1.Problem Statement: Write a program non-recursive and recursive program to calculate Fibonacci numbers and analyze their time and space complexity.

```
# Program to display the Fibonacci sequence up to n-th term
nterms = int(input("How many terms? "))
# first two terms
n1, n2 = 0, 1
count = 0
# check if the number of terms is valid
if nterms <= 0:
   print("Please enter a positive integer")
elif nterms == 1:
      print("Fibonacci sequence upto",nterms,":")
      print(n1)
# generate fibonacci sequence
else:
   print("Fibonacci sequence:")
   while count < nterms:
      print(n1)
      nth = n1 + n2
# update values
      n1 = n2
      n2 = nth
      count += 1
```

OUTPUT:

```
>
========= RESTART: C:/Users/saksh/OneDrive/Desktop/fibonacci_series.py =========
How many terms? 7
Fibonacci sequence:
0
1
1
2
3
5
8
>
```

2.Problem Statement: Write a program to implement Huffman Encoding using a greedy strategy.

```
class NodeTree(object):
    def __init__(self, left=None, right=None):
        self.left = left
        self.right = right

    def children(self):
        return (self.left, self.right)

    def __str__(self):
        return '%s_%s' % (self.left, self.right)

def huffman_code_tree(node, left=True, binString=''):
    if type(node) is str:
        return {node: binString}
    (l, r) = node.children()
    d = dict()
    d.update(huffman_code_tree(l, True, binString + '0'))
    d.update(huffman_code_tree(r, False, binString + '1'))
    return d

# Input string
input_string = 'BCAADDDCCACACAC'

# Calculate frequency of each character
freq = {}
for c in input_string:
    if c in freq:
        freq[c] += 1
```

```
    else:
        freq[c] = 1

# Sort frequency dictionary by frequency in descending order
freq = sorted(freq.items(), key=lambda x: x[1], reverse=True)

# Create initial nodes (characters and their frequencies)
nodes = freq

# Build the Huffman tree
while len(nodes) > 1:
    (key1, c1) = nodes[-1]
    (key2, c2) = nodes[-2]
    nodes = nodes[:-2]
    node = NodeTree(key1, key2)
    nodes.append((node, c1 + c2))
    nodes = sorted(nodes, key=lambda x: x[1], reverse=True)

# Generate Huffman codes
huffmanCode = huffman_code_tree(nodes[0][0])

# Print the results
print(' Char | Huffman code ')
print('----------------------')
for (char, frequency) in freq:
    print(' %-4r |%12s' % (char, huffmanCode[char]))
```

OUTPUT:

```
= RESTART: C:/Users/saksh/OneDrive/Desktop/Huffman_code.py
 Char | Huffman code
----------------------
 'C'  |           0
 'A'  |          11
 'D'  |         101
 'B'  |         100
```

3.Problem Statement: Write a program to solve a fractional Knapsack problem using a greedy method.

```
class Item:
    def __init__(self, value, weight):
        self.value = value
        self.weight = weight


def fractionalKnapsack(W, arr):
    arr.sort(key=lambda x: (x.value / x.weight), reverse=True)

    finalvalue = 0.0  # Variable to store the final value (maximum value)

    for item in arr:
        # If the item can fit in the knapsack, take it fully
        if item.weight <= W:
            W -= item.weight
            finalvalue += item.value
        else:
            # If the item cannot fit, take the fraction of it
            finalvalue += item.value * W / item.weight
            break  # Knapsack is full now, no more items can be added

    return finalvalue


if __name__ == "__main__":
    W = 50  # Knapsack capacity
    arr = [Item(60, 10), Item(100, 20), Item(120, 30)]  # List of items (value, weight)

    max_val = fractionalKnapsack(W, arr)  # Get the maximum value the knapsack can hold
    print(f"Maximum value in Knapsack = {max_val}")
```

OUTPUT:

```
= RESTART: C:/Users/saksh/OneDrive/Desktop/Knapsack.py
Maximum value in Knapsack = 240.0
```

4.Problem Statement: Write a program to solve a 0-1 Knapsack problem using dynamic programming or branch and bound strategy.

```
def knapSack(W, wt, val, n):
    # Create a 2D DP array to store the maximum value for each subproblem
    K = [[0 for x in range(W + 1)] for x in range(n + 1)]

    # Build the DP array K[][]
    for i in range(n + 1):
        for w in range(W + 1):
            if i == 0 or w == 0:
                K[i][w] = 0
            elif wt[i-1] <= w:
                K[i][w] = max(val[i-1] + K[i-1][w-wt[i-1]], K[i-1][w])
            else:
                K[i][w] = K[i-1][w]

    # The result is stored in K[n][W]
    return K[n][W]

# Example usage
val = [60, 100, 120]  # Values of the items
wt = [10, 20, 30]     # Weights of the items
W = 50                # Maximum capacity of the knapsack
n = len(val)          # Number of items

# Print the maximum value that can be obtained
print(knapSack(W, wt, val, n))
```

OUTPUT:

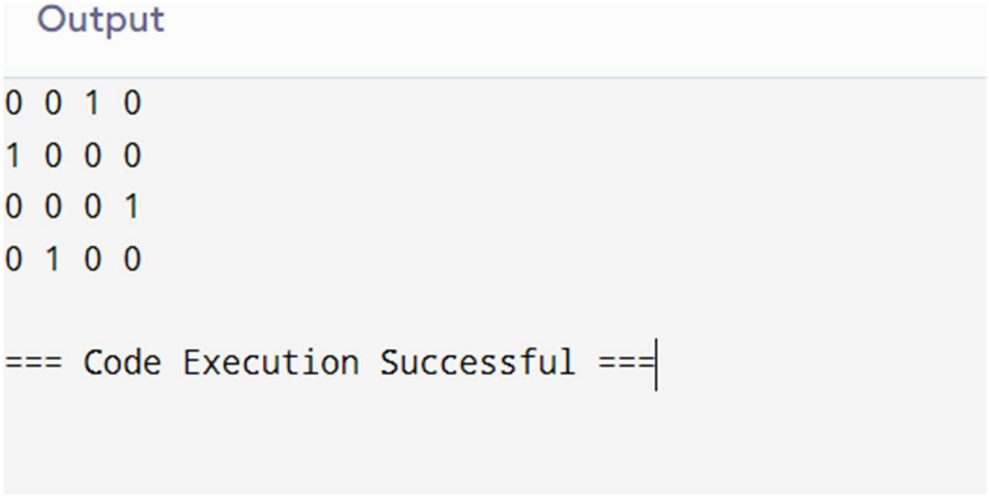
```
= RESTART: C:/Users/saksh/OneDrive/Desktop/Knapsack.py
220
```

5.Problem Statement: Design n-Queens matrix having first Queen placed. Use backtracking to place remaining Queens to generate the final n-queen's matrix.

```
global N
N = 4

# Function to print the solution (board with placed queens)
def printSolution(board):
    for i in range(N):
        for j in range(N):
            print(board[i][j], end=' ')
        print()

# Function to check if it's safe to place a queen at board[row][col]
def isSafe(board, row, col):
    # Check this row on the left side
    for i in range(col):
        if board[row][i] == 1:
            return False

    # Check the upper diagonal on the left side
    for i, j in zip(range(row, -1, -1), range(col, -1, -1)):
        if board[i][j] == 1:
            return False

    # Check the lower diagonal on the left side
    for i, j in zip(range(row, N, 1), range(col, -1, -1)):
        if board[i][j] == 1:
            return False

    return True
```

```
# Recursive utility function to solve the N-Queens problem
def solveNQUtil(board, col):
    # If all queens are placed, return True
    if col >= N:
        return True
    for i in range(N):
        if isSafe(board, i, col):
            board[i][col] = 1  # Place the queen
            if solveNQUtil(board, col + 1) == True:
                return True


            board[i][col] = 0  # Backtrack (remove the queen)


    return False  # If the queen can't be placed in any row


def solveNQ():
    # Initialize the chessboard with 0s
    board = [[0, 0, 0, 0],
             [0, 0, 0, 0],
             [0, 0, 0, 0],
             [0, 0, 0, 0]]
    # Call the recursive utility function to solve the problem
    if solveNQUtil(board, 0) == False:
        print("Solution does not exist")
        return False


    printSolution(board)
    return True
solveNQ()
```

OUTPUT:



1.Problem Statement:

#Predict the price of the Uber ride from a given pickup point to the agreed drop-off location. Perform following tasks:

1. Pre-process the dataset.
2. Identify outliers.
3. Check the correlation.
4. Implement linear regression and random forest regression models.
5. Evaluate the models and compare their respective scores like R2, RMSE, etc. Dataset link:
   https://www.kaggle.com/datasets/yasserh/uber-fares-dataset (https://www.kaggle.com/datasets/yasserh/uber-fares-dataset)

In [ ]:
```
#Importing the required libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [ ]:
```
#importing the dataset
df  = pd.read_csv("uber.csv")
```

1. Pre-process the dataset.

In [3]:
```
df.head()
```

Out[3]:

	Unnamed: 0	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	pa
0	24238194	2015-05-07 19:52:06.0000003	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	-73.999512	40.723217	
1	27835199	2009-07-17 20:04:56.0000002	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	-73.994710	40.750325	
2	44984355	2009-08-24 21:45:00.00000061	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	-73.962565	40.772647	
3	25894730	2009-06-26 08:22:21.0000001	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844	-73.965316	40.803349	
4	17610152	2014-08-28 17:47:00.000000188	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085	-73.973082	40.761247	

In [4]:
```
df.info() #To get the required information of the dataset
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 9 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Unnamed: 0         200000 non-null  int64
 1   key                200000 non-null  object
 2   fare_amount        200000 non-null  float64
 3   pickup_datetime    200000 non-null  object
 4   pickup_longitude   200000 non-null  float64
 5   pickup_latitude    200000 non-null  float64
 6   dropoff_longitude  199999 non-null  float64
 7   dropoff_latitude   199999 non-null  float64
 8   passenger_count    200000 non-null  int64
dtypes: float64(5), int64(2), object(2)
memory usage: 13.7+ MB
```

In [5]:
```
df.columns #TO get number of columns in the dataset
```

Out[5]:
```
Index(['Unnamed: 0', 'key', 'fare_amount', 'pickup_datetime',
       'pickup_longitude', 'pickup_latitude', 'dropoff_longitude',
       'dropoff_latitude', 'passenger_count'],
      dtype='object')
```

In [6]:
```
df = df.drop(['Unnamed: 0', 'key'], axis= 1) #To drop unnamed column as it isn't required
```

In [7]:
```
df.head()
```

Out[7]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
0	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	-73.999512	40.723217	1
1	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	-73.994710	40.750325	1
2	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	-73.962565	40.772647	1
3	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844	-73.965316	40.803349	3
4	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085	-73.973082	40.761247	5

In [8]:
```
df.shape #To get the total (Rows,Columns)
```

Out[8]:
```
(200000, 7)
```

In [9]:
```
df.dtypes #To get the type of each column
```

Out[9]:
```
fare_amount          float64
pickup_datetime       object
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count        int64
dtype: object
```


In [10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 7 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   fare_amount        200000 non-null  float64
 1   pickup_datetime    200000 non-null  object
 2   pickup_longitude   200000 non-null  float64
 3   pickup_latitude    200000 non-null  float64
 4   dropoff_longitude  199999 non-null  float64
 5   dropoff_latitude   199999 non-null  float64
 6   passenger_count    200000 non-null  int64
dtypes: float64(5), int64(1), object(1)
memory usage: 10.7+ MB
```

In [11]:
```
df.describe() #To get statistics of each columns
```

Out[11]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
count	200000.000000	200000.000000	200000.000000	199999.000000	199999.000000	200000.000000
mean	11.359955	-72.527638	39.935885	-72.525292	39.923890	1.684535
std	9.901776	11.437787	7.720539	13.117408	6.794829	1.385997
min	-52.000000	-1340.648410	-74.015515	-3356.666300	-881.985513	0.000000
25%	6.000000	-73.992065	40.734796	-73.991407	40.733823	1.000000
50%	8.500000	-73.981823	40.752592	-73.980093	40.753042	1.000000
75%	12.500000	-73.967154	40.767158	-73.963658	40.768001	2.000000
max	499.000000	57.418457	1644.421482	1153.572603	872.697628	208.000000

Filling Missing values

In [12]:
```
df.isnull().sum()
```

Out[12]:
```
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    1
dropoff_latitude     1
passenger_count      0
dtype: int64
```

In [13]:
```
df['dropoff_latitude'].fillna(value=df['dropoff_latitude'].mean(),inplace = True)
df['dropoff_longitude'].fillna(value=df['dropoff_longitude'].median(),inplace = True)
```

In [14]:
```
df.isnull().sum()
```

Out[14]:
```
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
dtype: int64
```

In [15]:
```
df.dtypes
```

Out[15]:
```
fare_amount          float64
pickup_datetime       object
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count        int64
dtype: object
```

Column pickup_datetime is in wrong format (Object). Convert it to DateTime Format

In [16]:
```
df.pickup_datetime = pd.to_datetime(df.pickup_datetime, errors='coerce')
```


In [17]:
```
df.dtypes
```

Out[17]:
```
fare_amount                      float64
pickup_datetime      datetime64[ns, UTC]
pickup_longitude                 float64
pickup_latitude                  float64
dropoff_longitude                float64
dropoff_latitude                 float64
passenger_count                    int64
dtype: object
```

To segregate each time of date and time

In [18]:
```
df= df.assign(hour = df.pickup_datetime.dt.hour,
              day= df.pickup_datetime.dt.day,
              month = df.pickup_datetime.dt.month,
              year = df.pickup_datetime.dt.year,
              dayofweek = df.pickup_datetime.dt.dayofweek)
```

In [19]:
```
df.head()
```

Out[19]:

	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	hour	day	mon
0	7.5	2015-05-07 19:52:06+00:00	-73.999817	40.738354	-73.999512	40.723217	1	19	7	
1	7.7	2009-07-17 20:04:56+00:00	-73.994355	40.728225	-73.994710	40.750325	1	20	17	
2	12.9	2009-08-24 21:45:00+00:00	-74.005043	40.740770	-73.962565	40.772647	1	21	24	
3	5.3	2009-06-26 08:22:21+00:00	-73.976124	40.790844	-73.965316	40.803349	3	8	26	
4	16.0	2014-08-28 17:47:00+00:00	-73.925023	40.744085	-73.973082	40.761247	5	17	28	

In [20]:
```
# drop the column 'pickup_daetime' using drop()
# 'axis = 1' drops the specified column

df = df.drop('pickup_datetime',axis=1)
```

In [21]:
```
df.head()
```

Out[21]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	hour	day	month	year	dayofwe
0	7.5	-73.999817	40.738354	-73.999512	40.723217	1	19	7	5	2015	
1	7.7	-73.994355	40.728225	-73.994710	40.750325	1	20	17	7	2009	
2	12.9	-74.005043	40.740770	-73.962565	40.772647	1	21	24	8	2009	
3	5.3	-73.976124	40.790844	-73.965316	40.803349	3	8	26	6	2009	
4	16.0	-73.925023	40.744085	-73.973082	40.761247	5	17	28	8	2014	

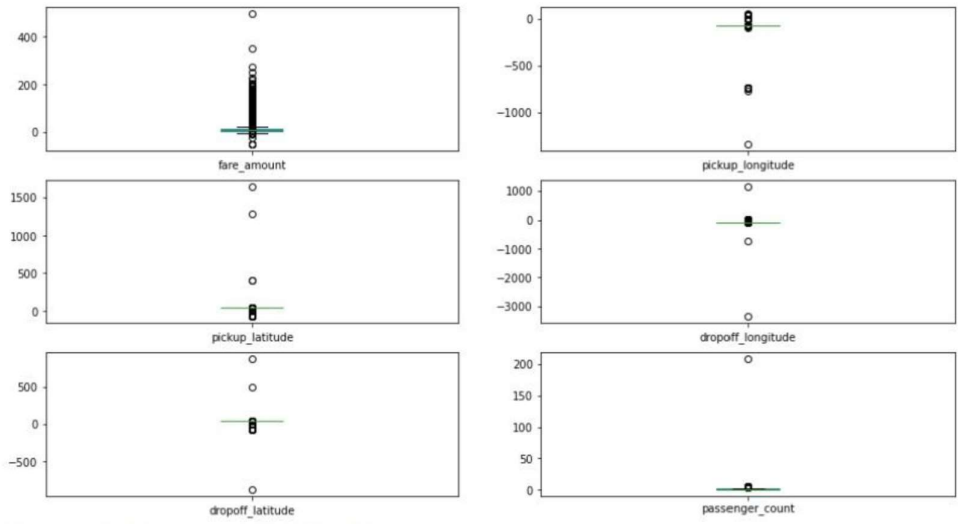
In [22]:
```
df.dtypes
```

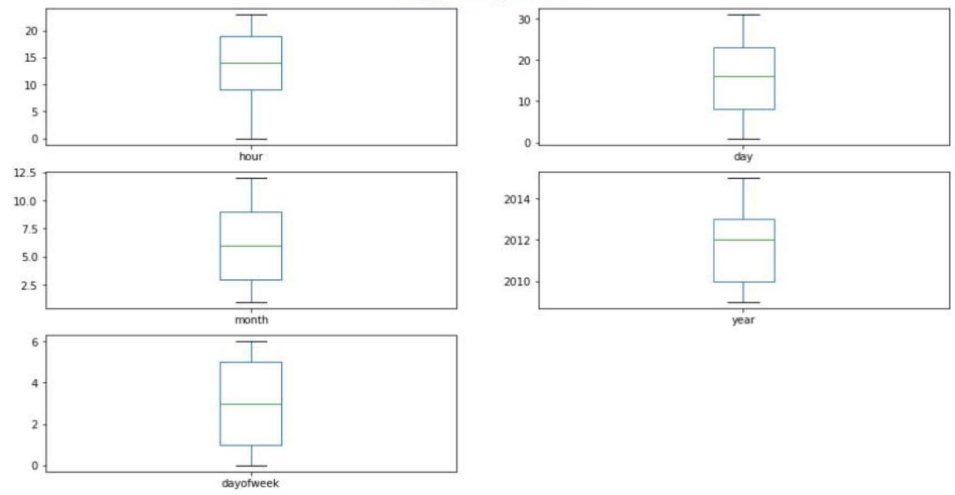
Out[22]:
```
fare_amount          float64
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count        int64
hour                   int64
day                    int64
month                  int64
year                   int64
dayofweek              int64
dtype: object
```

Checking outliers and filling them

In [23]:
```
df.plot(kind = "box",subplots = True,layout = (7,2),figsize=(15,20)) #Boxplot to check the outliers
```

Out[23]:
```
fare_amount          AxesSubplot(0.125,0.787927;0.352273x0.0920732)
pickup_longitude     AxesSubplot(0.547727,0.787927;0.352273x0.0920732)
pickup_latitude      AxesSubplot(0.125,0.677439;0.352273x0.0920732)
dropoff_longitude    AxesSubplot(0.547727,0.677439;0.352273x0.0920732)
dropoff_latitude     AxesSubplot(0.125,0.566951;0.352273x0.0920732)
passenger_count      AxesSubplot(0.547727,0.566951;0.352273x0.0920732)
hour                 AxesSubplot(0.125,0.456463;0.352273x0.0920732)
day                  AxesSubplot(0.547727,0.456463;0.352273x0.0920732)
month                AxesSubplot(0.125,0.345976;0.352273x0.0920732)
year                 AxesSubplot(0.547727,0.345976;0.352273x0.0920732)
dayofweek            AxesSubplot(0.125,0.235488;0.352273x0.0920732)
dtype: object
```

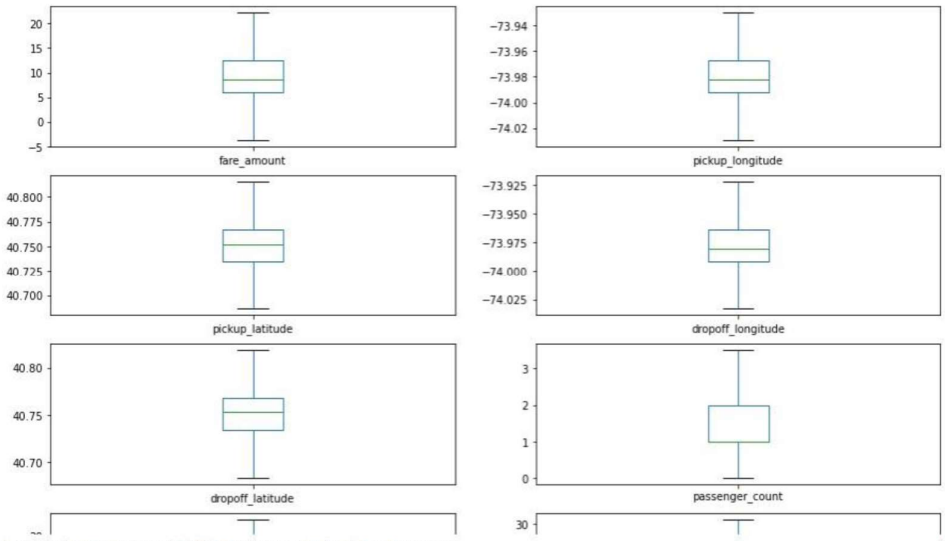


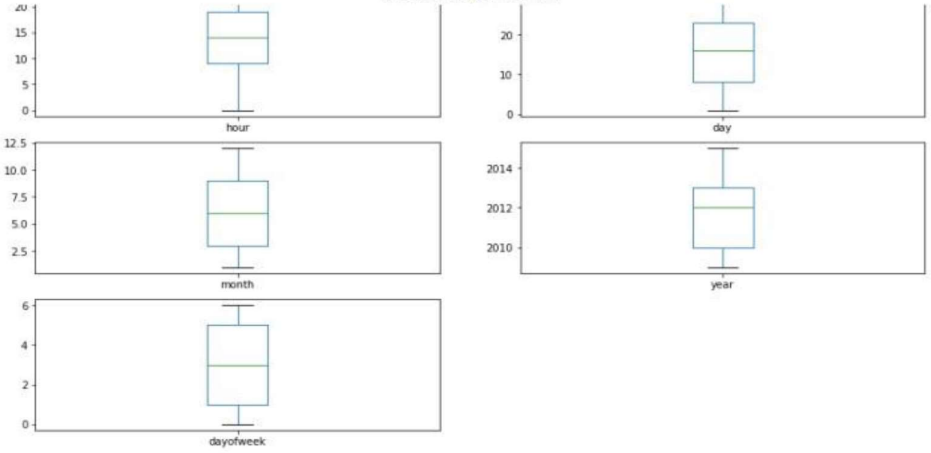


In [24]:
```
#Using the InterQuartile Range to fill the values
def remove_outlier(df1 , col):
    Q1 = df1[col].quantile(0.25)
    Q3 = df1[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_whisker = Q1-1.5*IQR
    upper_whisker = Q3+1.5*IQR
    df[col] = np.clip(df1[col] , lower_whisker , upper_whisker)
    return df1

def treat_outliers_all(df1 , col_list):
    for c in col_list:
        df1 = remove_outlier(df , c)
    return df1
```


In [26]:
```
df.plot(kind = "box",subplots = True,layout = (7,2),figsize=(15,20)) #Boxplot shows that dataset is free from ou
```

Out[26]:
```
fare_amount            AxesSubplot(0.125,0.787927;0.352273x0.0920732)
pickup_longitude     AxesSubplot(0.547727,0.787927;0.352273x0.0920732)
pickup_latitude        AxesSubplot(0.125,0.677439;0.352273x0.0920732)
dropoff_longitude    AxesSubplot(0.547727,0.677439;0.352273x0.0920732)
dropoff_latitude       AxesSubplot(0.125,0.566951;0.352273x0.0920732)
passenger_count      AxesSubplot(0.547727,0.566951;0.352273x0.0920732)
hour                   AxesSubplot(0.125,0.456463;0.352273x0.0920732)
day                  AxesSubplot(0.547727,0.456463;0.352273x0.0920732)
month                  AxesSubplot(0.125,0.345976;0.352273x0.0920732)
year                 AxesSubplot(0.547727,0.345976;0.352273x0.0920732)
dayofweek              AxesSubplot(0.125,0.235488;0.352273x0.0920732)
dtype: object
```





In [27]:
```
#pip install haversine
import haversine as hs  #Calculate the distance using Haversine to calculate the distance between to points. Can
travel_dist = []
for pos in range(len(df['pickup_longitude'])):
        long1,lati1,long2,lati2 = [df['pickup_longitude'][pos],df['pickup_latitude'][pos],df['dropoff_longitude'
        loc1=(lati1,long1)
        loc2=(lati2,long2)
        c = hs.haversine(loc1,loc2)
        travel_dist.append(c)

print(travel_dist)
df['dist_travel_km'] = travel_dist
df.head()
```

```
IOPub data rate exceeded.
The notebook server will temporarily stop sending output
to the client in order to avoid crashing it.
To change this limit, set the config variable
`--NotebookApp.iopub_data_rate_limit`.

Current values:
NotebookApp.iopub_data_rate_limit=1000000.0 (bytes/sec)
NotebookApp.rate_limit_window=3.0 (secs)
```

Out[27]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	hour	day	month	year	dayofwe
0	7.5	-73.999817	40.738354	-73.999512	40.723217	1.0	19	7	5	2015	
1	7.7	-73.994355	40.728225	-73.994710	40.750325	1.0	20	17	7	2009	
2	12.9	-74.005043	40.740770	-73.962565	40.772647	1.0	21	24	8	2009	
3	5.3	-73.976124	40.790844	-73.965316	40.803349	3.0	8	26	6	2009	
4	16.0	-73.929786	40.744085	-73.973082	40.761247	3.5	17	28	8	2014	

In [28]:
```
#Uber doesn't travel over 130 kms so minimize the distance
df= df.loc[(df.dist_travel_km >= 1) | (df.dist_travel_km <= 130)]
print("Remaining observastions in the dataset:", df.shape)
```

```
Remaining observastions in the dataset: (200000, 12)
```

In [29]:
```
#Finding inccorect latitude (Less than or greater than 90) and Longitude (greater than or less than 180)
incorrect_coordinates = df.loc[(df.pickup_latitude > 90) |(df.pickup_latitude < -90) |
                               (df.dropoff_latitude > 90) |(df.dropoff_latitude < -90) |
                               (df.pickup_longitude > 180) |(df.pickup_longitude < -180) |
                               (df.dropoff_longitude > 90) |(df.dropoff_longitude < -90)
                                ]
```

In [30]:
```
df.drop(incorrect_coordinates, inplace = True, errors = 'ignore')
```

In [31]:
```
df.head()
```

Out[31]:

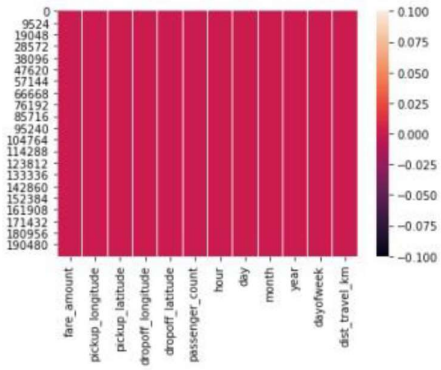
	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	hour	day	month	year	dayofwe
0	7.5	-73.999817	40.738354	-73.999512	40.723217	1.0	19	7	5	2015	
1	7.7	-73.994355	40.728225	-73.994710	40.750325	1.0	20	17	7	2009	
2	12.9	-74.005043	40.740770	-73.962565	40.772647	1.0	21	24	8	2009	
3	5.3	-73.976124	40.790844	-73.965316	40.803349	3.0	8	26	6	2009	
4	16.0	-73.929786	40.744085	-73.973082	40.761247	3.5	17	28	8	2014	

In [32]:
```
df.isnull().sum()
```

Out[32]:
```
fare_amount          0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
hour                 0
day                  0
month                0
year                 0
dayofweek            0
dist_travel_km       0
dtype: int64
```


In [33]:
```
sns.heatmap(df.isnull()) #Free for null values
```

Out[33]: <AxesSubplot:>



In [34]:
```
corr = df.corr() #Function to find the correlation
```

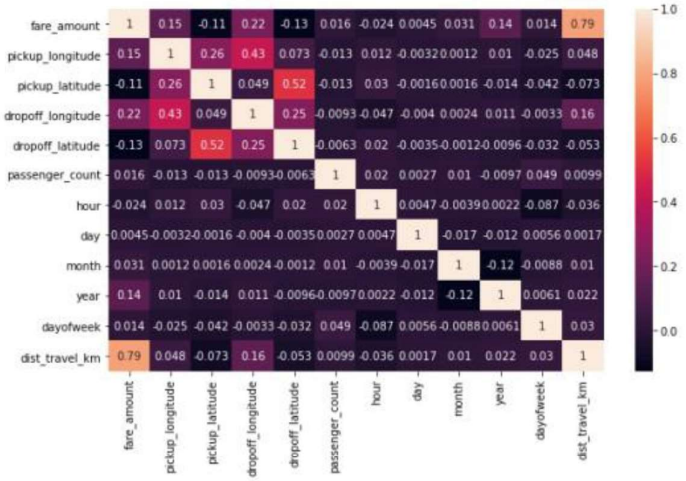
In [35]:
```
corr
```

Out[35]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	hour	d
fare_amount	1.000000	0.154069	-0.110842	0.218675	-0.125898	0.015778	-0.023623	0.0045
pickup_longitude	0.154069	1.000000	0.259497	0.425619	0.073290	-0.013213	0.011579	-0.0032
pickup_latitude	-0.110842	0.259497	1.000000	0.048889	0.515714	-0.012889	0.029681	-0.0015
dropoff_longitude	0.218675	0.425619	0.048889	1.000000	0.245667	-0.009303	-0.046558	-0.0040
dropoff_latitude	-0.125898	0.073290	0.515714	0.245667	1.000000	-0.006308	0.019783	-0.0034
passenger_count	0.015778	-0.013213	-0.012889	-0.009303	-0.006308	1.000000	0.020274	0.0027
hour	-0.023623	0.011579	0.029681	-0.046558	0.019783	0.020274	1.000000	0.0046
day	0.004534	-0.003204	-0.001553	-0.004007	-0.003479	0.002712	0.004677	1.0000
month	0.030817	0.001169	0.001562	0.002391	-0.001193	0.010351	-0.003926	-0.0173
year	0.141277	0.010198	-0.014243	0.011346	-0.009603	-0.009749	0.002156	-0.0121
dayofweek	0.013652	-0.024652	-0.042310	-0.003336	-0.031919	0.048550	-0.086947	0.0056
dist_travel_km	0.786385	0.048446	-0.073362	0.155191	-0.052701	0.009884	-0.035708	0.0017

In [36]:
```
fig,axis = plt.subplots(figsize = (10,6))
sns.heatmap(df.corr(),annot = True) #Correlation Heatmap (Light values means highly correlated)
```

Out[36]: <AxesSubplot:>



Dividing the dataset into feature and target values

In [182]:
```
x = df[['pickup_longitude','pickup_latitude','dropoff_longitude','dropoff_latitude','passenger_count','hour','da
```

In [183]:
```
y = df['fare_amount']
```

Dividing the dataset into training and testing dataset

In [184]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(x,y,test_size = 0.33)
```

Linear Regression

In [185]:
```
from sklearn.linear_model import LinearRegression
regression = LinearRegression()
```

In [186]:
```
regression.fit(X_train,y_train)
```

Out[186]:
```
LinearRegression()
```

In [80]:
```
regression.intercept_ #To find the linear intercept
```

Out[80]:
```
2640.1356169149753
```

In [187]:
```
regression.coef_ #To find the linear coeeficient
```

Out[187]:
```
array([ 2.54805415e+01, -7.18365435e+00,  1.96232986e+01, -1.79401980e+01,
        5.48472723e-02,  5.32910041e-03,  4.05930990e-03,  5.74261856e-02,
        3.66574831e-01, -3.03753790e-02,  1.84233728e+00])
```


In [188]:
```
prediction = regression.predict(X_test) #To predict the target values
```

In [189]:
```
print(prediction)
```

```
[ 5.47848314 10.11016249 12.19490542 ...  7.11952609 20.2482979
  8.82791961]
```

In [190]:
```
y_test
```

Out[190]:
```
155740     4.90
47070     10.00
116192    14.50
164589     6.50
154309    11.30
          ...
76552      7.70
27926     10.90
38972      6.50
120341    22.25
178449     8.10
Name: fare_amount, Length: 66000, dtype: float64
```

Metrics Evaluation using R2, Mean Squared Error, Root Mean Sqared Error

In [191]:
```
from sklearn.metrics import r2_score
```

In [192]:
```
r2_score(y_test,prediction)
```

Out[192]:
```
0.6651880468683617
```

In [193]:
```
from sklearn.metrics import mean_squared_error
```

In [194]:
```
MSE = mean_squared_error(y_test,prediction)
```

In [195]:
```
MSE
```

Out[195]:
```
9.961516917717704
```

In [196]:
```
RMSE = np.sqrt(MSE)
```

In [197]:
```
RMSE
```

Out[197]:
```
3.156187085348032
```

Random Forest Regression

In [198]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [199]:
```
rf = RandomForestRegressor(n_estimators=100) #Here n_estimators means number of trees you want to build before m
```

In [200]:
```
rf.fit(X_train,y_train)
```

Out[200]:
```
RandomForestRegressor()
```

In [201]:
```
y_pred = rf.predict(X_test)
```

In [202]:
```
y_pred
```

Out[202]:
```
array([ 5.714 , 10.285 , 12.68  , ...,  6.338 , 19.4685,  7.712 ])
```

Metrics evaluatin for Random Forest

In [210]:
```
R2_Random = r2_score(y_test,y_pred)
```

In [211]:
```
R2_Random
```

Out[211]:
```
0.7948374920410631
```

In [205]:
```
MSE_Random = mean_squared_error(y_test,y_pred)
```


In [206]:
```
MSE_Random
```

Out[206]:
```
6.104112397417331
```

In [207]:
```
RMSE_Random = np.sqrt(MSE_Random)
```

In [208]:
```
RMSE_Random
```

Out[208]:
```
2.4706501972997574
```

2.Problem Statement:

Assignment 2

2. Classify the email using the binary classification method. Email Spam detection has two states: a) Normal State – Not Spam, b) Abnormal State – Spam. Use K-Nearest Neighbors and Support Vector Machine for classification. Analyze their performance. Dataset link: The emails.csv dataset on the Kaggle https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv (https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv)

In [19]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn import metrics
```

In [20]:
```
df=pd.read_csv('emails.csv')
```


In [21]:
```
df.head()
```

Out[21]:

	Email No.	the	to	ect	and	for	of	a	you	hou	...	connevey	jay	valued	lay	infrastructure	military	allowing	ff	dry	Prediction
0	Email 1	0	0	1	0	0	0	2	0	0	...	0	0	0	0	0	0	0	0	0	0
1	Email 2	8	13	24	6	6	2	102	1	27	...	0	0	0	0	0	0	0	1	0	0
2	Email 3	0	0	1	0	0	0	8	0	0	...	0	0	0	0	0	0	0	0	0	0
3	Email 4	0	5	22	0	5	1	51	2	10	...	0	0	0	0	0	0	0	0	0	0
4	Email 5	7	6	17	1	5	2	57	0	9	...	0	0	0	0	0	0	0	1	0	0

5 rows × 3002 columns

In [22]:
```
df.columns
```

Out[22]:
```
Index(['Email No.', 'the', 'to', 'ect', 'and', 'for', 'of', 'a', 'you', 'hou',
       ...
       'connevey', 'jay', 'valued', 'lay', 'infrastructure', 'military',
       'allowing', 'ff', 'dry', 'Prediction'],
      dtype='object', length=3002)
```

In [23]:
```
df.isnull().sum()
```

Out[23]:
```
Email No.     0
the           0
to            0
ect           0
and           0
             ..
military      0
allowing      0
ff            0
dry           0
Prediction    0
Length: 3002, dtype: int64
```

In [24]:
```
df.dropna(inplace = True)
```

In [25]:
```
df.drop(['Email No.'],axis=1,inplace=True)
X = df.drop(['Prediction'],axis = 1)
y = df['Prediction']
```

In [26]:
```
from sklearn.preprocessing import scale
X = scale(X)
# split into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 42)
```

##KNN classifier

In [35]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=7)

knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
```

In [36]:
```
print("Prediction",y_pred)
```

```
Prediction [0 0 1 ... 1 1 1]
```


In [37]:
```
print("KNN accuracy = ",metrics.accuracy_score(y_test,y_pred))
```

```
KNN accuracy =  0.8009020618556701
```

In [39]:
```
print("Confusion matrix",metrics.confusion_matrix(y_test,y_pred))
```

```
Confusion matrix [[804 293]
 [ 16 439]]
```

SVM classifier

In [27]:
```
# cost C = 1
model = SVC(C = 1)

# fit
model.fit(X_train, y_train)

# predict
y_pred = model.predict(X_test)
```

In [28]:
```
metrics.confusion_matrix(y_true=y_test, y_pred=y_pred)
```

Out[28]:
```
array([[1091,    6],
       [  90,  365]])
```

In [29]:
```
print("SVM accuracy = ",metrics.accuracy_score(y_test,y_pred))
```

```
SVM accuracy =  0.9381443298969072
```

3.Problem Statement:

Given a bank customer, build a neural network-based classifier that can determine whether they will leave or not in the next 6 months.

Dataset Description: The case study is from an open-source dataset from Kaggle. The dataset contains 10,000 sample points with 14 distinct features such as CustomerId, CreditScore, Geography, Gender, Age, Tenure, Balance, etc. Link to the Kaggle project: https://www.kaggle.com/barelydedicated/bank-customer-churn-modeling (https://www.kaggle.com/barelydedicated/bank-customer-churn-modeling) Perform following steps:

1. Read the dataset.
2. Distinguish the feature and target set and divide the data set into training and test sets.
3. Normalize the train and test data.
4. Initialize and build the model. Identify the points of improvement and implement the same.
5. Print the accuracy score and confusion matrix.

In [46]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt #Importing the libraries
```

In [47]:
```
df = pd.read_csv("Churn_Modelling.csv")
```

Preprocessing.

In [48]:
```
df.head()
```

Out[48]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveM
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	

In [49]:
```
df.shape
```

Out[49]:
```
(10000, 14)
```

In [50]:
```
df.describe()
```

Out[50]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMembe
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.0000(
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.5151(
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.4997(
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.0000(
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.0000(
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.0000(
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.0000(
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.0000(

In [51]:
```
df.isnull()
```

Out[51]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActive
0	False	False	False	False	False	False	False	False	False	False	False	
1	False	False	False	False	False	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	False	False	False	False	
3	False	False	False	False	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	False	False	False	False	
...	...	...	...	...	...	...	...	...	...	...	...	...
9995	False	False	False	False	False	False	False	False	False	False	False	
9996	False	False	False	False	False	False	False	False	False	False	False	
9997	False	False	False	False	False	False	False	False	False	False	False	
9998	False	False	False	False	False	False	False	False	False	False	False	
9999	False	False	False	False	False	False	False	False	False	False	False	

10000 rows × 14 columns

In [52]:
```
df.isnull().sum()
```

Out[52]:
```
RowNumber          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 [53]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   RowNumber        10000 non-null  int64
 1   CustomerId       10000 non-null  int64
 2   Surname          10000 non-null  object
 3   CreditScore      10000 non-null  int64
 4   Geography        10000 non-null  object
 5   Gender           10000 non-null  object
 6   Age              10000 non-null  int64
 7   Tenure           10000 non-null  int64
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64
 10  HasCrCard        10000 non-null  int64
 11  IsActiveMember   10000 non-null  int64
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

In [54]:
```
df.dtypes
```

Out[54]:
```
RowNumber            int64
CustomerId           int64
Surname             object
CreditScore          int64
Geography           object
Gender              object
Age                  int64
Tenure               int64
Balance            float64
NumOfProducts        int64
HasCrCard            int64
IsActiveMember       int64
EstimatedSalary    float64
Exited               int64
dtype: object
```

In [55]:
```
df.columns
```

Out[55]:
```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

In [56]:
```
df = df.drop(['RowNumber', 'Surname', 'CustomerId'], axis= 1) #Dropping the unnecessary columns
```

In [57]:
```
df.head()
```

Out[57]:

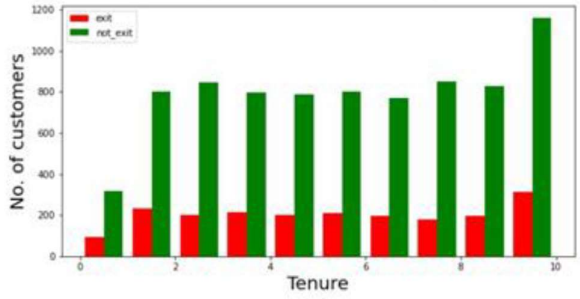
	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

Visualization

In [101]:
```
def visualization(x, y, xlabel):
    plt.figure(figsize=(10,5))
    plt.hist([x, y], color=['red', 'green'], label = ['exit', 'not_exit'])
    plt.xlabel(xlabel,fontsize=20)
    plt.ylabel("No. of customers", fontsize=20)
    plt.legend()
```

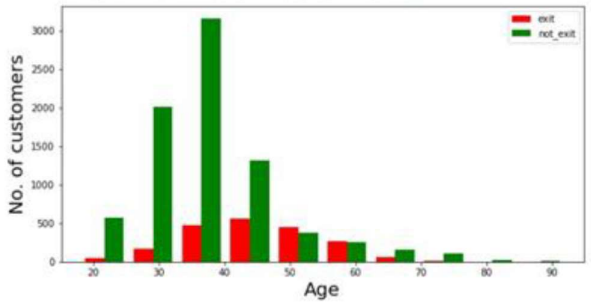
In [102]:
```
df_churn_exited = df[df['Exited']==1]['Tenure']
df_churn_not_exited = df[df['Exited']==0]['Tenure']
```

In [103]:
```
visualization(df_churn_exited, df_churn_not_exited, "Tenure")
```



In [105]:
```
df_churn_exited2 = df[df['Exited']==1]['Age']
df_churn_not_exited2 = df[df['Exited']==0]['Age']
```

In [106]:
```
visualization(df_churn_exited2, df_churn_not_exited2, "Age")
```



Converting the Categorical Variables

In [59]:
```
X = df[['CreditScore','Gender','Age','Tenure','Balance','NumOfProducts','HasCrCard','IsActiveMember','EstimatedS
states = pd.get_dummies(df['Geography'],drop_first = True)
gender = pd.get_dummies(df['Gender'],drop_first = True)
```

In [61]:
```
df = pd.concat([df,gender,states], axis = 1)
```

Splitting the training and testing Dataset

In [62]:
```
df.head()
```

Out[62]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Male
0	619	France	Female	42	2	0.00	1	1	1	101348.88	1	0
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0	0
2	502	France	Female	42	8	159660.80	3	1	0	113931.57	1	0
3	699	France	Female	39	1	0.00	2	0	0	93826.63	0	0
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0	0

In [63]:
```
X = df[['CreditScore','Age','Tenure','Balance','NumOfProducts','HasCrCard','IsActiveMember','EstimatedSalary','
```

In [64]:
```
y = df['Exited']
```

In [65]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.30)
```

Normalizing the values with mean as 0 and Standard Deviation as 1

In [66]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
```

In [67]:
```
X_train  = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [68]:
```
X_train
```

Out[68]:
```
array([[ 4.56838557e-01, -9.45594735e-01,  1.58341939e-03, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01],
       [-2.07591864e-02, -2.77416637e-01,  3.47956411e-01, ...,
        -1.09507222e+00, -5.81969145e-01,  1.74334114e+00],
       [-1.66115021e-01,  1.82257167e+00, -1.38390855e+00, ...,
        -1.09507222e+00, -5.81969145e-01, -5.73611200e-01],
       ...,
       [-3.63383654e-01, -4.68324665e-01,  1.73344838e+00, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01],
       [ 4.67221117e-01, -1.42286480e+00,  1.38707539e+00, ...,
         9.13181783e-01, -5.81969145e-01,  1.74334114e+00],
       [-8.82511636e-01,  2.95307447e-01, -6.91162564e-01, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01]])
```

In [69]:
```
X_test
```

Out[69]:
```
array([[ 3.63395520e-01,  1.99853433e-01,  1.58341939e-03, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01],
       [-4.15243057e-02,  4.86215475e-01,  1.58341939e-03, ...,
        -1.09507222e+00, -5.81969145e-01,  1.74334114e+00],
       [-1.87923736e+00, -3.72870651e-01, -1.38390855e+00, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01],
       ...,
       [-6.02182526e-01, -5.63778679e-01, -1.73028154e+00, ...,
        -1.09507222e+00, -5.81969145e-01, -5.73611200e-01],
       [ 1.51585964e+00, -6.59232693e-01,  1.73344838e+00, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01],
       [-5.19122049e-01,  1.04399419e-01,  1.73344838e+00, ...,
         9.13181783e-01, -5.81969145e-01, -5.73611200e-01]])
```

Building the Classifier Model using Keras

In [70]:
```
import keras #Keras is the wrapper on the top of tenserflow
#Can use Tenserflow as well but won't be able to understand the errors initially.
```


In [71]:
```
from keras.models import Sequential #To create sequential neural network
from keras.layers import Dense #To create hidden layers
```

In [72]:
```
classifier = Sequential()
```

In [74]:
```
#To add the layers
#Dense helps to contruct the neurons
#Input Dimension means we have 11 features
# Units is to create the hidden layers
#Uniform helps to distribute the weight uniformly
classifier.add(Dense(activation = "relu",input_dim = 11,units = 6,kernel_initializer = "uniform"))
```

In [75]:
```
classifier.add(Dense(activation = "relu",units = 6,kernel_initializer = "uniform"))   #Adding second hidden laye
```

In [76]:
```
classifier.add(Dense(activation = "sigmoid",units = 1,kernel_initializer = "uniform")) #Final neuron will be hav
```

In [77]:
```
classifier.compile(optimizer="adam",loss = 'binary_crossentropy',metrics = ['accuracy']) #To compile the Artific
```

In [79]:
```
classifier.summary() #3 layers created. 6 neurons in 1st,6neurons in 2nd layer and 1 neuron in last
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_3 (Dense)              (None, 6)                 72
_________________________________________________________________
dense_4 (Dense)              (None, 6)                 42
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 7
=================================================================
Total params: 121
Trainable params: 121
Non-trainable params: 0
_________________________________________________________________
```

In [89]:
```
classifier.fit(X_train,y_train,batch_size=10,epochs=50) #Fitting the ANN to training dataset
```

```
Epoch 1/50
700/700 [==============================] - 0s 674us/step - loss: 0.4293 - accuracy: 0.7947
Epoch 2/50
700/700 [==============================] - 0s 647us/step - loss: 0.4239 - accuracy: 0.7947
Epoch 3/50
700/700 [==============================] - 0s 657us/step - loss: 0.4203 - accuracy: 0.8067
Epoch 4/50
700/700 [==============================] - 0s 664us/step - loss: 0.4167 - accuracy: 0.8260
Epoch 5/50
700/700 [==============================] - 0s 674us/step - loss: 0.4153 - accuracy: 0.8287
Epoch 6/50
700/700 [==============================] - 0s 653us/step - loss: 0.4137 - accuracy: 0.8310
Epoch 7/50
700/700 [==============================] - 0s 658us/step - loss: 0.4125 - accuracy: 0.8317
Epoch 8/50
700/700 [==============================] - 1s 842us/step - loss: 0.4116 - accuracy: 0.8306
Epoch 9/50
700/700 [==============================] - 0s 671us/step - loss: 0.4103 - accuracy: 0.8331
Epoch 10/50
700/700 [==============================] - 0s 682us/step - loss: 0.4100 - accuracy: 0.8326
Epoch 11/50
700/700 [==============================] - 0s 690us/step - loss: 0.4093 - accuracy: 0.8337
Epoch 12/50
700/700 [==============================] - 0s 688us/step - loss: 0.4087 - accuracy: 0.8339
Epoch 13/50
700/700 [==============================] - 0s 675us/step - loss: 0.4081 - accuracy: 0.8341
Epoch 14/50
700/700 [==============================] - 1s 722us/step - loss: 0.4071 - accuracy: 0.8331
Epoch 15/50
700/700 [==============================] - 1s 811us/step - loss: 0.4065 - accuracy: 0.8341
Epoch 16/50
700/700 [==============================] - 0s 711us/step - loss: 0.4056 - accuracy: 0.8356
Epoch 17/50
700/700 [==============================] - 0s 702us/step - loss: 0.4046 - accuracy: 0.8366
Epoch 18/50
700/700 [==============================] - 0s 688us/step - loss: 0.4035 - accuracy: 0.8343
Epoch 19/50
700/700 [==============================] - 1s 715us/step - loss: 0.4024 - accuracy: 0.8363
Epoch 20/50
700/700 [==============================] - 0s 714us/step - loss: 0.4020 - accuracy: 0.8337
Epoch 21/50
```



```
700/700 [==============================] - 0s 705us/step - loss: 0.4010 - accuracy: 0.8374
Epoch 22/50
700/700 [==============================] - 1s 720us/step - loss: 0.4003 - accuracy: 0.8370
Epoch 23/50
700/700 [==============================] - 0s 692us/step - loss: 0.3993 - accuracy: 0.8374
Epoch 24/50
700/700 [==============================] - 0s 709us/step - loss: 0.3990 - accuracy: 0.8356
Epoch 25/50
700/700 [==============================] - 1s 871us/step - loss: 0.3984 - accuracy: 0.8366
Epoch 26/50
700/700 [==============================] - 1s 719us/step - loss: 0.3984 - accuracy: 0.8367
Epoch 27/50
700/700 [==============================] - 1s 719us/step - loss: 0.3980 - accuracy: 0.8366
Epoch 28/50
700/700 [==============================] - 0s 695us/step - loss: 0.3981 - accuracy: 0.8366
Epoch 29/50
700/700 [==============================] - 0s 667us/step - loss: 0.3976 - accuracy: 0.8374
Epoch 30/50
700/700 [==============================] - 0s 669us/step - loss: 0.3972 - accuracy: 0.8373
Epoch 31/50
700/700 [==============================] - 0s 670us/step - loss: 0.3970 - accuracy: 0.8370
Epoch 32/50
700/700 [==============================] - 1s 720us/step - loss: 0.3972 - accuracy: 0.8376
Epoch 33/50
700/700 [==============================] - 0s 675us/step - loss: 0.3965 - accuracy: 0.8367
Epoch 34/50
700/700 [==============================] - 0s 680us/step - loss: 0.3961 - accuracy: 0.8364
Epoch 35/50
700/700 [==============================] - 0s 685us/step - loss: 0.3962 - accuracy: 0.8379
Epoch 36/50
700/700 [==============================] - 1s 771us/step - loss: 0.3960 - accuracy: 0.8370
Epoch 37/50
700/700 [==============================] - 1s 1ms/step - loss: 0.3963 - accuracy: 0.8366
Epoch 38/50
700/700 [==============================] - 1s 764us/step - loss: 0.3962 - accuracy: 0.8373
Epoch 39/50
700/700 [==============================] - 1s 823us/step - loss: 0.3950 - accuracy: 0.8384
Epoch 40/50
700/700 [==============================] - 1s 759us/step - loss: 0.3956 - accuracy: 0.8361
Epoch 41/50
700/700 [==============================] - 1s 773us/step - loss: 0.3949 - accuracy: 0.8366
Epoch 42/50
700/700 [==============================] - 0s 695us/step - loss: 0.3953 - accuracy: 0.8369
```

```
Epoch 43/50
700/700 [==============================] - 0s 701us/step - loss: 0.3952 - accuracy: 0.8369
Epoch 44/50
700/700 [==============================] - 0s 707us/step - loss: 0.3952 - accuracy: 0.8366
Epoch 45/50
700/700 [==============================] - 0s 680us/step - loss: 0.3955 - accuracy: 0.8376
Epoch 46/50
700/700 [==============================] - 0s 665us/step - loss: 0.3947 - accuracy: 0.8373
Epoch 47/50
700/700 [==============================] - 0s 708us/step - loss: 0.3947 - accuracy: 0.8371
Epoch 48/50
700/700 [==============================] - 0s 681us/step - loss: 0.3944 - accuracy: 0.8371
Epoch 49/50
700/700 [==============================] - 0s 678us/step - loss: 0.3947 - accuracy: 0.8383
Epoch 50/50
700/700 [==============================] - 1s 869us/step - loss: 0.3944 - accuracy: 0.8370
```

Out[89]:
```
<tensorflow.python.keras.callbacks.History at 0x1fb1eb93df0>
```

In [90]:
```
y_pred =classifier.predict(X_test)
y_pred = (y_pred > 0.5) #Predicting the result
```

In [97]:
```
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report
```

In [92]:
```
cm = confusion_matrix(y_test,y_pred)
```

In [93]:
```
cm
```

Out[93]:
```
array([[2328,   72],
       [ 425,  175]], dtype=int64)
```

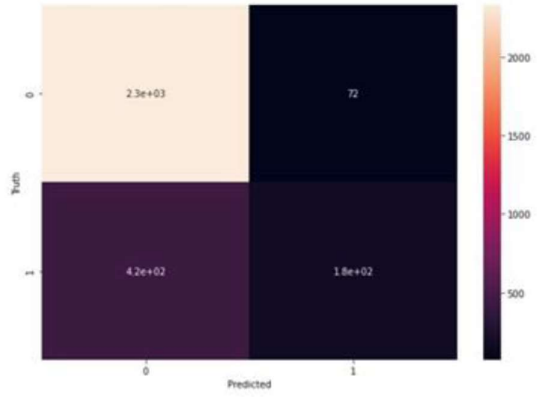
In [94]:
```
accuracy = accuracy_score(y_test,y_pred)
```

In [95]:
```
accuracy
```

Out[95]:
```
0.8343333333333334
```


In [98]:
```
plt.figure(figsize = (10,7))
sns.heatmap(cm,annot = True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

Out[98]:
```
Text(69.0, 0.5, 'Truth')
```



In [100]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.85      0.97      0.90      2400
           1       0.71      0.29      0.41       600

    accuracy                           0.83      3000
   macro avg       0.78      0.63      0.66      3000
weighted avg       0.82      0.83      0.81      3000
```

In [ ]:
```

```

4.Problem Statement:

KNN algorithm on diabetes dataset

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn import metrics
```

In [2]:
```
df=pd.read_csv('diabetes.csv')
```

In [3]:
```
df.columns
```

Out[3]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'Pedigree', 'Age', 'Outcome'],
      dtype='object')
```

Check for null values. If present remove null values from the dataset

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
Pregnancies      0
Glucose          0
BloodPressure    0
SkinThickness    0
Insulin          0
BMI              0
Pedigree         0
Age              0
Outcome          0
dtype: int64
```


In [ ]:
```

```

Outcome is the label/target, other columns are features

In [7]:
```
X = df.drop('Outcome',axis = 1)
y = df['Outcome']
```

In [8]:
```
from sklearn.preprocessing import scale
X = scale(X)
# split into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 42)
```

In [9]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=7)

knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
```

In [17]:
```
print("Confusion matrix: ")
cs = metrics.confusion_matrix(y_test,y_pred)
print(cs)
```

```
Confusion matrix:
[[123  28]
 [ 37  43]]
```

In [12]:
```
print("Acccuracy ",metrics.accuracy_score(y_test,y_pred))
```

```
Acccuracy  0.7186147186147186
```

Classification error rate: proportion of instances misclassified over the whole set of instances. Error rate is calculated as the total number of two incorrect predictions (FN + FP) divided by the total number of a dataset (examples in the dataset.

Also error_rate = 1- accuracy

In [29]:
```
total_misclassified = cs[0,1] + cs[1,0]
print(total_misclassified)
total_examples = cs[0,0]+cs[0,1]+cs[1,0]+cs[1,1]
print(total_examples)
print("Error rate",total_misclassified/total_examples)
print("Error rate ",1-metrics.accuracy_score(y_test,y_pred))
```

```
65
231
Error rate 0.2813852813852814
Error rate  0.2813852813852814
```

In [13]:
```
print("Precision score",metrics.precision_score(y_test,y_pred))
```

```
Precision score 0.6056338028169014
```

In [14]:
```
print("Recall score ",metrics.recall_score(y_test,y_pred))
```

```
Recall score  0.5375
```

In [15]:
```
print("Classification report ",metrics.classification_report(y_test,y_pred))
```

```
Classification report               precision    recall  f1-score   support

           0       0.77      0.81      0.79       151
           1       0.61      0.54      0.57        80

    accuracy                           0.72       231
   macro avg       0.69      0.68      0.68       231
weighted avg       0.71      0.72      0.71       231
```

5.Problem Statement: Develop a program in Python to create a Gradient Descent

```
# Gradient Descent Algorithm to minimize f(x) = x^2
def gradient_descent(derivative_func, initial_x, learning_rate, num_iterations):
    # Starting point (initial guess)
    x = initial_x

    # List to store the value of x at each iteration (for tracking the progress)
    x_history = []

    # Perform the gradient descent steps
    for i in range(num_iterations):
        # Calculate the gradient (derivative of the function at the current point)
        gradient = derivative_func(x)

        # Update the current point x using the gradient and the learning rate
        x = x - learning_rate * gradient

        # Save the updated value of x in history for later analysis
        x_history.append(x)

        # Print progress every 100 iterations
        if i % 100 == 0:
            print(f"Iteration {i}: x = {x}, f(x) = {x**2}")

    return x, x_history

# Define the derivative of the function f(x) = x^2
def derivative_f(x):
    return 2 * x
```

```
# Hyperparameters for the gradient descent
initial_x = 10          # Starting point for x
learning_rate = 0.1     # Learning rate (step size)
num_iterations = 1000   # Number of iterations to run the algorithm

# Run the gradient descent algorithm
optimal_x, x_history = gradient_descent(derivative_f, initial_x, learning_rate,
num_iterations)

# Print the optimal x value found
print(f"\nOptimal x: {optimal_x}")
print(f'Minimum value of f(x) = {optimal_x**2}")
```

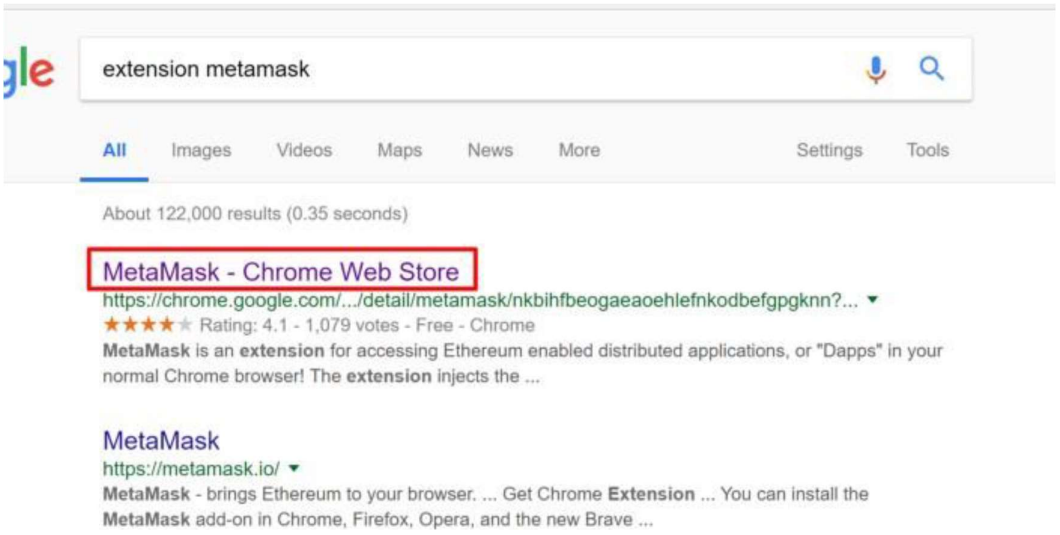
OUTPUT:

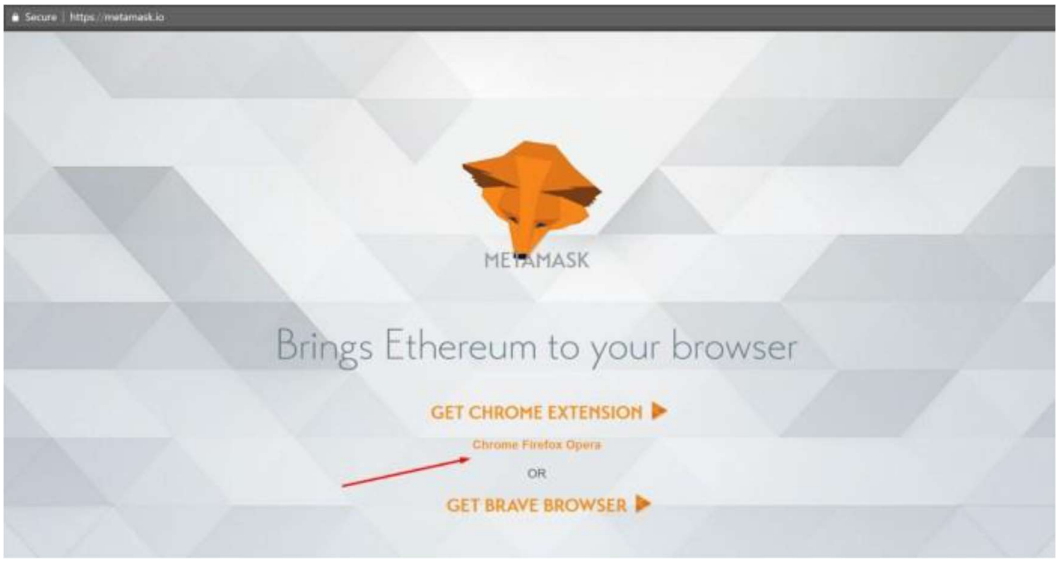
Output Clear

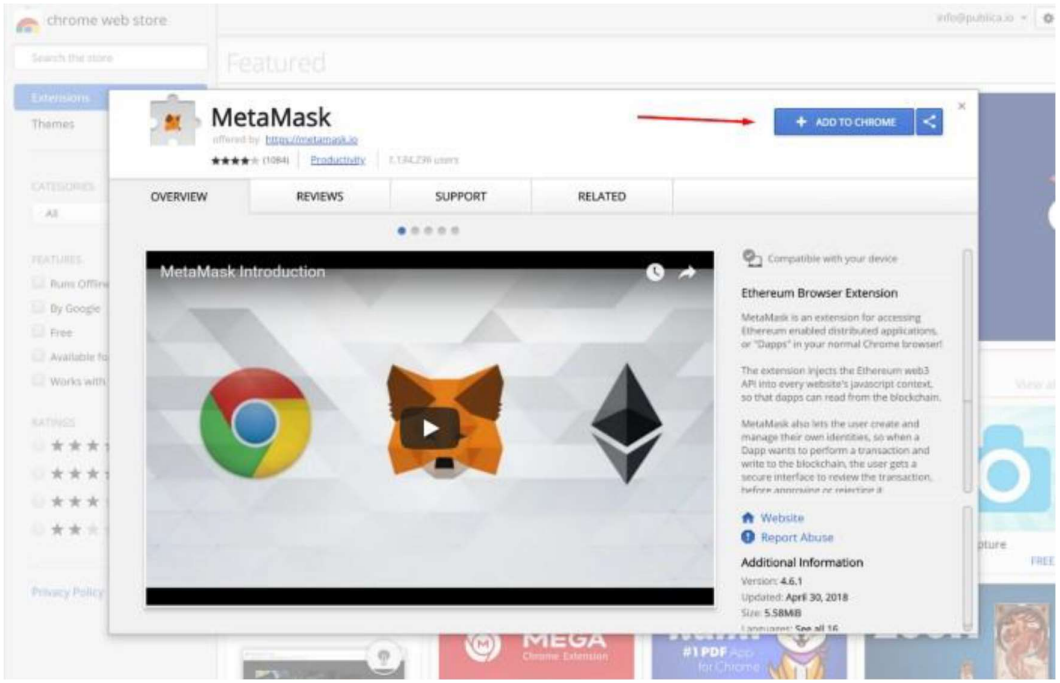
```
Iteration 0: x = 8.0, f(x) = 64.0
Iteration 100: x = 1.6296287810675901e-09, f(x) = 2.6556899640838397e-18
Iteration 200: x = 3.3196124551047986e-19, f(x) = 1.1019826852086909e-37
Iteration 300: x = 6.76216999853653e-29, f(x) = 4.572694308910753e-57
Iteration 400: x = 1.3774783565108623e-38, f(x) = 1.8974466226558662e-76
Iteration 500: x = 2.805972968834729e-48, f(x) = 7.873484301831182e-96
Iteration 600: x = 5.71586788613843e-58, f(x) = 3.267114569178861e-115
Iteration 700: x = 1.1643428520038935e-67, f(x) = 1.3556942770125606e-134
Iteration 800: x = 2.37180827831983e-77, f(x) = 5.6254745091064764e-154
Iteration 900: x = 4.831458791905451e-87, f(x) = 2.3342994057880482e-173

Optimal x: 1.2302319221611203e-96
Minimum value of f(x) = 1.5134705823042446e-192

=== Code Execution Successful ===
```

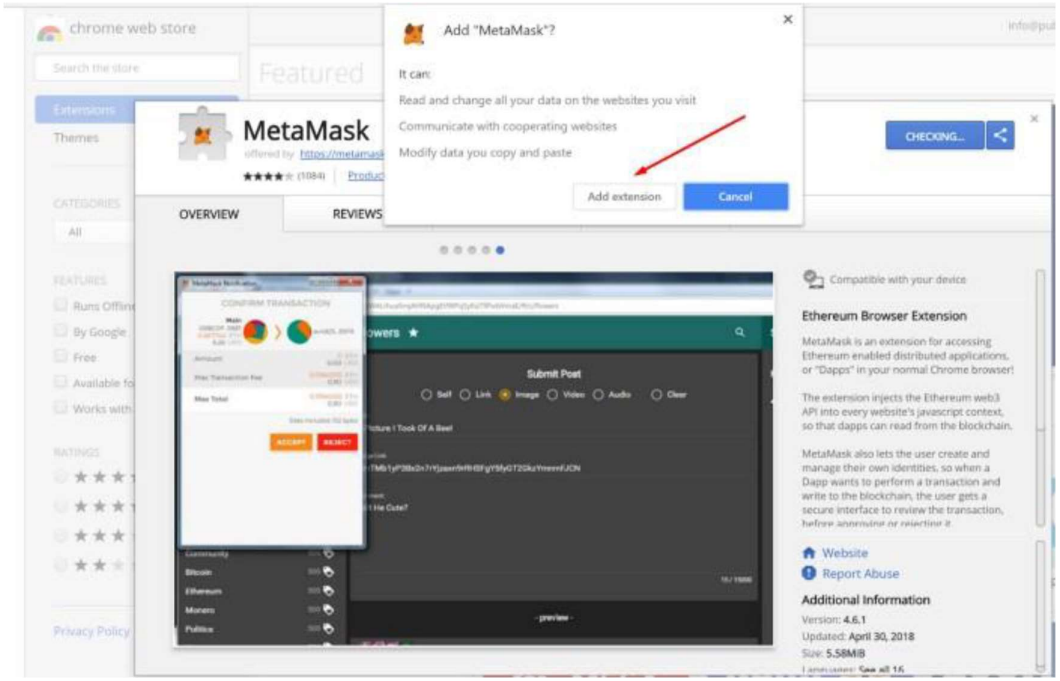
1.Problem Statement: Installation of MetaMask and study spending Ether per transaction.

Step 1. Install MetaMask on your browser.

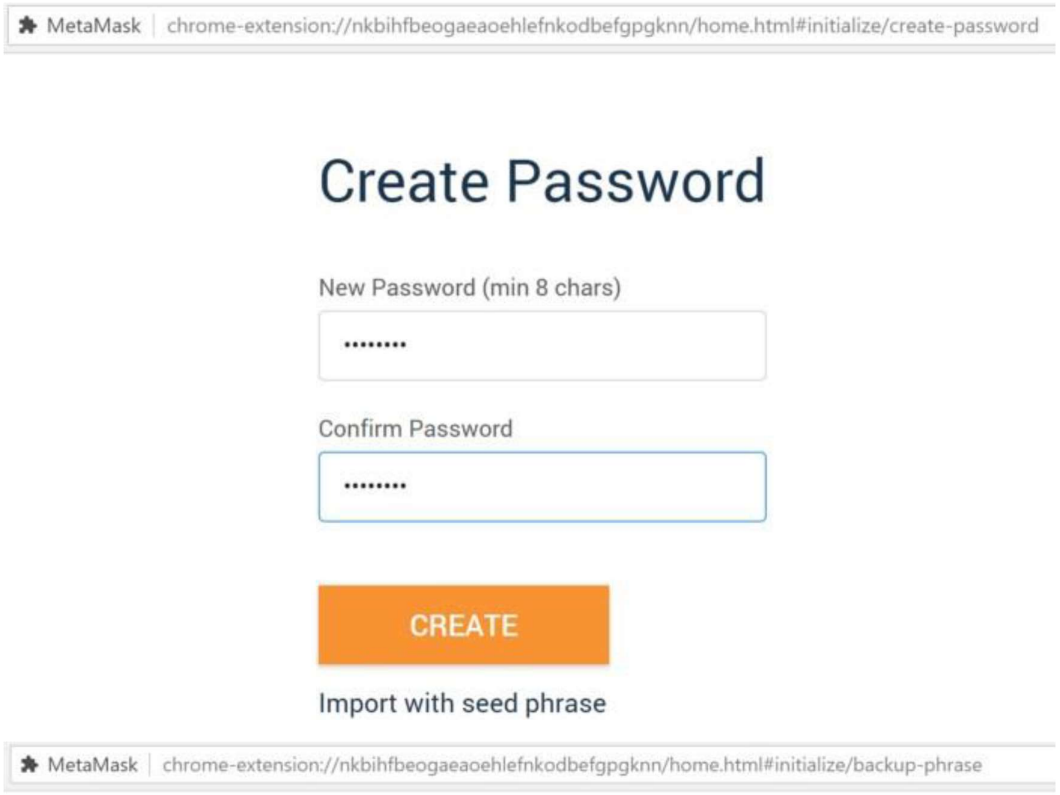


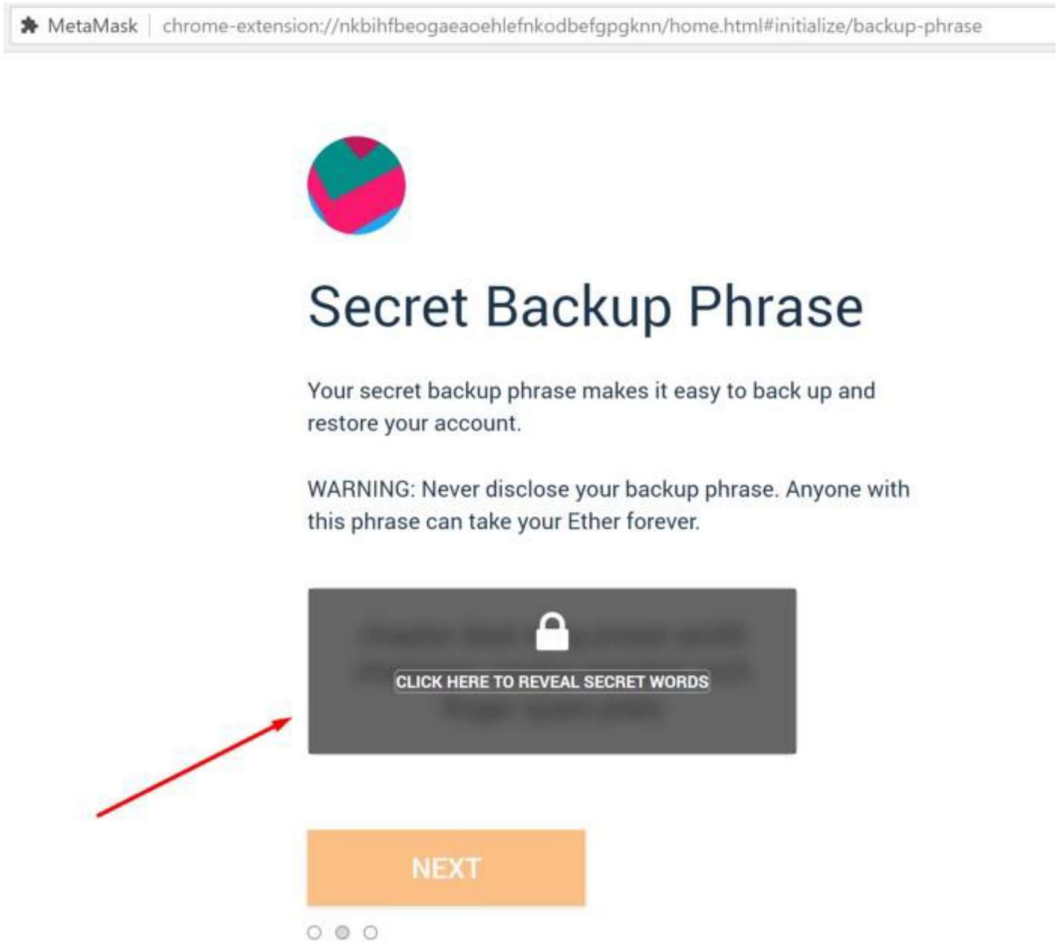


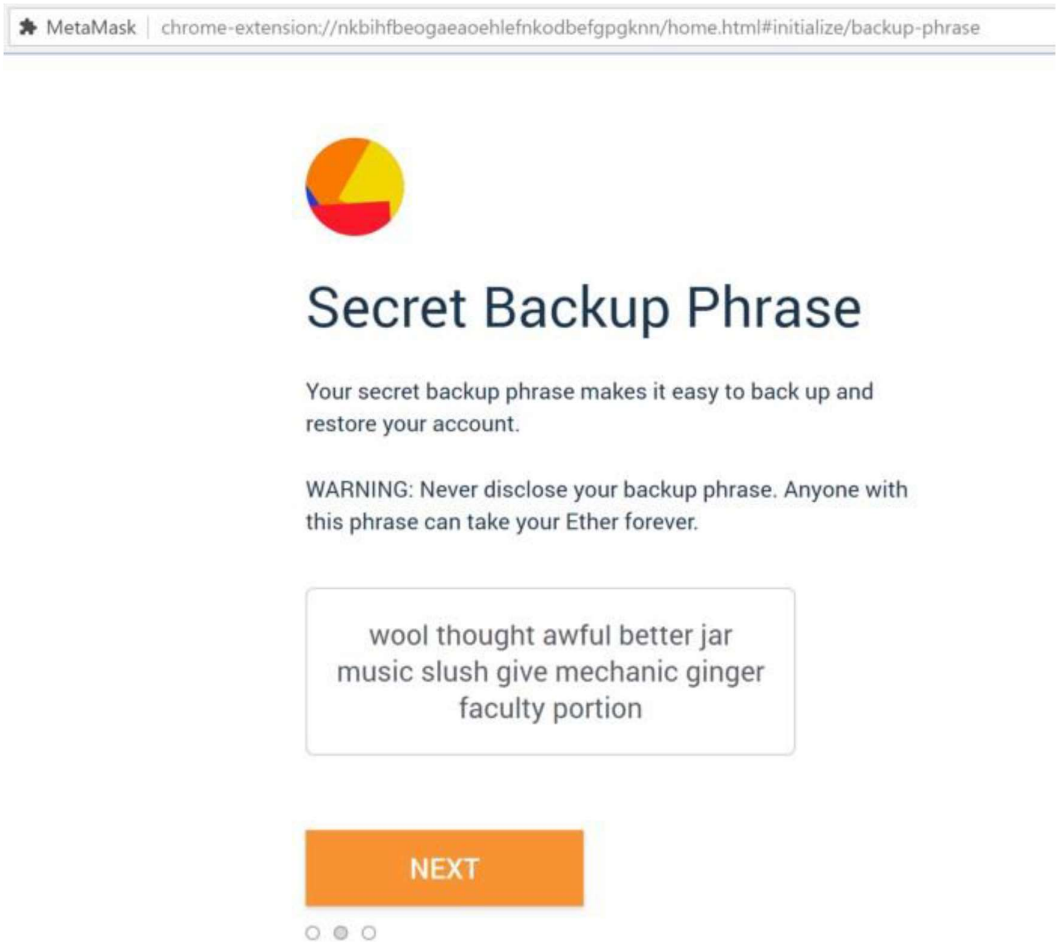

chrome web store
Featured
MetaMask
ADD TO CHROME
OVERVIEW
REVIEWS
SUPPORT
RELATED
MetaMask Introduction
Ethereum Browser Extension
Website
Report Abuse
Additional Information
Version: 4.6.1
Updated: April 30, 2018
Size: 5.58MiB


chrome web store
Add "MetaMask"?
It can:
Read and change all your data on the websites you visit
Communicate with cooperating websites
Modify data you copy and paste
Add extension
Cancel
MetaMask
CHECKING...
OVERVIEW
Submit Post
Ethereum Browser Extension
Website
Report Abuse
Additional Information
Version: 4.6.1
Updated: April 30, 2018
Size: 5.58MiB

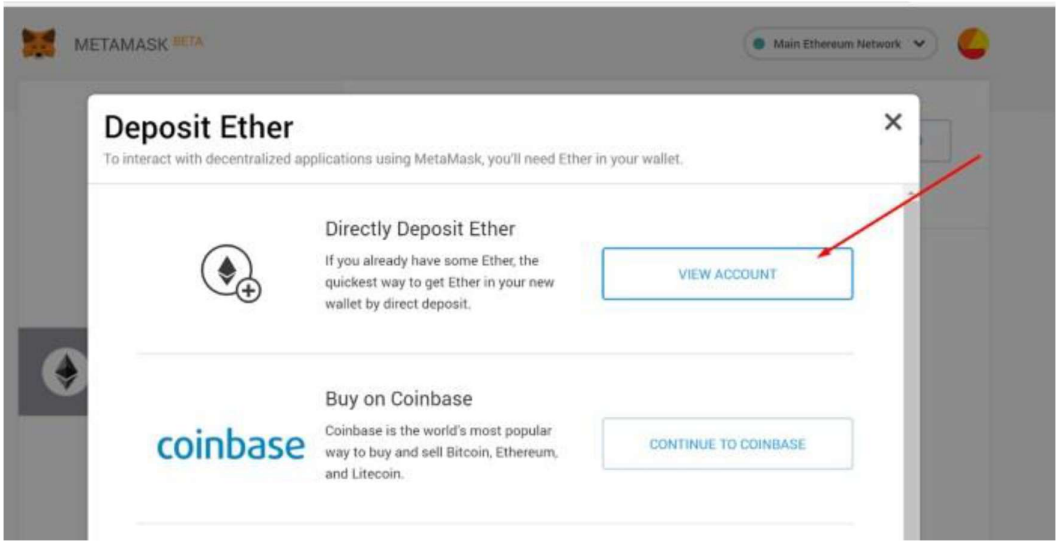
Step 2. Create an account.

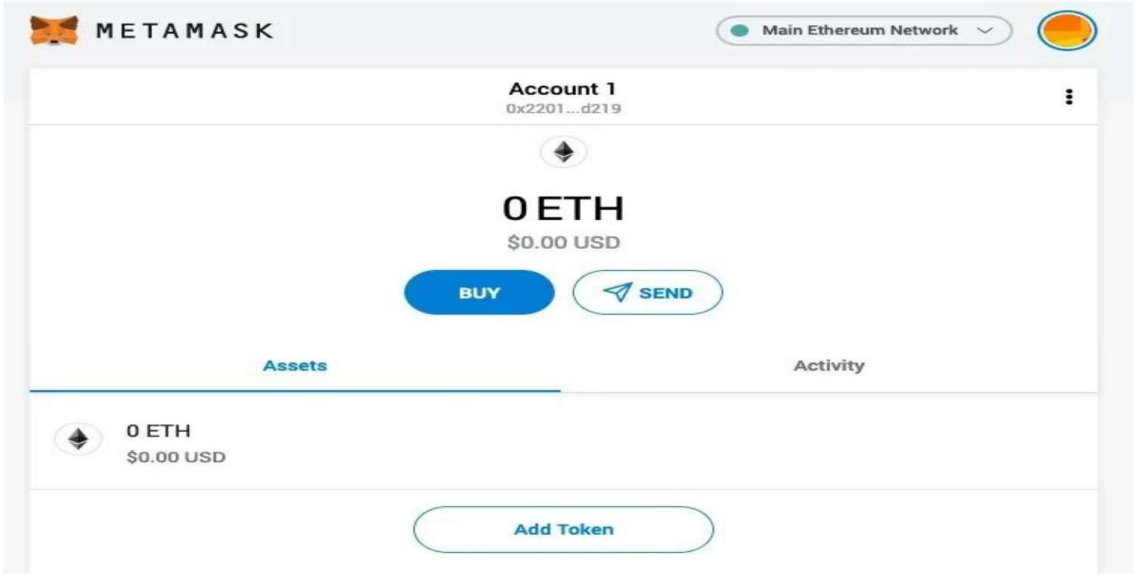


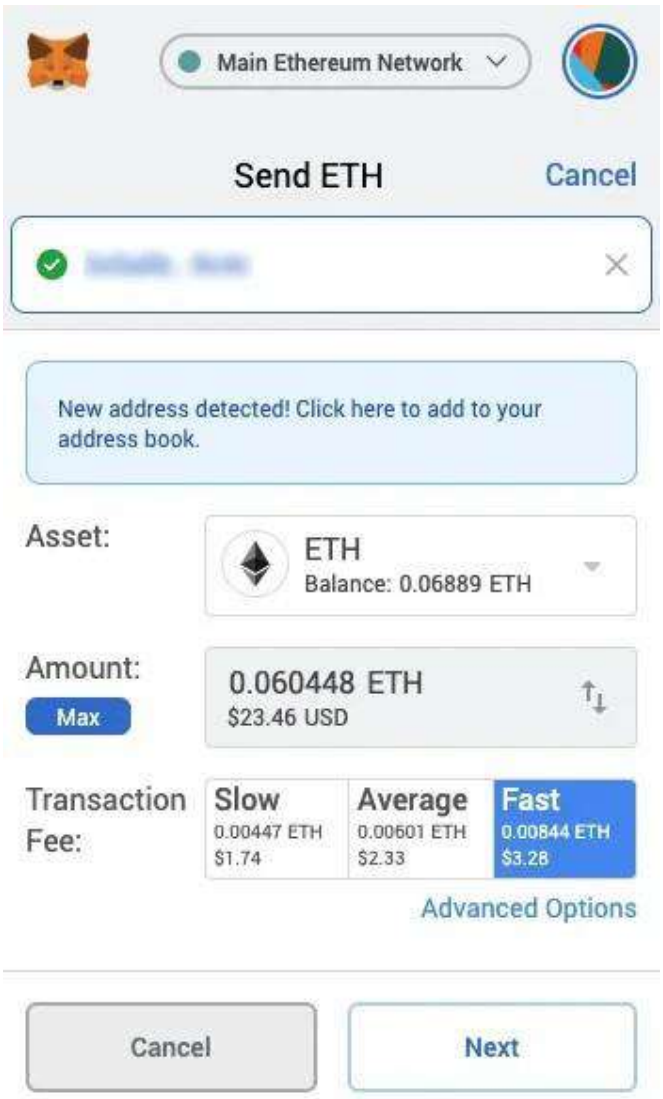




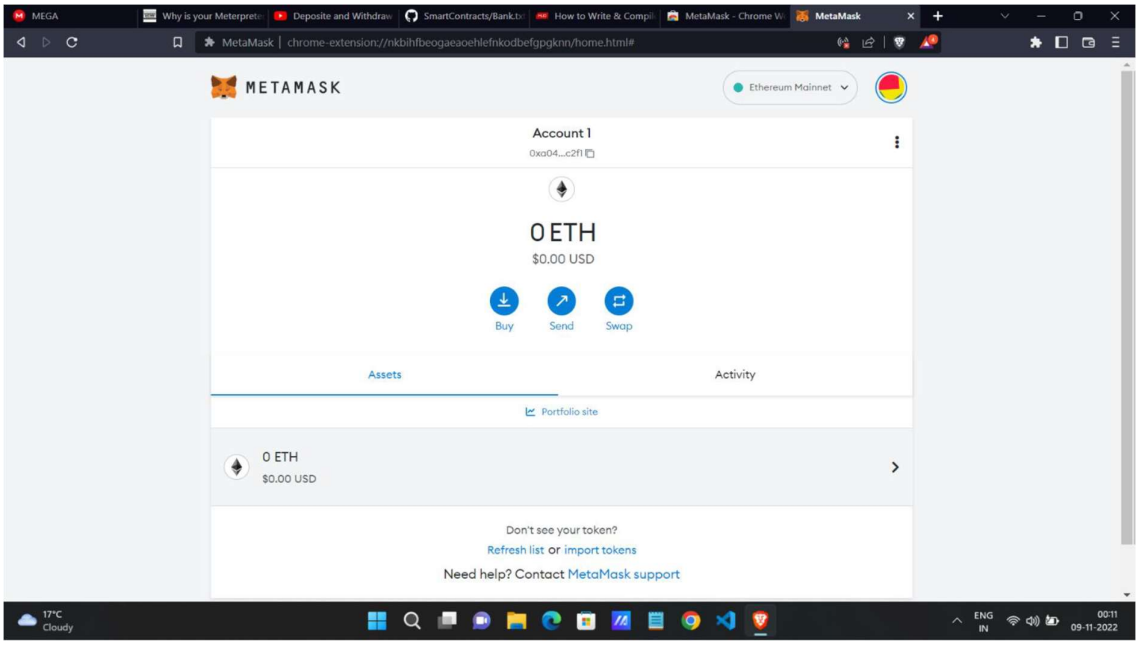
Step 3. Depositing funds.




METAMASK
Main Ethereum Network
Account 1
0x2201...d219
0 ETH
$0.00 USD
BUY
SEND
Assets
Activity
0 ETH
$0.00 USD
Add Token


Main Ethereum Network
Send ETH
Cancel
New address detected! Click here to add to your address book.
Asset:
ETH
Balance: 0.06889 ETH
Amount:
Max
0.060448 ETH
$23.46 USD
Transaction Fee:
Slow
0.00447 ETH
$1.74
Average
0.00601 ETH
$2.33
Fast
0.00844 ETH
$3.28
Advanced Options
Cancel
Next

2.Problem Statement: Create your own wallet using Metamask for crypto transactions.



3.Problem Statement: Write a smart contract on a test network, for Bank account of a customer for following operations:

- • Deposit money
- • Withdraw Money
- • Show balance

```
// SPDX-License-Identifier: MIT
pragma solidity ^0.8.0;

contract BankAccount {

    // Mapping to store the balance of each user (using their Ethereum address)
    mapping(address => uint) private balances;

    // Deposit event (useful for logging deposits on the blockchain)
    event Deposit(address indexed user, uint amount);

    // Withdrawal event (useful for logging withdrawals on the blockchain)
    event Withdrawal(address indexed user, uint amount);

    // Function to deposit money into the account
    function deposit() public payable {
        require(msg.value > 0, "Deposit amount should be greater than 0");

        // Add the deposit amount to the user's balance
        balances[msg.sender] += msg.value;

        // Emit the deposit event
        emit Deposit(msg.sender, msg.value);
    }
```

```
    // Function to withdraw money from the account
    function withdraw(uint _amount) public {
        require(_amount > 0, "Withdraw amount should be greater than 0");
        require(balances[msg.sender] >= _amount, "Insufficient balance");

        // Subtract the withdrawal amount from the user's balance
        balances[msg.sender] -= _amount;

        // Transfer the amount to the user
        payable(msg.sender).transfer(_amount);

        // Emit the withdrawal event
        emit Withdrawal(msg.sender, _amount);
    }

    // Function to check the account balance
    function checkBalance() public view returns (uint) {
        return balances[msg.sender];
    }
}
```

5.Problem Statement: create Student data and follow the Structures Arrays Fallback Deploy this as smart contract on Ethereum and Observe the transaction fee and Gas values.

```
// SPDX-License-Identifier: MIT

pragma solidity ^0.8.0;


contract StudentRecords {


    // Structure to define student details

    struct Student {

        uint id;

        string name;

        uint age;

        string course;

        bool isEnrolled;

    }


    // Array to store multiple students

    Student[] public students;


    // Mapping to store which addresses added which students

    mapping(address => uint) public studentByOwner;


    // Event emitted whenever a student is added

    event StudentAdded(uint id, string name, uint age, string course, bool isEnrolled);


    // Function to add a student to the contract

    function addStudent(uint _id, string memory _name, uint _age, string memory _course)
public {

        // Create a new student struct and push it to the array

        students.push(Student({

            id: _id,
```

```
            name: _name,
            age: _age,
            course: _course,
            isEnrolled: true
        }));

        // Store which address added this student
        studentByOwner[msg.sender] = _id;

        // Emit an event to track the addition of a student
        emit StudentAdded(_id, _name, _age, _course, true);
    }

    // Function to retrieve student information by ID
    function getStudent(uint _id) public view returns (uint, string memory, uint, string memory, bool) {
        for (uint i = 0; i < students.length; i++) {
            if (students[i].id == _id) {
                return (students[i].id, students[i].name, students[i].age, students[i].course, students[i].isEnrolled);
            }
        }
        revert("Student not found");
    }

    // Function to get total number of students in the contract
    function getStudentCount() public view returns (uint) {
        return students.length;
    }
}
```