```
1 from google.colab import drive
 2 drive.mount('/content/drive')
Fr Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force remount=True).
1 cd '/content/drive/MyDrive/Colab Notebooks/'
/content/drive/MyDrive/Colab Notebooks
1 # Import necessary libraries
2 import pandas as pd
3 from sklearn.model_selection import train_test_split
4 from sklearn.preprocessing import StandardScaler, LabelEncoder
 5 from tensorflow.keras.utils import to_categorical
 6 import numpy as np
 7 !pip install missingno
8 !pip install plotly.express
9 import missingno as msno
10 import matplotlib.pyplot as plt
11 import plotly.express as px
12 from sklearn.compose import ColumnTransformer
13 from sklearn.pipeline import Pipeline
14 from sklearn.impute import SimpleImputer
15 from keras.utils import plot_model
16 from IPython.display import Image
17 from sklearn.metrics import classification_report, accuracy_score
18
19 from keras_tuner.engine.hyperparameters import HyperParameters
20 from keras_tuner import RandomSearch, Hyperband, BayesianOptimization
21 from tensorflow.keras.utils import plot_model
22 from tensorflow.keras.callbacks import LearningRateScheduler, TensorBoard
23 import keras tuner as kt
24 from sklearn.metrics import classification_report, confusion_matrix
25
Requirement already satisfied: missingno in /usr/local/lib/python3.10/dist-packages (0.5.2)
    Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from missingno) (1.26.4)
    Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from missingno) (3.7.1)
    Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from missingno) (1.13.1)
    Requirement already satisfied: seaborn in /usr/local/lib/python3.10/dist-packages (from missingno) (0.13.1)
    Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->missingno) (1.3.0)
    Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib->missingno) (0.12.1)
    Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->missingno) (4.53.1)
    Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->missingno) (1.4.7)
    Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->missingno) (24.1)
    Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->missingno) (10.4.0)
    Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->missingno) (3.1.4)
    Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib->missingno) (2.8.2)
    Requirement already satisfied: pandas>=1.2 in /usr/local/lib/python3.10/dist-packages (from seaborn->missingno) (2.1.4)
    Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.2->seaborn->missingno) (2024.2)
    Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.2->seaborn->missingno) (2024.1)
    Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib->missingno) (1
    Requirement already satisfied: plotly.express in /usr/local/lib/python3.10/dist-packages (0.4.1)
    Requirement already satisfied: pandas>=0.20.0 in /usr/local/lib/python3.10/dist-packages (from plotly.express) (2.1.4)
    Requirement already satisfied: plotly>=4.1.0 in /usr/local/lib/python3.10/dist-packages (from plotly.express) (5.24.1)
    Requirement already satisfied: statsmodels>=0.9.0 in /usr/local/lib/python3.10/dist-packages (from plotly.express) (0.14.3)
    Requirement already satisfied: scipy>=0.18 in /usr/local/lib/python3.10/dist-packages (from plotly.express) (1.13.1)
    Requirement already satisfied: patsy>=0.5 in /usr/local/lib/python3.10/dist-packages (from plotly.express) (0.5.6)
    Requirement already satisfied: numpy>=1.11 in /usr/local/lib/python3.10/dist-packages (from plotly.express) (1.26.4)
    Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.20.0->plotly.express) (
    Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.20.0->plotly.express) (2024.2)
    Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.20.0->plotly.express) (2024.1)
    Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from patsy>=0.5->plotly.express) (1.16.0)
    Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from plotly>=4.1.0->plotly.express) (9.0.0)
    Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from plotly>=4.1.0->plotly.express) (24.1)
 1 # Define the paths for train and test datasets in your Google Drive
 2 train_path = '/content/drive/MyDrive/Colab Notebooks/train.csv'
 3 test path = '/content/drive/MyDrive/Colab Notebooks/test.csv'
5 # Load the datasets
 6 import pandas as pd
 7 train_df = pd.read_csv(train_path)
 8 test_df = pd.read_csv(test_path)
```

```
1 # Check for missing values in train and test data
 2 print(train_df.isnull().sum())
Ð ID
                         0
    Gender
                         0
    Ever_Married
                       140
     Age
                         0
    Graduated
                        78
     Profession
                       124
     Work_Experience
                       829
     Spending_Score
                        0
     Family_Size
                        76
     Var_1
     Segmentation
                         0
     dtype: int64
1 print(test_df.isnull().sum())
→ ID
    Gender
                         0
     Ever_Married
                        50
    Age
                         0
    Graduated
                        24
    Profession
                        38
     Work_Experience
                       269
     Spending_Score
                        0
    Family_Size
                       113
     Var_1
                        32
    dtype: int64
1 !pip install missingno
 2 !pip install plotly.express
 {\tt 3} import missingno as msno
{\tt 4} import matplotlib.pyplot as plt
 5 import plotly.express as px
 6 # Visualize missing values
7 msno.matrix(train_df, figsize=(10, 6)) #removed extra indentation
8 plt.show() #removed extra indentation
9 msno.matrix(test_df, figsize=(10, 6)) #removed extra indentation
10 plt.show() #removed extra indentation
11
12 # Plot distributions of numerical columns
```

13 for column in train_df.select_dtypes(include=['float64', 'int64']).columns:

16 for column in test_df.select_dtypes(include=['float64', 'int64']).columns:

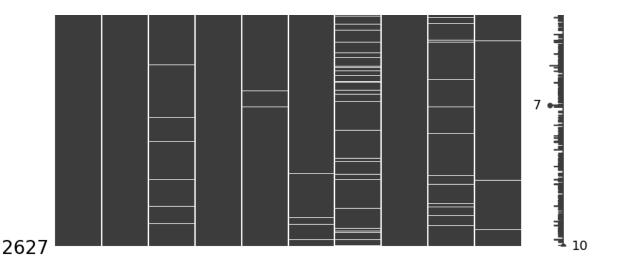
14 15

17 18 fig.show()

fig.show()

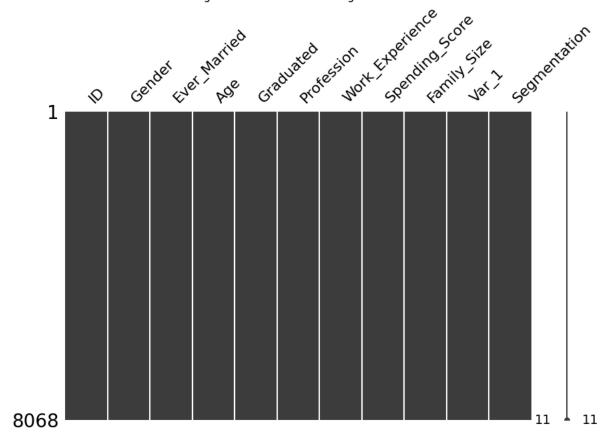
fig = px.histogram(train_df, x=column, title=f'Distribution of {column} in Train data')

fig = px.histogram(test_df, x=column, title=f'Distribution of {column} in Test data')

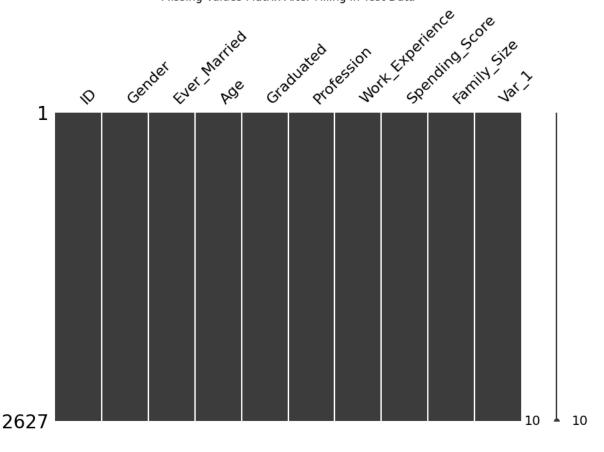


		•

```
1 # Copy the original datasets to new variables
 2 train_df_copy = train_df.copy()
 3 test_df_copy = test_df.copy()
 5 # Handle missing values for categorical variables (mode)
 6 for df in [train_df_copy, test_df_copy]:
      categorical_columns = df.select_dtypes(include=['object']).columns
 8
      for column in categorical_columns:
9
          df[column].fillna(df[column].mode()[0], inplace=True) \\
10
11 # Handle missing values for numerical variables (median)
12 for df in [train_df_copy, test_df_copy]:
13
      numerical_columns = df.select_dtypes(include=['float64', 'int64']).columns
14
      for column in numerical_columns:
15
           df[column].fillna(df[column].median(), inplace=True)
16
17\ \mbox{\# Visualize missing values for both train and test datasets}
18 # Train dataset visualization
19 msno.matrix(train_df_copy, figsize=(10, 6))
20 plt.title('Missing Values Matrix After Filling in Train Data')
21 plt.show()
22
23 # Test dataset visualization
24 msno.matrix(test_df_copy, figsize=(10, 6))
25 plt.title('Missing Values Matrix After Filling in Test Data')
26 plt.show()
27
```



Missing Values Matrix After Filling in Test Data



Split the data into X_train (features) and y_train (target labels).

For test.csv:

Prepare the features (X_test), ensuring that all preprocessing steps (scaling, encoding) applied to train.csv are replicated on test.csv.

```
1 categorical_columns = X_train.select_dtypes(include=['object']).columns # Categorical columns
 2 numerical_columns = X_train.select_dtypes(include=['float64', 'int64']).columns # Numerical columns
 4 #Create a preprocessor that applies OneHotEncoder to categorical columns and StandardScaler to numerical columns
 5 preprocessor = ColumnTransformer(
 6
      transformers=[
          ('num', Pipeline(steps=[
 8
              ('imputer', SimpleImputer(strategy='median')), # Impute missing numerical data with median
9
               ('scaler', StandardScaler()) # Scale numerical data
10
          ]), numerical_columns),
11
12
          ('cat', Pipeline(steps=[
13
               ('imputer', SimpleImputer(strategy='most_frequent')), # Impute missing categorical data with most frequent
14
               ('encoder', OneHotEncoder(drop='first')) # OneHotEncode categorical data
15
          ]), categorical_columns)
16
      1)
17
18 #Apply the preprocessor to X_train and fit the transformer
19 X_train_prepared = preprocessor.fit_transform(X_train)
20
21 #Apply the same preprocessor to the test data (X_test)
22 X_test_prepared = preprocessor.transform(test_data) # Only transform, do not fit on test data
23
24 #Check the shapes of the prepared data
25 print(f'Shape of X_train_prepared: {X_train_prepared.shape}')
26 print(f'Shape of X_test_prepared: {X_test_prepared.shape}')
27
    Shape of X_train_prepared: (8068, 23)
     Shape of X_test_prepared: (2627, 23)
```

```
1 # One-hot encode the target labels
2 y_train_transformed = pd.get_dummies(y_train).values
3
4 # Display the shape of the encoded labels
```

```
→ Shape of y_train_transformed: (8068, 4)
```

Model 1 - Best Practices Model

Build a neural network model with at least two hidden layers using the ReLU activation function.

Use softmax as the activation function for the output layer to handle multi-class classification.

Use categorical cross-entropy as the loss function and Adam optimizer.

5 print("Shape of y_train_transformed:", y_train_transformed.shape)

```
1 model = Sequential([
2     Dense(64, activation='relu', input_shape=(X_train_prepared.shape[1],)), # First hidden layer
3     Dense(32, activation='relu'), # Second hidden layer
4     Dense(y_train_transformed.shape[1], activation='softmax') # Output layer
5 ])
6
7 # Step 4: Compile the model
8 model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/dense.py:87: UserWarning:
```

Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the

```
←
```

Model Training:

Train the model using the train.csv data (X_train, y_train) for 50 epochs with a batch size of 32.

Use early stopping to prevent overfitting (monitor the validation loss and set a patience of 5 epochs).

Use 20% of the training data as a validation set during training

```
1 # Import necessary libraries
2 from tensorflow.keras.callbacks import EarlyStopping
4 # Step 1: Define early stopping callback
5 early_stopping = EarlyStopping(
     monitor='val_loss',
6
7
      patience=5,
8
      restore_best_weights=True
9)
10
11 # Step 2: Train the model with early stopping
12 history = model.fit(
13 X_train_prepared,
14
      y_train_transformed,
15
      epochs=50,
16
      batch_size=32,
17
      validation_split=0.2,
      callbacks=[early_stopping],
18
19
      verbose=1
20)
21
22
→ Epoch 1/50
     202/202
                                - 6s 5ms/step - accuracy: 0.3914 - loss: 1.2837 - val_accuracy: 0.5031 - val_loss: 1.1336
    Epoch 2/50
    202/202
                                - 1s 4ms/step - accuracy: 0.5061 - loss: 1.1118 - val_accuracy: 0.4957 - val_loss: 1.0961
    Epoch 3/50
    202/202
                                - 1s 5ms/step - accuracy: 0.5248 - loss: 1.0896 - val_accuracy: 0.5161 - val_loss: 1.0869
    Epoch 4/50
    202/202 -
                                - 1s 4ms/step - accuracy: 0.5352 - loss: 1.0566 - val_accuracy: 0.5130 - val_loss: 1.0804
    Epoch 5/50
                                - 1s 4ms/step - accuracy: 0.5251 - loss: 1.0611 - val_accuracy: 0.5130 - val_loss: 1.0786
    202/202
    Epoch 6/50
    202/202 -
                                - 1s 4ms/step - accuracy: 0.5432 - loss: 1.0429 - val_accuracy: 0.5124 - val_loss: 1.0747
    Epoch 7/50
                                - 2s 5ms/step - accuracy: 0.5439 - loss: 1.0387 - val_accuracy: 0.5124 - val_loss: 1.0698
    202/202 -
    Epoch 8/50
    202/202
                                - 1s 5ms/step - accuracy: 0.5515 - loss: 1.0198 - val_accuracy: 0.5217 - val_loss: 1.0721
    Epoch 9/50
                                - 2s 8ms/step - accuracy: 0.5580 - loss: 1.0187 - val_accuracy: 0.5198 - val_loss: 1.0715
    202/202
    Epoch 10/50
    202/202
                                - 3s 9ms/step - accuracy: 0.5566 - loss: 1.0214 - val_accuracy: 0.5186 - val_loss: 1.0662
    Epoch 11/50
    202/202 -
                                - 1s 3ms/step - accuracy: 0.5519 - loss: 1.0119 - val_accuracy: 0.5118 - val_loss: 1.0661
    Epoch 12/50
    202/202 -
                                - 1s 5ms/step - accuracy: 0.5685 - loss: 1.0028 - val_accuracy: 0.5211 - val_loss: 1.0674
    Epoch 13/50
    202/202 ·
                                - 1s 4ms/step - accuracy: 0.5617 - loss: 1.0173 - val_accuracy: 0.5242 - val_loss: 1.0690
    Epoch 14/50
    202/202
                                - 1s 4ms/step - accuracy: 0.5587 - loss: 1.0040 - val_accuracy: 0.5198 - val_loss: 1.0640
```

Model Summary:

Epoch 15/50 202/202 ----

Epoch 16/50

Epoch 18/50 **202/202** —

Epoch 19/50

202/202

202/202 —— Epoch 17/50 202/202 ——

Print the model architecture summary to review the structure.

```
1 # Print the model architecture summary
2 model.summary()
3 # Show the model structure
4 plot_model(model, to_file='model_1_structure.png', show_shapes=True, show_layer_names=True)
5 from IPython.display import Image
6 Image(filename='model_1_structure.png')
```

- 1s 4ms/step - accuracy: 0.5667 - loss: 0.9941 - val_accuracy: 0.5266 - val_loss: 1.0709

- **1s** 3ms/step - accuracy: 0.5774 - loss: 0.9750 - val_accuracy: 0.5310 - val_loss: 1.0711

- **2s** 6ms/step - accuracy: 0.5706 - loss: 0.9950 - val_accuracy: 0.5242 - val_loss: 1.0798

- 1s 5ms/step - accuracy: 0.5674 - loss: 0.9838 - val_accuracy: 0.5149 - val_loss: 1.0694

- 2s 7ms/step - accuracy: 0.5797 - loss: 0.9561 - val_accuracy: 0.5149 - val_loss: 1.0688