Module 3

May 20, 2019

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*You are currently looking at **version 1.0** of this notebook. To download notebooks and datafiles, as well as get help on Jupyter notebooks in the Coursera platform, visit the Jupyter Notebook FAQ course resource.*

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1 Applied Machine Learning: Module 3 (Evaluation)

1.1 Evaluation for Classification

1.1.1 Preamble

```
In [1]: %matplotlib notebook
        import numpy as np
        import pandas as pd
        import seaborn as sns
        import matplotlib.pyplot as plt
        from sklearn.model_selection import train_test_split
        from sklearn.datasets import load_digits

        dataset = load_digits()
        X, y = dataset.data, dataset.target

        for class_name, class_count in zip(dataset.target_names, np.bincount(datase
            print(class_name,class_count)
```

```
0 178
1 182
2 177
3 183
4 181
5 182
6 181
7 179
8 174
9 180
```

```
In [2]: # Creating a dataset with imbalanced binary classes:
        # Negative class (0) is 'not digit 1'
        # Positive class (1) is 'digit 1'
        y_binary_imbalanced = y.copy()
        y_binary_imbalanced[y_binary_imbalanced != 1] = 0

        print('Original labels:\t', y[1:30])
        print('New binary labels:\t', y_binary_imbalanced[1:30])
```

```
Original labels:         [1 2 3 4 5 6 7 8 9 0 1 2 3 4 5 6 7 8 9 0 1 2 3 4 5 6 7 8 9
New binary labels:         [1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 (
```

```
In [3]: np.bincount(y_binary_imbalanced)    # Negative class (0) is the most freque
```

```
Out[3]: array([1615,  182])
```

```
In [4]: X_train, X_test, y_train, y_test = train_test_split(X, y_binary_imbalanced,

        # Accuracy of Support Vector Machine classifier
        from sklearn.svm import SVC

        svm = SVC(kernel='rbf', C=1).fit(X_train, y_train)
        svm.score(X_test, y_test)
```

```
Out[4]: 0.90888888888888886
```

1.1.2 Dummy Classifiers

DummyClassifier is a classifier that makes predictions using simple rules, which can be useful as a baseline for comparison against actual classifiers, especially with imbalanced classes.

```
In [5]: from sklearn.dummy import DummyClassifier

        # Negative class (0) is most frequent
        dummy_majority = DummyClassifier(strategy = 'most_frequent').fit(X_train, y
        # Therefore the dummy 'most_frequent' classifier always predicts class 0
        y_dummy_predictions = dummy_majority.predict(X_test)

        y_dummy_predictions
```

```
Out[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, 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, 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, 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, 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, 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, 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, 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, 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, 0, 0, 0, 0, 0, 0, 0,
                   0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

In [6]:
```
dummy_majority.score(X_test, y_test)
```

Out[6]:
```
0.9044444444444445
```

In [7]:
```
svm = SVC(kernel='linear', C=1).fit(X_train, y_train)
svm.score(X_test, y_test)
```

Out[7]:
```
0.9777777777777775
```

1.1.3 Confusion matrices

Binary (two-class) confusion matrix

In [8]:
```
from sklearn.metrics import confusion_matrix

# Negative class (0) is most frequent
dummy_majority = DummyClassifier(strategy = 'most_frequent').fit(X_train, y
y_majority_predicted = dummy_majority.predict(X_test)
confusion = confusion_matrix(y_test, y_majority_predicted)

print('Most frequent class (dummy classifier)\n', confusion)
```

```
Most frequent class (dummy classifier)
 [[407   0]
 [ 43   0]]
```

In [9]:
```
# produces random predictions w/ same class proportion as training set
dummy_classprop = DummyClassifier(strategy='stratified').fit(X_train, y_tra
y_classprop_predicted = dummy_classprop.predict(X_test)
confusion = confusion_matrix(y_test, y_classprop_predicted)

print('Random class-proportional prediction (dummy classifier)\n', confusio
```

```
Random class-proportional prediction (dummy classifier)
 [[369  38]
 [ 39   4]]
```

In [10]:
```
svm = SVC(kernel='linear', C=1).fit(X_train, y_train)
svm_predicted = svm.predict(X_test)
confusion = confusion_matrix(y_test, svm_predicted)

print('Support vector machine classifier (linear kernel, C=1)\n', confusio
```

```
Support vector machine classifier (linear kernel, C=1)
 [[402   5]
 [  5  38]]
```

In [11]:
```
from sklearn.linear_model import LogisticRegression

lr = LogisticRegression().fit(X_train, y_train)
lr_predicted = lr.predict(X_test)
confusion = confusion_matrix(y_test, lr_predicted)

print('Logistic regression classifier (default settings)\n', confusion)
```

```
Logistic regression classifier (default settings)
 [[401   6]
 [  6  37]]
```

In [12]:
```
from sklearn.tree import DecisionTreeClassifier

dt = DecisionTreeClassifier(max_depth=2).fit(X_train, y_train)
tree_predicted = dt.predict(X_test)
confusion = confusion_matrix(y_test, tree_predicted)

print('Decision tree classifier (max_depth = 2)\n', confusion)
```

```
Decision tree classifier (max_depth = 2)
 [[400   7]
 [ 17  26]]
```

1.1.4 Evaluation metrics for binary classification

In [13]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score,
# Accuracy = TP + TN / (TP + TN + FP + FN)
# Precision = TP / (TP + FP)
# Recall = TP / (TP + FN)  Also known as sensitivity, or True Positive Rat
# F1 = 2 * Precision * Recall / (Precision + Recall)
print('Accuracy: {:.2f}'.format(accuracy_score(y_test, tree_predicted)))
print('Precision: {:.2f}'.format(precision_score(y_test, tree_predicted)))
print('Recall: {:.2f}'.format(recall_score(y_test, tree_predicted)))
print('F1: {:.2f}'.format(f1_score(y_test, tree_predicted)))
```

```
Accuracy: 0.95
Precision: 0.79
Recall: 0.60
F1: 0.68
```

In [14]:
```python
# Combined report with all above metrics
from sklearn.metrics import classification_report

print(classification_report(y_test, tree_predicted, target_names=['not 1',
```

```
             precision    recall  f1-score   support

      not 1       0.96      0.98      0.97       407
          1       0.79      0.60      0.68        43

avg / total       0.94      0.95      0.94       450
```

In [15]:
```python
print('Random class-proportional (dummy)\n',
      classification_report(y_test, y_classprop_predicted, target_names=['
print('SVM\n',
      classification_report(y_test, svm_predicted, target_names = ['not 1'
print('Logistic regression\n',
      classification_report(y_test, lr_predicted, target_names = ['not 1',
print('Decision tree\n',
      classification_report(y_test, tree_predicted, target_names = ['not 1
```

```
Random class-proportional (dummy)
              precision    recall  f1-score   support

      not 1       0.90      0.91      0.91       407
          1       0.10      0.09      0.09        43

avg / total       0.83      0.83      0.83       450

SVM
              precision    recall  f1-score   support

      not 1       0.99      0.99      0.99       407
          1       0.88      0.88      0.88        43

avg / total       0.98      0.98      0.98       450

Logistic regression
              precision    recall  f1-score   support

      not 1       0.99      0.99      0.99       407
```

```
          1       0.86      0.86      0.86        43

avg / total       0.97      0.97      0.97       450

Decision tree
              precision    recall  f1-score   support

      not 1       0.96      0.98      0.97       407
          1       0.79      0.60      0.68        43

avg / total       0.94      0.95      0.94       450
```

1.1.5 Decision functions

In [16]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y_binary_imbalanced
y_scores_lr = lr.fit(X_train, y_train).decision_function(X_test)
y_score_list = list(zip(y_test[0:20], y_scores_lr[0:20]))

# show the decision_function scores for first 20 instances
y_score_list
```

Out[16]:
```
[(0, -23.172292973469546),
 (0, -13.542576515500063),
 (0, -21.717588760007867),
 (0, -18.903065133316439),
 (0, -19.733169947138638),
 (0, -9.7463217496747667),
 (1, 5.2327155658831135),
 (0, -19.308012306288916),
 (0, -25.099330209728528),
 (0, -21.824312362996),
 (0, -24.14378275072049),
 (0, -19.578811099762508),
 (0, -22.568371393280199),
 (0, -10.822590225240777),
 (0, -11.907918741521932),
 (0, -10.977026853802803),
 (1, 11.206811164226373),
 (0, -27.64415761980748),
 (0, -12.857692102545409),
 (0, -25.848149140240199)]
```

In [17]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y_binary_imbalanced
y_proba_lr = lr.fit(X_train, y_train).predict_proba(X_test)
y_proba_list = list(zip(y_test[0:20], y_proba_lr[0:20,1]))
```

```
# show the probability of positive class for first 20 instances
y_proba_list
```

Out[17]:
```
[(0, 8.6377579220606777e-11),
 (0, 1.3138118599563783e-06),
 (0, 3.6997386039099529e-10),
 (0, 6.1730972504865465e-09),
 (0, 2.6914925394345074e-09),
 (0, 5.8506057771143608e-05),
 (1, 0.99468934644404694),
 (0, 4.1175302368500096e-09),
 (0, 1.2574750894253029e-11),
 (0, 3.3252290754668869e-10),
 (0, 3.2695529799373086e-11),
 (0, 3.1407283576084884e-09),
 (0, 1.5800864117150149e-10),
 (0, 1.9943442430612578e-05),
 (0, 6.7368003023860014e-06),
 (0, 1.7089540581641637e-05),
 (1, 0.99998641880911131),
 (0, 9.8694940340195476e-13),
 (0, 2.6059983600823893e-06),
 (0, 5.9469113009063784e-12)]
```

1.1.6 Precision-recall curves

In [18]:
```
from sklearn.metrics import precision_recall_curve

precision, recall, thresholds = precision_recall_curve(y_test, y_scores_lr
closest_zero = np.argmin(np.abs(thresholds))
closest_zero_p = precision[closest_zero]
closest_zero_r = recall[closest_zero]

plt.figure()
plt.xlim([0.0, 1.01])
plt.ylim([0.0, 1.01])
plt.plot(precision, recall, label='Precision-Recall Curve')
plt.plot(closest_zero_p, closest_zero_r, 'o', markersize = 12, fillstyle =
plt.xlabel('Precision', fontsize=16)
plt.ylabel('Recall', fontsize=16)
plt.axes().set_aspect('equal')
plt.show()
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

1.1.7 ROC curves, Area-Under-Curve (AUC)

```
In [19]: from sklearn.metrics import roc_curve, auc

         X_train, X_test, y_train, y_test = train_test_split(X, y_binary_imbalanced

         y_score_lr = lr.fit(X_train, y_train).decision_function(X_test)
         fpr_lr, tpr_lr, _ = roc_curve(y_test, y_score_lr)
         roc_auc_lr = auc(fpr_lr, tpr_lr)

         plt.figure()
         plt.xlim([-0.01, 1.00])
         plt.ylim([-0.01, 1.01])
         plt.plot(fpr_lr, tpr_lr, lw=3, label='LogRegr ROC curve (area = {:0.2f})'.
         plt.xlabel('False Positive Rate', fontsize=16)
         plt.ylabel('True Positive Rate', fontsize=16)
         plt.title('ROC curve (1-of-10 digits classifier)', fontsize=16)
         plt.legend(loc='lower right', fontsize=13)
         plt.plot([0, 1], [0, 1], color='navy', lw=3, linestyle='--')
         plt.axes().set_aspect('equal')
         plt.show()
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
In [20]: from matplotlib import cm

         X_train, X_test, y_train, y_test = train_test_split(X, y_binary_imbalanced

         plt.figure()
         plt.xlim([-0.01, 1.00])
         plt.ylim([-0.01, 1.01])
         for g in [0.01, 0.1, 0.20, 1]:
             svm = SVC(gamma=g).fit(X_train, y_train)
             y_score_svm = svm.decision_function(X_test)
             fpr_svm, tpr_svm, _ = roc_curve(y_test, y_score_svm)
             roc_auc_svm = auc(fpr_svm, tpr_svm)
             accuracy_svm = svm.score(X_test, y_test)
             print("gamma = {:.2f}  accuracy = {:.2f}   AUC = {:.2f}".format(g, acc
                                                                                roc_au
             plt.plot(fpr_svm, tpr_svm, lw=3, alpha=0.7,
                      label='SVM (gamma = {:0.2f}, area = {:0.2f})'.format(g, roc_a

         plt.xlabel('False Positive Rate', fontsize=16)
         plt.ylabel('True Positive Rate (Recall)', fontsize=16)
         plt.plot([0, 1], [0, 1], color='k', lw=0.5, linestyle='--')
```

```
plt.legend(loc="lower right", fontsize=11)
plt.title('ROC curve: (1-of-10 digits classifier)', fontsize=16)
plt.axes().set_aspect('equal')

plt.show()
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
gamma = 0.01  accuracy = 0.91   AUC = 1.00
gamma = 0.10  accuracy = 0.90   AUC = 0.98
gamma = 0.20  accuracy = 0.90   AUC = 0.66
gamma = 1.00  accuracy = 0.90   AUC = 0.50
```

1.1.8 Evaluation measures for multi-class classification

Multi-class confusion matrix

```
In [21]: dataset = load_digits()
         X, y = dataset.data, dataset.target
         X_train_mc, X_test_mc, y_train_mc, y_test_mc = train_test_split(X, y, ranc


         svm = SVC(kernel = 'linear').fit(X_train_mc, y_train_mc)
         svm_predicted_mc = svm.predict(X_test_mc)
         confusion_mc = confusion_matrix(y_test_mc, svm_predicted_mc)
         df_cm = pd.DataFrame(confusion_mc,
                              index = [i for i in range(0,10)], columns = [i for i

         plt.figure(figsize=(5.5,4))
         sns.heatmap(df_cm, annot=True)
         plt.title('SVM Linear Kernel \nAccuracy:{0:.3f}'.format(accuracy_score(y_t
                                                                                svn
         plt.ylabel('True label')
         plt.xlabel('Predicted label')


         svm = SVC(kernel = 'rbf').fit(X_train_mc, y_train_mc)
         svm_predicted_mc = svm.predict(X_test_mc)
         confusion_mc = confusion_matrix(y_test_mc, svm_predicted_mc)
         df_cm = pd.DataFrame(confusion_mc, index = [i for i in range(0,10)],
                           columns = [i for i in range(0,10)])

         plt.figure(figsize = (5.5,4))
         sns.heatmap(df_cm, annot=True)
```

```
plt.title('SVM RBF Kernel \nAccuracy:{0:.3f}'.format(accuracy_score(y_test
                                                                    svm_pr
plt.ylabel('True label')
plt.xlabel('Predicted label');
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

Multi-class classification report

```
In [22]: print(classification_report(y_test_mc, svm_predicted_mc))
```

```
             precision    recall  f1-score   support

          0       1.00      0.65      0.79        37
          1       1.00      0.23      0.38        43
          2       1.00      0.39      0.56        44
          3       1.00      0.93      0.97        45
          4       0.14      1.00      0.25        38
          5       1.00      0.33      0.50        48
          6       1.00      0.54      0.70        52
          7       1.00      0.35      0.52        48
          8       1.00      0.02      0.04        48
          9       1.00      0.55      0.71        47

avg / total       0.93      0.49      0.54       450
```

Micro- vs. macro-averaged metrics

```
In [23]: print('Micro-averaged precision = {:.2f} (treat instances equally)'
               .format(precision_score(y_test_mc, svm_predicted_mc, average = 'micr
         print('Macro-averaged precision = {:.2f} (treat classes equally)'
               .format(precision_score(y_test_mc, svm_predicted_mc, average = 'macr
```

```
Micro-averaged precision = 0.49 (treat instances equally)
Macro-averaged precision = 0.91 (treat classes equally)
```

```
In [24]: print('Micro-averaged f1 = {:.2f} (treat instances equally)'
               .format(f1_score(y_test_mc, svm_predicted_mc, average = 'micro')))
         print('Macro-averaged f1 = {:.2f} (treat classes equally)'
               .format(f1_score(y_test_mc, svm_predicted_mc, average = 'macro')))
```

```
Micro-averaged f1 = 0.49 (treat instances equally)
Macro-averaged f1 = 0.54 (treat classes equally)
```

1.1.9 Regression evaluation metrics

```
In [25]: %matplotlib notebook
         import matplotlib.pyplot as plt
         import numpy as np
         from sklearn.model_selection import train_test_split
         from sklearn import datasets
         from sklearn.linear_model import LinearRegression
         from sklearn.metrics import mean_squared_error, r2_score
         from sklearn.dummy import DummyRegressor

         diabetes = datasets.load_diabetes()

         X = diabetes.data[:, None, 6]
         y = diabetes.target

         X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)

         lm = LinearRegression().fit(X_train, y_train)
         lm_dummy_mean = DummyRegressor(strategy = 'mean').fit(X_train, y_train)

         y_predict = lm.predict(X_test)
         y_predict_dummy_mean = lm_dummy_mean.predict(X_test)

         print('Linear model, coefficients: ', lm.coef_)
         print("Mean squared error (dummy): {:.2f}".format(mean_squared_error(y_tes
                                                                              y_pre
         print("Mean squared error (linear model): {:.2f}".format(mean_squared_erro
         print("r2_score (dummy): {:.2f}".format(r2_score(y_test, y_predict_dummy_m
         print("r2_score (linear model): {:.2f}".format(r2_score(y_test, y_predict)

         # Plot outputs
         plt.scatter(X_test, y_test,  color='black')
         plt.plot(X_test, y_predict, color='green', linewidth=2)
         plt.plot(X_test, y_predict_dummy_mean, color='red', linestyle = 'dashed',
                  linewidth=2, label = 'dummy')

         plt.show()
```

```
Linear model, coefficients:  [-698.80206267]
```

```
Mean squared error (dummy): 4965.13
Mean squared error (linear model): 4646.74
r2_score (dummy): -0.00
r2_score (linear model): 0.06
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

1.1.10 Model selection using evaluation metrics

Cross-validation example

```
In [26]: from sklearn.model_selection import cross_val_score
         from sklearn.svm import SVC

         dataset = load_digits()
         # again, making this a binary problem with 'digit 1' as positive class
         # and 'not 1' as negative class
         X, y = dataset.data, dataset.target == 1
         clf = SVC(kernel='linear', C=1)

         # accuracy is the default scoring metric
         print('Cross-validation (accuracy)', cross_val_score(clf, X, y, cv=5))
         # use AUC as scoring metric
         print('Cross-validation (AUC)', cross_val_score(clf, X, y, cv=5, scoring =
         # use recall as scoring metric
         print('Cross-validation (recall)', cross_val_score(clf, X, y, cv=5, scorin
```

```
Cross-validation (accuracy) [ 0.91944444  0.98611111  0.97214485  0.97493036  0.96
Cross-validation (AUC) [ 0.9641871   0.9976571   0.99372205  0.99699002  0.9867561
Cross-validation (recall) [ 0.81081081  0.89189189  0.83333333  0.83333333  0.8333
```

Grid search example

```
In [27]: from sklearn.svm import SVC
         from sklearn.model_selection import GridSearchCV
         from sklearn.metrics import roc_auc_score

         dataset = load_digits()
         X, y = dataset.data, dataset.target == 1
         X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)

         clf = SVC(kernel='rbf')
         grid_values = {'gamma': [0.001, 0.01, 0.05, 0.1, 1, 10, 100]}
```

```
# default metric to optimize over grid parameters: accuracy
grid_clf_acc = GridSearchCV(clf, param_grid = grid_values)
grid_clf_acc.fit(X_train, y_train)
y_decision_fn_scores_acc = grid_clf_acc.decision_function(X_test)

print('Grid best parameter (max. accuracy): ', grid_clf_acc.best_params_)
print('Grid best score (accuracy): ', grid_clf_acc.best_score_)

# alternative metric to optimize over grid parameters: AUC
grid_clf_auc = GridSearchCV(clf, param_grid = grid_values, scoring = 'roc_
grid_clf_auc.fit(X_train, y_train)
y_decision_fn_scores_auc = grid_clf_auc.decision_function(X_test)

print('Test set AUC: ', roc_auc_score(y_test, y_decision_fn_scores_auc))
print('Grid best parameter (max. AUC): ', grid_clf_auc.best_params_)
print('Grid best score (AUC): ', grid_clf_auc.best_score_)
```

```
Grid best parameter (max. accuracy):  {'gamma': 0.001}
Grid best score (accuracy):  0.996288047513
Test set AUC:  0.999828581224
Grid best parameter (max. AUC):  {'gamma': 0.001}
Grid best score (AUC):  0.99987412783
```

Evaluation metrics supported for model selection

```
In [28]: from sklearn.metrics.scorer import SCORERS

         print(sorted(list(SCORERS.keys())))
```

```
['accuracy', 'adjusted_rand_score', 'average_precision', 'f1', 'f1_macro', 'f1_micr
```

1.1.11 Two-feature classification example using the digits dataset

Optimizing a classifier using different evaluation metrics

```
In [29]: from sklearn.datasets import load_digits
         from sklearn.model_selection import train_test_split
         from adspy_shared_utilities import plot_class_regions_for_classifier_subpl
         from sklearn.svm import SVC
         from sklearn.model_selection import GridSearchCV


         dataset = load_digits()
         X, y = dataset.data, dataset.target == 1
         X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)
```

```
# Create a two-feature input vector matching the example plot above
# We jitter the points (add a small amount of random noise) in case there
# in feature space where many instances have the same features.
jitter_delta = 0.25
X_twovar_train = X_train[:,[20,59]]+ np.random.rand(X_train.shape[0], 2) -
X_twovar_test  = X_test[:,[20,59]] + np.random.rand(X_test.shape[0], 2) -

clf = SVC(kernel = 'linear').fit(X_twovar_train, y_train)
grid_values = {'class_weight':['balanced', {1:2},{1:3},{1:4},{1:5},{1:10},
plt.figure(figsize=(9,6))
for i, eval_metric in enumerate(('precision','recall', 'f1','roc_auc')):
    grid_clf_custom = GridSearchCV(clf, param_grid=grid_values, scoring=ev
    grid_clf_custom.fit(X_twovar_train, y_train)
    print('Grid best parameter (max. {0}): {1}'
          .format(eval_metric, grid_clf_custom.best_params_))
    print('Grid best score ({0}): {1}'
          .format(eval_metric, grid_clf_custom.best_score_))
    plt.subplots_adjust(wspace=0.3, hspace=0.3)
    plot_class_regions_for_classifier_subplot(grid_clf_custom, X_twovar_te
                                              None, None,  plt.subplot(2, 2

    plt.title(eval_metric+'-oriented SVC')
plt.tight_layout()
plt.show()
```

```
<IPython.core.display.Javascript object>


<IPython.core.display.HTML object>


Grid best parameter (max. precision): {'class_weight': {1: 2}}
Grid best score (precision): 0.54595698747338
Grid best parameter (max. recall): {'class_weight': {1: 50}}
Grid best score (recall): 0.9284310837047003
Grid best parameter (max. f1): {'class_weight': {1: 4}}
Grid best score (f1): 0.5089202199818385
Grid best parameter (max. roc_auc): {'class_weight': {1: 10}}
Grid best score (roc_auc): 0.887982061141558
```

Precision-recall curve for the default SVC classifier (with balanced class weights)

In [30]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import precision_recall_curve
from adspy_shared_utilities import plot_class_regions_for_classifier
from sklearn.svm import SVC
```

```python
dataset = load_digits()
X, y = dataset.data, dataset.target == 1
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)

# create a two-feature input vector matching the example plot above
jitter_delta = 0.25
X_twovar_train = X_train[:,[20,59]]+ np.random.rand(X_train.shape[0], 2) -
X_twovar_test  = X_test[:,[20,59]] + np.random.rand(X_test.shape[0], 2) -

clf = SVC(kernel='linear', class_weight='balanced').fit(X_twovar_train, y_

y_scores = clf.decision_function(X_twovar_test)

precision, recall, thresholds = precision_recall_curve(y_test, y_scores)
closest_zero = np.argmin(np.abs(thresholds))
closest_zero_p = precision[closest_zero]
closest_zero_r = recall[closest_zero]

plot_class_regions_for_classifier(clf, X_twovar_test, y_test)
plt.title("SVC, class_weight = 'balanced', optimized for accuracy")
plt.show()

plt.figure()
plt.xlim([0.0, 1.01])
plt.ylim([0.0, 1.01])
plt.title ("Precision-recall curve: SVC, class_weight = 'balanced'")
plt.plot(precision, recall, label = 'Precision-Recall Curve')
plt.plot(closest_zero_p, closest_zero_r, 'o', markersize=12, fillstyle='nc
plt.xlabel('Precision', fontsize=16)
plt.ylabel('Recall', fontsize=16)
plt.axes().set_aspect('equal')
plt.show()
print('At zero threshold, precision: {:.2f}, recall: {:.2f}'
      .format(closest_zero_p, closest_zero_r))
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
At zero threshold, precision: 0.22, recall: 0.74
```

```
In [ ]:
```