In [1]:
```python
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt # data visualization
import seaborn as sns # statistical data visualization
from sklearn.metrics import roc_auc_score, accuracy_score, precision_score, recall_score, f1_score
from sklearn.model_selection import cross_validate
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, PrecisionRecallDisplay
from sklearn.metrics import classification_report, precision_recall_fscore_support, roc_curve
```

In [2]:
```python
initial_data = pd.read_csv('data.csv')
```

In [3]:
```python
# Removing 'ID' column
initial_data.drop(initial_data.columns[0], axis=1, inplace=True)

for column in initial_data.columns:
    if "Unnamed" in column:
        initial_data.drop(column, axis = 1, inplace=True)
```

In [4]:
```python
# preview the dataset
initial_data.head()
```

Out[4]:

	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	sym
0	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	
1	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	
2	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	
3	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	
4	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	

5 rows × 31 columns

In [5]:
```python
# Convert to binary data
initial_data['diagnosis']=initial_data['diagnosis'].map({'M':1,'B':0})
initial_data.head()
```

Out[5]:

	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	sym
0	1	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	
1	1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	
2	1	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	
3	1	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	
4	1	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	

5 rows × 31 columns

In [6]:
```python
# Get X and y
X = initial_data[['radius_mean', 'texture_mean', 'perimeter_mean', 'area_mean', 'smoothness_mean', 'compactne
                  'radius_se', 'texture_se', 'perimeter_se', 'area_se', 'smoothness_se', 'compactness_se', 'co
                  'radius_worst', 'texture_worst', 'perimeter_worst', 'area_worst', 'smoothness_worst', 'compa

y = initial_data['diagnosis']
```

1. Split the dataset into training set and test set (80, 20).

In [7]:
```python
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2)
```

In [8]:
```
print("Shape of X_train: ",X_train.shape)
print("Shape of X_test: ", X_test.shape)
print("Shape of y_train: ",y_train.shape)
print("Shape of y_test",y_test.shape)
```

```
Shape of X_train:  (455, 30)
Shape of X_test:  (114, 30)
Shape of y_train:  (455,)
Shape of y_test (114,)
```

2. Using scikit-learn's DecisionTreeClassifier, train a supervised learning model that can be used to generate predictions for your data.

In [9]:
```
# DecisionTreeClassifier
classifier = DecisionTreeClassifier()
classifier.fit(X_train, y_train)

y_pred = classifier.predict(X_test)
```

Accuracy, Precision, Recall values

In [10]:
```
accuracy_score = accuracy_score(y_test, y_pred)
print("Accuracy of the model in test data: ", accuracy_score)
```

```
Accuracy of the model in test data:  0.9122807017543859
```

In [11]:
```
precision_recall_fscore_support(y_test, y_pred)

precision_values = precision_recall_fscore_support(y_test, y_pred)[0]
recall_values = precision_recall_fscore_support(y_test, y_pred)[1]

print("precision values: ", precision_values)
print("recall values: ", recall_values)
```

```
precision values:  [0.94285714 0.86363636]
recall values:  [0.91666667 0.9047619 ]
```

Classification Report

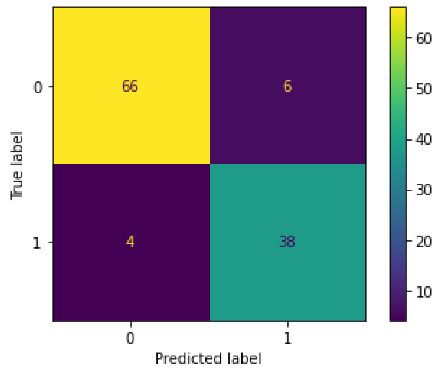
In [12]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.94      0.92      0.93        72
           1       0.86      0.90      0.88        42

    accuracy                           0.91       114
   macro avg       0.90      0.91      0.91       114
weighted avg       0.91      0.91      0.91       114
```

Confusion Matrix

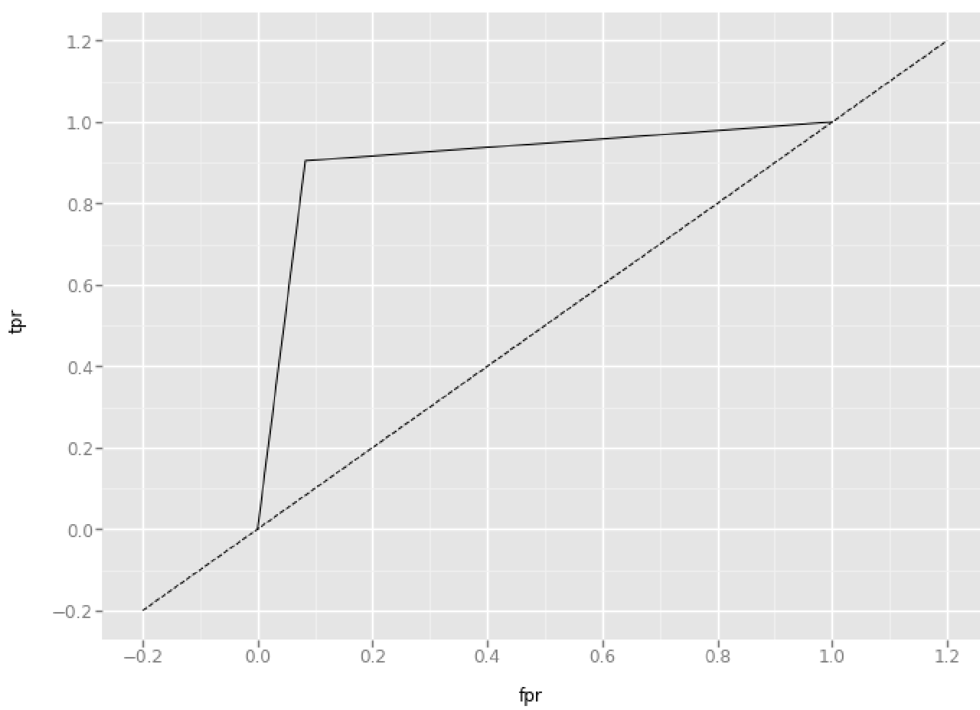
In [13]:
```
ConfusionMatrixDisplay.from_predictions(y_test, y_pred)
```

Out[13]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fb21bcef7c0>



ROC curve

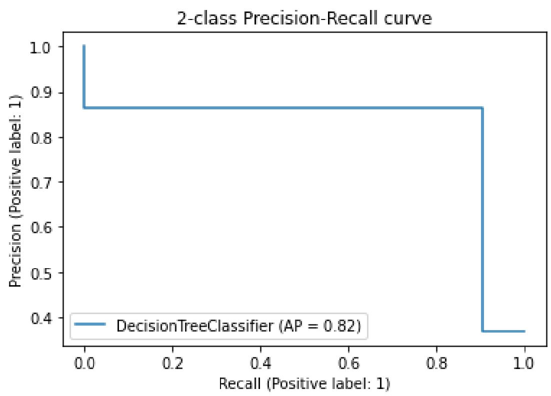
In [14]:
```
from sklearn.metrics import roc_curve, auc
from pandas import Timestamp
import rpy2
from ggplot import *

preds = classifier.predict_proba(X_test)[:,1]
fpr, tpr, _ = roc_curve(y_test, preds)

df = pd.DataFrame(dict(fpr=fpr, tpr=tpr))
ggplot(df, aes(x='fpr', y='tpr')) +\
 geom_line() +\
 geom_abline(linetype='dashed')
```



Out[14]: <ggplot: (8775185147923)>

Precision Recall Display

In [15]:
```
display = PrecisionRecallDisplay.from_estimator(
    classifier, X_test, y_test, name="DecisionTreeClassifier"
)
_ = display.ax_.set_title("2-class Precision-Recall curve")
```



3. Similarly as in previous step, train another Decision Tree Classifier - but in this case set the maximum depth of the tree to 1 (max_depth = 1). Use the same training and test set as you used for the Decision Tree in the previous step.

In [23]:
```
# DecisionTreeClassifier
clf = DecisionTreeClassifier(max_depth=1)
clf.fit(X_train, y_train)

y_pred = clf.predict(X_test)
```

In [29]:
```
from sklearn.metrics import accuracy_score
accuracy_score = accuracy_score(y_test, y_pred)
print("Accuracy of the model in test data: ", accuracy_score)
```

```
Accuracy of the model in test data:  0.8859649122807017
```

In [18]:
```
precision_recall_fscore_support(y_test, y_pred)

precision_values = precision_recall_fscore_support(y_test, y_pred)[0]
recall_values = precision_recall_fscore_support(y_test, y_pred)[1]

print("precision values: ", precision_values)
print("recall values: ", recall_values)
```

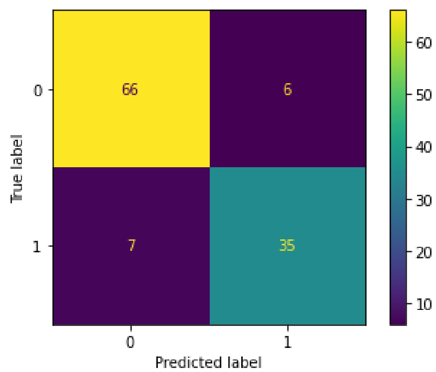
```
precision values:  [0.90410959 0.85365854]
recall values:  [0.91666667 0.83333333]
```

In [19]:
```
print(classification_report(y_test, y_pred))
```

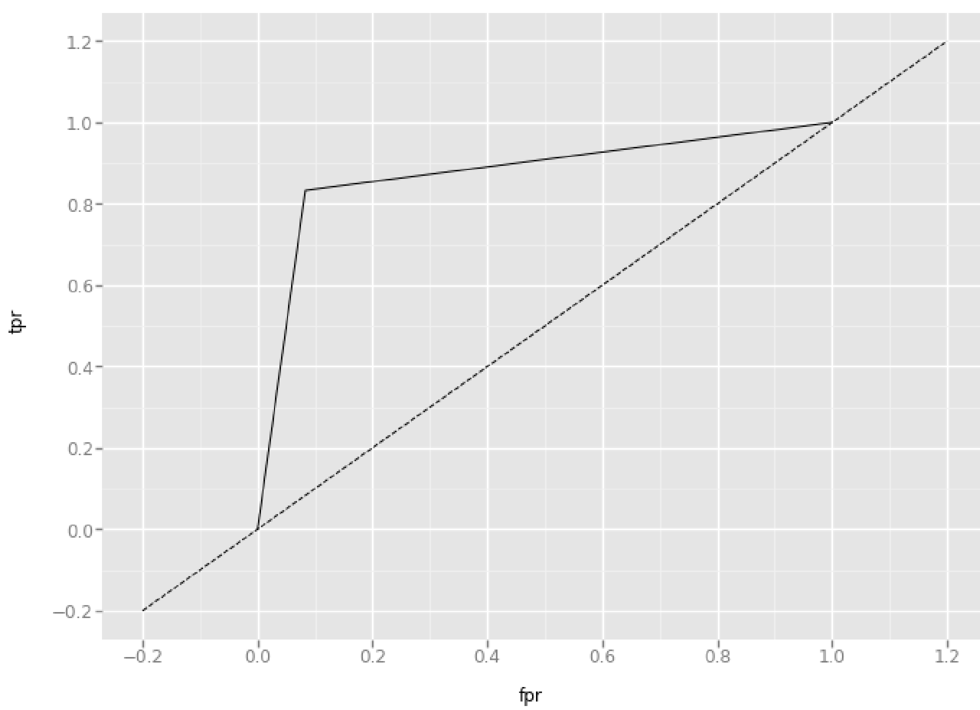
```
              precision    recall  f1-score   support

           0       0.90      0.92      0.91        72
           1       0.85      0.83      0.84        42

    accuracy                           0.89       114
   macro avg       0.88      0.88      0.88       114
weighted avg       0.89      0.89      0.89       114
```

In [20]:
```
ConfusionMatrixDisplay.from_predictions(y_test, y_pred)
```

Out[20]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fb21bafa2e0>
```

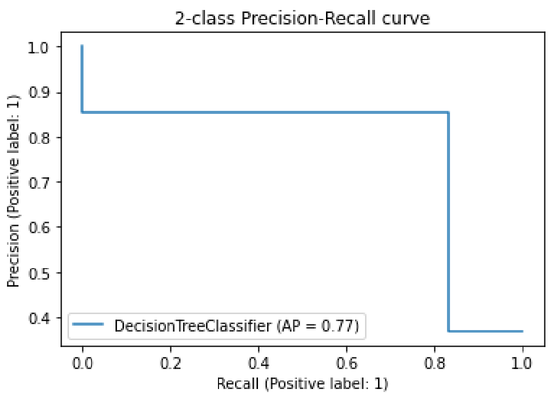


In [21]:
```
preds = clf.predict_proba(X_test)[:,1]
fpr, tpr, _ = roc_curve(y_test, preds)

df = pd.DataFrame(dict(fpr=fpr, tpr=tpr))
ggplot(df, aes(x='fpr', y='tpr')) +\
 geom_line() +\
 geom_abline(linetype='dashed')
```



Out[21]:
```
<ggplot: (8775185389891)>
```

In [22]:
```python
display = PrecisionRecallDisplay.from_estimator(
    clf, X_test, y_test, name="DecisionTreeClassifier"
)
_ = display.ax_.set_title("2-class Precision-Recall curve")
```



4. Report on the six evaluation metrics listed in objective for both the models, and com- pare their results.

The second stats are for max_depth=1

1. The accuracy of your model on the test data

0.912 vs 0.886 first model gives better result.

2. The precision and recall values

precision values: [0.94285714 0.86363636] recall values: [0.91666667 0.9047619]

precision values: [0.90410959 0.85365854] recall values: [0.91666667 0.83333333]

first model gives better result.

3. A classification report

```
              precision    recall  f1-score   support

           0       0.94      0.92      0.93        72
           1       0.86      0.90      0.88        42

    accuracy                           0.91       114
```

macro avg 0.90 0.91 0.91 114 weighted avg 0.91 0.91 0.91 114

```
              precision    recall  f1-score   support

           0       0.90      0.92      0.91        72
           1       0.85      0.83      0.84        42

    accuracy                           0.89       114
```

macro avg 0.88 0.88 0.88 114 weighted avg 0.89 0.89 0.89 114

first model gives better result.

4. The confusion matrix for this experiment

The first model has 4 in FP, 6 in FN The second model has 7 in FP, 6 in FN

first model gives better result.

5. An ROC curve

The first model is closer to the upper left corner.

6. A Precision/Recall curve

The first model is closer to the upper right corner.

In conclusion, DecisionTreeClassifier with more depths provides more accurate result for predictions, compared to DecisionTreeClassifier with 1 as the max depth.