machine learning exercise

in this exercies we will be working with titanic dataset to descover patterns and extract information from the data after preprocessing it

work by sharifah saleh

import libraries and dataset

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

```
titanic = pd.read_csv("/content/titanic.csv")
titanic
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN
...	...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	NaN
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500	NaN
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	NaN

891 rows × 12 columns

```
titanic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

preprocessing the data

in this section we will deal with missing data, standrizing the data and prepare it before the training process

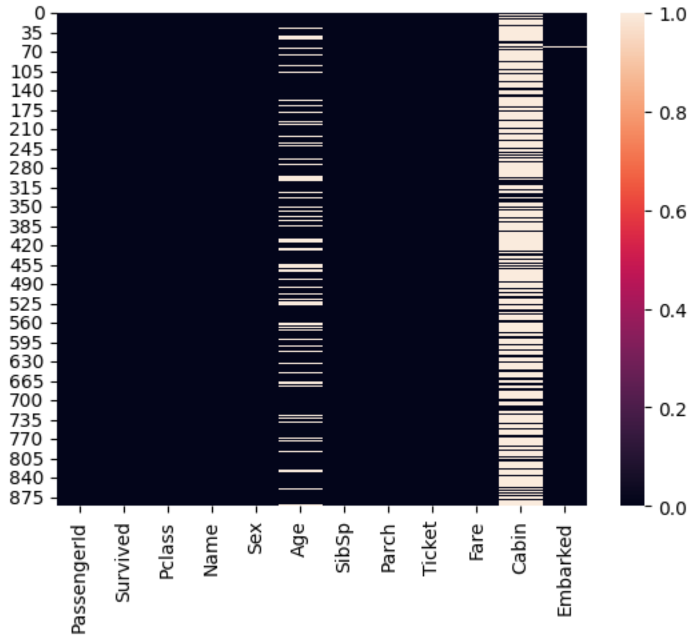
missing data

```
titanic.isna().sum()
```

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

```
sns.heatmap(titanic.isna()) #visulaze the missing data
```

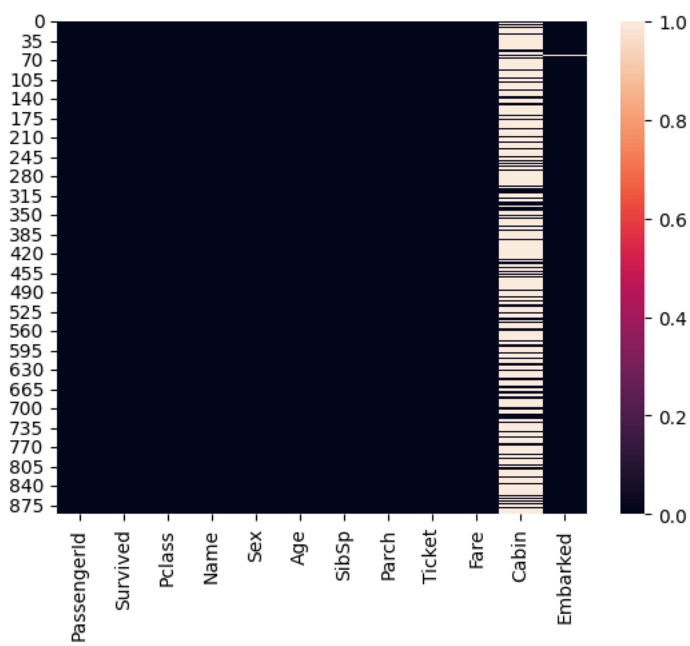
```
<Axes: >
```




```
titanic['Age'] = titanic['Age'].fillna(titanic['Age'].mean())
#fill the column age from the titanic dataset with it's mean
```

```
sns.heatmap(titanic.isna())
```

```
<Axes: >
```



```
titanic.drop('Cabin',axis=1 , inplace= True)
#drop this column because we won't need it and it has missing values
```

```
titanic.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarke
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	

```
titanic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          891 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(4)
memory usage: 76.7+ KB
```

converting categorical features(encoding) *the process of encoding categorical data into 1s and 0s to be easier to work with later on*

```
titanic['Sex'].value_counts()
```

```
male      577
female    314
Name: Sex, dtype: int64
```

```
titanic['Embarked'].value_counts()
#where did the passengers come from
```

```
S    644
C    168
Q     77
Name: Embarked, dtype: int64
```

```
#start incodinf with the get dummies function
sex = pd.get_dummies(titanic['Sex'])
sex
```

	female	male
0	0	1
1	1	0

```
sex = pd.get_dummies(titanic['Sex'], drop_first=True)
sex
#we will drop one of the two columns with the drop first function
#because we want the dataset to be as simple as possible
# 1 indecate male, 0 indecate female
```

	male
0	1
1	0
2	0
3	0
4	1
...	...
886	1
887	0
888	0
889	1
890	1

891 rows × 1 columns

```
emb = pd.get_dummies(titanic['Embarked'])
emb
```

	C	Q	S
0	0	0	1
1	1	0	0
2	0	0	1
3	0	0	1
4	0	0	1
...	...	...	...
886	0	0	1
887	0	0	1
888	0	0	1
889	1	0	0
890	0	1	0

891 rows × 3 columns

now we want to merge the column we just created into the dataset

```
titanic ['Sex']= sex
```

```
emb = pd.Series(['C', 'S', 'C'], name='emb')
titanic['emb'] = emb
```

```
titanic = pd.concat([titanic, sex, emb], axis = 1)
```

```
encoded_emb = pd.get_dummies(titanic['emb'], prefix='emb')
titanic = pd.concat([titanic, encoded_emb], axis=1)
```

```
titanic = titanic.drop('emb', axis=1)
```

now we want to drop the columns that won't be useful in determine if the person dies or sruvives

```
titanic.drop(['PassengerId', 'Name','Ticket','Embarked', 'Sex'], axis = 1 , inplace= True)
#remove columns that wo't affect survival chances
```

```
print(titanic.columns)
```

```
Index(['Survived', 'Pclass', 'Age', 'SibSp', 'Parch', 'Fare', 'male', 'emb_C',
       'emb_S', 'emb_C', 'emb_S'],
      dtype='object')
```

```
titanic
```

	Survived	Pclass	Age	SibSp	Parch	Fare	male	emb_C	emb_S	emb_C	emb_S
0	0	3	22.000000	1	0	7.2500	1	1	0	1	0
1	1	1	38.000000	1	0	71.2833	0	0	1	0	1
2	1	3	26.000000	0	0	7.9250	0	1	0	1	0
3	1	1	35.000000	1	0	53.1000	0	0	0	0	0
4	0	3	35.000000	0	0	8.0500	1	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...
886	0	2	27.000000	0	0	13.0000	1	0	0	0	0
887	1	1	19.000000	0	0	30.0000	0	0	0	0	0
888	0	3	29.699118	1	2	23.4500	0	0	0	0	0
889	1	1	26.000000	0	0	30.0000	1	0	0	0	0
890	0	3	32.000000	0	0	7.7500	1	0	0	0	0

891 rows × 11 columns

```
titanic.rename(columns={'male':'Gender'}, inplace = True)
```

```
titanic
```

	Survived	Pclass	Age	SibSp	Parch	Fare	Gender	emb_C	emb_S	emb_C	emb_S
0	0	3	22.000000	1	0	7.2500	1	1	0	1	0
1	1	1	38.000000	1	0	71.2833	0	0	1	0	1
2	1	3	26.000000	0	0	7.9250	0	1	0	1	0
3	1	1	35.000000	1	0	53.1000	0	0	0	0	0
4	0	3	35.000000	0	0	8.0500	1	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...
886	0	2	27.000000	0	0	13.0000	1	0	0	0	0
887	1	1	19.000000	0	0	30.0000	0	0	0	0	0
888	0	3	29.699118	1	2	23.4500	0	0	0	0	0
889	1	1	26.000000	0	0	30.0000	1	0	0	0	0
890	0	3	32.000000	0	0	7.7500	1	0	0	0	0

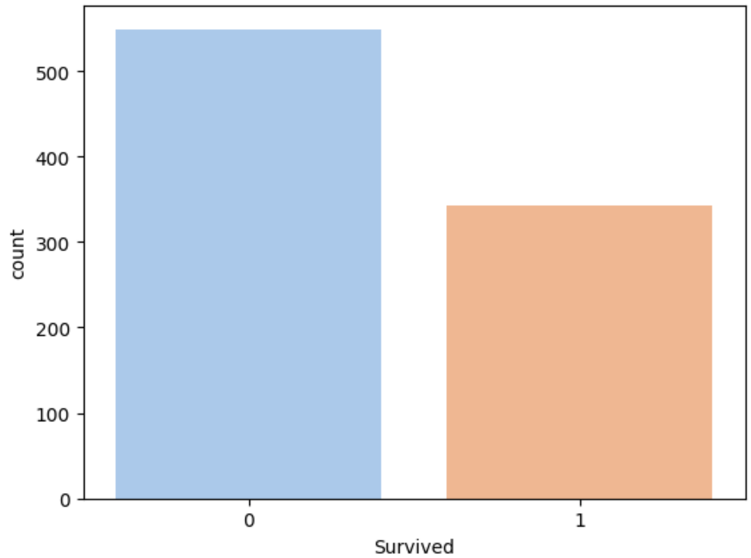
891 rows × 11 columns

Data analysis

here we will begin analysing the data to see how can we predect a person's sruvival chances with the given data

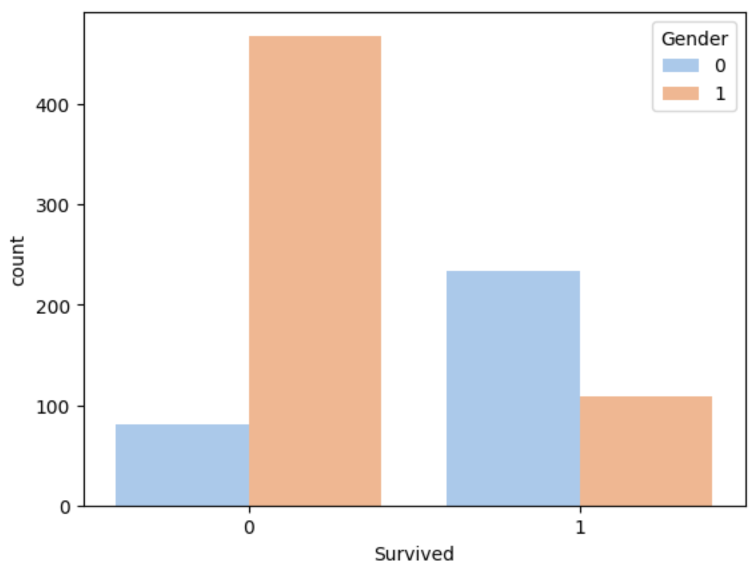
```
sns.countplot(x='Survived', data= titanic, palette= 'pastel')
```

```
<Axes: xlabel='Survived', ylabel='count'>
```




```
sns.countplot(x='Survived', data= titanic, hue='Gender', palette= 'pastel')
#print the surivial rate depending on the Gender feature
```

```
<Axes: xlabel='Survived', ylabel='count'>
```




```
titanic['Age'].hist(bins=12)
#hisograph shows sruvival rate depending on age feature
```

```
<Axes: >
```

building the model

now we will start working in the model that will predict sruvival chances of the test data

starting by split the data into train and test sets

```
titanic
```

	Survived	Pclass	Age	SibSp	Parch	Fare	Gender	emb_C	emb_S	emb_C	emb_S
0	0	3	22.000000	1	0	7.2500	1	1	0	1	0
1	1	1	38.000000	1	0	71.2833	0	0	1	0	1
2	1	3	26.000000	0	0	7.9250	0	1	0	1	0
3	1	1	35.000000	1	0	53.1000	0	0	0	0	0
4	0	3	35.000000	0	0	8.0500	1	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...
886	0	2	27.000000	0	0	13.0000	1	0	0	0	0
887	1	1	19.000000	0	0	30.0000	0	0	0	0	0
888	0	3	29.699118	1	2	23.4500	0	0	0	0	0
889	1	1	26.000000	0	0	30.0000	1	0	0	0	0
890	0	3	32.000000	0	0	7.7500	1	0	0	0	0

891 rows × 11 columns

```
y = titanic['Survived']
#this is the class feature we want to predict using the data
```

```
X = titanic.drop('Survived', axis = 1)
#this way x will store all the columns of dataset after dropping the class label
```

```
X
```

	Pclass	Age	SibSp	Parch	Fare	Gender	emb_C	emb_S	emb_C	emb_S
0	3	22.000000	1	0	7.2500	1	1	0	1	0
1	1	38.000000	1	0	71.2833	0	0	1	0	1
2	3	26.000000	0	0	7.9250	0	1	0	1	0
3	1	35.000000	1	0	53.1000	0	0	0	0	0
4	3	35.000000	0	0	8.0500	1	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...
886	2	27.000000	0	0	13.0000	1	0	0	0	0
887	1	19.000000	0	0	30.0000	0	0	0	0	0
888	3	29.699118	1	2	23.4500	0	0	0	0	0
889	1	26.000000	0	0	30.0000	1	0	0	0	0
890	3	32.000000	0	0	7.7500	1	0	0	0	0

891 rows × 10 columns

```
y
```

```
0    0
1    1
2    1
3    1
4    0
```

```
       ..
886    0
887    1
888    0
889    1
890    0
Name: Survived, Length: 891, dtype: int64
```

now we will split the data using sklearn model

```
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=40 )
```

```
X_train.shape
```

```
(623, 10)
```

```
y_train.shape
```

```
(623,)
```

training the model

```
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
```

```
classifier.fit(X_train, y_train)
```

```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

```
y_pred = classifier.predict(X_test)
```

```
y_pred
#it's in series form and we will have to turn it into array later
```

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

now we will compare the y_pred with the y_test to see how accurate our model was

```
y_test.values
#values funtion turn array into series
```

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

model evaluation

here we will work on inhancing our model's predictions to be more accurate

```
from sklearn.metrics import confusion_matrix
#shows how many wrong predictions we made
```

```
confusion_matrix(y_pred, y_test)
#takes the arguments containing the prediction we made and the acutal data
```

```
array([[122,  48],
       [ 34,  64]])
```

the sum of 26 + 24 is 50 and that's the number of wrong predictions we made

```
from sklearn.metrics import classification_report
```

The classification_report function in scikit-learn (sklearn) is used to generate a text report that provides a comprehensive evaluation of a classification model's performance. It is particularly useful for evaluating the quality of predictions made by a classifier on a classification task

```
print(classification_report(y_pred, y_test))
```

```
              precision    recall  f1-score   support

           0       0.78      0.72      0.75       170
           1       0.57      0.65      0.61        98

    accuracy                           0.69       268
   macro avg       0.68      0.69      0.68       268
weighted avg       0.71      0.69      0.70       268
```