```
Start coding or generate with AI.
from google.colab import drive
drive.mount('/content/drive')
     Mounted at /content/drive
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean squared error
from sklearn.model_selection import train_test_split
import os
Directotry
# Upload your dataset CSV (for example: nhanes 2017 2020.csv) via Colab file upload or specify path if dow
from google.colab import files
uploaded = files.upload() # Upload the CSV file here manually
\rightarrow
      Choose Files demographic.csv (1).zip

    demographic.csv (1).zip(application/x-zip-compressed) - 376594 bytes, last modified: 7/3/2025 - 100% done

      Saving demographic.csv (1).zip to demographic.csv (1).zip
download the file from kaggle
filename = list(uploaded.keys())[0]
print(f"Loaded file: {filename}")
df = pd.read csv(filename)
     Loaded file: demographic.csv (1).zip
name the file
# Step 4: Explore data columns and preview
print("Columns in dataset:")
print(df.columns)
print("\nFirst 5 rows:")
print(df.head())
→ Columns in dataset:
      Index(['SEQN', 'SDDSRVYR', 'RIDSTATR', 'RIAGENDR', 'RIDAGEYR', 'RIDAGEMN',
              'RIDRETH1', 'RIDRETH3', 'RIDEXMON', 'RIDEXAGM', 'DMQMILIZ', 'DMQADFC', 'DMDBORN4', 'DMDCITZN', 'DMDYRSUS', 'DMDEDUC3', 'DMDEDUC2', 'DMDMARTL', 'RIDEXPRG', 'SIALANG', 'SIAPROXY', 'SIAINTRP', 'FIALANG', 'FIAPROXY', 'FIAINTRP', 'MIALANG', 'MIAPROXY', 'MIAINTRP', 'AIALANGA', 'DMDHHSIZ',
               'DMDFMSIZ', 'DMDHHSZA', 'DMDHHSZB', 'DMDHHSZE', 'DMDHRGND', 'DMDHRAGE',
```

```
'DMDHRBR4', 'DMDHREDU', 'DMDHRMAR', 'DMDHSEDU', 'WTINT2YR', 'WTMEC2YR',
       'SDMVPSU', 'SDMVSTRA', 'INDHHIN2', 'INDFMIN2', 'INDFMPIR'],
     dtype='object')
First 5 rows:
   SEQN SDDSRVYR RIDSTATR RIAGENDR RIDAGEYR RIDAGEMN RIDRETH1 \
0
 73557
              8
                         2
                                   1
                                            69
                                                    NaN
1 73558
                8
                         2
                                   1
                                            54
                                                    NaN
                                                                3
2 73559
               8
                         2
                                   1
                                            72
                                                    NaN
                                                                3
3 73560
                8
                         2
                                            9
                                                    NaN
                                                                3
                                   1
4 73561
                8
                                   2
                                            73
                                                    NaN
                                                                3
  RIDRETH3 RIDEXMON RIDEXAGM ... DMDHREDU DMDHRMAR DMDHSEDU \
0
         4
               1.0
                                         3.0
                                                  4.0
                          NaN ...
1
         3
                 1.0
                          NaN ...
                                         3.0
                                                  1.0
                                                            1.0
2
         3
                                         4.0
                                                  1.0
                                                            3.0
                 2.0
                          NaN ...
3
         3
                                                            4.0
                 1.0
                         119.0
                               . . .
                                         3.0
                                                  1.0
4
         3
                                         5.0
                                                  1.0
                                                            5.0
                 1.0
                          NaN ...
                    WTMEC2YR SDMVPSU SDMVSTRA INDHHIN2 INDFMIN2 INDFMPIR
      WTINT2YR
 13281.237386 13481.042095 1
                                          112
                                                    4.0
                                                           4.0
                                                                       0.84
1 23682.057386 24471.769625
                                   1
                                           108
                                                    7.0
                                                              7.0
                                                                       1.78
2 57214.803319 57193.285376
                                   1
                                           109
                                                   10.0
                                                             10.0
                                                                       4.51
3 55201.178592 55766.512438
                                   2
                                           109
                                                    9.0
                                                             9.0
                                                                       2.52
4 63709.667069 65541.871229
                                   2
                                           116
                                                   15.0
                                                             15.0
                                                                       5.00
[5 rows x 47 columns]
```

Select relevant columns

```
print("Columns in dataset:")
print(df.columns.tolist())
→ Columns in dataset:
     ['SEQN', 'SDDSRVYR', 'RIDSTATR', 'RIAGENDR', 'RIDAGEYR', 'RIDAGEMN', 'RIDRETH1', 'RIDRETH3', 'RIDEXMON
relevant columns = ['RIDAGEYR', 'BMXHT', 'BMXWT', 'PAQ620']
# Check which of these columns exist in the dataframe
existing columns = [col for col in relevant columns if col in df.columns]
print(f"Using columns: {existing_columns}")
# Select only existing columns
data = df[existing_columns].copy()
# Rename columns to standard names for convenience
rename dict = {
    'RIDAGEYR': 'Age',
    'BMXHT': 'Height_cm',
    'BMXWT': 'Weight kg',
    'PAQ605': 'Exercise_Level',
    'PAQ620': 'Exercise_Level' # adjust key according to your dataset
}
# Rename only the columns present
data.rename(columns={k: v for k, v in rename_dict.items() if k in data.columns}, inplace=True)
```

```
print("\nSelected data preview:")
print(data.head())
→ Using columns: ['RIDAGEYR']
     Selected data preview:
        Age
         69
     1
         54
     2
        72
         9
         73
Drop rows with missing values
data.dropna(inplace=True)
Filter Exercise_Level and encode it
if 'Exercise_Level' in data.columns:
    # Keep only rows with Exercise_Level 1 or 2 (yes or no)
    data = data[data['Exercise_Level'].isin([1, 2])]
    # Use .loc to avoid SettingWithCopyWarning and map values
    data.loc[:, 'Exercise_Level'] = data.loc[:, 'Exercise_Level'].map({1: 2, 2: 1}) # Active=2, Inactive=
else:
    print("Warning: 'Exercise_Level' column not found in dataset. Skipping filtering and mapping.")
→ Warning: 'Exercise_Level' column not found in dataset. Skipping filtering and mapping.
# Step 8: Preview cleaned data
print("\nCleaned data sample:")
print(data.head())
\rightarrow
     Cleaned data sample:
        Age
         69
     1
         54
     2
         72
     3
         9
     4
         73
Define features, target and split data
# Step 1: Check all columns in your original dataframe
print("Columns in original dataframe:")
print(df.columns.tolist())
# Step 2: Look for weight-related columns (commonly BMXWT or similar)
weight_candidates = [col for col in df.columns if 'WT' in col.upper()]
print("Possible weight columns found:")
print(weight_candidates)
```

```
# Step 3: Define candidate columns for Age, Height, Weight, Exercise
candidate cols = {
    'Age': 'RIDAGEYR',
    'Height cm': 'BMXHT',
    'Weight_kg': None,
                              # To find below
    'Exercise_Level': None
                              # To find below
}
# Step 4: Select weight column from candidates found
for w_col in weight_candidates:
    if w col in df.columns:
        candidate_cols['Weight_kg'] = w_col
        print(f"Using weight column: {w_col}")
        break
if candidate_cols['Weight_kg'] is None:
    raise KeyError("No weight column found in dataset. Cannot proceed.")
# Step 5: Find exercise column if exists
possible exercise cols = ['PAQ605', 'PAQ620', 'PAQ665', 'PAQ650']
for col in possible exercise cols:
    if col in df.columns:
        candidate cols['Exercise Level'] = col
        print(f"Using exercise column: {col}")
        break
# Step 6: Build list of columns that actually exist
existing cols = [col for col in candidate cols.values() if col is not None and col in df.columns]
print("Columns to select from dataframe:")
print(existing_cols)
# Step 7: Select columns
data = df[existing_cols].copy()
# Step 8: Rename to standard names
rename map = {v: k for k, v in candidate cols.items() if v is not None}
data.rename(columns=rename_map, inplace=True)
print("\nColumns after renaming:")
print(data.columns.tolist())
# Step 9: Drop rows with missing values
data.dropna(inplace=True)
print(f"Data shape after dropping NA: {data.shape}")
# Step 10: Filter Exercise_Level if it exists
if 'Exercise_Level' in data.columns:
    data = data[data['Exercise Level'].isin([1, 2])]
    data.loc[:, 'Exercise_Level'] = data.loc[:, 'Exercise_Level'].map({1: 2, 2: 1})
else:
    print("Exercise Level column missing; proceeding without it.")
print(f"Data shape after filtering Exercise_Level: {data.shape}")
# Step 11: Check if essential columns exist
essential_cols = ['Age', 'Weight_kg']
for col in essential_cols:
    if col not in data.columns:
```

```
raise KeyError(f"Essential column '{col}' missing from data. Cannot proceed.")
# Step 12: Define features (Height_cm optional)
features = ['Age']
if 'Height cm' in data.columns:
    features.append('Height_cm')
if 'Exercise_Level' in data.columns:
    features.append('Exercise_Level')
print(f"Features used: {features}")
X = data[features]
y = data['Weight_kg']
print(f"Feature matrix shape: {X.shape}")
print(f"Target vector shape: {y.shape}")
# Step 13: Split data
from sklearn.model selection import train test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
print(f"Training samples: {X train.shape[0]}, Testing samples: {X test.shape[0]}")
Columns in original dataframe:
     ['SEQN', 'SDDSRVYR', 'RIDSTATR', 'RIAGENDR', 'RIDAGEYR', 'RIDAGEMN', 'RIDRETH1', 'RIDRETH3', 'RIDEXMON
     Possible weight columns found:
     ['WTINT2YR', 'WTMEC2YR']
     Using weight column: WTINT2YR
     Columns to select from dataframe:
     ['RIDAGEYR', 'WTINT2YR']
     Columns after renaming:
     ['Age', 'Weight_kg']
     Data shape after dropping NA: (10175, 2)
     Exercise Level column missing; proceeding without it.
     Data shape after filtering Exercise_Level: (10175, 2)
     Features used: ['Age']
     Feature matrix shape: (10175, 1)
     Target vector shape: (10175,)
     Training samples: 8140, Testing samples: 2035
Train Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)
\rightarrow
      ▼ LinearRegression ① ?
     LinearRegression()
```

Predict on test data

```
y_pred = model.predict(X_test)
```

Calculate Mean Squared Error

```
mse = mean_squared_error(y_test, y_pred)
print(f"\nMean Squared Error (MSE) on Test Set: {mse:.2f}")

Mean Squared Error (MSE) on Test Set: 717804367.81
```

Plot Actual vs Predicted

```
plt.figure(figsize=(7,7))
sns.scatterplot(x=y_test, y=y_pred)
plt.xlabel('Actual Weight (kg)')
plt.ylabel('Predicted Weight (kg)')
plt.title('Actual vs Predicted Weight')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.show()
```

