Ex 9 - Neural Networks

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1.Implement a neural network from scratch. Take any dataset. Run minimum 200 iterations and get the result. Use the gradient descent optimization technique for weight optimization.

Forward propagation

$$Z^{[1]} = W^{[1]}X + b^{[1]}$$
$$A^{[1]} = g_{\text{ReLU}}(Z^{[1]}))$$
$$Z^{[2]} = W^{[2]}A^{[1]} + b^{[2]}$$
$$A^{[2]} = g_{\text{softmax}}(Z^{[2]})$$

Backward propagation

$$dZ^{[2]} = A^{[2]} - Y$$
$$dW^{[2]} = \frac{1}{m}dZ^{[2]}A^{[1]T}$$
$$dB^{[2]} = \frac{1}{m}\Sigma dZ^{[2]}$$
$$dZ^{[1]} = W^{[2]T}dZ^{[2]}.*g^{[1]\prime}(z^{[1]})$$
$$dW^{[1]} = \frac{1}{m}dZ^{[1]}A^{[0]T}$$
$$dB^{[1]} = \frac{1}{m}\Sigma dZ^{[1]}$$

Parameter updates

$$W^{[2]} := W^{[2]} - \alpha dW^{[2]}$$
$$b^{[2]} := b^{[2]} - \alpha db^{[2]}$$
$$W^{[1]} := W^{[1]} - \alpha dW^{[1]}$$
$$b^{[1]} := b^{[1]} - \alpha db^{[1]}$$

2.For the same dataset, build a neural network using keras library. Run the same number of epochs and compare the results obtained with your model vs the built-in keras mode.

Importing the libraries and reading the dataset

In [ ]:
```
import pandas as pd
import numpy as np
```

```
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.callbacks import EarlyStopping
```

In [ ]:
```
df = pd.read_csv("diabetes.csv")
```

In [ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Pregnancies               768 non-null    int64  
 1   Glucose                   768 non-null    int64  
 2   BloodPressure             768 non-null    int64  
 3   SkinThickness             768 non-null    int64  
 4   Insulin                   768 non-null    int64  
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64  
 8   Outcome                   768 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

In [ ]:
```
df.describe()
```

Out[ ]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Diabete
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	

Checking for Null Values

In [ ]:
```
df.isna().sum()
```

```
Out[ ]: Pregnancies                 0
        Glucose                     0
        BloodPressure               0
        SkinThickness               0
        Insulin                     0
        BMI                         0
        DiabetesPedigreeFunction    0
        Age                         0
        Outcome                     0
        dtype: int64
```

Split Training and Test Data

```
In [ ]: X=df.drop('Outcome',axis=1)
        y=df['Outcome'].values.reshape(X.shape[0], 1)
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
```

Standard Scaler

```
In [ ]: sc = StandardScaler()
        sc.fit(X_train)
        X_train = sc.transform(X_train)
        X_test = sc.transform(X_test)
```

```
In [ ]: print(X_train.shape)
        print(X_test.shape)
```

```
(614, 8)
(154, 8)
```

Implementing Neural Network

Initializing Parameters

```
In [ ]: def initialize_parameters(layers):
            np.random.seed(42)
            parameters = {}
            parameters["W1"] = np.random.randn(layers[0], layers[1])
            parameters['b1']  = np.random.randn(layers[1],)
            parameters['W2'] = np.random.randn(layers[1], layers[2])
            parameters['b2'] = np.random.randn(layers[2],)
            return parameters
```

Rectified Linear Unit Activation Function, Sigmoid and ETA

```
In [ ]: def relu(Z):
            return np.maximum(0, Z)

        def relu_derivative(x):
            x[x<=0] = 0
            x[x>0] = 1
            return x

        def eta(x):
            ETA = 0.00000001
```

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

def sigmoid(Z):
    return 1/(1+np.exp(-Z))
```

Entropy Loss

In [ ]:
```
def entropy_loss(y, yhat):
    nsample = len(y)
    yhat_inv = 1.0 - yhat
    y_inv = 1.0 - y
    yhat = eta(yhat)
    yhat_inv = eta(yhat_inv)
    loss = -1/nsample * (np.sum(np.multiply(np.log(yhat), y) + np.multiply((y_in
    return loss
```

Forward Propagation

In [ ]:
```
def forward_propagation(X, parameters, y):
    Z1 = X.dot(parameters['W1']) + parameters['b1']
    A1 = relu(Z1)
    Z2 = A1.dot(parameters['W2']) + parameters['b2']
    yhat = sigmoid(Z2)
    loss = entropy_loss(y, yhat)

    parameters['Z1'] = Z1
    parameters['Z2'] = Z2
    parameters['A1'] = A1

    return yhat, loss
```

Backward Propagation

In [ ]:
```
def backward_propagation(parameters, yhat, X, y, lr):

    y_inv = 1 - y
    yhat_inv = 1 - yhat

    dl_wrt_yhat = np.divide(y_inv, eta(yhat_inv)) - np.divide(y, eta(yhat))
    dl_wrt_sig = yhat * (yhat_inv)
    dl_wrt_z2 = dl_wrt_yhat * dl_wrt_sig

    dl_wrt_A1 = dl_wrt_z2.dot(parameters['W2'].T)
    dl_wrt_w2 = parameters['A1'].T.dot(dl_wrt_z2)
    dl_wrt_b2 = np.sum(dl_wrt_z2, axis=0, keepdims=True)

    dl_wrt_z1 = dl_wrt_A1 * relu_derivative(parameters['Z1'])
    dl_wrt_w1 = X.T.dot(dl_wrt_z1)
    dl_wrt_b1 = np.sum(dl_wrt_z1, axis=0, keepdims=True)

    parameters['W1'] = parameters['W1'] - lr * dl_wrt_w1
    parameters['W2'] = parameters['W2'] - lr * dl_wrt_w2
    parameters['b1'] = parameters['b1'] - lr * dl_wrt_b1
    parameters['b2'] = parameters['b2'] - lr * dl_wrt_b2
```

Train Neural Network

In [ ]:
```
def train_neural_network(X_train, y_train, layers, lr=0.005, epochs=100):
    parameters = initialize_parameters(layers)
    losses = []

    for i in range(epochs):
        yhat, loss = forward_propagation(X_train, parameters, y_train)
        backward_propagation(parameters, yhat, X_train, y_train, lr)
        losses.append(loss)

    return parameters, losses
```

Prediction and Accuracy

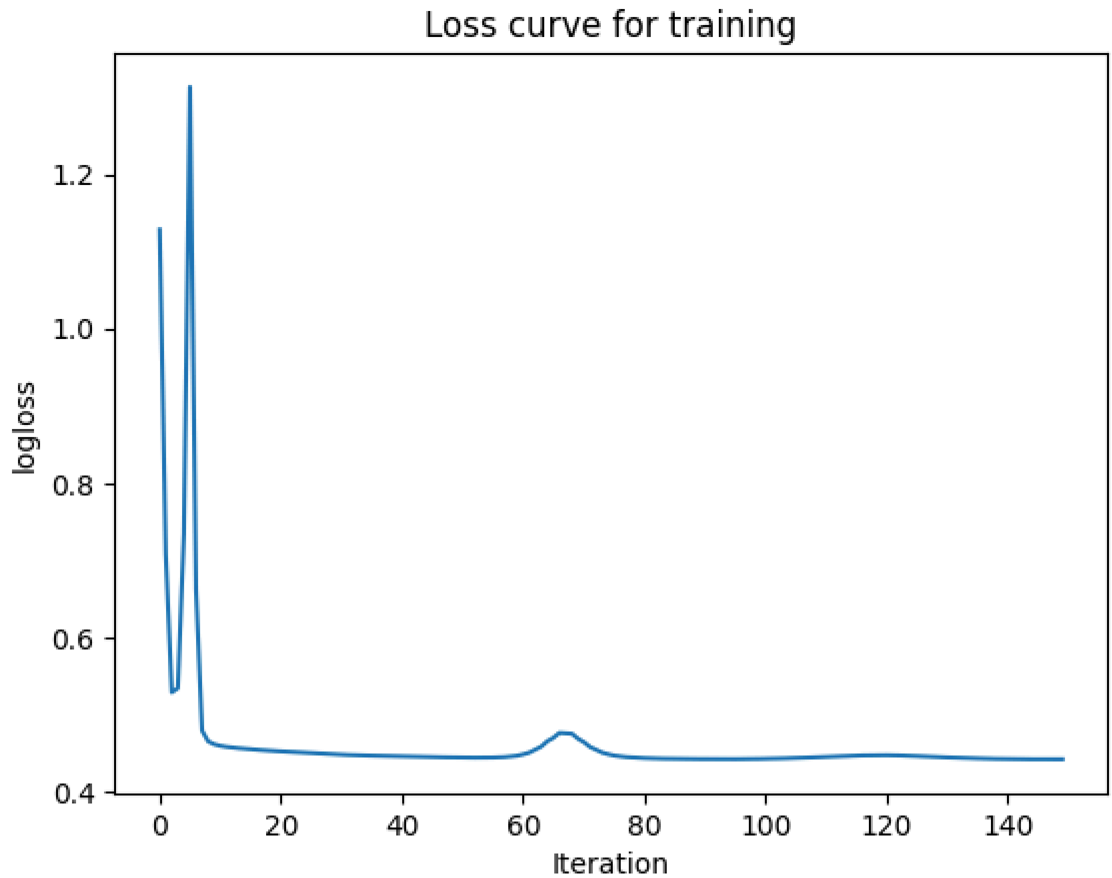
In [ ]:
```
def predict(X, parameters):

    Z1 = X.dot(parameters['W1']) + parameters['b1']
    A1 = relu(Z1)
    Z2 = A1.dot(parameters['W2']) + parameters['b2']
    pred = sigmoid(Z2)
    return np.round(pred)

def calculate_accuracy(y, yhat):

    acc = int(sum(y == yhat) / len(y) * 100)
    return acc
```

Loss Curve Plotting

In [ ]:
```
def plot_loss_curve(losses):

    import matplotlib.pyplot as plt
    plt.plot(losses)
    plt.xlabel("Iteration")
    plt.ylabel("Loss")
    plt.title("Loss Curve for Training")
    plt.show()
```

Usage

In [ ]:
```
parameters, losses = fit(X_train, y_train, layers=[8, 5, 1], lr=0.005, epochs=15
plot_loss(losses)
prediction = predict(X_train, parameters)
predictions = predict(X_test, parameters)
train_accuracy = acc(y_train, prediction)
accuracy = acc(y_test, predictions)

print("Accuracy of Training Data:", train_accuracy)
print("Accuracy of Test Data:", accuracy)
```




```
Accuracy of Training Data: 78
Accuracy of Test Data: 75
```

Implementing Neural Netowork using Keras

2) For the same dataset, build a neural network using keras library. Run the same number of epochs and compare the results obtained with your model vs the built-in keras model.

Model Creating and Training

In [ ]:
```
def create_model(input_dim):
    model = Sequential([
        Dense(5, input_dim=input_dim, activation='relu'),  # Hidden layer with 5
        Dense(1, activation='sigmoid')  # Output layer with 1 node and Sigmoid a
    ])
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accura
    return model

def train_model(model, X_train, y_train, epochs, batch_size):
    early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_
    history = model.fit(X_train, y_train, epochs=epochs, batch_size=batch_size,
    return history
```

Model Evaluation

In [ ]:
```
def evaluate_model(model, X_test, y_test):
    loss, accuracy = model.evaluate(X_test, y_test)
```

```
    return loss, accuracy
```

Split the dataset into training and testing sets & Feature Scaling

In [ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

#  Feature Scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

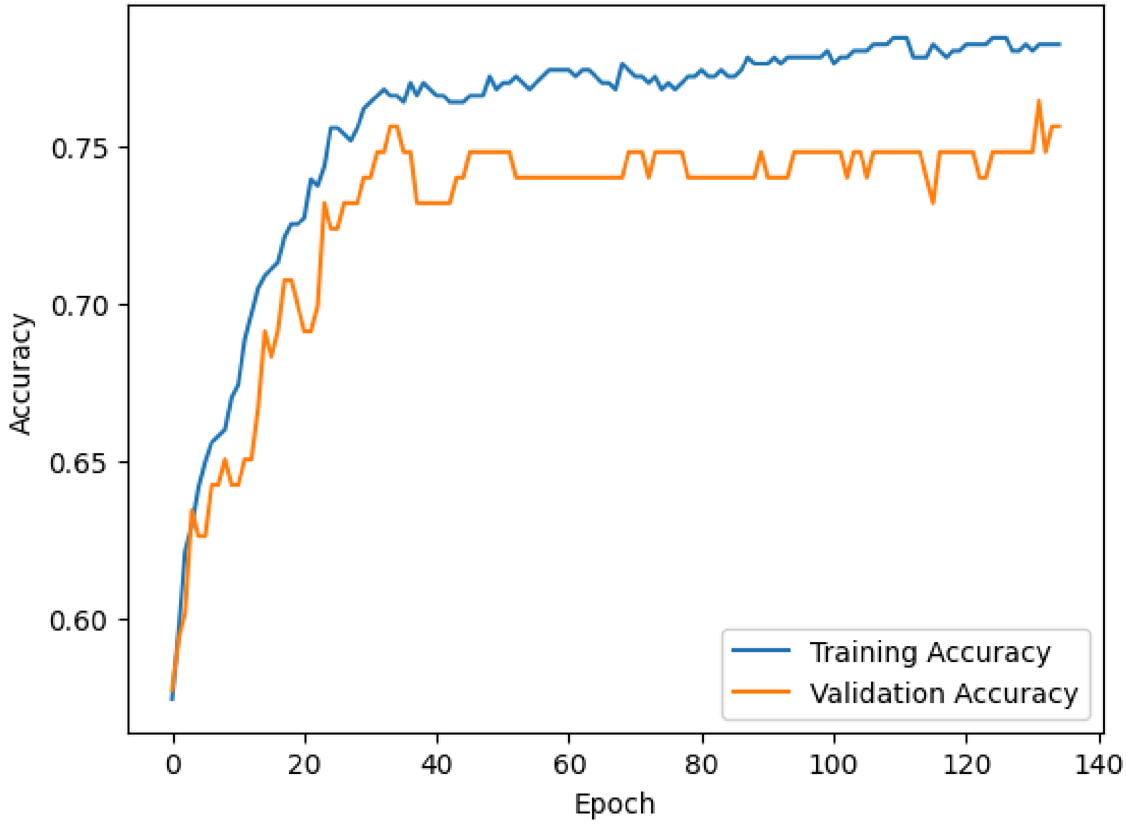
Model Training and Evaluation

In [ ]:
```
model = create_model(input_dim=X_train.shape[1])

# Train the model
epochs = 150
batch_size = 32
history = train_model(model, X_train_scaled, y_train, epochs=epochs, batch_size=

#Evaluate the model on test data
loss, accuracy = evaluate_model(model, X_test_scaled, y_test)
print("Test Loss:", loss)
print("Test Accuracy:", accuracy)
```

```
5/5 [==============================] - 0s 2ms/step - loss: 0.5089 - accuracy:
0.7403
5/5 [==============================] - 0s 2ms/step - loss: 0.5089 - accuracy:
0.7403
Test Loss: 0.5088787078857422
Test Accuracy: 0.7402597665786743
```

Plotting

In [ ]:
```
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



Conclusion

1. **Training from Scratch:**
   - Accuracy: 75%
2. **Using Keras with KMeans:**
   - Accuracy: 74.03%

Training a neural network from scratch achieved a slightly higher accuracy (75%) compared to using Keras with KMeans (74.03%). This suggests that while KMeans clustering can be helpful for preprocessing and feature engineering, it may not always lead to better performance compared to training a neural network from scratch.