In [3]:
```python
# read the data into a pandas DataFrame
import pandas as pd
path = 'dataset/pima-indians-diabetes.data'
col_names = ['pregnant', 'glucose', 'bp', 'skin', 'insulin', 'bmi', 'pe
digree', 'age', 'label']
pima = pd.read_csv(path, header=None, names=col_names)
```

In [5]:
```python
# print the first five data
pima.head()
```

Out[5]:

	pregnant	glucose	bp	skin	insulin	bmi	pedigree	age	label
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 [6]:
```python
# define X and y
feature_cols = ['pregnant', 'insulin', 'bmi', 'age']
X = pima[feature_cols]
y = pima.label
```

In [8]:
```python
# split X and y into training and testing sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=
0)
```

In [70]:
```python
import warnings
warnings.filterwarnings('ignore')
# train a logistic regression model on the training set
from sklearn.linear_model import LogisticRegression
```

```
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

Out[70]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=
True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='warn', tol=0.0001, verbos
e=0,
                   warm_start=False)
```

In [11]:

```
# make class predication for the testing set
y_pred_class = logreg.predict(X_test)
```

Classification accuracy: percentage of correct predictions

In [12]:

```
# calculation accuracy
from sklearn import metrics
print(metrics.accuracy_score(y_test, y_pred_class))
```

```
0.6927083333333334
```

Null accuracy: accuracy that could be achieved by always predicting the most frequent class

In [13]:

```
# examise the class distribution of the testing set (using a Pandas Ser
ies Method)
y_test.value_counts()
```

Out[13]:

```
0    130
1     62
Name: label, dtype: int64
```

In [14]:

```
# calculate the percentage of ones
y_test.mean()
```

Out[14]:

```
0.3229166666666667
```

In [16]:
```python
y_pred_class.mean()
```

Out[16]:
```
0.140625
```

In [17]:
```python
# calculate the percentage of zeros
1 - y_test.mean()
```

Out[17]:
```
0.6770833333333333
```

In [18]:
```python
# calculate null accuracy (for binary classification problems coded as
 0/1)
max(y_test.mean(), 1 - y_test.mean())
```

Out[18]:
```
0.6770833333333333
```

In [19]:
```python
# calculate null accuracy (for multi-class classification problems)
y_test.value_counts() / len(y_test)
```

Out[19]:
```
0    0.677083
1    0.322917
Name: label, dtype: float64
```

In [20]:
```python
# calculate null accuracy (for multi-class classification problems)
y_test.value_counts().head(1) / len(y_test)
```

Out[20]:
```
0    0.677083
Name: label, dtype: float64
```

Comparing the true and predicted response values

In [21]:
```python
# print the first 25 true and predicted response
print('True:', y_test.values[0:25])
print('Pred:', y_pred_class[0:25])
```

```
True: [1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 0 1 0 0 0 1 1 0 0 0]
Pred: [0 0 0 0 0 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
```

Conclusion: . Classification accuracy is the easiest classification metric to understand . But, it does not tell you the underlying distribution of response values . And, it does not tell you what "types" of errors your classifier is making

Confusion matrix

Table that describes the performance of a classification model

In [22]:
```
# Important: first argument is true values, second argumnet is predicte
d values
print(metrics.confusion_matrix(y_test, y_pred_class))
```

```
[[118  12]
 [ 47  15]]
```

```
    . Every observation in the testing set is represented in exa
ctly one box.
    . It's a 2x2 matrix because there are 2 response classes.
    . The format shown here is not universal.
```

Basic terminology:

```
    . True Positives (TP): we correctly predicted that they do h
ave diabetes
    . True Negatives (TN): we correctly predicted that they do
n't have diabetes
    . False Positives (FP): we incorrectly predicted that they d
o have diabetes (a "Type I error")
    . False Negatives (FN): we incorrectly predicted that they d
on't have diabetes (a "Type II error")
```

In [23]:
```
# print the first 25 true and predicated response
print('True:', y_test.values[0:25])
print('Pred:', y_pred_class[0:25])
```

```
True: [1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 0 1 0 0 0 1 1 0 0 0]
Pred: [0 0 0 0 0 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
```

In [24]:
```
# save confusion matrix and slice into four pieces
confusion = metrics.confusion_matrix(y_test, y_pred_class)
TP = confusion[1, 1]
TN = confusion[0, 0]
FP = confusion[0, 1]
FN = confusion[1, 0]
```

Metrics computed from a confusion matrix

Classification Accuracy: Overall, how often is the classifier correct?

In [25]:
```
print((TP + TN) / float(TP + TN + FP + FN))
print(metrics.accuracy_score(y_test, y_pred_class))
```

```
0.6927083333333334
0.6927083333333334
```

Classification Error: Overall, how often is the classifier incorrect?

Also known as "Misclassification Rate"

In [26]:
```
print((FP + FN) / float(TP + TN + FP + FN))
print(metrics.accuracy_score(y_test, y_pred_class))
```

```
0.3072916666666667
0.6927083333333334
```

Sensitivity: When the actual value is positive, how often is the prediction correct?

```
. How "sensitive" is the classifier to detecting positive in
stances?
    . Also known as "True Positive Rate" or "Recall"
```

In [27]:
```
print(TP / float(TP + FN))
print(metrics.recall_score(y_test, y_pred_class))
```

```
0.24193548387096775
0.24193548387096775
```

Specificity: When the actual value is negative, how often is the prediction correct?

```
    .How "specific" (or "selective") is the classifier in pred
icting positive instances?
```

In [31]:
```
print(TN / float(TN + FP))
```

```
0.9076923076923077
```

False Positive Rate: When the actual value is negative, how often is the prediction incorrect?

In [32]:
```
print(FP / float(TN + FP))
```

```
0.09230769230769231
```

Precision: When a positive value is predicted, how often is the prediction correct?

```
. How "precise" is the classifier when predicting positive in
stances?
```

In [34]:
```
print(TP / float(TP + FP))
print(metrics.precision_score(y_test, y_pred_class))
```

```
0.5555555555555556
0.5555555555555556
```

In [ ]:
```
print(TP / float(TP + FP))
print(metrics.precision_score(y_test, y_pred_class))
```

Many other metrics can be computed: F1 score, Matthews correlation coefficient, etc.

Conclusion:

```
    . Confusion matrix gives you a more complete picture of how
 your classifier is performing.
    . Also allows you to compute various classification metrics,
 and these metrics can guide your model selection.
```

Which metrics should you focus on?

```
    . Choice of metric depends on your business objective.
    . Spam filter (positive class is "spam"): Optimize for preci
sion or specificity because false negatives
      (spam goes to the inbox) are more acceptable than false po
sitives (non-spam is caught by the spam filter).
    . Fraudulent transaction detector (positive class is "frau
d"): Optimize for sensitivity because false positives
      (normal transactions that are flagged as possible fraud) a
re more acceptable than false negatives
      (fraudulent transactions that are not detected).
```

Adjusting the classification threshold

In [35]:
```
# print the first 10 predicted responses
logreg.predict(X_test)[0:10]
```

Out[35]: array([0, 0, 0, 0, 0, 0, 0, 1, 0, 1], dtype=int64)

In [38]:
```
# print the first 10 predicated probabilites of class membership
logreg.predict_proba(X_test)[0:10, :]
```

Out[38]:
```
array([[0.63247571, 0.36752429],
       [0.71643656, 0.28356344],
       [0.71104114, 0.28895886],
       [0.5858938 , 0.4141062 ],
       [0.84103973, 0.15896027],
       [0.82934844, 0.17065156],
       [0.50110974, 0.49889026],
       [0.48658459, 0.51341541],
       [0.72321388, 0.27678612],
       [0.32810562, 0.67189438]])
```

In [39]:
```
# print the first 10 predicated probabilites for class 1
logreg.predict_proba(X_test)[0:10, 1]
```

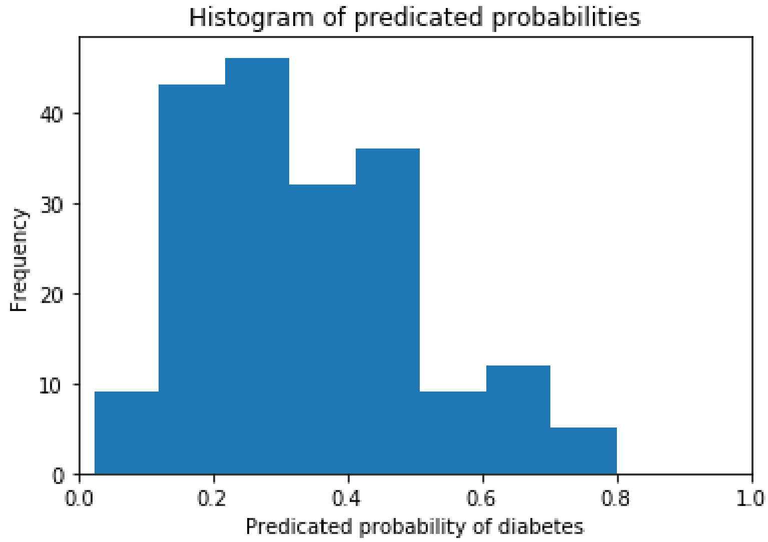
Out[39]:
```
array([0.36752429, 0.28356344, 0.28895886, 0.4141062 , 0.15896027,
       0.17065156, 0.49889026, 0.51341541, 0.27678612, 0.67189438])
```

In [42]:
```
y_pred_prob = logreg.predict_proba(X_test)[:, 1]
```

In [43]:
```
# allow plots to appear in the notebook
%matplotlib inline
import matplotlib.pyplot as plt
```

In [44]:
```
# histogram of predicated probabilites
plt.hist(y_pred_prob, bins=8)
plt.xlim(0, 1)
plt.title('Histogram of predicated probabilities')
plt.xlabel('Predicated probability of diabetes')
plt.ylabel('Frequency')
```

Out[44]: Text(0, 0.5, 'Frequency')



Decrease the threshold for predicting diabetes in order to increase the sensitivity of the classifier

In [45]:
```
# predicate diabetes if the predicated probability is greater than 0.3
from sklearn.preprocessing import binarize
y_pred_class = binarize([y_pred_prob], 0.3)[0]
```

In [46]:
```
# print the first 10 predicated probabilites
y_pred_prob[0:10]
```

Out[46]:
```
array([0.36752429, 0.28356344, 0.28895886, 0.4141062 , 0.15896027,
       0.17065156, 0.49889026, 0.51341541, 0.27678612, 0.67189438])
```

In [47]:
```
# print the first 10 predicated class with the lower threshold
y_pred_class[0:10]
```

Out[47]:
```
array([1., 0., 0., 1., 0., 0., 1., 1., 0., 1.])
```

In [49]:
```
# previous confusion matrix (default threshold of 0.5)
print(confusion)
```

```
[[118  12]
 [ 47  15]]
```

In [50]:
```
# new confusion matrix (threshold of 0.3)
print(metrics.confusion_matrix(y_test, y_pred_class))
```

```
[[80 50]
 [16 46]]
```

In [51]:
```
# sensitivity has increased (used to be 0.24)
print(46 / float(46 + 16))
```

```
0.7419354838709677
```

In [52]:
```
# specificity has decreased (used to be 0.91)
print(80 / float(80 + 50))
```

```
0.6153846153846154
```

Conclusion: . Threshold of 0.5 is used by default (for binary problems) to convert predicted probabilities into class predictions. . Threshold can be adjusted to increase sensitivity or specificity. . Sensitivity and specificity have an inverse relationship.

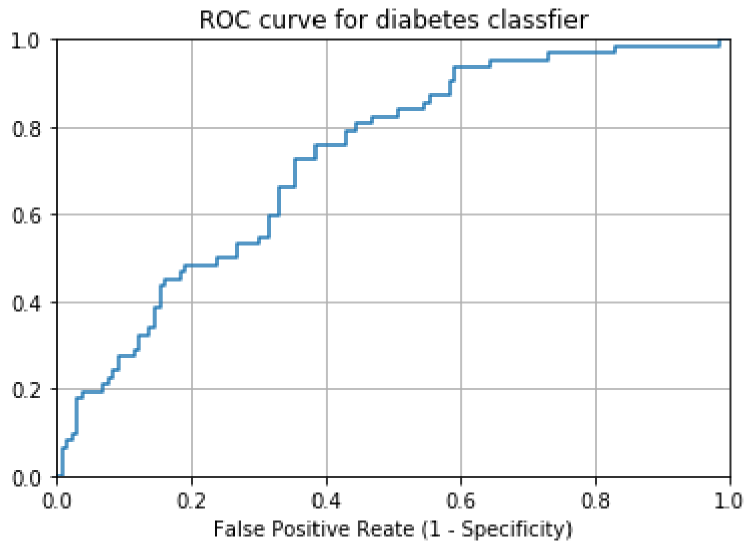
ROC Curves and Area Under the Curve (AUC)

Question: Wouldn't it be nice if we could see how sensitivity and specificity are affected by various thresholds, without actually changing the threshold?

Answer: Plot the ROC curve!

In [53]:
```
# Important : first argument is true values, second argument is predicated probabilities
fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred_prob)
plt.plot(fpr, tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
```

```python
plt.title('ROC curve for diabetes classfier')
plt.xlabel('False Positive Reate (1 - Specificity)')
plt.grid(True)
```



. ROC curve can help you to choose a threshold that balances sensitivity and specificity in a way that makes sense for your particular context. . You can't actually see the thresholds used to generate the curve on the ROC curve itself.

In [63]:
```python
# define a function that accepts a threshold and prints sensitivity and
 specificity
def evaluate_threshold(threshold):
    print('Sensitivity:', tpr[thresholds > threshold][-1])
    print('Specificity:', 1 - fpr[thresholds > threshold][-1])
```

In [64]:
```python
evaluate_threshold(0.5)
```

```
Sensitivity: 0.24193548387096775
Specificity: 0.9076923076923077
```

In [65]:
```python
evaluate_threshold(0.3)
```

```
Sensitivity: 0.7258064516129032
Specificity: 0.6153846153846154
```

AUC is the percentage of the ROC plot that is underneath the curve:

In [67]:
```
# Important: first argument is true  values, second argument is predica
ted probabilities
print(metrics.roc_auc_score(y_test, y_pred_prob))
```

```
0.7245657568238213
```

. AUC is useful as a single number summary of classifier performance. . If you randomly chose one positive and one negative observation, AUC represents the likelihood that your classifier will assign a higher predicted probability to the positive observation. . AUC is useful even when there is high class imbalance (unlike classification accuracy).

In [69]:
```
import warnings
warnings.filterwarnings('ignore')
# calculate cross-validated AUC
from sklearn.model_selection import cross_val_score
cross_val_score(logreg, X, y, cv=10, scoring='roc_auc').mean()
```

Out[69]:
```
0.7378233618233618
```

Confusion matrix advantages: . Allows you to calculate a variety of metrics . Useful for multi-class problems (more than two response classes)

ROC/AUC advantages: . Does not require you to set a classification threshold . Still useful when there is high class imbalance

In [ ]:

In [ ]: