Healthcare

October 15, 2022

[1]:
```python
#Import Lybraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```python
data=pd.read_csv('health care diabetes.csv')
```

[3]:
```python
data.head()
```

[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

   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
```

[4]:
```python
data.isnull().any()
```

[4]:
```
Pregnancies                 False
Glucose                     False
BloodPressure               False
SkinThickness               False
Insulin                     False
BMI                         False
DiabetesPedigreeFunction    False
Age                         False
Outcome                     False
dtype: bool
```

[5]:
```python
data.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
```

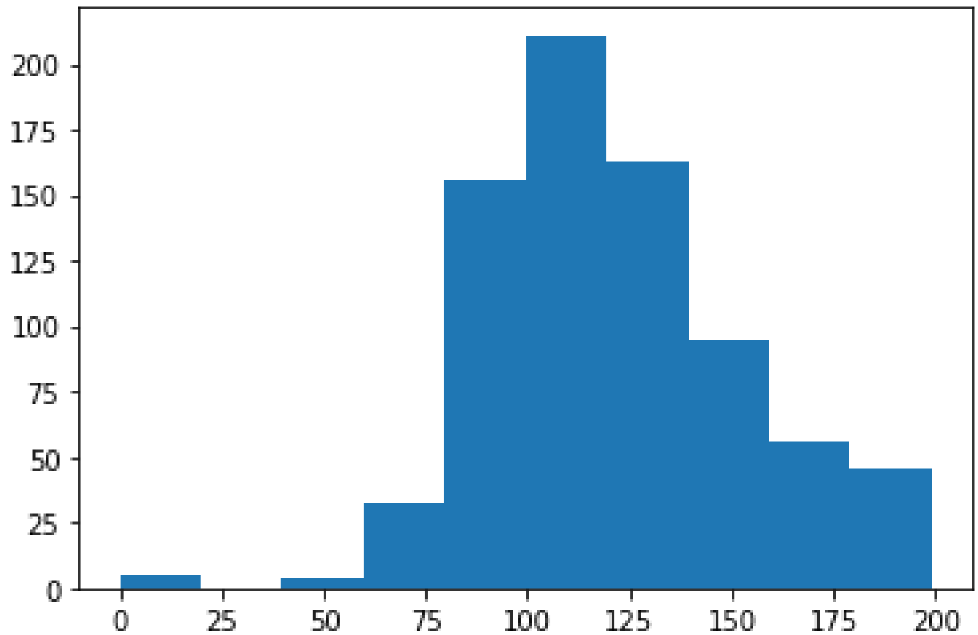
0.1 Using Histograms

[6]:
```python
data['Glucose'].value_counts().head(7)
```

[6]:
```
100    17
99     17
129    14
125    14
111    14
106    14
95     13
Name: Glucose, dtype: int64
```

[7]:
```python
plt.hist(data['Glucose'])
```

[7]:
```
(array([  5.,   0.,   4.,  32., 156., 211., 163.,  95.,  56.,  46.]),
 array([  0. ,  19.9,  39.8,  59.7,  79.6,  99.5, 119.4, 139.3, 159.2,
        179.1, 199. ]),
 <BarContainer object of 10 artists>)
```

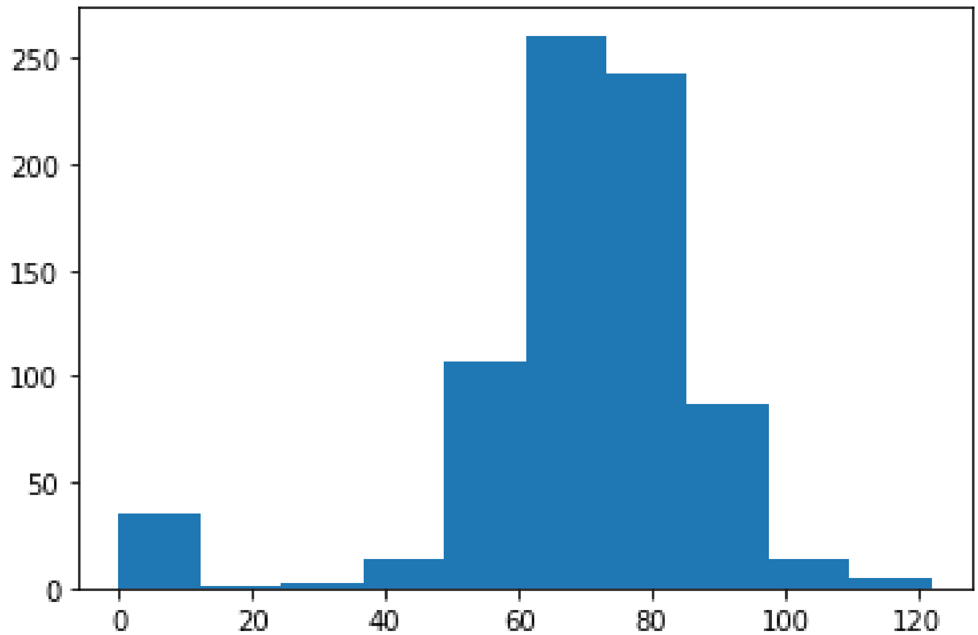


[8]:
```
data['BloodPressure'].value_counts().head(7)
```

[8]:
```
70    57
74    52
68    45
78    45
72    44
64    43
80    40
Name: BloodPressure, dtype: int64
```

[9]:
```
plt.hist(data['BloodPressure'])
```

[9]:
```
(array([ 35.,   1.,   2.,  13., 107., 261., 243.,  87.,  14.,   5.]),
 array([  0. ,  12.2,  24.4,  36.6,  48.8,  61. ,  73.2,  85.4,  97.6,
        109.8, 122. ]),
 <BarContainer object of 10 artists>)
```

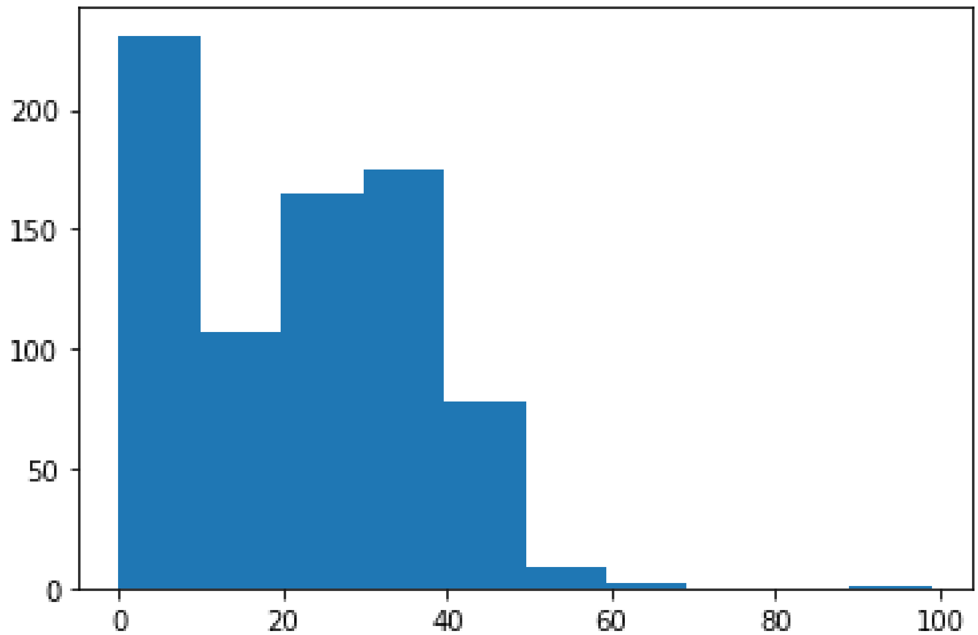


[10]:
```
data['SkinThickness'].value_counts().head(7)
```

[10]:
```
0     227
32     31
30     27
27     23
23     22
33     20
18     20
Name: SkinThickness, dtype: int64
```

[11]:
```
plt.hist(data['SkinThickness'])
```

[11]:
```
(array([231., 107., 165., 175.,  78.,   9.,   2.,   0.,   0.,   1.]),
 array([ 0. ,  9.9, 19.8, 29.7, 39.6, 49.5, 59.4, 69.3, 79.2, 89.1, 99. ]),
 <BarContainer object of 10 artists>)
```

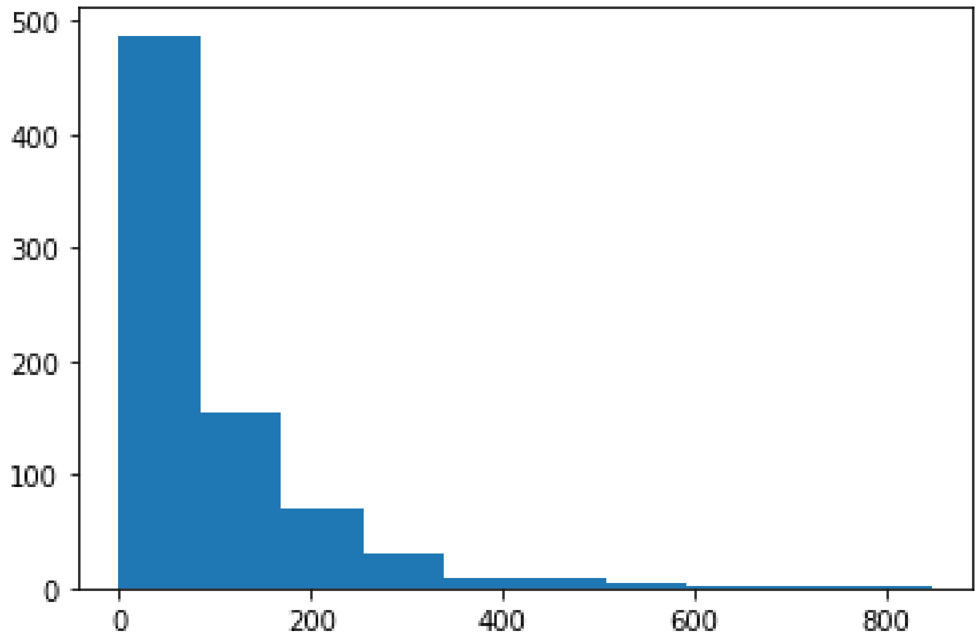


[12]:
```
data['Insulin'].value_counts().head(7)
```

[12]:
```
0      374
105     11
140      9
130      9
120      8
100      7
94       7
Name: Insulin, dtype: int64
```

[13]:
```
plt.hist(data['Insulin'])
```

[13]:
```
(array([487., 155.,  70.,  30.,   8.,   9.,   5.,   1.,   2.,   1.]),
 array([  0. ,  84.6, 169.2, 253.8, 338.4, 423. , 507.6, 592.2, 676.8,
        761.4, 846. ]),
 <BarContainer object of 10 artists>)
```

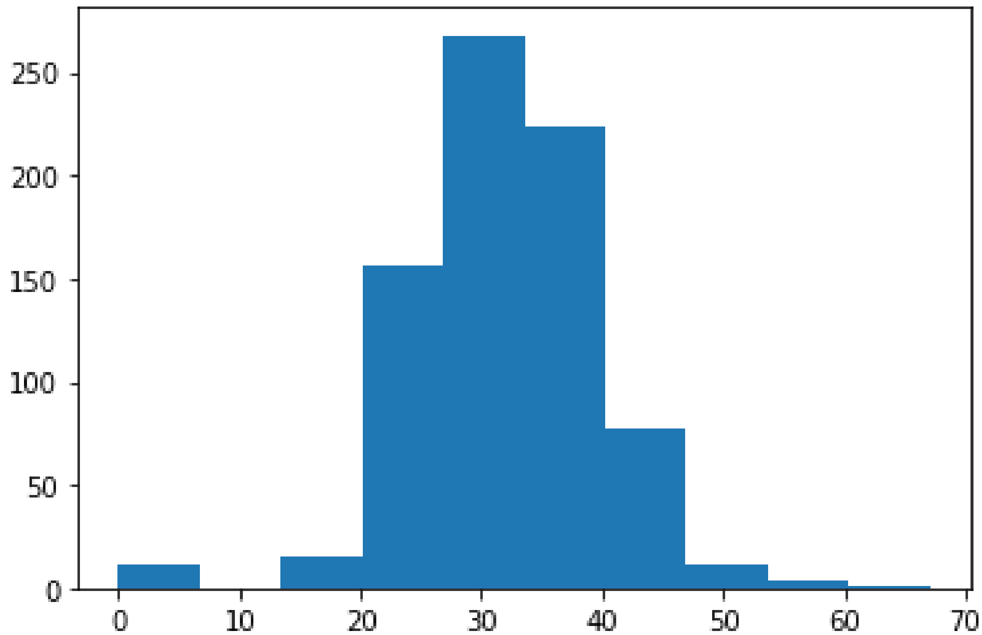


[14]:
```
data['BMI'].value_counts().head(7)
```

[14]:
```
32.0    13
31.6    12
31.2    12
0.0     11
33.3    10
32.4    10
32.8     9
Name: BMI, dtype: int64
```

[15]:
```
plt.hist(data['BMI'])
```

[15]:
```
(array([ 11.,   0.,  15., 156., 268., 224.,  78.,  12.,   3.,   1.]),
 array([ 0.  ,  6.71, 13.42, 20.13, 26.84, 33.55, 40.26, 46.97, 53.68,
        60.39, 67.1 ]),
 <BarContainer object of 10 artists>)
```



[16]:
```
data.describe().transpose()
```

[16]:
```
                          count        mean         std     min       25%  \
Pregnancies               768.0    3.845052    3.369578   0.000   1.00000
Glucose                   768.0  120.894531   31.972618   0.000  99.00000
BloodPressure             768.0   69.105469   19.355807   0.000  62.00000
SkinThickness             768.0   20.536458   15.952218   0.000   0.00000
Insulin                   768.0   79.799479  115.244002   0.000   0.00000
BMI                       768.0   31.992578    7.884160   0.000  27.30000
DiabetesPedigreeFunction  768.0    0.471876    0.331329   0.078   0.24375
Age                       768.0   33.240885   11.760232  21.000  24.00000
Outcome                   768.0    0.348958    0.476951   0.000   0.00000

                               50%        75%     max
Pregnancies                 3.0000    6.00000   17.00
Glucose                   117.0000  140.25000  199.00
BloodPressure              72.0000   80.00000  122.00
SkinThickness              23.0000   32.00000   99.00
Insulin                    30.5000  127.25000  846.00
BMI                        32.0000   36.60000   67.10
DiabetesPedigreeFunction    0.3725    0.62625    2.42
Age                        29.0000   41.00000   81.00
Outcome                     0.0000    1.00000    1.00
```

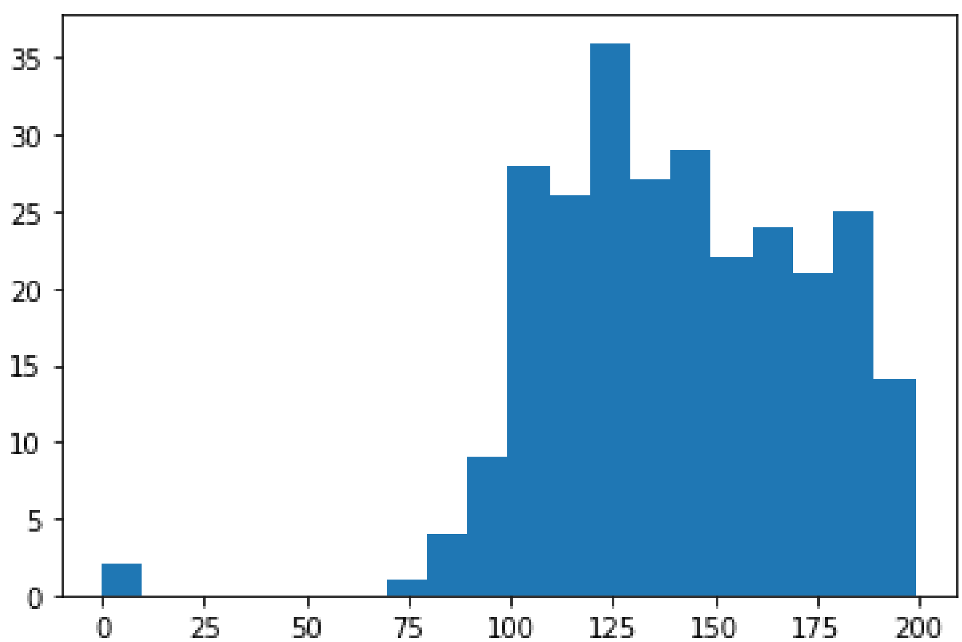
[17]:
```
Positive=data[data['Outcome']==1]
Positive.head(5)
```

[17]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
2            8      183             64              0        0  23.3
4            0      137             40             35      168  43.1
6            3       78             50             32       88  31.0
8            2      197             70             45      543  30.5

   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
2                     0.672   32        1
4                     2.288   33        1
6                     0.248   26        1
8                     0.158   53        1
```

0.2 Using histograms treat the missing values

[18]:
```python
plt.hist(Positive['Glucose'],histtype='stepfilled',bins=20)
```

[18]:
```
(array([ 2.,  0.,  0.,  0.,  0.,  0.,  0.,  1.,  4.,  9., 28., 26., 36.,
        27., 29., 22., 24., 21., 25., 14.]),
 array([  0.  ,   9.95,  19.9 ,  29.85,  39.8 ,  49.75,  59.7 ,  69.65,
         79.6 ,  89.55,  99.5 , 109.45, 119.4 , 129.35, 139.3 , 149.25,
        159.2 , 169.15, 179.1 , 189.05, 199.  ]),
 [<matplotlib.patches.Polygon at 0x7f2aadc9fa50>])
```

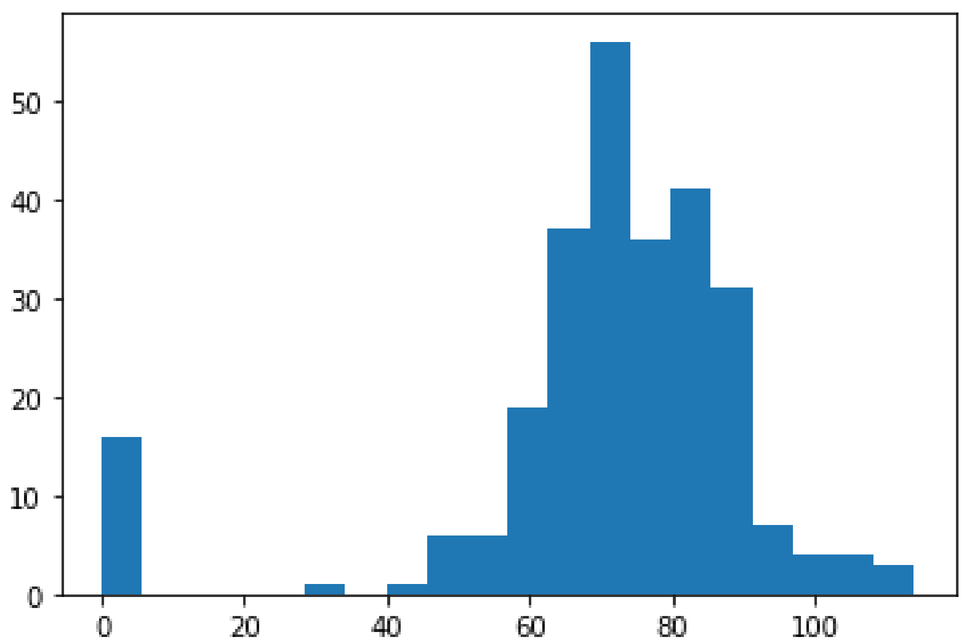


[19]:
```
Positive['Glucose'].value_counts().head(7)
```

[19]:
```
125    7
158    6
128    6
115    6
129    6
146    5
162    5
Name: Glucose, dtype: int64
```

[20]:
```
plt.hist(Positive['BloodPressure'],histtype='stepfilled',bins=20)
```

[20]:
```
(array([16.,  0.,  0.,  0.,  0.,  1.,  0.,  1.,  6.,  6., 19., 37., 56.,
        36., 41., 31.,  7.,  4.,  4.,  3.]),
 array([  0. ,   5.7,  11.4,  17.1,  22.8,  28.5,  34.2,  39.9,  45.6,
         51.3,  57. ,  62.7,  68.4,  74.1,  79.8,  85.5,  91.2,  96.9,
        102.6, 108.3, 114. ]),
 [<matplotlib.patches.Polygon at 0x7f2aadc2ead0>])
```



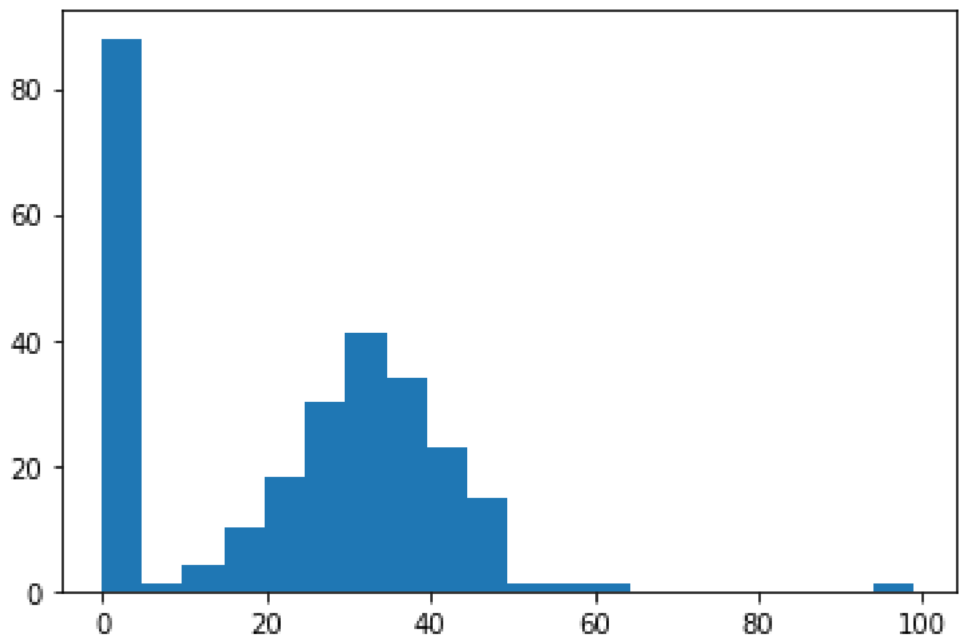
[21]:
```
Positive['BloodPressure'].value_counts().head(7)
```

[21]:
```
70    23
76    18
78    17
74    17
```

```
72    16
0     16
82    13
Name: BloodPressure, dtype: int64
```

[22]:
```
plt.hist(Positive['SkinThickness'],histtype='stepfilled',bins=20)
```

[22]:
```
(array([88.,  1.,  4., 10., 18., 30., 41., 34., 23., 15.,  1.,  1.,  1.,
         0.,  0.,  0.,  0.,  0.,  0.,  1.]),
 array([ 0.  ,  4.95,  9.9 , 14.85, 19.8 , 24.75, 29.7 , 34.65, 39.6 ,
        44.55, 49.5 , 54.45, 59.4 , 64.35, 69.3 , 74.25, 79.2 , 84.15,
        89.1 , 94.05, 99.  ]),
 [<matplotlib.patches.Polygon at 0x7f2aadbb82d0>])
```

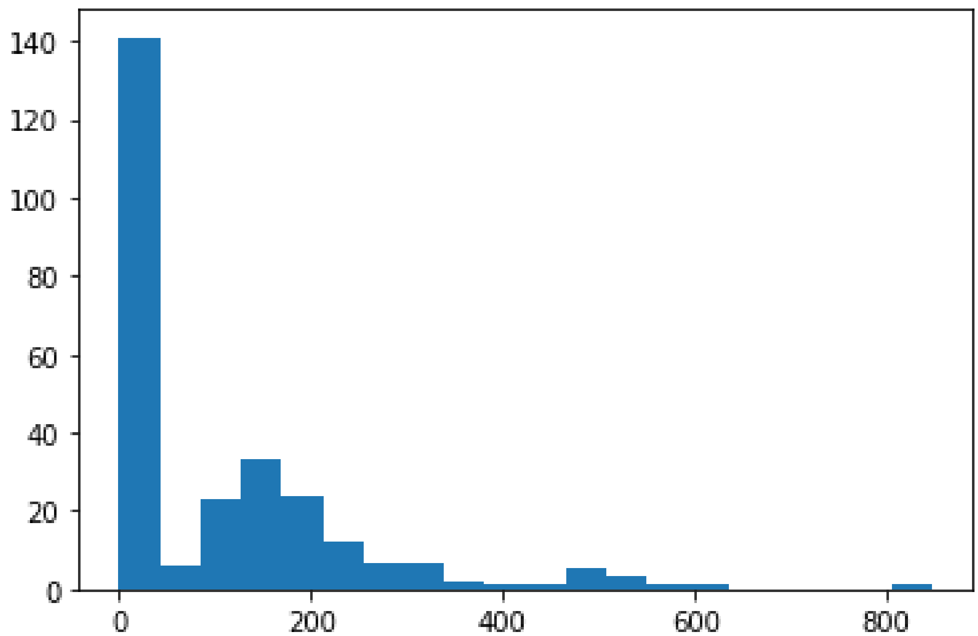


[23]:
```
Positive['SkinThickness'].value_counts().head(7)
```

[23]:
```
0     88
32    14
33     9
30     9
39     8
35     8
36     8
Name: SkinThickness, dtype: int64
```

[24]:
```
plt.hist(Positive['Insulin'],histtype='stepfilled',bins=20)
```

[24]:
```
(array([141.,   6.,  23.,  33.,  24.,  12.,   7.,   7.,   2.,   1.,   1.,
          5.,   3.,   1.,   1.,   0.,   0.,   0.,   0.,   1.]),
 array([  0. ,  42.3,  84.6, 126.9, 169.2, 211.5, 253.8, 296.1, 338.4,
        380.7, 423. , 465.3, 507.6, 549.9, 592.2, 634.5, 676.8, 719.1,
        761.4, 803.7, 846. ]),
 [<matplotlib.patches.Polygon at 0x7f2aadb9bf50>])
```

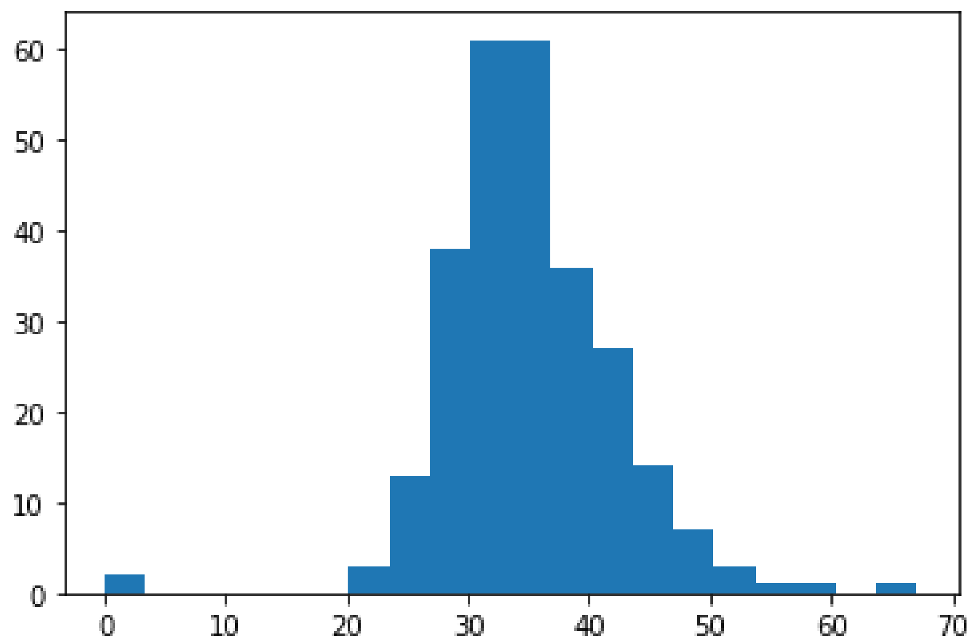


[25]:
```
Positive['Insulin'].value_counts().head(7)
```

[25]:
```
0      138
130      6
180      4
156      3
175      3
194      2
125      2
Name: Insulin, dtype: int64
```

[26]:
```
plt.hist(Positive['BMI'],histtype='stepfilled',bins=20)
```

[26]:
```
(array([ 2.,  0.,  0.,  0.,  0.,  0.,  3., 13., 38., 61., 61., 36., 27.,
        14.,  7.,  3.,  1.,  1.,  0.,  1.]),
 array([ 0.   ,  3.355,  6.71 , 10.065, 13.42 , 16.775, 20.13 , 23.485,
        26.84 , 30.195, 33.55 , 36.905, 40.26 , 43.615, 46.97 , 50.325,
        53.68 , 57.035, 60.39 , 63.745, 67.1  ]),
 [<matplotlib.patches.Polygon at 0x7f2aadaa80d0>])
```



[27]:
```
Positive['BMI'].value_counts().head(7)
```

[27]:
```
32.9    8
31.6    7
33.3    6
30.5    5
32.0    5
31.2    5
32.4    4
Name: BMI, dtype: int64
```

[28]:
```
Positive.describe().transpose()
```

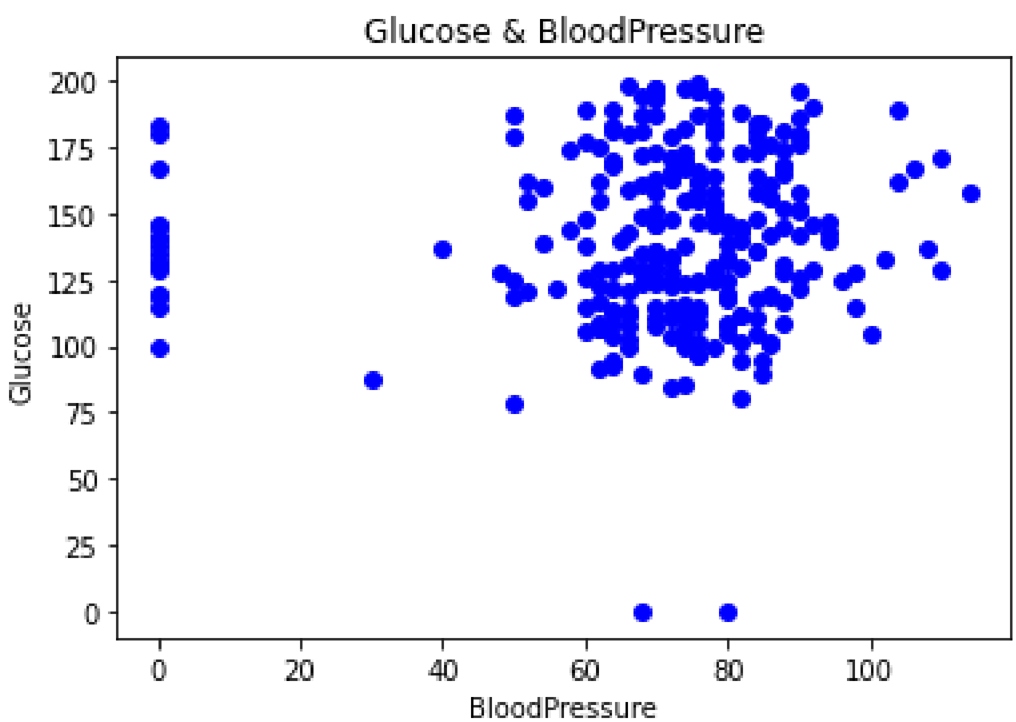
[28]:
```
                          count        mean         std     min       25%  \
Pregnancies               268.0    4.865672    3.741239   0.000    1.7500
Glucose                   268.0  141.257463   31.939622   0.000  119.0000
BloodPressure             268.0   70.824627   21.491812   0.000   66.0000
SkinThickness             268.0   22.164179   17.679711   0.000    0.0000
Insulin                   268.0  100.335821  138.689125   0.000    0.0000
BMI                       268.0   35.142537    7.262967   0.000   30.8000
DiabetesPedigreeFunction  268.0    0.550500    0.372354   0.088    0.2625
Age                       268.0   37.067164   10.968254  21.000   28.0000
Outcome                   268.0    1.000000    0.000000   1.000    1.0000

                            50%      75%     max
Pregnancies               4.000    8.000   17.00
```

```
Glucose                      140.000  167.000  199.00
BloodPressure                 74.000   82.000  114.00
SkinThickness                 27.000   36.000   99.00
Insulin                        0.000  167.250  846.00
BMI                           34.250   38.775   67.10
DiabetesPedigreeFunction       0.449    0.728    2.42
Age                           36.000   44.000   70.00
Outcome                        1.000    1.000    1.00
```

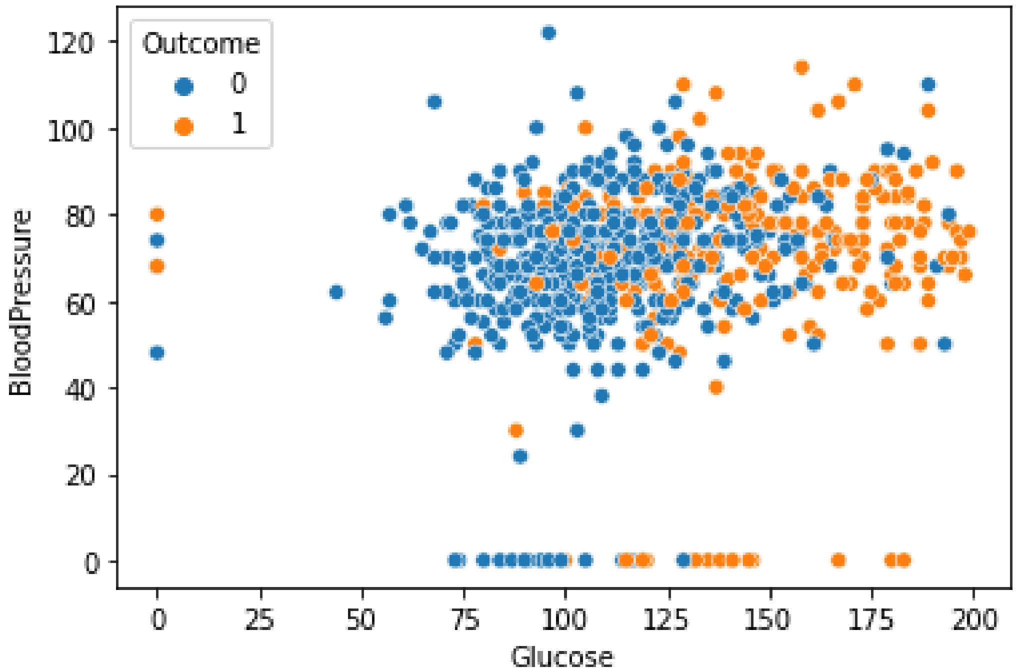
1 Scatter Plot

[29]:
```
BloodPressure= Positive['BloodPressure']
Glucose=       Positive['Glucose']
SkinThickness= Positive['SkinThickness']
Insulin=       Positive['Insulin']
BMI=           Positive['BMI']
```

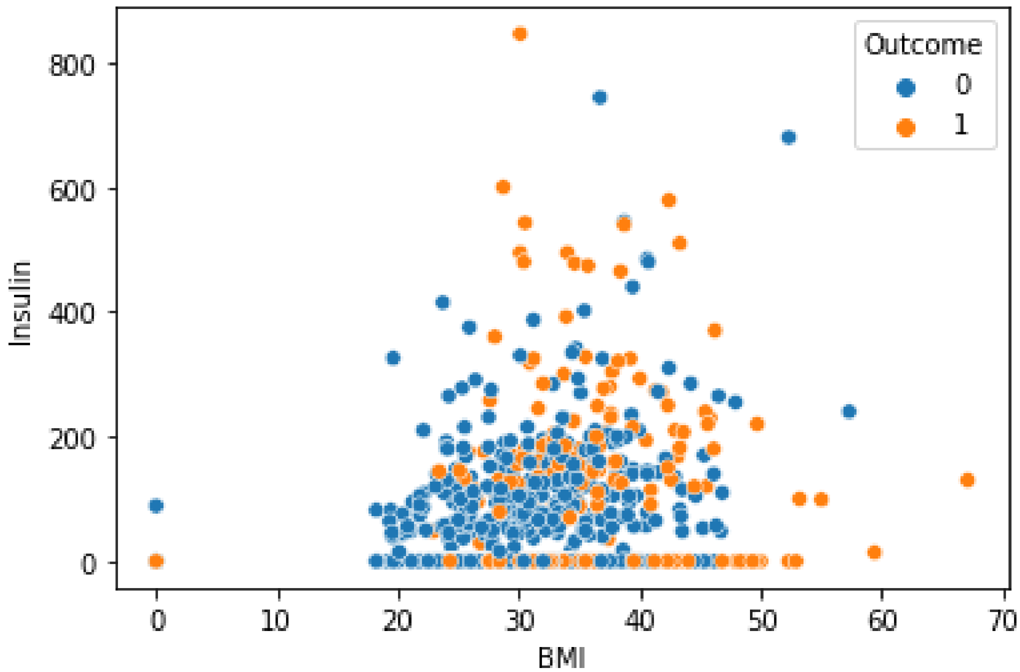
[30]:
```
plt.scatter(BloodPressure,Glucose,color=['blue'])
plt.xlabel('BloodPressure')
plt.ylabel('Glucose')
plt.title('Glucose & BloodPressure')
plt.show()
```



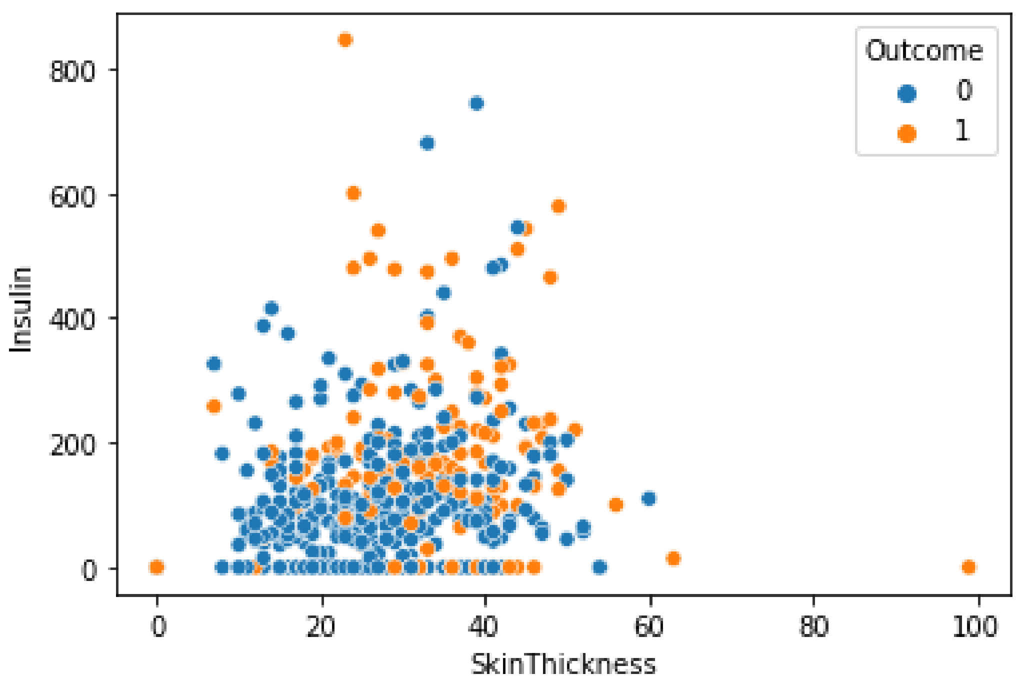
[31]:
```
g = sns.scatterplot(x='Glucose', y='BloodPressure',
                    hue='Outcome',
                    data=data);
```



[32]:
```
B = sns.scatterplot(x='BMI', y='Insulin',
                    hue='Outcome',
                    data=data);
```



[33]:
```
g = sns.scatterplot(x='SkinThickness', y='Insulin',
                    hue='Outcome',
                    data=data);
```



1.1 Correlation analysis

[34]:
```
data.corr()
```

[34]:

	Pregnancies	Glucose	BloodPressure	SkinThickness
Pregnancies	1.000000	0.129459	0.141282	-0.081672
Glucose	0.129459	1.000000	0.152590	0.057328
BloodPressure	0.141282	0.152590	1.000000	0.207371
SkinThickness	-0.081672	0.057328	0.207371	1.000000
Insulin	-0.073535	0.331357	0.088933	0.436783
BMI	0.017683	0.221071	0.281805	0.392573
DiabetesPedigreeFunction	-0.033523	0.137337	0.041265	0.183928
Age	0.544341	0.263514	0.239528	-0.113970
Outcome	0.221898	0.466581	0.065068	0.074752

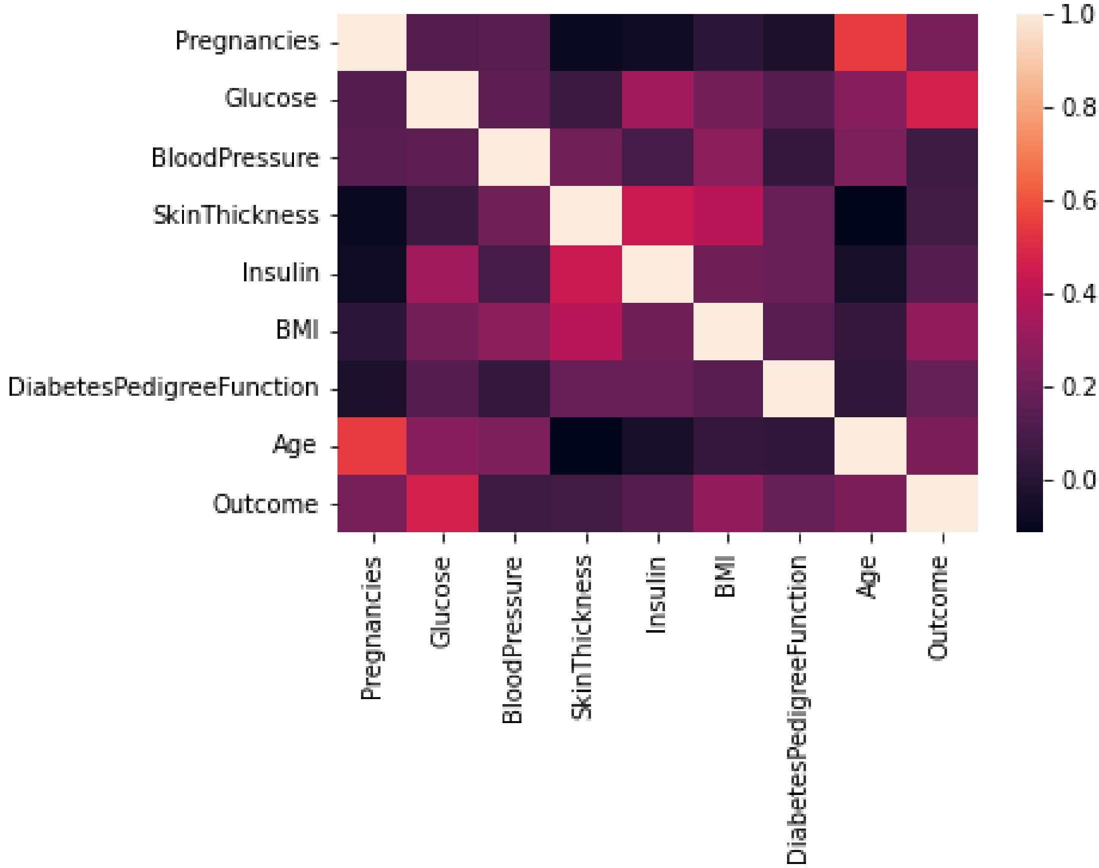
	Insulin	BMI	DiabetesPedigreeFunction
Pregnancies	-0.073535	0.017683	-0.033523
Glucose	0.331357	0.221071	0.137337
BloodPressure	0.088933	0.281805	0.041265
SkinThickness	0.436783	0.392573	0.183928
Insulin	1.000000	0.197859	0.185071
BMI	0.197859	1.000000	0.140647
DiabetesPedigreeFunction	0.185071	0.140647	1.000000
Age	-0.042163	0.036242	0.033561
Outcome	0.130548	0.292695	0.173844

	Age	Outcome
Pregnancies	0.544341	0.221898
Glucose	0.263514	0.466581
BloodPressure	0.239528	0.065068
SkinThickness	-0.113970	0.074752
Insulin	-0.042163	0.130548
BMI	0.036242	0.292695
DiabetesPedigreeFunction	0.033561	0.173844
Age	1.000000	0.238356
Outcome	0.238356	1.000000

2 Heatmaps

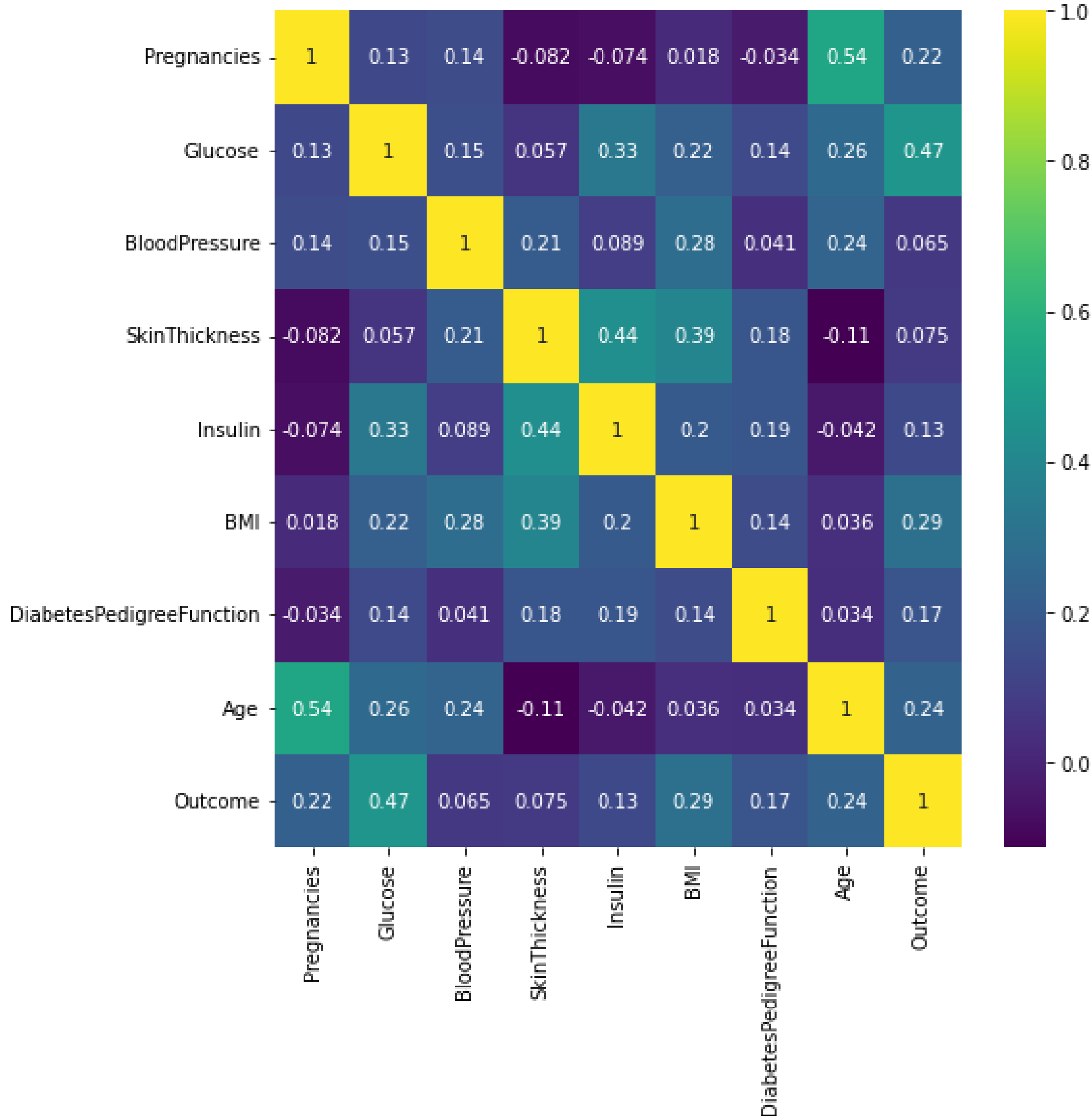
[35]:
```
sns.heatmap(data.corr())
```

[35]: <AxesSubplot:>



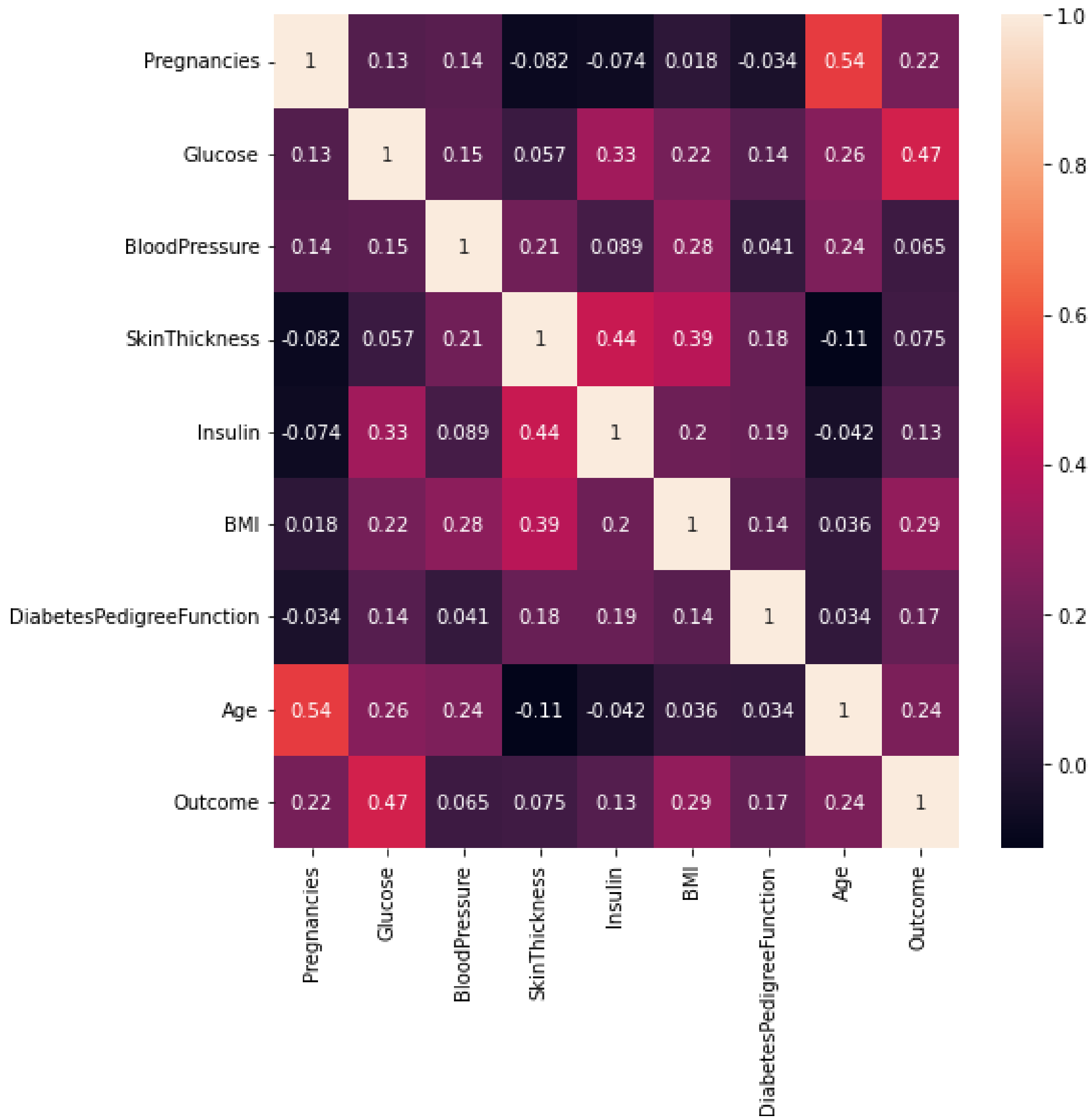
[36]:
```
plt.subplots(figsize=(8,8))
sns.heatmap(data.corr(),annot=True,cmap='viridis')
```

[36]: <AxesSubplot:>



[37]:
```
plt.subplots(figsize=(8,8))
sns.heatmap(data.corr(),annot=True)


# Given Correlation Values
```

[37]: <AxesSubplot:>



3 Week 2 / Data Modeling

[38]:
```
# Logistic Regreesion & Model Building

data.head()
```

[38]:

	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

   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
```

[39]:
```
#Train Test Split
features=data.iloc[:,[0,1,2,3,4,5,6,7,]].values
label= data.iloc[:,8].values
```

[40]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(features,
                                               label,
                                               test_size=0.2,
                                               random_state=10)
```

[41]:
```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
model.fit(X_train,y_train)
```

[41]:
```
LogisticRegression()
```

[42]:
```
print(model.score(X_train,y_train))
print(model.score(X_test,y_test))
```

```
0.7719869706840391
0.7662337662337663
```

[43]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(label,model.predict(features))
cm
```

[43]:
```
array([[446,  54],
       [122, 146]])
```

[44]:
```
from sklearn.metrics import classification_report
print(classification_report(label,model.predict(features)))
```

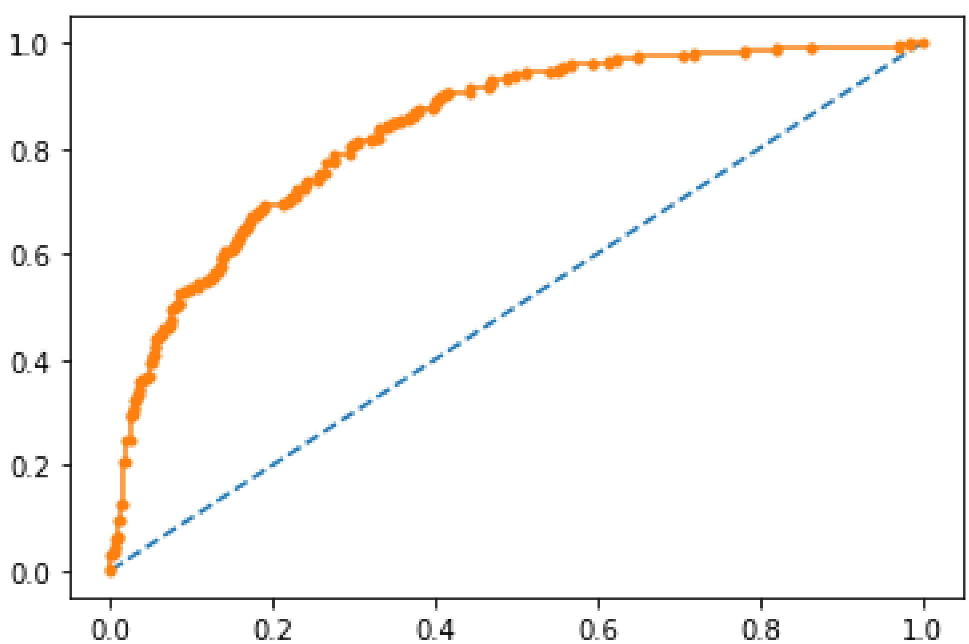
```
              precision    recall  f1-score   support

           0       0.79      0.89      0.84       500
           1       0.73      0.54      0.62       268

    accuracy                           0.77       768
```

```
   macro avg       0.76      0.72      0.73       768
weighted avg       0.77      0.77      0.76       768
```

[45]:
```
#Preparing ROC Curve(Receiver Operating Characteristics Curve)
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score

#Predict Probabilities
probs = model.predict_proba(features)
# keep probabilities for the positive outcome only
probs = probs[:, 1]
# calculate AUC
auc = roc_auc_score(label, probs)
print('AUC: %.3f' % auc)
# calculate roc curve
fpr, tpr, thresholds = roc_curve(label, probs)
# plot no skill
plt.plot([0, 1], [0, 1], linestyle='--')
# plot the roc curve for the model
plt.plot(fpr, tpr, marker='.')
```

```
AUC: 0.837
```

[45]:
```
[<matplotlib.lines.Line2D at 0x7f2aa65b8d50>]
```



[46]:
```
#Applying Decission Tree Classifier
from sklearn.tree import DecisionTreeClassifier
model3 = DecisionTreeClassifier(max_depth=5)
model3.fit(X_train,y_train)
```

[46]:
```
DecisionTreeClassifier(max_depth=5)
```

[47]:
```
model3.score(X_train,y_train)
```

[47]:
```
0.8289902280130294
```

[48]:
```
model3.score(X_test,y_test)
```

[48]:
```
0.7597402597402597
```

[49]:
```
#Applying Random Forest
from sklearn.ensemble import RandomForestClassifier
model4= RandomForestClassifier(n_estimators=1)
model4.fit(X_train,y_train)
```

[49]:
```
RandomForestClassifier(n_estimators=1)
```

[50]:
```
model4.score(X_train,y_train)
```

[50]:
```
0.8990228013029316
```

[51]:
```
model4.score(X_test,y_test)
```

[51]:
```
0.7077922077922078
```

[52]:
```
#Support Vector Classifier

from sklearn.svm import SVC
model5 = SVC(kernel='rbf',
           gamma='auto')
model5.fit(X_train,y_train)
```

[52]:
```
SVC(gamma='auto')
```

[53]:
```
model5.score(X_test,y_test),model5.score(X_train,y_train)
```

[53]:
```
(0.6168831168831169, 1.0)
```

[54]:
```
#Applying K-NN
from sklearn.neighbors import KNeighborsClassifier
model2 = KNeighborsClassifier(n_neighbors=7,
                             metric='minkowski',
```

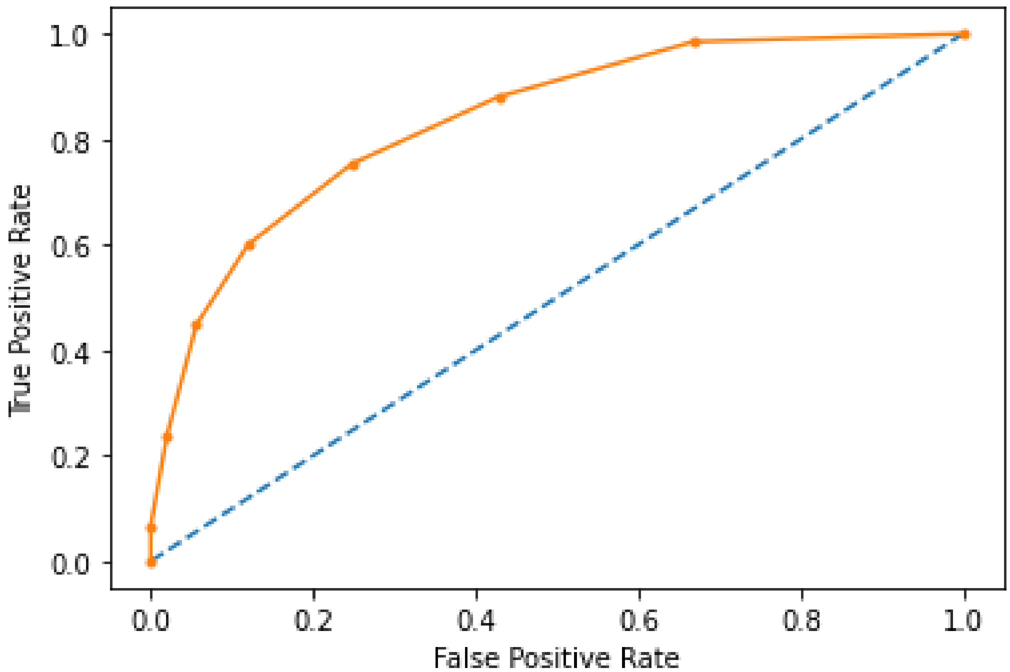
```
                                   p = 2)
model2.fit(X_train,y_train)
```

[54]: KNeighborsClassifier(n_neighbors=7)

[55]:
```
#Preparing ROC Curve (Receiver Operating Characteristics Curve)
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score

# predict probabilities
probs = model2.predict_proba(features)
# keep probabilities for the positive outcome only
probs = probs[:, 1]
# calculate AUC
auc = roc_auc_score(label, probs)
print('AUC: %.3f' % auc)
# calculate roc curve
fpr, tpr, thresholds = roc_curve(label, probs)
print("True Positive Rate - {}, False Positive Rate - {} Thresholds - {}".
 ↪format(tpr,fpr,thresholds))
# plot no skill
plt.plot([0, 1], [0, 1], linestyle='--')
# plot the roc curve for the model
plt.plot(fpr, tpr, marker='.')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
```

```
AUC: 0.836
True Positive Rate - [0.         0.06716418 0.23880597 0.44776119 0.60074627
0.75373134
 0.88059701 0.98507463 1.        ], False Positive Rate - [0.    0.    0.02
0.056 0.12  0.248 0.428 0.668 1.   ] Thresholds - [2.         1.
0.85714286 0.71428571 0.57142857 0.42857143
 0.28571429 0.14285714 0.        ]
```

[55]: Text(0, 0.5, 'True Positive Rate')

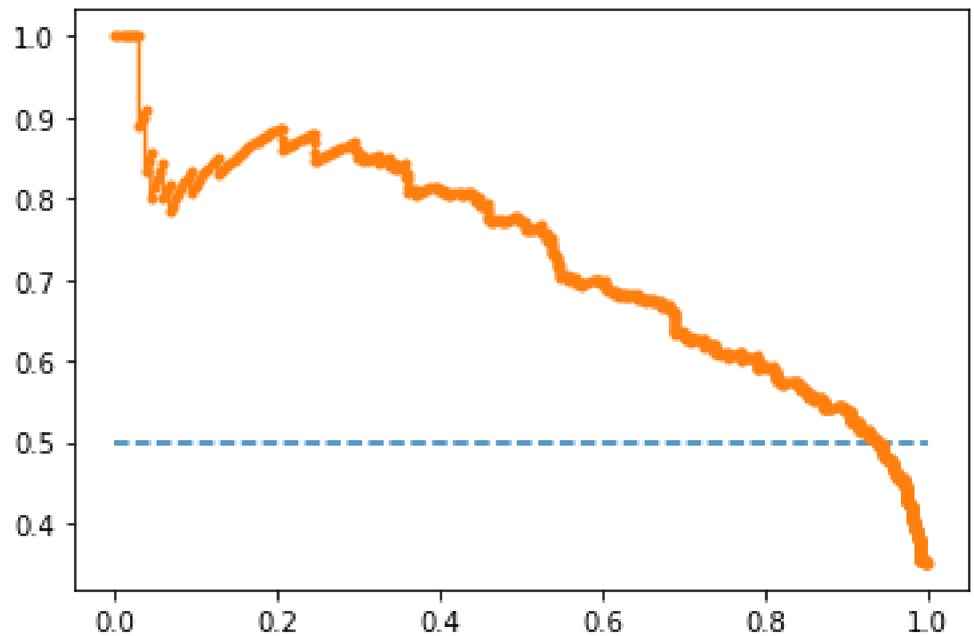


[56]:
```python
#Precision Recall Curve for Logistic Regression

from sklearn.metrics import precision_recall_curve
from sklearn.metrics import f1_score
from sklearn.metrics import auc
from sklearn.metrics import average_precision_score
# predict probabilities
probs = model.predict_proba(features)
# keep probabilities for the positive outcome only
probs = probs[:, 1]
# predict class values
yhat = model.predict(features)
# calculate precision-recall curve
precision, recall, thresholds = precision_recall_curve(label, probs)
# calculate F1 score
f1 = f1_score(label, yhat)
# calculate precision-recall AUC
auc = auc(recall, precision)
# calculate average precision score
ap = average_precision_score(label, probs)
print('f1=%.3f auc=%.3f ap=%.3f' % (f1, auc, ap))
# plot no skill
plt.plot([0, 1], [0.5, 0.5], linestyle='--')
# plot the precision-recall curve for the model
plt.plot(recall, precision, marker='.')
```

```
f1=0.624 auc=0.726 ap=0.727
```

[56]:

```
[<matplotlib.lines.Line2D at 0x7f2aa591de50>]
```



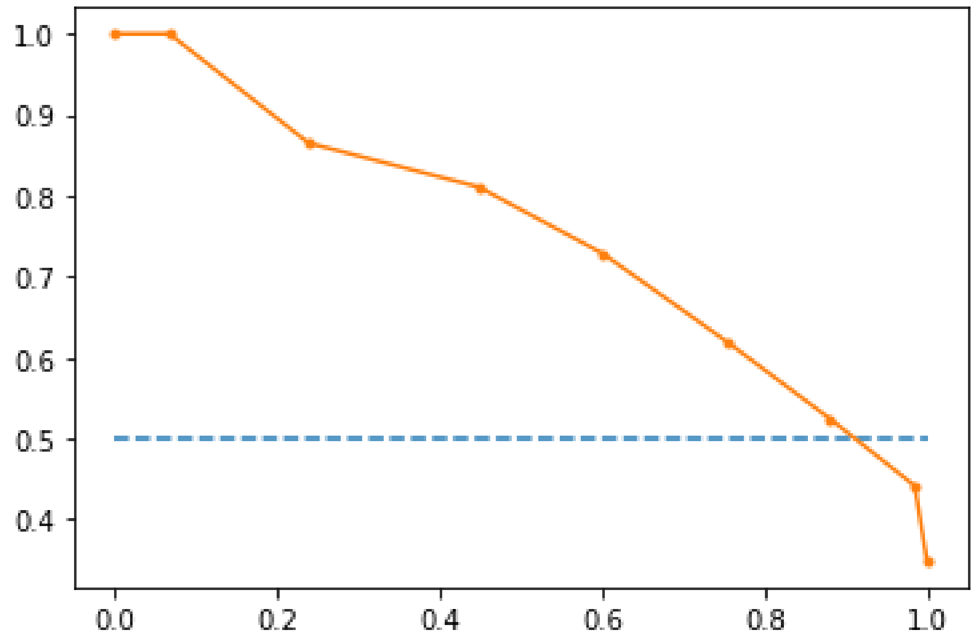
[57]:

```
#Precision Recall Curve for KNN Algorithms

from sklearn.metrics import precision_recall_curve
from sklearn.metrics import f1_score
from sklearn.metrics import auc
from sklearn.metrics import average_precision_score
# predict probabilities
probs = model2.predict_proba(features)
# keep probabilities for the positive outcome only
probs = probs[:, 1]
# predict class values
yhat = model2.predict(features)
# calculate precision-recall curve
precision, recall, thresholds = precision_recall_curve(label, probs)
# calculate F1 score
f1 = f1_score(label, yhat)
# calculate precision-recall AUC
auc = auc(recall, precision)
# calculate average precision score
ap = average_precision_score(label, probs)
print('f1=%.3f auc=%.3f ap=%.3f' % (f1, auc, ap))
# plot no skill
```

```
plt.plot([0, 1], [0.5, 0.5], linestyle='--')
# plot the precision-recall curve for the model
plt.plot(recall, precision, marker='.')
```

f1=0.658 auc=0.752 ap=0.709

[57]: [<matplotlib.lines.Line2D at 0x7f2aa58a9810>]

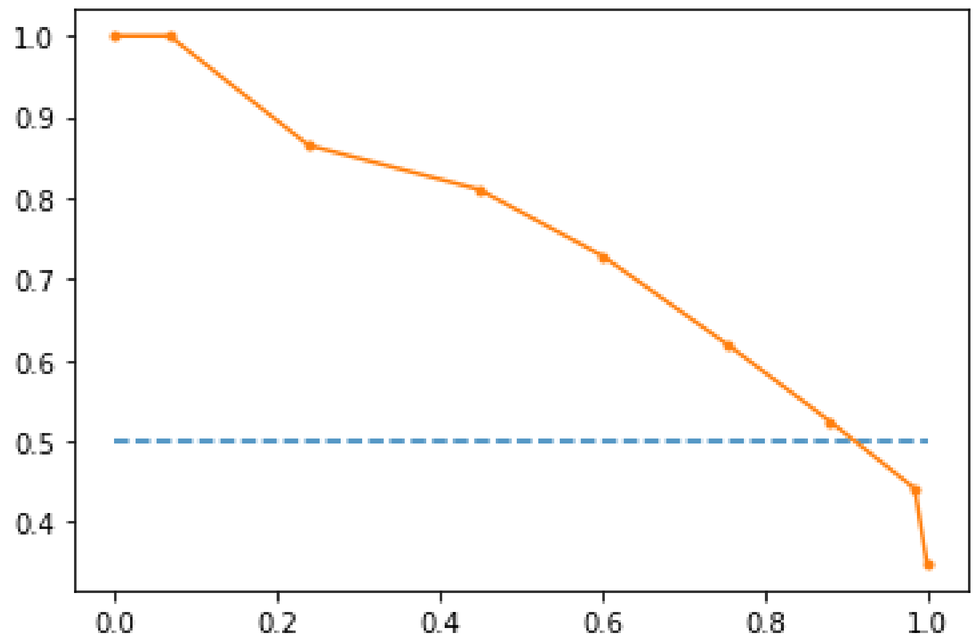


[58]:
```
#Precision Recall Curve for Decission Tree Classifier

from sklearn.metrics import precision_recall_curve
from sklearn.metrics import f1_score
from sklearn.metrics import auc
from sklearn.metrics import average_precision_score

# predict probabilities
probs = model3.predict_proba(features)

# keep probabilities for the positive outcome only
probs = probs[:, 1]

# predict class values
#yhat = model3.predict(features)

# calculate precision-recall curve
#precision, recall, thresholds = precision_recall_curve(label, probs)
```

```
# calculate F1 score
f1 = f1_score(label, yhat)
# calculate precision-recall AUC
auc = auc(recall, precision)

# calculate average precision score
ap = average_precision_score(label, probs)
print('f1=%.3f auc=%.3f ap=%.3f' % (f1, auc, ap))

# plot no skill
plt.plot([0, 1], [0.5, 0.5], linestyle='--')

# plot the precision-recall curve for the model
plt.plot(recall, precision, marker='.')
```

```
f1=0.658 auc=0.752 ap=0.761
```

[58]:
```
[<matplotlib.lines.Line2D at 0x7f2aa582bf90>]
```

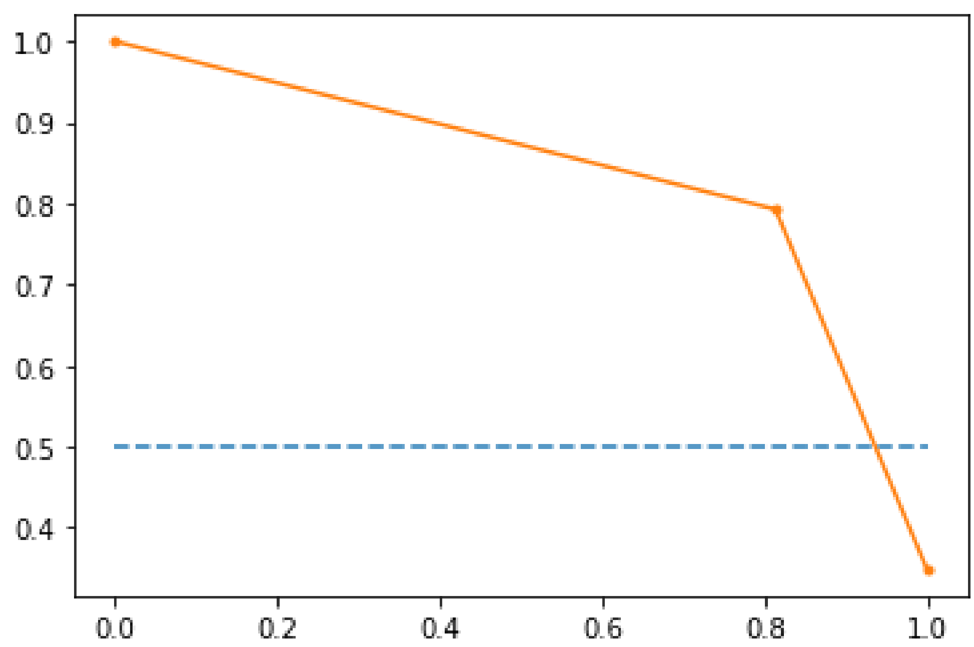


[59]:
```
#Precision Recall Curve for Random Forest

from sklearn.metrics import precision_recall_curve
from sklearn.metrics import f1_score
from sklearn.metrics import auc
from sklearn.metrics import average_precision_score
```

```
# predict probabilities
probs = model4.predict_proba(features)
# keep probabilities for the positive outcome only
probs = probs[:, 1]
# predict class values
yhat = model4.predict(features)
# calculate precision-recall curve
precision, recall, thresholds = precision_recall_curve(label, probs)
# calculate F1 score
f1 = f1_score(label, yhat)
# calculate precision-recall AUC
auc = auc(recall, precision)
# calculate average precision score
ap = average_precision_score(label, probs)
print('f1=%.3f auc=%.3f ap=%.3f' % (f1, auc, ap))
# plot no skill
plt.plot([0, 1], [0.5, 0.5], linestyle='--')
# plot the precision-recall curve for the model
plt.plot(recall, precision, marker='.')
```

```
f1=0.803 auc=0.836 ap=0.710
```

[59]:
```
[<matplotlib.lines.Line2D at 0x7f2aa57b2b50>]
```



3.0.1 Thank You

[ ]:
```
```