NEURAL NETWORK

Classifier on the Iris dataset.

In [289…

```
import numpy as np
import pandas as pd
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder
import matplotlib.pyplot as plt
```

1-DATASET (Iris)

In [ ]:

```
iris = datasets.load_iris()
iris_df = pd.DataFrame(iris.data, columns=iris.feature_names)
iris_df['class'] = iris.target

iris_df.head()
```

Out[ ]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	class
0	5.1	3.5	1.4	0.2	0
1	4.9	3.0	1.4	0.2	0
2	4.7	3.2	1.3	0.2	0
3	4.6	3.1	1.5	0.2	0
4	5.0	3.6	1.4	0.2	0

In [291…

```
# Preprocessing
x = iris_df.iloc[:, :4].values  # Features
y = iris_df['class'].values      # Labels
```

In [ ]:

```
# Normalization
def normalize(x):
    min_values = np.min(x, axis=0)
    max_values = np.max(x, axis=0)
    norm_matrix = (x - min_values) / (max_values - min_values)

    # Substitute old training data with normalized values in matrix
    x[:] = norm_matrix

normalize(x)
```

```
# Train and Test set
X_train, X_test, y_train, y_test = train_test_split(
    x, y, test_size=0.2, random_state=42, stratify=y
)


# One-hot encoding
encoder = OneHotEncoder(sparse_output=False)
y_train_encoded = encoder.fit_transform(y_train.reshape(-1, 1))
y_test_encoded = encoder.transform(y_test.reshape(-1, 1))

print(X_train.shape)
print(y_train_encoded.shape)
```

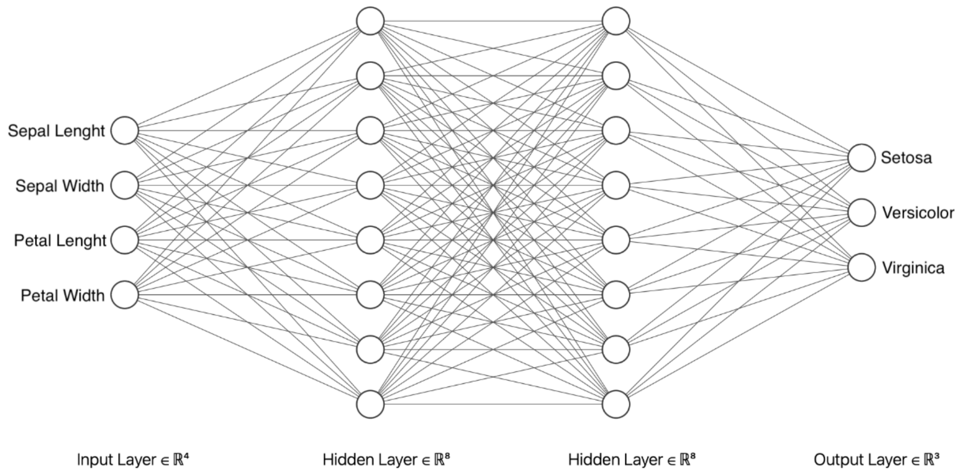
```
(120, 4)
(120, 3)
```

2-NET

The net is composed by the input layer two hidden layer, and the output layer.

$$\begin{aligned}
\underset{(120,4)}{X}\underset{(4,8)}{W_1} + \mathrm{b}_1 &= \underset{(120,8)}{z_1} \\
\phi_{\text{ReLu}}(z_1) &= \underset{(120,8)}{A_1} \\
\underset{(120,8)}{A_1}\underset{(8,8)}{W_2} + \mathrm{b}_2 &= \underset{(120,8)}{z_2} \\
\phi_{\text{ReLu}}(z_2) &= \underset{(120,8)}{A_2} \\
A_2\underset{(8,3)}{W_3} + \mathrm{b}_3 &= \underset{(120,3)}{\hat{z}} \\
\phi_{\text{softmax}}(\hat{z}) &= \underset{(120,3)}{\hat{y}}
\end{aligned}$$

In [ ]:
```
max_epochs = 200

dim_input = 4
dim_hidden1 = 8
dim_hidden2 = 8
dim_output = 3  # Setosa, Versicolor, Virginica

learning_rate = 0.1
```



In [ ]:
```python
class Layer:
    def __init__(self, input_size, neurons):
        # Initialize weights and biases
        self.weights = np.random.normal(0,1, (input_size, neurons))
        self.biases = np.zeros((1, neurons))

    def forward_propagation(self, inputs):
        # Linear transformation
        return np.dot(inputs, self.weights) + self.biases


layer1 = Layer(dim_input, dim_hidden1)  # Input layer to first hidden lay
layer2 = Layer(dim_hidden1, dim_hidden2)  # First hidden layer to second
output_layer = Layer(dim_hidden2, dim_output)  # Second hidden layer to o
```

Example, weight and bias for Hidden 1:

$$W_1 = \begin{bmatrix} w^{(1)}1,1 & w^{(1)}1,2 & \dots & w^{(1)}_{1,4} \\ w^{(1)}2,1 & w^{(1)}2,2 & \dots & w^{(1)}_{2,4} \\ \vdots & \vdots & \ddots & \vdots \\ w^{(1)}8,1 & w^{(1)}8,2 & \dots & w^{(1)}_{8,4} \end{bmatrix} \qquad \mathbf{b}_1 = \begin{bmatrix} b^{(1)}_1 & b^{(1)}_2 & \dots & b^{(1)}_8 \end{bmatrix} = \mathbf{0}$$

Let's define the activation functions, ReLU and Softmax:

$$\phi_{\mathrm{R}}(x) = \begin{cases} 0 & \text{if } x < 0 \\ x & \text{if } x \geq 0 \end{cases} \; ; \quad \phi_{\mathrm{S}}(x) = \frac{e^{x_i}}{\sum e^{x_j}}$$

In [295…
```python
def ReLu(x):
```

```
    return np.maximum(0, x)

def softmax(x):
    x_max = np.max(x)
    e_x = np.exp(x - x_max)
    return e_x / np.sum(e_x, axis=-1, keepdims=True)
```

Relu derivative: Matrix T/F --> 1/0

In [296…

```
def ReLU_derivative(x):
    return (x > 0).astype(float)
```

As loss function we'll use the cross-entropy:

$$J(\hat{y}, y) = -\frac{1}{m}\sum_{m=1}^{m}\sum_{i=1}^{C} y_{m,i} \cdot \log(\hat{y}_{m,i})$$

In [297…

```
def cross_entropy(y_true, y_pred):
    return -np.mean(np.sum(y_true * np.log(np.clip(y_pred, 1e-15, 1 - 1e-
```

Derivatives for backward propagation:

$$\begin{aligned}
&\frac{\partial J}{\partial \hat{z}} = \hat{y} - y \\
&\frac{\partial \hat{z}}{\partial A_2} = W_3^T, \quad \frac{\partial \hat{z}}{\partial W_3} = A_2^T; \quad \frac{\partial \hat{z}}{\partial \mathrm{b}_3} = 1 \\
&\frac{\partial A_2}{\partial z_2} = \begin{cases} 0 & \text{if } z_2 < 0 \\ 1 & \text{if } z_2 \geq 0 \end{cases} \\
&\frac{\partial z_2}{\partial A_1} = W_2, \quad \frac{\partial z_2}{\partial W_2} = A_1^T; \quad \frac{\partial z_2}{\partial \mathrm{b}_2} = 1 \\
&\frac{\partial A_1}{\partial z_1} = \begin{cases} 0 & \text{if } z_1 < 0 \\ 1 & \text{if } z_1 \geq 0 \end{cases} \\
&\frac{\partial z_1}{\partial X} = W_1^T; \quad \frac{\partial z_1}{\partial \mathrm{b}_1} = 1
\end{aligned}$$

So:

$$\begin{aligned}
\frac{\partial J}{\partial W_3} &= \frac{\partial J}{\partial \hat{z}} \cdot \frac{\partial \hat{z}}{\partial W_3} = \frac{\partial J}{\partial \hat{z}} \cdot A_2 = A_2^T \cdot \frac{\partial J}{\partial \hat{z}} \\
\frac{\partial J}{\partial W_2} &= \frac{\partial J}{\partial z_2} \cdot \frac{\partial z_2}{\partial W_2} = \left(\frac{\partial J}{\partial A_2} \odot \phi_{\mathrm{R}}'(z_2)\right) \cdot A_1 = A_1^T \cdot \frac{\partial J}{\partial z_2} \\
\frac{\partial J}{\partial W_1} &= \frac{\partial J}{\partial z_1} \cdot \frac{\partial z_1}{\partial W_1} = \left(\frac{\partial J}{\partial A_1} \odot \phi_{\mathrm{R}}'(z_1)\right) \cdot X = X^T \cdot \frac{\partial J}{\partial z_1}
\end{aligned}$$

$$\frac{\partial J}{\partial A_2} = \frac{\partial J}{\partial \hat{z}} \frac{\partial \hat{z}}{\partial A_2} = (\hat{y} - y) \cdot W_3^T$$
$$\frac{\partial J}{\partial z_2} = \frac{\partial J}{\partial A_2} \odot \phi\prime_{\mathrm{R}}(z_2)$$
$$\frac{\partial J}{\partial A_1} = \frac{\partial J}{\partial z_2} \cdot \frac{\partial z_2}{\partial A_1} = \frac{\partial J}{\partial z_2} \cdot W_2^T$$
$$\frac{\partial J}{\partial z_1} = \frac{\partial J}{\partial A_1} \odot \phi\prime_{\mathrm{R}}(z_1)$$

Update weights:

$$\begin{cases} W_1 \leftarrow W_1 - \eta \frac{\partial J}{\partial W_1} \\ W_2 \leftarrow W_2 - \eta \frac{\partial J}{\partial W_2} \\ W_3 \leftarrow W_3 - \eta \frac{\partial J}{\partial W_3} \end{cases}$$

For the biases, we are just multiplying the matrix for an all-ones array (the derivative), so it is like doing an internal sum.

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix}; \quad b' = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}$$

Example:

$$A \cdot b' = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} (1 \cdot 1) + (2 \cdot 1) + (3 \cdot 1) \\ (4 \cdot 1) + (5 \cdot 1) + (6 \cdot 1) \\ (7 \cdot 1) + (8 \cdot 1) + (9 \cdot 1) \end{bmatrix}$$

In [ ]:
```
def train(X_train, y_train_encoded, layer1, layer2, output_layer, epochs,

    losses = []

    for epoch in range(epochs):

        # Forward pass
        z1 = layer1.forward_propagation(X_train)
        A1 = ReLu(z1)
        z2 = layer2.forward_propagation(A1)
        A2 = ReLu(z2)
        z_hat = output_layer.forward_propagation(A2)
        y_pred = softmax(z_hat)

        J = cross_entropy(y_train_encoded, y_pred)
```

```
        losses.append(J)

        '''Backward Propagation'''
        samples = X_train.shape[0]

        # Gradients output
        dJ_dz_hat = y_pred - y_train_encoded
        dJ_dW3 = np.dot(A2.T, dJ_dz_hat) / samples
        dJ_db3 = np.sum(dJ_dz_hat, axis=0, keepdims=True) / samples # mat
        dJ_dA2 = np.dot(dJ_dz_hat, output_layer.weights.T)

        # Gradients hidden 2
        dJ_dz2 = dJ_dA2 * ReLU_derivative(z2)
        dJ_dW2 = np.dot(A1.T, dJ_dz2) / samples
        dJ_db2 = np.sum(dJ_dz2, axis=0, keepdims=True) / samples
        dJ_dA1 = np.dot(dJ_dz2, layer2.weights.T)

        # Gradients hidden 1
        dJ_dz1 = dJ_dA1 * ReLU_derivative(z1)
        dJ_dW1 = np.dot(X_train.T, dJ_dz1) / samples
        dJ_db1 = np.sum(dJ_dz1, axis=0, keepdims=True) / samples

        # Update weights and biases
        output_layer.weights -= learning_rate * dJ_dW3
        layer2.weights -= learning_rate * dJ_dW2
        layer1.weights -= learning_rate * dJ_dW1

        output_layer.biases -= learning_rate * dJ_db3
        layer2.biases -= learning_rate * dJ_db2
        layer1.biases -= learning_rate * dJ_db1

    return losses
```

In [299…

```
losses = train(X_train, y_train_encoded, layer1, layer2, output_layer, ma
```

In [300…

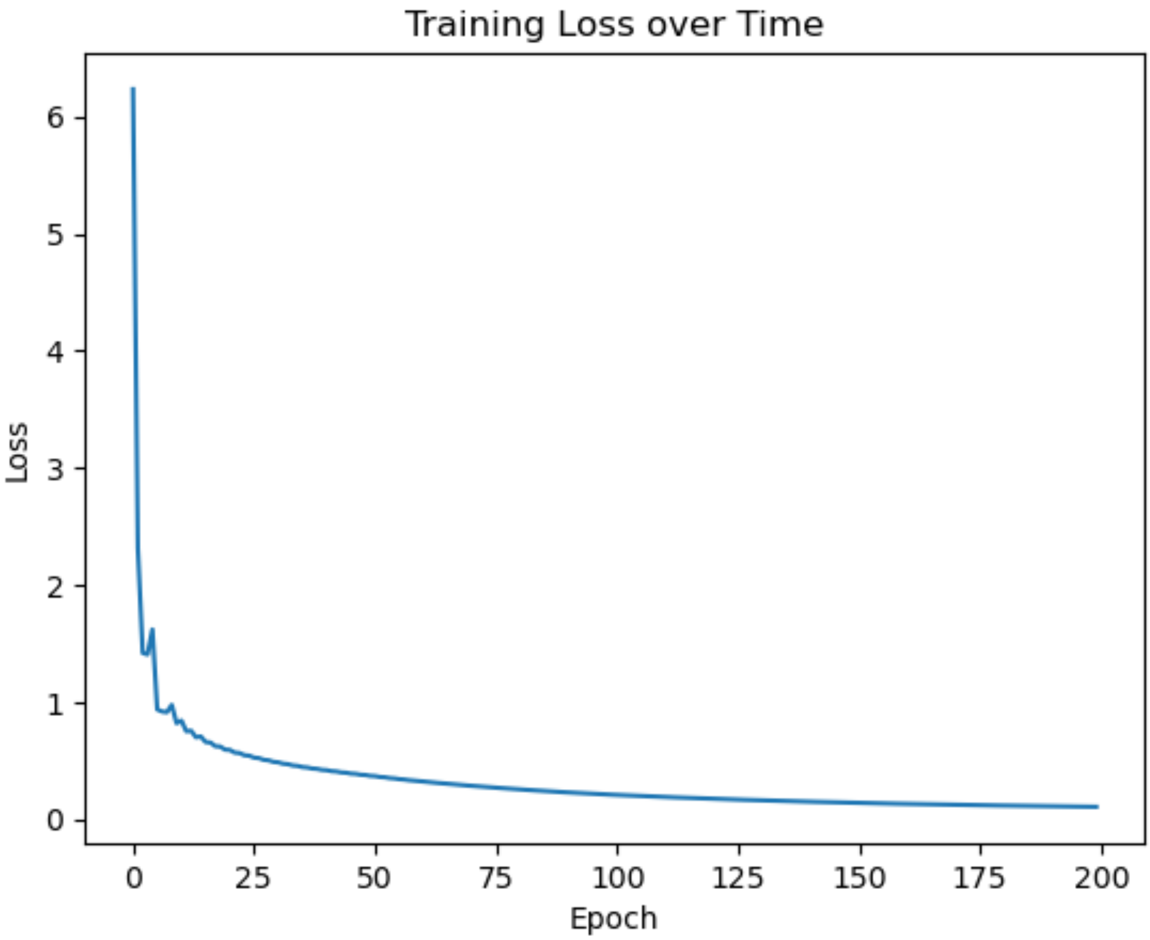
```
def predict(X, layer1, layer2, output_layer):
    z1 = layer1.forward_propagation(X)
    A1 = ReLu(z1)
    z2 = layer2.forward_propagation(A1)
    A2 = ReLu(z2)
    z_hat = output_layer.forward_propagation(A2)
    y_pred = softmax(z_hat)
    return y_pred
```

3-PERFORMANCE:

In [ ]:

```
def calculate_accuracy(X, y_true, layer1, layer2, output_layer):
    predictions = predict(X, layer1, layer2, output_layer)
    predicted_classes = np.argmax(predictions, axis=1)
    true_classes = np.argmax(y_true, axis=1)
    return np.mean(predicted_classes == true_classes)
```

```
train_accuracy = calculate_accuracy(X_train, y_train_encoded, layer1, lay
test_accuracy = calculate_accuracy(X_test, y_test_encoded, layer1, layer2

plt.plot(losses)
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training Loss over Time')
plt.show()
```



In [302…

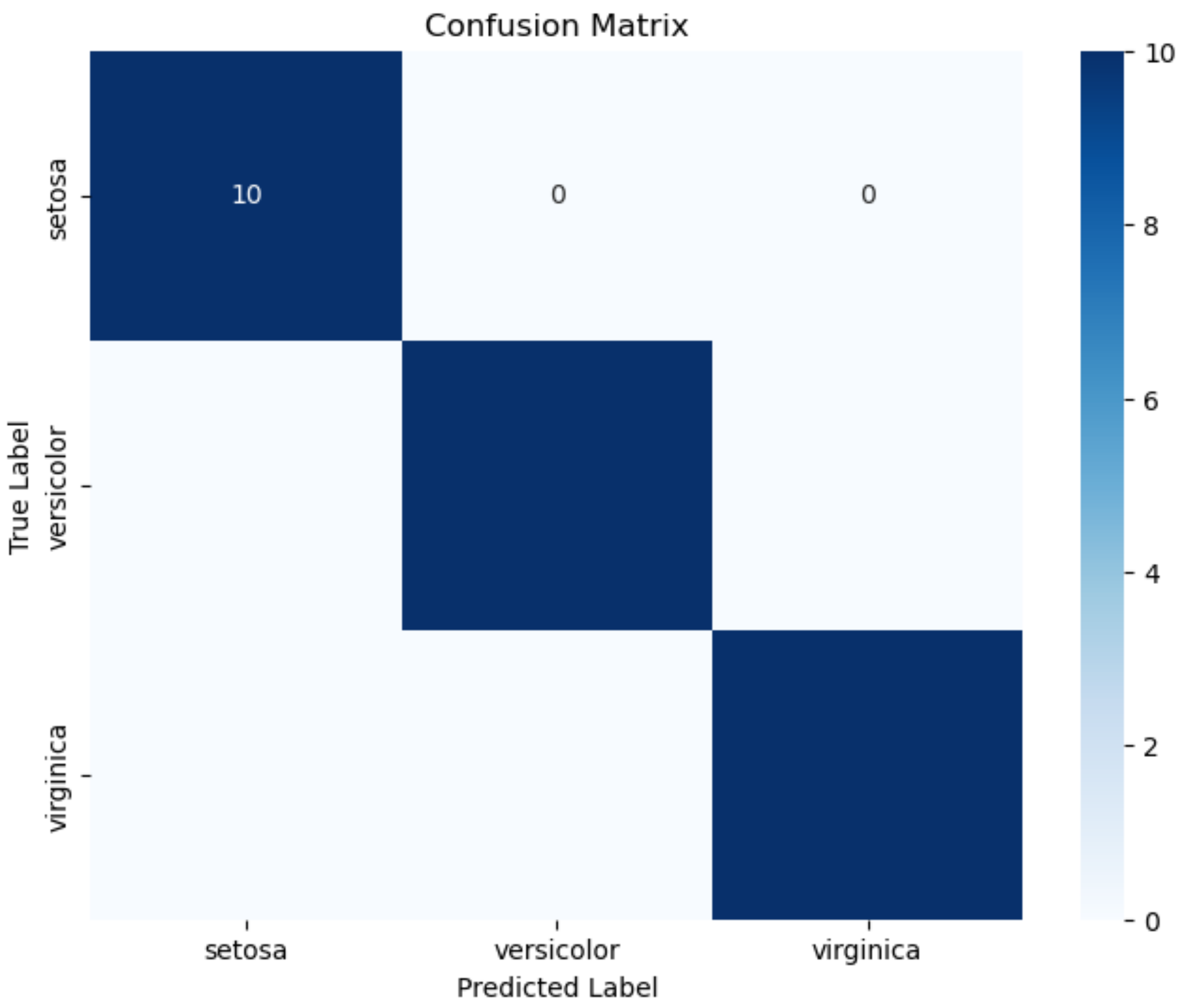
```
test_accuracy
```

Out[302… 1.0

In [303…

```
from sklearn.metrics import confusion_matrix
import seaborn as sns

def plot_confusion_matrix(y_true, y_pred, class_names):
    # Convert one-hot encoded labels back to class indices
    if len(y_true.shape) > 1:  # if one-hot encoded
        y_true = np.argmax(y_true, axis=1)
    if len(y_pred.shape) > 1:  # if one-hot encoded
        y_pred = np.argmax(y_pred, axis=1)

    # Compute confusion matrix
    cm = confusion_matrix(y_true, y_pred)
```

```
    # Create heatmap
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=class_names,
                yticklabels=class_names)
    plt.title('Confusion Matrix')
    plt.ylabel('True Label')
    plt.xlabel('Predicted Label')
    plt.show()

# Get predictions
test_predictions = predict(X_test, layer1, layer2, output_layer)

# Plot confusion matrix
class_names = ['setosa', 'versicolor', 'virginica']
plot_confusion_matrix(y_test_encoded, test_predictions, class_names)
```



In [304…

```
# Check the actual predictions distribution
test_predictions = predict(X_test, layer1, layer2, output_layer)
predicted_classes = np.argmax(test_predictions, axis=1)
print("Predicted class distribution:")
print(np.bincount(predicted_classes))
```

```
# Check the true labels distribution
true_classes = np.argmax(y_test_encoded, axis=1)
print("\nTrue class distribution:")
print(np.bincount(true_classes))
```

```
Predicted class distribution:
[10 10 10]

True class distribution:
[10 10 10]
```

The accuracy is **100%** (sometimes around 97%).