Module-3

July 3, 2020

*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.*

1 Applied Machine Learning: Module 3 (Evaluation)

1.1 Evaluation for Classification

1.1.1 Preamble

[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(dataset.
 ↪target)):
    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
```

[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 0]
```

[3]:
```
np.bincount(y_binary_imbalanced)    # Negative class (0) is the most frequent␣
↪class
```

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

[4]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y_binary_imbalanced,␣
↪random_state=0)

# 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)
```

[4]:
```
0.9088888888888886
```

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.

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

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

y_dummy_predictions
```

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

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

[6]:
```
0.9044444444444445
```

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

[7]:
```
0.9777777777777775
```

1.1.3 Confusion matrices

Binary (two-class) confusion matrix

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

# Negative class (0) is most frequent
dummy_majority = DummyClassifier(strategy = 'most_frequent').fit(X_train,␣
 ↪y_train)
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]]
```

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

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

```
Random class-proportional prediction (dummy classifier)
 [[375  32]
 [ 39   4]]
```

[10]:
```python
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', confusion)
```

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

[11]:
```python
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]]
```

[12]:
```python
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

[13]:
```python
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score
# Accuracy = TP + TN / (TP + TN + FP + FN)
# Precision = TP / (TP + FP)
# Recall = TP / (TP + FN)  Also known as sensitivity, or True Positive Rate
# 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
```

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

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

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

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

      not 1       0.91      0.92      0.91       407
          1       0.11      0.09      0.10        43

avg / total       0.83      0.84      0.84       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

[16]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y_binary_imbalanced,
 ↪random_state=0)
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
```

[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)]
```

[17]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y_binary_imbalanced,␣
 ↪random_state=0)
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
```

[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, 0.9999864188091131),
 (0, 9.8694940340195476e-13),
 (0, 2.6059983600823893e-06),
 (0, 5.9469113009063784e-12)]
```

1.1.6 Precision-recall curves

[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 =␣
 ↪'none', c='r', mew=3)
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)

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

X_train, X_test, y_train, y_test = train_test_split(X, y_binary_imbalanced,␣
 ↪random_state=0)

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})'.
 ↪format(roc_auc_lr))
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>
```

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

```
X_train, X_test, y_train, y_test = train_test_split(X, y_binary_imbalanced,␣
 ↪random_state=0)

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,␣
 ↪accuracy_svm,
                                                                              ␣
 ↪roc_auc_svm))
    plt.plot(fpr_svm, tpr_svm, lw=3, alpha=0.7,
             label='SVM (gamma = {:0.2f}, area = {:0.2f})'.format(g,␣
 ↪roc_auc_svm))

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

[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,␣
 ↪random_state=0)
```

```
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 in␣
 ↪range(0,10)])

plt.figure(figsize=(5.5,4))
sns.heatmap(df_cm, annot=True)
plt.title('SVM Linear Kernel \nAccuracy:{0:.3f}'.
 ↪format(accuracy_score(y_test_mc,
                                                                      ␣
 ↪svm_predicted_mc)))
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_mc,
                                                                   ␣
 ↪svm_predicted_mc)))
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

[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

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

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

[24]:
```python
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

[25]:
```python
%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_test,
                                                                      ␣
 ↪y_predict_dummy_mean)))
print("Mean squared error (linear model): {:.2f}".
 ↪format(mean_squared_error(y_test, y_predict)))
print("r2_score (dummy): {:.2f}".format(r2_score(y_test, y_predict_dummy_mean)))
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

[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 =␣
↪'roc_auc'))
# use recall as scoring metric
print('Cross-validation (recall)', cross_val_score(clf, X, y, cv=5, scoring =␣
↪'recall'))
```

```
Cross-validation (accuracy) [ 0.91944444  0.98611111  0.97214485  0.97493036
0.96935933]
Cross-validation (AUC) [ 0.9641871   0.9976571   0.99372205  0.99699002
0.98675611]
Cross-validation (recall) [ 0.81081081  0.89189189  0.83333333  0.83333333
0.83333333]
```

Grid search example

[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_auc')
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

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

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

```
['accuracy', 'adjusted_rand_score', 'average_precision', 'f1', 'f1_macro',
'f1_micro', 'f1_samples', 'f1_weighted', 'log_loss', 'mean_absolute_error',
'mean_squared_error', 'median_absolute_error', 'neg_log_loss',
'neg_mean_absolute_error', 'neg_mean_squared_error',
'neg_median_absolute_error', 'precision', 'precision_macro', 'precision_micro',
'precision_samples', 'precision_weighted', 'r2', 'recall', 'recall_macro',
'recall_micro', 'recall_samples', 'recall_weighted', 'roc_auc']
```

1.1.11 Two-feature classification example using the digits dataset

Optimizing a classifier using different evaluation metrics

[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_subplot
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 are␣
↪areas
# 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) -␣
↪jitter_delta
X_twovar_test  = X_test[:,[20,59]] + np.random.rand(X_test.shape[0], 2) -␣
↪jitter_delta

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},{1:
 ↪20},{1:50}]}
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=eval_metric)
    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_test,␣
 ↪y_test, None,
                                              None, None,  plt.subplot(2, 2,␣
 ↪i+1))

    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): 0.5515981123040191
Grid best parameter (max. recall): {'class_weight': {1: 50}}
Grid best score (recall): 0.9428915594801756
Grid best parameter (max. f1): {'class_weight': {1: 4}}
Grid best score (f1): 0.5137748532777203
Grid best parameter (max. roc_auc): {'class_weight': {1: 20}}
Grid best score (roc_auc): 0.8900938758700303
```

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

[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

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) -␣
 ↪jitter_delta
X_twovar_test  = X_test[:,[20,59]] + np.random.rand(X_test.shape[0], 2) -␣
 ↪jitter_delta

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

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='none',␣
 ↪c='r', mew=3)
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: 0.21, recall: 0.74
```