Copy_of_Lab_8_Data_Pre_processing_Classwork

November 4, 2024

Necessary Libraries

```
[ ]: import pandas as pd
```

Loading the datasets

```
[ ]: !unzip Titanic\ Dataset.zip
```

```
Archive:  Titanic Dataset.zip
  inflating: Titanic Dataset/train.csv
  inflating: Titanic Dataset/test.csv
```

```
[ ]: !mv Titanic\ Dataset/* .
```

```
[ ]: test_data = pd.read_csv('test.csv')
train_data = pd.read_csv('train.csv')
```

```
[ ]: train_data.head()
```

```
[ ]:    PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

[ ]:
```
X = train_data.drop(columns=['Survived','Ticket', 'PassengerId',␣
↪'Cabin','Name'])
```

[ ]:
```
y = train_data['Survived']
```

Imputation (Fill in missing values)

[ ]:
```
from sklearn.impute import SimpleImputer
import numpy as np
```

[ ]:
```
X.isna().sum()
```

[ ]:
```
Pclass        0
Sex           0
Age         177
SibSp         0
Parch         0
Fare          0
Embarked      2
dtype: int64
```

[ ]:
```
X.Age
```

[ ]:
```
0      22.0
1      38.0
2      26.0
3      35.0
4      35.0
       …
886    27.0
887    19.0
888     NaN
889    26.0
890    32.0
Name: Age, Length: 891, dtype: float64
```

[ ]:
```
imp_numerical = SimpleImputer(missing_values=np.nan, strategy='mean')
```

[ ]:
```
imp_numerical.fit(X[['Age']])
```

[ ]:
```
SimpleImputer()
```

[ ]:
```
X['Age'] = imp_numerical.transform(X[['Age']])
```

[ ]:
```
X['Age'].isna().sum()
```

[ ]:
```
0
```

[ ]:
```
X['Embarked'].unique()
```

[ ]:
```
array(['S', 'C', 'Q', nan], dtype=object)
```

[ ]:
```
imp_categorical = SimpleImputer(missing_values = np.nan,␣
↪strategy='most_frequent')
```

[ ]:
```
imp_categorical.fit(X[['Embarked']])
```

[ ]:
```
SimpleImputer(strategy='most_frequent')
```

[ ]:
```
X['Embarked'] = imp_categorical.transform(X[['Embarked']]).ravel()
```

[ ]:
```
X['Embarked'].isna().sum()
```

[ ]:
```
0
```

Standardization and Scaling

Three ways to do it: Standard Scaler, Minmax Scaler and Robust Scaler

[ ]:
```
X.head()
```

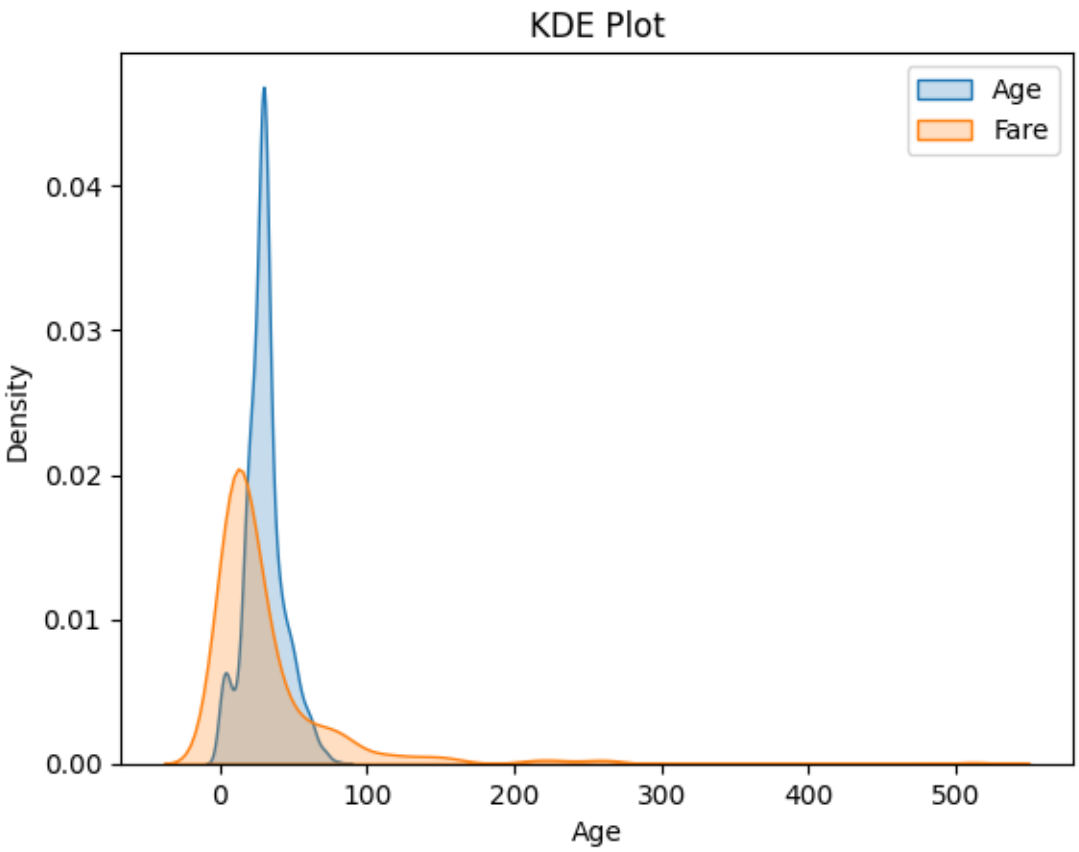
[ ]:

	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	3	male	22.0	1	0	7.2500	S
1	1	female	38.0	1	0	71.2833	C
2	3	female	26.0	0	0	7.9250	S
3	1	female	35.0	1	0	53.1000	S
4	3	male	35.0	0	0	8.0500	S

[ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

[ ]:
```
sns.kdeplot(X['Age'], fill=True, label='Age')
sns.kdeplot(X['Fare'], fill=True, label='Fare')

# Set labels and title
# plt.xlabel('Age')
plt.ylabel('Density')
plt.title('KDE Plot')
plt.legend()
# Display the KDE plot
plt.show()
```



[ ]:
```
import scipy.stats as stats
stats.probplot(X['Fare'], dist="norm", plot=plt)
```

[ ]:
```
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         -2.33618969e+00, -2.29513992e+00, -2.25762808e+00, -2.22304736e+00,
         -2.19093694e+00, -2.16093830e+00, -2.13276686e+00, -2.10619283e+00,
         -2.08102787e+00, -2.05711563e+00, -2.03432484e+00, -2.01254418e+00,
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        83.1583,  83.475 ,  83.475 ,  86.5   ,  86.5   ,  86.5   ,
        89.1042,  89.1042,  90.    ,  90.    ,  90.    ,  90.    ,
        91.0792,  91.0792,  93.5   ,  93.5   , 106.425 , 106.425 ,
       108.9   , 108.9   , 110.8833, 110.8833, 110.8833, 110.8833,
       113.275 , 113.275 , 113.275 , 120.    , 120.    , 120.    ,
       120.    , 133.65  , 133.65  , 134.5   , 134.5   , 135.6333,
       135.6333, 135.6333, 146.5208, 146.5208, 151.55  , 151.55  ,
       151.55  , 151.55  , 153.4625, 153.4625, 153.4625, 164.8667,
       164.8667, 211.3375, 211.3375, 211.3375, 211.5   , 221.7792,
       227.525 , 227.525 , 227.525 , 227.525 , 247.5208, 247.5208,
       262.375 , 262.375 , 263.    , 263.    , 263.    , 263.    ,
       512.3292, 512.3292, 512.3292])),
(35.891199361614504, 32.204207968574636, 0.7204363989046636))
```
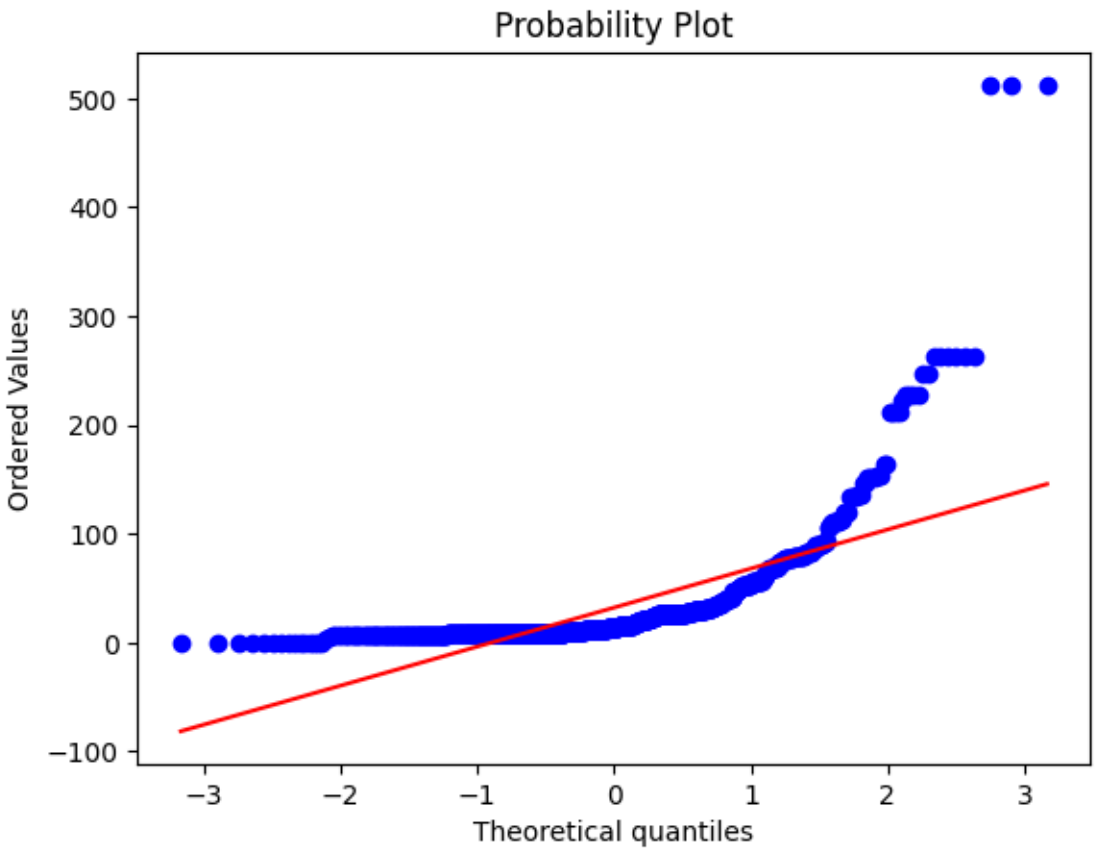



[ ]:
```
from sklearn.preprocessing import StandardScaler, MinMaxScaler
```

[ ]:
```
standardScaler = StandardScaler()
```

[ ]:
```
standardScaler.fit(X[['Age']])
```

[ ]:
```
StandardScaler()
```

[ ]:
```
X['Age'] = standardScaler.transform(X[['Age']])
```

[ ]:
```
X['Age']
```

[ ]:
```
0     -0.592481
1      0.638789
2     -0.284663
3      0.407926
4      0.407926
         ...
886   -0.207709
887   -0.823344
```

```
888    0.000000
889   -0.284663
890    0.177063
Name: Age, Length: 891, dtype: float64
```

[ ]:
```
minmaxScaler = MinMaxScaler()
```

[ ]:
```
minmaxScaler.fit(X[['Fare']])
X['Fare'] = minmaxScaler.transform(X[['Fare']])
```

[ ]:
```
X['Fare']
```

[ ]:
```
0      0.014151
1      0.139136
2      0.015469
3      0.103644
4      0.015713
         …
886    0.025374
887    0.058556
888    0.045771
889    0.058556
890    0.015127
Name: Fare, Length: 891, dtype: float64
```

Encoding the categorical values

Two ways: Ordinal and OneHotEncoder

[ ]:
```
from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder
```

[ ]:
```
ordinal = OrdinalEncoder()
```

[ ]:
```
X['Sex'] = ordinal.fit_transform(X[['Sex']])
```

[ ]:
```
onehot = OneHotEncoder(sparse_output=True)
```

[ ]:
```
embarked = onehot.fit_transform(X[['Embarked']])
```

[ ]:
```
feature_names = onehot.get_feature_names_out()
```

[ ]:
```
feature_names
```

[ ]:
```
array(['Embarked_C', 'Embarked_Q', 'Embarked_S'], dtype=object)
```

[ ]:
```
embarked_df = pd.DataFrame(embarked.toarray(), columns=feature_names)
```

[ ]:
```
embarked_df
```

[ ]:
```
     Embarked_C  Embarked_Q  Embarked_S
0           0.0         0.0         1.0
1           1.0         0.0         0.0
2           0.0         0.0         1.0
3           0.0         0.0         1.0
4           0.0         0.0         1.0
..          …           …           …
886         0.0         0.0         1.0
887         0.0         0.0         1.0
888         0.0         0.0         1.0
889         1.0         0.0         0.0
890         0.0         1.0         0.0

[891 rows x 3 columns]
```

[ ]:
```
X = pd.concat([X, embarked_df],axis=1).drop(columns=['Embarked'])
```

Combining and Pipelining

[ ]:
```
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
```

[ ]:
```
X_pipeline = train_data.drop(columns=['Survived','Ticket', 'PassengerId',␣
↪'Cabin','Name'])
```

[ ]:
```
age_transformer = Pipeline([
    ('imputer', SimpleImputer(strategy='mean')),
    ('scaler', StandardScaler())
])

fare_transformer = Pipeline([
    ('imputer', SimpleImputer(strategy='mean')),
    ('scaler', MinMaxScaler())
])

embarked_transformer = Pipeline([
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('encoder', OneHotEncoder())
])

sex_transformer = Pipeline([
    ('encoder', OrdinalEncoder())
])

preprocessor = ColumnTransformer(
    transformers=[
        ('sex_transformer', sex_transformer, ['Sex']),
        ('age_transformer', age_transformer, ['Age']),
```

```
        ('fare_transformer', fare_transformer, ['Fare']),
        ('embarked_transformer', embarked_transformer, ['Embarked'])
    ],remainder='passthrough',)

pipeline = Pipeline([
    ('preprocessor', preprocessor),
])

X_transformed = pipeline.fit_transform(X_pipeline)
```

[ ]:
```
new_order = ['Sex','Age','Fare','Embarked_C',␣
 ↪'Embarked_Q',        'Embarked_S','Pclass', 'SibSp',        'Parch']
```

[ ]:
```
pd.DataFrame(X_transformed,columns=new_order)
```

[ ]:
```
      Sex       Age      Fare  Embarked_C  Embarked_Q  Embarked_S  Pclass  \
0     1.0 -0.592481  0.014151         0.0         0.0         1.0     3.0
1     0.0  0.638789  0.139136         1.0         0.0         0.0     1.0
2     0.0 -0.284663  0.015469         0.0         0.0         1.0     3.0
3     0.0  0.407926  0.103644         0.0         0.0         1.0     1.0
4     1.0  0.407926  0.015713         0.0         0.0         1.0     3.0
..    …       …       …          …           …           …      …
886   1.0 -0.207709  0.025374         0.0         0.0         1.0     2.0
887   0.0 -0.823344  0.058556         0.0         0.0         1.0     1.0
888   0.0  0.000000  0.045771         0.0         0.0         1.0     3.0
889   1.0 -0.284663  0.058556         1.0         0.0         0.0     1.0
890   1.0  0.177063  0.015127         0.0         1.0         0.0     3.0

     SibSp  Parch
0      1.0    0.0
1      1.0    0.0
2      0.0    0.0
3      1.0    0.0
4      0.0    0.0
..     …    …
886    0.0    0.0
887    0.0    0.0
888    1.0    2.0
889    0.0    0.0
890    0.0    0.0

[891 rows x 9 columns]
```

[ ]:
```
X.head(1)
```

[ ]:
```
   Pclass  Sex       Age  SibSp  Parch      Fare  Embarked_C  Embarked_Q  \
0       3  1.0 -0.592481      1      0  0.014151         0.0         0.0
```

```
   Embarked_S
0         1.0
```

0.1 Do the same for the Dataset in link: https://www.kaggle.com/datasets/sujithmandala/s loan-classification-dataset - [10 marks]

[ ]:
```
from google.colab import files
files.upload()
```

```
<IPython.core.display.HTML object>

Saving kaggle.json to kaggle.json
```

[ ]:
```
{'kaggle.json':
b'{"username":"ulugbekshernazarov","key":"04a6f70b9e9b10a3c9cfb00e5ddb14c2"}'}
```

[ ]:
```
!mkdir ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json
!kaggle datasets download sujithmandala/simple-loan-classification-dataset
```

```
Dataset URL: https://www.kaggle.com/datasets/sujithmandala/simple-loan-
classification-dataset
License(s): CC-BY-SA-4.0
Downloading simple-loan-classification-dataset.zip to /content
  0% 0.00/1.05k [00:00<?, ?B/s]
100% 1.05k/1.05k [00:00<00:00, 2.34MB/s]
```

[ ]:
```
!unzip simple-loan-classification-dataset.zip
```

```
Archive:  simple-loan-classification-dataset.zip
  inflating: loan.csv
```

[ ]:
```
df = pd.read_csv('loan.csv')
df.head()
```

[ ]:
```
   age  gender  occupation education_level marital_status  income  \
0   32    Male    Engineer      Bachelor's        Married   85000
1   45  Female     Teacher        Master's         Single   62000
2   28    Male     Student     High School         Single   25000
3   51  Female     Manager      Bachelor's        Married  105000
4   36    Male  Accountant      Bachelor's        Married   75000

   credit_score loan_status
0           720    Approved
1           680    Approved
2           590      Denied
3           780    Approved
```

```
4           710    Approved
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 61 entries, 0 to 60
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   age              61 non-null     int64
 1   gender           61 non-null     object
 2   occupation       61 non-null     object
 3   education_level  61 non-null     object
 4   marital_status   61 non-null     object
 5   income           61 non-null     int64
 6   credit_score     61 non-null     int64
 7   loan_status      61 non-null     object
dtypes: int64(3), object(5)
memory usage: 3.9+ KB
```

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

[ ]:

	age	income	credit_score
count	61.000000	61.000000	61.000000
mean	37.081967	78983.606557	709.836066
std	8.424755	33772.025802	72.674888
min	24.000000	25000.000000	560.000000
25%	30.000000	52000.000000	650.000000
50%	36.000000	78000.000000	720.000000
75%	43.000000	98000.000000	770.000000
max	55.000000	180000.000000	830.000000

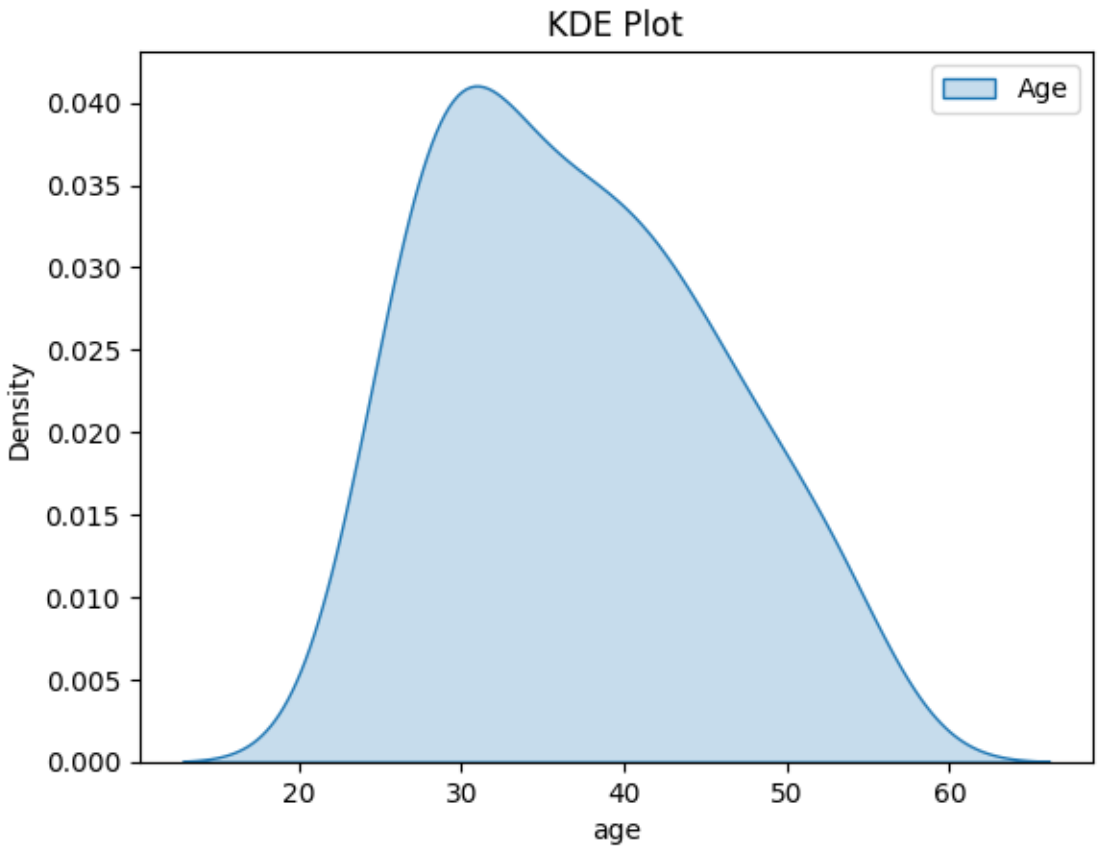
[ ]:
```
df.isna().sum()
```

[ ]:
```
age                0
gender             0
occupation         0
education_level    0
marital_status     0
income             0
credit_score       0
loan_status        0
dtype: int64
```

Standardization and Scaling

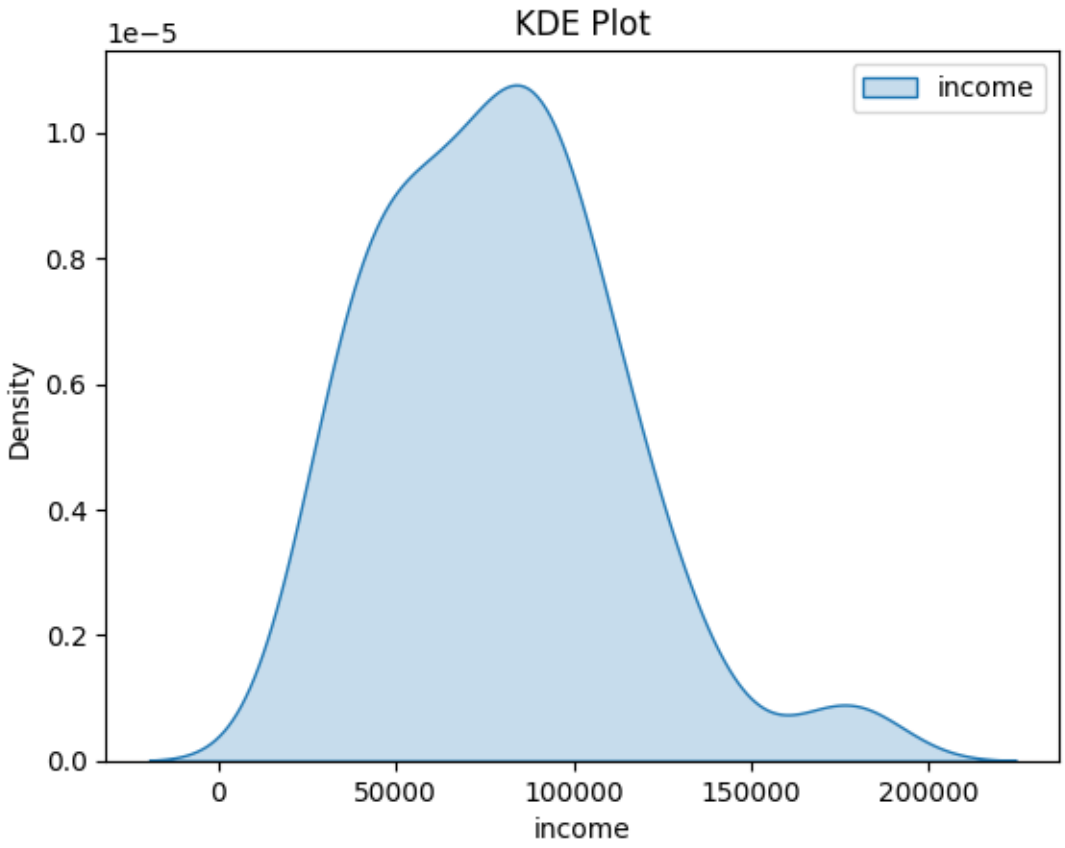
[ ]:
```
sns.kdeplot(df['age'], fill=True, label='Age')
# sns.kdeplot(df['income'], fill=True, label='income')
```

```
# sns.kdeplot(df['credit_score'], fill=True, label='credit_score')

# Set labels and title
# plt.xlabel('Age')
plt.ylabel('Density')
plt.title('KDE Plot')
plt.legend()
# Display the KDE plot
plt.show()
```

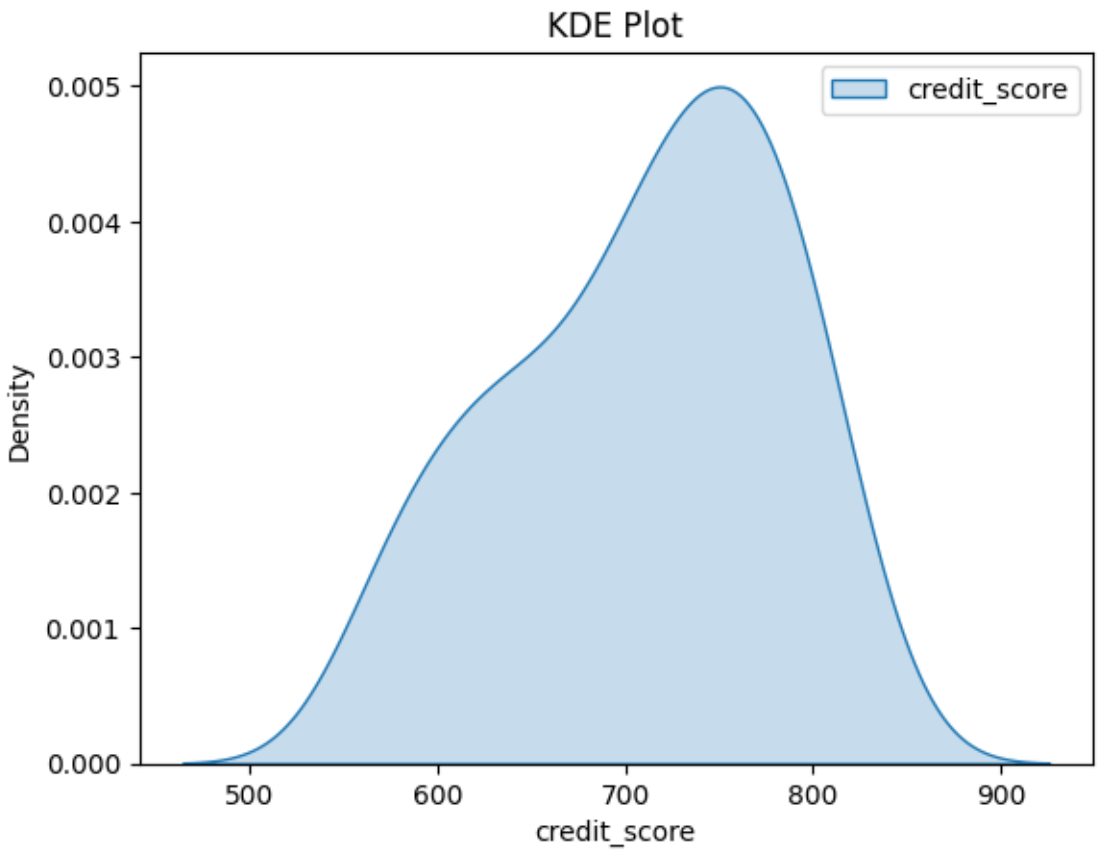


[ ]:
```
# sns.kdeplot(df['age'], fill=True, label='Age')
sns.kdeplot(df['income'], fill=True, label='income')
# sns.kdeplot(df['credit_score'], fill=True, label='credit_score')

# Set labels and title
# plt.xlabel('Age')
plt.ylabel('Density')
plt.title('KDE Plot')
plt.legend()
```

```
# Display the KDE plot
plt.show()
```



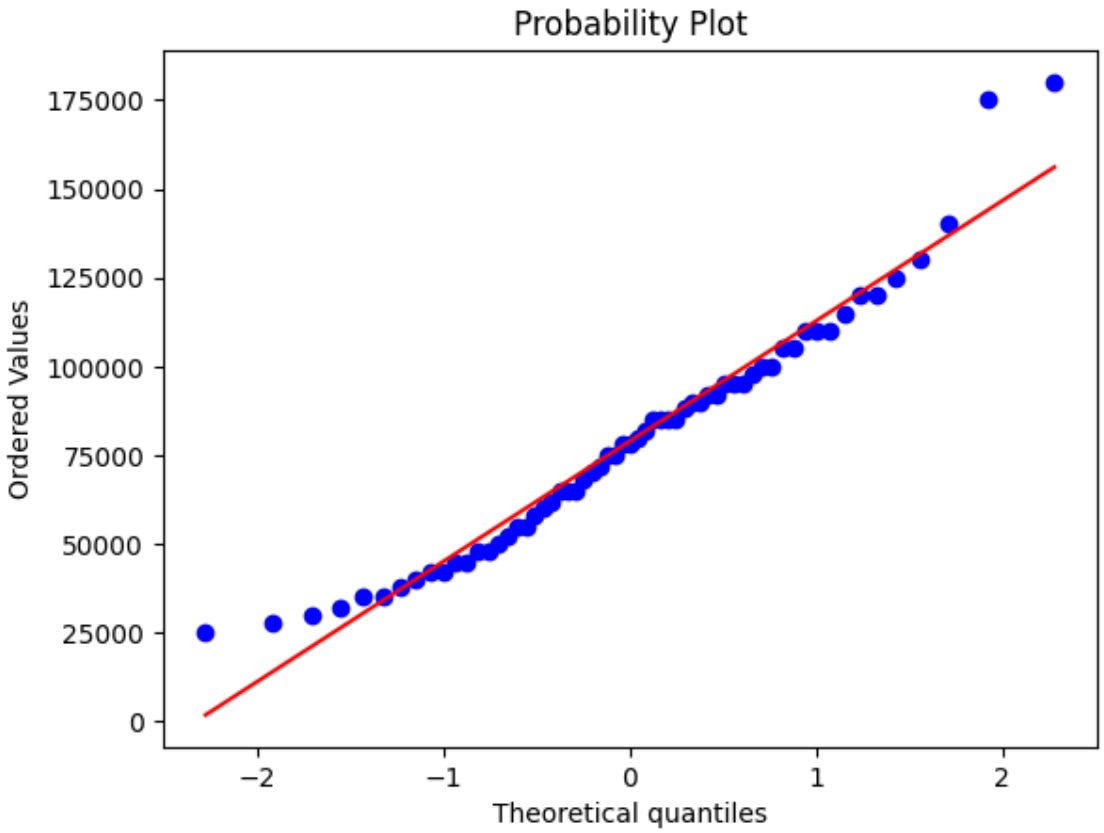
[ ]:
```
# sns.kdeplot(df['age'], fill=True, label='Age')
# sns.kdeplot(df['income'], fill=True, label='income')
sns.kdeplot(df['credit_score'], fill=True, label='credit_score')

# Set labels and title
# plt.xlabel('Age')
plt.ylabel('Density')
plt.title('KDE Plot')
plt.legend()
# Display the KDE plot
plt.show()
```



[ ]:
```
import scipy.stats as stats
stats.probplot(df['income'], dist="norm", plot=plt)
```

[ ]:
```
((array([-2.28017173, -1.92017484, -1.7091256 , -1.55469152, -1.43036801,
         -1.3249031 , -1.23241216, -1.14940983, -1.07365152, -1.00360143,
         -0.93815914, -0.87650695, -0.81801894, -0.76220403, -0.70866868,
         -0.65709167, -0.60720655, -0.55878903, -0.51164772, -0.46561731,
         -0.42055328, -0.37632784, -0.33282677, -0.28994682, -0.24759369,
         -0.20568029, -0.16412527, -0.12285188, -0.08178679, -0.04085922,
          0.        ,  0.04085922,  0.08178679,  0.12285188,  0.16412527,
          0.20568029,  0.24759369,  0.28994682,  0.33282677,  0.37632784,
          0.42055328,  0.46561731,  0.51164772,  0.55878903,  0.60720655,
          0.65709167,  0.70866868,  0.76220403,  0.81801894,  0.87650695,
          0.93815914,  1.00360143,  1.07365152,  1.14940983,  1.23241216,
          1.3249031 ,  1.43036801,  1.55469152,  1.7091256 ,  1.92017484,
          2.28017173]),
  array([ 25000,  28000,  30000,  32000,  35000,  35000,  38000,  40000,
          42000,  42000,  45000,  45000,  48000,  48000,  50000,  52000,
          55000,  55000,  58000,  60000,  62000,  65000,  65000,  65000,
          68000,  70000,  72000,  75000,  75000,  78000,  78000,  80000,
```

```
        82000,  85000,  85000,  85000,  85000,  88000,  90000,  90000,
        92000,  92000,  95000,  95000,  95000,  98000, 100000, 100000,
       105000, 105000, 110000, 110000, 110000, 115000, 120000, 120000,
       125000, 130000, 140000, 175000, 180000])),
(33819.21078234064, 78983.60655737705, 0.9792044418708735))
```



[ ]:
```
from sklearn.preprocessing import StandardScaler, MinMaxScaler
```

[ ]:
```
standardScaler = StandardScaler()
```

[ ]:
```
standardScaler.fit(df[['age']])
```

[ ]:
```
StandardScaler()
```

[ ]:
```
df['age'] = standardScaler.transform(df[['age']])
```

[ ]:
```
df['age']
```

[ ]:
```
0    -0.608224
1     0.947653
```

```
2    -1.086956
3     1.665750
4    -0.129493
        …
56    0.229556
57   -1.446005
58    0.708287
59   -0.847590
60    0.109873
Name: age, Length: 61, dtype: float64
```

[ ]:
```
standardScaler.fit(df[['credit_score']])
df['credit_score'] = standardScaler.transform(df[['credit_score']])
df['credit_score']
```

[ ]:
```
0     0.141015
1    -0.413949
2    -1.662618
3     0.973462
4     0.002274
        …
56    0.834721
57   -1.940100
58    0.695980
59   -0.830172
60   -0.136467
Name: credit_score, Length: 61, dtype: float64
```

[ ]:
```
minmaxScaler = MinMaxScaler()
```

[ ]:
```
minmaxScaler.fit(df[['income']])
df['income'] = minmaxScaler.transform(df[['income']])
```

[ ]:
```
X['Fare']
```

[ ]:
```
0      0.014151
1      0.139136
2      0.015469
3      0.103644
4      0.015713
         …
886    0.025374
887    0.058556
888    0.045771
889    0.058556
890    0.015127
Name: Fare, Length: 891, dtype: float64
```

Encoding the categorical values

Two ways: Ordinal and OneHotEncoder

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

[ ]:
```
        age  gender  occupation education_level marital_status    income  \
0 -0.608224    Male    Engineer      Bachelor's        Married  0.387097
1  0.947653  Female     Teacher        Master's         Single  0.238710
2 -1.086956    Male     Student     High School         Single  0.000000
3  1.665750  Female     Manager      Bachelor's        Married  0.516129
4 -0.129493    Male  Accountant      Bachelor's        Married  0.322581

   credit_score loan_status
0      0.141015    Approved
1     -0.413949    Approved
2     -1.662618      Denied
3      0.973462    Approved
4      0.002274    Approved
```

[ ]:
```
from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder
```

[ ]:
```
ordinal = OrdinalEncoder()
```

[ ]:
```
df['occupation'] = ordinal.fit_transform(df[['occupation']])
```

[ ]:
```
df['gender'] = ordinal.fit_transform(df[['gender']])
df['marital_status'] = ordinal.fit_transform(df[['marital_status']])
df['loan_status'] = ordinal.fit_transform(df[['loan_status']])
```

[ ]:
```
onehot = OneHotEncoder(sparse_output=True)
```

[ ]:
```
embarked = onehot.fit_transform(df[['education_level']])
```

[ ]:
```
feature_names = onehot.get_feature_names_out()
```

[ ]:
```
feature_names
```

[ ]:
```
array(["education_level_Associate's", "education_level_Bachelor's",
       'education_level_Doctoral', 'education_level_High School',
       "education_level_Master's"], dtype=object)
```

[ ]:
```
embarked_df = pd.DataFrame(embarked.toarray(), columns=feature_names)
```

[ ]:
```
embarked_df
```

[ ]:
```
    education_level_Associate's  education_level_Bachelor's  \
0                           0.0                         1.0
1                           0.0                         0.0
```

```
2                           0.0                           0.0
3                           0.0                           1.0
4                           0.0                           1.0
..                          …                             …
56                          0.0                           0.0
57                          0.0                           0.0
58                          0.0                           1.0
59                          0.0                           0.0
60                          1.0                           0.0

    education_level_Doctoral  education_level_High School  \
0                        0.0                           0.0
1                        0.0                           0.0
2                        0.0                           1.0
3                        0.0                           0.0
4                        0.0                           0.0
..                       …                             …
56                       0.0                           0.0
57                       0.0                           1.0
58                       0.0                           0.0
59                       0.0                           0.0
60                       0.0                           0.0

    education_level_Master's
0                        0.0
1                        1.0
2                        0.0
3                        0.0
4                        0.0
..                       …
56                       1.0
57                       0.0
58                       0.0
59                       1.0
60                       0.0

[61 rows x 5 columns]
```

[ ]:
```
df = pd.concat([df, embarked_df],axis=1).drop(columns=['education_level'])
```

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

[ ]:
```
        age  gender  occupation  marital_status    income  credit_score  \
0 -0.608224     1.0        12.0             0.0  0.387097      0.141015
1  0.947653     0.0        35.0             1.0  0.238710     -0.413949
2 -1.086956     1.0        33.0             1.0  0.000000     -1.662618
3  1.665750     0.0        16.0             0.0  0.516129      0.973462
```

```
4 -0.129493     1.0         0.0             0.0  0.322581      0.002274

   loan_status  education_level_Associate's  education_level_Bachelor's  \
0          0.0                          0.0                         1.0
1          0.0                          0.0                         0.0
2          1.0                          0.0                         0.0
3          0.0                          0.0                         1.0
4          0.0                          0.0                         1.0

   education_level_Doctoral  education_level_High School  \
0                       0.0                          0.0
1                       0.0                          0.0
2                       0.0                          1.0
3                       0.0                          0.0
4                       0.0                          0.0

   education_level_Master's
0                       0.0
1                       1.0
2                       0.0
3                       0.0
4                       0.0
```

Combining and Pipelining

[ ]:
```
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
```

[ ]:
```
df = pd.read_csv('loan.csv')
df.head()
```

[ ]:
```
   age  gender  occupation education_level marital_status  income  \
0   32    Male    Engineer      Bachelor's        Married   85000
1   45  Female     Teacher        Master's         Single   62000
2   28    Male     Student     High School         Single   25000
3   51  Female     Manager      Bachelor's        Married  105000
4   36    Male  Accountant      Bachelor's        Married   75000

   credit_score loan_status
0           720    Approved
1           680    Approved
2           590      Denied
3           780    Approved
4           710    Approved
```

[ ]:
```
X_pipeline = df
```

[ ]:
```
age_transformer = Pipeline([
    ('imputer', SimpleImputer(strategy='mean')),
    ('scaler', StandardScaler())
])

fare_transformer = Pipeline([
    ('imputer', SimpleImputer(strategy='mean')),
    ('scaler', MinMaxScaler())
])

embarked_transformer = Pipeline([
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('encoder', OneHotEncoder())
])

sex_transformer = Pipeline([
    ('encoder', OrdinalEncoder())
])

preprocessor = ColumnTransformer(
    transformers=[
        ('gender_transformer', sex_transformer, ['gender']),
        ('occupation_transformer', sex_transformer, ['occupation']),
        ('marital_status_transformer', sex_transformer, ['marital_status']),
        ('loan_status_status_transformer', sex_transformer, ['loan_status']),
        ('age_transformer', age_transformer, ['age']),
        ('income_transformer', fare_transformer, ['income']),
        ('credit_score_transformer', fare_transformer, ['credit_score']),
        ('education_level_status_transformer', embarked_transformer,␣
 ↪['education_level'])
    ],remainder='passthrough',)

pipeline = Pipeline([
    ('preprocessor', preprocessor),
])

X_transformed = pipeline.fit_transform(X_pipeline)
```

[ ]:
```
new_order = ['gender','occupation','marital_status', 'loan_status', 'age',␣
 ↪'income',        'credit_score','education_level_A',␣
 ↪'education_level_B',        'education_level_C', 'education_level_M',␣
 ↪'education_level_D']
```

[ ]:
```
df_train = pd.DataFrame(X_transformed,columns=new_order)
df_train.head()
```

[ ]:
```
   gender  occupation  marital_status  loan_status       age    income  \
0     1.0        12.0             0.0          0.0 -0.608224  0.387097
1     0.0        35.0             1.0          0.0  0.947653  0.238710
2     1.0        33.0             1.0          1.0 -1.086956  0.000000
3     0.0        16.0             0.0          0.0  1.665750  0.516129
4     1.0         0.0             0.0          0.0 -0.129493  0.322581

   credit_score  education_level_A  education_level_B  education_level_C  \
0      0.592593                0.0                1.0                0.0
1      0.444444                0.0                0.0                0.0
2      0.111111                0.0                0.0                0.0
3      0.814815                0.0                1.0                0.0
4      0.555556                0.0                1.0                0.0

   education_level_M  education_level_D
0                0.0                0.0
1                0.0                1.0
2                1.0                0.0
3                0.0                0.0
4                0.0                0.0
```

[ ]:
```
df.head(1)
```

[ ]:
```
   age gender occupation education_level marital_status  income  credit_score  \
0   32   Male   Engineer      Bachelor's        Married   85000           720

  loan_status
0    Approved
```

[ ]:
```
X = df_train.drop(['loan_status'], axis=1)
y = df_train['loan_status']

X.shape, y.shape
```

[ ]:
```
((61, 11), (61,))
```

[ ]:
```
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_state=42)
X_train.shape, X_test.shape
```

[ ]:
```
((48, 11), (13, 11))
```

[ ]:
```
X_train.head()
```

[ ]:
```
     gender  occupation  marital_status       age    income  credit_score  \
3       0.0        16.0             0.0  1.665750  0.516129      0.814815
53      0.0        17.0             0.0  0.827970  0.387097      0.666667
17      0.0        20.0             0.0  0.468921  0.645161      0.888889
8       1.0        14.0             0.0 -0.009810  0.432258      0.703704
6       1.0        15.0             0.0  0.588604  0.612903      0.851852

     education_level_A  education_level_B  education_level_C  \
3                  0.0                1.0                0.0
53                 0.0                0.0                0.0
17                 0.0                0.0                1.0
8                  0.0                0.0                0.0
6                  0.0                0.0                1.0

     education_level_M  education_level_D
3                  0.0                0.0
53                 0.0                1.0
17                 0.0                0.0
8                  0.0                1.0
6                  0.0                0.0
```

[ ]:
```
y_train.head()
```

[ ]:
```
3     0.0
53    0.0
17    0.0
8     0.0
6     0.0
Name: loan_status, dtype: float64
```

[ ]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

logistic_pipeline = Pipeline([
    ('classifier', LogisticRegression())
])

svm_pipeline = Pipeline([
    ('classifier', SVC())
])

random_forest_pipeline = Pipeline([
    ('classifier', RandomForestClassifier())
])
```

```
logistic_pipeline.fit(X_train, y_train)
svm_pipeline.fit(X_train, y_train)
random_forest_pipeline.fit(X_train, y_train)

logistic_pred = logistic_pipeline.predict(X_test)
svm_pred = svm_pipeline.predict(X_test)
rf_pred = random_forest_pipeline.predict(X_test)

accuracy_score(y_test, logistic_pred), accuracy_score(y_test, svm_pred),␣
↪accuracy_score(y_test, rf_pred)
```

[ ]:
```
(1.0, 0.6923076923076923, 0.9230769230769231)
```

[ ]:
```
from sklearn.model_selection import GridSearchCV

pipeline = Pipeline([
    ('classifier', LogisticRegression())
])

param_grid = [
    {
        'classifier': [LogisticRegression()],
        'classifier__C': [0.1, 1, 10]
    },
    {
        'classifier': [SVC()],
        'classifier__C': [0.1, 1, 10],
        'classifier__kernel': ['linear', 'rbf']
    },
    {
        'classifier': [RandomForestClassifier()],
        'classifier__n_estimators': [100, 200],
        'classifier__max_depth': [10, 20]
    }
]

grid_search = GridSearchCV(pipeline, param_grid, cv=5)
grid_search.fit(X_train, y_train)

best_model = grid_search.best_estimator_

y_pred = best_model.predict(X_test)

accuracy_score(y_test, y_pred), best_model
```

[ ]:
```
(1.0,
 Pipeline(steps=[('classifier',
```

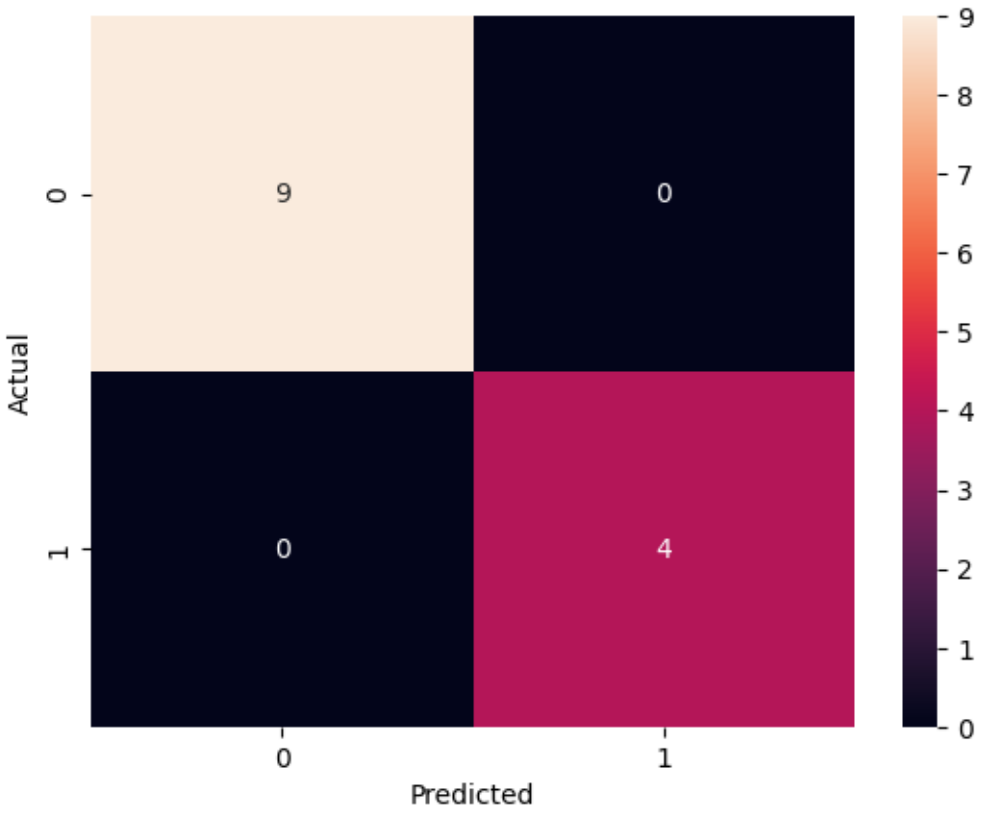
```
                    RandomForestClassifier(max_depth=20, n_estimators=200))]))
```

[ ]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00         9
         1.0       1.00      1.00      1.00         4

    accuracy                           1.00        13
   macro avg       1.00      1.00      1.00        13
weighted avg       1.00      1.00      1.00        13
```

[ ]:
```
from sklearn.metrics import confusion_matrix
print(confusion_matrix(y_test, y_pred))

import seaborn as sns
import matplotlib.pyplot as plt

cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
[[9 0]
 [0 4]]
```


9
0
0
4
0
1
Actual
Predicted
9
8
7
6
5
4
3
2
1
0