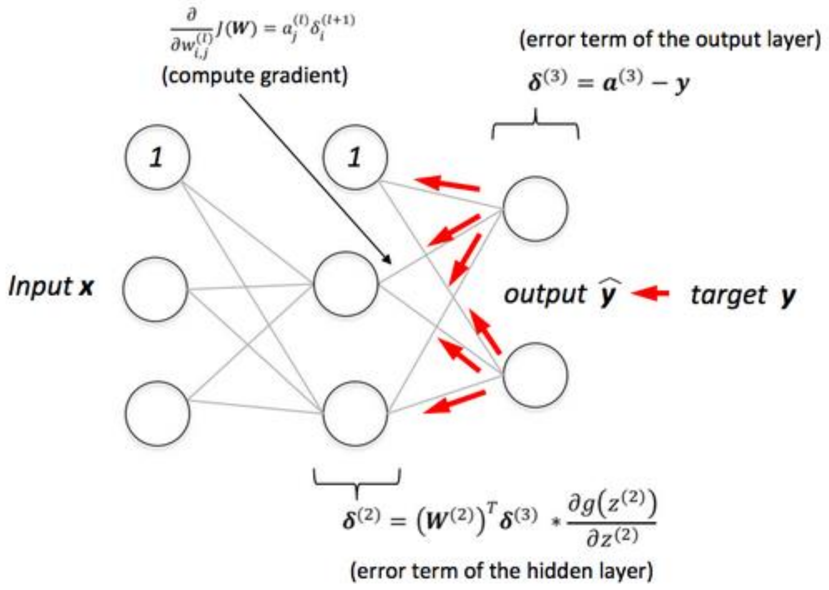
Implement the Backpropagation algorithm in Python to classify iris data set.

Backpropagation Neural Network (BPN) is used to improve the accuracy of neural network and make them capable of self-learning. Backpropagation means "backward propagation of errors". Here error is spread into the reverse direction in order to achieve better performance.

Backpropagation is an algorithm for supervised learning of artificial neural networks that uses the gradient descent method to minimize the cost function. It searches for optimal weights that optimize the mean-squared distance between the predicted and actual labels.

BPN was discovered by Rumelhart, Williams & Honton in 1986. The core concept of BPN is to backpropagate or spread the error from units of output layer to internal hidden layers in order to tune the weights to ensure lower error rates. It is considered a practice of fine-tuning the weights of neural networks in each iteration. Proper tuning of the weights will make a sure minimum loss and this will make a more robust, and generalizable trained neural network.


$\frac{\partial}{\partial w_{i,j}^{(l)}} J(\boldsymbol{W}) = a_j^{(l)} \delta_i^{(l+1)}$
(compute gradient)
(error term of the output layer)
$\boldsymbol{\delta}^{(3)} = \boldsymbol{a}^{(3)} - \boldsymbol{y}$
1
1
Input **x**
output $\hat{\boldsymbol{y}}$
target **y**
$\boldsymbol{\delta}^{(2)} = \left(\boldsymbol{W}^{(2)}\right)^T \boldsymbol{\delta}^{(3)} * \frac{\partial g(z^{(2)})}{\partial z^{(2)}}$
(error term of the hidden layer)

BPN learns in an iterative manner. In each iteration, it compares training examples with the actual target label. Target label can be a class label or continuous value. The backpropagation algorithm works in the following steps:

Initialize Network: BPN randomly initializes the weights.
Forward Propagate: After initialization, we will propagate into the forward direction. In this phase, we will compute the output and calculate the error from the target output.
Back Propagate Error: For each observation, weights are modified in order to reduce the error in a technique called the delta rule or gradient descent. It modifies weights in a "backward" direction to all the hidden layers.

Import Libraries:

```
#Import Libraries

import numpy as np

import pandas as pd

from sklearn.datasets import load_iris

from sklearn.model_selection import train_test_split

import matplotlib.pyplot as plt
```

Load Dataset:

```
# Load dataset

data = load_iris()

# Get features and target

X=data.data

y=data.target
```

Prepare Dataset:

```
# Get dummy variable

y = pd.get_dummies(y).values

y[:3]
```

>>

```
array([[1, 0, 0],

       [1, 0, 0],

       [1, 0, 0]], dtype=uint8)
```

Split train and test set:

```
#Split data into train and test data

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=20,
random_state=4)
```

Initialize Hyper parameters and Weights:

```
# Initialize variables

learning_rate = 0.1

iterations = 5000

N = y_train.size

# number of input features

input_size = 4

# number of hidden layers neurons

hidden_size = 2

# number of neurons at the output layer

output_size = 3

results = pd.DataFrame(columns=["mse", "accuracy"])
```

Initialize the weights for hidden and output layers with random values.

```
# Initialize weights

np.random.seed(10)

# initializing weight for the hidden layer

W1 = np.random.normal(scale=0.5, size=(input_size, hidden_size))

# initializing weight for the output layer

W2 = np.random.normal(scale=0.5, size=(hidden_size , output_size))
```

Helper Functions:

Create helper functions such as sigmoid, mean_square_error, and accuracy.

```
def sigmoid(x):

    return 1 / (1 + np.exp(-x))

def mean_squared_error(y_pred, y_true):
    return ((y_pred - y_true)**2).sum() / (2*y_pred.size)



def accuracy(y_pred, y_true):

    acc = y_pred.argmax(axis=1) == y_true.argmax(axis=1)

    return acc.mean()
```

Backpropagation Neural Network:

In this phase, we are creating BPN in three steps feedforward propagation, error calculation and backpropagation phase. To do this, we are creating a for loop for given number of iterations that execute the three steps (feedforward propagation, error calculation and backpropagation phase) and update the weights in each iteration.

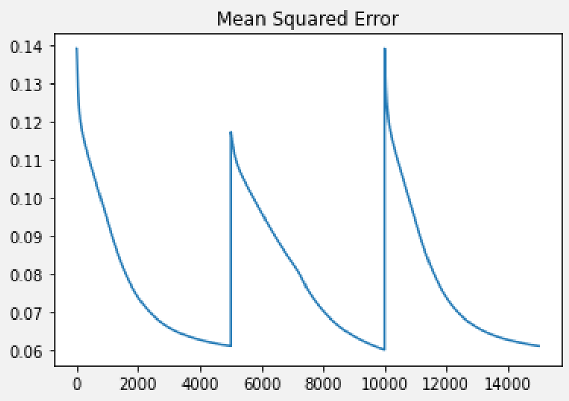
```

for itr in range(iterations):

    # feedforward propagation

    # on hidden layer

    Z1 = np.dot(x_train, W1)

    A1 = sigmoid(Z1)

    # on output layer

    Z2 = np.dot(A1, W2)

    A2 = sigmoid(Z2)



    # Calculating error

    mse = mean_squared_error(A2, y_train)

    acc = accuracy(A2, y_train)

    results=results.append({"mse":mse, "accuracy":acc},ignore_index=True
)

    # backpropagation

    E1 = A2 - y_train

    dW1 = E1 * A2 * (1 - A2)

    E2 = np.dot(dW1, W2.T)
    dW2 = E2 * A1 * (1 - A1)
```

```
    # weight updates

    W2_update = np.dot(A1.T, dW1) / N

    W1_update = np.dot(x_train.T, dW2) / N

    W2 = W2 - learning_rate * W2_update

    W1 = W1 - learning_rate * W1_update
```

Plot MSE and Accuracy:

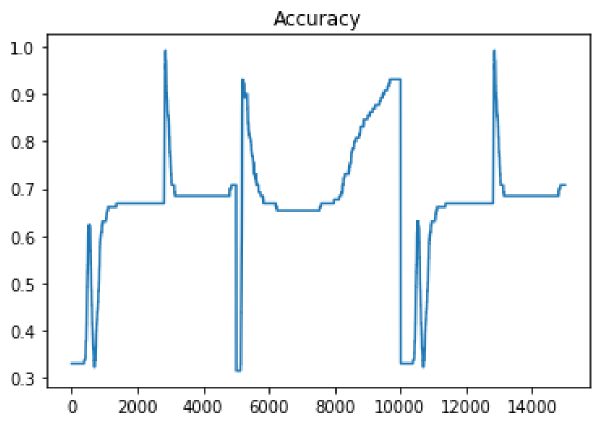
Let's plot mean squared error in each iteration using pandas plot() function.

```
results.mse.plot(title="Mean Squared Error")
```



Lets plot accuracy in each iteration using pandas plot() function.

```
results.accuracy.plot(title="Accuracy")
```



Predict for Test Data and Evaluate the Performance:

Let’s make prediction for the test data and assess the performance of Backpropagation neural network.

```
# feedforward

Z1 = np.dot(x_test, W1)

A1 = sigmoid(Z1)

Z2 = np.dot(A1, W2)

A2 = sigmoid(Z2)

acc = accuracy(A2, y_test)

print("Accuracy: {}".format(acc))

>>

Accuracy: 0.8
```