

```
Logistic Regression has 94.0 % cross validation score
Random Forest Classifier has 93.0 % cross validation score
```

8 Use confusion matrix for visualization

[24]:
```
from sklearn.metrics import confusion_matrix

# Logistic Regression confusion matrix
lr_cm = confusion_matrix(y_test, y_lr_pred)

# Support Vector Classififer confusion matrix
rf_cm = confusion_matrix(y_test, y_rf_pred)
```

[44]:
```
lr_cm
```

[44]:
```
array([[56213,   658],
       [   14,    76]], dtype=int64)
```

[45]:
```
rf_cm
```

[45]:
```
array([[55287,  1584],
       [   13,    77]], dtype=int64)
```

[42]:
```
print("\t\t Resampled Log Regression \n\n",classification_report(y_test,␣
 ↪y_lr_pred))
```

```
print("\t\t Resampled Random Forest \n\n",classification_report(y_test,␣
↪y_rf_pred))
```

```
                  Resampled Log Regression

                precision    recall  f1-score   support

           0       1.00      0.99      0.99     56871
           1       0.10      0.84      0.18        90

    accuracy                           0.99     56961
   macro avg       0.55      0.92      0.59     56961
weighted avg       1.00      0.99      0.99     56961

                  Resampled Random Forest

                precision    recall  f1-score   support

           0       1.00      0.97      0.99     56871
           1       0.05      0.86      0.09        90

    accuracy                           0.97     56961
   macro avg       0.52      0.91      0.54     56961
weighted avg       1.00      0.97      0.98     56961
```

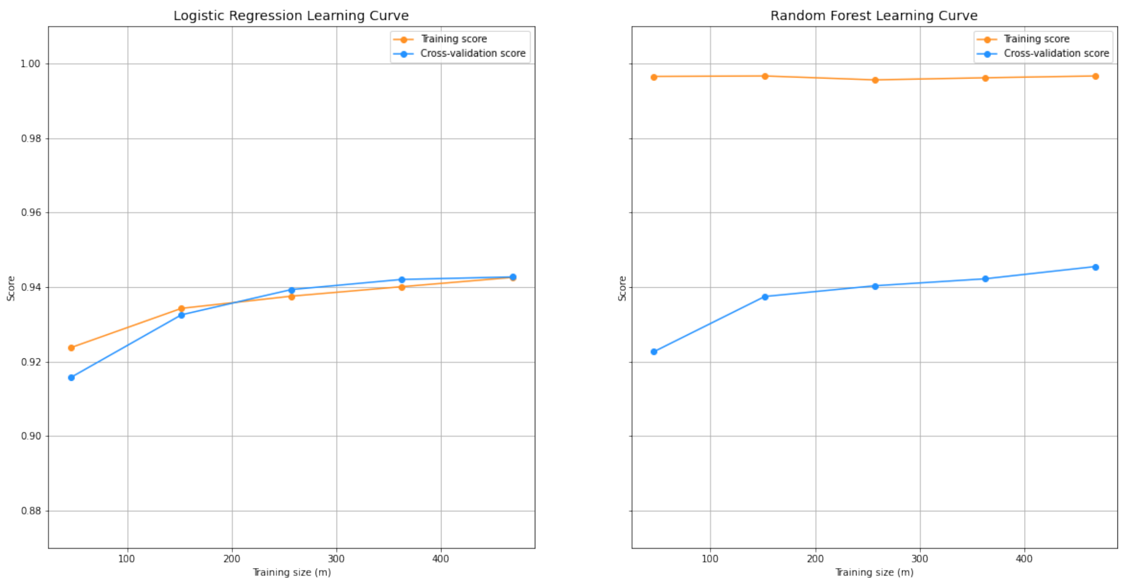
[51]:

```
# Let's Plot LogisticRegression Learning Curve
from sklearn.model_selection import ShuffleSplit
from sklearn.model_selection import learning_curve

def plot_learning_curve(estimator1, estimator2, X, y, ylim=None, cv=None,␣
↪n_jobs=1, train_sizes=np.linspace(.1, 1.0, 5)):

    f, (ax1, ax2) = plt.subplots(1,2, figsize=(20,10), sharey=True)

    if ylim is not None:
        plt.ylim(*ylim)

    # First Estimator
    train_sizes, train_scores, test_scores = learning_curve(estimator1, X, y,␣
↪cv=cv, n_jobs=n_jobs, train_sizes=train_sizes)

    ax1.plot(train_sizes, np.mean(train_scores, axis=1), 'o-', color="#ff9124",␣
↪label="Training score")
    ax1.plot(train_sizes, np.mean(test_scores, axis=1), 'o-', color="#2492ff",␣
↪label="Cross-validation score")
```

```
    ax1.set_title("Logistic Regression Learning Curve", fontsize=14)
    ax1.set_xlabel('Training size (m)')
    ax1.set_ylabel('Score')
    ax1.grid(True)
    ax1.legend(loc="best")

    # Second Estimator
    train_sizes, train_scores, test_scores = learning_curve( estimator2, X, y,␣
↪cv=cv, n_jobs=n_jobs, train_sizes=train_sizes)

    ax2.plot(train_sizes, np.mean(train_scores, axis=1), 'o-', color="#ff9124",␣
↪label="Training score")
    ax2.plot(train_sizes, np.mean(test_scores, axis=1), 'o-', color="#2492ff",␣
↪label="Cross-validation score")

    ax2.set_title("Random Forest Learning Curve", fontsize=14)
    ax2.set_xlabel('Training size (m)')
    ax2.set_ylabel('Score')
    ax2.grid(True)
    ax2.legend(loc="best")

    return plt
```

[52]:
```
cv = ShuffleSplit(n_splits=100, test_size=0.2, random_state=0)

plot_learning_curve(lr, rf, X_train_us, y_train_us, (0.87, 1.01), cv=cv,␣
↪n_jobs=2)
```

[52]:
```
<module 'matplotlib.pyplot' from 'D:\\Python\\lib\\site-
packages\\matplotlib\\pyplot.py'>
```



[ ]:

[29]:
```
import tensorflow as tf
from tensorflow 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 keras.optimizers import Adam
from keras.metrics import categorical_crossentropy

n_inputs = X_train_us.shape[1]

nn_model = keras.models.Sequential([
    keras.layers.Dense(n_inputs, input_shape=(n_inputs, ), activation='relu'),
    keras.layers.Dense(32, activation = "relu"),
    keras.layers.Dense(2, activation = "softmax")
])
```

[30]:
```
nn_model.compile(optimizer="adam", loss='sparse_categorical_crossentropy',␣
↪metrics=['accuracy'])
```

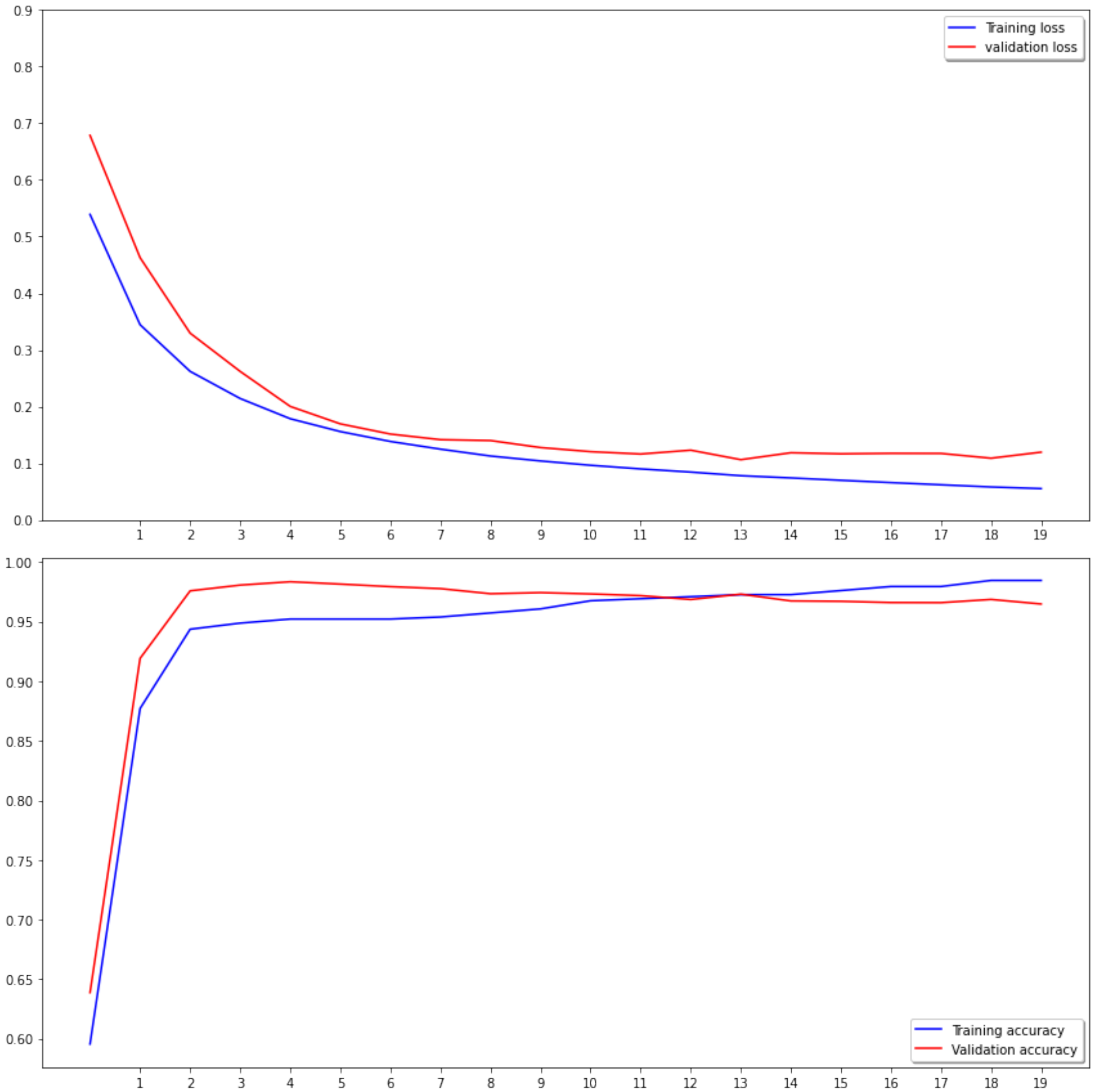
[32]:
```
epoch = 20

history = nn_model.fit(X_train_us, y_train_us, validation_data=(X_val,y_val),␣
↪batch_size=25, epochs = epoch, shuffle=True, verbose=2)
```

```
Epoch 1/20
WARNING:tensorflow:Callbacks method `on_test_batch_end` is slow compared to the
batch time (batch time: 0.0000s vs `on_test_batch_end` time: 0.0010s). Check
your callbacks.
24/24 - 2s - loss: 0.5391 - accuracy: 0.5956 - val_loss: 0.6786 - val_accuracy:
0.6388
Epoch 2/20
24/24 - 2s - loss: 0.3445 - accuracy: 0.8771 - val_loss: 0.4628 - val_accuracy:
0.9192
Epoch 3/20
24/24 - 2s - loss: 0.2622 - accuracy: 0.9437 - val_loss: 0.3296 - val_accuracy:
0.9759
Epoch 4/20
24/24 - 2s - loss: 0.2143 - accuracy: 0.9488 - val_loss: 0.2621 - val_accuracy:
0.9807
Epoch 5/20
24/24 - 2s - loss: 0.1786 - accuracy: 0.9522 - val_loss: 0.2003 - val_accuracy:
0.9835
```

```
Epoch 6/20
24/24 - 2s - loss: 0.1560 - accuracy: 0.9522 - val_loss: 0.1696 - val_accuracy:
0.9815
Epoch 7/20
24/24 - 2s - loss: 0.1385 - accuracy: 0.9522 - val_loss: 0.1516 - val_accuracy:
0.9794
Epoch 8/20
24/24 - 2s - loss: 0.1249 - accuracy: 0.9539 - val_loss: 0.1417 - val_accuracy:
0.9777
Epoch 9/20
24/24 - 2s - loss: 0.1128 - accuracy: 0.9573 - val_loss: 0.1401 - val_accuracy:
0.9735
Epoch 10/20
24/24 - 2s - loss: 0.1041 - accuracy: 0.9608 - val_loss: 0.1278 - val_accuracy:
0.9744
Epoch 11/20
24/24 - 2s - loss: 0.0965 - accuracy: 0.9676 - val_loss: 0.1205 - val_accuracy:
0.9733
Epoch 12/20
24/24 - 2s - loss: 0.0901 - accuracy: 0.9693 - val_loss: 0.1163 - val_accuracy:
0.9719
Epoch 13/20
24/24 - 2s - loss: 0.0845 - accuracy: 0.9710 - val_loss: 0.1231 - val_accuracy:
0.9686
Epoch 14/20
24/24 - 2s - loss: 0.0781 - accuracy: 0.9727 - val_loss: 0.1064 - val_accuracy:
0.9731
Epoch 15/20
24/24 - 2s - loss: 0.0742 - accuracy: 0.9727 - val_loss: 0.1186 - val_accuracy:
0.9674
Epoch 16/20
24/24 - 2s - loss: 0.0700 - accuracy: 0.9761 - val_loss: 0.1167 - val_accuracy:
0.9671
Epoch 17/20
24/24 - 2s - loss: 0.0659 - accuracy: 0.9795 - val_loss: 0.1175 - val_accuracy:
0.9661
Epoch 18/20
24/24 - 2s - loss: 0.0620 - accuracy: 0.9795 - val_loss: 0.1174 - val_accuracy:
0.9660
Epoch 19/20
24/24 - 1s - loss: 0.0582 - accuracy: 0.9846 - val_loss: 0.1090 - val_accuracy:
0.9687
Epoch 20/20
24/24 - 1s - loss: 0.0553 - accuracy: 0.9846 - val_loss: 0.1196 - val_accuracy:
0.9649
```

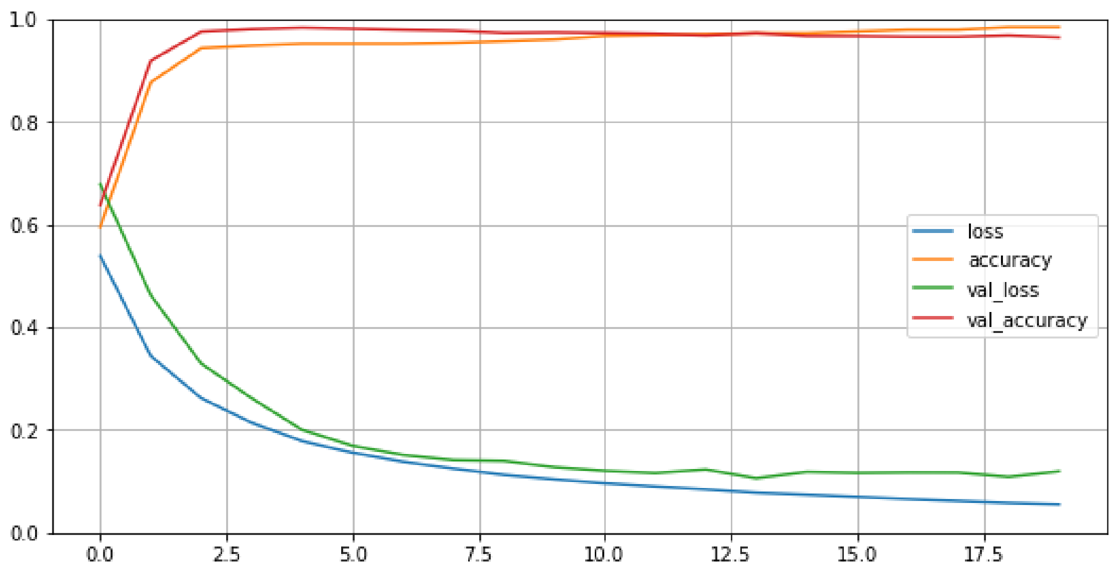
[33]:

```
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(12, 12))
ax1.plot(history.history['loss'], color='b', label="Training loss")
ax1.plot(history.history['val_loss'], color='r', label="validation loss")
ax1.set_xticks(np.arange(1, epoch, 1))
ax1.set_yticks(np.arange(0, 1, 0.1))
ax1.legend(loc='best', shadow=True)

ax2.plot(history.history['accuracy'], color='b', label="Training accuracy")
ax2.plot(history.history['val_accuracy'], color='r',label="Validation accuracy")
ax2.set_xticks(np.arange(1, epoch, 1))
ax2.legend(loc='best', shadow=True)

plt.tight_layout()
plt.show()
```



[34]:
```
pd.DataFrame(history.history).plot(figsize=(10,5))
plt.grid(True)
plt.gca().set_ylim(0,1)
```

[34]: (0.0, 1.0)



[41]:
```
history.model.evaluate(X_test, y_test)
```

```
1781/1781 [==============================] - 1s 841us/step - loss: 0.1160 -
accuracy: 0.9660
```

[41]: [0.11600951850414276, 0.9659942984580994]