Machine Learning with scikit-learn

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Overview

- Basic concepts of machine learning
- Introduction to scikit-learn
- Some useful algorithms
- Selecting a model
- Working with text data

scikit-learn

- Collection of machine learning algorithms and tools in Python.
- BSD Licensed, used in academia and industry (Spotify, bit.ly, Evernote).
- ~20 core developers.
- Take pride in good code and documentation.
- We want YOU to participate!

Two (three) kinds of learning

- Supervised
- Unsupervised
- Reinforcement

Supervised learning

Training: Examples X_train together with labels y_train.

Testing: Given X_test, predict y_test.

Examples

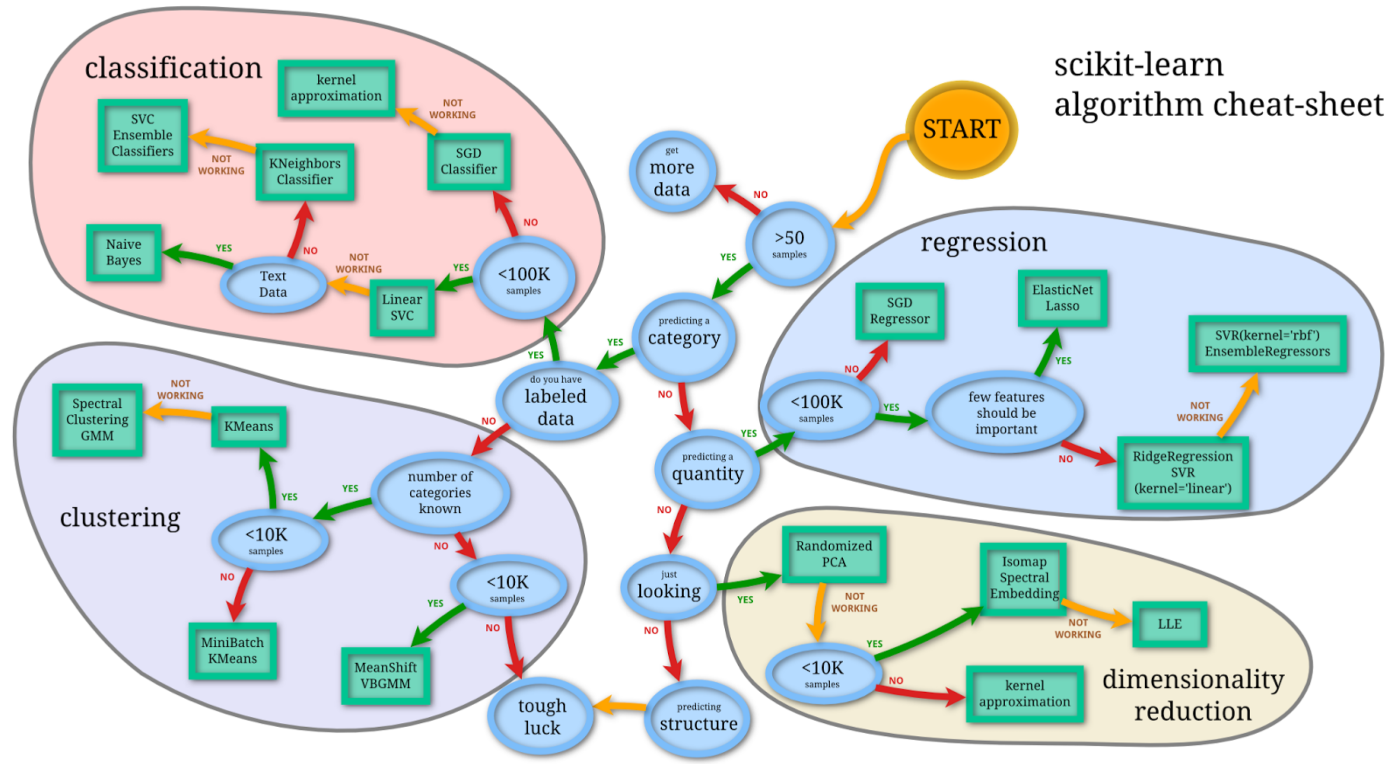
- Classification (spam, sentiment analysis, ...)
- Regression (stocks, sales, ...)
- Ranking (retrieval, search, ...)

Unsupervised Learning

Examples X. Learn something about X.

Examples

- Dimensionality reduction
- Clustering
- Manifold learning



scikit-learn
algorithm cheat-sheet
START
>50 samples
get more data
predicting a category
do you have labeled data
predicting a quantity
just looking
predicting structure
tough luck
classification
<100K samples
SGD Classifier
kernel approximation
Linear SVC
Text Data
Naive Bayes
KNeighbors Classifier
SVC Ensemble Classifiers
clustering
number of categories known
<10K samples
KMeans
Spectral Clustering GMM
MiniBatch KMeans
<10K samples
MeanShift VBGMM
regression
<100K samples
SGD Regressor
few features should be important
ElasticNet Lasso
RidgeRegression SVR (kernel='linear')
SVR(kernel='rbf') EnsembleRegressors
dimensionality reduction
Randomized PCA
<10K samples
Isomap Spectral Embedding
LLE
kernel approximation
YES
NO
NOT WORKING

Data representation

Everything is a **numpy array** (or a scipy sparse matrix)!

Let's get some toy data.

In [1]:

```
from sklearn.datasets import load_digits
digits = load_digits()
```

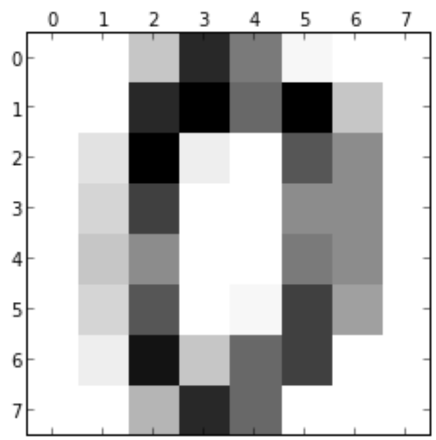
In [2]:

```
print("images shape: %s" % str(digits.images.shape))
print("targets shape: %s" % str(digits.target.shape))
```

```
images shape: (1797, 8, 8)
targets shape: (1797,)
```

In [3]:

```
plt.matshow(digits.images[0], cmap=plt.cm.Greys);
```



In [4]:

```
digits.target
```

Out[4]:

```
array([0, 1, 2, ..., 8, 9, 8])
```

Prepare the data

In [6]:

```
X = digits.data.reshape(-1, 64)
print(X.shape)
```

```
(1797, 64)
```

In [7]:

```
y = digits.target
print(y.shape)
```

```
(1797,)
```

We have 1797 data points, each an 8x8 image -> 64 dimensional vector.

X.shape is always (n_samples, n_feature)

In [8]:

```
print(X)
```

```
[[ 0.      0.      0.3125 ...,  0.      0.      0.    ]
 [ 0.      0.      0.     ...,  0.625   0.      0.    ]
 [ 0.      0.      0.     ...,  1.      0.5625  0.    ]
 ...,
 [ 0.      0.      0.0625 ...,  0.375   0.      0.    ]
 [ 0.      0.      0.125  ...,  0.75    0.      0.    ]
 [ 0.      0.      0.625  ...,  0.75    0.0625  0.    
]]
```

Taking a Peek

Dimensionality Reduction and Manifold Learning

- Always first have a look at your data!
- Projecting to two dimensions is the easiest way.

Principal Component Analysis (PCA)

In [9]:

```
from sklearn.decomposition import PCA
```

Instantiate the model. Set parameters.

In [10]:

```
pca = PCA(n_components=2)
```

Fit the model.

In [11]:

```
pca.fit(X);
```

Apply the model. For embeddings / decompositions, this is `transform`.

In [12]:

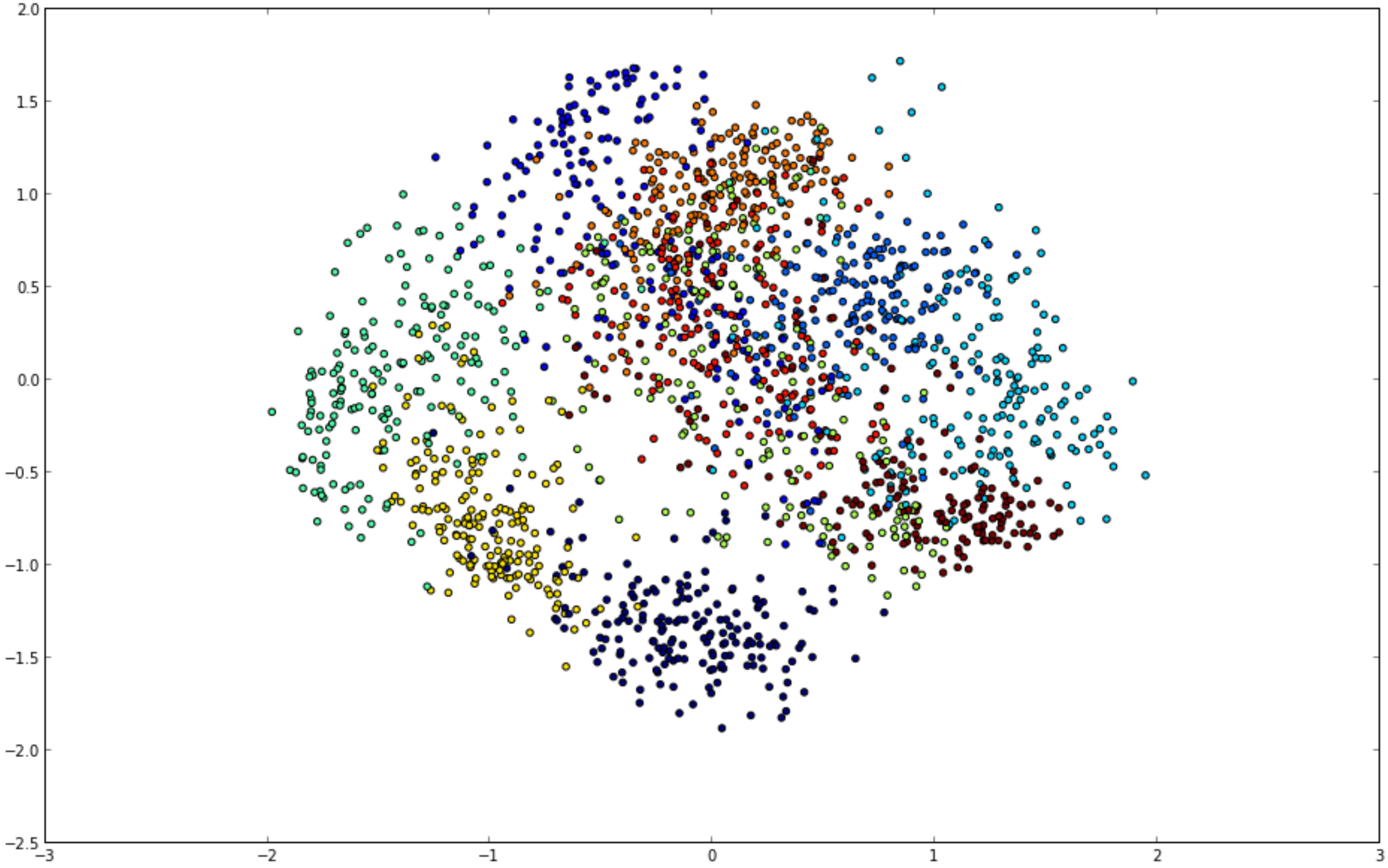
```
X_pca = pca.transform(X)
X_pca.shape
```

Out[12]:

```
(1797, 2)
```

In [13]:

```
plt.figsize(16, 10)
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y);
```



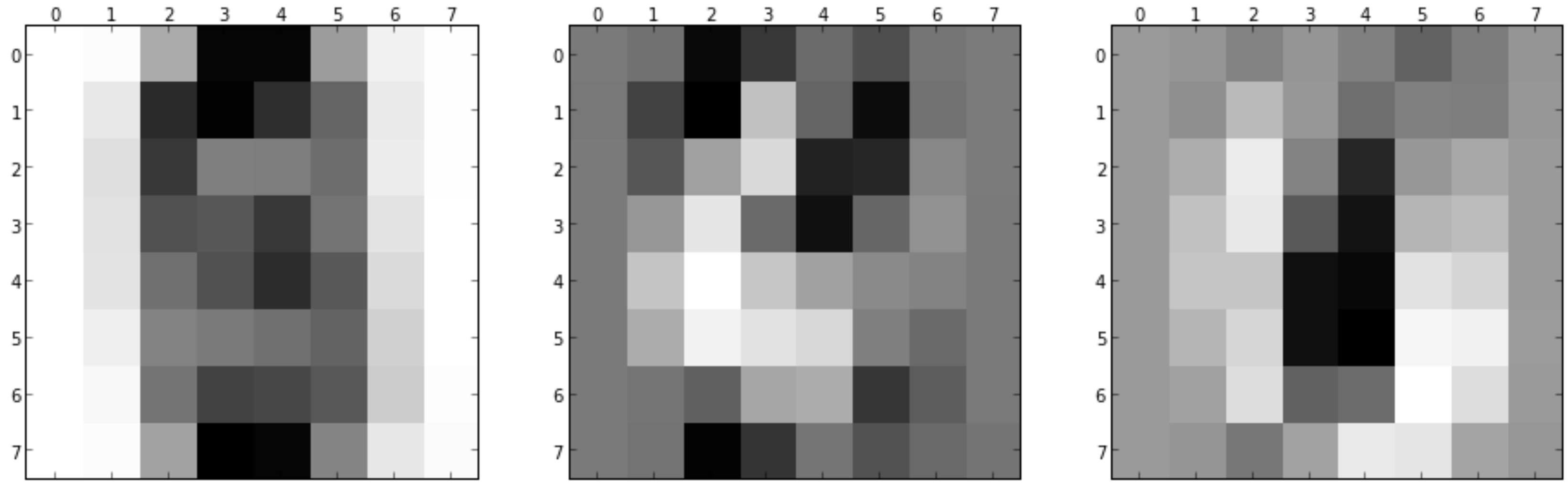
In [14]:

```
print(pca.mean_.shape)
print(pca.components_.shape)
```

```
(64,)
(2,
64)
```

In [15]:

```
fix, ax = plt.subplots(1, 3)
ax[0].matshow(pca.mean_.reshape(8, 8), cmap=plt.cm.Greys)
ax[1].matshow(pca.components_[0, :].reshape(8, 8), cmap=plt.cm.Greys)
ax[2].matshow(pca.components_[1, :].reshape(8, 8), cmap=plt.cm.Greys);
```



Isomap

In [16]:
```
from sklearn.manifold import Isomap
```

Instantiate the model. Set parameters.

In [17]:
```
isomap = Isomap(n_components=2, n_neighbors=20)
```

Fit the model.

In [18]:
```
isomap.fit(X);
```

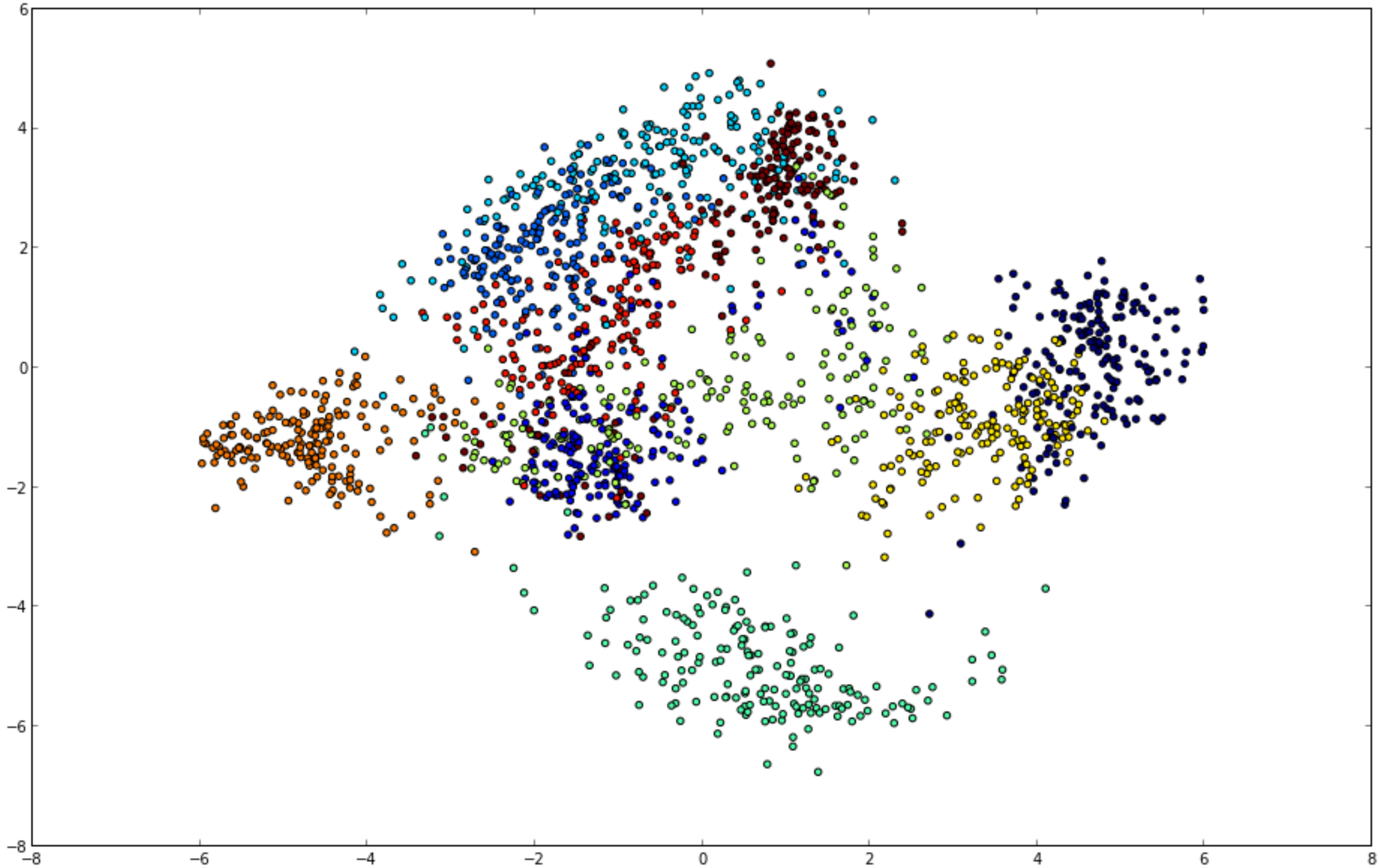
Apply the model.

In [19]:
```
X_isomap = isomap.transform(X)
X_isomap.shape
```

Out[19]:
```
(1797, 2)
```

In [20]:

```
plt.scatter(X_isomap[:, 0], X_isomap[:, 1], c=y);
```



Classification

To evaluate the algorithm, split data into training and testing part.

In [21]:

```
from sklearn.cross_validation import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)
```

In [22]:

```
print("X_train shape: %s" % repr(X_train.shape))
print("y_train shape: %s" % repr(y_train.shape))
print("X_test shape: %s" % repr(X_test.shape))
print("y_test shape: %s" % repr(y_test.shape))
```

```
X_train shape: (1347, 64)
y_train shape: (1347,)
X_test shape: (450, 64)
y_test shape: (450,)
```

Start Simple: Linear SVMs

In [23]:

```
from sklearn.svm import LinearSVC
```

Finds a linear separation between the classes.

Instantiate the model.

In [24]:

```
svm = LinearSVC()
```

Fit the model using the known labels.

In [25]:

```
svm.fit(X_train, y_train);
```

Apply the model. For supervised algorithms, this is `predict`.

In [26]:

```
svm.predict(X_train)
```

Out[26]:

```
array([2, 8, 9, ..., 7, 7, 8])
```

Evaluate the model.

In [27]:

```
svm.score(X_train, y_train)
```

Out[27]:

```
0.99257609502598365
```

In [28]:

```
svm.score(X_test, y_test)
```

Out[28]:

```
0.9644444444444444
```

More complex: Random Forests

In [29]:

```
from sklearn.ensemble import RandomForestClassifier
```

Builds many randomized decision trees and averages their results.

Instantiate the model.

In [30]:

```
rf = RandomForestClassifier()
```

Fit the model.

In [31]:

```
rf.fit(X_train, y_train);
```

Evaluate.

In [32]:

```
rf.score(X_train, y_train)
```

Out[32]:

```
0.99925760950259834
```

In [33]:

```
rf.score(X_test, y_test)
```

Out[33]:

```
0.95111111111111113
```

Model Selection and Evaluation

Always keep a separate test set to the end.

- Measure performance using cross-validation

In [34]:

```
from sklearn.cross_validation import cross_val_score
scores =  cross_val_score(rf, X_train, y_train, cv=5)
print("scores: %s  mean: %f  std: %f" % (str(scores), np.mean(scores),
np.std(scores)))
```

```
scores: [ 0.95185185  0.94074074  0.93680297  0.95910781  0.92936803]  mean: 0.943574  std: 0.010635
```

Maybe more trees will help?

In [35]:

```
rf2 = RandomForestClassifier(n_estimators=50)
scores =  cross_val_score(rf2, X_train, y_train, cv=5)
print("scores: %s  mean: %f  std: %f" % (str(scores), np.mean(scores),
np.std(scores)))
```

```
scores: [ 0.95555556  0.97407407  0.97026022  0.97769517  0.96282528]  mean: 0.968082  std: 0.007970
```

Adjust important parameters using grid search

In [36]:

```
from sklearn.grid_search import GridSearchCV
```

- Let's look at LinearSVC again.
- Only important parameter: C

In [37]:

```
param_grid = {'C': 10. ** np.arange(-3, 4)}
grid_search = GridSearchCV(svm, param_grid=param_grid, cv=3, verbose=3,
compute_training_score=True)
```

In [38]:

```
grid_search.fit(X_train, y_train);
```

```
[GridSearchCV] C=0.001 .........................................................
[GridSearchCV] ................................ C=0.001, score=0.902004 -   0.1s
[GridSearchCV] C=0.001 .........................................................
[GridSearchCV] ................................ C=0.001, score=0.895323 -   0.1s
[GridSearchCV] C=0.001 .........................................................
[GridSearchCV] ................................ C=0.001, score=0.879733 -   0.1s
[GridSearchCV] C=0.01 ..........................................................
[GridSearchCV] ................................. C=0.01, score=0.953229 -   0.1s
[GridSearchCV] C=0.01 ..........................................................
[GridSearchCV] ................................. C=0.01, score=0.937639 -   0.1s
[GridSearchCV] C=0.01 ..........................................................
[GridSearchCV] ................................. C=0.01, score=0.919822 -   0.1s
[GridSearchCV] C=0.1 ...........................................................
[GridSearchCV] .................................. C=0.1, score=0.973274 -   0.1s
[GridSearchCV] C=0.1 ...........................................................
[GridSearchCV] .................................. C=0.1, score=0.951002 -   0.1s
[GridSearchCV] C=0.1 ...........................................................
[GridSearchCV] .................................. C=0.1, score=0.951002 -   0.1s
[GridSearchCV] C=1.0 ...........................................................
[GridSearchCV] .................................. C=1.0, score=0.977728 -   0.2s
[GridSearchCV] C=1.0 ...........................................................
[GridSearchCV] .................................. C=1.0, score=0.957684 -   0.2s
[GridSearchCV] C=1.0 ...........................................................
[GridSearchCV] .................................. C=1.0, score=0.964365 -   0.2s
[GridSearchCV] C=10.0 ..........................................................
[GridSearchCV] ................................. C=10.0, score=0.975501 -   0.2s
[GridSearchCV] C=10.0 ..........................................................
[GridSearchCV] ................................. C=10.0, score=0.944321 -   0.2s
[GridSearchCV] C=10.0 ..........................................................
[GridSearchCV] ................................. C=10.0, score=0.962138 -   0.2s
[GridSearchCV] C=100.0 .........................................................
```

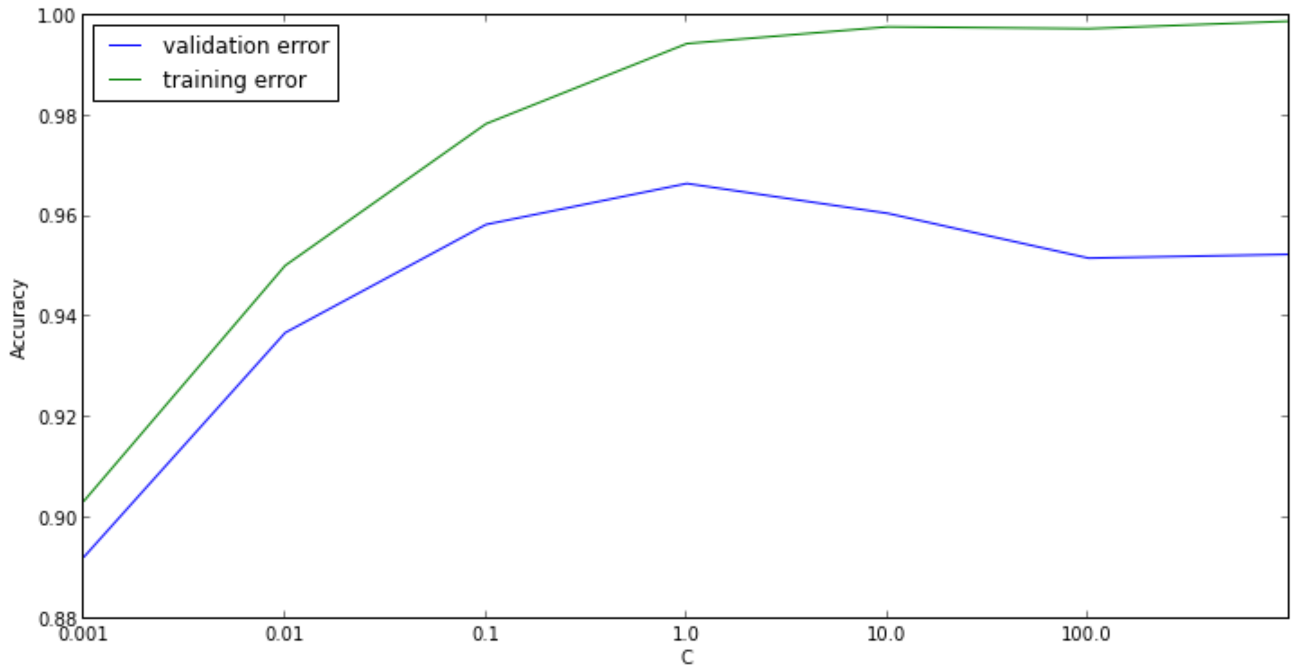
In [39]:

```
print(grid_search.best_params_)
print(grid_search.best_score_)
```

```
{'C': 1.0}
0.96659242761
7
```

In [41]:

```
plt.figsize(12, 6)
plt.plot([c.mean_validation_score for c in grid_search.cv_scores_],
label="validation error")
plt.plot([c.mean_training_score for c in grid_search.cv_scores_],
label="training error")
plt.xticks(np.arange(6), param_grid['C']); plt.xlabel("C");
plt.ylabel("Accuracy");plt.legend(loc='best');
```

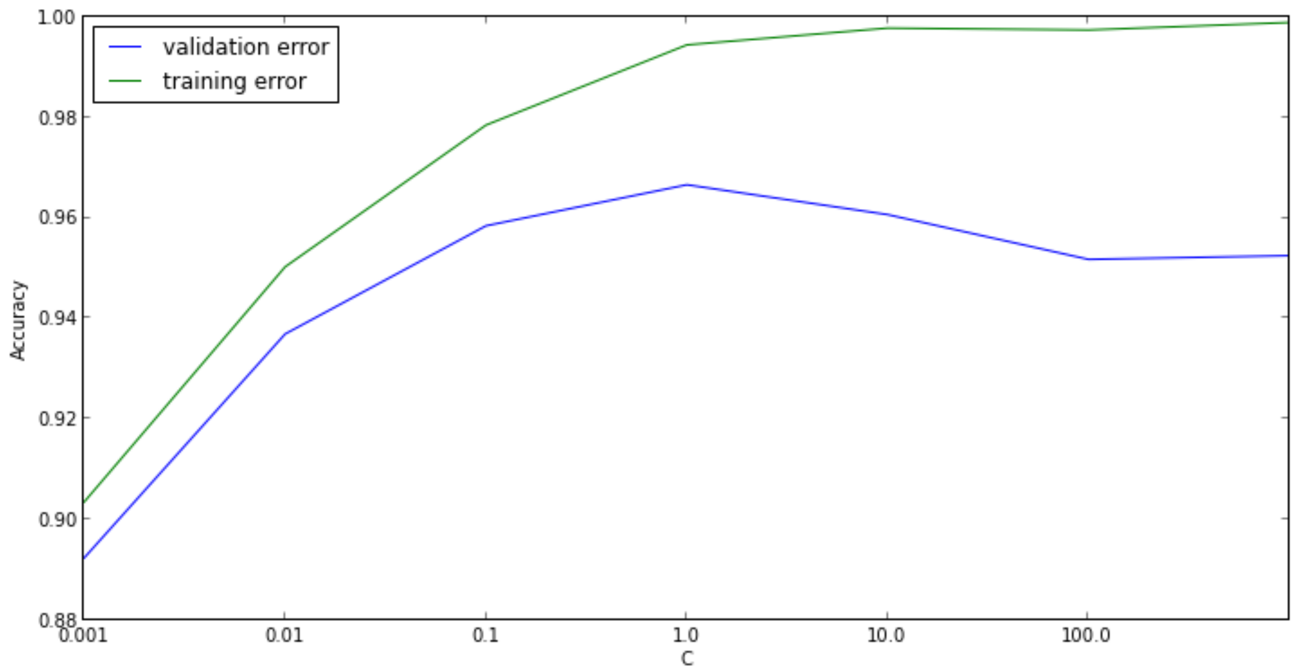


Overfitting and Complexity Control

- to the right: overfitting aka high variance.
  - Means no generalization.
- to the left: underfitting aka high bias.
  - Means bad even on training set.

In [42]:

```
plt.plot([c.mean_validation_score for c in grid_search.cv_scores_],
label="validation error")
plt.plot([c.mean_training_score for c in grid_search.cv_scores_],
label="training error")
plt.xticks(np.arange(6), param_grid['C']); plt.xlabel("C");
plt.ylabel("Accuracy");plt.legend(loc='best');
```



Detecting Insults in Social Commentary

- My first (and only) kaggle entry.
- Classify short forum posts as insulting or not.
- A simple bag of word model carries quite far.
- Linear classifiers are usually the best for text data.

Read the CSV using Pandas (a bit overkill).

In [43]:

```
import pandas as pd
train_data = pd.read_csv("kaggle_insult/train.csv")
test_data = pd.read_csv("kaggle_insult/test_with_solutions.csv")
```

- The column "Insult" contains the target.
- The column "Comment" contains the text.

In [44]:

```
y_train = np.array(train_data.Insult)
comments_train = np.array(train_data.Comment)
print(comments_train.shape)
print(y_train.shape)
```

```
(3947,)
(3947,)
```

In [45]:

```
print(comments_train[0])
print("Insult: %d" % y_train[0])
```

```
"You fuck your dad."
Insult: 1
```

In [46]:

```
print(comments_train[5])
print("Insult: %d" % y_train[5])
```

```
"@SDL OK, but I would hope they'd sign him to a one-year contract to start with. Give him the chance
Insult: 0
```

Vectorizing the Data

In [47]:

```
from sklearn.feature_extraction.text import CountVectorizer
```

- Use bag of words model as implemented in CountVectorizer.
- Extracts a dictionary, then counts word occurences.

In [48]:

```
cv = CountVectorizer()
cv.fit(comments_train)
print(cv.get_feature_names()[:15])
```

```
[u'00', u'000', u'01', u'014', u'01k4wu4w', u'02', u'034', u'05', u'06', u'0612', u'07', u'075', u'0
```

In [49]:

```
print(cv.get_feature_names()[1000:1015])
```

```
[u'argue', u'argued', u'arguement', u'arguements', u'arguing', u'argument', u'arguments', u'aries', 
```

In [50]:

```
X_train = cv.transform(comments_train).tocsr()
print("X_train.shape: %s" % str(X_train.shape))
print(X_train[0, :])
```

```
X_train.shape: (3947, 16469)
  (0, 3409)	1
  (0, 5434)	1
  (0, 16397)	1
  (0, 16405)	1
```

Training a Classifier

- LinearSVC : linear SVM that is efficient for sparse data.

In [51]:

```
from sklearn.svm import LinearSVC
svm = LinearSVC()
svm.fit(X_train, y_train)
```

Out[51]:

```
LinearSVC(C=1.0, class_weight=None, dual=True, fit_intercept=True,
     intercept_scaling=1, loss='l2', multi_class='ovr',
penalty='l2',
     random_state=None, tol=0.0001, verbose=0)
```

In [52]:

```
comments_test = np.array(test_data.Comment)
y_test = np.array(test_data.Insult)
X_test = cv.transform(comments_test)
svm.score(X_test, y_test)
```

Out[52]:

```
0.83037400831129582
```

In [53]:

```
print(comments_test[8])
print("Target: %d, prediction: %d" % (y_test[8], svm.predict(X_test.tocsr()
[8])[0]))
```

```
"To engage in an intelligent debate with you is like debating to a retarded person.  It's useless.
Target: 1, prediction: 1
```

Next Steps

- Grid search `C` parameter of LinearSVC.
- Build a pipeline, adjust parameters of feature extraction.
- Combine different feature extraction methods.

Take Away

- Get your data into an array `(n_samples, n_features)`.
- model.fit(X), model.predict(X) / model.transform(X)
- Always do cross-validation. Leave the test set until the end.
- Internalize the complexity / generalization tradeoff.

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