Classification - Support Vector Machines (SVM)

- Support vector machines (SVMs) are a set of supervised learning methods used for classification, regression and outliers detection.

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt

# use seaborn plotting defaults
import seaborn as sns
sns.set_style('whitegrid')
```

In [2]:
```
from sklearn.datasets.samples_generator import make_blobs
```

In [3]:
```
# default n_features = 2

X, y = make_blobs(n_samples=50, centers=2,
                  random_state=0, cluster_std=0.60)
```

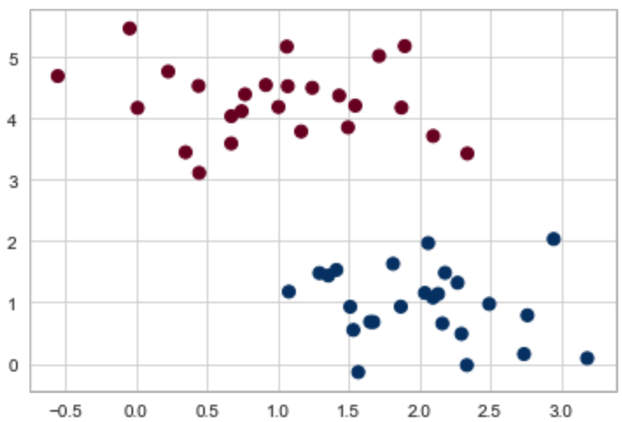
In [4]:
```
X[0:5,]
```

Out[4]:
```
array([[1.41281595, 1.5303347 ],
       [1.81336135, 1.6311307 ],
       [1.43289271, 4.37679234],
       [1.87271752, 4.18069237],
       [2.09517785, 1.0791468 ]])
```

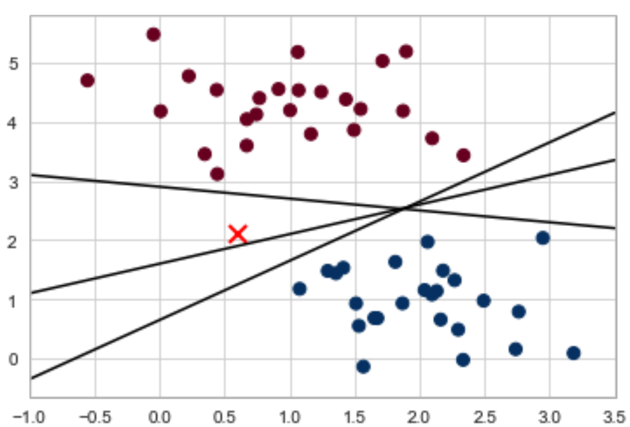
In [5]:
```
y[0:5]
```

Out[5]:
```
array([1, 1, 0, 0, 1])
```

In [6]:
```
plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='RdBu');
```



In [7]:
```
# Draw a line separating the data - more than one possible lines
# Sample lines  (y = mx + b)

xfit = np.linspace(-1, 3.5)
plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='RdBu')
plt.plot([0.6], [2.1], 'x', color='red', markeredgewidth=2, markersize=10)

for m, b in [(1, 0.65), (0.5, 1.6), (-0.2, 2.9)]:
    plt.plot(xfit, m * xfit + b, '-k')

plt.xlim(-1, 3.5);
```

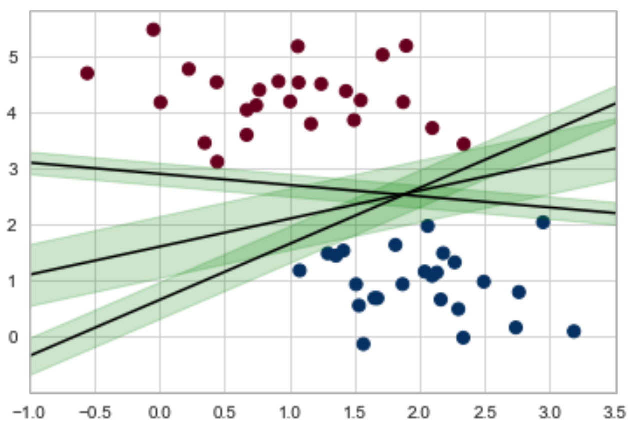


Depending on which line you choose, a new data point (e.g., the one marked by the "X" in this plot) will be assigned a different label

Support Vector Machines - Maximizing the Margin

Rather than simply drawing a zero-width line between the classes, we can draw around each line a margin of some width, up to the nearest point.

In [8]:
```
xfit = np.linspace(-1, 3.5)
plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='RdBu')

for m, b, d in [(1, 0.65, 0.33), (0.5, 1.6, 0.55), (-0.2, 2.9, 0.2)]:
    yfit = m * xfit + b
    plt.plot(xfit, yfit, '-k')
    plt.fill_between(xfit, yfit - d, yfit + d, edgecolor='none',
                     color='g', alpha=0.2)

plt.xlim(-1, 3.5);
```



In support vector machines, the line that maximizes this margin is the one we will choose as the optimal model.

Support vector machines are an example of such a maximum margin estimator.

In [9]:
```
from sklearn.svm import SVC    # "Support vector classifier"
```

In [10]:
```
model = SVC(kernel='linear')

model.fit(X, y)
```

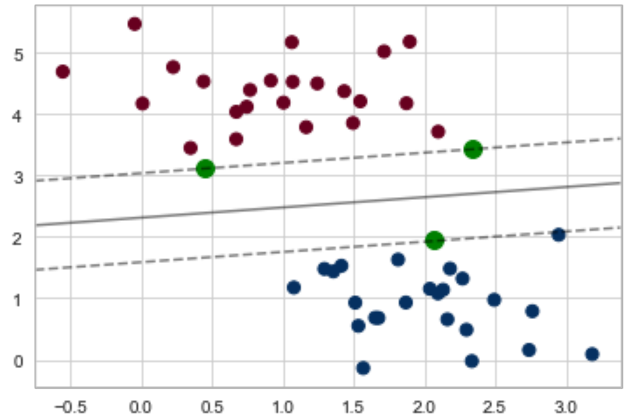
Out[10]:
```
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
    kernel='linear', max_iter=-1, probability=False, random_state=None,
    shrinking=True, tol=0.001, verbose=False)
```

In [11]:
```
model.support_vectors_
```

Out[11]:
```
array([[0.44359863, 3.11530945],
       [2.33812285, 3.43116792],
       [2.06156753, 1.96918596]])
```

In [12]:
```
def plot_svc_decision_function(model, ax=None, plot_support=True):
    """Plot the decision function for a 2D SVC"""
    if ax is None:
        ax = plt.gca()
    xlim = ax.get_xlim()
    ylim = ax.get_ylim()

    # create grid to evaluate model
    x = np.linspace(xlim[0], xlim[1], 30)
    y = np.linspace(ylim[0], ylim[1], 30)
    Y, X = np.meshgrid(y, x)
    xy = np.vstack([X.ravel(), Y.ravel()]).T
    P = model.decision_function(xy).reshape(X.shape)

    # plot decision boundary and margins
    ax.contour(X, Y, P, colors='k',
               levels=[-1, 0, 1],
               alpha=0.5,
               linestyles=['--', '-', '--'])

    # plot support vectors
    if plot_support:
        ax.scatter(model.support_vectors_[:, 0],
                   model.support_vectors_[:, 1],
                   s=100, linewidth=1, facecolors='g');
    ax.set_xlim(xlim)
    ax.set_ylim(ylim)
```

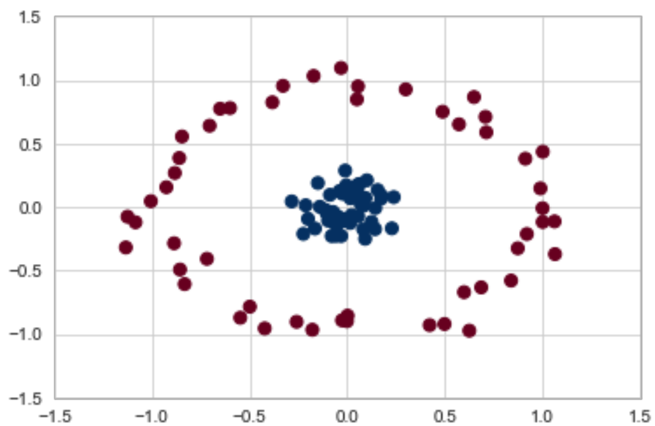
In [13]:
```
plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='RdBu')

plot_svc_decision_function(model);
```



In [ ]:
```
```

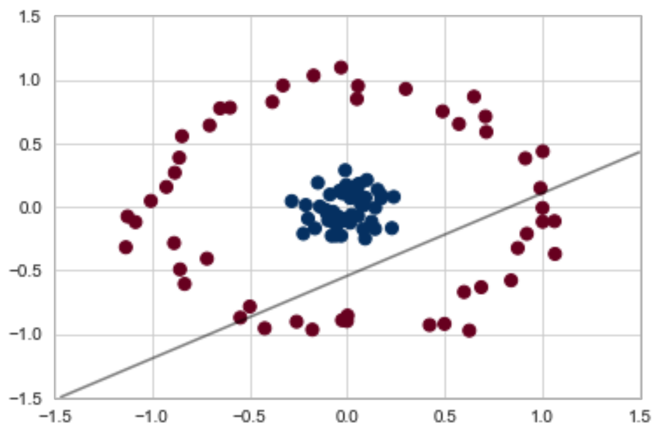
In [14]:
```
from sklearn.datasets.samples_generator import make_circles
```

In [15]:
```
X, y = make_circles(100, factor=.1, noise=.1)

plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='RdBu')
plt.xlim(-1.5, 1.5)
plt.ylim(-1.5, 1.5);
```



In [16]:
```
# Linear kernel will not work
model2 = SVC(kernel='linear').fit(X, y)
```

In [17]:
```
plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='RdBu')
plt.xlim(-1.5, 1.5)
plt.ylim(-1.5, 1.5)
plot_svc_decision_function(model2, plot_support=False);
```

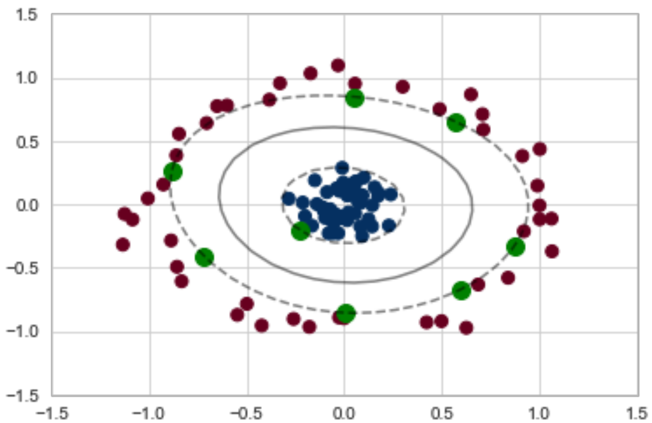


In Scikit-Learn, we can apply kernelized SVM simply by changing our linear kernel to an RBF (radial basis function) kernel, using the kernel model hyperparameter:

In [18]:
```
model3 = SVC(kernel='rbf', C=1E6, gamma='auto')
model3.fit(X, y)
```

Out[18]:
```
SVC(C=1000000.0, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
    max_iter=-1, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)
```

In [19]:
```
plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='RdBu')
plt.xlim(-1.5, 1.5)
plt.ylim(-1.5, 1.5)
plot_svc_decision_function(model3)
```



In [20]:
```
model3.support_vectors_
```

Out[20]:
```
array([[ 0.87458364, -0.32529304],
       [-0.88285475,  0.26816679],
       [ 0.0503305 ,  0.84845701],
       [ 0.00243228, -0.85618398],
       [ 0.59933641, -0.6709688 ],
       [ 0.5734485 ,  0.65138603],
       [-0.71816916, -0.40812948],
       [-0.22407102, -0.21182966]])
```

In [ ]:

Case Study - Face Recognition

In [21]:
```
from sklearn.datasets import fetch_lfw_people
```

In [22]:
```
faces = fetch_lfw_people(min_faces_per_person=70)
```

```
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/sklearn/externals/joblib/__init_
_.py:15: DeprecationWarning: sklearn.externals.joblib is deprecated in 0.21 and will be removed in 0.23. Please
import this functionality directly from joblib, which can be installed with: pip install joblib. If this warnin
g is raised when loading pickled models, you may need to re-serialize those models with scikit-learn 0.21+.
  warnings.warn(msg, category=DeprecationWarning)
```

In [23]:
```
print(faces.target_names)
print(faces.images.shape)
```

```
['Ariel Sharon' 'Colin Powell' 'Donald Rumsfeld' 'George W Bush'
 'Gerhard Schroeder' 'Hugo Chavez' 'Tony Blair']
(1288, 62, 47)
```

In [24]:
```
faces.images[0].shape
```

Out[24]:
```
(62, 47)
```

In [25]:
```
# Plot a few of the faces

fig, ax = plt.subplots(3, 5, figsize=(12,8))
for i, axi in enumerate(ax.flat):
    axi.imshow(faces.images[i], cmap='bone')
    axi.set(xticks=[], yticks=[],
            xlabel=faces.target_names[faces.target[i]])
```

Each image contains [62×47] or nearly 3,000 pixels. Not effective to use each pixel value as a feature. We will use a principal component analysis to extract 150 fundamental components to feed into our support vector machine classifier

In [26]:
```
from sklearn.svm import SVC
from sklearn.decomposition import PCA

from sklearn.pipeline import Pipeline
```

In [27]:
```
pca = PCA(n_components=150, svd_solver='randomized', whiten=True)

svc = SVC(kernel='rbf',  gamma=0.005, C=1000, class_weight='balanced')


model = Pipeline([('pca', pca),
                  ('svc', svc)])
```

For testing the classifier output, we will split the data into a training and testing set

In [28]:
```
from sklearn.model_selection import train_test_split
```

In [29]:
```
Xtrain, Xtest, ytrain, ytest = train_test_split(faces.data, faces.target,
                                                random_state=42)  # default test_size 0.25
```

In [30]:
```
np.unique(faces.target)
```

Out[30]:
```
array([0, 1, 2, 3, 4, 5, 6])
```

In [31]:
```
model.fit(Xtrain, ytrain)
```

Out[31]:
```
Pipeline(memory=None,
         steps=[('pca',
                 PCA(copy=True, iterated_power='auto', n_components=150,
                     random_state=None, svd_solver='randomized', tol=0.0,
                     whiten=True)),
                ('svc',
                 SVC(C=1000, cache_size=200, class_weight='balanced', coef0=0.0,
                     decision_function_shape='ovr', degree=3, gamma=0.005,
                     kernel='rbf', max_iter=-1, probability=False,
                     random_state=None, shrinking=True, tol=0.001,
                     verbose=False))],
         verbose=False)
```

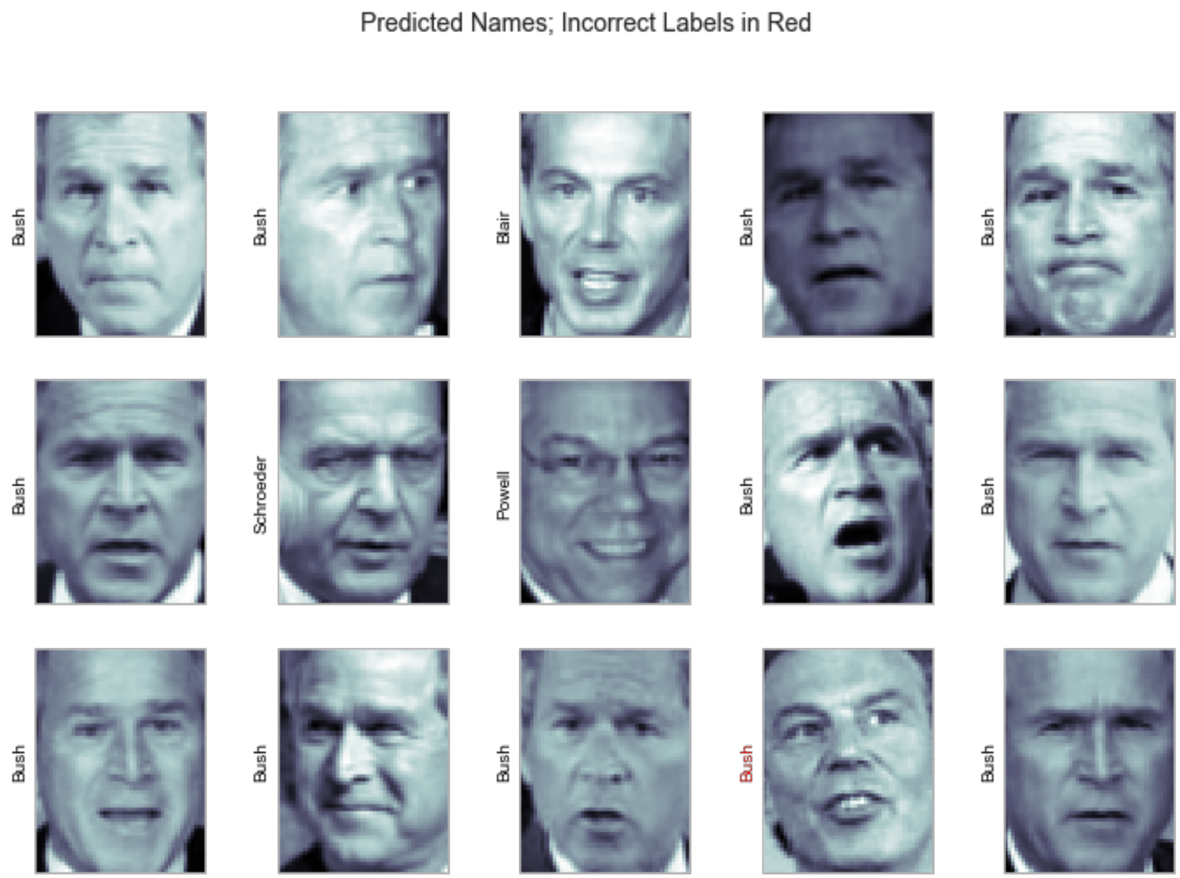
In [32]:
```
yfit = model.predict(Xtest)
```

In [33]:
```
from sklearn.metrics import confusion_matrix
```

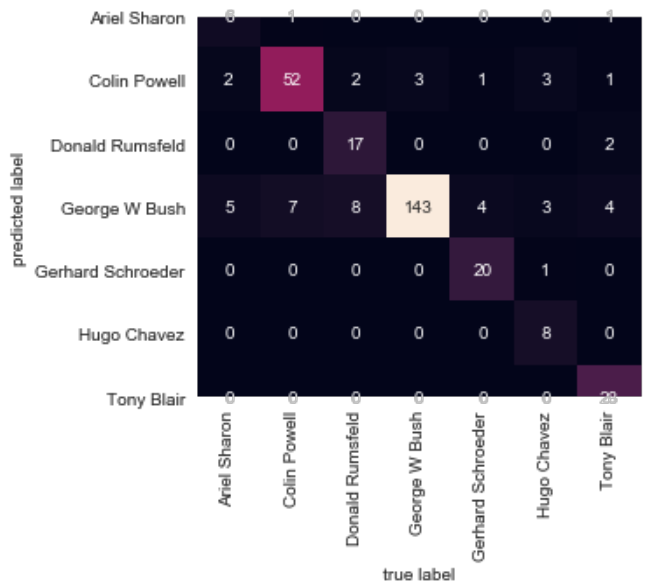
In [34]:
```
confusion_matrix(ytest, yfit)
```

Out[34]:
```
array([[  6,   2,   0,   5,   0,   0,   0],
       [  1,  52,   0,   7,   0,   0,   0],
       [  0,   2,  17,   8,   0,   0,   0],
       [  0,   3,   0, 143,   0,   0,   0],
       [  0,   1,   0,   4,  20,   0,   0],
       [  0,   3,   0,   3,   1,   8,   0],
       [  1,   1,   2,   4,   0,   0,  28]])
```

In [35]:
```
fig, ax = plt.subplots(3, 5, figsize=(12,8))

for i, axi in enumerate(ax.flat):
    axi.imshow(Xtest[i].reshape(62,47), cmap='bone')
    axi.set(xticks=[], yticks=[])
    axi.set_ylabel(faces.target_names[yfit[i]].split()[-1],
                   color='black' if yfit[i] == ytest[i] else 'red')
fig.suptitle('Predicted Names; Incorrect Labels in Red', size=14);
```



In [36]:
```
mat = confusion_matrix(ytest, yfit)
sns.heatmap(mat.T, square=True, annot=True, fmt='d', cbar=False,
            xticklabels=faces.target_names,
            yticklabels=faces.target_names)
plt.xlabel('true label')
plt.ylabel('predicted label');
```



GridSearchCV

In [37]:
```
from sklearn.model_selection import GridSearchCV
```

In [38]:
```
Xtrain_pca = pca.transform(Xtrain)
```

In [39]:
```
param_grid = {'C': [1e3, 5e3, 1e4, 5e4, 1e5],
              'gamma': [0.0001, 0.0005, 0.001, 0.005, 0.01, 0.1], }

clf = GridSearchCV(SVC(kernel='rbf', class_weight='balanced'),
                   param_grid, cv=5)  # 5 Fold cross validation
```

In [40]:
```
clf = clf.fit(Xtrain_pca, ytrain)
```

In [41]:
```python
print("Best estimator found by grid search:")
print(clf.best_estimator_)
```

```
Best estimator found by grid search:
SVC(C=1000.0, cache_size=200, class_weight='balanced', coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma=0.005, kernel='rbf',
    max_iter=-1, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)
```

PCA - # of features

In [42]:
```python
pca = PCA(n_components=10, svd_solver='randomized', whiten=True)
pca.fit(faces.data)
```

Out[42]:
```
PCA(copy=True, iterated_power='auto', n_components=10, random_state=None,
    svd_solver='randomized', tol=0.0, whiten=True)
```

In [43]:
```python
components = pca.transform(faces.data)
projected_ = pca.inverse_transform(components)
```

In [44]:
```python
# Plot the results

fig, ax = plt.subplots(2, 10, figsize=(10, 2.5),
                       subplot_kw={'xticks':[], 'yticks':[]},
                       gridspec_kw=dict(hspace=0.1, wspace=0.1))

for i in range(10):
    ax[0, i].imshow(faces.data[i].reshape(62, 47), cmap='bone')
    ax[1, i].imshow(projected[i].reshape(62, 47), cmap='bone')

ax[0, 0].set_ylabel('full-dim\ninput')
ax[1, 0].set_ylabel('10-dim\nreconstruction');
```

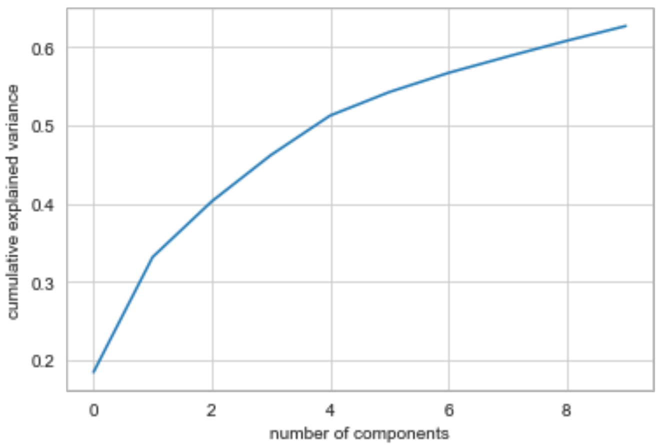
In [45]:
```python
pca.explained_variance_ratio_
```

Out[45]:
```
array([0.1841573 , 0.1474062 , 0.07128289, 0.05923904, 0.05049089,
       0.03009569, 0.02451012, 0.02092452, 0.02018103, 0.01896057],
      dtype=float32)
```

In [46]:
```python
np.cumsum(pca.explained_variance_ratio_)
```

Out[46]:
```
array([0.1841573 , 0.3315635 , 0.4028464 , 0.46208543, 0.51257634,
       0.54267204, 0.5671822 , 0.5881067 , 0.6082877 , 0.6272483 ],
      dtype=float32)
```

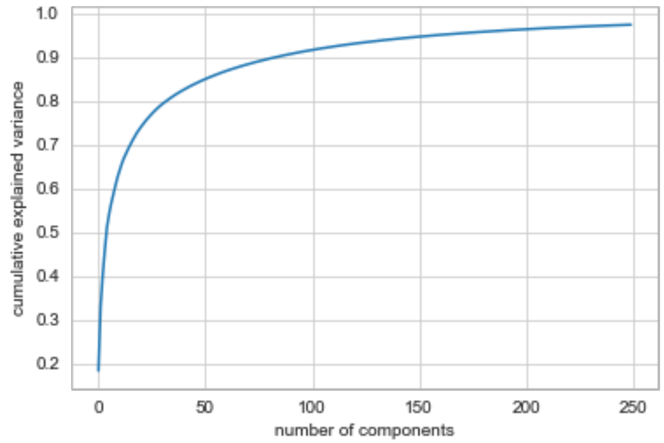
In [47]:
```python
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance');
```



In [48]:
```python
pca = PCA(n_components=250, svd_solver='randomized', whiten=True)
pca.fit(faces.data)
```

Out[48]:
```
PCA(copy=True, iterated_power='auto', n_components=250, random_state=None,
    svd_solver='randomized', tol=0.0, whiten=True)
```

In [49]:
```
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance');
```



In [50]:
```
components = pca.transform(faces.data)
projected = pca.inverse_transform(components)
```

In [51]:
```
# Plot the results

fig, ax = plt.subplots(2, 10, figsize=(10, 2.5),
                       subplot_kw={'xticks':[], 'yticks':[]},
                       gridspec_kw=dict(hspace=0.1, wspace=0.1))

for i in range(10):
    ax[0, i].imshow(faces.data[i].reshape(62, 47), cmap='bone')
    ax[1, i].imshow(projected[i].reshape(62, 47), cmap='bone')

ax[0, 0].set_ylabel('full-dim\ninput')
ax[1, 0].set_ylabel('250-dim\nreconstruction');
```

In [ ]:

```

```