```
# import nercessary libraraies
import numpy as np
import pandas as pd
```

```
df = pd.read_csv('credit_score.csv')
df.sample(5)
```

	status	seniority	home	time	age	marital	records	job	expenses	in
1753	0	10	owner	60	37	married	yes	fixed	90	1
3242	0	2	owner	36	37	married	no	fixed	60	1
3588	0	0	owner	24	30	married	no	partime	60	
761	1	0	parents	48	25	single	no	freelance	45	1
3756	0	9	private	48	46	married	no	fixed	45	1

Data Understanding

```
df.shape
```

```
(4454, 14)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4454 entries, 0 to 4453
Data columns (total 14 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   status     4454 non-null   int64
 1   seniority  4454 non-null   int64
 2   home       4454 non-null   object
 3   time       4454 non-null   int64
 4   age        4454 non-null   int64
 5   marital    4454 non-null   object
 6   records    4454 non-null   object
 7   job        4454 non-null   object
 8   expenses   4454 non-null   int64
 9   income     4420 non-null   float64
 10  assets     4407 non-null   float64
 11  debt       4436 non-null   float64
 12  amount     4454 non-null   int64
 13  price      4454 non-null   int64
dtypes: float64(3), int64(7), object(4)
memory usage: 487.3+ KB
```

```
# missing values
df.isna().sum().sort_values(ascending=False)
```

	0
assets	47
income	34
debt	18
home	0
status	0
seniority	0
marital	0
age	0
time	0
records	0
expenses	0
job	0
amount	0
price	0

dtype: int64

```
df.debt.unique()
```

```
array([0.000e+00, 2.500e+03, 2.600e+02, 2.000e+03, 5.000e+02,       nan,
       3.300e+03, 3.000e+03, 4.500e+03, 1.000e+03, 1.200e+03, 8.000e+02,
       4.000e+03, 2.140e+04, 1.400e+03, 4.000e+02, 1.500e+03, 9.000e+03,
       1.947e+03, 9.000e+02, 2.000e+02, 1.550e+04, 1.200e+02, 9.600e+01,
       3.700e+03, 7.000e+02, 2.500e+02, 3.500e+03, 3.000e+02, 2.660e+02,
       4.200e+03, 4.800e+02, 1.000e+02, 1.700e+03, 3.600e+03, 1.300e+03,
       6.000e+02, 1.749e+03, 7.500e+02, 1.260e+03, 7.500e+01, 2.800e+03,
       7.200e+02, 3.400e+01, 2.000e+04, 4.500e+02, 1.810e+03, 4.800e+03,
       1.800e+03, 5.000e+01, 2.400e+03, 1.950e+03, 1.978e+03, 2.160e+03,
       1.440e+03, 6.000e+03, 5.000e+03, 1.000e+00, 1.900e+03, 2.900e+03,
       1.728e+03, 3.500e+02, 4.090e+03, 4.350e+02, 7.000e+03, 5.500e+02,
       2.350e+03, 3.900e+03, 1.641e+03, 9.700e+03, 3.800e+03, 5.600e+02,
       9.300e+03, 3.650e+03, 2.050e+03, 1.100e+03, 6.300e+03, 1.980e+02,
       8.500e+02, 5.750e+02, 1.600e+03, 1.620e+03, 1.980e+03, 8.000e+01,
       2.040e+03, 2.432e+03, 2.300e+03, 1.500e+02, 9.500e+03, 2.900e+02,
       1.300e+02, 6.060e+02, 3.000e+04, 3.400e+03, 1.500e+04, 2.700e+03,
       3.648e+03, 1.080e+02, 3.378e+03, 4.700e+02, 1.250e+02, 1.440e+02,
       1.680e+03, 4.200e+02, 1.920e+02, 1.000e+01, 4.000e+01, 2.900e+01,
```

```
       1.365e+03, 3.250e+02, 7.920e+02, 3.900e+01, 2.880e+03, 2.100e+03,
       6.720e+02, 2.800e+02, 7.700e+02, 2.686e+03, 1.485e+03, 5.700e+03,
       3.000e+01, 1.050e+04, 8.000e+03, 1.408e+03, 3.200e+03, 2.969e+03,
       2.700e+02, 9.000e+01, 1.394e+03, 1.172e+03, 1.800e+02, 3.360e+03,
       2.200e+03, 1.379e+03, 9.910e+02, 3.600e+02, 6.700e+02, 3.530e+03,
       4.350e+03, 3.055e+03, 1.250e+03, 2.640e+03, 2.600e+03, 8.400e+02,
       1.781e+03, 2.520e+03, 5.500e+03, 5.400e+02, 2.400e+02, 3.130e+03,
       5.100e+01, 4.380e+03, 8.700e+02, 1.200e+01, 2.235e+03, 1.751e+03,
       1.690e+03, 1.125e+03, 1.380e+03, 9.330e+02, 1.857e+03, 1.120e+02,
       4.300e+03, 1.750e+03, 3.100e+03, 2.500e+01, 2.850e+03, 1.200e+04,
       6.200e+01, 3.950e+03, 1.960e+02, 1.170e+03, 9.600e+02, 4.500e+01,
       1.122e+03, 1.692e+03, 3.400e+02, 2.880e+02, 4.750e+03, 7.200e+03,
       4.200e+01, 6.500e+03, 2.350e+04])
```

```
df.duplicated().sum()
```

```
np.int64(2)
```

Notice

- missing rows
- duplicate values exist

Data Exploration

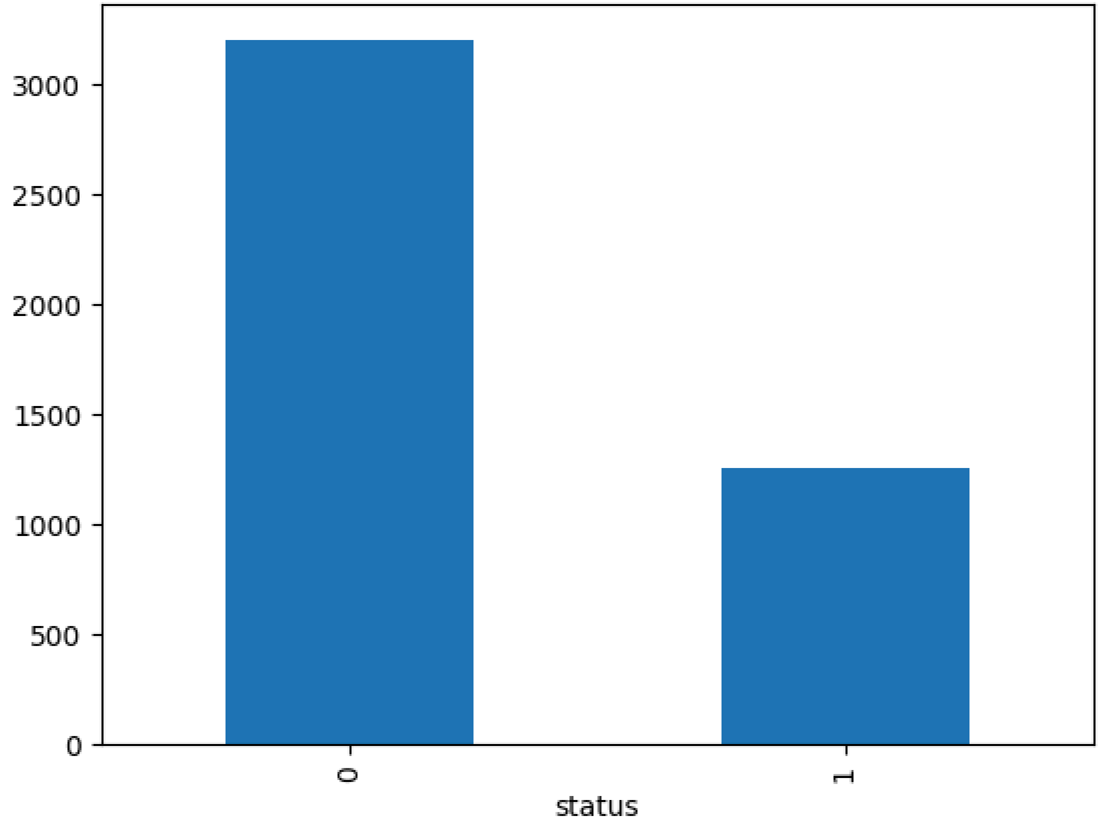
```
# target columns
df.status.value_counts()
```

	count
status	
0	3200
1	1254

dtype: int64

```
df.status.value_counts().plot(kind='bar')
```

<Axes: xlabel='status'>



- Tareget column is not balanced,there is need for balancing it

Data Preparation

```
x = df.drop('status', axis=1)
y = df['status']
```

```
# split into train and test
from sklearn.model_selection import train_test_split
```

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_stat
```

Data Preprocessing

```
# separate into cat and num cols
num_cols = x.select_dtypes(include=np.number).columns.tolist()
cat_cols = x.select_dtypes(include='object').columns.tolist()
```

```
cat_cols
```

```
['home', 'marital', 'records', 'job']
```

```
df.home.unique()
```

```
array(['rent', 'owner', 'parents', 'private', 'other', 'ignore', 'unk'],
      dtype=object)
```

```
num_cols
```

```
['seniority',
 'time',
 'age',
 'expenses',
 'income',
 'assets',
 'debt',
 'amount',
 'price']
```

Encoder

```
from sklearn.preprocessing import OneHotEncoder, StandardScaler
```

```
encoder = OneHotEncoder(sparse_output=False).fit(df[cat_cols])
```

```
encoder
```

```
OneHotEncoder
OneHotEncoder(sparse_output=False)
```

```
encoded_cols = list(encoder.get_feature_names_out(cat_cols))
```

```
encoded_cols
```

```
['home_ignore',
 'home_other',
 'home_owner',
 'home_parents',
 'home_private',
 'home_rent',
 'home_unk',
 'marital_divorced',
 'marital_married',
 'marital_separated',
 'marital_single',
 'marital_unk',
```

```
    'marital_widow',
    'records_no',
    'records_yes',
    'job_fixed',
    'job_freelance',
    'job_others',
    'job_partime',
    'job_unk']
```

```
x_train[encoded_cols] = encoder.transform(x_train[cat_cols])
x_test[encoded_cols] = encoder.transform(x_test[cat_cols])
```

```
x_train
```

	seniority	home	time	age	marital	records	job	expenses	income	as
478	15	owner	48	34	separated	no	freelance	45	0.0	5
39	30	owner	60	64	married	no	fixed	45	120.0	14
2449	2	parents	60	23	single	no	fixed	35	106.0	
3633	13	owner	48	45	married	no	fixed	45	106.0	4
2782	2	owner	60	31	married	no	fixed	60	306.0	4
...	...	...	...	...	...	...	...	...	...	
663	5	owner	60	25	single	no	freelance	35	250.0	14
3476	15	parents	60	42	married	no	freelance	60	0.0	
3842	14	rent	60	38	married	no	fixed	71	108.0	
4401	12	rent	36	36	married	yes	fixed	74	140.0	
3176	0	owner	48	31	married	no	fixed	45	122.0	4

3563 rows × 33 columns

```
# Scaling the numerical columns
scaler = StandardScaler()
```

```
x_train[num_cols] = scaler.fit_transform(x_train[num_cols])
x_test[num_cols]= scaler.transform(x_test[num_cols])
```

```
x_train
```

	seniority	home	time	age	marital	records	job	expenses	i
478	0.847911	owner	0.10246	-0.276942	separated	no	freelance	-0.542730	-1.5
39	2.679329	owner	0.92191	2.474972	married	no	fixed	-0.542730	-0.1
2449	-0.739318	parents	0.92191	-1.285977	single	no	fixed	-1.056313	-0.2
3633	0.603722	owner	0.10246	0.732093	married	no	fixed	-0.542730	-0.2
2782	-0.739318	owner	0.92191	-0.552134	married	no	fixed	0.227646	2.0
...	...	...	...	...	...	...	...	...	
663	-0.373034	owner	0.92191	-1.102516	single	no	freelance	-1.056313	1.4
3476	0.847911	parents	0.92191	0.456902	married	no	freelance	0.227646	-1.5
3842	0.725816	rent	0.92191	0.089980	married	no	fixed	0.792588	-0.2
4401	0.481627	rent	-0.71699	-0.093481	married	yes	fixed	0.946663	0.1
3176	-0.983507	owner	0.10246	-0.552134	married	no	fixed	-0.542730	-0.0

3563 rows × 33 columns

```
# combine
train_processed = x_train[num_cols+encoded_cols]
test_processed = x_test[num_cols+encoded_cols]
```

```
train_processed
```

	seniority	time	age	expenses	income	assets	debt	amount
478	0.847911	0.10246	-0.276942	-0.542730	-1.525045	-0.035818	-0.29364	-0.286525
39	2.679329	0.92191	2.474972	-0.542730	-0.119758	0.711326	-0.29364	0.186537
2449	-0.739318	0.92191	-1.285977	-1.056313	-0.283708	-0.450898	-0.29364	-0.454725
3633	0.603722	0.10246	0.732093	-0.542730	-0.283708	-0.118834	-0.29364	-1.337775
2782	-0.739318	0.92191	-0.552134	0.227646	2.058437	-0.118834	-0.29364	-0.076275
...	...	...	...	...	...	...	...	...
663	-0.373034	0.92191	-1.102516	-1.056313	1.402636	0.711326	-0.29364	0.764725
3476	0.847911	0.92191	0.456902	0.227646	-1.525045	-0.450898	-0.29364	0.133975
3842	0.725816	0.92191	0.089980	0.792588	-0.260287	-0.450898	-0.29364	0.764725
4401	0.481627	-0.71699	-0.093481	0.946663	0.114456	-0.450898	-0.29364	0.764725
3176	-0.983507	0.10246	-0.552134	-0.542730	-0.096337	-0.118834	-0.29364	-0.076275

3563 rows × 29 columns

```
train_processed.columns
```

```
Index(['seniority', 'time', 'age', 'expenses', 'income', 'assets', 'debt',
       'amount', 'price', 'home_ignore', 'home_other', 'home_owner',
       'home_parents', 'home_private', 'home_rent', 'home_unk',
       'marital_divorced', 'marital_married', 'marital_separated',
       'marital_single', 'marital_unk', 'marital_widow', 'records_no',
       'records_yes', 'job_fixed', 'job_freelance', 'job_others',
       'job_partime', 'job_unk'],
      dtype='object')
```

```
['records', 'job', 'assests']
```

```
['records', 'job', 'assests']
```

```
df['records'].unique()
```

```
array(['no', 'yes'], dtype=object)
```

```
df['job'].unique()
```

```
array(['freelance', 'fixed', 'partime', 'unk', 'others'], dtype=object)
```

```
df['records'].unique()
```

```
array(['no', 'yes'], dtype=object)
```

```
def risk(client):
  if client['records']=='yes':
     if client['job']=='pertime':
        return 'Defaulter'
     else:
        return 'Okay'
  else:
    if client['assets'] > 6000:
        return 'Okay'
    else:
        return 'Defaulter'
```

```
x = df.iloc[10]
```

```
x
```

	10
status	0
seniority	6
home	owner
time	48
age	34
marital	married
records	no
job	freelance
expenses	60
income	125.0
assets	4000.0
debt	0.0
amount	1150
price	1577

dtype: object

```
risk(x)
```

```
'Defaulter'
```

Building the decision tree classifier

```
from sklearn.tree import DecisionTreeClassifier
```

```
model = DecisionTreeClassifier(random_state=42)
```

```
%%time
model.fit(train_processed, y_train)
```

```
CPU times: user 38.2 ms, sys: 902 µs, total: 39.1 ms
Wall time: 39 ms
```

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(random_state=42)
```

```
from sklearn.metrics import accuracy_score
```

```
train_pred = model.predict(train_processed)
train_score = accuracy_score(train_pred, y_train)

# test
test_pred = model.predict(test_processed)
test_score = accuracy_score(test_pred, y_test)
```

```
train_score, test_score
```

```
(0.9997193376368229, 0.7081930415263749)
```

```
train_pred = model.predict(train_processed)
```

```
train_pred
```

```
array([0, 0, 0, ..., 1, 1, 0])
```

```
y_train
```

	status
478	0
39	0
2449	0
3633	0
2782	0
...	...
663	0
3476	0
3842	1
4401	1
3176	0

3563 rows × 1 columns

```
from sklearn.tree import plot_tree, export_text

import matplotlib.pyplot as plt


plt.figure(figsize=(80,20))

plot_tree(model, feature_names=train_processed.columns.tolist(),max_dept
```