Chapter_2_Training_Simple_Machine_Learning_Algorithms

March 17, 2024

[4]:
```
import numpy as np

class Perceptron(object):
    """
    Perceptron classifier.
    Parameters
    ------------
    eta : float
    Learning rate (between 0.0 and 1.0)
    n_iter : int
    Passes over the training dataset.
    random_state : int
    Random number generator seed for random weight
    initialization.
    Attributes
    -----------
    w_ : 1d-array
    Weights after fitting.
    errors_ : list
    Number of misclassifications (updates) in each epoch.

    """

    def __init__(self, eta=0.01, n_iter=50, random_state=1):
        self.eta = eta
        self.n_iter = n_iter
        self.random_state = random_state

    def fit(self, X, y):

        """
        Fit training data.
        Parameters
        ----------
        X : {array-like}, shape = [n_samples, n_features]
        Training vectors, where n_samples is the number of
        samples and
```

```
        n_features is the number of features.
        y : array-like, shape = [n_samples]
        Target values.
        Returns
        -------
        self : object
        """
        rgen = np.random.RandomState(self.random_state)
        self.w_ = rgen.normal(loc=0.0, scale=0.01,size=1 + X.shape[1])
        self.errors_ = []
        for _ in range(self.n_iter):
            errors = 0
            for xi, target in zip(X, y):
                update = self.eta * (target - self.predict(xi))
                self.w_[1:] += update * xi
                self.w_[0] += update
                errors += int(update != 0.0)
            #print(errors)
            self.errors_.append(errors)
        return self
    def net_input(self, X):
        """Calculate net input"""
        return np.dot(X, self.w_[1:]) + self.w_[0]
    def predict(self, X):
        """Return class label after unit step"""
        return np.where(self.net_input(X) >= 0.0, 1, -1)
```

[5]:
```
# ## angle between two vectors

# v1 = np.array([1, 2, 3])
# v2 = 0.5 * v1
# np.arccos(v1.dot(v2) / (np.linalg.norm(v1) * np.linalg.norm(v2)))
```

[6]:
```
# for _ in range(3):
#     print("hello")
```

[7]:
```
# rgen = np.random.RandomState(1)
# w = rgen.normal(loc=0.0, scale=0.01,size=1 + 5)
```

[8]:
```
# rgen
```

[9]:
```
# w
```

[10]:
```
# int(2.7 != 0.0)
```

[11]:
```
# for i,j in zip([2,5,8],[3,6,8]):
#     print("hello")
```

0.1 Training a perceptron model on the Iris dataset

[12]:
```python
import pandas as pd
df = pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-databases/
 ↪iris/iris.data',header=None)
df.tail()
```

[12]:

	0	1	2	3	4
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

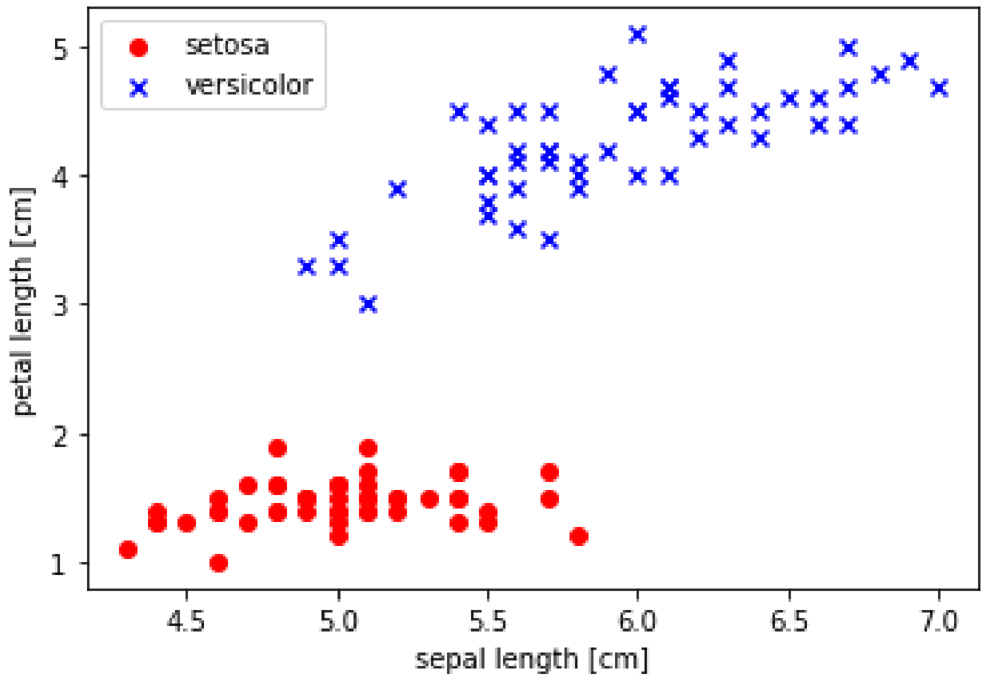
[13]:
```python
import matplotlib.pyplot as plt
# select setosa and versicolor
y = df.iloc[0:100, 4].values
y = np.where(y == 'Iris-setosa', -1, 1)
```

[14]:
```python
#y
```

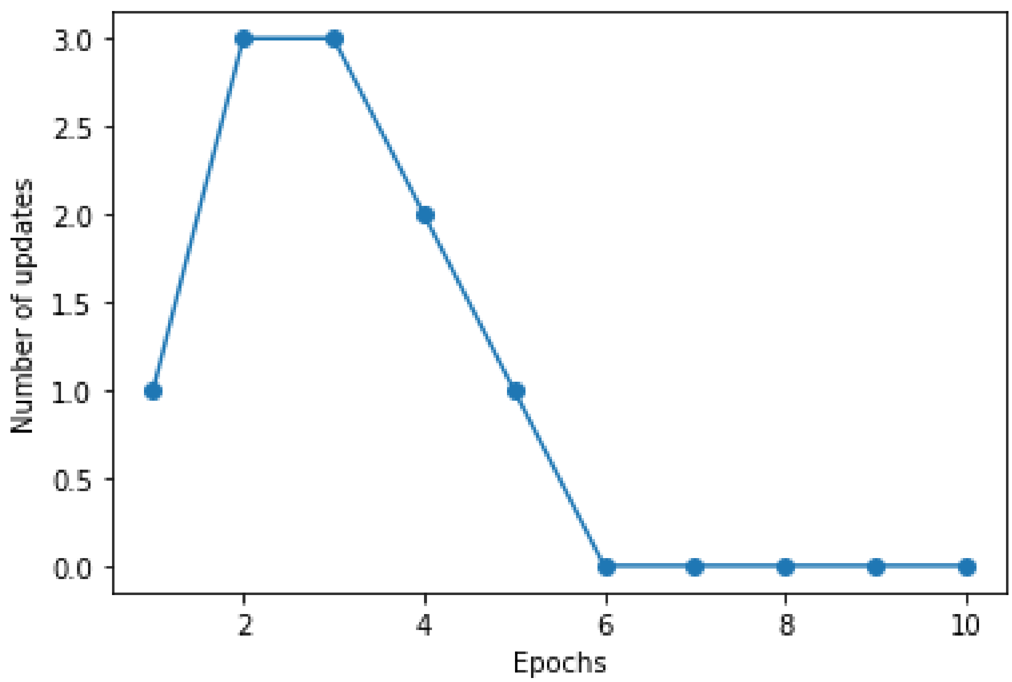
[15]:
```python
# extract sepal length and petal length
X = df.iloc[0:100, [0, 2]].values
```

[16]:
```python
#X
```

[17]:
```python
# plot data
plt.scatter(X[:50, 0], X[:50, 1],color='red', marker='o', label='setosa')
plt.scatter(X[50:100, 0], X[50:100, 1],color='blue', marker='x',␣
 ↪label='versicolor')
plt.xlabel('sepal length [cm]')
plt.ylabel('petal length [cm]')
plt.legend(loc='upper left')
plt.show()
```



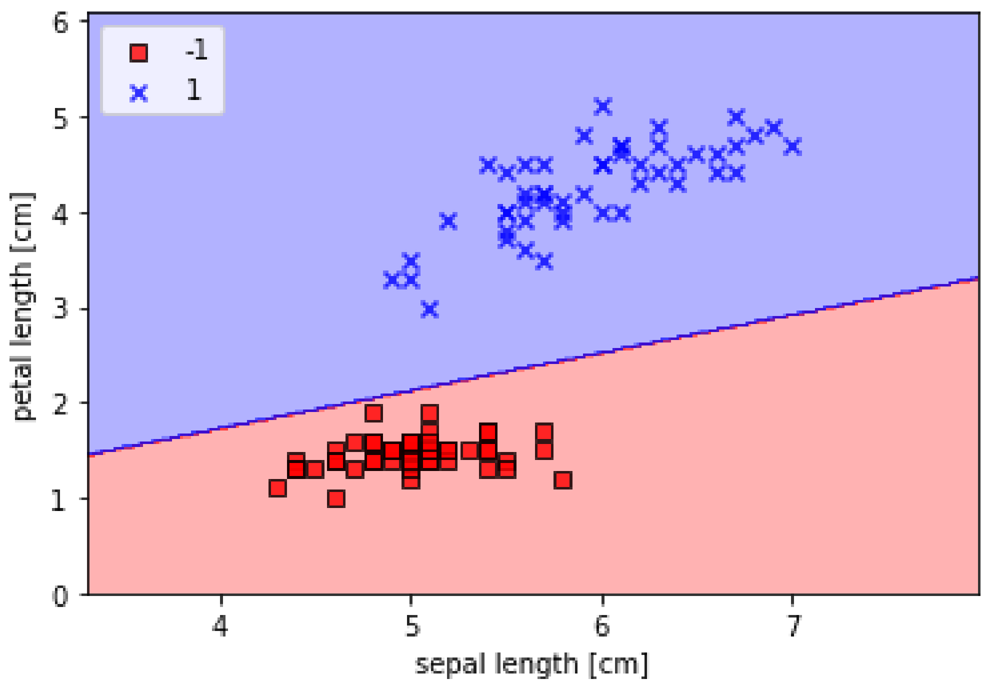
[18]:
```
ppn = Perceptron(eta=0.01, n_iter=10)
ppn.fit(X, y)
plt.plot(range(1, len(ppn.errors_) + 1),ppn.errors_, marker='o')
plt.xlabel('Epochs')
plt.ylabel('Number of updates')
plt.show()
```



[19]:
```
from matplotlib.colors import ListedColormap
def plot_decision_regions(X, y, classifier, resolution=0.02):
    # setup marker generator and color map
    markers = ('s', 'x', 'o', '^', 'v')
    colors = ('red', 'blue', 'lightgreen', 'gray', 'cyan')
    cmap = ListedColormap(colors[:len(np.unique(y))])
    # plot the decision surface
    x1_min, x1_max = X[:, 0].min() - 1, X[:, 0].max() + 1
    x2_min, x2_max = X[:, 1].min() - 1, X[:, 1].max() + 1
    xx1, xx2 = np.meshgrid(np.arange(x1_min, x1_max, resolution),np.
 ↪arange(x2_min, x2_max, resolution))
    Z = classifier.predict(np.array([xx1.ravel(), xx2.ravel()]).T)
    Z = Z.reshape(xx1.shape)
    plt.contourf(xx1, xx2, Z, alpha=0.3, cmap=cmap)
    plt.xlim(xx1.min(), xx1.max())
    plt.ylim(xx2.min(), xx2.max())
    # plot class samples
    for idx, cl in enumerate(np.unique(y)):
        plt.scatter(x=X[y == cl, 0],
        y=X[y == cl, 1],
        alpha=0.8,
        c=colors[idx],
        marker=markers[idx],
        label=cl,
```

```
        edgecolor='black')
```

[20]:
```
plot_decision_regions(X, y, classifier=ppn)
plt.xlabel('sepal length [cm]')
plt.ylabel('petal length [cm]')
plt.legend(loc='upper left')
plt.show()
```



0.2 Adaptive linear neurons and the convergence of learning

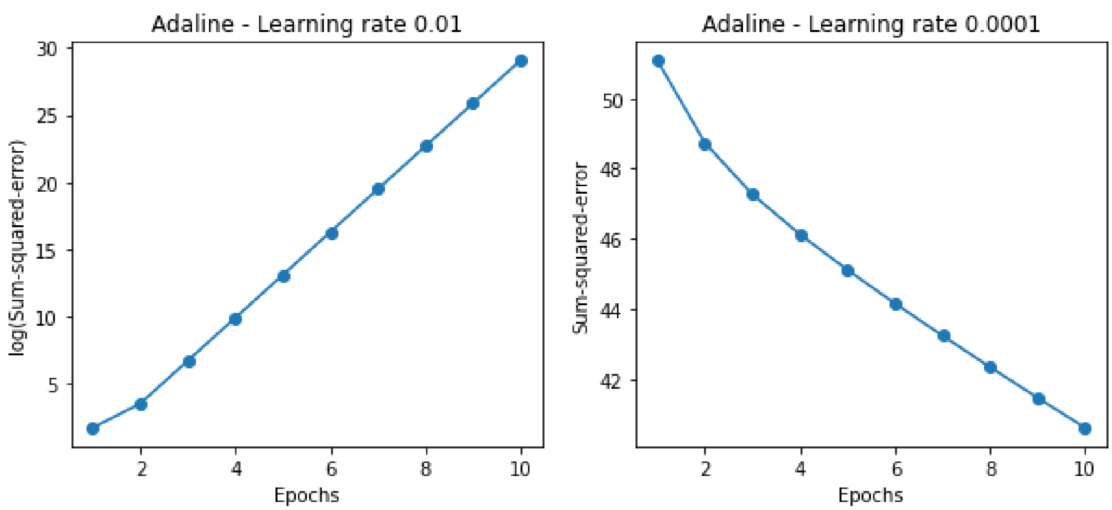
0.2.1 Implementing Adaline in Python

[21]:
```
class AdalineGD(object):
    """ADAptive LInear NEuron classifier.
    Parameters
    ------------
    eta : float
    Learning rate (between 0.0 and 1.0)
    n_iter : int
    Passes over the training dataset.
    random_state : int
    Random number generator seed for random weight
    initialization.
    Attributes
    -----------
```

```
    w_ : 1d-array
    Weights after fitting.
    cost_ : list
    Sum-of-squares cost function value in each epoch.
    """
    def __init__(self, eta=0.01, n_iter=50, random_state=1):
        self.eta = eta
        self.n_iter = n_iter
        self.random_state = random_state
    def fit(self, X, y):
        """ Fit training data.
        Parameters
        ----------
        X : {array-like}, shape = [n_samples, n_features]
        Training vectors, where n_samples is the number of
        samples and
        n_features is the number of features.
        y : array-like, shape = [n_samples]
        Target values.
        Returns
        -------
        self : object
        """
        rgen = np.random.RandomState(self.random_state)
        self.w_ = rgen.normal(loc=0.0, scale=0.01,size=1 + X.shape[1])
        self.cost_ = []
        for i in range(self.n_iter):
            net_input = self.net_input(X)
            output = self.activation(net_input)
            errors = (y - output)
            self.w_[1:] += self.eta * X.T.dot(errors)
            self.w_[0] += self.eta * errors.sum()
            cost = (errors**2).sum() / 2.0
            self.cost_.append(cost)
        return self
    def net_input(self, X):
        """Calculate net input"""
        return np.dot(X, self.w_[1:]) + self.w_[0]
    def activation(self, X):
        """Compute linear activation"""
        return X
    def predict(self, X):
        """Return class label after unit step"""
        return np.where(self.activation(self.net_input(X))>= 0.0, 1, -1)
```

[22]:
```
import matplotlib.pyplot as plt
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(10, 4))
```

```
ada1 = AdalineGD(n_iter=10, eta=0.01).fit(X, y)
ax[0].plot(range(1, len(ada1.cost_) + 1),np.log10(ada1.cost_), marker='o')
ax[0].set_xlabel('Epochs')
ax[0].set_ylabel('log(Sum-squared-error)')
ax[0].set_title('Adaline - Learning rate 0.01')
ada2 = AdalineGD(n_iter=10, eta=0.0001).fit(X, y)
ax[1].plot(range(1, len(ada2.cost_) + 1),ada2.cost_, marker='o')
ax[1].set_xlabel('Epochs')
ax[1].set_ylabel('Sum-squared-error')
ax[1].set_title('Adaline - Learning rate 0.0001')
plt.show()
```

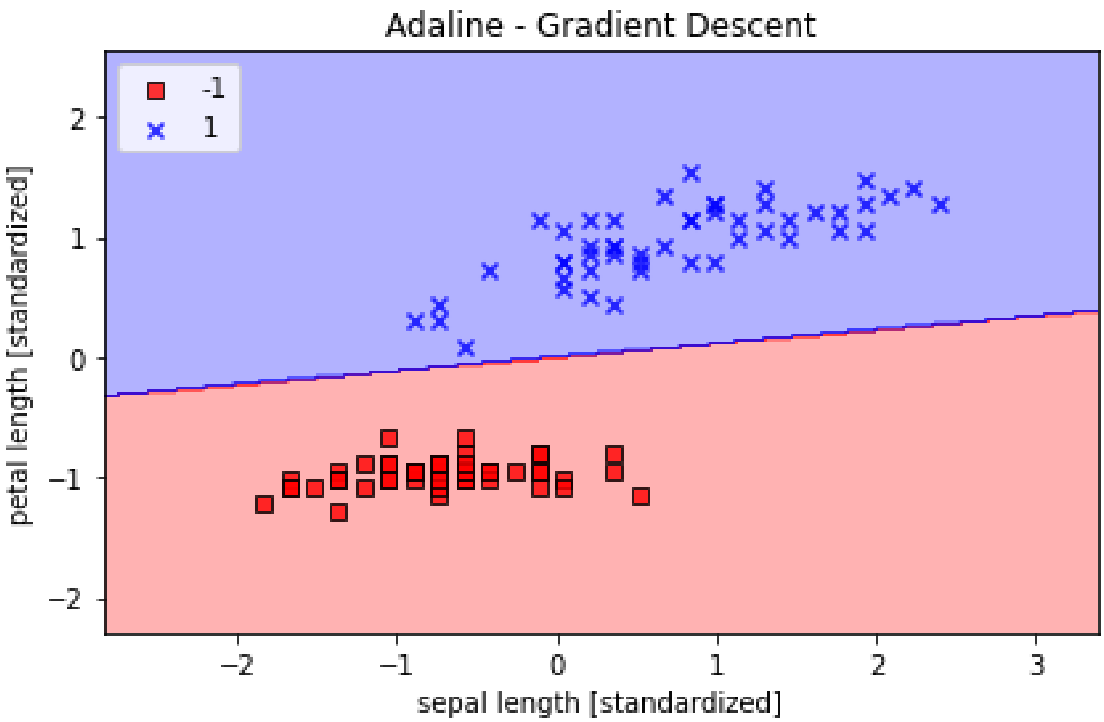


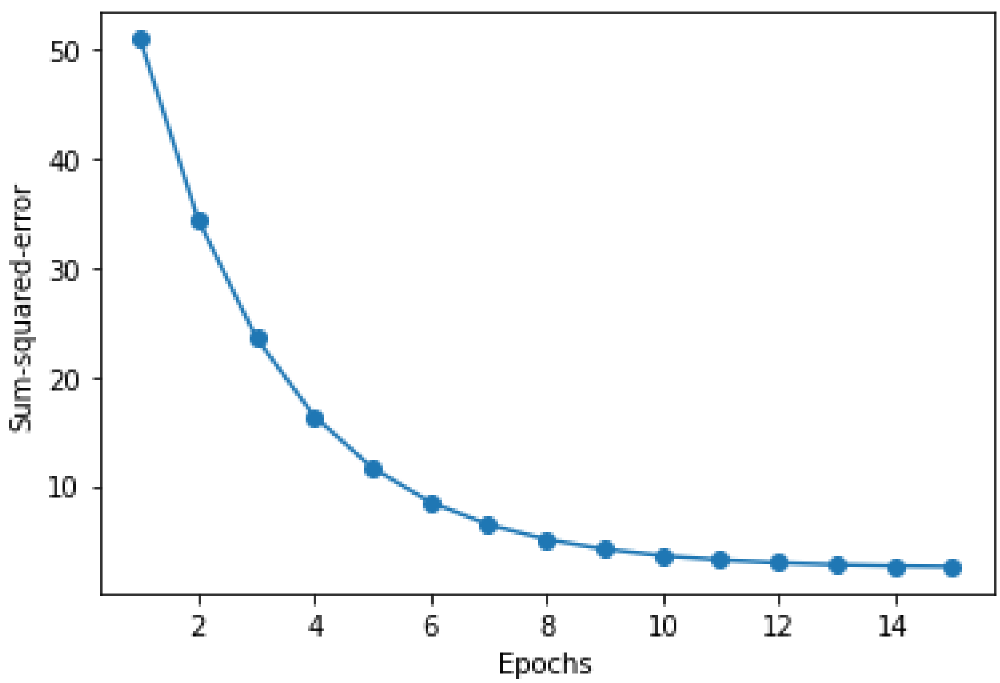
0.3 Improving gradient descent through feature scaling

[23]:
```
X_std = np.copy(X)
X_std[:,0] = (X[:,0] - X[:,0].mean()) / X[:,0].std()
X_std[:,1] = (X[:,1] - X[:,1].mean()) / X[:,1].std()
```

[24]:
```
ada = AdalineGD(n_iter=15, eta=0.01)
ada.fit(X_std, y)
plot_decision_regions(X_std, y, classifier=ada)
plt.title('Adaline - Gradient Descent')
plt.xlabel('sepal length [standardized]')
plt.ylabel('petal length [standardized]')
plt.legend(loc='upper left')
plt.tight_layout()
plt.show()
plt.plot(range(1, len(ada.cost_) + 1), ada.cost_, marker='o')
plt.xlabel('Epochs')
```

```
plt.ylabel('Sum-squared-error')
plt.show()
```



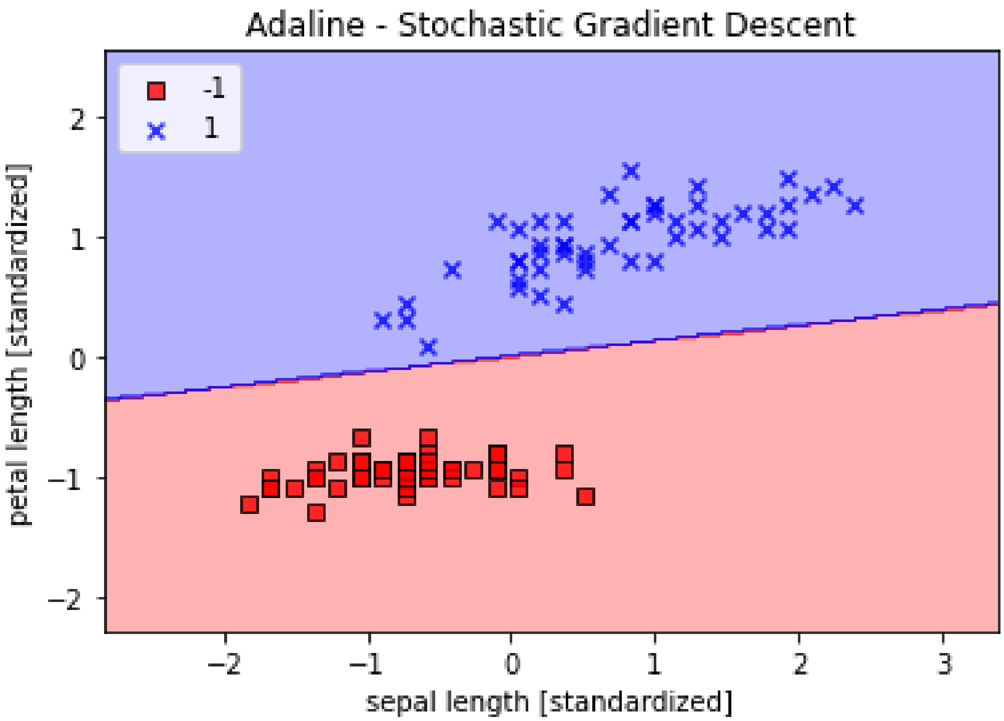


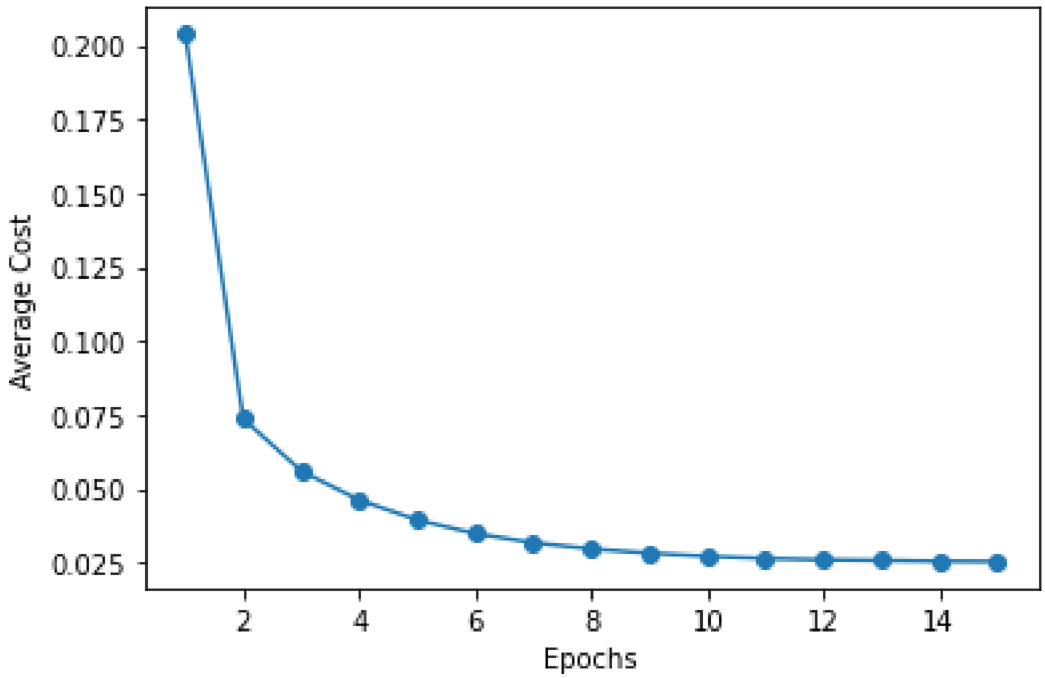
0.4 Large-scale machine learning and stochastic gradient descent

[26]:
```
class AdalineSGD(object):
    """ADAptive LInear NEuron classifier.
    Parameters
    ------------
    eta : float
    Learning rate (between 0.0 and 1.0)
    n_iter : int
    Passes over the training dataset.
    shuffle : bool (default: True)
    Shuffles training data every epoch if True
    to prevent cycles.
    random_state : int
    Random number generator seed for random weight
    initialization.
    Attributes
    -----------
    w_ : 1d-array
    Weights after fitting.
    cost_ : list
    Sum-of-squares cost function value averaged over all
    training samples in each epoch.
    """
    def __init__(self, eta=0.01, n_iter=10,shuffle=True, random_state=None):
        self.eta = eta
        self.n_iter = n_iter
        self.w_initialized = False
        self.shuffle = shuffle
        self.random_state = random_state
    def fit(self, X, y):
        """ Fit training data.
        Parameters
        ----------
        X : {array-like}, shape = [n_samples, n_features]
        Training vectors, where n_samples is the number
        of samples and
        n_features is the number of features.
        y : array-like, shape = [n_samples]
        Target values.
        Returns
        -------
        self : object
        """
        self._initialize_weights(X.shape[1])
```

```python
        self.cost_ = []
        for i in range(self.n_iter):
            if self.shuffle:
                X, y = self._shuffle(X, y)
            cost = []
            for xi, target in zip(X, y):
                cost.append(self._update_weights(xi, target))
            avg_cost = sum(cost) / len(y)
            self.cost_.append(avg_cost)
        return self
    def partial_fit(self, X, y):
        """Fit training data without reinitializing the weights"""
        if not self.w_initialized:
            self._initialize_weights(X.shape[1])
        if y.ravel().shape[0] > 1:
            for xi, target in zip(X, y):
                self._update_weights(xi, target)
        else:
            self._update_weights(X, y)
        return self
    def _shuffle(self, X, y):
        """Shuffle training data"""
        r = self.rgen.permutation(len(y))
        return X[r], y[r]
    def _initialize_weights(self, m):
        """Initialize weights to small random numbers"""
        self.rgen = np.random.RandomState(self.random_state)
        self.w_ = self.rgen.normal(loc=0.0, scale=0.01,size=1 + m)
        self.w_initialized = True
    def _update_weights(self, xi, target):
        """Apply Adaline learning rule to update the weights"""
        output = self.activation(self.net_input(xi))
        error = (target - output)
        self.w_[1:] += self.eta * xi.dot(error)
        self.w_[0] += self.eta * error
        cost = 0.5 * error**2
        return cost
    def net_input(self, X):
        """Calculate net input"""
        return np.dot(X, self.w_[1:]) + self.w_[0]
    def activation(self, X):
        """Compute linear activation"""
        return X
    def predict(self, X):
        """Return class label after unit step"""
        return np.where(self.activation(self.net_input(X))>= 0.0, 1, -1)
```

[27]:
```
ada = AdalineSGD(n_iter=15, eta=0.01, random_state=1)
ada.fit(X_std, y)
plot_decision_regions(X_std, y, classifier=ada)
plt.title('Adaline - Stochastic Gradient Descent')
plt.xlabel('sepal length [standardized]')
plt.ylabel('petal length [standardized]')
plt.legend(loc='upper left')
plt.show()
plt.plot(range(1, len(ada.cost_) + 1), ada.cost_, marker='o')
plt.xlabel('Epochs')
plt.ylabel('Average Cost')
plt.show()
```




0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
Average Cost
2
4
6
8
10
12
14
Epochs

```
[ ]:
```