03

Task-03

cc

Build a decision tree classifier to predict whether a customer will purchase a product or service based on their demographic and behavioral data. Use a dataset such as the Bank Marketing dataset from the UCI Machine Learning Repository.

Sample Dateset:https://archive.ics.uci.edu/ml/datasets/Bank+Marketing

PRODIGY INFOTECH

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from sklearn.model_selection import train_test_split
from scipy.stats import chi2_contingency
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
import warnings
warnings.filterwarnings("ignore")
da =pd.read_csv("/content/bank-full.csv",sep=";")
```

Input variables:

bank client data:

- 1 age (numeric)
- 2 job : type of job (categorical:
- "admin.","unknown","unemployed","management","housemaid","entrepreneur","student", "blue-collar","self-employed","retired","technician","services")
- 3 marital: marital status (categorical: "married", "divorced", "single"; note: "divorced" means divorced or widowed)

- 4 education (categorical: "unknown", "secondary", "primary", "tertiary")
- 5 default: has credit in default? (binary: "yes","no")
- 6 balance: average yearly balance, in euros (numeric)
- 7 housing: has housing loan? (binary: "yes","no")
- 8 loan: has personal loan? (binary: "yes", "no")

related with the last contact of the current campaign:

- 9 contact: contact communication type (categorical: "unknown", "telephone", "cellular")
- 10 day: last contact day of the month (numeric)
- 11 month: last contact month of year (categorical: "jan", "feb", "mar", ..., "nov", "dec")
- 12 duration: last contact duration, in seconds (numeric)

other attributes:

- 13 campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)
- 14 pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric, -1 means client was not previously contacted)
- 15 previous: number of contacts performed before this campaign and for this client (numeric)
- 16 poutcome: outcome of the previous marketing campaign (categorical:

```
"unknown","other","failure","success")
```

Output variable (desired target):

17 - y - has the client subscribed a term deposit? (binary: "yes","no")

```
da.columns
```

```
da.head()
```

	age	job	marital	education	default	balance	housing	loan	contact	day
0	58	management	married	tertiary	no	2143	yes	no	unknown	5
1	44	technician	single	secondary	no	29	yes	no	unknown	5
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5
4	33	unknown	single	unknown	no	1	no	no	unknown	5
4										•

da.tail()

	age	job	marital	education	default	balance	housing	loan	contact
45206	51	technician	married	tertiary	no	825	no	no	cellular
45207	71	retired	divorced	primary	no	1729	no	no	cellular
45208	72	retired	married	secondary	no	5715	no	no	cellular
45209	57	blue-collar	married	secondary	no	668	no	no	telephone
45210	37	entrepreneur	married	secondary	no	2971	no	no	cellular
4									•

da.shape

(45211, 17)

da.isnull().sum()

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

da.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):

#	Column	Non-Null Count	Dtype						
0	age	45211 non-null	int64						
1	job	45211 non-null	object						
2	marital	45211 non-null	object						
3	education	45211 non-null	object						
4	default	45211 non-null	object						
5	balance	45211 non-null	int64						
6	housing	45211 non-null	object						
7	loan	45211 non-null	object						
8	contact	45211 non-null	object						
9	day	45211 non-null	int64						
10	month	45211 non-null	object						
11	duration	45211 non-null	int64						
12	campaign	45211 non-null	int64						
13	pdays	45211 non-null	int64						
14	previous	45211 non-null	int64						
15	poutcome	45211 non-null	object						
16	У	45211 non-null	object						
dtyp	dtypes: int64(7), object(10)								
nomo	nv ucago: E	OT WB							

memory usage: 5.9+ MB

da.describe()

	age	balance	day	duration	campaign	pda
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.0000
mean	40.936210	1362.272058	15.806419	258.163080	2.763841	40.1978
std	10.618762	3044.765829	8.322476	257.527812	3.098021	100.1287
min	18.000000	-8019.000000	1.000000	0.000000	1.000000	-1.0000
25%	33.000000	72.000000	8.000000	103.000000	1.000000	-1.0000
50%	39.000000	448.000000	16.000000	180.000000	2.000000	-1.0000
75%	48.000000	1428.000000	21.000000	319.000000	3.000000	-1.0000
max	95.000000	102127.000000	31.000000	4918.000000	63.000000	871.0000
4						•

da["y"].value_counts()

39922 no yes 5289

Name: y, dtype: int64

```
yes=da.loc[da["y"]=="yes","y"].count()/len(da)*100
no = da.loc[da["y"]=="no","y"].count()/len(da)*100
print("Percentage of yes:", yes)
print("Percentage of no:", no)
```

Percentage of yes: 11.698480458295547 Percentage of no: 88.30151954170445

```
df=da.copy()
```

```
df.columns
```

df.shape

```
(45211, 17)
```

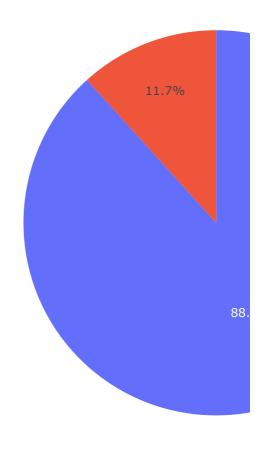
```
df["target"]=df["y"].map({"yes":1,"no":0})
```

```
df["target"].value_counts()
```

0 399221 5289

Name: target, dtype: int64

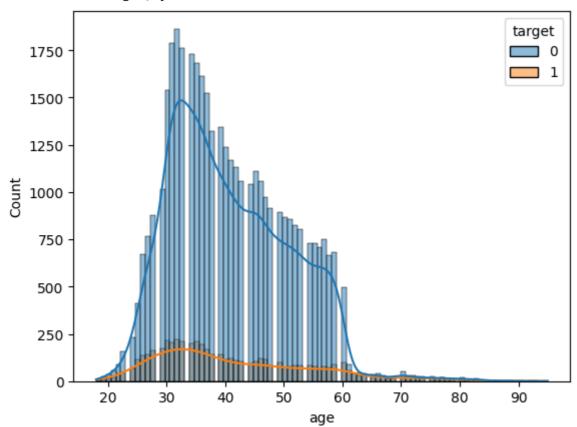
px.pie(df,"target")



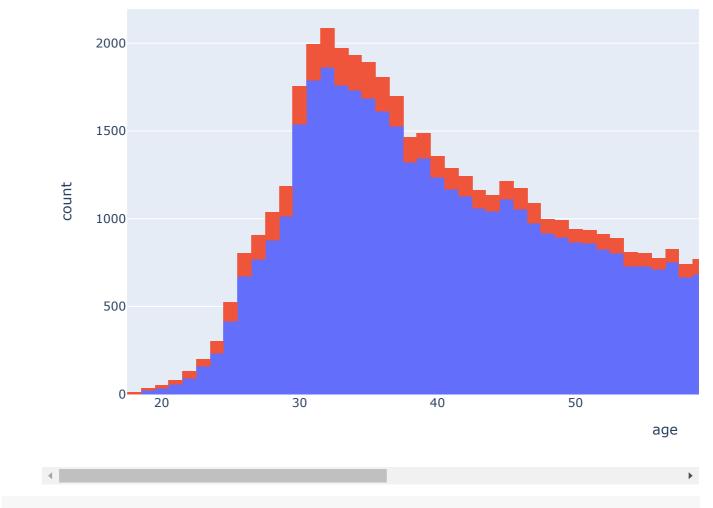
https://colab.research.google.com/drive/1u3OGkYgZxZpDvYXUQPg7LX9vqP5HfVWV#printMode=truewards and the property of the proper

sns.histplot(data=df,x="age",kde=True,hue="target")

<Axes: xlabel='age', ylabel='Count'>

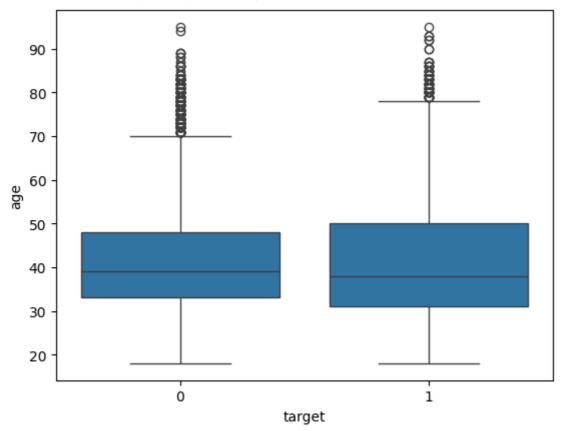


px.histogram(df,x="age",color="target")



sns.boxplot(data=df,y="age",x="target")

<Axes: xlabel='target', ylabel='age'>



df["job"].value_counts()

blue-collar 9732 management 9458 technician 7597 admin. 5171 services 4154 retired 2264 self-employed 1579 entrepreneur 1487 unemployed 1303 housemaid 1240 student 938 288 unknown Name: job, dtype: int64

df["job"].value_counts()

blue-collar 9732 9458 management 7597 technician admin. 5171 services 4154 retired 2264 self-employed 1579 1487 entrepreneur unemployed 1303 housemaid 1240 student 938 unknown 288 Name: job, dtype: int64

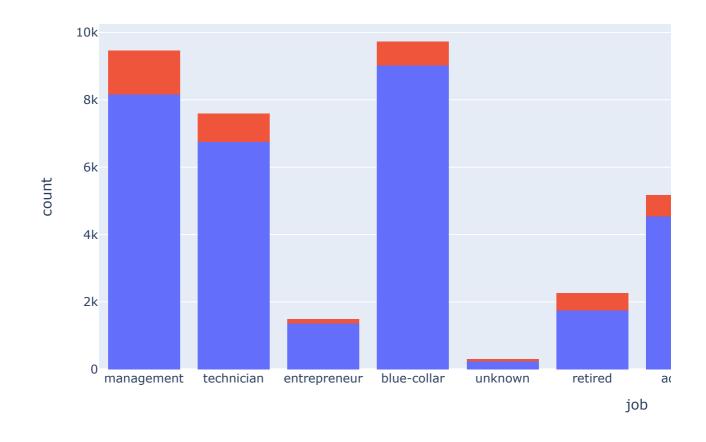
df.groupby("job")["target"].agg(sum)

job admin. 631 blue-collar 708 entrepreneur 123 housemaid 109 management 1301 retired 516 self-employed 187 services 369 student 269 technician 840 unemployed 202 unknown 34

Name: target, dtype: int64

px.histogram(df,x="job",color="target",title='count of Jobs by Target',)

count of Jobs by Target

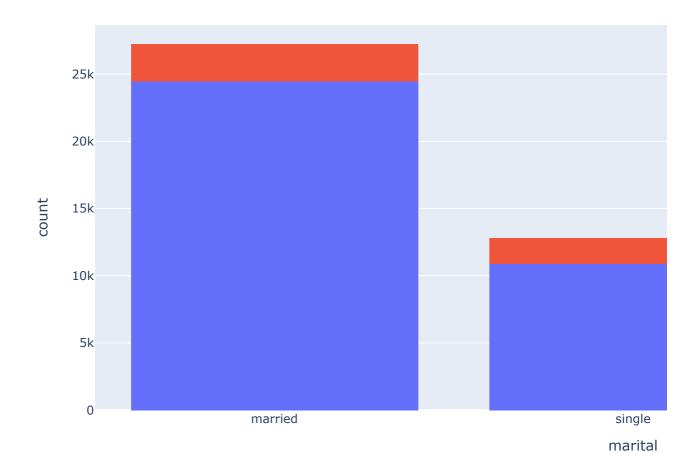


df["marital"].value_counts()

married 27214 single 12790 divorced 5207

Name: marital, dtype: int64

```
px.histogram(df,x="marital",color="target")
```



df.groupby("marital")["target"].agg(sum)

marital

4

divorced 622 married 2755 single 1912

Name: target, dtype: int64

df["education"].value_counts()

secondary 23202 tertiary 13301 primary 6851 unknown 1857

Name: education, dtype: int64

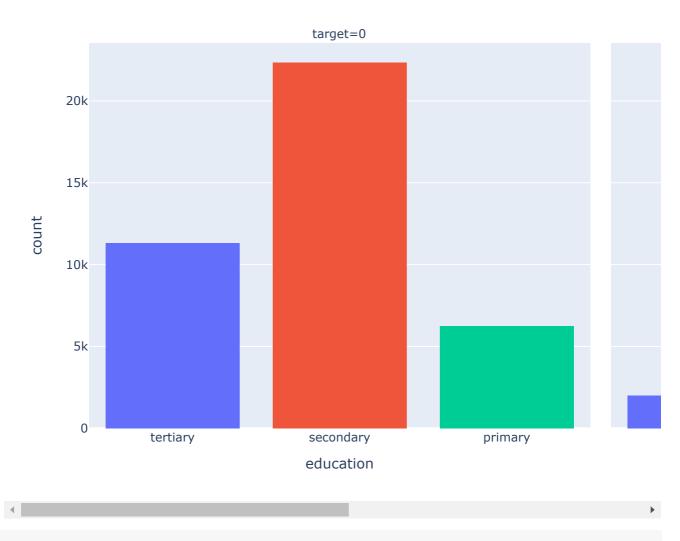
df["education"].replace("unknown",df["education"].mode()[0],inplace=True)

df["education"].value_counts()

secondary 25059 tertiary 13301 primary 6851

Name: education, dtype: int64

px.histogram(df,x="education",color="education",facet_col="target")



df.default.value_counts()

no 44396 yes 815

Name: default, dtype: int64

df.groupby("default")["target"].agg(sum)

default

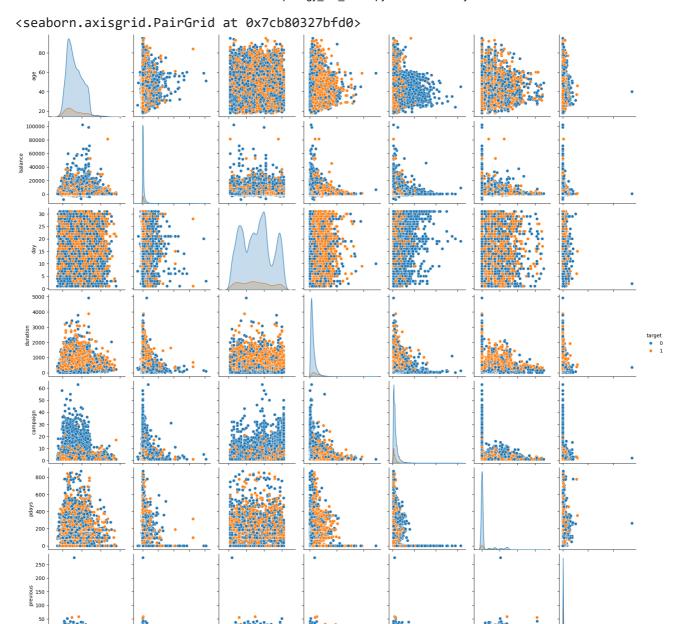
no 5237 yes 52

Name: target, dtype: int64

num=df.loc[:,['age','balance', 'day', 'duration', 'campaign','loan', 'pdays','previous','

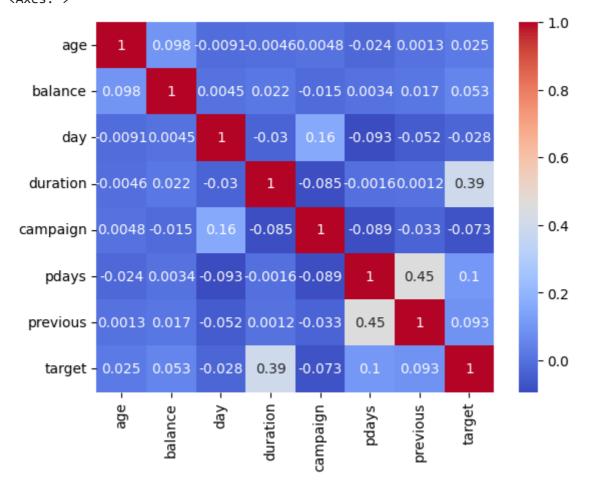
?sns.pairplot

sns.pairplot(num,hue="target")

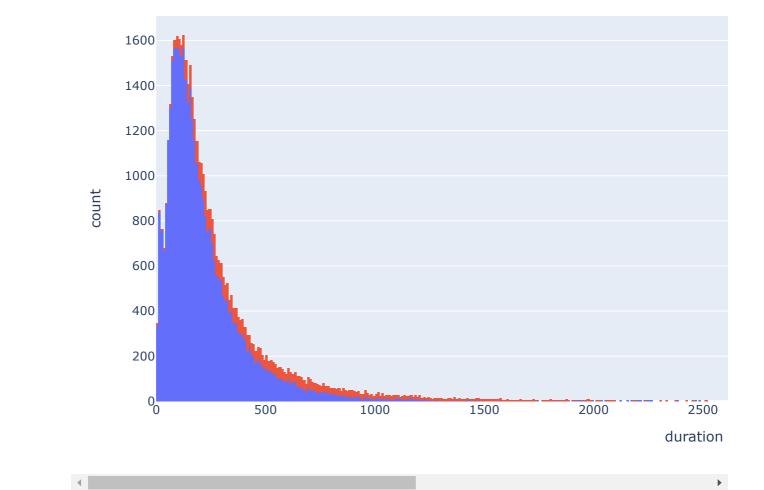


cm=num.corr()
sns.heatmap(cm,annot=True,cmap="coolwarm")



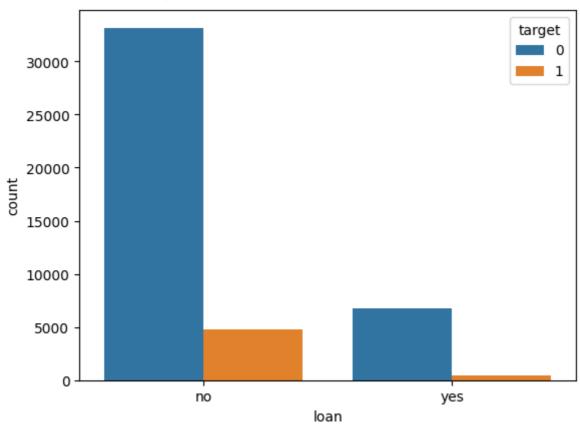


px.histogram(df,x="duration",color="target")



sns.countplot(data=df,x="loan",hue="target")

<Axes: xlabel='loan', ylabel='count'>



Based on these correlations, variables such as duration, pdays, and previous seem to have relatively stronger correlations with the target variable compared to others.

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 18 columns):
#
    Column
               Non-Null Count Dtype
---
    _____
               45211 non-null int64
0
    age
    job
1
               45211 non-null object
    marital
 2
               45211 non-null object
 3
    education 45211 non-null object
4
    default
               45211 non-null object
 5
    balance
               45211 non-null int64
6
    housing
              45211 non-null object
7
    loan
               45211 non-null object
               45211 non-null object
8
    contact
9
    day
               45211 non-null int64
10 month
               45211 non-null object
 11 duration 45211 non-null int64
12 campaign
               45211 non-null int64
    pdays
               45211 non-null int64
13
 14
               45211 non-null int64
    previous
 15
    poutcome
               45211 non-null object
 16
               45211 non-null
                               object
    У
                               int64
 17
    target
               45211 non-null
dtypes: int64(8), object(10)
memory usage: 6.2+ MB
```

```
cat=df.loc[:,['job', 'marital', 'education', 'default', 'housing','loan', 'contact', 'mon
cat.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 10 columns):
           Non-Null Count Dtype
   Column
             45211 non-null object
0
   job
1 marital 45211 non-null object
2 education 45211 non-null object
 3 default 45211 non-null object
4 housing 45211 non-null object
             45211 non-null object
5
    loan
 6 contact 45211 non-null object
             45211 non-null object
7
   month
8
    poutcome 45211 non-null object
9
              45211 non-null object
    У
dtypes: object(10)
memory usage: 3.4+ MB
```

```
categorical_columns = ["job", "marital", "education", "default", "housing", "loan", "cont
target_variable = "y"

association_results = pd.DataFrame(columns=["Column", "Chi-square", "P-value"])

for column in categorical_columns:
    contingency_table = pd.crosstab(df[column], df[target_variable])
    chi2, p, _, _ = chi2_contingency(contingency_table)
    association_results = association_results.append({"Column": column, "Chi-square": chi
print(association_results)
```

```
Column
             Chi-square
                              P-value
        job 836.105488 3.337122e-172
0
1
    marital 196.495946 2.145100e-43
2 education 223.834823 2.482480e-49
3
    default
             22.202250 2.453861e-06
4
    housing 874.822449 2.918798e-192
5
       loan 209.616980 1.665061e-47
   contact 1035.714225 1.251738e-225
6
7
      month 3061.838938 0.000000e+00
   poutcome 4391.506589 0.000000e+00
```

```
x=df[['job', 'marital', 'education', 'default', 'housing', 'loan', 'contact', 'month', 'pou
```

```
dq=df.copy()
```

x.info()

```
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 14 columns):
           Non-Null Count Dtype
    Column
    -----
             -----
   job 45211 non-null object
0
1 marital 45211 non-null object
 2 education 45211 non-null object
 3 default 45211 non-null object
4 housing 45211 non-null object
            45211 non-null object
5
    loan
 6 contact 45211 non-null object
7 month 45211 non-null object
    poutcome 45211 non-null object
 8
9 duration 45211 non-null int64
10 pdays 45211 non-null int64
11 previous 45211 non-null int64
12 campaign 45211 non-null int64
13 balance 45211 non-null int64
dtypes: int64(5), object(9)
memory usage: 4.8+ MB
```

<class 'pandas.core.frame.DataFrame'>

y=df["target"] y.info()

Χ

	job	marital	education	default	housing	loan	contact	month	poutc
0	management	married	tertiary	no	yes	no	unknown	may	unkn
1	technician	single	secondary	no	yes	no	unknown	may	unkn
2	entrepreneur	married	secondary	no	yes	yes	unknown	may	unkn
3	blue-collar	married	secondary	no	yes	no	unknown	may	unkn
4	unknown	single	secondary	no	no	no	unknown	may	unkn
45206	technician	married	tertiary	no	no	no	cellular	nov	unkn
45207	retired	divorced	primary	no	no	no	cellular	nov	unkn
45208	retired	married	secondary	no	no	no	cellular	nov	succ
45209	blue-collar	married	secondary	no	no	no	telephone	nov	unkn
45210	entrepreneur	married	secondary	no	no	no	cellular	nov	О
45211 ro	ws × 14 columr	าร							•

x_org=x.copy()

x_org

	job	marital	education	default	housing	loan	contact	month	poutc	
0	management	married	tertiary	no	yes	no	unknown	may	unkn	
1	technician	single	secondary	no	yes	no	unknown	may	unkn	
2	entrepreneur	married	secondary	no	yes	yes	unknown	may	unkn	
3	blue-collar	married	secondary	no	yes	no	unknown	may	unkn	
4	unknown	single	secondary	no	no	no	unknown	may	unkn	
45206	technician	married	tertiary	no	no	no	cellular	nov	unkn	
45207	retired	divorced	primary	no	no	no	cellular	nov	unkn	
45208	retired	married	secondary	no	no	no	cellular	nov	succ	
45209	blue-collar	married	secondary	no	no	no	telephone	nov	unkn	
45210	entrepreneur	married	secondary	no	no	no	cellular	nov	О	
45211 rows × 14 columns										

x1=pd.get_dummies(x_org)
x1

	duration	pdays	previous	campaign	balance	job_admin.	job_blue- collar	job_entre
0	261	-1	0	1	2143	0	0	
1	151	-1	0	1	29	0	0	
2	76	-1	0	1	2	0	0	
3	92	-1	0	1	1506	0	1	
4	198	-1	0	1	1	0	0	
45206	977	-1	0	3	825	0	0	
45207	456	-1	0	2	1729	0	0	
45208	1127	184	3	5	5715	0	0	
45209	508	-1	0	4	668	0	1	
45210	361	188	11	2	2971	0	0	

45211 rows × 48 columns

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x1,y,test_size=0.2,random_state=42)
```

```
x_train.shape,y_train.shape
```

((36168, 48), (36168,))

x_test.shape,y_test.shape

((9043, 48), (9043,))

```
dt=DecisionTreeClassifier()
dt.fit(x_train,y_train)
```

y_train_pred = dt.predict(x_train)

train acc-accuracy score(v train v train nred)