Out[6]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

Week1

```
In [7]: data.isnull().any()
Out[7]: Pregnancies
                                    False
        Glucose
                                    False
        BloodPressure
                                    False
        SkinThickness
                                    False
                                    False
        Insulin
        BMI
                                    False
        DiabetesPedigreeFunction
                                    False
                                    False
        Age
                                    False
        Outcome
        dtype: bool
```

In [8]: | data.describe().transpose()

Out[8]:

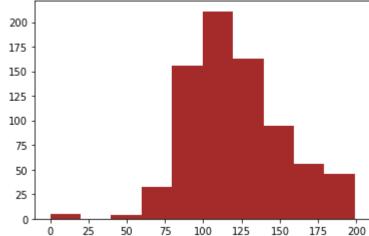
	count	mean	std	min	25%	50%	75%	max
Pregnancies	768.0	3.845052	3.369578	0.000	1.00000	3.0000	6.00000	17.00
Glucose	768.0	120.894531	31.972618	0.000	99.00000	117.0000	140.25000	199.00
BloodPressure	768.0	69.105469	19.355807	0.000	62.00000	72.0000	80.00000	122.00
SkinThickness	768.0	20.536458	15.952218	0.000	0.00000	23.0000	32.00000	99.00
Insulin	768.0	79.799479	115.244002	0.000	0.00000	30.5000	127.25000	846.00
ВМІ	768.0	31.992578	7.884160	0.000	27.30000	32.0000	36.60000	67.10
DiabetesPedigreeFunction	768.0	0.471876	0.331329	0.078	0.24375	0.3725	0.62625	2.42
Age	768.0	33.240885	11.760232	21.000	24.00000	29.0000	41.00000	81.00
Outcome	768.0	0.348958	0.476951	0.000	0.00000	0.0000	1.00000	1.00

In [9]: positive=data[data['Outcome']==1]
positive.head()

Out[9]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	ВМІ	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
2	8	183	64	0	0	23.3	0.672	32	1
4	0	137	40	35	168	43.1	2.288	33	1
6	3	78	50	32	88	31.0	0.248	26	1
8	2	197	70	45	543	30.5	0.158	53	1

```
In [10]: | data['Glucose'].value_counts().head(10)
Out[10]: 100
                17
         99
                17
                14
         129
         125
                14
         111
                14
         106
                14
         95
               13
                13
         108
         105
                13
         102
                13
         Name: Glucose, dtype: int64
In [11]: plt.hist(data['Glucose'],color='Brown')
Out[11]: (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>)
          200
```



250 -200 -150 -100 -

60

80

100

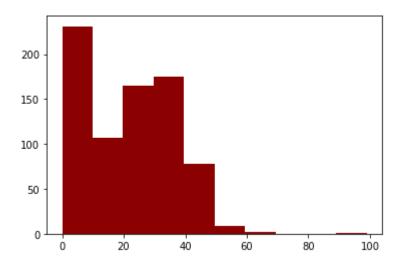
120

<BarContainer object of 10 artists>)

20

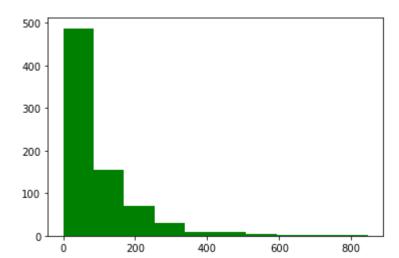
```
In [13]: plt.hist(data['SkinThickness'],color='DarkRed')
```

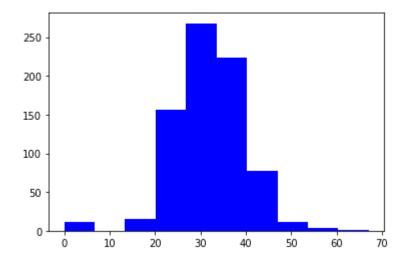
Out[13]: (array([231., 107., 165., 175., 78., 9., 2., 0., 0., 1.]), array([0., 9.9, 19.8, 29.7, 39.6, 49.5, 59.4, 69.3, 79.2, 89.1, 99.]), <BarContainer object of 10 artists>)



```
In [14]: plt.hist(data['Insulin'],color='Green')
```

Out[14]: (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>)





```
In [16]: print(data['Glucose'].value_counts().head())
         print(data['BloodPressure'].value_counts().head())
         print(data['SkinThickness'].value_counts().head())
         print(data['Insulin'].value_counts().head())
         data['BMI'].value_counts().head()
         100
                17
         99
                17
         129
                14
         125
                14
         111
                14
         Name: Glucose, dtype: int64
          70
               57
               52
          74
         68
               45
         78
               45
         72
               44
         Name: BloodPressure, dtype: int64
         0
               227
          32
                 31
          30
                 27
         27
                 23
                22
         23
         Name: SkinThickness, dtype: int64
         0
                 374
         105
                 11
                  9
         140
                   9
         130
         120
         Name: Insulin, dtype: int64
Out[16]: 32.0
                 13
         31.6
                 12
         31.2
                 12
         0.0
                 11
         33.3
                  10
         Name: BMI, dtype: int64
```

Week2

```
In [17]: print(positive['Glucose'].value_counts().head())
   plt.hist(positive['Glucose'],histtype='stepfilled',bins=20)
125 7
```

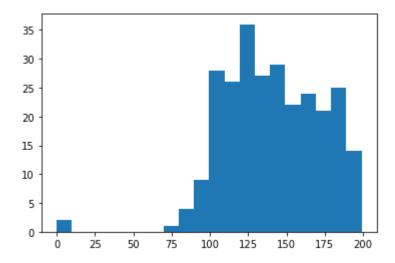
158 6 128 6 115 6

129 6
Name: Glucose, dtype: int64

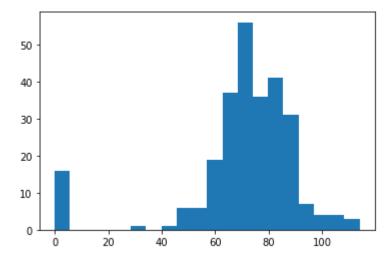
Out[17]: (array([2., 0., 0., 0., 0., 0., 0., 1., 4., 9., 28., 26., 36., 27., 29., 22., 24., 21., 25., 14.]),

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 0x24ecb5ff070>])



```
In [18]: |print(positive['BloodPressure'].value_counts().head())
         plt.hist(positive['BloodPressure'], histtype='stepfilled', bins=20)
         70
              23
         76
              18
         78
              17
              17
         74
              16
         72
         Name: BloodPressure, dtype: int64
Out[18]: (array([16., 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 0x24ecb657d30>])
```



```
In [19]: print(positive['SkinThickness'].value_counts().head())
   plt.hist(positive['SkinThickness'],histtype='stepfilled',bins=20)
```

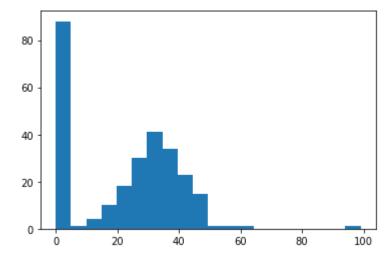
0883214339309

39 8
Name: SkinThickness, dtype: int64

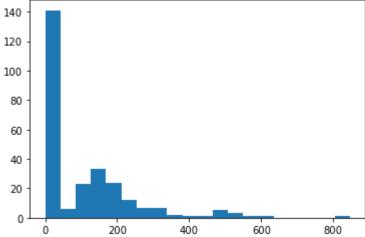
Out[19]: (array([88., 1., 4., 10., 18., 30., 41., 34., 23., 15., 1., 1., 1., 0., 0., 0., 0., 0., 0., 1.]),

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 0x24ecb6a9f40>])



```
In [20]: |print(positive['Insulin'].value_counts().head())
         plt.hist(positive['Insulin'],histtype='stepfilled',bins=20)
         0
               138
         130
                 6
         180
         156
                 3
         175
         Name: Insulin, dtype: int64
Out[20]: (array([141., 6., 23., 33., 24., 12., 7., 7., 2., 1., 1.,
                                                    0.,
                  5., 3., 1., 1., 0.,
                                              0.,
                                                          0.,
          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 0x24ecb6feeb0>])
          140
          120
```



```
In [21]: print(positive['BMI'].value counts().head())
         plt.hist(positive['BMI'], histtype='stepfilled', bins=20)
         32.9
                 8
         31.6
                 7
         33.3
         30.5
                 5
         32.0
                 5
         Name: BMI, dtype: int64
Out[21]: (array([ 2., 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 0x24ecb75c400>])
          60
          50
          40
          30
          20
          10
```

```
In [22]: BloodPressure = positive['BloodPressure']
    Glucose = positive['Glucose']
    SkinThickness = positive['SkinThickness']
    Insulin = positive['Insulin']
    BMI = positive['BMI']
```

10

20

30

40

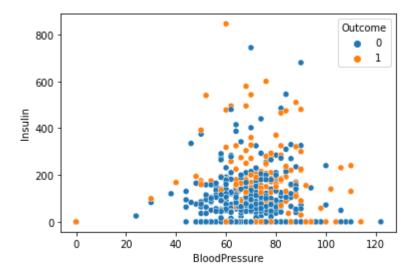
50

60

70

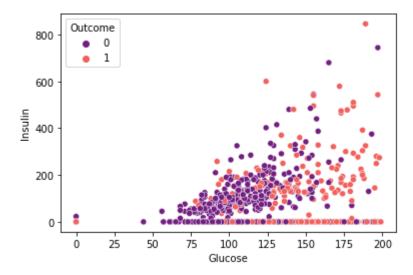
```
In [23]: sns.scatterplot(x='BloodPressure',y='Insulin',hue='Outcome',data=data)
```

Out[23]: <AxesSubplot:xlabel='BloodPressure', ylabel='Insulin'>



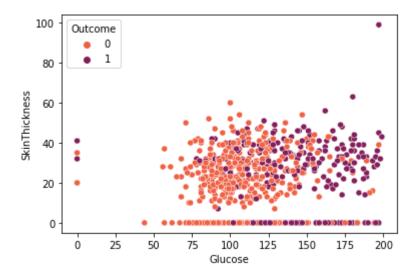
In [24]: sns.scatterplot(x='Glucose',y='Insulin',hue='Outcome',data=data,palette='magma')

Out[24]: <AxesSubplot:xlabel='Glucose', ylabel='Insulin'>



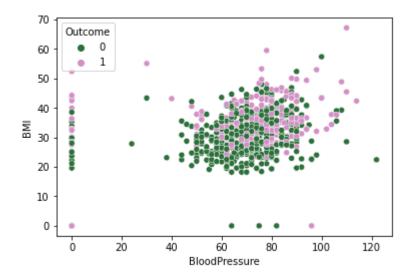
```
In [25]: sns.scatterplot(x='Glucose',y='SkinThickness',hue='Outcome',data=data,palette='rocket_r')
```

Out[25]: <AxesSubplot:xlabel='Glucose', ylabel='SkinThickness'>



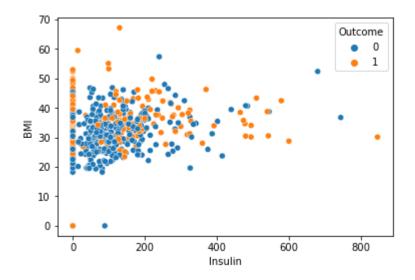
In [26]: sns.scatterplot(x='BloodPressure',y='BMI',hue='Outcome',data=data,palette='cubehelix')

Out[26]: <AxesSubplot:xlabel='BloodPressure', ylabel='BMI'>



```
In [27]: sns.scatterplot(x='Insulin',y='BMI',hue='Outcome',data=data,palette='tab10')
```

Out[27]: <AxesSubplot:xlabel='Insulin', ylabel='BMI'>



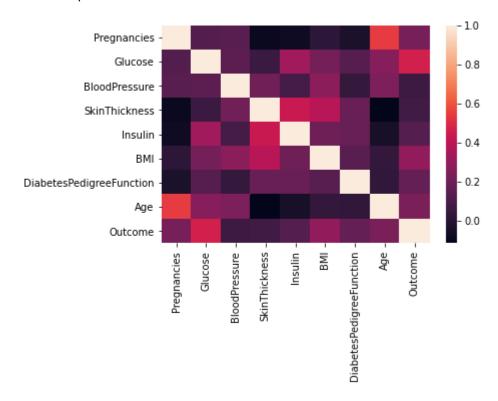
In [28]: data.corr()

Out[28]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age
Pregnancies	1.000000	0.129459	0.141282	-0.081672	-0.073535	0.017683	-0.033523	0.544341
Glucose	0.129459	1.000000	0.152590	0.057328	0.331357	0.221071	0.137337	0.263514
BloodPressure	0.141282	0.152590	1.000000	0.207371	0.088933	0.281805	0.041265	0.239528
SkinThickness	-0.081672	0.057328	0.207371	1.000000	0.436783	0.392573	0.183928	-0.113970
Insulin	-0.073535	0.331357	0.088933	0.436783	1.000000	0.197859	0.185071	-0.042163
ВМІ	0.017683	0.221071	0.281805	0.392573	0.197859	1.000000	0.140647	0.036242
DiabetesPedigreeFunction	-0.033523	0.137337	0.041265	0.183928	0.185071	0.140647	1.000000	0.033561
Age	0.544341	0.263514	0.239528	-0.113970	-0.042163	0.036242	0.033561	1.000000
Outcome	0.221898	0.466581	0.065068	0.074752	0.130548	0.292695	0.173844	0.238356
4								

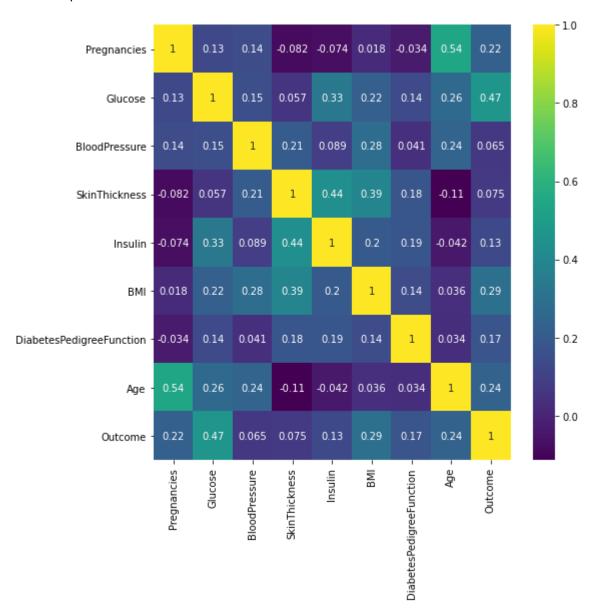
In [29]: sns.heatmap(data.corr())

Out[29]: <AxesSubplot:>



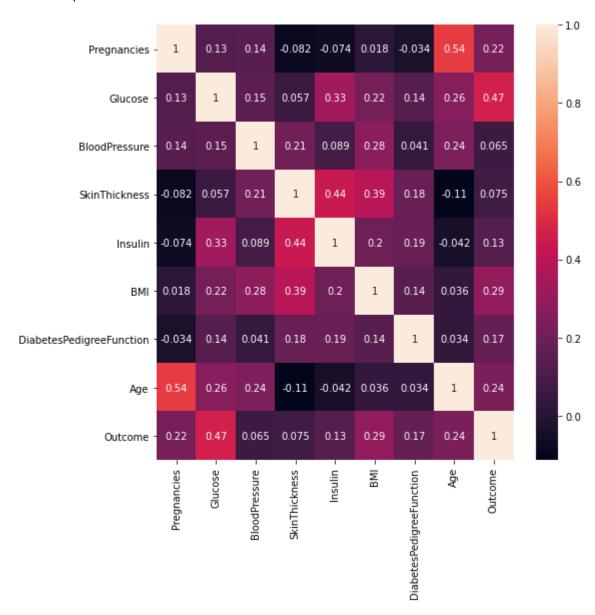
```
In [30]: plt.subplots(figsize=(8,8))
sns.heatmap(data.corr(),annot=True,cmap='viridis')
```

Out[30]: <AxesSubplot:>



```
In [31]: plt.subplots(figsize=(8,8))
sns.heatmap(data.corr(),annot=True)
```

Out[31]: <AxesSubplot:>



Week3

```
In [32]: data.head(5)
```

Out[32]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

```
In [33]: features = data.iloc[:,[0,1,2,3,4,5,6,7]].values
label = data.iloc[:,8].values
```

```
In [35]: from sklearn.linear_model import LogisticRegression
    model = LogisticRegression()
    model.fit(X_train,y_train)
```

Out[35]: LogisticRegression()

```
In [36]: print(model.score(X_train,y_train))
    print(model.score(X_test,y_test))
```

0.7719869706840391
0.7662337662337663

```
In [37]: from sklearn.metrics import confusion_matrix
cm = confusion_matrix(label,model.predict(features))
cm
```

```
Out[37]: array([[446, 54], [122, 146]], dtype=int64)
```

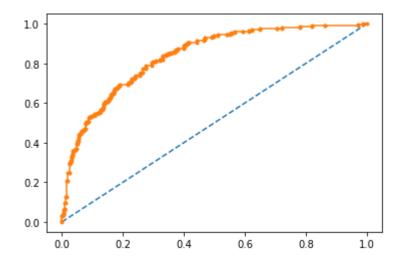
In [38]: from sklearn.metrics import classification_report
 print(classification_report(label,model.predict(features)))

support	f1-score	recall	precision	
500	0.84	0.89	0.79	0
268	0.62	0.54	0.73	1
768	0.77			accuracy
768	0.73	0.72	0.76	macro avg
768	0.76	0.77	0.77	weighted avg

```
In [39]: #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

Out[39]: [<matplotlib.lines.Line2D at 0x24ecd707310>]

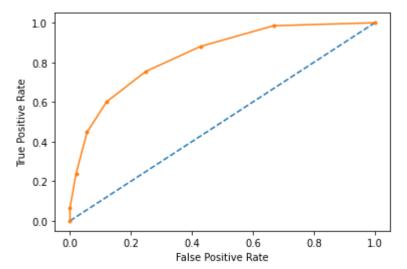


```
In [40]: #Applying Decission Tree Classifier
         from sklearn.tree import DecisionTreeClassifier
         model3 = DecisionTreeClassifier(max depth=5)
         model3.fit(X train,y train)
Out[40]: DecisionTreeClassifier(max depth=5)
In [41]: model3.score(X train,y train)
Out[41]: 0.8289902280130294
In [42]: model3.score(X_test,y_test)
Out[42]: 0.7727272727272727
In [43]: #Applying Random Forest
         from sklearn.ensemble import RandomForestClassifier
         model4 = RandomForestClassifier(n estimators=11)
         model4.fit(X train,y train)
Out[43]: RandomForestClassifier(n_estimators=11)
In [44]: model4.score(X_train,y_train)
Out[44]: 0.99185667752443
In [45]: model4.score(X test,y test)
Out[45]: 0.7532467532467533
In [46]: #Support Vector Classifier
         from sklearn.svm import SVC
         model5 = SVC(kernel='rbf',
                    gamma='auto')
         model5.fit(X train,y train)
Out[46]: SVC(gamma='auto')
```

```
In [49]: #Applying K-NN
from sklearn.neighbors import KNeighborsClassifier
model2 = KNeighborsClassifier(n_neighbors=7, metric='minkowski', p = 2)
model2.fit(X_train,y_train)
```

Out[49]: KNeighborsClassifier(n_neighbors=7)

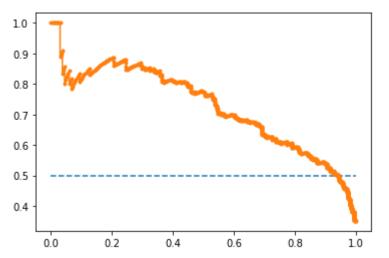
```
In [50]: #Preparing ROC Curve (Receiver Operating Characteristics Curve)
         from sklearn.metrics import roc curve
         from sklearn.metrics import roc auc score
         # predict probabilities
         probs = model2.predict proba(features)
         # keep probabilities for the positive 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.vlabel("True Positive Rate")
         AUC: 0.836
         True Positive Rate - [0.
                                          0.06716418 0.23880597 0.44776119 0.60074627 0.75373134
                                         ], False Positive Rate - [0. 0. 0.02 0.056 0.12 0.248 0.428 0.668 1.
          0.88059701 0.98507463 1.
                                               0.85714286 0.71428571 0.57142857 0.42857143
         ] Thresholds - [2.
                              1.
          0.28571429 0.14285714 0.
Out[50]: Text(0, 0.5, 'True Positive Rate')
```



```
In [51]: #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

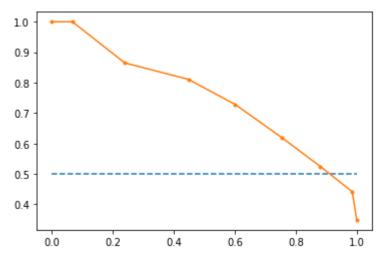
Out[51]: [<matplotlib.lines.Line2D at 0x24ecda306a0>]



```
In [52]: #Precision Recall Curve for KNN
         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

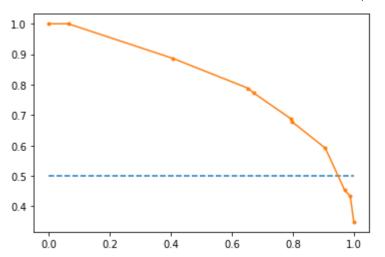
Out[52]: [<matplotlib.lines.Line2D at 0x24ecda8f7c0>]



```
In [53]: #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=0.714 auc=0.815 ap=0.768

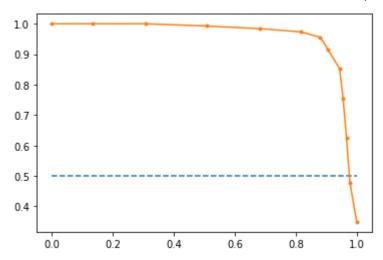
Out[53]: [<matplotlib.lines.Line2D at 0x24ecdae9910>]



```
In [54]: #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=0.917 auc=0.962 ap=0.954

Out[54]: [<matplotlib.lines.Line2D at 0x24ecdb44a60>]



In []:
In []:
In []:

In []: