Lecture 3 Classification Techniques

May 11, 2022

1 Classification Workbook

Welcome to the Classification workbook. Let's start by importing some of our custom libraries.

[1]:
```
import numpy as np
import pandas as pd

from matplotlib import pyplot as plt
%matplotlib inline

import seaborn as sns
sns.set_style('darkgrid')
```

1.1 1. Classification Algorithms

In the class, we discussed five different classification methods. Let's investigate them in more detail here.

1.1.1 1.1. Binary Classification

Binary classification is when the target is determined with True or False. Let's create a simple x and y arrays for exploring conditional classification.

[2]:
```
x = np.linspace(0, 1, 100)
```

[3]:
```
np.random.seed(123)
noise = np.random.uniform(-0.2, 0.2, 100)
```

[4]:
```
y = ((x+noise)>0.5).astype(int)
```

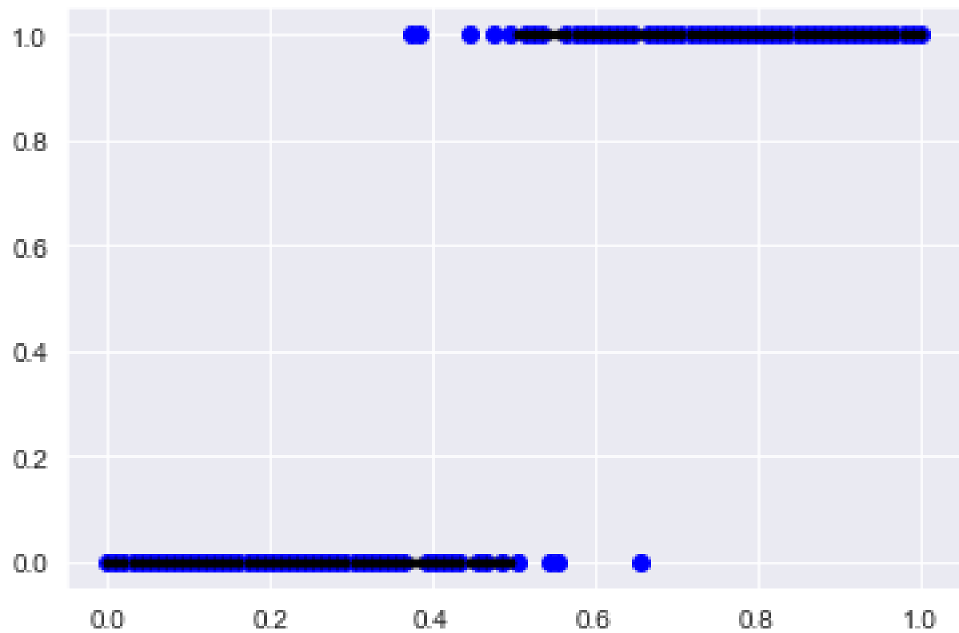
[5]:
```
y
```

[5]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0,
       1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
```

```
[6]: fig = plt.figure(figsize=(6,4))
ax = plt.subplot(111)

ax.plot(x, x>0.5, 'k.')
ax.scatter(x, y, color='b')
```

```
[6]: <matplotlib.collections.PathCollection at 0x13d9037c0>
```



Simple as that, we built a mask that attributes values below 0.5 to 0 and above 0.5 to 1. When we use an encoder for a binary classification problem, we can use this type of classification easily.

1.1.2 1.2. Logistic Regression

We have used Logistic Regression before, but unlike the name implies LogisticRegression is best suited for classification problems.

```
[7]: from sklearn.linear_model import LogisticRegression
```

```
[8]: lr_model = LogisticRegression()
```

```
[9]: lr_model.fit(x.reshape(100,1),y)
```

```
[9]: LogisticRegression()
```

```
[10]: lr_model.predict(x.reshape(100,1))
```

[10]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
```

[11]:
```
(lr_model.predict(x.reshape(100,1))==y)[:40]
```

[11]:
```
array([ True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True,  True,  True,  True,  True,
        True, False, False,  True])
```

This tells us model doesn't always predict the values of y. Remember with LogisticRegression, it is always wise to look at the probability.

[12]:
```
lr_model.predict_proba(x.reshape(100,1))[:40]
```

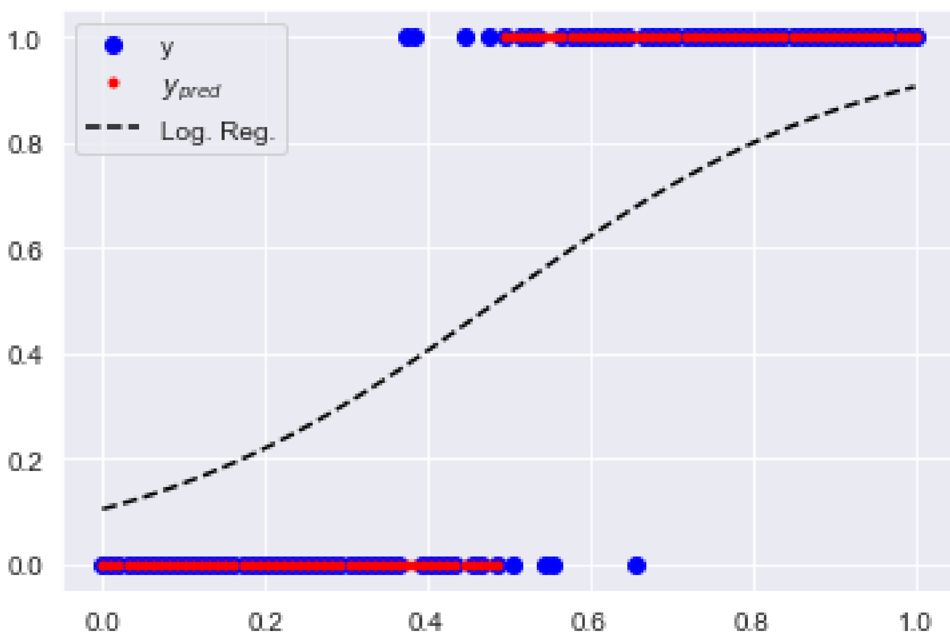
[12]:
```
array([[0.89531454, 0.10468546],
       [0.89107222, 0.10892778],
       [0.88667974, 0.11332026],
       [0.88213356, 0.11786644],
       [0.87743021, 0.12256979],
       [0.87256629, 0.12743371],
       [0.8675385 , 0.1324615 ],
       [0.86234363, 0.13765637],
       [0.85697862, 0.14302138],
       [0.85144054, 0.14855946],
       [0.84572661, 0.15427339],
       [0.83983425, 0.16016575],
       [0.83376108, 0.16623892],
       [0.82750492, 0.17249508],
       [0.82106385, 0.17893615],
       [0.8144362 , 0.1855638 ],
       [0.80762059, 0.19237941],
       [0.80061592, 0.19938408],
       [0.79342145, 0.20657855],
       [0.78603676, 0.21396324],
       [0.77846179, 0.22153821],
       [0.77069688, 0.22930312],
       [0.76274275, 0.23725725],
       [0.75460057, 0.24539943],
       [0.74627191, 0.25372809],
       [0.73775882, 0.26224118],
       [0.72906379, 0.27093621],
       [0.72018981, 0.27981019],
```

```
       [0.71114034, 0.28885966],
       [0.70191933, 0.29808067],
       [0.69253123, 0.30746877],
       [0.682981  , 0.317019  ],
       [0.67327408, 0.32672592],
       [0.66341641, 0.33658359],
       [0.65341443, 0.34658557],
       [0.64327504, 0.35672496],
       [0.63300563, 0.36699437],
       [0.62261402, 0.37738598],
       [0.61210848, 0.38789152],
       [0.60149767, 0.39850233]])
```

[13]:
```
fig = plt.figure(figsize=(6,4))
ax = plt.subplot(111)

ax.plot(x, y, 'bo', label='y')
ax.plot(x, lr_model.predict(x.reshape(100,1)), 'r.', label='$y_{pred}$')
ax.plot(x, lr_model.predict_proba(x.reshape(100,1))[:,1], 'k--', label='Log.␣
↪Reg.')
ax.legend()
```

[13]:
```
<matplotlib.legend.Legend at 0x13e26ba00>
```



The probabilities are not as "certain". Remember, we can always fine tune the logistic regression with C, penalty parameter.

1.1.3 1.3. Decision Tree and Random Forest Classification

This is also an old friend of ours. Let's see how we can use RandomForest as a classifier.

[14]:
```
from sklearn.ensemble import RandomForestClassifier
```

[15]:
```
rf_model = RandomForestClassifier(random_state=123)
```

[16]:
```
rf_model.fit(x.reshape(100,1),y)
```

[16]:
```
RandomForestClassifier(random_state=123)
```

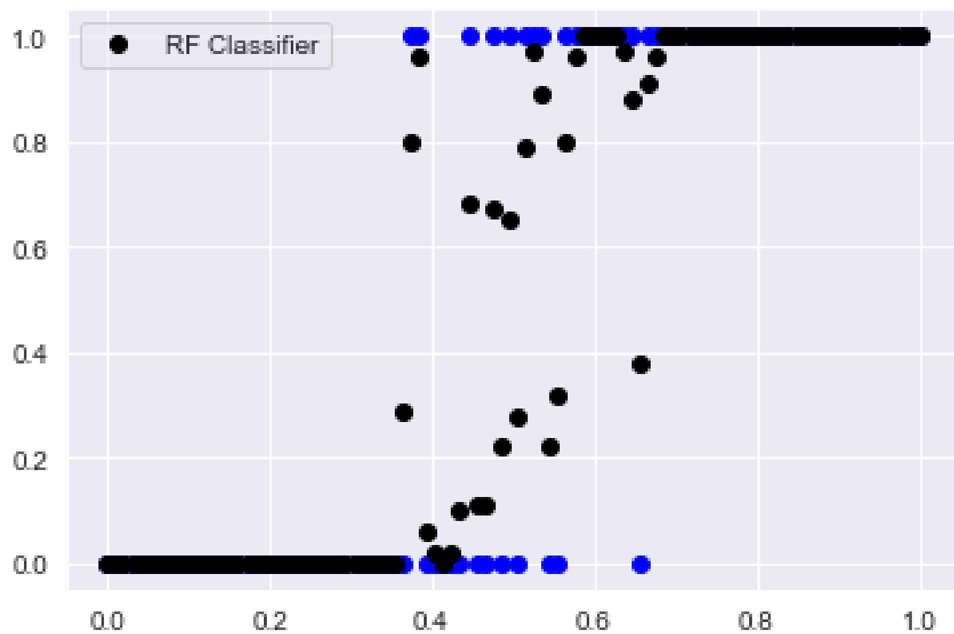
[17]:
```
X = x.reshape(100,1)
```

[18]:
```
pred = rf_model.predict_proba(X)
```

[19]:
```
fig = plt.figure(figsize=(6,4))
ax = plt.subplot(111)

ax.scatter(x, y, color='b')
ax.plot(X, pred[:,1], 'ko', label='RF Classifier')
ax.legend()
```

[19]:
```
<matplotlib.legend.Legend at 0x13e7abd60>
```



Not a great fit, but luckily we have learnt how to tune Random Forests.

[20]:
```
rf_model2 = RandomForestClassifier(random_state=123, n_estimators=10,␣
    ↪min_samples_leaf=20)
```

[21]:
```
rf_model2.fit(X,y)
```

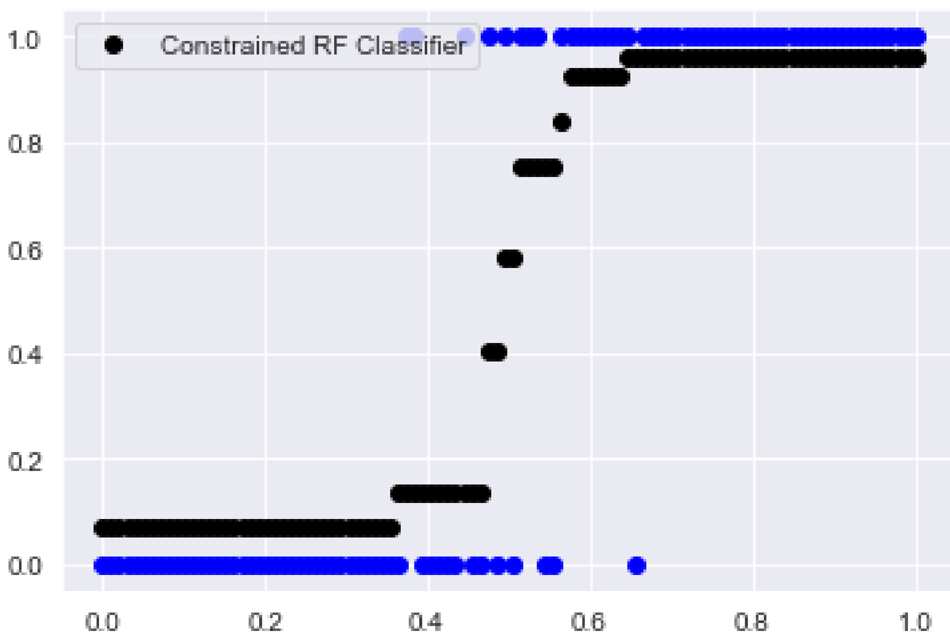
[21]:
```
RandomForestClassifier(min_samples_leaf=20, n_estimators=10, random_state=123)
```

[22]:
```
pred2 = rf_model2.predict_proba(X)
```

[23]:
```
fig = plt.figure(figsize=(6,4))
ax = plt.subplot(111)

ax.scatter(x, y, color='b')
ax.plot(X, pred2[:,1], 'ko', label='Constrained RF Classifier')
ax.legend(loc=2)
```

[23]:
```
<matplotlib.legend.Legend at 0x13e825f70>
```



1.1.4 1.4. k-Nearest Neighbour Classification

[24]:
```
from sklearn.neighbors import KNeighborsClassifier
```

[25]:
```
knn_model = KNeighborsClassifier(n_neighbors=3)
```

[26]:
```
knn_model.fit(X,y)
```

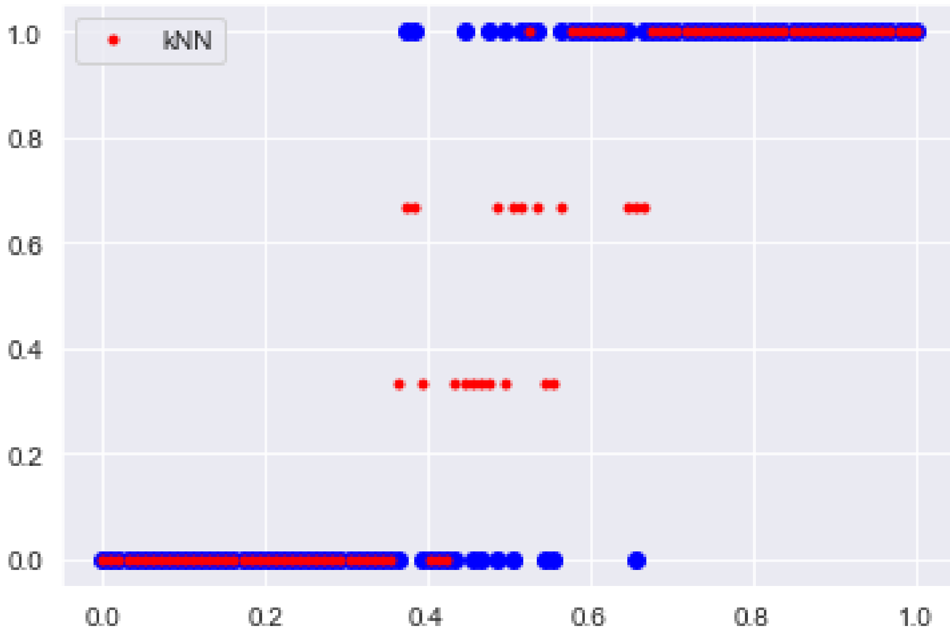
[26]: KNeighborsClassifier(n_neighbors=3)

[27]:
```
pred4 = knn_model.predict_proba(X)
```

[28]:
```
fig = plt.figure(figsize=(6,4))
ax = plt.subplot(111)

ax.scatter(x, y, color='b')
ax.plot(X, pred4[:,1], 'r.', label='kNN')
ax.legend(loc=2)
```

[28]: <matplotlib.legend.Legend at 0x13d951df0>



Again, we can finetune the kNN to get better results.

[29]:
```
knn_model2 = KNeighborsClassifier(n_neighbors=10, weights='uniform')
knn_model2.fit(X,y)
```

[29]: KNeighborsClassifier(n_neighbors=10)

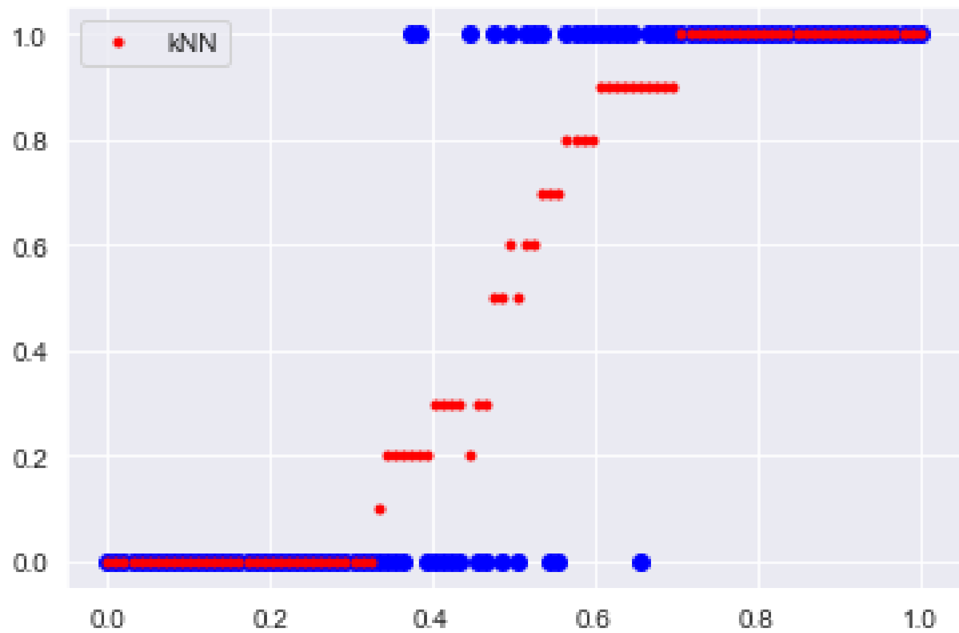
[30]:
```
pred5 = knn_model2.predict_proba(X)
```

[31]:
```
fig = plt.figure(figsize=(6,4))
ax = plt.subplot(111)

ax.scatter(x, y, color='b')
```

```
ax.plot(X, pred5[:,1], 'r.', label='kNN')
ax.legend(loc=2)
```

[31]: <matplotlib.legend.Legend at 0x13e8cc790>



1.2 2. Evaluation Methods

Let's remember what our x and y were.

[32]:
```
print(X, y)
```

```
[[0.        ]
 [0.01010101]
 [0.02020202]
 [0.03030303]
 [0.04040404]
 [0.05050505]
 [0.06060606]
 [0.07070707]
 [0.08080808]
 [0.09090909]
 [0.1010101 ]
 [0.11111111]
 [0.12121212]
 [0.13131313]
 [0.14141414]
```

```
[0.15151515]
[0.16161616]
[0.17171717]
[0.18181818]
[0.19191919]
[0.2020202 ]
[0.21212121]
[0.22222222]
[0.23232323]
[0.24242424]
[0.25252525]
[0.26262626]
[0.27272727]
[0.28282828]
[0.29292929]
[0.3030303 ]
[0.31313131]
[0.32323232]
[0.33333333]
[0.34343434]
[0.35353535]
[0.36363636]
[0.37373737]
[0.38383838]
[0.39393939]
[0.4040404 ]
[0.41414141]
[0.42424242]
[0.43434343]
[0.44444444]
[0.45454545]
[0.46464646]
[0.47474747]
[0.48484848]
[0.49494949]
[0.50505051]
[0.51515152]
[0.52525253]
[0.53535354]
[0.54545455]
[0.55555556]
[0.56565657]
[0.57575758]
[0.58585859]
[0.5959596 ]
[0.60606061]
[0.61616162]
[0.62626263]
```

```
 [0.63636364]
 [0.64646465]
 [0.65656566]
 [0.66666667]
 [0.67676768]
 [0.68686869]
 [0.6969697 ]
 [0.70707071]
 [0.71717172]
 [0.72727273]
 [0.73737374]
 [0.74747475]
 [0.75757576]
 [0.76767677]
 [0.77777778]
 [0.78787879]
 [0.7979798 ]
 [0.80808081]
 [0.81818182]
 [0.82828283]
 [0.83838384]
 [0.84848485]
 [0.85858586]
 [0.86868687]
 [0.87878788]
 [0.88888889]
 [0.8989899 ]
 [0.90909091]
 [0.91919192]
 [0.92929293]
 [0.93939394]
 [0.94949495]
 [0.95959596]
 [0.96969697]
 [0.97979798]
 [0.98989899]
 [1.        ]] [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0
 1 1 0 0 0 0 0 1 0 0 1 0 1 0 1 1 1 0 0 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
```

1.2.1 2.1. Accuracy Score

We start with the simple accuracy score.

[33]:
```python
from sklearn.metrics import accuracy_score
```

[34]:
```python
pred = lr_model.predict(X)
```

[35]:
```
pred2 = rf_model.predict(X)
```

[36]:
```
pred3 = rf_model2.predict(X)
```

[37]:
```
pred4 = knn_model.predict(X)
```

[38]:
```
print( 'Logistic Reg. Acc:', accuracy_score(y, pred))
print( 'Random Forest Acc:', accuracy_score(y, pred2))
print( 'Constrained Random Forest Acc:', accuracy_score(y, pred3))
print( 'KNN Acc:', accuracy_score(y, pred4))
```

```
Logistic Reg. Acc: 0.92
Random Forest Acc: 1.0
Constrained Random Forest Acc: 0.92
KNN Acc: 0.94
```

This is what the metric says, but is something fishy?

1.2.2 2.2. Confusion Matrix

[39]:
```
from sklearn.metrics import confusion_matrix
```

[40]:
```
print('Log. Reg.:\n', confusion_matrix(y, pred))
```

```
Log. Reg.:
 [[45  4]
 [ 4 47]]
```

[41]:
```
print('Random Forest:\n',confusion_matrix(y, pred2))
```

```
Random Forest:
 [[49  0]
 [ 0 51]]
```

[42]:
```
print('Const. RF.:\n', confusion_matrix(y, pred3))
```

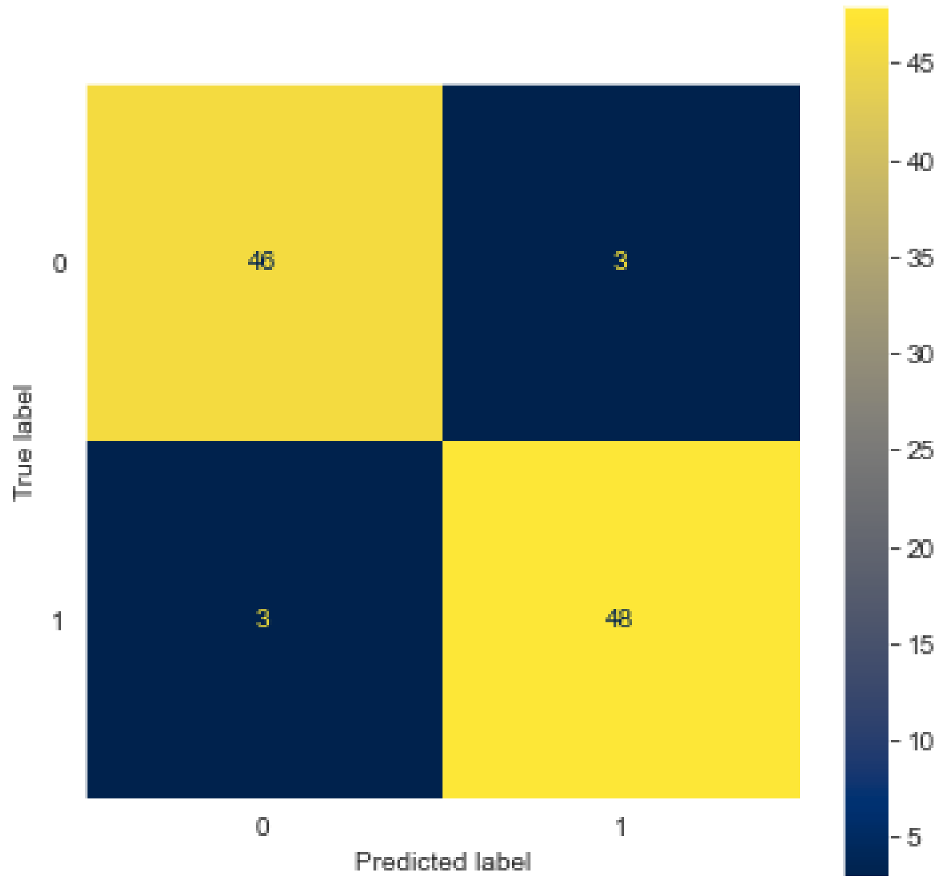
```
Const. RF.:
 [[45  4]
 [ 4 47]]
```

[43]:
```
print('KNN:\n', confusion_matrix(y, pred4))
```

```
KNN:
 [[46  3]
 [ 3 48]]
```

[44]:
```
from sklearn.metrics import plot_confusion_matrix
fig = plt.figure(figsize=[6,6])
```

```
ax = plt.subplot(111)
cb = plot_confusion_matrix(knn_model, X, y, ax=ax,cmap='cividis')
ax.grid()
plt.show()
```



Okay, this is more revealing about the performance of the individual model.

1.2.3 2.3. Precision-Recall

Precision and recall is another way of assessing the performance of a model.

[45]:
```
from sklearn.metrics import precision_recall_curve
```

[46]:
```
print('Log. Reg.:\n', precision_recall_curve(y, pred))
print('Random Forest:\n',precision_recall_curve(y, pred2))
print('Const. RF.:\n', precision_recall_curve(y, pred3))
print('KNN:\n', precision_recall_curve(y, pred4))
```

```
Log. Reg.:
 (array([0.51      , 0.92156863, 1.        ]), array([1.        , 0.92156863, 0.
```

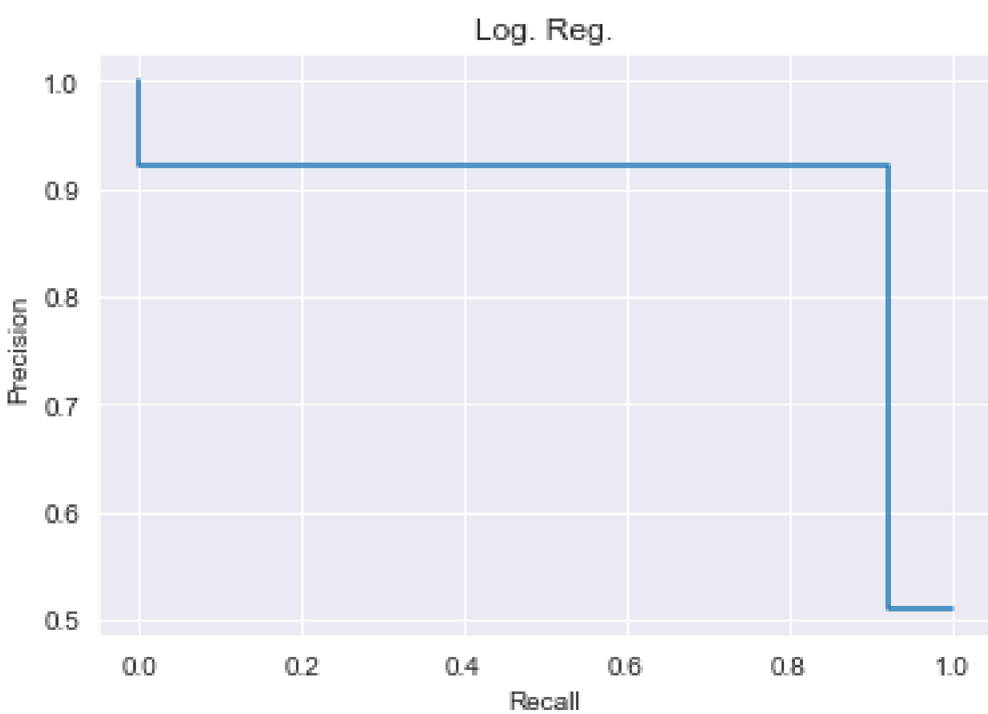
```
]), array([0, 1]))
Random Forest:
 (array([1., 1.]), array([1., 0.]), array([1]))
Const. RF.:
 (array([0.51      , 0.92156863, 1.        ]), array([1.        , 0.92156863, 0.
]), array([0, 1]))
KNN:
 (array([0.51      , 0.94117647, 1.        ]), array([1.        , 0.94117647, 0.
]), array([0, 1]))
```

Well, this didn't explain much.

[47]:
```python
from sklearn.metrics import PrecisionRecallDisplay
```

[48]:
```python
precision, recall, thresholds = precision_recall_curve(y, pred)
disp = PrecisionRecallDisplay(precision=precision, recall=recall)
disp.plot()
disp.ax_.set_title('Log. Reg.')
```

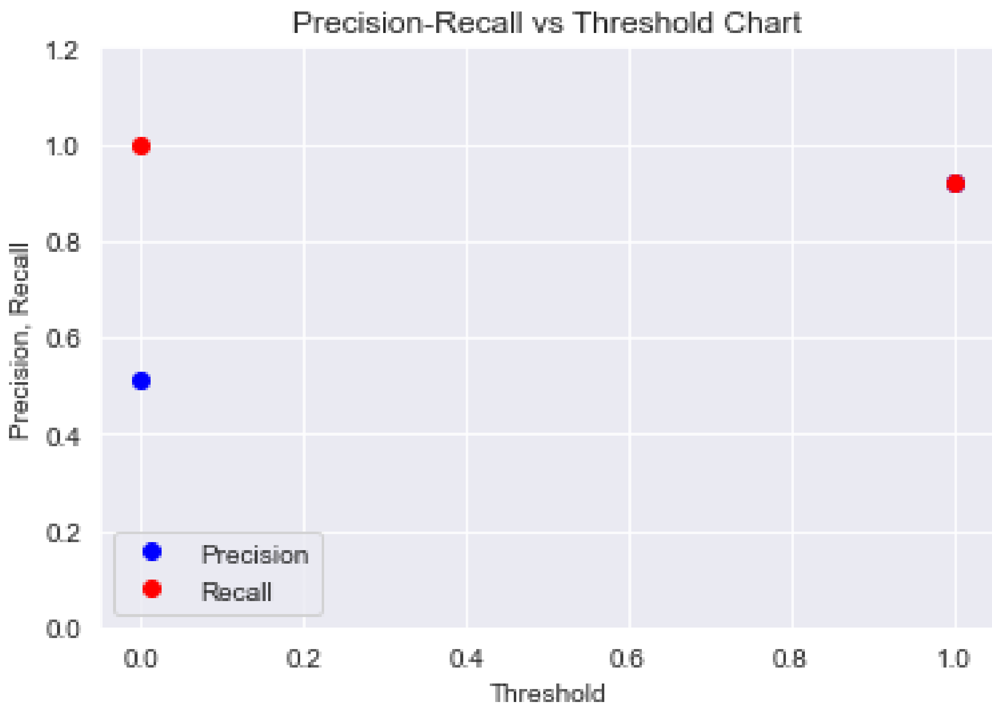
[48]:
```
Text(0.5, 1.0, 'Log. Reg.')
```



[49]:
```python
precision, recall, thresholds = precision_recall_curve(y, pred)
plt.title("Precision-Recall vs Threshold Chart")
plt.plot(thresholds, precision[: -1], "bo", label="Precision")
plt.plot(thresholds, recall[: -1], "ro", label="Recall")
```

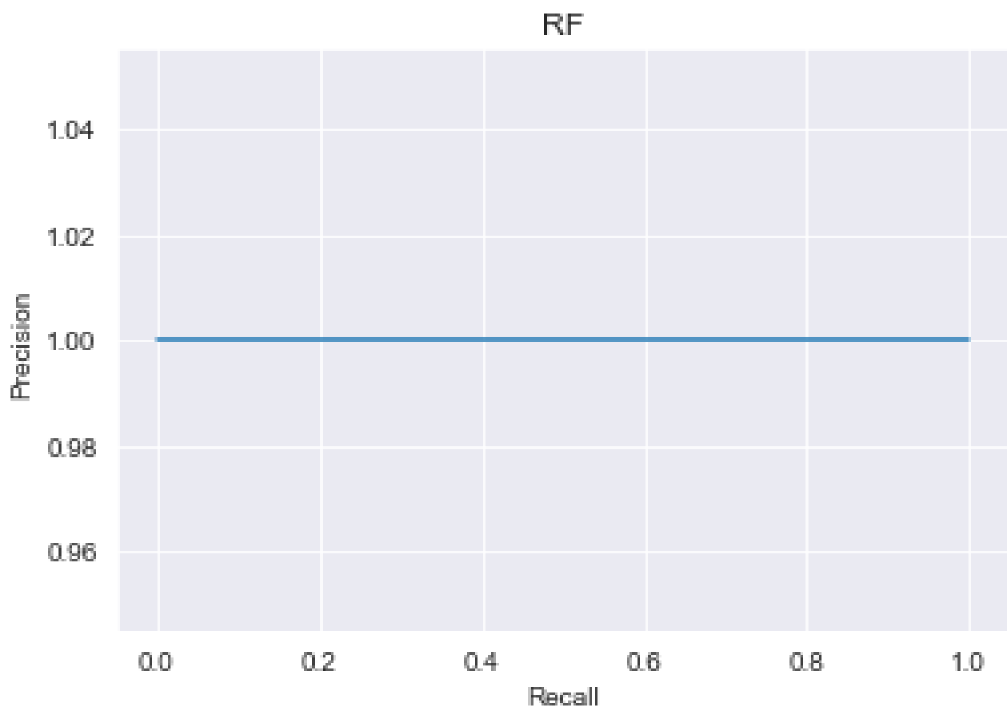
```python
plt.ylabel("Precision, Recall")
plt.xlabel("Threshold")
plt.legend(loc="lower left")
plt.ylim([0,1.2])
```

[49]: (0.0, 1.2)



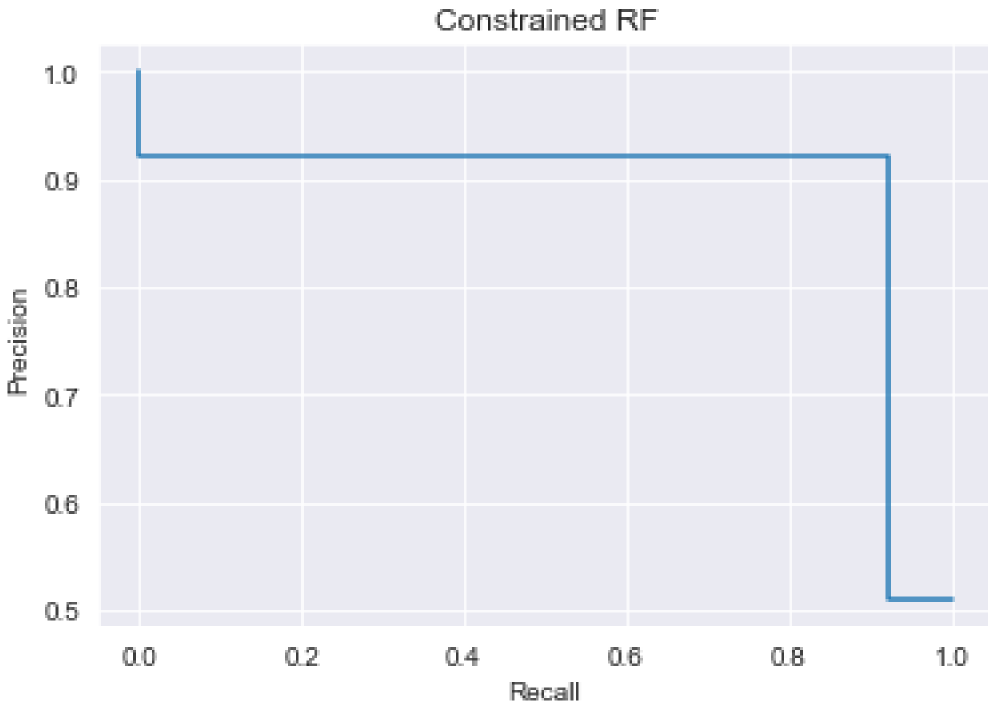
[50]:
```python
precision, recall, _ = precision_recall_curve(y, pred2)
disp = PrecisionRecallDisplay(precision=precision, recall=recall)
disp.plot()
disp.ax_.set_title('RF')
```

[50]: Text(0.5, 1.0, 'RF')



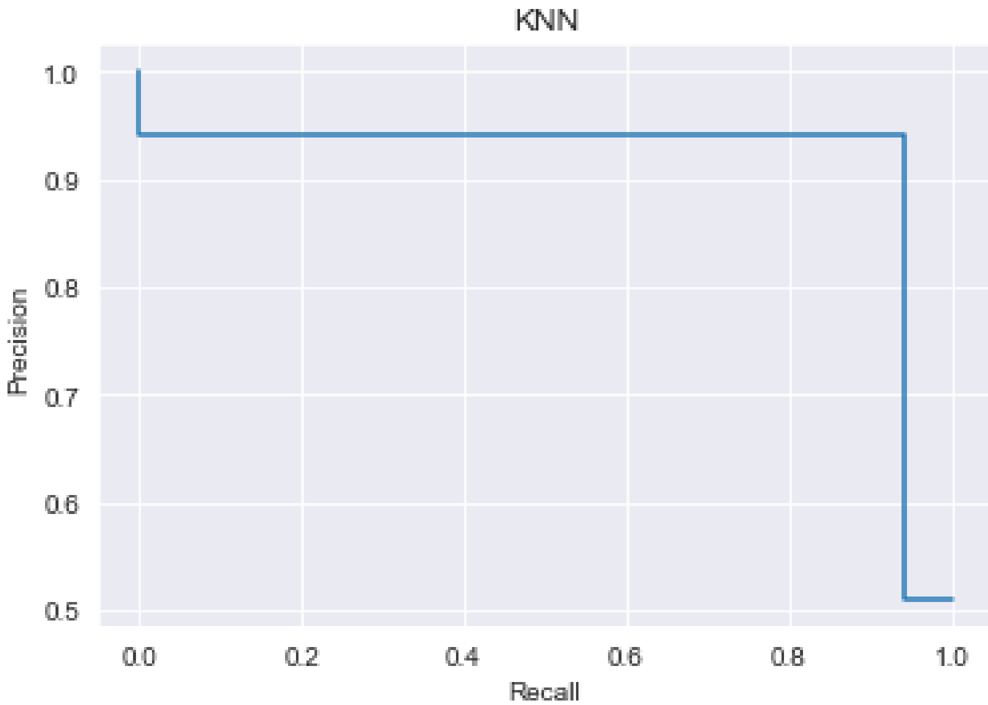
[51]:
```
precision, recall, _ = precision_recall_curve(y, pred3)
disp = PrecisionRecallDisplay(precision=precision, recall=recall)
disp.plot()
disp.ax_.set_title('Constrained RF')
```

[51]: Text(0.5, 1.0, 'Constrained RF')



[52]:
```
precision, recall, _ = precision_recall_curve(y, pred4)
disp = PrecisionRecallDisplay(precision=precision, recall=recall)
disp.plot()
disp.ax_.set_title('KNN')
```

[52]:
```
Text(0.5, 1.0, 'KNN')
```



Now we know! Unconstrained Random Forest is overfitting.

1.2.4 2.4. ROC Curve

The last performance metric for classifications we wil learn in class today is the ROC curves. This is also very popular among data scientists.

[53]:
```
from sklearn.metrics import roc_curve, roc_auc_score
```

[54]:
```
# Calculate ROC curve from y and predictions
fpr, tpr, thresholds = roc_curve(y, pred)
lr_df = pd.DataFrame({'FPR': fpr, 'TPR' : tpr, 'Thresholds' : thresholds})
```

[55]:
```
fpr, tpr, thresholds = roc_curve(y, pred2)
rf_df = pd.DataFrame({'FPR': fpr, 'TPR' : tpr, 'Thresholds' : thresholds})
```

[56]:
```
fpr, tpr, thresholds = roc_curve(y, pred3)
crf_df = pd.DataFrame({'FPR': fpr, 'TPR' : tpr, 'Thresholds' : thresholds})
```

[57]:
```
fpr, tpr, thresholds = roc_curve(y, pred4)
knn_df = pd.DataFrame({'FPR': fpr, 'TPR' : tpr, 'Thresholds' : thresholds})
```

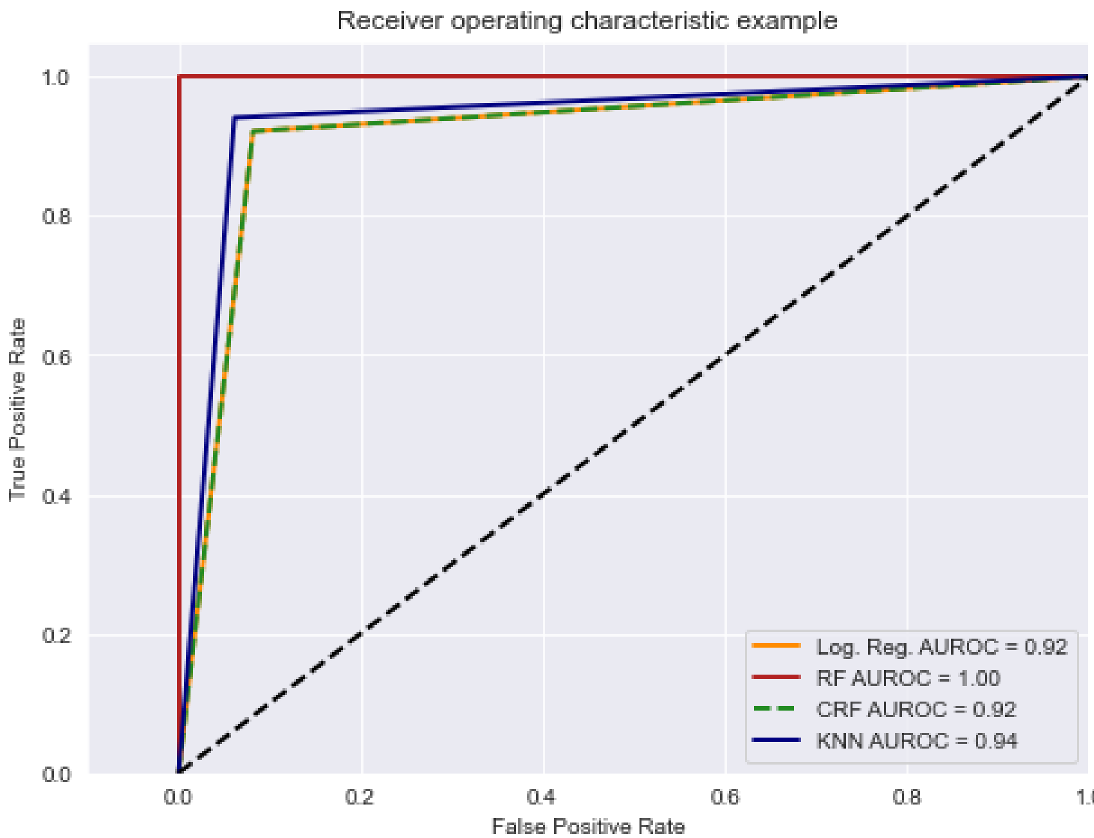
[58]:
```
lr_df.head()
```

[58]:
```
        FPR       TPR  Thresholds
0  0.000000  0.000000           2
1  0.081633  0.921569           1
2  1.000000  1.000000           0
```

[59]:
```
fig = plt.figure(figsize=(8,6))

ax = plt.subplot(111)
ax.plot(lr_df.FPR, lr_df.TPR, color='darkorange',
         linewidth=2, label='Log. Reg. AUROC = {:0.2f}'.format(roc_auc_score(y,␣
 ↪pred)))
ax.plot(rf_df.FPR, rf_df.TPR, color='firebrick',
         linewidth=2, label='RF AUROC = {:0.2f}'.format(roc_auc_score(y,␣
 ↪pred2)))
ax.plot(crf_df.FPR, crf_df.TPR, color='forestgreen', linestyle='--',
         linewidth=2, label='CRF AUROC = {:0.2f}'.format(roc_auc_score(y,␣
 ↪pred3)))
ax.plot(knn_df.FPR, knn_df.TPR, color='navy',
         linewidth=2, label='KNN AUROC = {:0.2f}'.format(roc_auc_score(y,␣
 ↪pred4)))

ax.plot([0, 1], [0, 1], color='k', lw=2, linestyle='--')
ax.set_xlim([-0.1, 1.0])
ax.set_ylim([0.0, 1.05])
ax.set_xlabel('False Positive Rate')
ax.set_ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
ax.legend(loc="lower right")
plt.show()
```



Congratulations, you have completed the Classification Workbook!

```
[ ]:
```