

# INM427 Neural Computing

## Group work

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In [1]: # Import the relevant libraries.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import torch
import torch.nn as nn
import random
```

In [2]: # Generate random numbers.

```
random.seed(123)
```

In [3]: # The dataset is from Kaggle, and this dataset is about whether a customer will keep their bank account or not.  
# Dataset URL: <https://www.kaggle.com/competitions/playground-series-s4e1>

```
# We use only the train set in Kaggle
# since the test set does not have their target data(the column name with 'Exited') due to the competition.
# We renamed the file of the train set into 'bank_churn_data.csv'.
```

```
df = pd.read_csv('bank_churn_data.csv')
df
```

Out[3]:

	<b>id</b>	<b>CustomerId</b>	<b>Surname</b>	<b>CreditScore</b>	<b>Geography</b>	<b>Gender</b>	<b>Age</b>	<b>Tenure</b>	<b>Balance</b>	<b>NumOfProducts</b>	<b>HasCrCard</b>	<b>IsActiveMember</b>	<b>EstimatedSalary</b>	<b>Exited</b>
<b>0</b>	0	15674932	Okwudilichukwu	668	France	Male	33.0	3	0.00	2	1	0	181449.97	0
<b>1</b>	1	15749177	Okwudilolisa	627	France	Male	33.0	1	0.00	2	1	1	49503.50	0
<b>2</b>	2	15694510	Hsueh	678	France	Male	40.0	10	0.00	2	1	0	184866.69	0
<b>3</b>	3	15741417	Kao	581	France	Male	34.0	2	148882.54	1	1	1	84560.88	0
<b>4</b>	4	15766172	Chiemenam	716	Spain	Male	33.0	5	0.00	2	1	1	15068.83	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
<b>165029</b>	165029	15667085	Meng	667	Spain	Female	33.0	2	0.00	1	1	1	131834.75	0
<b>165030</b>	165030	15665521	Okechukwu	792	France	Male	35.0	3	0.00	1	0	0	131834.45	0
<b>165031</b>	165031	15664752	Hsia	565	France	Male	31.0	5	0.00	1	1	1	127429.56	0
<b>165032</b>	165032	15689614	Hsiung	554	Spain	Female	30.0	7	161533.00	1	0	1	71173.03	0
<b>165033</b>	165033	15732798	Ulyanov	850	France	Male	31.0	1	0.00	1	1	0	61581.79	1

165034 rows × 14 columns

## Data wrangling

In [4]: df.dtypes

```
id          int64
CustomerId  int64
Surname     object
CreditScore int64
Geography   object
Gender      object
Age         float64
Tenure      int64
Balance     float64
NumOfProducts int64
HasCrCard   int64
IsActiveMember int64
EstimatedSalary float64
Exited      int64
dtype: object
```

In [5]: df.isnull().sum()

```
id          0
CustomerId  0
Surname     0
CreditScore 0
Geography   0
Gender      0
Age         0
Tenure      0
Balance     0
NumOfProducts 0
HasCrCard   0
IsActiveMember 0
EstimatedSalary 0
Exited      0
dtype: int64
```

In [6]: # Check the number of values in 'Gender' and 'Geography'.

```
print(df['Gender'].nunique())
print(df['Geography'].nunique())
```

2  
3

In [7]: # Remove irrelevant features for a model.

```
df = df.drop(['id', 'CustomerId', 'Surname'], axis=1)
df
```

Out[7]:	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	668	France	Male	33.0	3	0.00	2	1	0	181449.97	0
1	627	France	Male	33.0	1	0.00	2	1	1	49503.50	0
2	678	France	Male	40.0	10	0.00	2	1	0	184866.69	0
3	581	France	Male	34.0	2	148882.54	1	1	1	84560.88	0
4	716	Spain	Male	33.0	5	0.00	2	1	1	15068.83	0
...	...	...	...	...	...	...	...	...	...	...	...
165029	667	Spain	Female	33.0	2	0.00	1	1	1	131834.75	0
165030	792	France	Male	35.0	3	0.00	1	0	0	131834.45	0
165031	565	France	Male	31.0	5	0.00	1	1	1	127429.56	0
165032	554	Spain	Female	30.0	7	161533.00	1	0	1	71173.03	0
165033	850	France	Male	31.0	1	0.00	1	1	0	61581.79	1

165034 rows × 11 columns

```
In [8]: # Change the string data to numeric one in 'Gender'.
map_dict = {'Female' : 0, 'Male' : 1}
df['Gender'] = df['Gender'].map(map_dict).astype(int)
```

```
In [9]: df['Gender'].value_counts()
```

```
Out[9]: 1 ... 93150
0 ... 71884
Name: Gender, dtype: int64
```

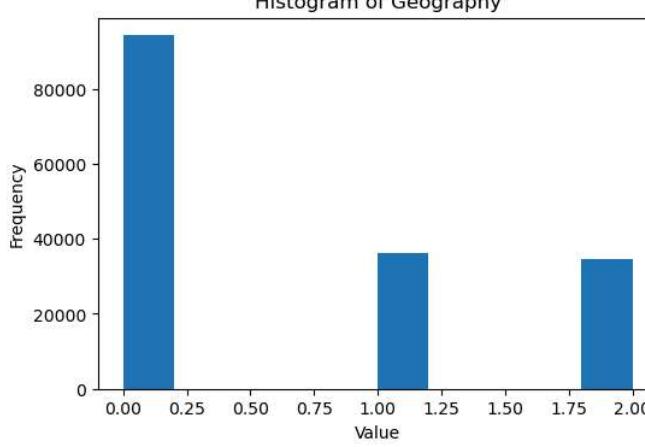
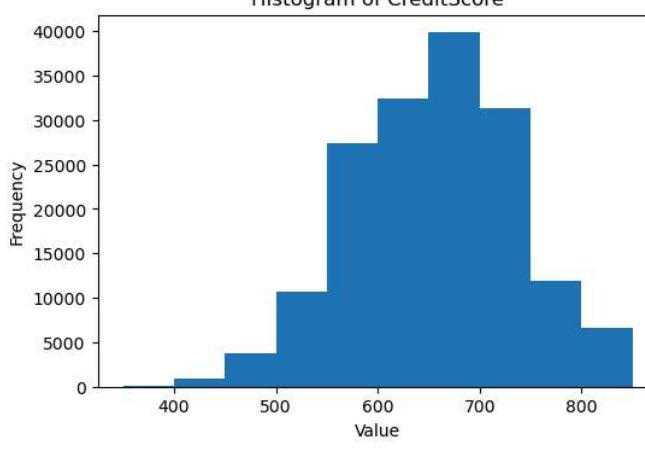
```
In [10]: df['Geography'].value_counts()
```

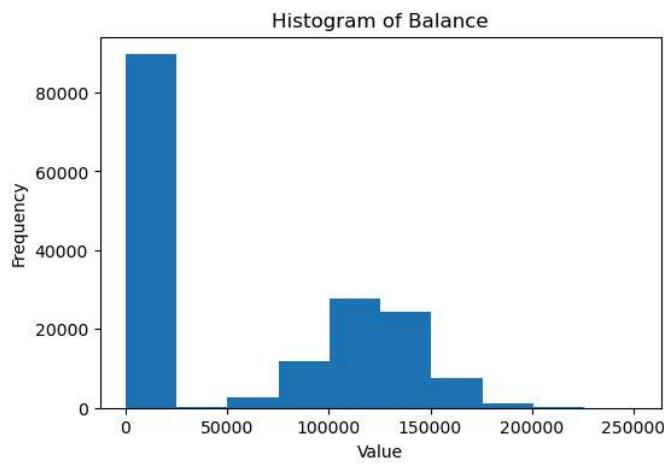
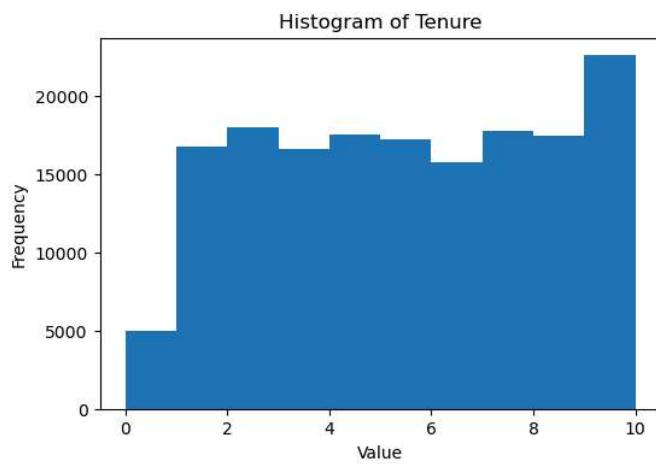
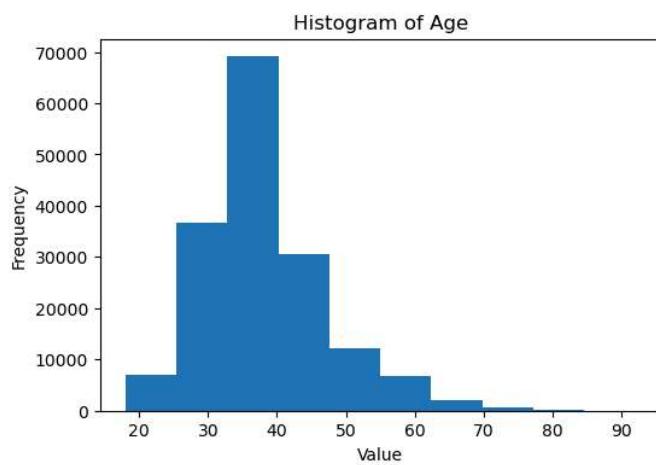
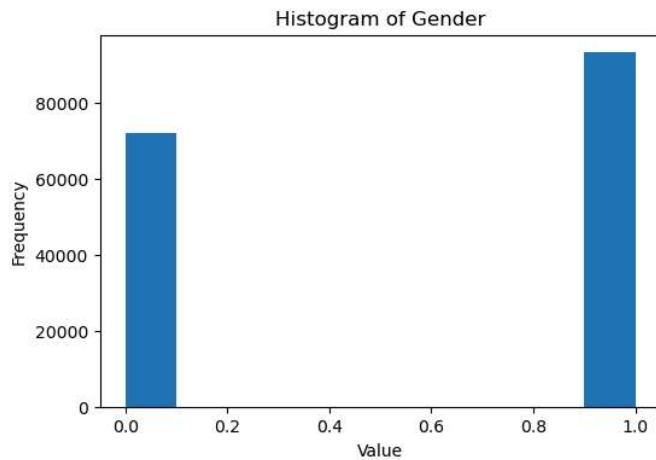
```
Out[10]: France .... 94215
Spain .... 36213
Germany .... 34606
Name: Geography, dtype: int64
```

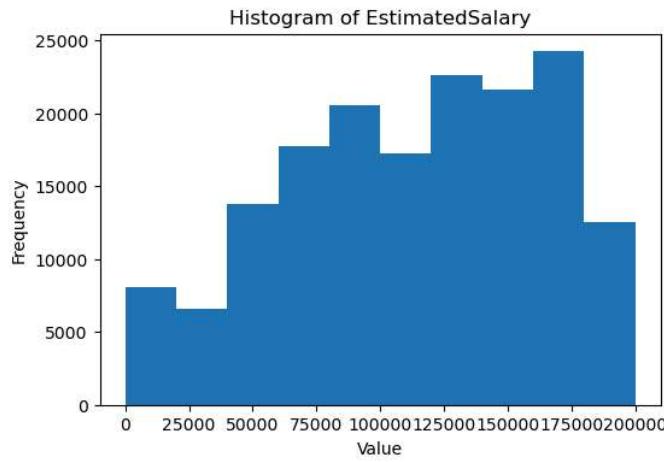
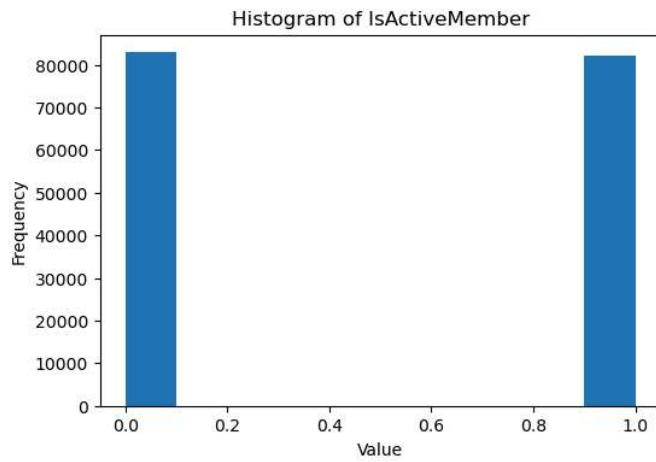
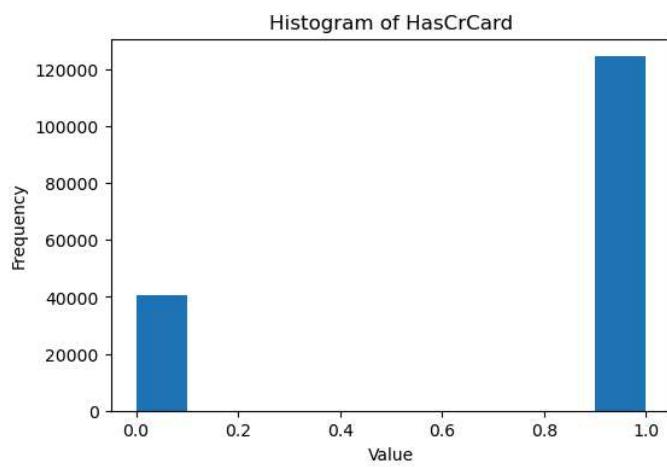
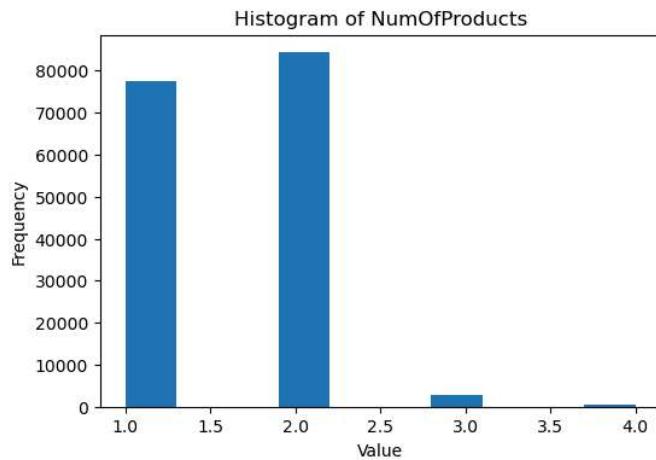
```
In [11]: # Change the string data to numeric one in 'Geography'.
map_dict = {'France' : 0, 'Spain' : 1, 'Germany' : 2}
df['Geography'] = df['Geography'].map(map_dict).astype(int)
```

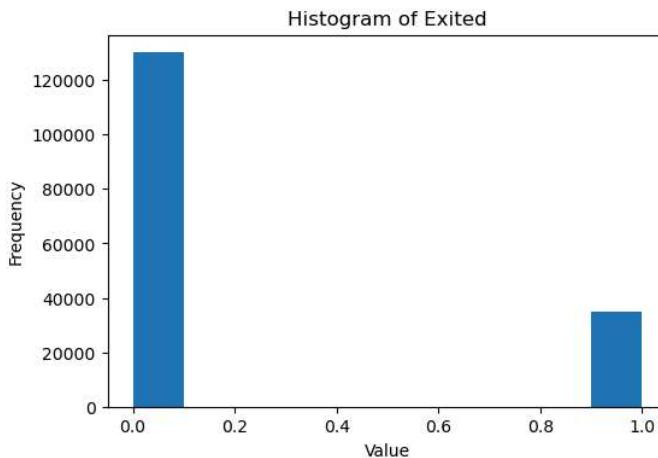
```
In [12]: # Check each distribution.
```

```
for column in df.columns:
    plt.figure(figsize=(6, 4))
    plt.hist(df[column], bins=10)
    plt.title('Histogram of {}'.format(column))
    plt.xlabel('Value')
    plt.ylabel('Frequency')
    plt.show()
```









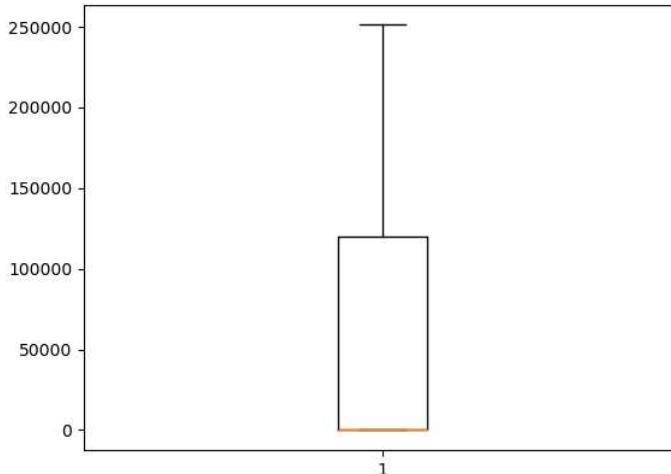
```
In [13]: # There is a large proportion of the 'Balance' being 0.  
# We will determine whether to remove the data with 0 in 'Balance'  
# by conducting statistical analysis on the 'Balance'  
# and rechecking the distribution of the other features and 'Exited'(target) that appear when the balance is 0.  
df['Balance'].value_counts()
```

```
Out[13]: 0.00      89648  
124577.33     88  
127864.40     64  
122314.50     63  
129855.32     59  
...  
125824.21      1  
158741.56      1  
126815.52      1  
61172.57      1  
110993.29      1  
Name: Balance, Length: 30075, dtype: int64
```

```
In [14]: df['Balance'].describe()
```

```
Out[14]: count    165034.000000  
mean     55478.086689  
std      62817.663278  
min      0.000000  
25%     0.000000  
50%     0.000000  
75%    119939.517500  
max    250898.090000  
Name: Balance, dtype: float64
```

```
In [15]: plt.boxplot(df['Balance']);
```



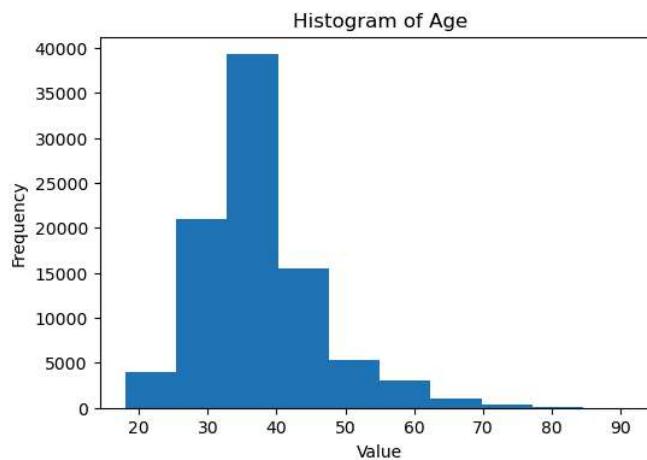
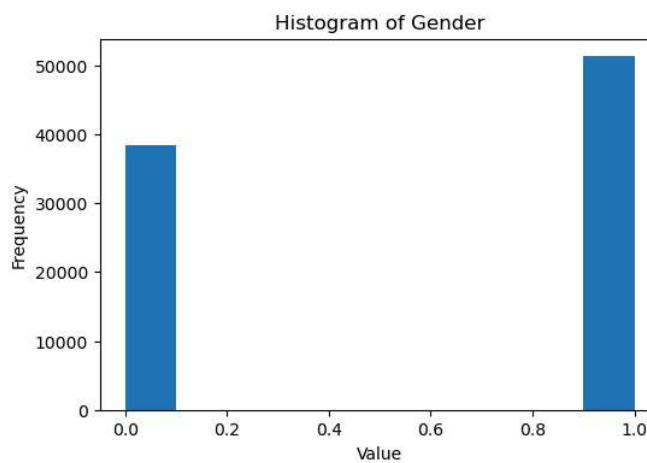
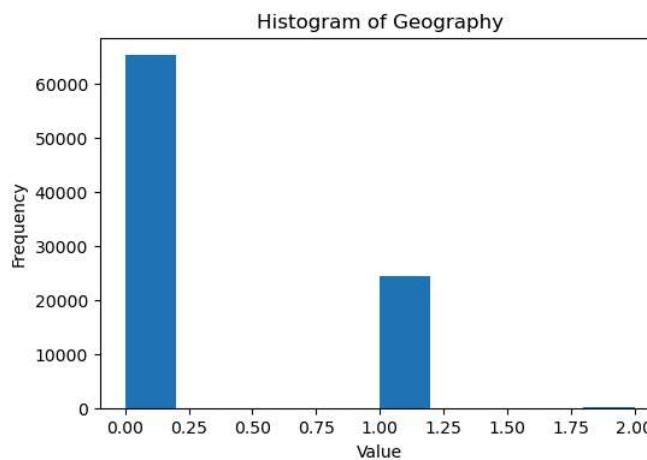
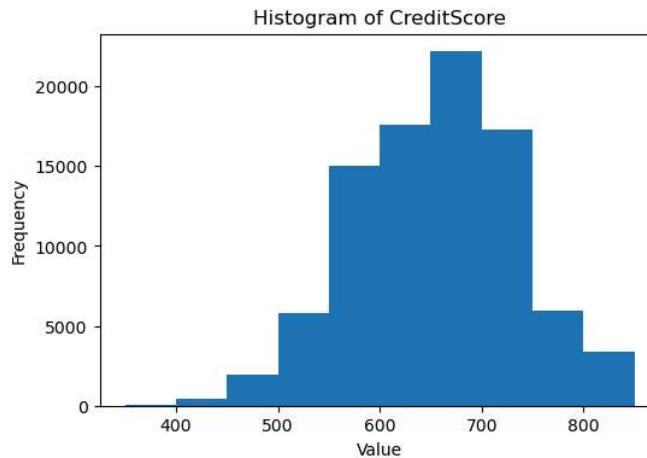
```
In [16]: # Select the data with 0 in 'Balance'.  
df_0_balance = df[df['Balance'] == 0]  
df_0_balance
```

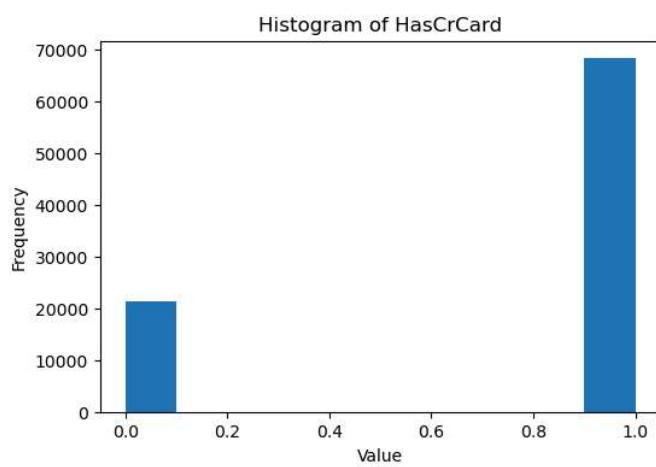
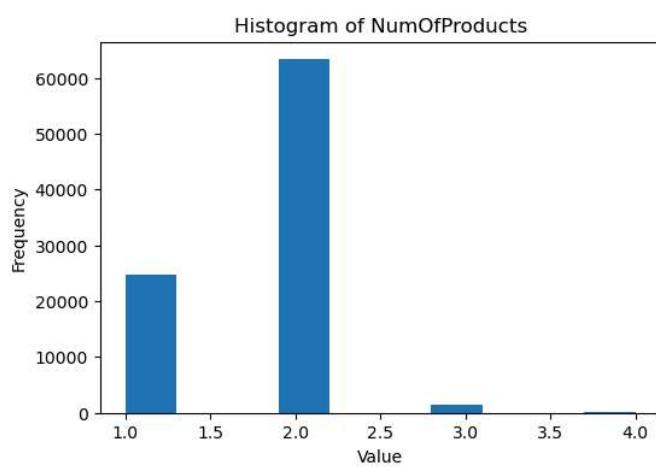
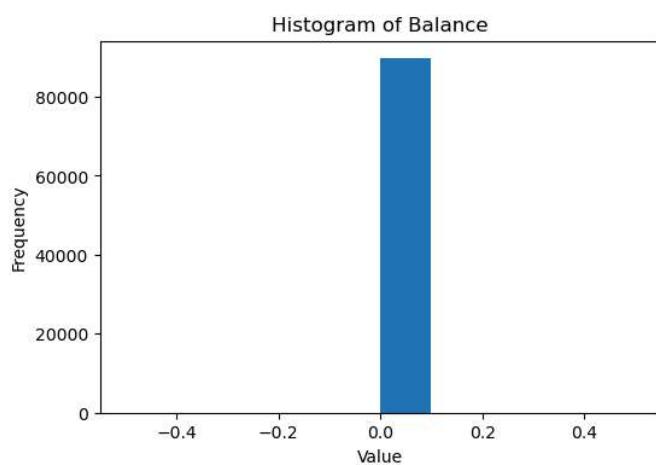
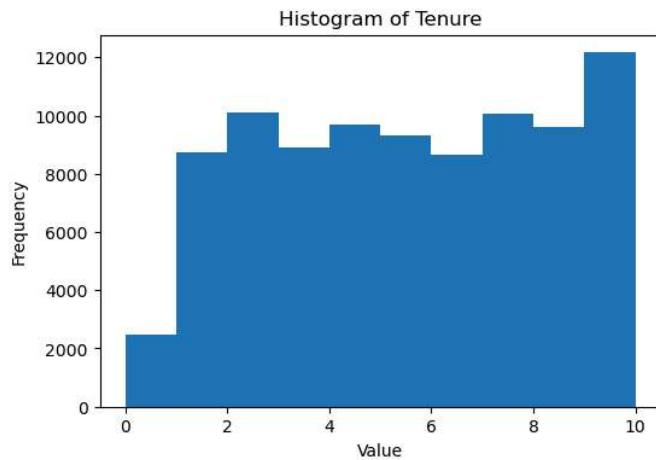
```
Out[16]:   CreditScore Geography Gender Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited  
0          668        0       1  33.0     3     0.0         2        1           0      181449.97      0  
1          627        0       1  33.0     1     0.0         2        1           1      49503.50      0  
2          678        0       1  40.0    10     0.0         2        1           0      184866.69      0  
4          716        1       1  33.0     5     0.0         2        1           1      15068.83      0  
8          676        0       1  43.0     4     0.0         2        1           0      142917.13      0  
...        ...      ...     ...    ...    ...    ...    ...    ...    ...    ...    ...  
165028     630        0       1  50.0     8     0.0         2        1           1      5962.50      0  
165029     667        1       0  33.0     2     0.0         1        1           1      131834.75      0  
165030     792        0       1  35.0     3     0.0         1        0           0      131834.45      0  
165031     565        0       1  31.0     5     0.0         1        1           1      127429.56      0  
165033     850        0       1  31.0     1     0.0         1        1           0      61581.79      1
```

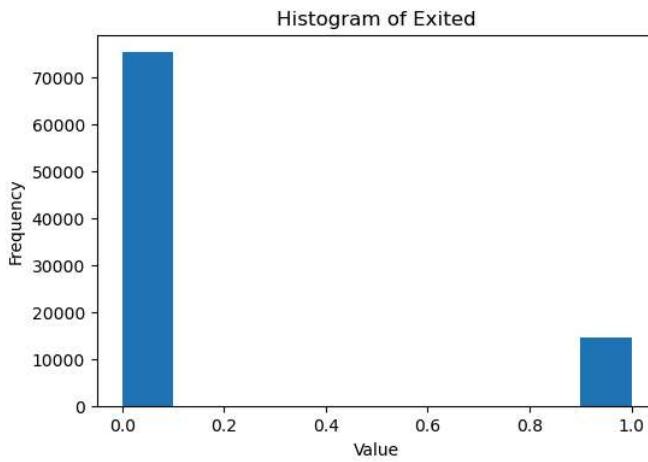
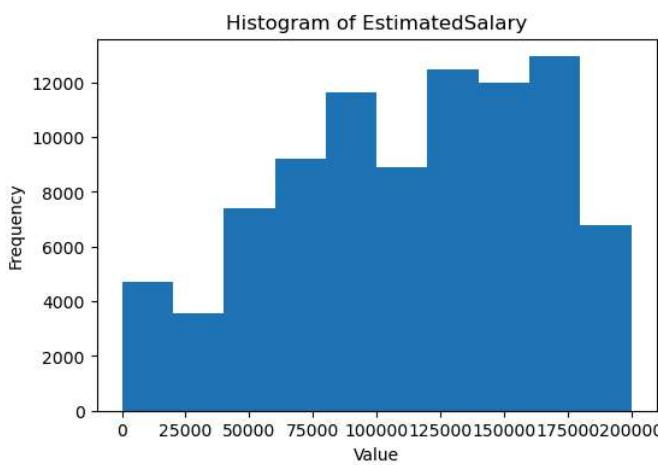
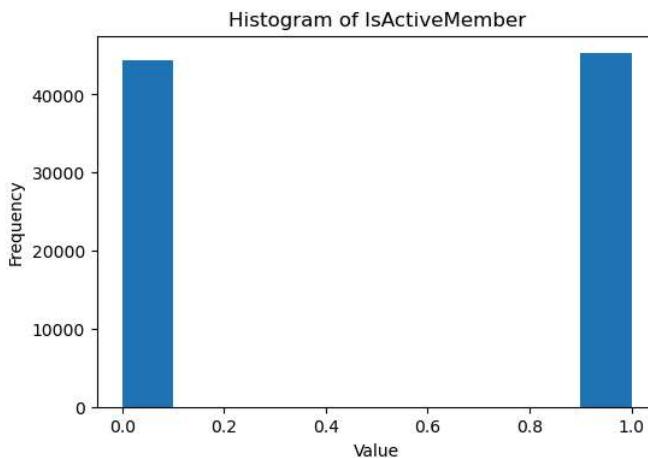
89648 rows × 11 columns

In [17]: # Check each distribution of the features in 'df\_0\_balance'.

```
for column in df_0_balance.columns:  
    plt.figure(figsize=(6, 4))  
    plt.hist(df_0_balance[column], bins=10)  
    plt.title('Histogram of {}'.format(column))  
    plt.xlabel('Value')  
    plt.ylabel('Frequency')  
    plt.show()
```

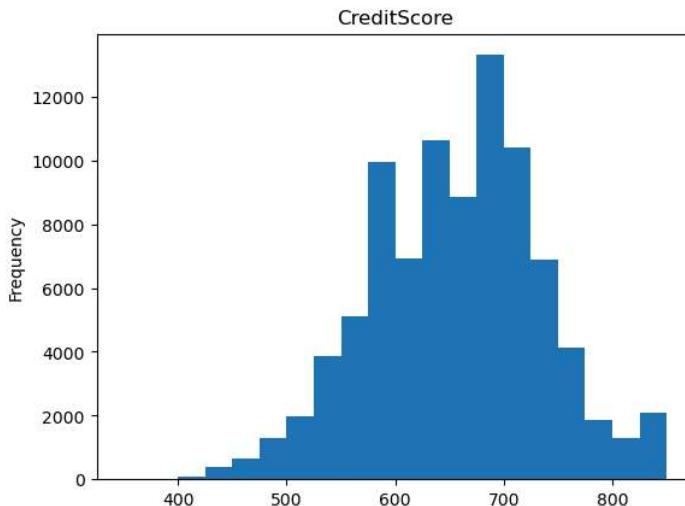






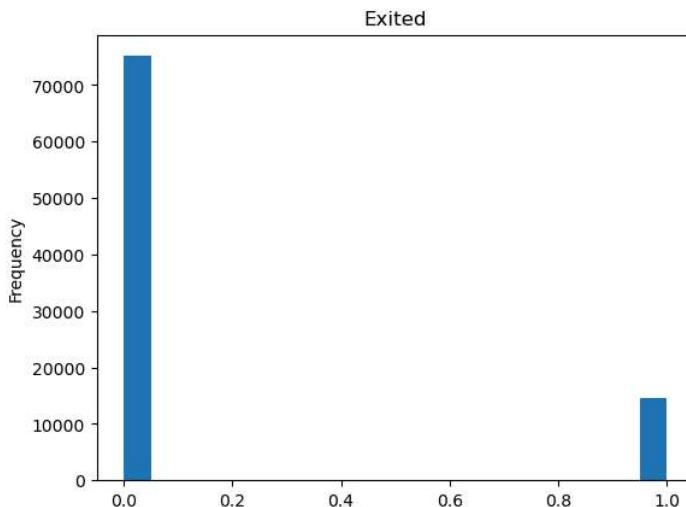
```
In [18]: df_0_balance['CreditScore'].plot(kind='hist', bins=20, title='CreditScore')
```

```
Out[18]: <Axes: title={'center': 'CreditScore'}, ylabel='Frequency'>
```



```
In [19]: df_0_balance['Exited'].plot(kind='hist', bins=20, title='Exited')
```

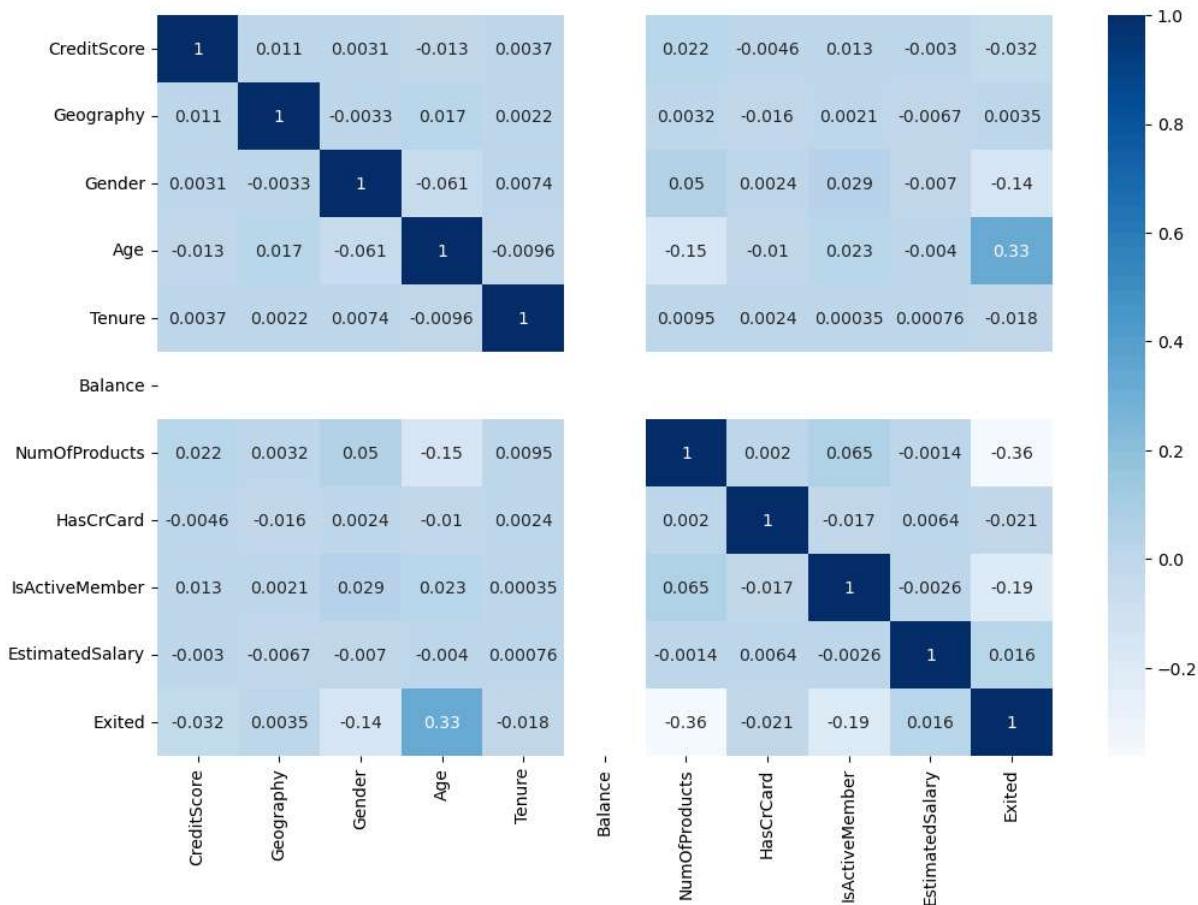
```
Out[19]: <Axes: title={'center': 'Exited'}, ylabel='Frequency'>
```



In [20]: # Check the correlation coefficient of each feature.

```
correlation_matrix = df_0_balance.corr()
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, cmap='Blues', annot=True)
```

Out[20]: <Axes: >



The data with the value of 0 in 'Balance' will be remained since 'Balance' has considerably low collinearity with 'Exited'. Although, it looks problematic as the quantile range of 'Balance' shows 0 in 25% and 0 in 50%, the data with 0 in 'Balance' is still meaningful as it shows a similar distribution of the features to the distribution in the data with 0 and the other values in 'Balance'.

## Split the data set

In [21]: # Split the dataset into features and the target.

```
X = df.iloc[:, 0:10]
y = df.iloc[:, 10]
print(X)
print(y)
```

```

CreditScore Geography Gender Age Tenure Balance W
0..... 668..... 0..... 1..... 33.0..... 3..... 0.00...
1..... 627..... 0..... 1..... 33.0..... 1..... 0.00...
2..... 678..... 0..... 1..... 40.0..... 10..... 0.00...
3..... 581..... 0..... 1..... 34.0..... 2..... 148882.54...
4..... 716..... 1..... 1..... 33.0..... 5..... 0.00...
.....
165029..... 667..... 1..... 0..... 33.0..... 2..... 0.00...
165030..... 792..... 0..... 1..... 35.0..... 3..... 0.00...
165031..... 565..... 0..... 1..... 31.0..... 5..... 0.00...
165032..... 554..... 1..... 0..... 30.0..... 7..... 161533.00...
165033..... 850..... 0..... 1..... 31.0..... 1..... 0.00...
.....
NumOfProducts HasCrCard IsActiveMember EstimatedSalary
0..... 2..... 1..... 0..... 181449.97
1..... 2..... 1..... 1..... 49503.50
2..... 2..... 1..... 0..... 184866.69
3..... 1..... 1..... 1..... 84560.88
4..... 2..... 1..... 1..... 15068.83
.....
165029..... 1..... 1..... 1..... 131834.75
165030..... 1..... 0..... 0..... 131834.45
165031..... 1..... 1..... 1..... 127429.56
165032..... 1..... 0..... 1..... 71173.03
165033..... 1..... 1..... 0..... 61581.79
Name: Exitted, Length: 165034, dtype: int64

```

```
In [22]: print(type(X))
print(type(y))
print(X.shape)
print(y.shape)
```

```
<class 'pandas.core.frame.DataFrame'>
<class 'pandas.core.series.Series'>
(165034, 10)
(165034,)
```

```
In [23]: # Convert Pandas to Numpy array.
X = X.values
y = y.values

print(type(X))
print(type(y))
print(X.shape)
print(y.shape)
```

```
<class 'numpy.ndarray'>
<class 'numpy.ndarray'>
(165034, 10)
(165034,)
```

```
In [24]: # Convert Numpy array to Tensor.
X = torch.tensor(X, dtype=torch.float32)
y = torch.tensor(y, dtype=torch.float32)
print(type(X))
print(type(y))
print(X.shape)
print(y.shape)
```

```
<class 'torch.Tensor'>
<class 'torch.Tensor'>
torch.Size([165034, 10])
torch.Size([165034])

In [25]: # Set the number of random state to shuffle the data.
random_state = 123

# Split the training set into 70% and testing set into 30%.
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    test_size=0.3,
                                                    random_state=random_state
)

# Check the data type.
print(X_train.dtype)

# Split the testing set into validation (50%) and test (50%).
X_test, X_vali, y_test, y_vali = train_test_split(X_test, y_test, test_size=0.5, random_state=random_state)

torch.float32
```

```
In [26]: # Check the dimensionality and data type of each set.
print("Training dataset")
print(X_train.dtype, X_train.shape)
print(y_train.dtype, y_train.shape)

print("Validation dataset")
print(X_vali.dtype, X_vali.shape)
print(y_vali.dtype, y_vali.shape)

print("Testing dataset")
print(X_test.dtype, X_test.shape)
print(y_test.dtype, y_test.shape)
```

```
Training dataset
torch.float32 torch.Size([115523, 10])
torch.float32 torch.Size([115523])
Validation dataset
torch.float32 torch.Size([24756, 10])
torch.float32 torch.Size([24756])
Testing dataset
torch.float32 torch.Size([24755, 10])
torch.float32 torch.Size([24755])
```

```
In [27]: # Import SMOTE to balance the target in training set.
from imblearn.over_sampling import SMOTE
```

```
# Create a variable for SMOTE
smote = SMOTE(random_state=random_state)

# Resampling the X and y in the training set using SMOTE.
X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)
```

```
In [28]: # Check the dimensionality and data type of each set.
```

```
print("Training dataset")
print(X_train.dtype, X_train.shape)
print(y_train.dtype, y_train.shape)

print("Training dataset (Smote)")
print(X_train_smote.dtype, X_train_smote.shape)
print(y_train_smote.dtype, y_train_smote.shape)

print("Validation dataset")
print(X_vali.dtype, X_vali.shape)
print(y_vali.dtype, y_vali.shape)

print("Testing dataset")
print(X_test.dtype, X_test.shape)
print(y_test.dtype, y_test.shape)
```

```
Training dataset
torch.float32 torch.Size([115523, 10])
torch.float32 torch.Size([115523])
Training dataset (Smote)
float32 (182382, 10)
float32 (182382.)
Validation dataset
torch.float32 torch.Size([24756, 10])
torch.float32 torch.Size([24756])
Testing dataset
torch.float32 torch.Size([24755, 10])
torch.float32 torch.Size([24755])
```

## Data scaling

```
In [29]: # Normalise the features in each set.
from sklearn.preprocessing import MinMaxScaler
```

```
normal_scaler = MinMaxScaler()

X_train_smote_normalized = normal_scaler.fit_transform(X_train_smote)
X_vali_normalized = normal_scaler.transform(X_vali)
X_test_normalized = normal_scaler.transform(X_test)
```

```
In [30]: # Convert to Tensor and rename the variables for the features in each set.
```

```
X_train = X_train_smote_normalized = torch.tensor(X_train_smote_normalized, dtype=torch.float32)
X_vali = X_vali_normalized = torch.tensor(X_vali_normalized, dtype=torch.float32)
X_test = X_test_normalized = torch.tensor(X_test_normalized, dtype=torch.float32)

# Rename y_train_smote to y_train.
y_train = torch.tensor(y_train_smote, dtype=torch.float32)
```

```
In [31]: # Check the size and type of datasets after the splitting
```

```
print("Training dataset (Smote)")
print(X_train.dtype, X_train.shape)
print(y_train.dtype, y_train.shape)

print("Validation dataset")
print(X_vali.dtype, X_vali.shape)
print(y_vali.dtype, y_vali.shape)

print("Testing dataset")
print(X_test.dtype, X_test.shape)
print(y_test.dtype, y_test.shape)
```

```
Training dataset (Smote)
torch.float32 torch.Size([182382, 10])
torch.float32 torch.Size([182382])
Validation dataset
torch.float32 torch.Size([24756, 10])
torch.float32 torch.Size([24756])
Testing dataset
torch.float32 torch.Size([24755, 10])
torch.float32 torch.Size([24755])
```

```
In [32]: # Increase the dimension of all target variables.
```

```
y_train = y_train.unsqueeze(1)
y_test = y_test.unsqueeze(1)
y_vali = y_vali.unsqueeze(1)

# Make sure that the data type and dimension of each set are all clear.
print("Training dataset")
print(X_train.dtype, X_train.shape, type(X_train))
print(y_train.dtype, y_train.shape, type(y_train))

print("Validation dataset")
print(X_vali.dtype, X_vali.shape, type(X_vali))
print(y_vali.dtype, y_vali.shape, type(y_vali))

print("Testing dataset")
print(X_test.dtype, X_test.shape, type(X_train))
print(y_test.dtype, y_test.shape, type(y_train))
```

```
Training dataset
torch.float32 torch.Size([182382, 10]) <class 'torch.Tensor'>
torch.float32 torch.Size([182382, 1]) <class 'torch.Tensor'>
Validation dataset
torch.float32 torch.Size([24756, 10]) <class 'torch.Tensor'>
torch.float32 torch.Size([24756, 1]) <class 'torch.Tensor'>
Testing dataset
torch.float32 torch.Size([24755, 10]) <class 'torch.Tensor'>
torch.float32 torch.Size([24755, 1]) <class 'torch.Tensor'>
```

```
In [33]: # To ensure a fair comparison between Python and Matlab,
# we use the same split datasets to train, validate, and test a model in both environments.
# Tensors are converted into CSV files for application in Matlab.
# After conversion, the following codes are commented out.

# Convert the datasets from Tensor to Numpy
#X_train_ndarray = X_train.numpy()
#X_test_ndarray = X_test.numpy()
#X_vali_ndarray = X_vali.numpy()
#y_train_ndarray = y_train.numpy()
#y_test_ndarray = y_test.numpy()
#y_vali_ndarray = y_vali.numpy()

# Save all datasets to CSV file
#np.savetxt('X_train_ndarray.csv', X_train_ndarray, delimiter=',')
#np.savetxt('X_test_ndarray.csv', X_test_ndarray, delimiter=',')
#np.savetxt('X_vali_ndarray.csv', X_vali_ndarray, delimiter=',')
#np.savetxt('y_train_ndarray.csv', y_train_ndarray, delimiter=',')
#np.savetxt('y_test_ndarray.csv', y_test_ndarray, delimiter=',')
#np.savetxt('y_vali_ndarray.csv', y_vali_ndarray, delimiter=',')
```

## Build a neural network model

```
In [34]: # Define the structure of the neural network model.
input_features = 10
output_features = 1

# Set the list of hyperparameters for grid search.
learning_rates_grid = [0.01, 0.1, 0.2, 0.3]
hidden_neurons_grid = [10, 25, 50, 100, 200]

# Set the number of epochs.
number_of_epochs = 1000

# Define variables to store the item from the result of the model.
best_accuracy = 0.0
best_hyperparameters = {}

# Make empty lists to store the result of every combination of hyperparameters for visualisation.
learning_rates_list_heatmap = []
hidden_neurons_list_heatmap = []
accuracy_list_heatmap = []

# Make an empty list to store the elapsed time from 1000 epochs of the best model.
import time
python_training_time_bestmodel = []
```

```
In [35]: # Make the class for the neural network model.
class Credit_Churn_NN_Model(nn.Module):
    def __init__(self, input_features, hidden_neurons, output_features):
        super(Credit_Churn_NN_Model, self).__init__()
        self.fc1 = nn.Linear(input_features, hidden_neurons)
        self.fc2 = nn.Linear(hidden_neurons, output_features)
        self.relu = nn.ReLU()
        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        output_layer1 = self.fc1(x)
        l1_activated = self.relu(output_layer1)
        output_layer2 = self.fc2(l1_activated)
        output_activated = self.sigmoid(output_layer2)
        return output_activated
```

```
In [36]: # Make the function to train the model.
def train_NN_model(learning_rate, hidden_neurons, X_train, y_train, X_vali, y_vali, number_of_epochs):
    model = Credit_Churn_NN_Model(input_features, hidden_neurons, output_features)
    criterion = torch.nn.BCELoss(reduction='mean')
    optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)

    # Make lists to store the item from the loss and elapsed time in order to plot a graph.
    plot_train_loss = []
    plot_vali_loss = []
    plot_train_time = []

    # Iterate the model following each epoch.
    for e in range(number_of_epochs):
        # Train the model.
        model.train()
        # Start the timer.
        start_time = time.time()
        # Make the gradient descent start from 0
        optimizer.zero_grad()
        y_train_pred = model(X_train)
        # Call the loss function.
        train_loss = criterion(y_train_pred, y_train)
        # Implement backpropagation.
        train_loss.backward()
        optimizer.step()
        # Stop the timer.
        end_time = time.time()
        # Calculate the elapsed time.
        Total_time = end_time - start_time
        plot_train_time.append(Total_time)
        # Append the loss value from training to the following list.
        plot_train_loss.append(train_loss)

        # Validate the model.
        model.eval()
        with torch.no_grad():
            y_vali_pred = model(X_vali)
            vali_loss = criterion(y_vali_pred, y_vali)
```

```
# Append the loss value from validation to the following list.  
plot_vali_loss.append(vali_loss)
```

```
return model, plot_train_loss, plot_vali_loss, plot_train_time
```

## Train the model with grid search

In [37]: # Define an empty list to store the training time from the best model.

```
Total_time = []  
  
# Apply a nested loop for grid search.  
for learning_rate in learning_rates_grid:  
    for hidden_neurons in hidden_neurons_grid:  
        print(f"\nTraining the NNet model with learning rate={learning_rate} and hidden neurons={hidden_neurons}")  
        # Call the function to train and evaluate the model with the nested loop.  
        trained_model, train_loss, vali_loss, train_time = train_NN_model(learning_rate, hidden_neurons,  
            X_train, y_train,  
            X_vali, y_vali,  
            number_of_epochs)  
  
        # Get the predictions from the X_vali, and convert them to either 1 or 0.  
        y_vali_pred = (trained_model(X_vali).detach().numpy() > 0.5).astype(int)  
        # Calculate the validation accuracy.  
        accuracy_validation_set = (y_vali_pred == y_vali.numpy()).mean()  
        print(f"The validation accuracy = {accuracy_validation_set*100}%")  
  
        # Append each value to the list for plotting.  
        learning_rates_list_heatmap.append(learning_rate)  
        hidden_neurons_list_heatmap.append(hidden_neurons)  
        accuracy_list_heatmap.append(accuracy_validation_set)  
        Total_time.append(train_time)  
  
    # Pick the best model comparing the validation accuracy from each model.  
    if accuracy_validation_set > best_accuracy: # If it is so,  
        best_accuracy = accuracy_validation_set # Reassign the validation accuracy to the variable of 'best_accuracy'.  
        # Define the best hyperparameters with the selected learning rate and the number of neurons.  
        best_hyperparameters = {'learning_rate': learning_rate, 'hidden_neurons': hidden_neurons}  
        # Pick the value of the loss and training time from the best model.  
        train_loss_for_plotting = train_loss  
        vali_loss_for_plotting = vali_loss  
        python_training_time_bestmodel = train_time  
        # Replace the model with the best model.  
        best_model = trained_model  
  
    # Print the best hyperparameters from grid search.  
print("\nThe Best Hyperparameters are ", best_hyperparameters)
```

Training the NNet model with learning rate=0.01 and hidden\_neurons=10  
The validation accuracy = 67.73%

Training the NNet model with learning rate=0.01 and hidden\_neurons=25  
The validation accuracy = 68.15%

Training the NNet model with learning rate=0.01 and hidden\_neurons=50  
The validation accuracy = 69.98%

Training the NNet model with learning rate=0.01 and hidden\_neurons=100  
The validation accuracy = 68.22%

Training the NNet model with learning rate=0.01 and hidden\_neurons=200  
The validation accuracy = 68.61%

Training the NNet model with learning rate=0.1 and hidden\_neurons=10  
The validation accuracy = 74.89%

Training the NNet model with learning rate=0.1 and hidden\_neurons=25  
The validation accuracy = 74.89%

Training the NNet model with learning rate=0.1 and hidden\_neurons=50  
The validation accuracy = 75.10%

Training the NNet model with learning rate=0.1 and hidden\_neurons=100  
The validation accuracy = 75.18%

Training the NNet model with learning rate=0.1 and hidden\_neurons=200  
The validation accuracy = 75.88%

Training the NNet model with learning rate=0.2 and hidden\_neurons=10  
The validation accuracy = 75.27%

Training the NNet model with learning rate=0.2 and hidden\_neurons=25  
The validation accuracy = 76.19%

Training the NNet model with learning rate=0.2 and hidden\_neurons=50  
The validation accuracy = 76.86%

Training the NNet model with learning rate=0.2 and hidden\_neurons=100  
The validation accuracy = 76.97%

Training the NNet model with learning rate=0.2 and hidden\_neurons=200  
The validation accuracy = 78.32%

Training the NNet model with learning rate=0.3 and hidden\_neurons=10  
The validation accuracy = 77.48%

Training the NNet model with learning rate=0.3 and hidden\_neurons=25  
The validation accuracy = 78.12%

Training the NNet model with learning rate=0.3 and hidden\_neurons=50  
The validation accuracy = 78.29%

Training the NNet model with learning rate=0.3 and hidden\_neurons=100  
The validation accuracy = 73.21%

Training the NNet model with learning rate=0.3 and hidden\_neurons=200  
The validation accuracy = 75.07%

The Best Hyperparameters are {'learning\_rate': 0.2, 'hidden\_neurons': 200}

In [38]: # Check the best combination of hyperparameters.  
print(best\_hyperparameters)

```
best_learning_rate = best_hyperparameters['learning_rate']
best_hidden_neurons = best_hyperparameters['hidden_neurons']

print(best_learning_rate)
print(best_hidden_neurons)

{'learning_rate': 0.2, 'hidden_neurons': 200}
0.2
200
```

```
In [39]: # Check the loss values from the best model.
train_loss_for_plotting
```

















```

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tensor(0.4429, grad_fn=<BinaryCrossEntropyBackward0>),
tensor(0.4428, grad_fn=<BinaryCrossEntropyBackward0>),
tensor(0.4427, grad_fn=<BinaryCrossEntropyBackward0>)

```

```

In [40]: # Convert from Tensor to list to plot using seaborn.
train_loss_for_plotting = [tensor_item.item() for tensor_item in train_loss_for_plotting]
vali_loss_for_plotting = [tensor_item.item() for tensor_item in vali_loss_for_plotting]
print(type(train_loss_for_plotting))
print(type(vali_loss_for_plotting))

# Create a numpy list for epochs which starts from 1 and ends with 1000.
Epochs = np.arange(1, number_of_epochs + 1)
type(Epochs)

```

```

<class 'list'>
<class 'list'>
numpy.ndarray

```

Out[40]:

## Model evaluation

```

In [41]: # Import the recorded performance from MATLAB to plot in Python.
import csv
with open('matlab_training_time_bestmodel.csv', 'r') as file1:
    reader1 = csv.reader(file1)
    matlab_training_time_bestmodel = np.array(list(reader1), dtype=float)

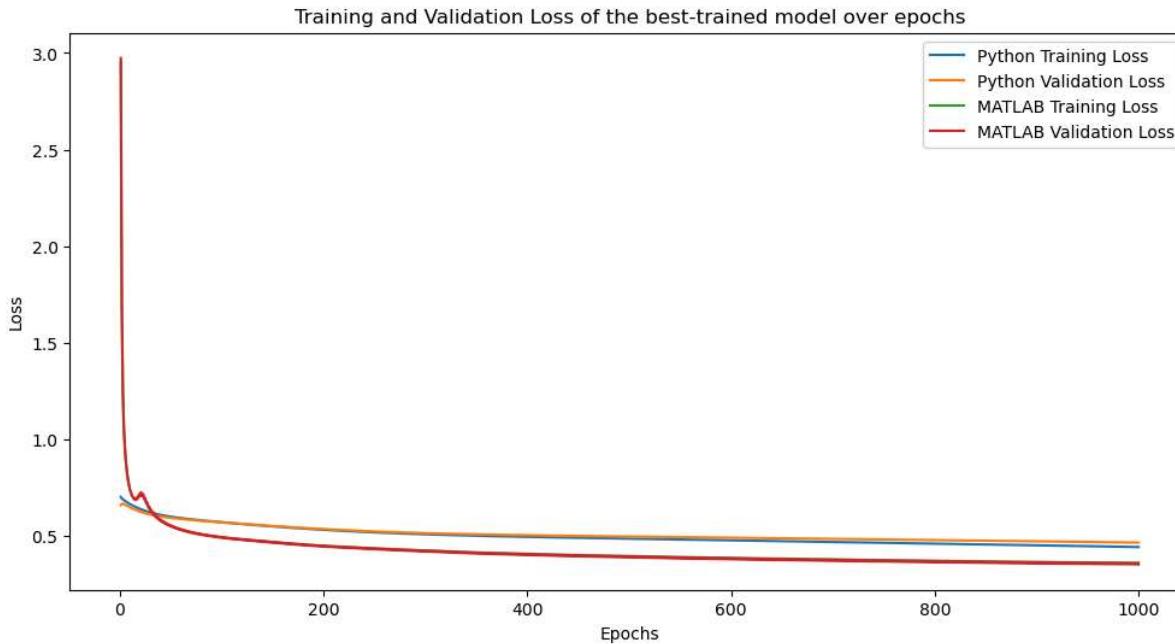
with open('matlab_train_loss_for_plotting.csv', 'r') as file2:
    reader2 = csv.reader(file2)
    matlab_train_loss_for_plotting = np.array(list(reader2), dtype=float)

with open('matlab_vali_loss_for_plotting.csv', 'r') as file3:
    reader3 = csv.reader(file3)
    matlab_vali_loss_for_plotting = np.array(list(reader3), dtype=float)

```

```
In [42]: # Change the nested list to flat lists
matlab_training_time_bestmodel = matlab_training_time_bestmodel.tolist()[0]
matlab_train_loss_for_plotting = matlab_train_loss_for_plotting.tolist()[0]
matlab_vali_loss_for_plotting = matlab_vali_loss_for_plotting.tolist()[0]
```

```
In [43]: # Plot the training time of the model in Python and that of the model in MATLAB.
fig = plt.figure(figsize=(12, 6))
plt.plot(Epochs, train_loss_for_plotting, label='Python Training Loss')
plt.plot(Epochs, vali_loss_for_plotting, label='Python Validation Loss')
plt.plot(Epochs, matlab_train_loss_for_plotting, label='MATLAB Training Loss')
plt.plot(Epochs, matlab_vali_loss_for_plotting, label='MATLAB Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.title('Training and Validation Loss of the best-trained model over epochs')
plt.show()
```



```
In [44]: # Since the value in the training time is continuous, it needs to be changed cumulatively.
python_training_time_bestmodel = np.cumsum(python_training_time_bestmodel)
```

```
len(python_training_time_bestmodel)
```

```
Out[44]: 1000
```

```
In [45]: python_training_time_bestmodel
```

Out[45]: array([ 1.30332232, 2.58863735, 3.87094259, 5.15135574,  
..... 6.43319321, 7.71303678, 9.00332785, 10.30966806,  
..... 11.60496116, 12.87815285, 14.1724906 , 15.4117082,  
..... 16.70859504, 18.00489402, 19.30119109, 20.58648157,  
..... 21.89680195, 23.18409252, 24.45637965, 25.72119737,  
..... 26.98779511, 28.27513671, 29.58646774, 30.86280274,  
..... 32.15514207, 33.44148135, 34.71978021, 36.00225878,  
..... 37.29054976, 38.5690825 , 39.85237122, 41.14368916,  
..... 42.4139843 , 43.70027518, 44.98661113, 46.24287534,  
..... 47.52716565, 48.80245376, 50.15575957, 51.47508287,  
..... 52.81146789, 54.11478496, 55.37011647, 56.65747929,  
..... 57.94228029, 59.2300797 , 60.50839996, 61.82270074,  
..... 63.10899854, 64.41471553, 65.68045616, 66.93678594,  
..... 68.24160409, 69.52590156, 70.81225491, 72.09055018,  
..... 73.40192986, 74.67630863, 75.93058301, 77.22088456,  
..... 78.5001862 , 79.78547668, 81.07176614, 82.38207126,  
..... 83.69441962, 85.00571513, 86.29701567, 87.54296231,  
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..... 93.97793627, 95.26276374, 96.54826927, 97.85056257,  
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..... 265.8126688 , 267.16149044, 268.56880808, 269.92815995,  
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..... 276.82635212, 278.20568919, 279.49407363, 280.82244039,  
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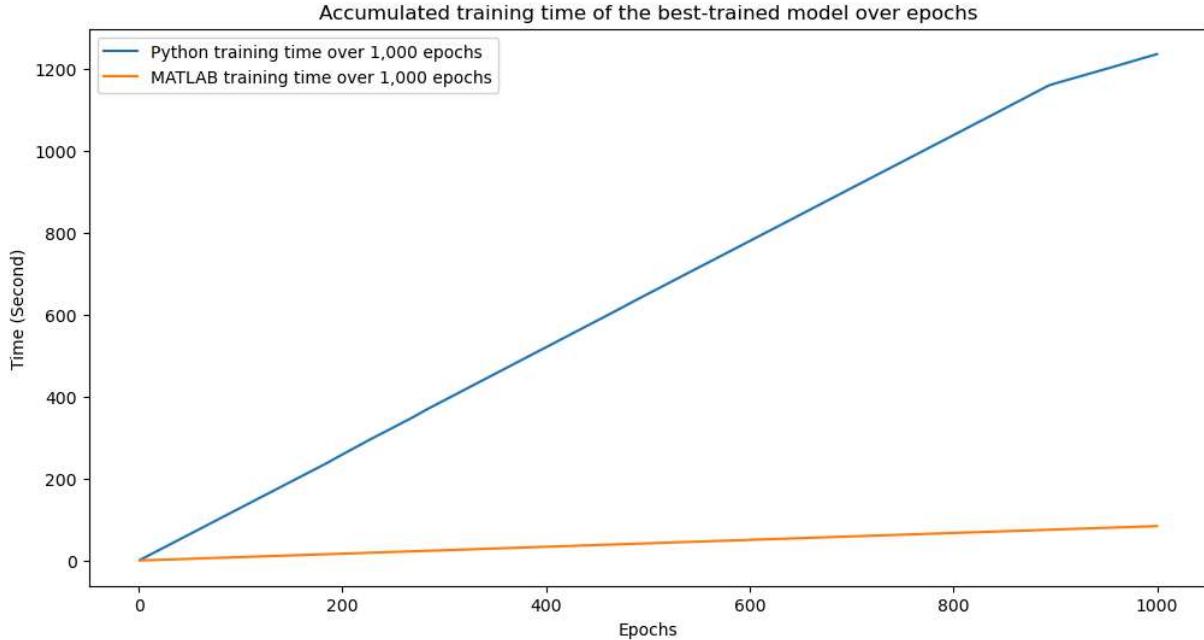
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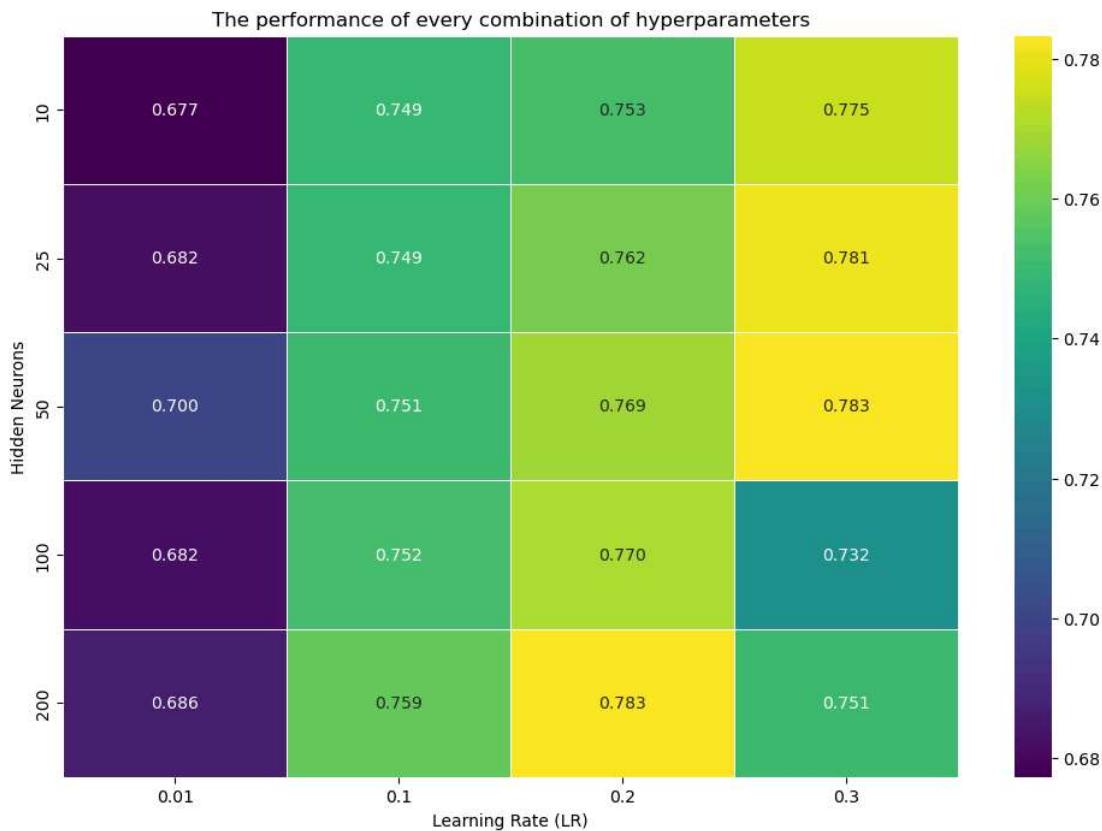
```
In [46]: # Plot the loss of the model in Python and that of the model in MATLAB.
fig = plt.figure(figsize=(12, 6))
plt.plot(Epochs, python_training_time_bestmodel, label='Python training time over 1,000 epochs')
plt.plot(Epochs, matlab_training_time_bestmodel, label='MATLAB training time over 1,000 epochs')
plt.xlabel('Epochs')
plt.ylabel('Time (Second)')
plt.legend()
plt.title('Accumulated training time of the best-trained model over epochs')
plt.show()
```



```
In [47]: # Combine the lists into a DataFrame
df_for_heatmap = pd.DataFrame({'Learning Rate': learning_rates_list_heatmap, 'Hidden Neurons': hidden_neurons_list_heatmap, 'Accuracy': accuracy_list_heatmap})

# Make a pivot table from the DataFrame to create a matrix which is suitable for a heatmap.
pivotized_heatmap_data = df_for_heatmap.pivot('Hidden Neurons', 'Learning Rate', 'Accuracy')

# Create a heatmap using seaborn.
plt.figure(figsize=(12, 8))
sns.heatmap(pivotized_heatmap_data, annot=True, cmap='viridis', fmt=".3f", linewidths=.5)
plt.title('The performance of every combination of hyperparameters')
plt.xlabel('Learning Rate (LR)')
plt.ylabel('Hidden Neurons')
plt.show()
```



```
In [53]: # Evaluate the model in Python with the testing set.
best_model.eval()

# Change the predictions into 0 or 1.
y_test_pred = best_model(X_test)
y_test_pred = y_test_pred.round()

# Calculate the accuracy rate.
accuracy_rate_test_set = (y_test_pred == y_test).float().mean()
accuracy_rate_test_set = float(accuracy_rate_test_set)
accuracy_rate_test_set_python = accuracy_rate_test_set * 100
print("The test accuracy for the best-trained model in Python = %.2f%%" % (accuracy_rate_test_set_python))

The test accuracy for the best-trained model in Python = 78.22%
```

```
In [54]: # The accuracy rate of the model in MATLAB.
# This number is derived from MATLAB.
accuracy_rate_test_set_MATLAB = 85.34
print("The test accuracy for the best-trained model in MATLAB = %.2f%%" % (accuracy_rate_test_set_MATLAB))

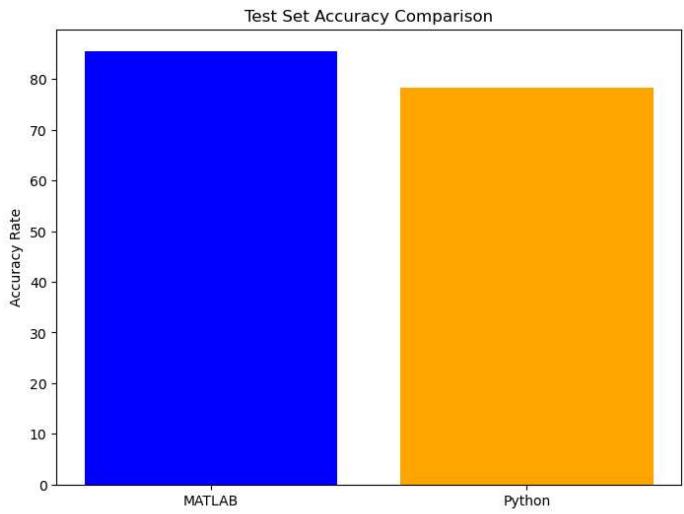
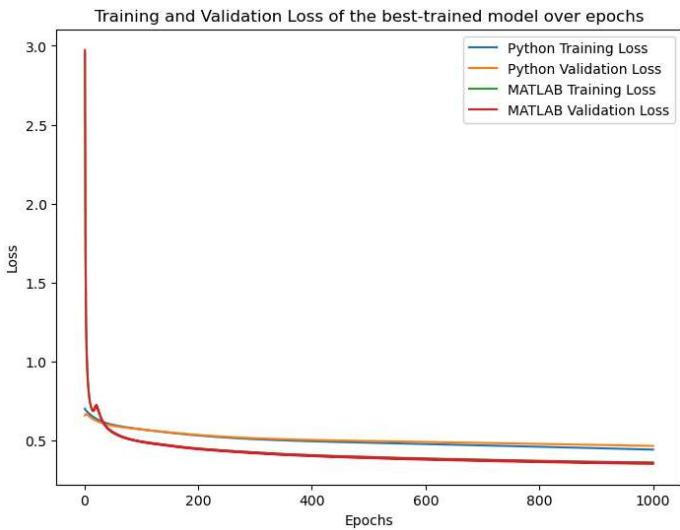
The test accuracy for the best-trained model in MATLAB = 85.34%
```

```
In [50]: # Make one figure for two graphs.
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(18, 6))

# Line chart about the training loss from the best model in Python and MATLAB.
ax1.plot(Epochs, train_loss_for_plotting, label='Python Training Loss')
ax1.plot(Epochs, vali_loss_for_plotting, label='Python Validation Loss')
ax1.plot(Epochs, matlab_train_loss_for_plotting, label='MATLAB Training Loss')
ax1.plot(Epochs, matlab_vali_loss_for_plotting, label='MATLAB Validation Loss')
ax1.set_xlabel('Epochs')
ax1.set_ylabel('Loss')
ax1.legend()
ax1.set_title('Training and Validation Loss of the best-trained model over epochs')

# Bar graph about the accuracy from the best model in Python and MATLAB.
accuracy_labels = ['MATLAB', 'Python']
accuracy_values = [accuracy_rate_test_set_MATLAB, accuracy_rate_test_set_python]
ax2.bar(accuracy_labels, accuracy_values, color=['blue', 'orange'])
ax2.set_ylabel('Accuracy Rate')
ax2.set_title('Test Set Accuracy Comparison')

plt.show()
```



```
In [51]: # Calculate True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN)
TP = ((y_test_pred.round() == 1) & (y_test == 1)).sum().item()
TN = ((y_test_pred.round() == 0) & (y_test == 0)).sum().item()
FP = ((y_test_pred.round() == 1) & (y_test == 0)).sum().item()
FN = ((y_test_pred.round() == 0) & (y_test == 1)).sum().item()

# Calculate the confusion matrix.
# Apart from the accuracy rate, measure Precision, Recall, and F1 score.
precision = TP / (TP + FP) if (TP + FP) > 0 else 0
recall = TP / (TP + FN) if (TP + FN) > 0 else 0
f1 = 2 * (precision * recall) / (precision + recall) if (precision + recall) > 0 else 0

print("Precision of the best-trained model = %.2f%%" % (precision*100))
print("Recall of best-trained model = %.2f%%" % (recall*100))
print("F1 score of best-trained model = %.2f%%" % (f1*100))
```

Precision of the best-trained model = 48.78%  
 Recall of best-trained model = 69.30%  
 F1 score of best-trained model = 57.26%

In [ ]:

In [ ]: