In [1]:
```python
# 라이브러리 import 후 iris.csv read (dataset link 사용)
import os
import pandas as pd


s = 'https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data'
print('URL:', s)

df = pd.read_csv(s, header=None, encoding='utf-8')
```

```
URL: https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data
```

In [2]:
```python
df[4].unique()
```

Out[2]:
```
array(['Iris-setosa', 'Iris-versicolor', 'Iris-virginica'], dtype=object)
```

In [3]:
```python
# 데이터 처리하기
X = df.iloc[:, [0, 2]].values

d = {'Iris-setosa':0, 'Iris-versicolor':1, 'Iris-virginica':2}
y = df[4].map(d).values
```

In [4]:
```python
y
```

Out[4]:
```
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, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

In [5]:
```python
import numpy as np
import sys

class NeuralNetMLP(object):
    """초기화"""
    def __init__(self, n_hidden=30,
                 l2=0., epochs=100, eta=0.001,
                 shuffle=True, minibatch_size=1, seed=None):

        self.random = np.random.RandomState(seed)
        self.n_hidden = n_hidden
        self.epochs = epochs
        self.eta = eta
        self.shuffle = shuffle
        self.minibatch_size = minibatch_size

    def _onehot(self, y, n_classes):
        onehot = np.zeros((n_classes, y.shape[0]))
        for idx, val in enumerate(y.astype(int)):
            onehot[val, idx] = 1.
        return onehot.T

    def _sigmoid(self, z):
        """로지스틱 함수(시그모이드)를 계산"""
        return 1. / (1. + np.exp(-np.clip(z, -250, 250)))

    def _forward(self, X):
        """정방향 계산을 수행"""

        # 단계 1: 은닉층의 최종 입력
        z_h = np.dot(X, self.w_h) + self.b_h
```

```python
        # 단계 2: 은닉층의 활성화 출력
        a_h = self._sigmoid(z_h)

        # 단계 3: 출력층의 최종 입력
        z_out = np.dot(a_h, self.w_out) + self.b_out

        # 단계 4: 출력층의 활성화 출력
        a_out = self._sigmoid(z_out)

        return z_h, a_h, z_out, a_out

    def _compute_cost(self, y_enc, output):
        """비용 계산"""
        term1 = -y_enc * (np.log(output))
        term2 = (1. - y_enc) * np.log(1. - output)
        cost = np.sum(term1 - term2)

        return cost

    def predict(self, X):
        """클래스 레이블을 예측"""
        z_h, a_h, z_out, a_out = self._forward(X)
        y_pred = np.argmax(z_out, axis=1)
        return y_pred

    def fit(self, X_train, y_train):
        """훈련 데이터에서 가중치를 학습"""
        n_output = np.unique(y_train).shape[0]  # number of class labels
        n_features = X_train.shape[1]

        # 입력층 -> 은닉층 사이의 가중치
        self.b_h = np.zeros(self.n_hidden)
        self.w_h = self.random.normal(loc=0.0, scale=0.1,
                                      size=(n_features, self.n_hidden))

        # 은닉층 -> 출력층 사이의 가중치
        self.b_out = np.zeros(n_output)
        self.w_out = self.random.normal(loc=0.0, scale=0.1,
                                        size=(self.n_hidden, n_output))

        epoch_strlen = len(str(self.epochs))
        self.eval_ = {'cost': [], 'train_acc': []}

        y_train_enc = self._onehot(y_train, n_output)

        for i in range(self.epochs):

            # 미니 배치로 반복
            indices = np.arange(X_train.shape[0])

            if self.shuffle:
                self.random.shuffle(indices)

            for start_idx in range(0, indices.shape[0]):
                batch_idx = [indices[start_idx]]

                # 정방향 계산 (forward)
                z_h, a_h, z_out, a_out = self._forward(X_train[batch_idx])

                # 역전파 계산 (backpropagation)
                delta_out = a_out - y_train_enc[batch_idx]

                sigmoid_derivative_h = a_h * (1. - a_h)
                delta_h = (np.dot(delta_out, self.w_out.T) *
```

```
                              sigmoid_derivative_h)

                # 가중치 업데이트
                self.w_h -= self.eta * np.dot(X_train[batch_idx].T, delta_h)
                self.b_h -= self.eta * np.sum(delta_h, axis=0)

                self.w_out -= self.eta * np.dot(a_h.T, delta_out)
                self.b_out -= self.eta * np.sum(delta_out, axis=0)

            # 훈련하는 동안 에포크마다 평가
            z_h, a_h, z_out, a_out = self._forward(X_train)
            cost = self._compute_cost(y_enc=y_train_enc,
                                      output=a_out)

            y_train_pred = self.predict(X_train)
            train_acc = ((np.sum(y_train == y_train_pred)).astype(np.float) /
                         X_train.shape[0])

            sys.stderr.write('\r%0*d/%d | 비용: %.2f | 훈련 정확도: %.2f ' %(epoch_strlen,
            sys.stderr.flush()

            self.eval_['cost'].append(cost)
            self.eval_['train_acc'].append(train_acc)

        return self
```

In [6]:

```
# Multi Layer Perceptron 학습
nn = NeuralNetMLP(n_hidden=3,
                  epochs=500,
                  eta=0.001,
                  shuffle=True,
                  seed=1)

nn.fit(X_train=X, y_train=y)
```

```
<ipython-input-5-fd81cad6b158>:112: DeprecationWarning: `np.float` is a deprecated alias fo
r the builtin `float`. To silence this warning, use `float` by itself. Doing this will not
modify any behavior and is safe. If you specifically wanted the numpy scalar type, use `np.
float64` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/
1.20.0-notes.html#deprecations
  train_acc = ((np.sum(y_train == y_train_pred)).astype(np.float) /
500/500 | 비용: 132.91 | 훈련 정확도: 93.33
```

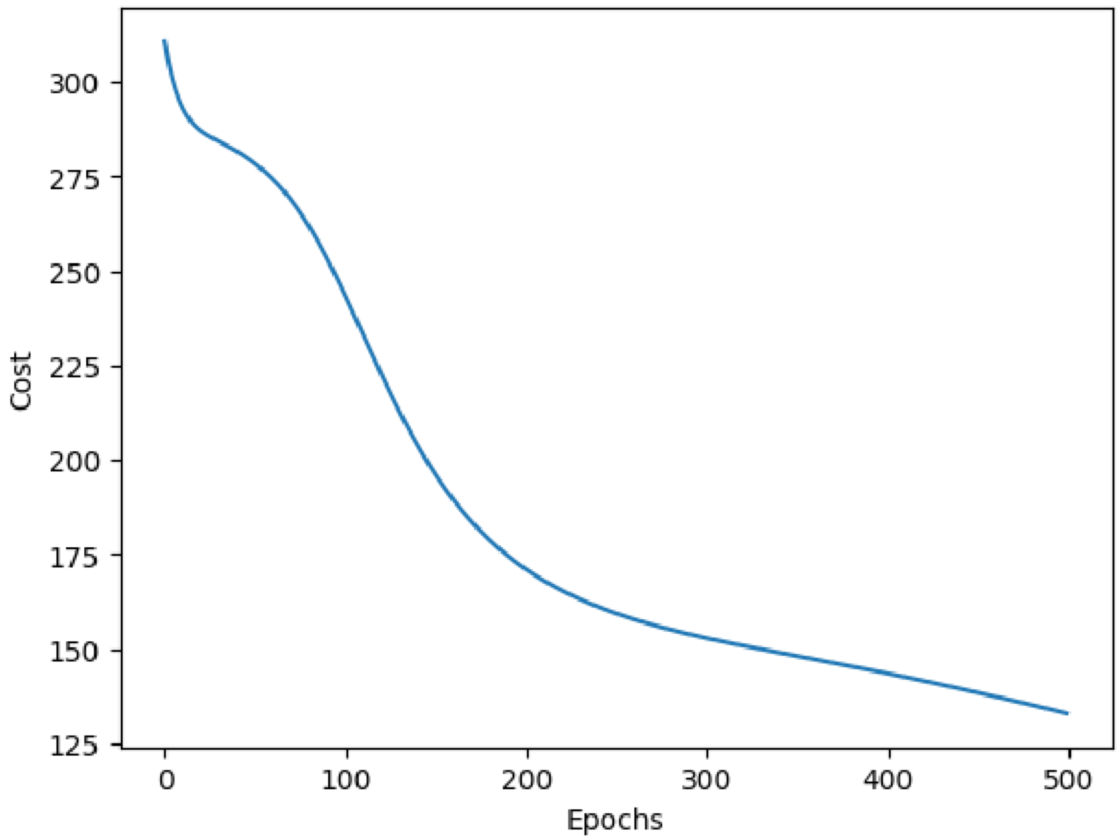
Out[6]:

```
<__main__.NeuralNetMLP at 0x7af8682ecc10>
```

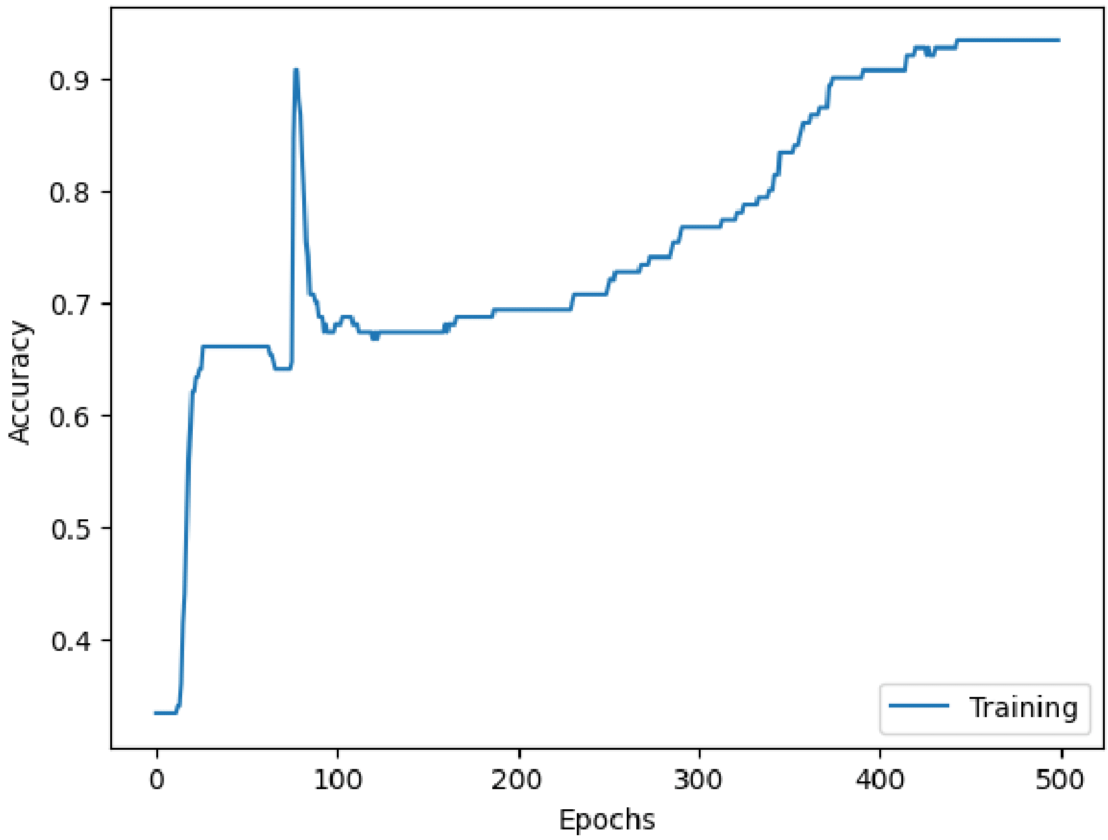
In [7]:

```
# Cost-Epochs 그래프 그리기
import matplotlib.pyplot as plt

plt.plot(range(nn.epochs), nn.eval_['cost'])
plt.ylabel('Cost')
plt.xlabel('Epochs')
plt.show()
```



In [8]:
```
# Train Accuracy-Epochs 그래프 그리기
plt.plot(range(nn.epochs), nn.eval_['train_acc'],
         label='Training')
plt.ylabel('Accuracy')
plt.xlabel('Epochs')
plt.legend(loc='lower right')
plt.show()
```



In [9]:
```
from matplotlib.colors import ListedColormap
```

```python
# 결정 경계 그래프 함수 정의
def plot_decision_regions(X, y, classifier, resolution=0.01):

    # 마커와 컬러맵을 설정합니다
    markers = ('s', 'x', 'o', '^', 'v')
    colors = ('red', 'blue', 'lightgreen', 'gray', 'cyan')
    cmap = ListedColormap(colors[:len(np.unique(y))])

    # 결정 경계를 그립니다
    x1_min, x1_max = X[:, 0].min() - 1, X[:, 0].max() + 1  # 꽃받침 길이 최소/최대
    x2_min, x2_max = X[:, 1].min() - 1, X[:, 1].max() + 1  # 꽃잎 길이 최소/최대
    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())

    # 샘플의 산점도를 그립니다
    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=None if idx==1 else 'black')
```

In [10]:
```python
# 결정 경계 그래프 출력
plot_decision_regions(X, y, classifier=nn)
plt.xlabel('sepal length [cm]')
plt.ylabel('petal length [cm]')
plt.legend(loc='upper left')

plt.show()
```