Untitled6

October 26, 2023

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
print('all lib imported')
```

```
all lib imported
```

[5]:
```
df=pd.read_csv('health care diabetes.csv capstone project dataset.csv')
```

[3]:
```
df
```

[3]:
```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0              6      148             72             35        0  33.6
1              1       85             66             29        0  26.6
2              8      183             64              0        0  23.3
3              1       89             66             23       94  28.1
4              0      137             40             35      168  43.1
..           …        …            …            …      …    …
763           10      101             76             48      180  32.9
764            2      122             70             27        0  36.8
765            5      121             72             23      112  26.2
766            1      126             60              0        0  30.1
767            1       93             70             31        0  30.4

     DiabetesPedigreeFunction  Age  Outcome
0                       0.627   50        1
1                       0.351   31        0
2                       0.672   32        1
3                       0.167   21        0
4                       2.288   33        1
..                        …  …      …
763                     0.171   63        0
764                     0.340   27        0
765                     0.245   30        0
766                     0.349   47        1
767                     0.315   23        0
```

```
[768 rows x 9 columns]
```

[4]:
```
df.shape
```

[4]:
```
(768, 9)
```

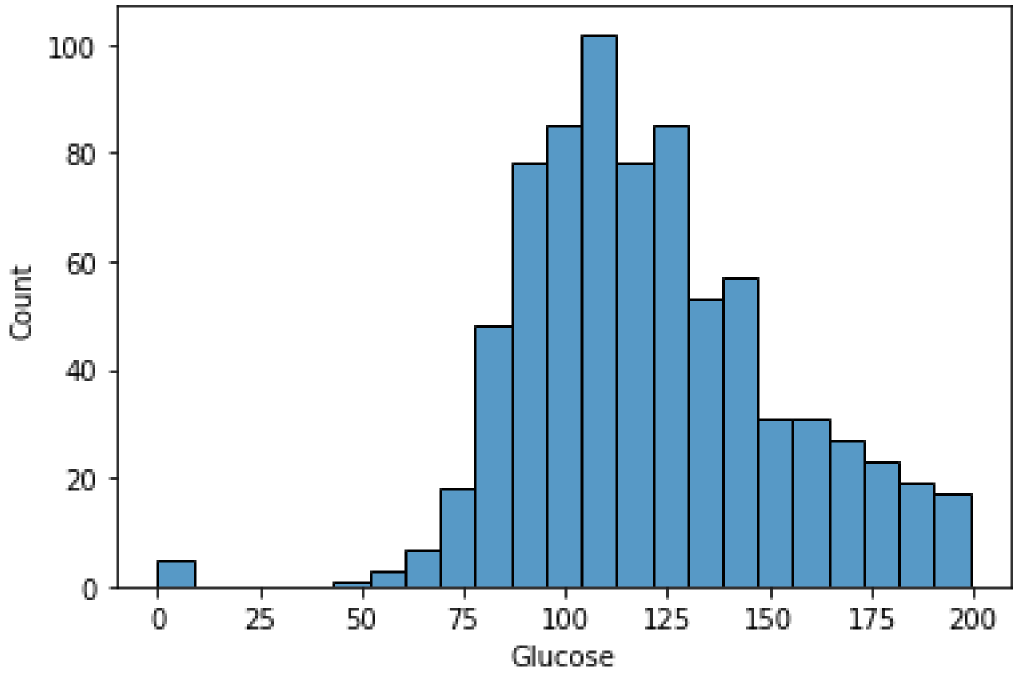
[78]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 non-null    int64
 2   BloodPressure             768 non-null    int64
 3   SkinThickness             768 non-null    int64
 4   Insulin                   768 non-null    int64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

[79]:
```
df.describe()
```

[79]:
```
       Pregnancies     Glucose  BloodPressure  SkinThickness     Insulin  \
count   768.000000  768.000000     768.000000     768.000000  768.000000
mean      3.845052  120.894531      69.105469      20.536458   79.799479
std       3.369578   31.972618      19.355807      15.952218  115.244002
min       0.000000    0.000000       0.000000       0.000000    0.000000
25%       1.000000   99.000000      62.000000       0.000000    0.000000
50%       3.000000  117.000000      72.000000      23.000000   30.500000
75%       6.000000  140.250000      80.000000      32.000000  127.250000
max      17.000000  199.000000     122.000000      99.000000  846.000000

              BMI  DiabetesPedigreeFunction         Age     Outcome
count  768.000000                768.000000  768.000000  768.000000
mean    31.992578                  0.471876   33.240885    0.348958
std      7.884160                  0.331329   11.760232    0.476951
min      0.000000                  0.078000   21.000000    0.000000
25%     27.300000                  0.243750   24.000000    0.000000
50%     32.000000                  0.372500   29.000000    0.000000
75%     36.600000                  0.626250   41.000000    1.000000
max     67.100000                  2.420000   81.000000    1.000000
```

```
[80]: # create histogram
      sns.histplot(x=df['Glucose'])
      plt.show()
```



```
[81]: df['Glucose'].value_counts()
```

```
[81]: 99     17
      100    17
      111    14
      129    14
      125    14
             ..
      191     1
      177     1
      44      1
      62      1
      190     1
      Name: Glucose, Length: 136, dtype: int64
```

```
[82]: df[df['Glucose']==0]
```

```
[82]:      Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
      75             1        0             48             20        0  24.7
      182            1        0             74             20       23  27.7
      342            1        0             68             35        0  32.0
```

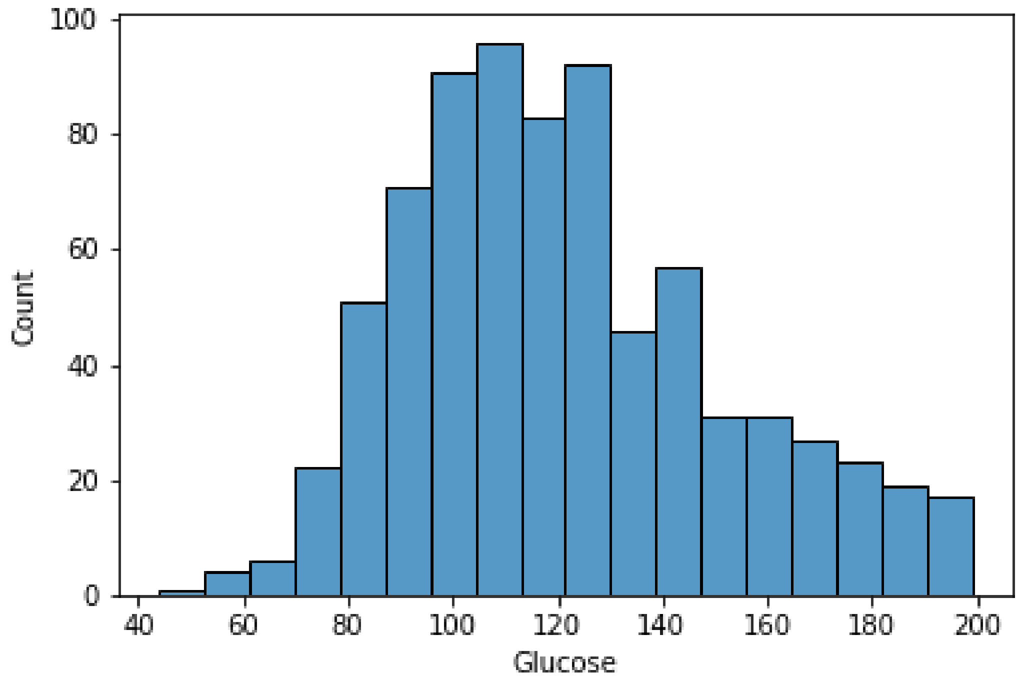
```
349                5        0              80             32         0  41.0
502                6        0              68             41         0  39.0

     DiabetesPedigreeFunction  Age  Outcome
75                      0.140   22        0
182                     0.299   21        0
342                     0.389   22        0
349                     0.346   37        1
502                     0.727   41        1
```

[8]:
```
df['Glucose'].mean()
```

[8]:
```
120.89453125
```

[85]:
```
#fill the zero value with mean of glucose
df['Glucose']=df['Glucose'].replace(0,df['Glucose'].mean())
```

[86]:
```
#create histogram
sns.histplot(df['Glucose'])
plt.show()
```



[87]:
```
df['BloodPressure'].value_counts()
```

[87]:
```
70     57
74     52
78     45
68     45
72     44
64     43
80     40
76     39
60     37
0      35
62     34
66     30
82     30
88     25
84     23
90     22
86     21
58     21
50     13
56     12
52     11
54     11
75      8
92      8
65      7
85      6
94      6
48      5
96      4
44      4
100     3
106     3
98      3
110     3
55      2
108     2
104     2
46      2
30      2
122     1
95      1
102     1
61      1
24      1
38      1
40      1
114     1
```

```
Name: BloodPressure, dtype: int64
```

[88]:
```
df[df['BloodPressure']==0]
```

[88]:
```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
7             10    115.0              0              0        0  35.3
15             7    100.0              0              0        0  30.0
49             7    105.0              0              0        0   0.0
60             2     84.0              0              0        0   0.0
78             0    131.0              0              0        0  43.2
81             2     74.0              0              0        0   0.0
172            2     87.0              0             23        0  28.9
193           11    135.0              0              0        0  52.3
222            7    119.0              0              0        0  25.2
261            3    141.0              0              0        0  30.0
266            0    138.0              0              0        0  36.3
269            2    146.0              0              0        0  27.5
300            0    167.0              0              0        0  32.3
332            1    180.0              0              0        0  43.3
336            0    117.0              0              0        0  33.8
347            3    116.0              0              0        0  23.5
357           13    129.0              0             30        0  39.9
426            0     94.0              0              0        0   0.0
430            2     99.0              0              0        0  22.2
435            0    141.0              0              0        0  42.4
453            2    119.0              0              0        0  19.6
468            8    120.0              0              0        0  30.0
484            0    145.0              0              0        0  44.2
494            3     80.0              0              0        0   0.0
522            6    114.0              0              0        0   0.0
533            6     91.0              0              0        0  29.8
535            4    132.0              0              0        0  32.9
589            0     73.0              0              0        0  21.1
601            6     96.0              0              0        0  23.7
604            4    183.0              0              0        0  28.4
619            0    119.0              0              0        0  32.4
643            4     90.0              0              0        0  28.0
697            0     99.0              0              0        0  25.0
703            2    129.0              0              0        0  38.5
706           10    115.0              0              0        0   0.0

     DiabetesPedigreeFunction  Age  Outcome
7                       0.134   29        0
15                      0.484   32        1
49                      0.305   24        0
60                      0.304   21        0
78                      0.270   26        1
```

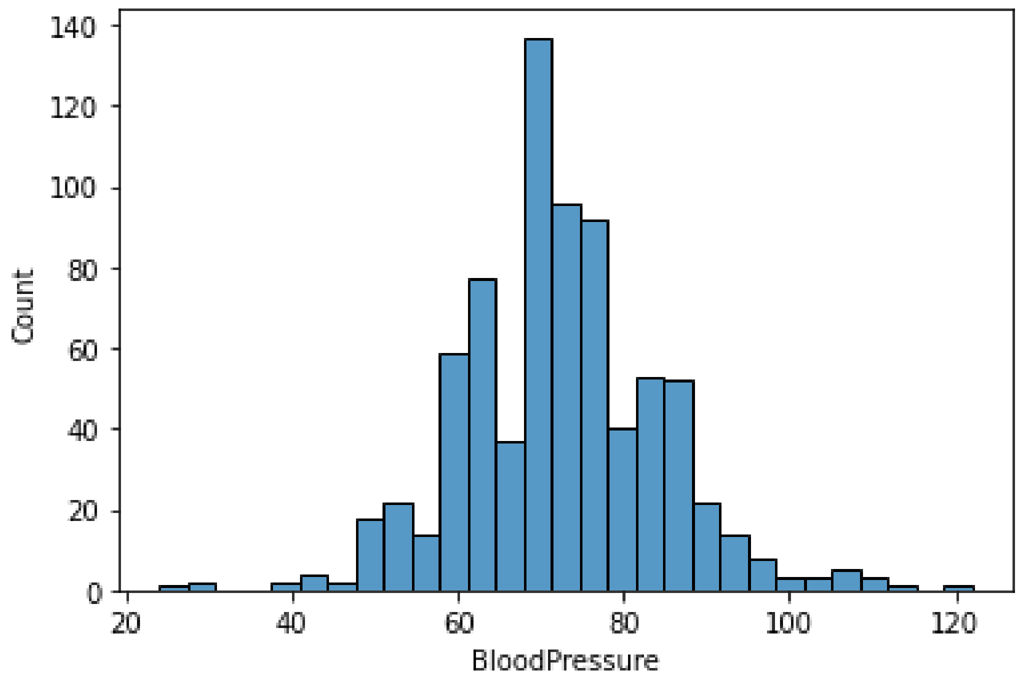
```
81                         0.102   22        0
172                        0.773   25        0
193                        0.578   40        1
222                        0.209   37        0
261                        0.761   27        1
266                        0.933   25        1
269                        0.240   28        1
300                        0.839   30        1
332                        0.282   41        1
336                        0.932   44        0
347                        0.187   23        0
357                        0.569   44        1
426                        0.256   25        0
430                        0.108   23        0
435                        0.205   29        1
453                        0.832   72        0
468                        0.183   38        1
484                        0.630   31        1
494                        0.174   22        0
522                        0.189   26        0
533                        0.501   31        0
535                        0.302   23        1
589                        0.342   25        0
601                        0.190   28        0
604                        0.212   36        1
619                        0.141   24        1
643                        0.610   31        0
697                        0.253   22        0
703                        0.304   41        0
706                        0.261   30        1
```

[89]:
```
df['BloodPressure'].mean()
```

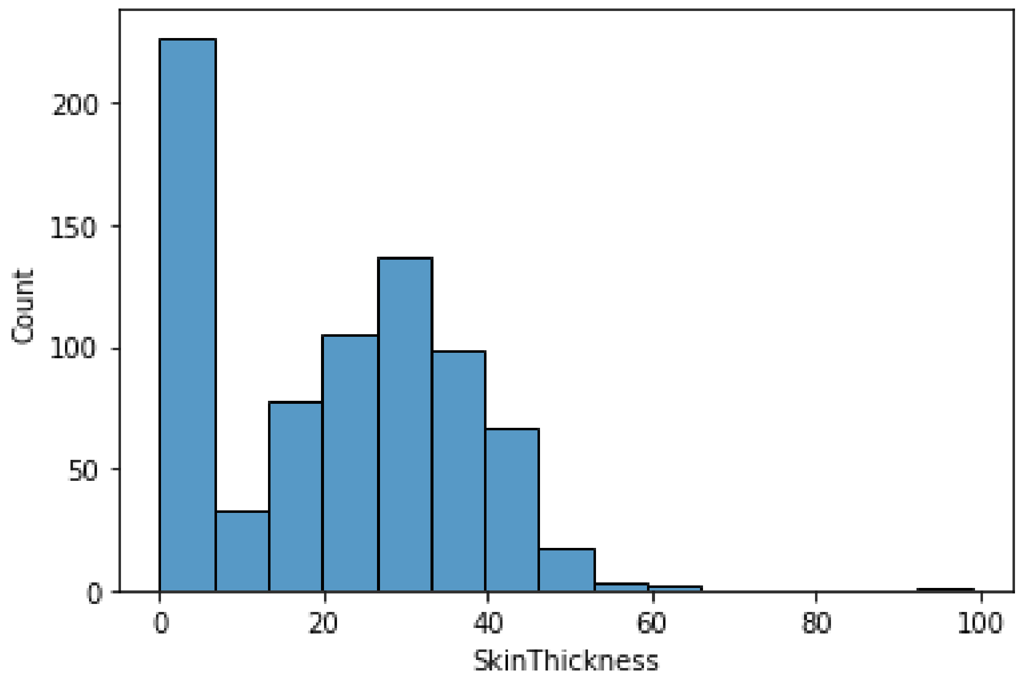
[89]:
```
69.10546875
```

[92]:
```
df['BloodPressure']=df['BloodPressure'].replace(0,df['BloodPressure'].mean())
```

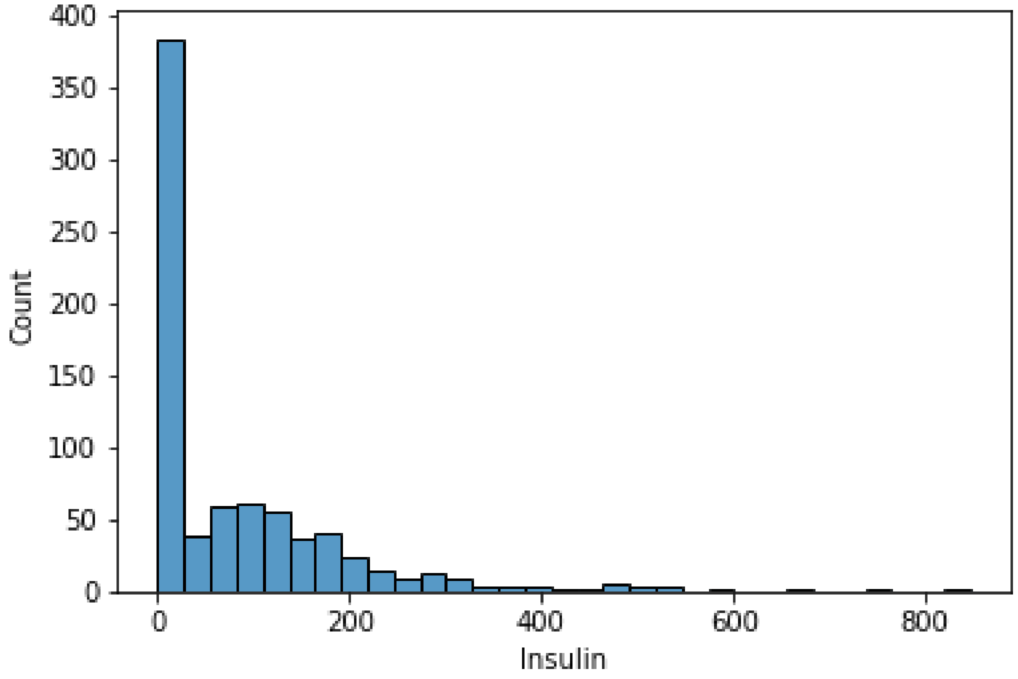
[93]:
```
sns.histplot(x=df['BloodPressure'])
plt.show()
```



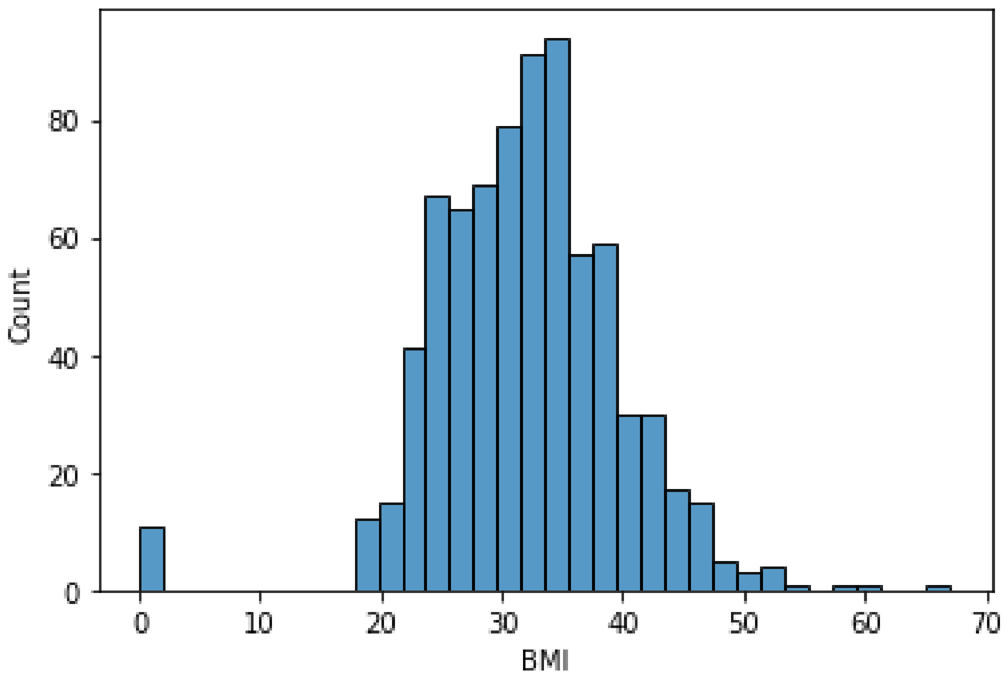
[94]:
```
sns.histplot(x=df['SkinThickness'])
plt.show()
```



[95]:
```
sns.histplot(x=df['Insulin'])
plt.show()
```



[96]:
```
sns.histplot(x=df['BMI'])
plt.show()
```



[97]:
```
df.columns
```

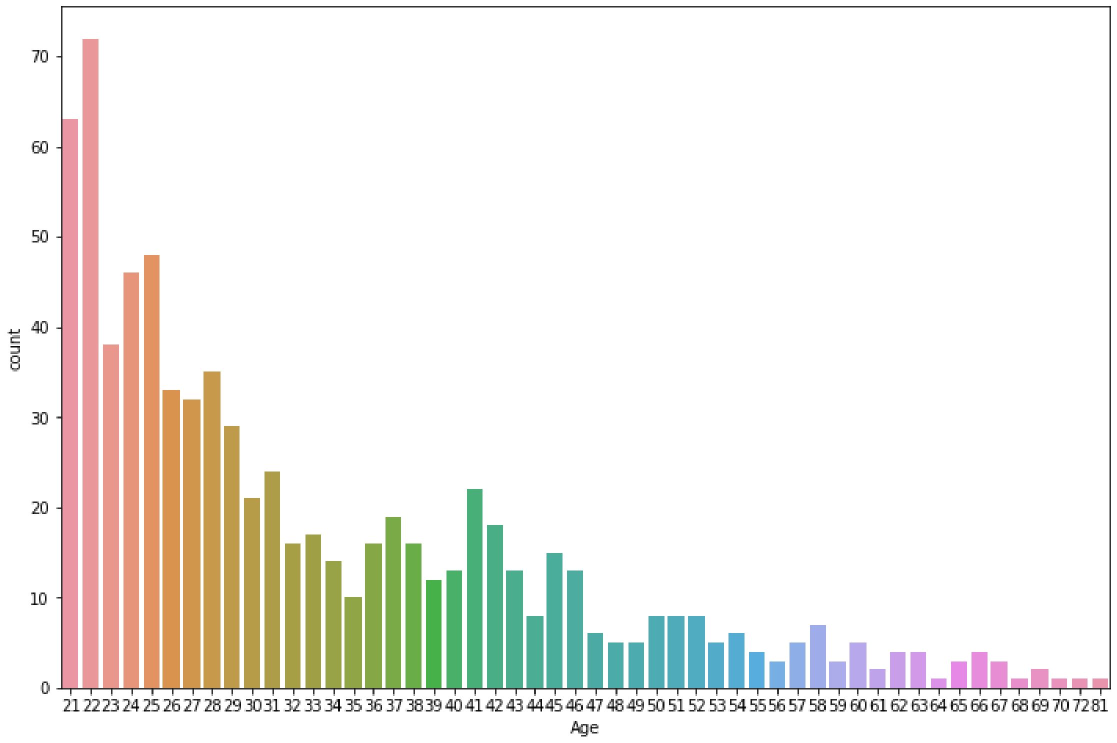
[97]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

[6]:
```
variables=['SkinThickness', 'Insulin','BMI']
for i in variables:
    df[i].replace(0,df[i].median(),inplace=True)
```

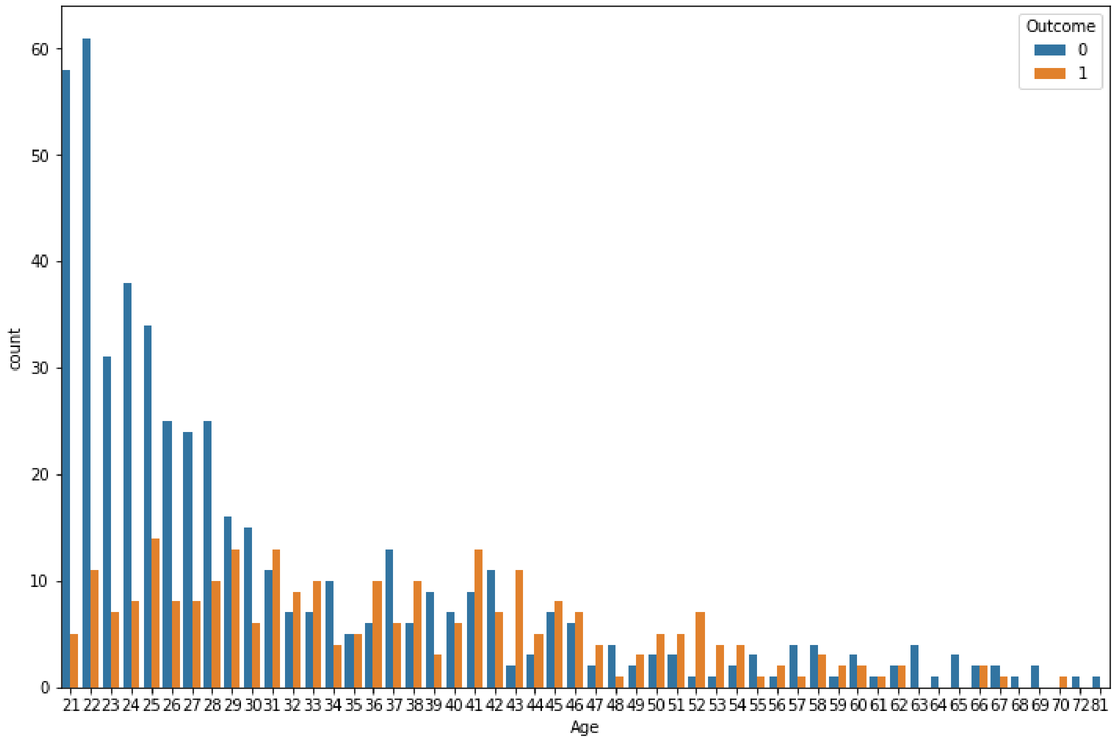
[99]:
```
df.dtypes
```

[99]:
```
Pregnancies                   int64
Glucose                     float64
BloodPressure               float64
SkinThickness                 int64
Insulin                     float64
BMI                         float64
DiabetesPedigreeFunction    float64
Age                           int64
Outcome                       int64
dtype: object
```

[100]:
```
plt.figure(figsize=(12,8))
sns.countplot(x=df['Age'])
plt.show()
```



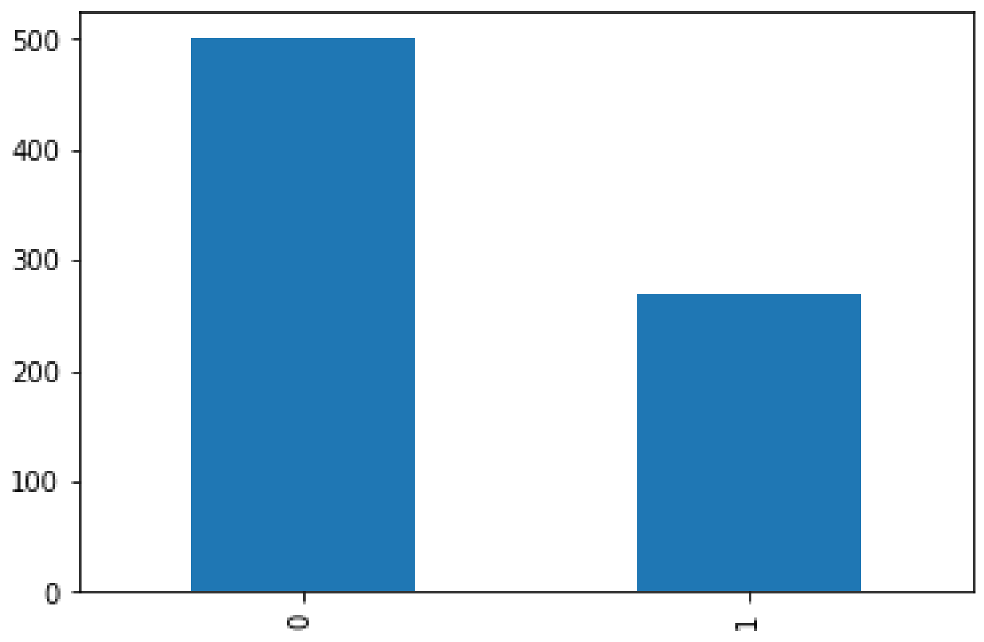
[101]:
```
plt.figure(figsize=(12,8))
sns.countplot(x=df['Age'],hue='Outcome',data=df)
plt.show()
```



```
[102]: df['Outcome'].value_counts()
```

```
[102]: 0    500
       1    268
       Name: Outcome, dtype: int64
```

```
[103]: df['Outcome'].value_counts().plot(kind='bar')
       plt.show()
```

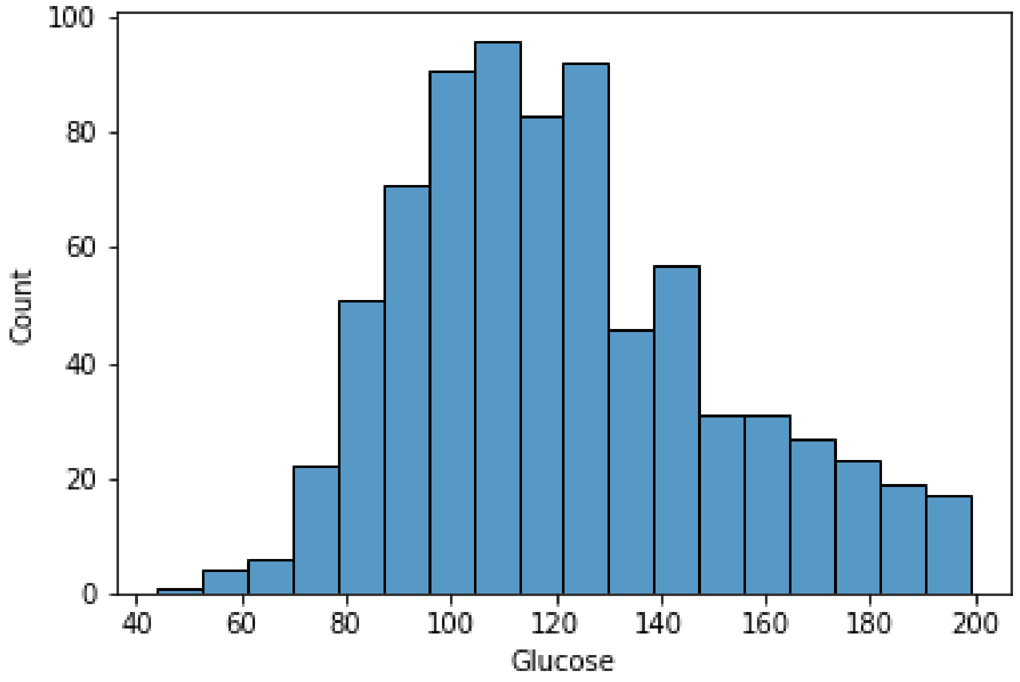


```
[104]: df['Glucose'].value_counts()
```

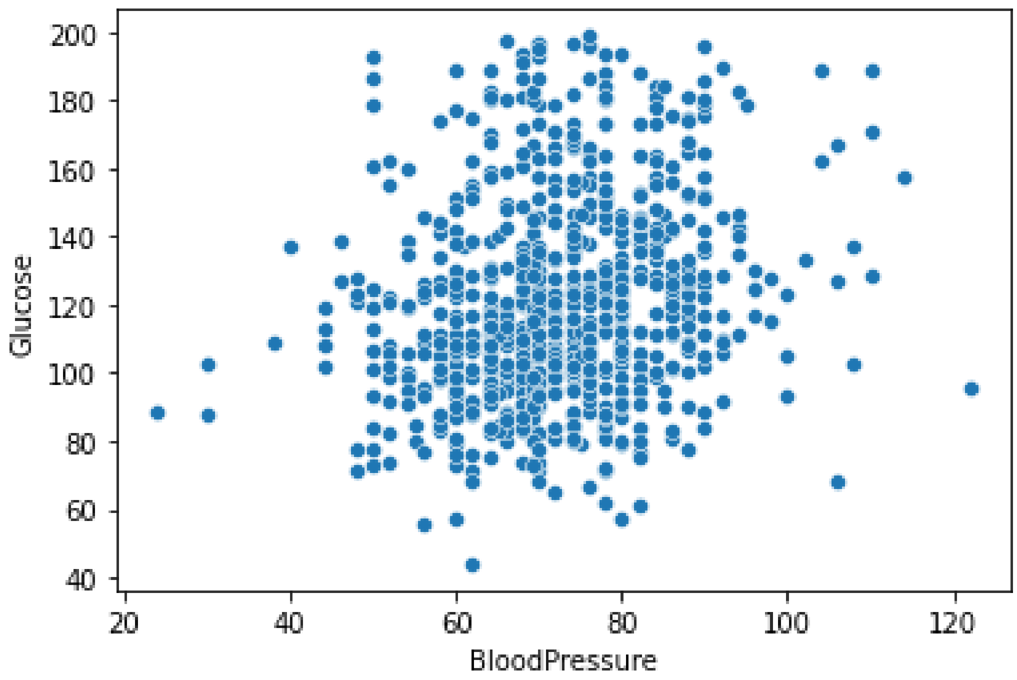
```
[104]: 99.0     17
       100.0    17
       111.0    14
       129.0    14
       125.0    14
                ..
       191.0     1
       177.0     1
       44.0      1
       62.0      1
       190.0     1
       Name: Glucose, Length: 136, dtype: int64
```

```
[105]: sns.histplot(x=df['Glucose'])
```

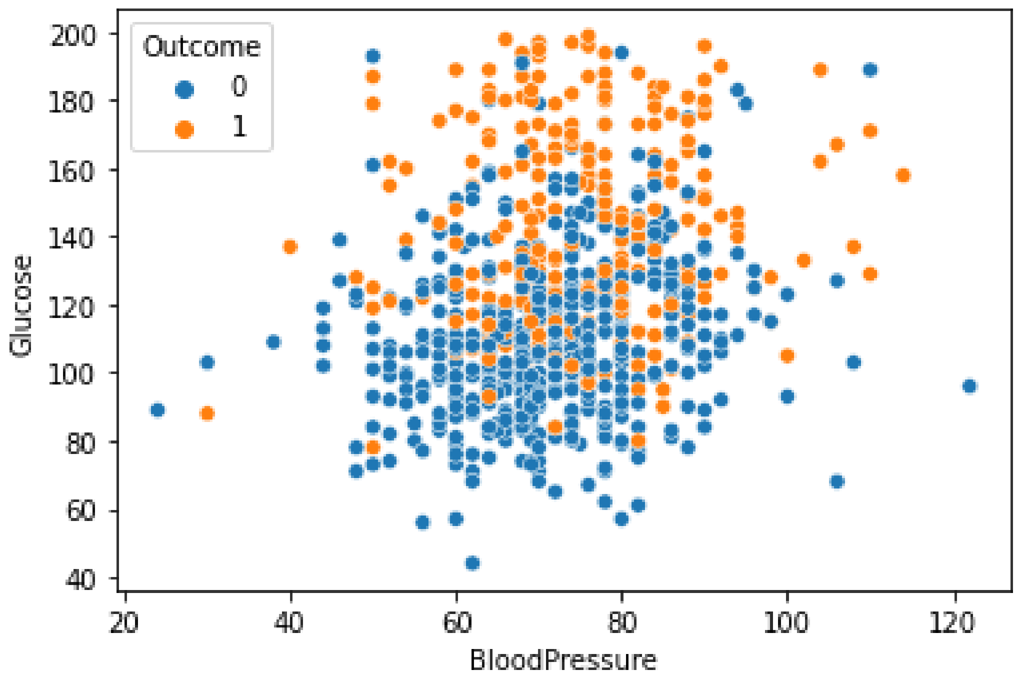
```
[105]: <AxesSubplot: xlabel='Glucose', ylabel='Count'>
```



[106]:
```
#scatter charts created here because to understand the relationships between␣
 ↪the pair of variables.
#bivariate
sns.scatterplot(x=df['BloodPressure'],y=df['Glucose'])
plt.show()
```



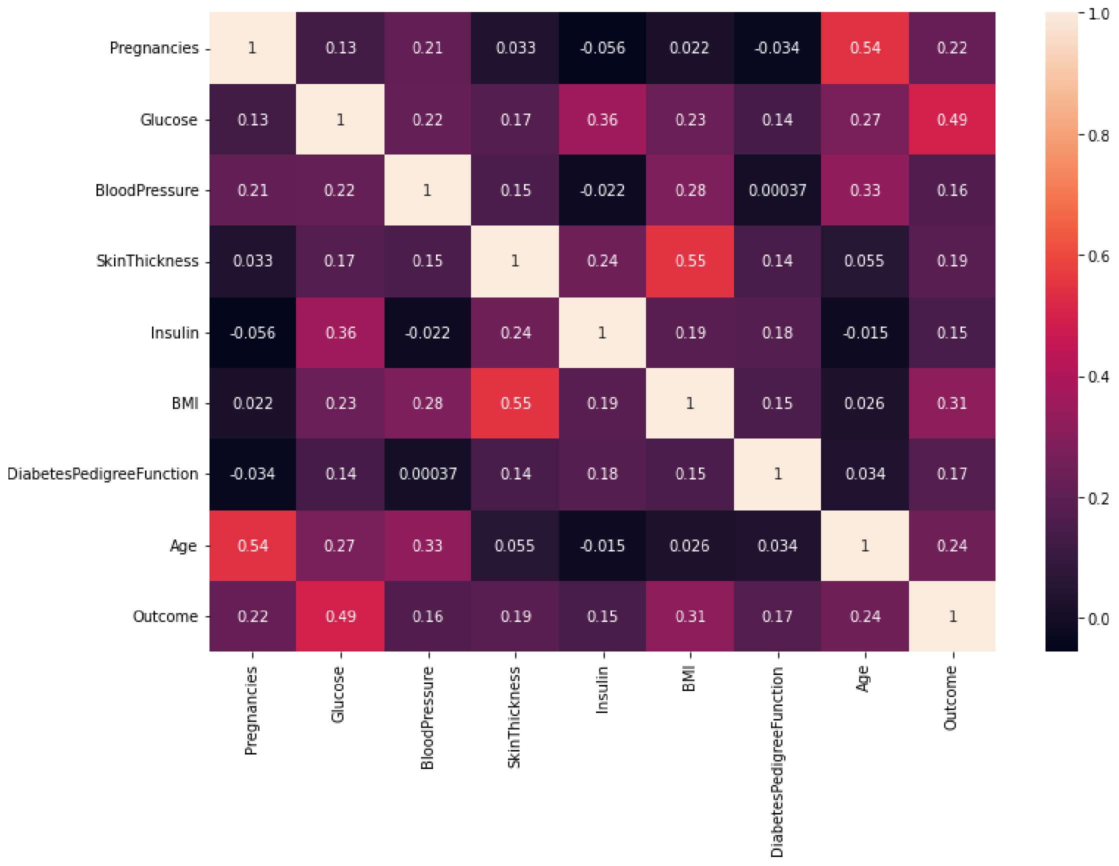
```
[107]: sns.scatterplot(x=df['BloodPressure'],y=df['Glucose'],hue='Outcome',data=df)
       plt.show()
```



```
[108]: df.corr()
```

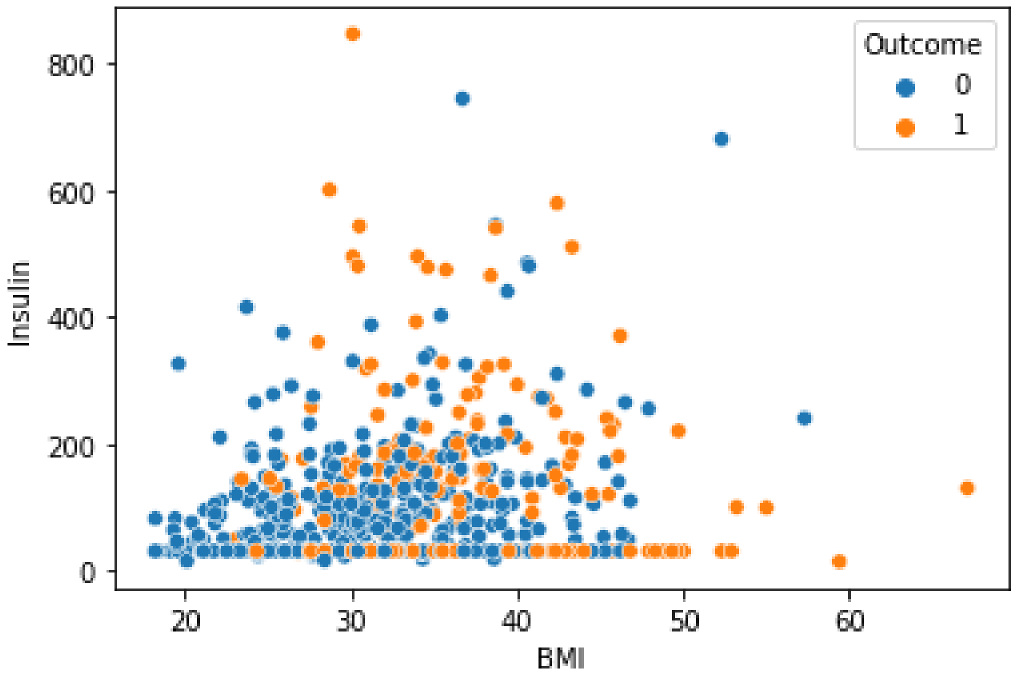
```
[108]:                           Pregnancies   Glucose  BloodPressure  SkinThickness  \
       Pregnancies                  1.000000  0.127964       0.208984       0.032568
       Glucose                      0.127964  1.000000       0.219666       0.172361
       BloodPressure                0.208984  0.219666       1.000000       0.152458
       SkinThickness                0.032568  0.172361       0.152458       1.000000
       Insulin                     -0.055697  0.357081      -0.022049       0.238188
       BMI                          0.021546  0.231469       0.281232       0.546951
       DiabetesPedigreeFunction    -0.033523  0.137106       0.000371       0.142977
       Age                          0.544341  0.266600       0.326740       0.054514
       Outcome                      0.221898  0.492908       0.162986       0.189065

                                  Insulin       BMI  DiabetesPedigreeFunction  \
       Pregnancies              -0.055697  0.021546                 -0.033523
       Glucose                   0.357081  0.231469                  0.137106
       BloodPressure            -0.022049  0.281232                  0.000371
       SkinThickness             0.238188  0.546951                  0.142977
       Insulin                   1.000000  0.189022                  0.178029
       BMI                       0.189022  1.000000                  0.153506
       DiabetesPedigreeFunction  0.178029  0.153506                  1.000000
       Age                      -0.015413  0.025744                  0.033561
       Outcome                   0.148457  0.312249                  0.173844

                                      Age   Outcome
       Pregnancies               0.544341  0.221898
       Glucose                   0.266600  0.492908
       BloodPressure             0.326740  0.162986
       SkinThickness             0.054514  0.189065
       Insulin                  -0.015413  0.148457
       BMI                       0.025744  0.312249
       DiabetesPedigreeFunction  0.033561  0.173844
       Age                       1.000000  0.238356
       Outcome                   0.238356  1.000000
```

```
[109]: plt.figure(figsize=(12,8))
       sns.heatmap(df.corr(),annot=True)
       plt.show()
```

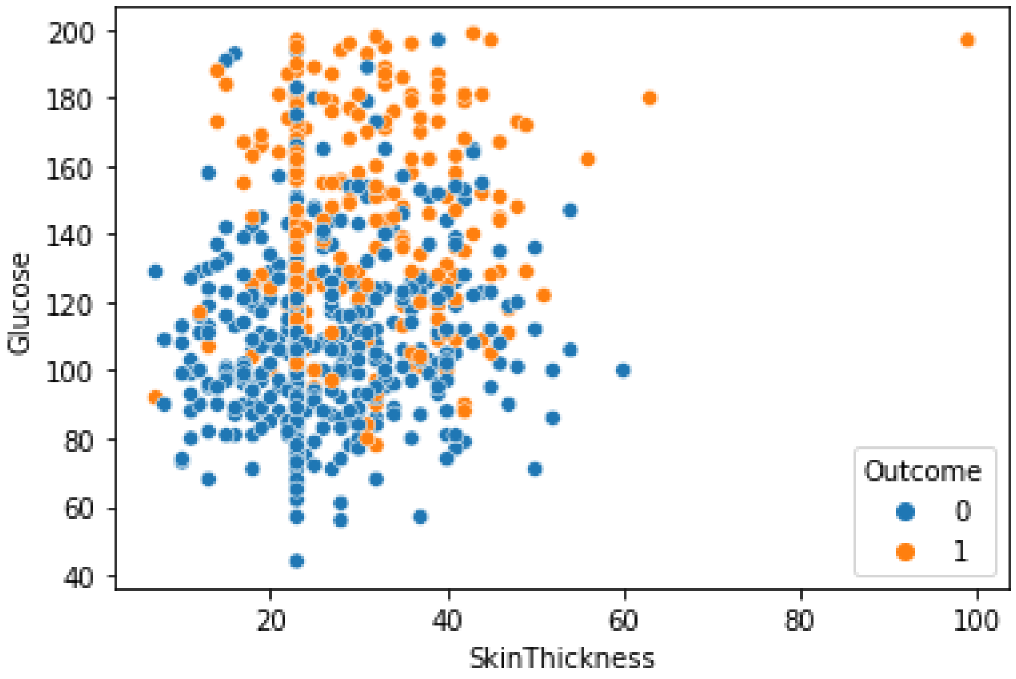


	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
Pregnancies	1	0.13	0.21	0.033	-0.056	0.022	-0.034	0.54	0.22
Glucose	0.13	1	0.22	0.17	0.36	0.23	0.14	0.27	0.49
BloodPressure	0.21	0.22	1	0.15	-0.022	0.28	0.00037	0.33	0.16
SkinThickness	0.033	0.17	0.15	1	0.24	0.55	0.14	0.055	0.19
Insulin	-0.056	0.36	-0.022	0.24	1	0.19	0.18	-0.015	0.15
BMI	0.022	0.23	0.28	0.55	0.19	1	0.15	0.026	0.31
DiabetesPedigreeFunction	-0.034	0.14	0.00037	0.14	0.18	0.15	1	0.034	0.17
Age	0.54	0.27	0.33	0.055	-0.015	0.026	0.034	1	0.24
Outcome	0.22	0.49	0.16	0.19	0.15	0.31	0.17	0.24	1

[135]:
```
sns.scatterplot(x=df['BMI'],y=df['Insulin'],hue='Outcome',data=df)
plt.show()
```



[111]:
```
sns.scatterplot(x=df['SkinThickness'],y=df['Glucose'],hue='Outcome',data=df)
plt.show()
```



[7]:
```
# Data Modeling
#create depth and indepth variables...
x=df.iloc[:,:-1].values
y=df.iloc[:,-1].values
```

[113]:
```
x
```

[113]:
```
array([[  6.   , 148.   ,  72.   , …,  33.6  ,   0.627,  50.   ],
       [  1.   ,  85.   ,  66.   , …,  26.6  ,   0.351,  31.   ],
       [  8.   , 183.   ,  64.   , …,  23.3  ,   0.672,  32.   ],
       …,
       [  5.   , 121.   ,  72.   , …,  26.2  ,   0.245,  30.   ],
       [  1.   , 126.   ,  60.   , …,  30.1  ,   0.349,  47.   ],
       [  1.   ,  93.   ,  70.   , …,  30.4  ,   0.315,  23.   ]])
```

[114]:
```
y
```

[114]:
```
array([1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0,
       1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1,
       0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0,
       1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1,
       1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1,
       0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1,
       1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1,
       1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0,
       1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0,
       1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0,
       0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0,
       1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0,
       0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0,
       0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0,
       0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1,
       0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
       1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0,
       0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0,
       0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0,
       1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1,
       0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1,
       0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0,
       0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0,
       1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0])
```

[8]:
```
#create split data
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)
```

[9]:
```
x_train.shape
```

[9]:
```
(614, 8)
```

[138]:
```
x_test.shape
```

[138]:
```
(154, 8)
```

[12]:
```
#Apply logistic Regression
from sklearn.linear_model import LogisticRegression
log_reg=LogisticRegression()
```

[13]:
```
log_reg.fit(x_train,y_train)
```

```
/usr/local/lib/python3.10/site-packages/sklearn/linear_model/_logistic.py:460:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[13]:
```
LogisticRegression()
```

[14]:
```
y_pred=log_reg.predict(x_test)
```

[15]:
```
#Evaluate the model1
from sklearn.metrics import␣
 ↪confusion_matrix,accuracy_score,classification_report
```

[16]:
```
confusion_matrix(y_test,y_pred)
```

```
[16]: array([[82, 17],
             [17, 38]])
```

```
[17]: #print Accuracy
      print('Accuracy_score=',accuracy_score(y_test,y_pred))
```

```
Accuracy_score= 0.7792207792207793
```

```
[18]: print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.83      0.83      0.83        99
           1       0.69      0.69      0.69        55

    accuracy                           0.78       154
   macro avg       0.76      0.76      0.76       154
weighted avg       0.78      0.78      0.78       154
```

```
[19]: from sklearn.metrics import roc_auc_score,roc_curve
      prob=log_reg.predict_proba(x)
```

```
[20]: prob
```

```
[20]: array([[0.21669737, 0.78330263],
             [0.95197413, 0.04802587],
             [0.28517013, 0.71482987],
             …,
             [0.88484086, 0.11515914],
             [0.61514118, 0.38485882],
             [0.93599551, 0.06400449]])
```

```
[21]: prob=prob[:,1]
      prob
```

```
[21]: array([0.78330263, 0.04802587, 0.71482987, 0.03075186, 0.97301334,
             0.09946202, 0.05829103, 0.57507876, 0.69890241, 0.3949515 ,
             0.19744866, 0.87238633, 0.8394048 , 0.62130257, 0.64410435,
             0.40120915, 0.4763238 , 0.13762706, 0.48602766, 0.28041873,
             0.39209429, 0.33951694, 0.94320208, 0.17960227, 0.65046505,
             0.33813868, 0.75190338, 0.03301445, 0.40100067, 0.26711034,
             0.58504649, 0.54944975, 0.03271877, 0.01717337, 0.36465334,
             0.1404747 , 0.55460954, 0.40222962, 0.20364543, 0.77173009,
             0.71624203, 0.7222478 , 0.08473635, 0.94064195, 0.57047882,
             0.98137169, 0.46791957, 0.03406521, 0.35580707, 0.36797164,
             0.02345093, 0.08164041, 0.04870012, 0.82757015, 0.69302601,
             0.01627194, 0.85968384, 0.54394706, 0.94552571, 0.20085351,
             0.16041524, 0.46532547, 0.02158147, 0.27561148, 0.33939674,
             0.08989962, 0.27976197, 0.69915019, 0.02302847, 0.21574614,
             0.22594116, 0.27844481, 0.79158201, 0.1607359 , 0.04746864,
             0.00150222, 0.07178552, 0.20468287, 0.78714334, 0.07470387,
             0.06458997, 0.09591164, 0.12338584, 0.03937939, 0.71541476,
             0.19706682, 0.44662208, 0.19963743, 0.66870044, 0.05692222,
             0.01269436, 0.22743575, 0.39908849, 0.35959147, 0.2055333 ,
             0.46369509, 0.06849049, 0.01240793, 0.09268621, 0.54117379,
             0.91032002, 0.22584123, 0.04102098, 0.02584384, 0.31481118,
             0.23866763, 0.01191253, 0.40164028, 0.10587822, 0.09999022,
             0.52452956, 0.64041557, 0.04699989, 0.08352966, 0.71659669,
             0.67893832, 0.34806951, 0.15410237, 0.08769909, 0.02850645,
             0.94209079, 0.22027987, 0.13366918, 0.45708458, 0.1326785 ,
             0.7148407 , 0.50888202, 0.18701774, 0.23379229, 0.30544059,
             0.5714211 , 0.68821471, 0.64503964, 0.27320609, 0.0441359 ,
             0.22784055, 0.1009822 , 0.066354  , 0.30501288, 0.11989486,
             0.18917211, 0.34311386, 0.15885214, 0.32307715, 0.34696055,
             0.11268926, 0.04687542, 0.41652881, 0.74587792, 0.03000017,
             0.34915174, 0.11717124, 0.85280985, 0.48526673, 0.96683836,
             0.89985335, 0.07026849, 0.11728124, 0.03683821, 0.96191383,
             0.38782366, 0.3107189 , 0.23612418, 0.08456216, 0.33659391,
             0.2279767 , 0.38197242, 0.33115438, 0.22013841, 0.10010638,
             0.12163325, 0.47470061, 0.24706437, 0.26985263, 0.05469434,
             0.8547314 , 0.12450306, 0.88165721, 0.8223703 , 0.7326887 ,
             0.02594875, 0.30921456, 0.00165237, 0.03427543, 0.32679567,
             0.95624612, 0.82803449, 0.48948821, 0.17432299, 0.26299444,
             0.0455168 , 0.42934795, 0.63854236, 0.9827361 , 0.0706379 ,
             0.63793418, 0.04599449, 0.08360387, 0.36693034, 0.26836571,
             0.18502051, 0.46470336, 0.17127787, 0.02662948, 0.40531774,
             0.08649446, 0.95810934, 0.73756759, 0.08386423, 0.86855726,
             0.04050918, 0.61947738, 0.86033624, 0.59128506, 0.22215566,
             0.87013987, 0.27144104, 0.2763039 , 0.19657175, 0.42593677,
             0.70039475, 0.84452621, 0.38082649, 0.71731093, 0.06593232,
             0.05277611, 0.11763551, 0.8083686 , 0.96733044, 0.33536058,
             0.70682456, 0.67058579, 0.02617467, 0.34766683, 0.03390157,
             0.8813836 , 0.89574695, 0.88038205, 0.7405312 , 0.03401891,
             0.04535485, 0.09484996, 0.23349014, 0.46981637, 0.47916485,
             0.94178067, 0.38160269, 0.67379574, 0.26550591, 0.0672056 ,
             0.35167668, 0.14109662, 0.02314194, 0.08708125, 0.22774721,
             0.22001694, 0.24435775, 0.09014097, 0.58816702, 0.92131511,
             0.74434889, 0.73177576, 0.14111046, 0.62075913, 0.30058498,
             0.38215541, 0.83588039, 0.72030897, 0.04131552, 0.5386443 ,
             0.78042881, 0.04950891, 0.1165917 , 0.03995048, 0.45944497,
             0.34195746, 0.11902796, 0.07174108, 0.35530124, 0.08374889,
             0.54250281, 0.48423856, 0.28973036, 0.59989724, 0.15686028,
             0.45752521, 0.54155391, 0.55453949, 0.03884774, 0.25234549,
             0.05990924, 0.30865534, 0.76537408, 0.55269231, 0.61341058,
             0.70006066, 0.18283975, 0.13293154, 0.37641838, 0.38943882,
             0.90306255, 0.37622794, 0.08486455, 0.6087116 , 0.1938848 ,
             0.31509282, 0.57823723, 0.08170618, 0.43448705, 0.36038568,
             0.06832688, 0.24603374, 0.30169845, 0.21463217, 0.62891655,
             0.17533331, 0.02369194, 0.6708649 , 0.2486017 , 0.77530845,
             0.21245026, 0.12634533, 0.16428558, 0.64212244, 0.14887692,
             0.1695345 , 0.37473279, 0.84383456, 0.21683268, 0.14574318,
             0.52955521, 0.07090384, 0.97481163, 0.11185516, 0.03252615,
             0.78074755, 0.78886835, 0.28798447, 0.72689408, 0.89413904,
             0.126062  , 0.08816954, 0.00359416, 0.28613485, 0.4900384 ,
             0.58292759, 0.36027042, 0.1740071 , 0.03629472, 0.01664225,
             0.2204286 , 0.27260651, 0.06435568, 0.06385464, 0.24034538,
             0.70703781, 0.47914068, 0.93457314, 0.31589777, 0.88503521,
             0.73823043, 0.7419924 , 0.45379797, 0.8842874 , 0.39966616,
             0.23709192, 0.19581474, 0.02572228, 0.02270205, 0.2507033 ,
             0.93189557, 0.53808467, 0.10198623, 0.16130824, 0.49800558,
             0.79524968, 0.02711064, 0.14374151, 0.86631409, 0.40096273,
             0.1732779 , 0.02524299, 0.10800667, 0.12291532, 0.07481243,
             0.06698794, 0.35520047, 0.45438226, 0.55696375, 0.22729112,
             0.16050288, 0.87053778, 0.05392314, 0.10434445, 0.69950317,
             0.43875402, 0.16831841, 0.25423623, 0.02035405, 0.80177714,
             0.10985714, 0.38011268, 0.407979  , 0.07726639, 0.71986109,
             0.56397281, 0.26193754, 0.03852141, 0.92485503, 0.74536515,
             0.24357333, 0.17669021, 0.64508919, 0.14939804, 0.36135144,
             0.38213396, 0.13410298, 0.69811804, 0.02083901, 0.14045542,
             0.43403477, 0.05067137, 0.26218364, 0.1594737 , 0.80256321,
             0.72903494, 0.20889094, 0.76270388, 0.34238275, 0.12077751,
             0.07857036, 0.11447178, 0.04299747, 0.15886438, 0.13399454,
             0.83004618, 0.66320473, 0.40155636, 0.01344178, 0.34363317,
             0.78456906, 0.07274051, 0.17683959, 0.36965464, 0.21105445,
             0.99861792, 0.07374774, 0.1088891 , 0.15343785, 0.13217694,
             0.01686346, 0.25329327, 0.13139552, 0.6821291 , 0.24427694,
             0.85788147, 0.64129819, 0.063745  , 0.86936699, 0.71054357,
             0.26510123, 0.01677697, 0.21705399, 0.06542886, 0.21617549,
             0.07610811, 0.0280366 , 0.19400366, 0.53984341, 0.84250849,
             0.67998389, 0.2490068 , 0.28605042, 0.39717084, 0.10908288,
             0.35820234, 0.17575847, 0.10078122, 0.19188545, 0.48064723,
             0.53172722, 0.20207661, 0.05858843, 0.0647947 , 0.93040968,
             0.44925233, 0.38625282, 0.97685983, 0.05874444, 0.92364697,
             0.1464516 , 0.11134259, 0.13657793, 0.53971592, 0.13219251,
             0.76765851, 0.10557028, 0.05450483, 0.78994289, 0.61953438,
             0.0506314 , 0.11792312, 0.03371528, 0.32178042, 0.22058151,
             0.09780219, 0.72303264, 0.21364686, 0.13154048, 0.38189952,
             0.15698393, 0.06936181, 0.1337415 , 0.06388733, 0.04862019,
             0.48348392, 0.66934755, 0.58097003, 0.15383146, 0.15617397,
             0.01341394, 0.18923678, 0.40935713, 0.67828907, 0.21062703,
             0.02843519, 0.01655311, 0.05946832, 0.12832783, 0.12582042,
             0.23312936, 0.47524526, 0.36099041, 0.30902493, 0.19888525,
             0.57414131, 0.11145134, 0.06817841, 0.32255061, 0.50006244,
             0.44050972, 0.26060659, 0.47501319, 0.08801539, 0.06799559,
             0.78997319, 0.98116097, 0.23332705, 0.7010114 , 0.71796678,
             0.0784328 , 0.08404462, 0.31108722, 0.06457504, 0.12603751,
             0.12728952, 0.18175407, 0.28248629, 0.63147807, 0.107795  ,
             0.46663487, 0.89767783, 0.12335863, 0.12728537, 0.09781482,
             0.08456347, 0.18592489, 0.14410365, 0.50448909, 0.21214967,
             0.08835803, 0.05468047, 0.1476116 , 0.0993072 , 0.24913833,
             0.32145161, 0.21678343, 0.48553972, 0.31193703, 0.96930669,
             0.58026596, 0.08972292, 0.41301938, 0.33566535, 0.23826293,
             0.03572503, 0.60462556, 0.07010878, 0.91170442, 0.03898747,
             0.86076435, 0.19581746, 0.49010578, 0.24208001, 0.3911346 ,
             0.65605071, 0.2068757 , 0.11088884, 0.73167601, 0.08326124,
             0.06149596, 0.13276898, 0.1195093 , 0.81934739, 0.87158104,
             0.35301856, 0.8883053 , 0.02735419, 0.4953253 , 0.03677046,
             0.11135546, 0.77543539, 0.82205883, 0.26028245, 0.75086301,
             0.06265208, 0.10008469, 0.00958805, 0.56824065, 0.35173615,
             0.18553612, 0.1949548 , 0.979958  , 0.19676068, 0.09403409,
             0.13974829, 0.0765086 , 0.21893713, 0.40971843, 0.03282449,
             0.28834777, 0.09418456, 0.09156802, 0.06432848, 0.07341488,
             0.30082035, 0.16210857, 0.09944884, 0.4666542 , 0.02013259,
             0.08750859, 0.29974252, 0.49843659, 0.26781396, 0.10654846,
             0.42938247, 0.33075092, 0.79373373, 0.33181344, 0.0571485 ,
             0.03387383, 0.24914223, 0.26501938, 0.1817275 , 0.09142465,
             0.41882151, 0.02891234, 0.64131654, 0.56759885, 0.20023186,
             0.64782409, 0.97855098, 0.65179695, 0.75998522, 0.3692774 ,
             0.12245704, 0.72009336, 0.17980617, 0.26023778, 0.56364541,
             0.83199127, 0.06653953, 0.09131197, 0.79632125, 0.51540377,
             0.81655321, 0.5013373 , 0.11802849, 0.30085507, 0.04829117,
             0.01162689, 0.8777894 , 0.26311295, 0.2841356 , 0.76111203,
             0.25903038, 0.11058535, 0.11113884, 0.18687467, 0.78616359,
             0.1790896 , 0.82231903, 0.50043221, 0.65062435, 0.03012703,
             0.18471599, 0.48714972, 0.11066679, 0.28744759, 0.7079578 ,
             0.2469424 , 0.3907304 , 0.88499324, 0.80389947, 0.07187447,
             0.12544609, 0.53320702, 0.18687258, 0.71808053, 0.19363138,
             0.28715379, 0.32454781, 0.76657939, 0.10237775, 0.08453648,
             0.88159795, 0.79430896, 0.19023064, 0.18155322, 0.33941352,
             0.0529662 , 0.18930324, 0.4304263 , 0.39176095, 0.18907439,
             0.38125608, 0.20399336, 0.27619553, 0.27000284, 0.06406877,
             0.2049692 , 0.11867375, 0.8610195 , 0.0929872 , 0.15759812,
             0.17462356, 0.0986799 , 0.11486468, 0.15155489, 0.32687244,
             0.79261565, 0.15488316, 0.07450818, 0.64989428, 0.92283892,
             0.23344183, 0.7682444 , 0.51174801, 0.83503306, 0.55596606,
             0.55125631, 0.30690151, 0.07651115, 0.62083706, 0.71348855,
             0.57984924, 0.43462423, 0.48616385, 0.17076424, 0.93778541,
             0.09766349, 0.94277867, 0.0453642 , 0.32827541, 0.33090686,
             0.11515914, 0.38485882, 0.06400449])
```

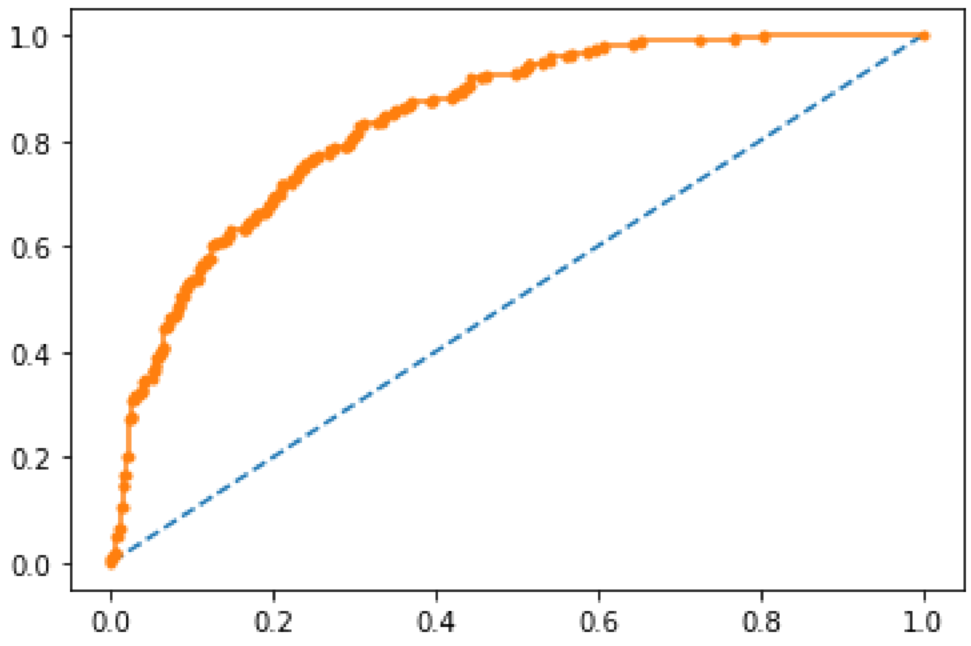
[153]:
```
#calculate roc_auc_score
auc=roc_auc_score(y,prob)
print('AUC Score is',auc)
```

```
AUC Score is 0.8410671641791044
```

[72]:
```
y.shape
```

[72]:
```
(768,)
```

[154]:
```
fpr,tpr,thresholds=roc_curve(y,prob)

plt.plot([0,1],[0,1],linestyle='--')
plt.plot(fpr,tpr,marker='.')
plt.show()
```



[159]:
```
#APPLY DECISION TREE CLASSIFIER
from sklearn.tree import DecisionTreeClassifier
decision_tree=DecisionTreeClassifier()
```

[160]:
```
decision_tree.fit(x_train,y_train)
```

[160]:
```
DecisionTreeClassifier()
```

[161]:
```
y_pred=decision_tree.predict(x_test)
```

[167]:
```
print('Accuracy score:',accuracy_score(y_test,y_pred))
```

```
Accuracy score: 0.7012987012987013
```

[22]:
```
from sklearn.neighbors import KNeighborsClassifier
clf=KNeighborsClassifier()
```

[23]:
```
clf.fit(x_train,y_train)
```

[23]:
```
KNeighborsClassifier()
```

[24]:
```
y_pred=clf.predict(x_test)
```

[25]:
```
print('Accuracy score:',accuracy_score(y_test,y_pred))
```

```
Accuracy score: 0.6753246753246753
```

[ ]:
```

```