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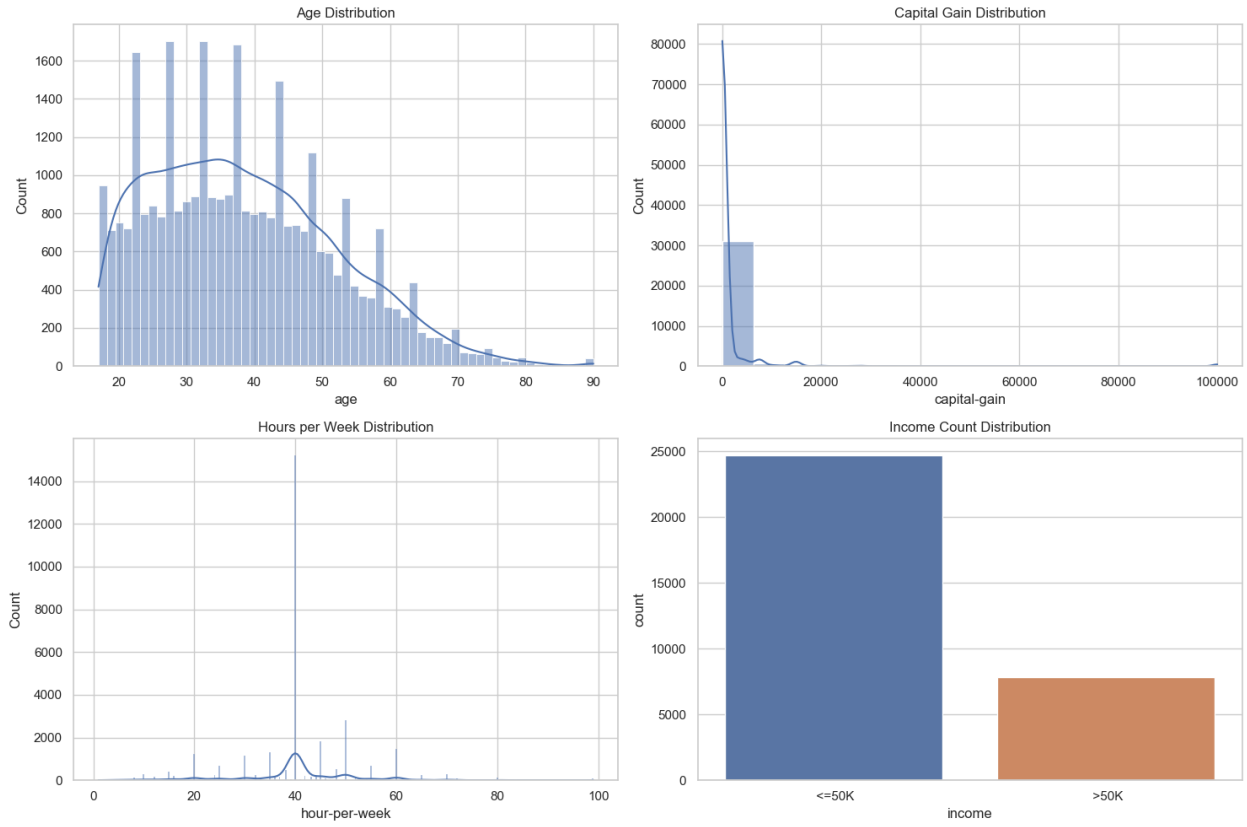
Q. Write a program implement backpropagation algorithm.

```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder



census_data = pd.read_csv("census.csv")

# Display basic information and the first few rows of the dataset
census_info = census_data.info()
census_head = census_data.head()

census_info, census_head
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int64 
 1   workclass       32561 non-null  object
 2   final-weight    32561 non-null  int64 
 3   education       32561 non-null  object
 4   education-num   32561 non-null  int64 
 5   marital-status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital-gain    32561 non-null  int64 
 11  capital-loos    32561 non-null  int64 
 12  hour-per-week   32561 non-null  int64 
 13  native-country  32561 non-null  object
 14  income          32561 non-null  object
```

```
dtypes: int64(6), object(9)
memory usage: 3.7+ MB

(None,
    age          workclass  final-weight   education  education-num  \
 0   39          State-gov         77516   Bachelors             13
 1   50   Self-emp-not-inc         83311   Bachelors             13
 2   38            Private        215646     HS-grad              9
 3   53            Private        234721        11th              7
 4   28            Private        338409   Bachelors             13

          marital-status          occupation    relationship    race
sex  \
 0        Never-married        Adm-clerical   Not-in-family   White
Male
 1   Married-civ-spouse     Exec-managerial         Husband   White
Male
 2             Divorced   Handlers-cleaners   Not-in-family   White
Male
 3   Married-civ-spouse   Handlers-cleaners         Husband   Black
Male
 4   Married-civ-spouse      Prof-specialty            Wife   Black
Female

    capital-gain  capital-loos  hour-per-week  native-country  income

 0          2174             0             40   United-States   <=50K

 1             0             0             13   United-States   <=50K

 2             0             0             40   United-States   <=50K

 3             0             0             40   United-States   <=50K

 4             0             0             40            Cuba   <=50K
)

# Set plot style
sns.set(style="whitegrid")

# Create a figure for multiple plots
fig, axes = plt.subplots(2, 2, figsize=(15, 10))

# Distribution of age
sns.histplot(census_data['age'], kde=True, ax=axes[0, 0])
axes[0, 0].set_title('Age Distribution')

# Capital gain distribution
sns.histplot(census_data['capital-gain'], kde=True, ax=axes[0, 1])
axes[0, 1].set_title('Capital Gain Distribution')
```

```
# Hours per week distribution
sns.histplot(census_data['hour-per-week'], kde=True, ax=axes[1, 0])
axes[1, 0].set_title('Hours per Week Distribution')

# Count plot of income levels
sns.countplot(x='income', data=census_data, ax=axes[1, 1])
axes[1, 1].set_title('Income Count Distribution')

plt.tight_layout()
plt.show()
```




```
# Drop rows with missing values (if any)
census_data_cleaned = census_data.dropna()

# Separate features and target variable
X = census_data_cleaned.drop('income', axis=1)
y = census_data_cleaned['income']

# Encode target variable ('<=50K' -> 0, '>50K' -> 1)
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)

# Define categorical columns to one-hot encode
categorical_columns = ['workclass', 'education', 'marital-status',
```

```
'occupation',
                        'relationship', 'race', 'sex', 'native-
country']

# Apply OneHotEncoder to categorical columns and standard scaling to
numeric columns
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), ['age', 'final-weight', 'education-
num', 'capital-gain', 'capital-loos', 'hour-per-week']),
        ('cat', OneHotEncoder(), categorical_columns)
    ])

# Transform the features
X_preprocessed = preprocessor.fit_transform(X)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_preprocessed,
y_encoded, test_size=0.3, random_state=42)

X_train.shape, X_test.shape
```

```
((22792, 108), (9769, 108))
```

```
import numpy as np

# Define the neural network architecture
class SimpleNeuralNetwork:
    def __init__(self, input_size, hidden_size, output_size):
        # Initialize weights
        self.weights_input_hidden = np.random.randn(input_size,
hidden_size)
        self.weights_hidden_output = np.random.randn(hidden_size,
output_size)
        # Initialize biases
        self.bias_hidden = np.zeros((1, hidden_size))
        self.bias_output = np.zeros((1, output_size))
        # Set learning rate
        self.learning_rate = 0.01

    def sigmoid(self, z):
        return 1 / (1 + np.exp(-z))

    def sigmoid_derivative(self, z):
        return z * (1 - z)

    def forward_propagation(self, X):
        # Convert sparse matrix to dense format if needed
        if hasattr(X, 'toarray'):
            X = X.toarray()
```

```
        # Input to hidden layer
        self.hidden_input = np.dot(X, self.weights_input_hidden) +
self.bias_hidden
        self.hidden_output = self.sigmoid(self.hidden_input)

        # Hidden to output layer
        self.output_input = np.dot(self.hidden_output,
self.weights_hidden_output) + self.bias_output
        self.output = self.sigmoid(self.output_input)
        return self.output

    def backward_propagation(self, X, y):
        # Calculate the error
        output_error = y - self.output
        output_delta = output_error *
self.sigmoid_derivative(self.output)

        # Calculate the error for the hidden layer
        hidden_error = np.dot(output_delta,
self.weights_hidden_output.T)
        hidden_delta = hidden_error *
self.sigmoid_derivative(self.hidden_output)

        # Update weights and biases
        self.weights_hidden_output += self.learning_rate *
np.dot(self.hidden_output.T, output_delta)
        self.weights_input_hidden += self.learning_rate * np.dot(X.T,
hidden_delta)
        self.bias_output += self.learning_rate * np.sum(output_delta,
axis=0, keepdims=True)
        self.bias_hidden += self.learning_rate * np.sum(hidden_delta,
axis=0, keepdims=True)

    def train(self, X, y, epochs, batch_size=32):
        num_samples = X.shape[0]
        for epoch in range(epochs):
            for i in range(0, num_samples, batch_size):
                # Fetch the batch
                X_batch = X[i:i+batch_size].toarray() if
hasattr(X[i:i+batch_size], 'toarray') else X[i:i+batch_size]
                y_batch = y[i:i+batch_size]

                # Forward propagation
                self.forward_propagation(X_batch)

                # Backward propagation and weight update
                self.backward_propagation(X_batch, y_batch)
```

```
            # Print loss every 100 epochs (calculate it for the entire
dataset)
            if epoch % 100 == 0:
                # Forward propagation for entire dataset
                self.forward_propagation(X)
                loss = np.mean(np.square(y - self.output))
                print(f"Epoch {epoch}, Loss: {loss}")

    def predict(self, X):
        return self.forward_propagation(X)

# Preprocessing the target variable
y_train_reshaped = y_train.reshape(-1, 1)

# Instantiate the neural network with one hidden layer
input_size = X_train.shape[1]
hidden_size = 10
output_size = 1  # Binary classification (<=50K or >50K)
nn = SimpleNeuralNetwork(input_size, hidden_size, output_size)

# Train the neural network using mini-batch gradient descent
nn.train(X_train, y_train_reshaped, epochs=1000, batch_size=32)

# Predict on test data
predictions = nn.predict(X_test)
predictions_binary = (predictions > 0.5).astype(int)

# Accuracy of the model
accuracy = np.mean(predictions_binary.flatten() == y_test)
print(f"Accuracy: {accuracy * 100:.2f}%")
```

```
Epoch 0, Loss: 0.14426026730830582
Epoch 100, Loss: 0.09761047108287228
Epoch 200, Loss: 0.09595407853827434
Epoch 300, Loss: 0.0950305826988264
Epoch 400, Loss: 0.09434131357058036
Epoch 500, Loss: 0.0937739612822311
Epoch 600, Loss: 0.09328907486632007
Epoch 700, Loss: 0.09287978782087805
Epoch 800, Loss: 0.09254421151491901
Epoch 900, Loss: 0.09226058829427113
Accuracy: 85.46%
```