Bank Marketing

For this project, I am using this dataset of bank marketing https://archive.ics.uci.edu/dataset /222/bank+marketing. It is a marketing campaigns of a Portuguese banking instituion. The goal is to predict if the client subscribe a term deposit. It has 45211 instances and 16 features.

1. Import packages and classes

Import all the required libraries:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn import metrics
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
import seaborn as sns
```

2. Import the data

This part helps to load the dataset from a csv file.

```
In [ ]: bank_data = pd.read_csv("Data/bank-full.csv",sep=';',quotechar='"')
```

Prints the first rows of the dataset

```
print(bank_data.head())
                job marital education default
                                                 balance housing loan
0
   58
         management married
                               tertiary
                                                    2143
                                                             yes
                                             no
                                                                   no
1
   44
         technician
                                                      29
                      single secondary
                                             no
                                                             yes
                                                                   no
2
   33 entrepreneur married secondary
                                                                 yes
                                             no
                                                             yes
3
   47
        blue-collar married
                                unknown
                                                    1506
                                             no
                                                             yes
                                                                   no
   33
            unknown
                      single
                                unknown
           day month
                      duration
                                campaign pdays
                                                 previous poutcome
  contact
0 unknown
                           261
             5
                 may
                                       1
                                             -1
                                                        0 unknown
1 unknown
             5
                 may
                           151
                                       1
                                             -1
                                                        0 unknown
                                       1
2 unknown
                            76
                                             -1
                                                        0 unknown
                 may
                                       1
3 unknown
             5
                 may
                            92
                                             -1
                                                        0 unknown
4 unknown
                           198
                                             -1
                                                        0 unknown
                 may
```

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Prints out the last few data rows.

```
print(bank_data.tail())
       age
                     job
                            marital education default
                                                         balance housing loan \
45206
        51
              technician
                            married
                                      tertiary
                                                             825
                                                     no
                                                                      no
                                                                            no
45207
        71
                                                            1729
                 retired
                           divorced
                                       primary
                                                     no
                                                                      no
                                                                            no
45208
        72
                 retired
                           married secondary
                                                            5715
                                                     no
                                                                      no
                                                                            no
45209
        57
             blue-collar
                           married
                                     secondary
                                                             668
                                                     no
                                                                      no
                                                                            no
45210
        37
            entrepreneur
                           married
                                     secondary
                                                            2971
                                                     no
                                                                      no
                                                                            no
         contact day month
                              duration
                                       campaign
                                                  pdays
                                                          previous poutcome
                                                                                У
45206
        cellular
                                   977
                                               3
                   17
                                                      -1
                                                                 0
                                                                    unknown
                         nov
                                                                             yes
45207
                                   456
                                                2
        cellular
                   17
                         nov
                                                      -1
                                                                 0
                                                                    unknown
                                                                              yes
45208
        cellular
                   17
                        nov
                                  1127
                                                5
                                                     184
                                                                 3
                                                                    success
                                                                              yes
45209
       telephone
                   17
                         nov
                                   508
                                                4
                                                      -1
                                                                 0
                                                                    unknown
                                                                               no
45210
        cellular
                   17
                         nov
                                   361
                                                2
                                                     188
                                                                11
                                                                       other
                                                                               no
```

Prints out the summary statistics of the dataset

```
In [ ]: print(bank_data.describe())
```

......

	age	balance	day	duration	campaign	\
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	
mean	40.936210	1362.272058	15.806419	258.163080	2.763841	
std	10.618762	3044.765829	8.322476	257.527812	3.098021	
min	18.000000	-8019.000000	1.000000	0.000000	1.000000	
25%	33.000000	72.000000	8.000000	103.000000	1.000000	
50%	39.000000	448.000000	16.000000	180.000000	2.000000	
75%	48.000000	1428.000000	21.000000	319.000000	3.000000	
max	95.000000	102127.000000	31.000000	4918.000000	63.000000	

	paays	previous
count	45211.000000	45211.000000
mean	40.197828	0.580323
std	100.128746	2.303441
min	-1.000000	0.000000
25%	-1.000000	0.000000
50%	-1.000000	0.000000
75%	-1.000000	0.000000
max	871.000000	275.000000

It checks if there is any missing data and prints out

```
In [ ]: print(bank_data.isnull().sum())
```

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```
0
age
job
marital
education
default
             0
balance
             0
housing
loan
contact
day
month
duration
campaign
pdays
previous
poutcome
dtype: int64
```

Prints out the column names of the dataset.

Feature_cols helps to select the set of features from the dataset. Here the X is the features and y is the target variable from the dataset.

One-Hot Coding

This part tries to convert the categorical features into a numerical features.

```
In [ ]: X = pd.get_dummies(X, columns=['job', 'marital', 'education', 'default', 'housing',
```

Split the data

This helps to split the datset into training and test dataset. The ration is 70%-30%.

```
In [ ]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
```

Prints out the X value.

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	age	balance	day	duration	campa	aign	pdays	previo	ous job	_admin.
0	58	2143	5	261		1	-1		0	False
1	44	29	5	151		1	-1		0	False
2	33	2	5	76		1	-1		0	False
3	47	1506	5	92		1	-1		0	False
4	33	1	5	198		1	-1		0	False
···	· · ·	•••	17	· · · · 977		•••				 Ealso
45206	51	825	17			3	-1		0	False
45207	71	1729	17	456		2	-1		0	False
45208	72	5715	17	1127		5	184		3	False
45209 45210	57 37	668 2971	17 17	508 361		4 2	-1 188		0 11	False False
	ioh k	olue-coll	an iol	o_entrepr	anaur		month	n iun m	nonth_ma	n \
0	יסס"ר	Fal			False			r_Jun r False	Fals	
1		Fal			False			False	Fals	
2		Fal			True			False	Fals	
3		Tr			False			False	Fals	
4		Fal			False			False	Fals	
							ı			
••• 45206		Fal			False	• • •		 False	 Fals	
45207		Fal			False			False	Fals	
45208		Fal			False			False	Fals	
45209		Tr			False	• • •		False	Fals	
45210		Fal			True			False	Fals	
0 1 2 3		True True True True	Falso Falso Falso Falso	e Fa e Fa	lse lse lse lse	Fa Fa	alse alse alse alse		Fals Fals Fals Fals	e e
4		True	False	s Fa	lse		-		_	_
					T26	Г	alse		Fals	е —
						Г	···		Fals	
	F	··· alse	 Tru	•						
45206				e Fa		Fa				е
45206 45207	F	alse	Tru	· e Fa e Fa	 lse	Fa Fa	 alse		 Fals Fals Fals	• e e
45206 45207 45208	F F	alse alse	True True	· e Fa e Fa	 lse lse	Fa Fa	 alse alse		 Fals Fals	• e e
45206 45207 45208 45209	F F	alse alse alse	Trud Trud Trud	· e Fa e Fa e Fa e Fa	lse lse lse	Fa Fa Fa	 alse alse alse		 Fals Fals Fals	e e e
45206 45207 45208 45209 45210	F F F	False False False False Come_othe	Trud Trud Trud Trud Trud	Fa e Fa e Fa e Fa e Fa e Fa	lse lse lse lse lse	Fa Fa Fa Fa	 alse alse alse alse		Fals Fals Fals Fals	e e e
45206 45207 45208 45209 45210	F F F	False False False False False False False False	Trud Trud Trud Trud Trud r pour	Factorme_suc	lse lse lse lse lse	Fa Fa Fa Fa	 alse alse alse alse	True	Fals Fals Fals Fals	e e e
45206 45207 45208 45209 45210	F F F	False False False False False Come_othe Fals	Trud Trud Trud Trud r pour e e	Factorme_such	lse lse lse lse cess alse alse	Fa Fa Fa Fa	 alse alse alse alse	True True	Fals Fals Fals Fals	e e e
45206 45207 45208 45209 45210 0 1	F F F	False False False False Come_othe Fals Fals	Trud Trud Trud Trud Trud r pour e e e	Factorne_suc	lse lse lse lse lse alse alse	Fa Fa Fa Fa	 alse alse alse alse	True True True	Fals Fals Fals Fals	e e e
45206 45207 45208 45209 45210 0 1 2	F F F	False False False False Come_othe Fals Fals Fals	Truc Truc Truc Truc Truc e e e e	Factorne_suc	lse lse lse lse lse lse lse lse lse cess alse alse alse alse alse	Fa Fa Fa Fa	 alse alse alse alse	True True True True	Fals Fals Fals Fals	e e e
45206 45207 45208 45209 45210 0 1 2 3	F F F	False False False Come_othe Fals Fals Fals Fals	Truc Truc Truc Truc r pou e e e e e	Factorne_suc	lse lse lse lse lse alse alse alse alse	Fa Fa Fa Fa	 alse alse alse alse	True True True True True	Fals Fals Fals Fals	e e e
45206 45207 45208 45209 45210 0 1 2 3 4	F F F	False False False Come_othe Fals Fals Fals Fals Fals	Truc Truc Truc r pou e e e e e	Fallower Fal	lse lse lse lse lse alse alse alse alse	Fa Fa Fa Fa	 alse alse alse alse	True True True True True	Fals Fals Fals Fals	e e e
45206 45207 45208 45209 45210 0 1 2 3 4 45206	F F F	False False False False Fals Fals Fals Fals Fals	Truc Truc Truc Truc r pour e e e e e e	Fallone Fallon	lse lse lse lse lse lse lse cess alse alse alse alse alse	Fa Fa Fa Fa	 alse alse alse alse	True True True True True True True	Fals Fals Fals Fals	e e e
45206 45207 45208 45209 45210 0 1 2 3 4 45206 45207	F F F	False False False False Fals Fals Fals Fals Fals Fals Fals	Truc Truc Truc Truc r pour e e e e e e	Factorne_such	lse lse lse lse lse lse lse cess alse alse alse alse alse	Fa Fa Fa Fa	 alse alse alse alse	True True True True True True True True	Fals Fals Fals Fals	e e e
45206 45207 45208 45209 45210 0 1 2 3 4	F F F	False False False False Fals Fals Fals Fals Fals	Truc Truc Truc r pour e e e e e e e e	Factorne_suctions	lse lse lse lse lse lse lse cess alse alse alse alse alse	Fa Fa Fa Fa	 alse alse alse alse	True True True True True True True	Fals Fals Fals Fals	e e e

[45211 rows x 51 columns]

Prints out the y value.

```
In [ ]:
        print(y)
       1
                  no
       2
                  no
       3
                  no
                  no
       45206
                 yes
       45207
       45208
       45209
       45210
       Name: y, Length: 45211, dtype: object
```

Creating the Decision Tree

In the Decision Tree, here it is using entropy.

```
In [ ]: bank_decision_tree = DecisionTreeClassifier(criterion = "entropy")
```

Train Decision Tree

Here, X_train and y_train is on the training data for the decision tree.

```
In [ ]: bank_decision_tree = bank_decision_tree.fit(X_train, y_train)
```

Prediction

Test data makes the prediction in the X_test.

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

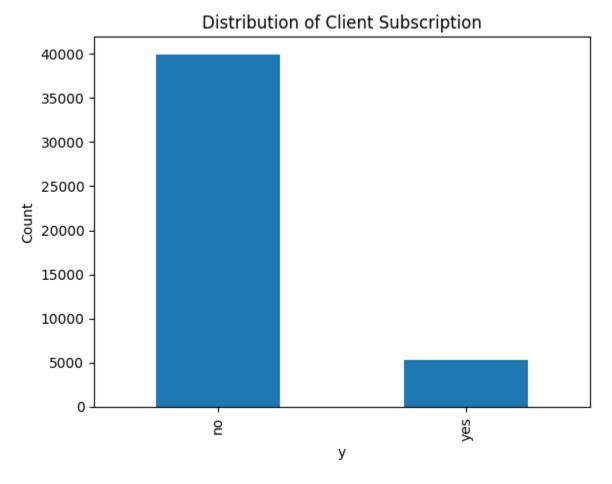
Accuracy

It calculates the accuracy of the decision tree model on the test data and prints out.

Here you can see the visualization of the distributed target variable of y.

```
In [ ]: bank_data['y'].value_counts().plot(kind='bar')
    plt.xlabel("y")
    plt.ylabel("Count")
```

```
plt.title("Distribution of Client Subscription")
plt.show()
```



K-Nearest Neighbors

First it creates a variable called bank_data_k for the K-Nearest Neighbors with 5 neighbors. Then it trains the X_train and y_train on the model of training data. It makes the prediction from the X_test. After that, it calculates and prints out the accuracy of the test data.

K-Nearest Neighbors Accuracy: 0.8815246240047184

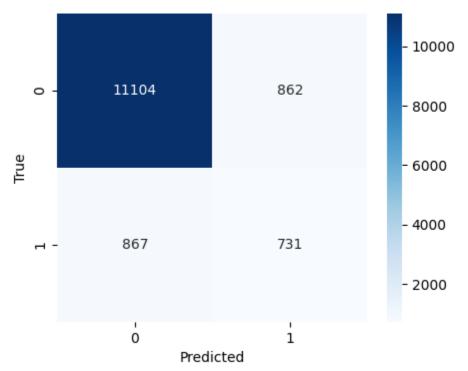
Confusion Matrix

First it calculates the confusion matrix from the decision tree. Prints out.

```
In [ ]: confusion_decision_tree = confusion_matrix(y_test,y_pred)
print("Confusion Matrix (Decision Tree):",confusion_decision_tree)
```

```
Confusion Matrix (Decision Tree): [[11104 862] [ 867 731]]
```

This is the visualization for the confusion matrix of the decision tree using the heatmap of seaborn. Basically, heatmap helps to preset the positive and negative true, positive and negative false. To make it understand for easily.



In the conclusion, I would like to say there is 0.87 accuracy of the term deposit of the client subscription. While working with the task i tried to search some of the ideas from chatgpt and other website https://machinelearningmastery.com/types-of-classification-in-machinelearning/. To learn about the classification of the machine learning.

This is the streamlit link: https://task-mlbenchmarking-two-ml-algorithms-ditzhsgzodqjlgtbyqerpv.streamlit.app/

Here is the github repository: https://github.com/SharonMaharjan/Task-ML_Benchmarking-two-ML-algorithms/tree/main