


```
1 import pandas as pd
2 import numpy as np
3 import matplotlib.pyplot as plt
4 from sklearn.model_selection import train_test_split
5 from sklearn.preprocessing import StandardScaler
6 from sklearn.impute import SimpleImputer
7 import seaborn as sns
8 import plotly.express as px
9 import plotly.graph_objects as go
10
11
```

Preprocessing

```
1 data = pd.read_csv('/content/dailyActivity_merged.csv')
2
3
4
```

```
1 print(data.head())
2
3
4
```



	Id	ActivityDate	TotalSteps	TotalDistance	TrackerDistance	\
0	1503960366	3/25/2016	11004	7.11	7.11	
1	1503960366	3/26/2016	17609	11.55	11.55	
2	1503960366	3/27/2016	12736	8.53	8.53	
3	1503960366	3/28/2016	13231	8.93	8.93	
4	1503960366	3/29/2016	12041	7.85	7.85	

	LoggedActivitiesDistance	VeryActiveDistance	ModeratelyActiveDistance	\
0	0.0	2.57	0.46	
1	0.0	6.92	0.73	
2	0.0	4.66	0.16	
3	0.0	3.19	0.79	
4	0.0	2.16	1.09	


  

	LightActiveDistance	SedentaryActiveDistance	VeryActiveMinutes	\
0	4.07	0.0	33	
1	3.91	0.0	89	
2	3.71	0.0	56	
3	4.95	0.0	39	
4	4.61	0.0	28	


	FairlyActiveMinutes	LightlyActiveMinutes	SedentaryMinutes	Calories
0	12	205	804	1819
1	17	274	588	2154
2	5	268	605	1944
3	20	224	1080	1932
4	28	243	763	1886

```
1 data.describe()
```



	Id	TotalSteps	TotalDistance	TrackerDistance	LoggedActivitiesDistance	VeryActiveDistance	ModeratelyActiveDistance
count	4.570000e+02	457.000000	457.000000	457.000000	457.000000	457.000000	457.000000
mean	4.628595e+09	6546.562363	4.663523	4.609847	0.179427	1.180897	0.478643
std	2.293781e+09	5398.493064	4.082072	4.068540	0.849232	2.487159	0.830995
min	1.503960e+09	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	2.347168e+09	1988.000000	1.410000	1.280000	0.000000	0.000000	0.000000
50%	4.057193e+09	5986.000000	4.090000	4.090000	0.000000	0.000000	0.020000
75%	6.391747e+09	10198.000000	7.160000	7.110000	0.000000	1.310000	0.670000
max	8.877689e+09	28497.000000	27.530001	27.530001	6.727057	21.920000	6.400000


```
1 data.info()
```



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 457 entries, 0 to 456
```

```
Data columns (total 15 columns):
#   Column                               Non-Null Count  Dtype
---  -
0   Id                                   457 non-null   int64
1   ActivityDate                         457 non-null   object
2   TotalSteps                           457 non-null   int64
3   TotalDistance                        457 non-null   float64
4   TrackerDistance                      457 non-null   float64
5   LoggedActivitiesDistance             457 non-null   float64
6   VeryActiveDistance                   457 non-null   float64
7   ModeratelyActiveDistance             457 non-null   float64
8   LightActiveDistance                  457 non-null   float64
9   SedentaryActiveDistance              457 non-null   float64
10  VeryActiveMinutes                    457 non-null   int64
11  FairlyActiveMinutes                  457 non-null   int64
12  LightlyActiveMinutes                  457 non-null   int64
13  SedentaryMinutes                      457 non-null   int64
14  Calories                             457 non-null   int64
dtypes: float64(7), int64(7), object(1)
memory usage: 53.7+ KB
```

```
1 data.isnull().sum()
```



	0
<b>Id</b>	0
<b>ActivityDate</b>	0
<b>TotalSteps</b>	0
<b>TotalDistance</b>	0
<b>TrackerDistance</b>	0
<b>LoggedActivitiesDistance</b>	0
<b>VeryActiveDistance</b>	0
<b>ModeratelyActiveDistance</b>	0
<b>LightActiveDistance</b>	0
<b>SedentaryActiveDistance</b>	0
<b>VeryActiveMinutes</b>	0
<b>FairlyActiveMinutes</b>	0
<b>LightlyActiveMinutes</b>	0
<b>SedentaryMinutes</b>	0
<b>Calories</b>	0

**dtype:** int64

```
1 data.dtypes
```



0

<b>Id</b>	int64
<b>ActivityDate</b>	object
<b>TotalSteps</b>	int64
<b>TotalDistance</b>	float64
<b>TrackerDistance</b>	float64
<b>LoggedActivitiesDistance</b>	float64
<b>VeryActiveDistance</b>	float64
<b>ModeratelyActiveDistance</b>	float64
<b>LightActiveDistance</b>	float64
<b>SedentaryActiveDistance</b>	float64
<b>VeryActiveMinutes</b>	int64
<b>FairlyActiveMinutes</b>	int64
<b>LightlyActiveMinutes</b>	int64
<b>SedentaryMinutes</b>	int64
<b>Calories</b>	int64

**dtype:** object

```
1 data.duplicated().sum()
```



0

```
1
2 data['ActivityDate'] = pd.to_datetime(data['ActivityDate'],format="%m/%d/%Y")
3
4 data['Day'] = data['ActivityDate'].dt.day_name()
5
6 data['TotalMinutes'] = data['VeryActiveMinutes'] + data['FairlyActiveMinutes'] + data['LightlyActiveMinutes'] + data['SedentaryMinutes']
7
8
```

Relation between calories and TotalSteps

```
1 fig = px.scatter(data_frame = data, x = 'Calories',y='TotalSteps',size = 'VeryActiveMinutes',trendline='ols',title="Relationship between Ca
2 fig.show()
```



### Relationship between Calories & Total Steps



### Distribution of calories on each day

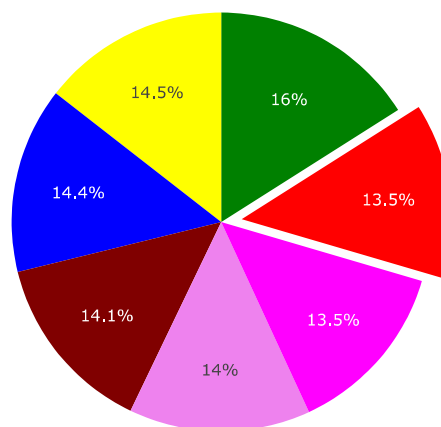
```

1 calories = data["Day"].value_counts()
2 label = calories.index
3 counts = data["Calories"]
4 Colors = ['red', 'green', 'yellow', 'blue', 'violet', 'magenta', 'maroon']
5 explode = (0.1, 0, 0, 0, 0, 0, 0)
6
7 fig = go.Figure(data=[go.Pie(
8     labels=label,
9     values=counts,
10    marker=dict(colors=Colors),
11    pull=explode
12 )])
13
14 fig.update_layout(title_text='Calories Burned Daily')
15 fig.show()

```



### Calories Burned Daily



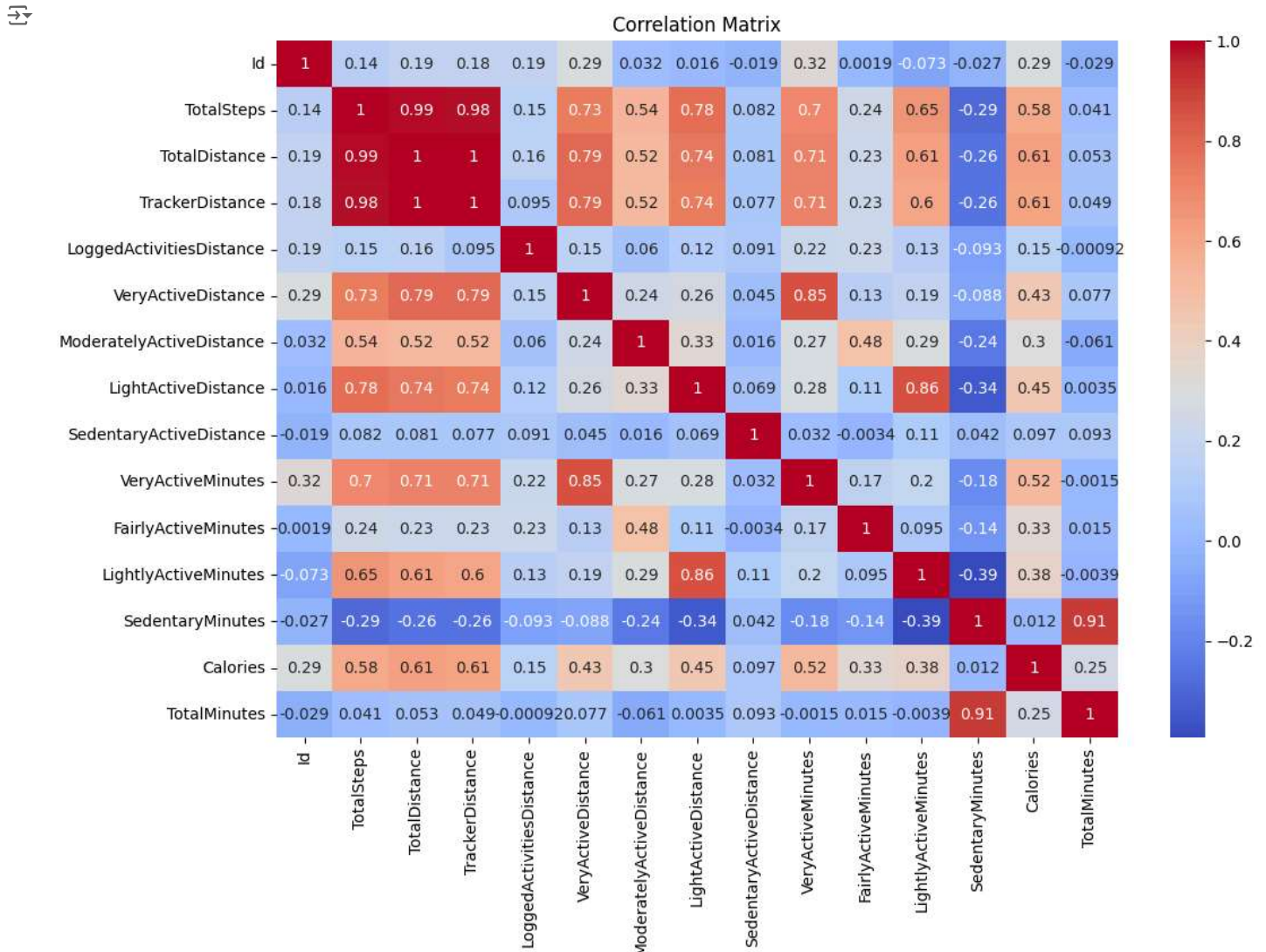
## Correlation Matrix

```


1
2 numeric_data = data.select_dtypes(include=['number'])
3 correlation_matrix = numeric_data.corr()

1 plt.figure(figsize=(12, 8))
2 sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
3 plt.title('Correlation Matrix')
4 plt.show()

```

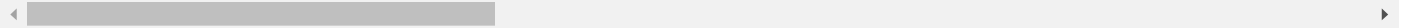


```
1 data.drop(columns=["LoggedActivitiesDistance", "SedentaryActiveDistance"])
```



	Id	ActivityDate	TotalSteps	TotalDistance	TrackerDistance	VeryActiveDistance	ModeratelyActiveDistance	LightActiveDist
	0	1503960366	2016-03-25	11004	7.110000	7.110000	2.57	0.46
	1	1503960366	2016-03-26	17609	11.550000	11.550000	6.92	0.73
	2	1503960366	2016-03-27	12736	8.530000	8.530000	4.66	0.16
	3	1503960366	2016-03-28	13231	8.930000	8.930000	3.19	0.79
	4	1503960366	2016-03-29	12041	7.850000	7.850000	2.16	1.09
	...	...	...	...	...	...	...	...
	452	8877689391	2016-04-08	23014	20.389999	20.389999	11.10	0.63
	453	8877689391	2016-04-09	16470	8.070000	8.070000	0.00	0.02
	454	8877689391	2016-04-10	28497	27.530001	27.530001	21.92	1.12
	455	8877689391	2016-04-11	10622	8.060000	8.060000	1.47	0.15
	456	8877689391	2016-04-12	2350	1.780000	1.780000	0.00	0.00

457 rows × 15 columns



1 Start coding or [generate](#) with AI.


Splitting of data into Train and Test

```
1
2 numeric_data = data.select_dtypes(include=['number'])
3 scaler = StandardScaler()
4 data_scaled = scaler.fit_transform(numeric_data)
5 X = data_scaled[:, :-1]
6 y = data_scaled[:, -1]
7 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Neural Network Model

1 Start coding or [generate](#) with AI.

```
1 import tensorflow as tf
2 from tensorflow.keras.models import Sequential
3 from tensorflow.keras.layers import Dense, Dropout
4 from tensorflow.keras.callbacks import EarlyStopping
5
6 # Define the neural network model
7 model = Sequential([
8     Dense(64, input_dim=X_train.shape[1], activation='relu'),
9     Dropout(0.5),
10    Dense(32, activation='relu'),
11    Dropout(0.5),
12    Dense(1, activation='linear') # Regression output
13 ])
14 model.compile(optimizer='adam', loss='mean_squared_error', metrics=['mean_absolute_error'])
15
16 early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)
17
18 history = model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=100, batch_size=32, callbacks=[early_stopping])
19
20 loss, mae = model.evaluate(X_test, y_test)
21 print(f'Mean Absolute Error on Test Set: {mae}')
22
```

 Epoch 1/100  
/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

12/12

1s 18ms/step - loss: 1.8104 - mean\_absolute\_error: 1.0691 - val\_loss: 0.6812 - val\_mean\_absolute\_error: 0.

Epoch 2/100

12/12

0s 5ms/step - loss: 1.5929 - mean\_absolute\_error: 0.9608 - val\_loss: 0.6100 - val\_mean\_absolute\_error: 0.7

Epoch 3/100

12/12

0s 4ms/step - loss: 1.0429 - mean\_absolute\_error: 0.8036 - val\_loss: 0.5573 - val\_mean\_absolute\_error: 0.6

Epoch 4/100

```
12/12 ————— 0s 6ms/step - loss: 1.1198 - mean_absolute_error: 0.8147 - val_loss: 0.5144 - val_mean_absolute_error: 0.6
Epoch 5/100
12/12 ————— 0s 6ms/step - loss: 0.8514 - mean_absolute_error: 0.7204 - val_loss: 0.4532 - val_mean_absolute_error: 0.6
Epoch 6/100
12/12 ————— 0s 5ms/step - loss: 0.6839 - mean_absolute_error: 0.6655 - val_loss: 0.4183 - val_mean_absolute_error: 0.5
Epoch 7/100
12/12 ————— 0s 6ms/step - loss: 0.8612 - mean_absolute_error: 0.7189 - val_loss: 0.3885 - val_mean_absolute_error: 0.5
Epoch 8/100
12/12 ————— 0s 6ms/step - loss: 0.8814 - mean_absolute_error: 0.7053 - val_loss: 0.3513 - val_mean_absolute_error: 0.5
Epoch 9/100
12/12 ————— 0s 5ms/step - loss: 0.7972 - mean_absolute_error: 0.6733 - val_loss: 0.3229 - val_mean_absolute_error: 0.5
Epoch 10/100
12/12 ————— 0s 7ms/step - loss: 0.6008 - mean_absolute_error: 0.6059 - val_loss: 0.2971 - val_mean_absolute_error: 0.4
Epoch 11/100
12/12 ————— 0s 5ms/step - loss: 0.5828 - mean_absolute_error: 0.6031 - val_loss: 0.2697 - val_mean_absolute_error: 0.4
Epoch 12/100
12/12 ————— 0s 5ms/step - loss: 0.5046 - mean_absolute_error: 0.5536 - val_loss: 0.2535 - val_mean_absolute_error: 0.4
Epoch 13/100
12/12 ————— 0s 6ms/step - loss: 0.5923 - mean_absolute_error: 0.5917 - val_loss: 0.2350 - val_mean_absolute_error: 0.4
Epoch 14/100
12/12 ————— 0s 5ms/step - loss: 0.4504 - mean_absolute_error: 0.5229 - val_loss: 0.2187 - val_mean_absolute_error: 0.4
Epoch 15/100
12/12 ————— 0s 6ms/step - loss: 0.4128 - mean_absolute_error: 0.5145 - val_loss: 0.2046 - val_mean_absolute_error: 0.3
Epoch 16/100
12/12 ————— 0s 6ms/step - loss: 0.5360 - mean_absolute_error: 0.5713 - val_loss: 0.1936 - val_mean_absolute_error: 0.3
Epoch 17/100
12/12 ————— 0s 6ms/step - loss: 0.4950 - mean_absolute_error: 0.5507 - val_loss: 0.1893 - val_mean_absolute_error: 0.3
Epoch 18/100
12/12 ————— 0s 6ms/step - loss: 0.3899 - mean_absolute_error: 0.4798 - val_loss: 0.1823 - val_mean_absolute_error: 0.3
Epoch 19/100
12/12 ————— 0s 5ms/step - loss: 0.3838 - mean_absolute_error: 0.4748 - val_loss: 0.1740 - val_mean_absolute_error: 0.3
Epoch 20/100
12/12 ————— 0s 5ms/step - loss: 0.4072 - mean_absolute_error: 0.4796 - val_loss: 0.1733 - val_mean_absolute_error: 0.3
Epoch 21/100
12/12 ————— 0s 5ms/step - loss: 0.4136 - mean_absolute_error: 0.4898 - val_loss: 0.1758 - val_mean_absolute_error: 0.3
Epoch 22/100
12/12 ————— 0s 5ms/step - loss: 0.4093 - mean_absolute_error: 0.4754 - val_loss: 0.1714 - val_mean_absolute_error: 0.3
Epoch 23/100
12/12 ————— 0s 5ms/step - loss: 0.3880 - mean_absolute_error: 0.4518 - val_loss: 0.1694 - val_mean_absolute_error: 0.3
Epoch 24/100
12/12 ————— 0s 7ms/step - loss: 0.3082 - mean_absolute_error: 0.4299 - val_loss: 0.1683 - val_mean_absolute_error: 0.3
Epoch 25/100
12/12 ————— 0s 6ms/step - loss: 0.3508 - mean_absolute_error: 0.4297 - val_loss: 0.1662 - val_mean_absolute_error: 0.3
Epoch 26/100
12/12 ————— 0s 7ms/step - loss: 0.2861 - mean_absolute_error: 0.4214 - val_loss: 0.1643 - val_mean_absolute_error: 0.3
Epoch 27/100
```

Linear Regression

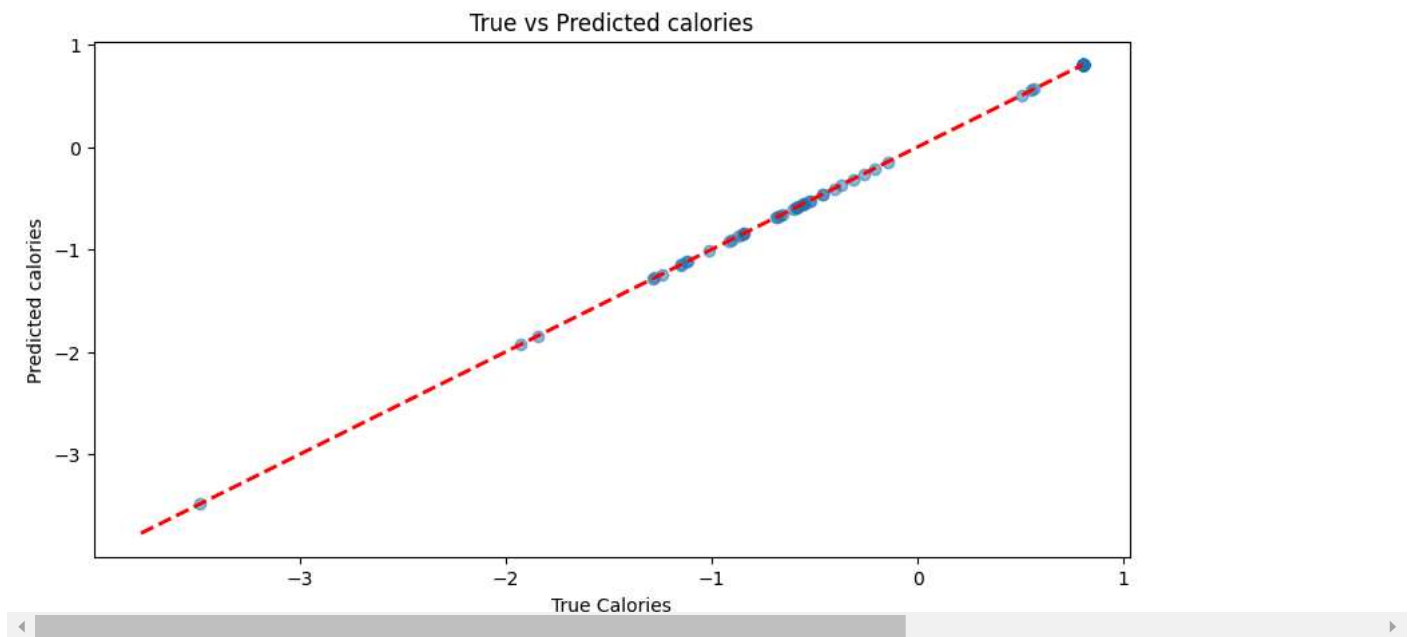
Double-click (or enter) to edit

```

1
2 from sklearn.linear_model import LinearRegression
3 from sklearn.metrics import mean_squared_error
4
5
6
7 # Split the data into training and testing sets
8 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
9
10 # Normalize the data
11 scaler = StandardScaler()
12 X_train_scaled = scaler.fit_transform(X_train)
13 X_test_scaled = scaler.transform(X_test)
14
15 # Train a simple linear regression model
16 model = LinearRegression()
17 model.fit(X_train_scaled, y_train)
18
19 # Predict on the test set
20 y_pred = model.predict(X_test_scaled)
21
22 # Evaluate the model
23 mse = mean_squared_error(y_test, y_pred)
24 print(f'Mean Squared Error: {mse}')
25
26
27 plt.figure(figsize=(10, 5))
28 plt.scatter(y_test, y_pred, alpha=0.5)
29 plt.plot([y.min(), y.max()], [y.min(), y.max()], 'r--', lw=2)
30 plt.xlabel('True Calories')
31 plt.ylabel('Predicted calories')
32 plt.title('True vs Predicted calories')
33 plt.show()
34
35
36

```

↗ Mean Squared Error: 1.3825916126417812e-30



Longitudinal Analysis



```
1
2 data['ActivityDate'] = pd.to_datetime(data['ActivityDate'])
3
4
5
6 # Filter data for the specific user
7 user_data = data[data['Id']==1503960366]
8
9 # Check if the user_data DataFrame is not empty
10 if not user_data.empty:
11     plt.figure(figsize=(14, 7))
12     plt.plot(user_data['ActivityDate'], user_data['TotalSteps'], label='Total Steps', color='blue')
13     plt.plot(user_data['ActivityDate'], user_data['Calories'], label='Calories', color='red')
14
15     plt.title(f'User {Id} - Longitudinal Analysis')
16     plt.xlabel('Date')
17     plt.ylabel('Values')
18     plt.legend()
19     plt.show()
20 else:
21     print(f"No data available for User {Id}.")
22
23
24
```

