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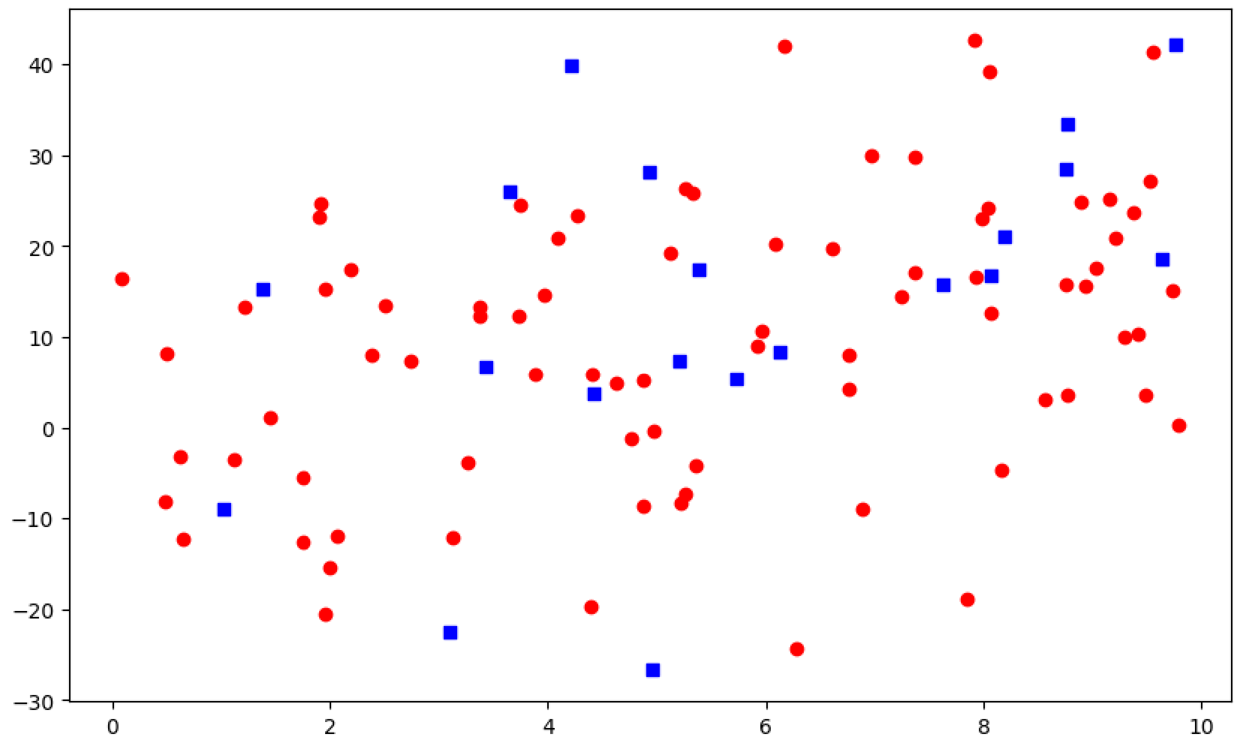
2 Learning from data

2.1. : Data generation.

```
import numpy as np
import matplotlib . pyplot as plt
from sklearn . model_selection import train_test_split
from sklearn . linear_model import LinearRegression
# Generate 100 samples
n_samples = 100
# Generate X values ( uniformly distributed between 0 and 10)
X = 10 * np.random.rand(n_samples, 1)
# Generate epsilon values ( normally distributed with mean 0 and
standard deviation 15)
epsilon = np . random . normal (0 , 15 , n_samples )
# Generate Y values using the model Y = 3 + 3X +
epsilon
Y = 3 + 2 * X + epsilon [: , np . newaxis ]
```

2.2. : Data visualization.

```
r=np.random.randint(104)
# Split the data into training and test sets (80% train,20% test)
X_train, X_test, Y_train, Y_test = train_test_split(X,
Y,test_size=0.2,random_state=r)
# Plot the data points


plt.figure(figsize=(10, 6))
plt.scatter(X_train, Y_train, alpha=1,
marker='o',color='red',label='Training␣Data')
plt.scatter(X_test, Y_test, alpha=1,
marker='s',color='blue',label='Testing␣Data')
plt.show()
```



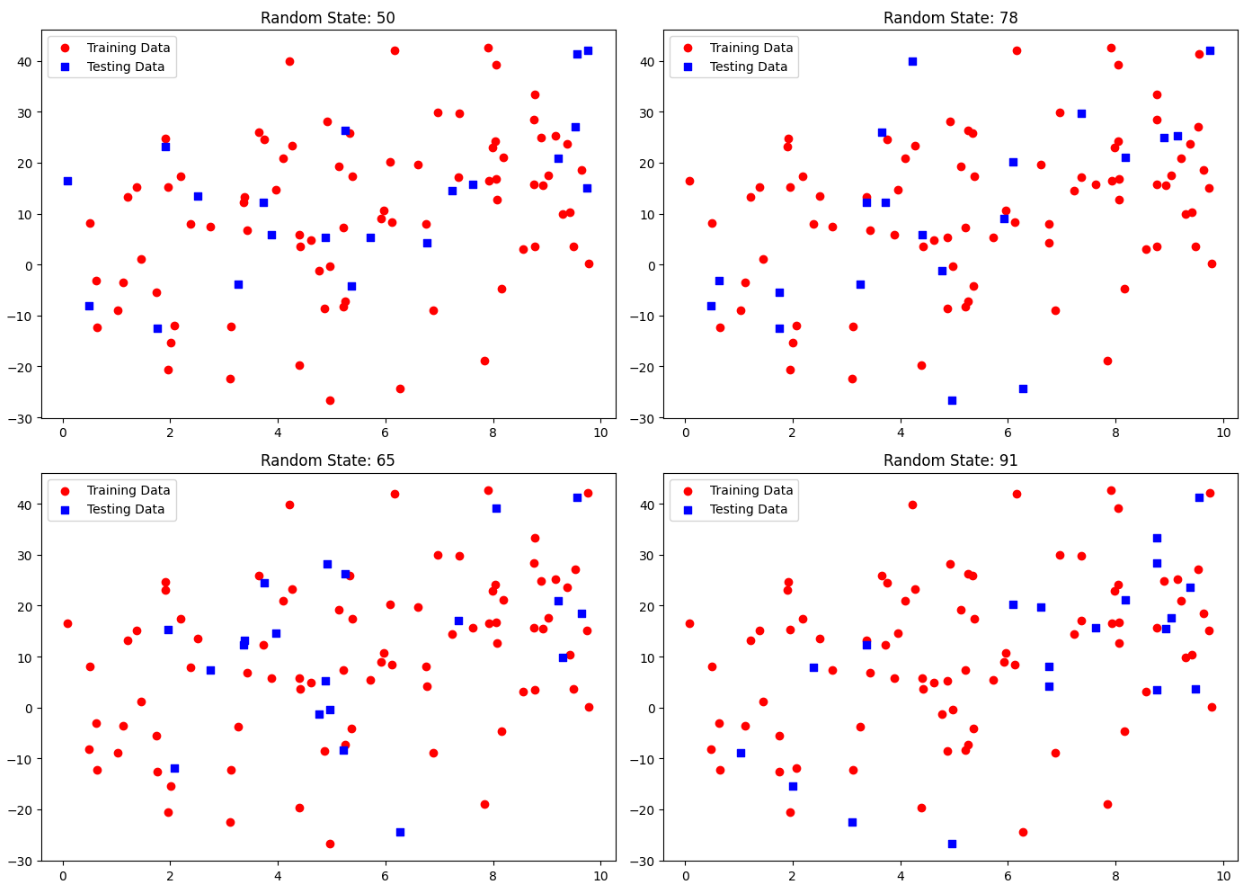
The reason the training and testing datasets differ in each run is due to the use of the `np.random.randint(104)` function, which generates a random integer each time it's called. This integer acts as a random seed for the `train_test_split` function, determining how the data is shuffled and then divided into training and testing sets.

When you set a specific value for the random state in the train-test data splitting, it guarantees that the same data points will be included in the training and testing sets every time the code is run, ensuring consistency. However, in this case, we are using `r=np.random.randint(104)` to generate a different random state for each run. Because `r` changes randomly every time the code is executed, it results in different data points being selected for training and testing, which is why we observe different scatter plots each time we run the code.

Extra part to compare difference

```
import numpy as np
import matplotlib.pyplot as plt
#from sklearn.model_selection import train_test_split

# Generate four different random states
random_states = [np.random.randint(104) for _ in range(4)]

# Create a 2x2 grid of subplots
fig, axes = plt.subplots(2, 2, figsize=(14, 10))

# Loop over the random states and axes to create the plots
for i, ax in enumerate(axes.flat):
    # Split the data using the current random state
```

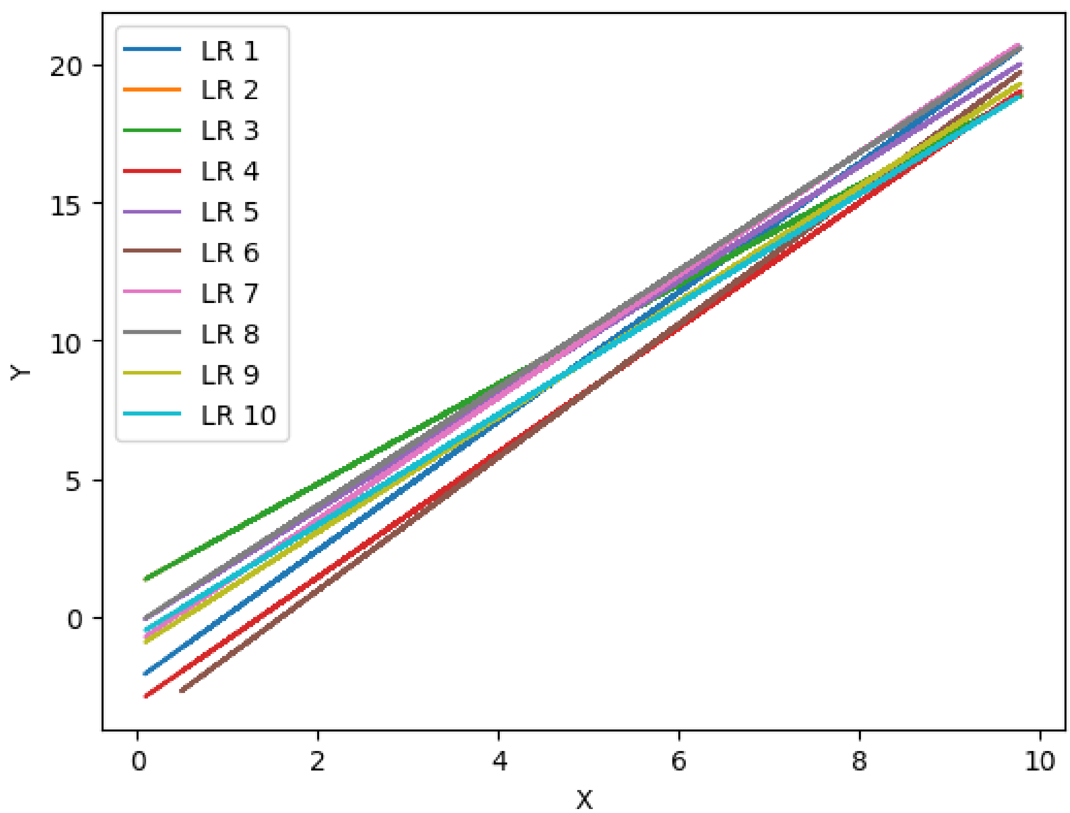
```
    X_train, X_test, Y_train, Y_test = train_test_split(X, Y,
test_size=0.2, random_state=random_states[i])

    # Plot the data points
    ax.scatter(X_train, Y_train, alpha=1, marker='o', color='red',
label='Training Data')
    ax.scatter(X_test, Y_test, alpha=1, marker='s', color='blue',
label='Testing Data')

    # Add title and legend to each subplot
    ax.set_title(f'Random State: {random_states[i]}')
    ax.legend()

# Display the grid of images
plt.tight_layout()
plt.show()
```



When state change testing and training data set will change.But overall same data set was choosen for both.

2.3. Linear regression

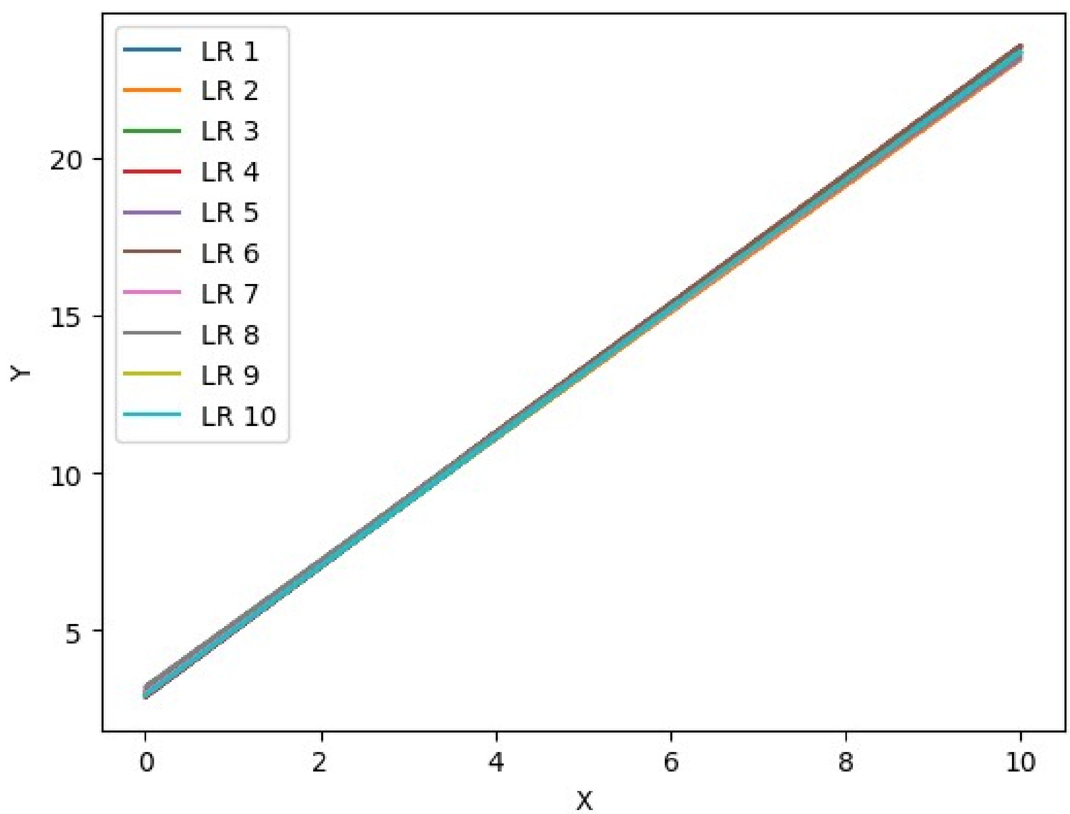
```
for i in range(10):# Plotting 10 different instances
  X_train, X_test, Y_train, Y_test = train_test_split(X,Y,
test_size=0.2, random_state=np.random.randint(104))
  model = LinearRegression()
  model.fit(X_train, Y_train)
  Y_pred_train = model.predict(X_train)
  plt.plot(X_train, Y_pred_train, label=f'LR {i+1}')
plt.xlabel('X')
plt.ylabel('Y')
plt.legend()
plt.show()
```



The linear regression model differs from one instance to another because the training dataset changes each time due to the random splitting of data using a randomly generated random state. Each time the `train_test_split` function is called with a new random state, different training data is selected. Since the model is trained on different data sets in each iteration, the model parameters (such as slope and intercept) change, resulting in different linear regression models for each iteration.

2.4.Repeat 3 with n_sample = 10,000

```
# Generate 10,000 samples
n_samples = 10000
# Generate X values ( uniformly distributed between 0 and 10)
X = 10 * np.random.rand(n_samples, 1)
# Generate epsilon values ( normally distributed with mean 0 and
standard deviation 15)
epsilon = np . random . normal (0 , 15 , n_samples )
# Generate Y values using the model Y = 3 + 3X +
epsilon
Y = 3 + 2 * X + epsilon [: , np . newaxis ]
for i in range(10):# Plotting 10 different instances
  X_train, X_test, Y_train, Y_test = train_test_split(X,Y,
test_size=0.2, random_state=np.random.randint(104))
  model = LinearRegression()
  model.fit(X_train, Y_train)
  Y_pred_train = model.predict(X_train)
  plt.plot(X_train, Y_pred_train, label=f'LR {i+1}')
plt.xlabel('X')
plt.ylabel('Y')
plt.legend()
plt.show()
```



When the number of data samples is increased to 10,000, the variation in the linear regression models across different iterations will generally decrease. This happens because larger datasets provide more information, leading to more stable and consistent model training. With 10,000 samples, the training data is more representative of the overall data distribution, reducing the impact of random variations caused by different random states in the data splitting process. Consequently, the model parameters (such as slope and intercept) become more stable, resulting in similar linear regression lines across different iterations. In contrast, with only 100 samples, the random splits lead to greater variability in the training data, causing more fluctuations in the model parameters and the resulting regression lines.(When we increase the sample size population mean will equal to sample mean)

3 Linear regression on real world data

3.1. Loading data

Installing missing packge

```
!pip install ucimlrepo
```

```
Collecting ucimlrepo
  Downloading ucimlrepo-0.0.7-py3-none-any.whl.metadata (5.5 kB)
Requirement already satisfied: pandas>=1.0.0 in
/usr/local/lib/python3.10/dist-packages (from ucimlrepo) (2.1.4)
Requirement already satisfied: certifi>=2020.12.5 in
/usr/local/lib/python3.10/dist-packages (from ucimlrepo) (2024.8.30)
Requirement already satisfied: numpy<2,>=1.22.4 in
/usr/local/lib/python3.10/dist-packages (from pandas>=1.0.0-
>ucimlrepo) (1.26.4)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.10/dist-packages (from pandas>=1.0.0-
>ucimlrepo) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=1.0.0-
>ucimlrepo) (2024.1)
Requirement already satisfied: tzdata>=2022.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=1.0.0-
>ucimlrepo) (2024.1)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.2-
>pandas>=1.0.0->ucimlrepo) (1.16.0)
Downloading ucimlrepo-0.0.7-py3-none-any.whl (8.0 kB)
Installing collected packages: ucimlrepo
Successfully installed ucimlrepo-0.0.7
```

```
# If package not installed, install it using pip install ucimlrepo
from ucimlrepo import fetch_ucirepo
# fetch dataset
infrared_thermography_temperature = fetch_ucirepo(id=925)
```

```python
# data (as pandas dataframes)
X = infrared_thermography_temperature.data.features
y = infrared_thermography_temperature.data.targets
# metadata
print(infrared_thermography_temperature.metadata)
# variable information
print(infrared_thermography_temperature.variables)
```


```
{'uci_id': 925, 'name': 'Infrared Thermography Temperature',
'repository_url':
'https://archive.ics.uci.edu/dataset/925/infrared+thermography+tempera
ture+dataset', 'data_url':
'https://archive.ics.uci.edu/static/public/925/data.csv', 'abstract':
'The Infrared Thermography Temperature Dataset contains temperatures
read from various locations of inferred images about patients, with
the addition of oral temperatures measured for each individual. The 33
features consist of gender, age, ethnicity, ambiant temperature,
humidity, distance, and other temperature readings from the thermal
images. The dataset is intended to be used in a regression task to
predict the oral temperature using the environment information as well
as the thermal image readings. ', 'area': 'Health and Medicine',
'tasks': ['Regression'], 'characteristics': ['Tabular'],
'num_instances': 1020, 'num_features': 33, 'feature_types': ['Real',
'Categorical'], 'demographics': ['Gender', 'Age', 'Ethnicity'],
'target_col': ['aveOralF', 'aveOralM'], 'index_col': ['SubjectID'],
'has_missing_values': 'no', 'missing_values_symbol': None,
'year_of_dataset_creation': 2021, 'last_updated': 'Tue Dec 12 2023',
'dataset_doi': '10.13026/9ay4-2c37', 'creators': ['Quanzeng Wang',
'Yangling Zhou', 'Pejman Ghassemi', 'David McBride', 'J. Casamento',
'T. Pfefer', 'Quanzeng Wang', 'Yangling Zhou', 'Pejman Ghassemi',
'David McBride', 'J. Casamento', 'T. Pfefer'], 'intro_paper':
{'title': 'Infrared Thermography for Measuring Elevated Body
Temperature: Clinical Accuracy, Calibration, and Evaluation',
'authors': 'Quanzeng Wang, Yangling Zhou, Pejman Ghassemi, David
McBride, J. Casamento, T. Pfefer', 'published_in': 'Italian National
Conference on Sensors', 'year': 2021, 'url':
'https://www.semanticscholar.org/paper/443b9932d295ca3a014e7d874b4bd77
a33a276bd', 'doi': None}, 'additional_info': {'summary': None,
'purpose': None, 'funded_by': None, 'instances_represent': None,
'recommended_data_splits': None, 'sensitive_data': None,
'preprocessing_description': None, 'variable_info': '- gender\n- age\
n- ethnicity\n- ambiant temperature\n- humidity\n- distance\n-
temperature readings from the thermal images', 'citation': None},
'external_url':
'https://physionet.org/content/face-oral-temp-data/1.0.0/'}
```


```
           name     role         type demographic  \
0     SubjectID       ID  Categorical        None
1      aveOralF   Target   Continuous        None
2      aveOralM   Target   Continuous        None
3        Gender  Feature  Categorical      Gender
```

```
4           Age  Feature  Categorical        Age
5     Ethnicity  Feature  Categorical  Ethnicity
6         T_atm  Feature   Continuous       None
7      Humidity  Feature   Continuous       None
8      Distance  Feature   Continuous       None
9     T_offset1  Feature   Continuous       None
10    Max1R13_1  Feature   Continuous       None
11    Max1L13_1  Feature   Continuous       None
12  aveAllR13_1  Feature   Continuous       None
13  aveAllL13_1  Feature   Continuous       None
14        T_RC1  Feature   Continuous       None
15    T_RC_Dry1  Feature   Continuous       None
16    T_RC_Wet1  Feature   Continuous       None
17    T_RC_Max1  Feature   Continuous       None
18        T_LC1  Feature   Continuous       None
19    T_LC_Dry1  Feature   Continuous       None
20    T_LC_Wet1  Feature   Continuous       None
21    T_LC_Max1  Feature   Continuous       None
22         RCC1  Feature   Continuous       None
23         LCC1  Feature   Continuous       None
24   canthiMax1  Feature   Continuous       None
25  canthi4Max1  Feature   Continuous       None
26       T_FHCC1  Feature   Continuous       None
27       T_FHRC1  Feature   Continuous       None
28       T_FHLC1  Feature   Continuous       None
29       T_FHBC1  Feature   Continuous       None
30       T_FHTC1  Feature   Continuous       None
31    T_FH_Max1  Feature   Continuous       None
32   T_FHC_Max1  Feature   Continuous       None
33       T_Max1  Feature   Continuous       None
34        T_OR1  Feature   Continuous       None
35    T_OR_Max1  Feature   Continuous       None

                                          description units
missing_values
0                                          Subject ID  None
no
1             Oral temperature measured in fast mode  None
no
2          Oral temperature measured in monitor mode  None
no
3                                      Male or Female  None
no
4                          Age ranges in categories\n  None
no
5   American Indian or Alaska Native, Asian, Black...  None
no
6                                 Ambiant temperature  None
no
```

```
7                                      Relative humidity  None
no
8        Distance between the subjects and the IRTs.    None
no
9    Temperature difference between the set and mea...  None
no
10   Max value of a circle with diameter of 13 pixe...  None
no
11   Max value of a circle with diameter of 13 pixe...  None
no
12   Average value of a circle with diameter of 13 ...  None
no
13   Average value of a circle with diameter of 13 ...  None
no
14   Average temperature of the highest four pixels...  None
no
15   Average temperature of the highest four pixels...  None
no
16   Average temperature of the highest four pixels...  None
no
17   Max value of a square of 24x24 pixels around t...  None
no
18   Average temperature of the highest four pixels...  None
no
19   Average temperature of the highest four pixels...  None
no
20   Average temperature of the highest four pixels...  None
no
21   Max value of a circle with diameter of 13 pixe...  None
no
22   Average value of a square of 3x3 pixels center...  None
no
23   Average value of a square of 3x3 pixels center...  None
no
24                Max value in the extended canthi area  None
no
25   Average temperature of the highest four pixels...  None
no
26   Average value in the center point of forehead,...  None
no
27   Average value in the right point of the forehe...  None
no
28   Average value in the left point of the forehea...  None
no
29   Average value in the bottom point of the foreh...  None
no
30   Average value in the top point of the forehead...  None
no
31   Maximum temperature within the extended forehe...  None
```

```
no
32  Max value in the center point of forehead, a s...  None
no
33  Maximum temperature within the whole face region.  None
no
34  Average temperature of the highest four pixels...  None
no
35       Maximum temperature within the mouth region.  None
no
```

3.2.

```
print(X.shape[1])#to cheak number of independent varibles
print(y.shape[1])#to cheak number of dependent variables

33
2
```

numer of independet varibles - 33

numer of dependet varibles - 2

3.3.

```
print(infrared_thermography_temperature.metadata)
print(infrared_thermography_temperature.variables)
```

{'uci_id': 925, 'name': 'Infrared Thermography Temperature', 'repository_url': 'https://archive.ics.uci.edu/dataset/925/infrared+thermography+temperature+dataset', 'data_url': 'https://archive.ics.uci.edu/static/public/925/data.csv', 'abstract': 'The Infrared Thermography Temperature Dataset contains temperatures read from various locations of inferred images about patients, with the addition of oral temperatures measured for each individual. The 33 features consist of gender, age, ethnicity, ambiant temperature, humidity, distance, and other temperature readings from the thermal images. The dataset is intended to be used in a regression task to predict the oral temperature using the environment information as well as the thermal image readings. ', 'area': 'Health and Medicine', 'tasks': ['Regression'], 'characteristics': ['Tabular'], 'num_instances': 1020, 'num_features': 33, 'feature_types': ['Real', 'Categorical'], 'demographics': ['Gender', 'Age', 'Ethnicity'], 'target_col': ['aveOralF', 'aveOralM'], 'index_col': ['SubjectID'], 'has_missing_values': 'no', 'missing_values_symbol': None, 'year_of_dataset_creation': 2021, 'last_updated': 'Tue Dec 12 2023', 'dataset_doi': '10.13026/9ay4-2c37', 'creators': ['Quanzeng Wang', 'Yangling Zhou', 'Pejman Ghassemi', 'David McBride', 'J. Casamento', 'T. Pfefer', 'Quanzeng Wang', 'Yangling Zhou', 'Pejman Ghassemi', 'David McBride', 'J. Casamento', 'T. Pfefer'], 'intro_paper':

{'title': 'Infrared Thermography for Measuring Elevated Body Temperature: Clinical Accuracy, Calibration, and Evaluation', 'authors': 'Quanzeng Wang, Yangling Zhou, Pejman Ghassemi, David McBride, J. Casamento, T. Pfefer', 'published_in': 'Italian National Conference on Sensors', 'year': 2021, 'url': 'https://www.semanticscholar.org/paper/443b9932d295ca3a014e7d874b4bd77a33a276bd', 'doi': None}, 'additional_info': {'summary': None, 'purpose': None, 'funded_by': None, 'instances_represent': None, 'recommended_data_splits': None, 'sensitive_data': None, 'preprocessing_description': None, 'variable_info': '- gender\n- age\n- ethnicity\n- ambiant temperature\n- humidity\n- distance\n- temperature readings from the thermal images', 'citation': None}, 'external_url': 'https://physionet.org/content/face-oral-temp-data/1.0.0/'}

	name	role	type	demographic \
0	SubjectID	ID	Categorical	None
1	aveOralF	Target	Continuous	None
2	aveOralM	Target	Continuous	None
3	Gender	Feature	Categorical	Gender
4	Age	Feature	Categorical	Age
5	Ethnicity	Feature	Categorical	Ethnicity
6	T_atm	Feature	Continuous	None
7	Humidity	Feature	Continuous	None
8	Distance	Feature	Continuous	None
9	T_offset1	Feature	Continuous	None
10	Max1R13_1	Feature	Continuous	None
11	Max1L13_1	Feature	Continuous	None
12	aveAllR13_1	Feature	Continuous	None
13	aveAllL13_1	Feature	Continuous	None
14	T_RC1	Feature	Continuous	None
15	T_RC_Dry1	Feature	Continuous	None
16	T_RC_Wet1	Feature	Continuous	None
17	T_RC_Max1	Feature	Continuous	None
18	T_LC1	Feature	Continuous	None
19	T_LC_Dry1	Feature	Continuous	None
20	T_LC_Wet1	Feature	Continuous	None
21	T_LC_Max1	Feature	Continuous	None
22	RCC1	Feature	Continuous	None
23	LCC1	Feature	Continuous	None
24	canthiMax1	Feature	Continuous	None
25	canthi4Max1	Feature	Continuous	None
26	T_FHCC1	Feature	Continuous	None
27	T_FHRC1	Feature	Continuous	None
28	T_FHLC1	Feature	Continuous	None
29	T_FHBC1	Feature	Continuous	None
30	T_FHTC1	Feature	Continuous	None
31	T_FH_Max1	Feature	Continuous	None
32	T_FHC_Max1	Feature	Continuous	None
33	T_Max1	Feature	Continuous	None

```
34        T_OR1  Feature   Continuous        None
35    T_OR_Max1  Feature   Continuous        None

                                          description units
missing_values
0                                          Subject ID  None
no
1                Oral temperature measured in fast mode  None
no
2             Oral temperature measured in monitor mode  None
no
3                                      Male or Female  None
no
4                          Age ranges in categories\n  None
no
5   American Indian or Alaska Native, Asian, Black...  None
no
6                                 Ambiant temperature  None
no
7                                   Relative humidity  None
no
8       Distance between the subjects and the IRTs.    None
no
9   Temperature difference between the set and mea...  None
no
10  Max value of a circle with diameter of 13 pixe...  None
no
11  Max value of a circle with diameter of 13 pixe...  None
no
12  Average value of a circle with diameter of 13 ...  None
no
13  Average value of a circle with diameter of 13 ...  None
no
14  Average temperature of the highest four pixels...  None
no
15  Average temperature of the highest four pixels...  None
no
16  Average temperature of the highest four pixels...  None
no
17  Max value of a square of 24x24 pixels around t...  None
no
18  Average temperature of the highest four pixels...  None
no
19  Average temperature of the highest four pixels...  None
no
20  Average temperature of the highest four pixels...  None
no
21  Max value of a circle with diameter of 13 pixe...  None
no
```

```
22  Average value of a square of 3x3 pixels center...  None
no
23  Average value of a square of 3x3 pixels center...  None
no
24              Max value in the extended canthi area  None
no
25  Average temperature of the highest four pixels...  None
no
26  Average value in the center point of forehead,...  None
no
27  Average value in the right point of the forehe...  None
no
28  Average value in the left point of the forehea...  None
no
29  Average value in the bottom point of the foreh...  None
no
30  Average value in the top point of the forehead...  None
no
31  Maximum temperature within the extended forehe...  None
no
32  Max value in the center point of forehead, a s...  None
no
33  Maximum temperature within the whole face region.  None
no
34  Average temperature of the highest four pixels...  None
no
35       Maximum temperature within the mouth region.  None
no
```

It is not possible to apply linear regression directly on this dataset because it contains categorical data, such as 'Gender', 'Age', and 'Ethnicity'. Linear regression requires numerical input, so categorical data must be converted into a numerical form to proceed.

Steps:

1. **One-Hot Encoding**: Convert the categorical features ('Gender', 'Age', 'Ethnicity') into numerical values using one-hot encoding. This will create binary columns for each category, making them suitable for linear regression.

2. **Feature Scaling**: After encoding, features are scaled appropriately.

3. **Handling Missing Values**: Check for any missing values in the dataset remove them or replce them with average values.

4. **Check for Multicollinearity**:Cheak highly correlated features. If present, combine or remove correlated features to avoid redundancy and improve model performance.

3.4.

The provided code snippet attempts to handle missing values by dropping them separately from X and y: # Drop rows with missing values from both X and y X = X.dropna() y = y.dropna()

The provided method is wong because it removes missing values from X and y independently. This separate handling can cause the features and target labels to become misaligned. In a dataset, each row in the feature set X should correspond directly to a row in the target variable y. If rows are removed from X without removing the corresponding rows from y, or vice versa, the pairing of data points with their respective labels is disrupted.

To correctly handle the missing values, we first need to inspect the dataset to understand how many missing values are present. If only a few values are missing, it might be acceptable to drop the corresponding rows.

```
import pandas as pd
data_set = pd.concat([X, y], axis=1)

print(data_set.isnull().sum())
```

```
Gender          0
Age             0
Ethnicity       0
T_atm           0
Humidity        0
Distance        2
T_offset1       0
Max1R13_1       0
Max1L13_1       0
aveAllR13_1     0
aveAllL13_1     0
T_RC1           0
T_RC_Dry1       0
T_RC_Wet1       0
T_RC_Max1       0
T_LC1           0
T_LC_Dry1       0
T_LC_Wet1       0
T_LC_Max1       0
RCC1            0
LCC1            0
canthiMax1      0
canthi4Max1     0
T_FHCC1         0
T_FHRC1         0
T_FHLC1         0
T_FHBC1         0
T_FHTC1         0
T_FH_Max1       0
T_FHC_Max1      0
```

```
T_Max1          0
T_OR1           0
T_OR_Max1       0
aveOralF        0
aveOralM        0
dtype: int64
```

Output showing that only 'Distance' column has two missing values. As there are only two missing values in 'Distance', it's okay to remove these rows (with respect to total data set).

```
data_set = data_set.dropna(subset=['Distance'])

#data_set =data_set.dropna()

print(data_set.isnull().sum())
```

```
Gender          0
Age             0
Ethnicity       0
T_atm           0
Humidity        0
Distance        0
T_offset1       0
Max1R13_1       0
Max1L13_1       0
aveAllR13_1     0
aveAllL13_1     0
T_RC1           0
T_RC_Dry1       0
T_RC_Wet1       0
T_RC_Max1       0
T_LC1           0
T_LC_Dry1       0
T_LC_Wet1       0
T_LC_Max1       0
RCC1            0
LCC1            0
canthiMax1      0
canthi4Max1     0
T_FHCC1         0
T_FHRC1         0
T_FHLC1         0
T_FHBC1         0
T_FHTC1         0
T_FH_Max1       0
T_FHC_Max1      0
T_Max1          0
T_OR1           0
T_OR_Max1       0
```

```
aveOralF       0
aveOralM       0
dtype: int64

#import pandas as pd
#data_set = pd.concat([X, y], axis=1)
print(data_set)
print("----------------------------------------------------------------------
--------")
data_set.head()

      Gender    Age                     Ethnicity  T_atm  Humidity  
Distance  \
0       Male  41-50                         White   24.0      28.0  
0.8
1     Female  31-40  Black or African-American   24.0      26.0  
0.8
2     Female  21-30                         White   24.0      26.0  
0.8
3     Female  21-30  Black or African-American   24.0      27.0  
0.8
4       Male  18-20                         White   24.0      27.0  
0.8
...      ...    ...                           ...    ...       ...  
...
1015  Female  21-25                         Asian   25.7      50.8  
0.6
1016  Female  21-25                         White   25.7      50.8  
0.6
1017  Female  18-20  Black or African-American   28.0      24.3  
0.6
1018    Male  26-30              Hispanic/Latino   25.0      39.8  
0.6
1019  Female  18-20                         White   23.8      45.6  
0.6

      T_offset1  Max1R13_1  Max1L13_1  aveAllR13_1  ...  T_FHLC1  
T_FHBC1  \
0        0.7025    35.0300    35.3775      34.4000  ...  33.3725  
33.4925
1        0.7800    34.5500    34.5200      33.9300  ...  33.6775  
33.9700
2        0.8625    35.6525    35.5175      34.2775  ...  34.6475  
34.8200
3        0.9300    35.2225    35.6125      34.3850  ...  34.6550  
34.3025
4        0.8950    35.5450    35.6650      34.9100  ...  34.3975  
34.6700
...         ...        ...        ...          ...  ...      ...  
...
```

```
1015     1.2225    35.6425    35.6525      34.8575  ...  35.4000
35.1375
1016     1.4675    35.9825    35.7575      35.4275  ...  35.2200
35.2075
1017     0.1300    36.4075    36.3400      35.8700  ...  35.2275
35.3675
1018     1.2450    35.8150    35.5250      34.2950  ...  34.9250
34.7150
1019     0.8675    35.7075    35.5825      34.8875  ...  34.6700
34.2150

      T_FHTC1  T_FH_Max1  T_FHC_Max1   T_Max1    T_OR1  T_OR_Max1
aveOralF  \
0     33.0025    34.5300     34.0075  35.6925  35.6350    35.6525
36.85
1     34.0025    34.6825     34.6600  35.1750  35.0925    35.1075
37.00
2     34.6700    35.3450     35.2225  35.9125  35.8600    35.8850
37.20
3     34.9175    35.6025     35.3150  35.7200  34.9650    34.9825
36.85
4     33.8275    35.4175     35.3725  35.8950  35.5875    35.6175
36.80
...       ...        ...         ...      ...      ...        ...
...
1015  35.2750    35.8525     35.7475  36.0675  35.6775    35.7100
36.95
1016  35.0700    35.7650     35.5525  36.5000  36.4525    36.4900
37.25
1017  35.3425    36.3750     35.7100  36.5350  35.9650    35.9975
37.35
1018  34.5950    35.4150     35.3100  35.8600  35.4150    35.4350
37.15
1019  34.7100    35.1525     35.1175  35.9725  35.8900    35.9175
37.05

      aveOralM
0        36.59
1        37.19
2        37.34
3        37.09
4        37.04
...        ...
1015     36.99
1016     37.19
1017     37.59
1018     37.29
1019     37.19

[1018 rows x 35 columns]
```

```
--------------------------------------------------------------------
-
```

{"type":"dataframe","variable_name":"data_set"}

3.5.

select "aveOralM" as the dependent feature and 'T_atm', 'Humidity', 'Distance', 'T_FH_Max1' , 'age' as independent varibles

```
# One-hot encode the 'Age' categorical variable
age_encoded = pd.get_dummies(data_set['Age'], prefix='Age')

# Add the one-hot encoded columns back to the dataset and drop the
original 'Age' column
data_set = pd.concat([data_set, age_encoded], axis=1)
data_set = data_set.drop('Age', axis=1)

# Select the dependent and independent variables
dependent_feature = data_set['aveOralM']
independent_features = data_set[['T_atm', 'Humidity', 'Distance',
'T_FH_Max1'] + list(age_encoded.columns)]

# Combine into a new DataFrame for modeling
model_data = pd.concat([independent_features, dependent_feature],
axis=1)

# Display the prepared dataset
print("Prepared dataset:")
independent_features.head()
```

```
Prepared dataset:
```

{"summary":"{\n \"name\": \"independent_features\",\n \"rows\": 1018,\n \"fields\": [\n   {\n   \"column\": \"T_atm\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 1.337616782238765,\n   \"min\": 20.2,\n   \"max\": 29.1,\n   \"num_unique_values\": 78,\n   \"samples\": [\n   26.1,\n   24.0,\n   25.4\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"Humidity\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 13.070899796157311,\n   \"min\": 9.9,\n   \"max\": 61.2,\n   \"num_unique_values\": 353,\n   \"samples\": [\n   53.2,\n   10.6,\n   50.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"Distance\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 2.4564860370861084,\n   \"min\": 0.54,\n   \"max\": 79.0,\n   \"num_unique_values\": 33,\n   \"samples\": [\n   0.57,\n   0.63,\n   0.67\n   ],\n   \"semantic_type\": \"\",\n

```
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"T_FH_Max1\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 0.5237026164644623,\n        \"min\":
33.4075,\n        \"max\": 38.0025,\n        \"num_unique_values\":
558,\n        \"samples\": [\n          34.925,\n          34.565,\n
35.355\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Age_18-20\",\n      \"properties\": {\n        \"dtype\":
\"boolean\",\n        \"num_unique_values\": 2,\n        \"samples\":
[\n          true,\n          false\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Age_21-25\",\n
\"properties\": {\n        \"dtype\": \"boolean\",\n
\"num_unique_values\": 2,\n        \"samples\": [\n          true,\n
false\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Age_21-30\",\n      \"properties\": {\n        \"dtype\":
\"boolean\",\n        \"num_unique_values\": 2,\n        \"samples\":
[\n          true,\n          false\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Age_26-30\",\n
\"properties\": {\n        \"dtype\": \"boolean\",\n
\"num_unique_values\": 2,\n        \"samples\": [\n          true,\n
false\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Age_31-40\",\n      \"properties\": {\n        \"dtype\":
\"boolean\",\n        \"num_unique_values\": 2,\n        \"samples\":
[\n          true,\n          false\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Age_41-50\",\n
\"properties\": {\n        \"dtype\": \"boolean\",\n
\"num_unique_values\": 2,\n        \"samples\": [\n          false,\n
true\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Age_51-60\",\n      \"properties\": {\n        \"dtype\":
\"boolean\",\n        \"num_unique_values\": 2,\n        \"samples\":
[\n          true,\n          false\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Age_>60\",\n      \"properties\":
{\n        \"dtype\": \"boolean\",\n        \"num_unique_values\": 2,\
n        \"samples\": [\n          true,\n          false\n        ],\
n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    }\n  ]\
n}","type":"dataframe","variable_name":"independent_features"}
```


```
dependent_feature.head()
```

```
0    36.59
1    37.19
2    37.34
```

```
3     37.09
4     37.04
Name: aveOralM, dtype: float64
```

3.6.

Split the data into training and testing sets with 80% of data points for training and 20% of data points for testing.

```
X_train,X_test, y_train, y_test =
train_test_split(independent_features, dependent_feature,
test_size=0.2, random_state=42)
```

3.7.

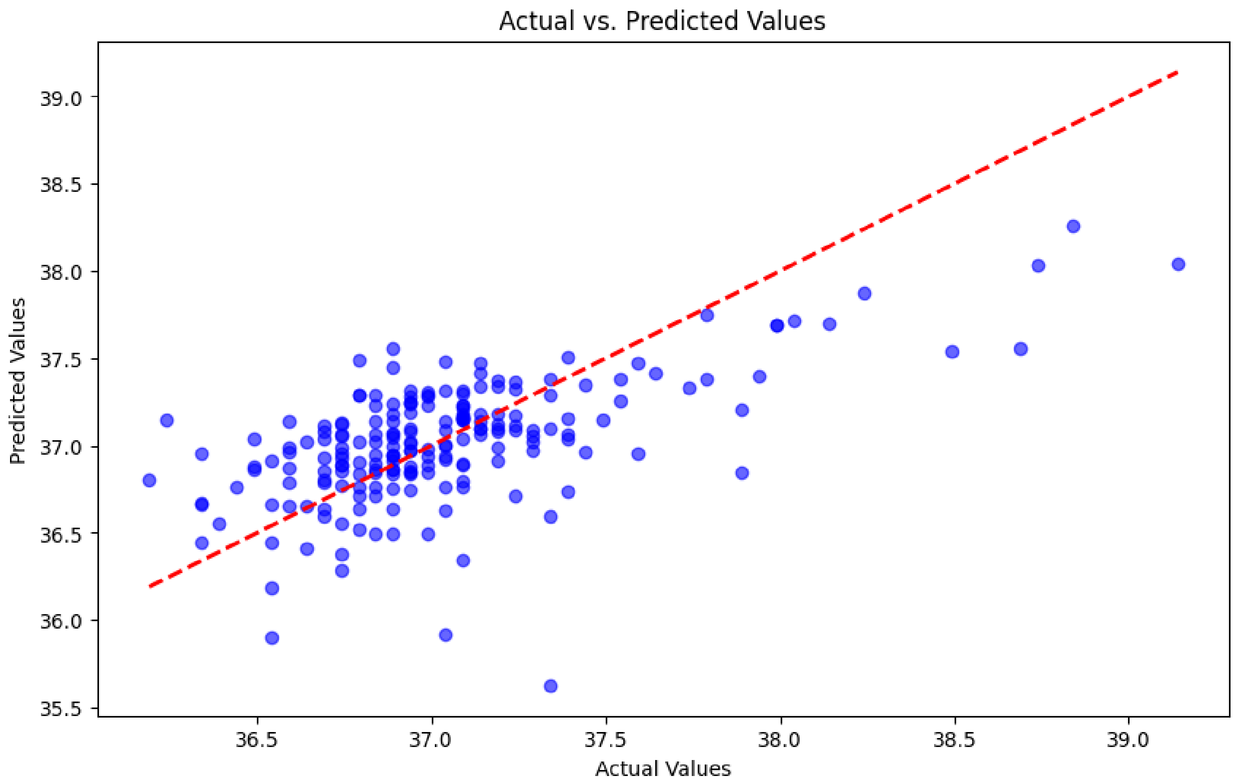
Train a linear regression model and estimate the coefficient corresponds to independent variables.

```
from sklearn import datasets, linear_model
from sklearn.metrics import mean_squared_error, r2_score

model = LinearRegression()
model.fit(X_train, y_train)

LinearRegression()

# Make predictions using the testing set
y_pred = model.predict(X_test)

# Creating the DataFrame with features and their coefficients
coeff_df = pd.DataFrame({'Feature': X_train.columns, 'Coefficient':
model.coef_})

# Install the tabulate module
!pip install tabulate

# Import the tabulate function
from tabulate import tabulate

# Displaying the DataFrame as a table
print("Intercept:", model.intercept_)
print("Estimated features vs coefficients:")
print(tabulate(coeff_df, headers='keys', tablefmt='pretty'))

Requirement already satisfied: tabulate in
/usr/local/lib/python3.10/dist-packages (0.9.0)
Intercept: 13.238798996804732
Estimated features vs coefficients:
+----+-----------+-----------------------+
```

```
|    |  Feature  |      Coefficient      |
+----+-----------+-----------------------+
| 0  |   T_atm   | -0.055535893239226766 |
| 1  | Humidity  | 0.003422392005267033  |
| 2  | Distance  | 0.0026393537872089093 |
| 3  | T_FH_Max1 |  0.7092038079633628   |
| 4  | Age_18-20 | -0.09521023788460654  |
| 5  | Age_21-25 | -0.10911840778186253  |
| 6  | Age_21-30 | -0.03372839990148858  |
| 7  | Age_26-30 | -0.08394109824533079  |
| 8  | Age_31-40 | -0.13698172540270473  |
| 9  | Age_41-50 |  0.21089662330066358  |
| 10 | Age_51-60 | -0.08176010339345889  |
| 11 |  Age_>60  |  0.32984334930878834  |
+----+-----------+-----------------------+
```

```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, alpha=0.6, color='blue')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)],
'k--', lw=2, color='red')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs. Predicted Values')
plt.show()
```

```
<ipython-input-22-53a471df34c0>:3: UserWarning: color is redundantly
defined by the 'color' keyword argument and the fmt string "k--" (->
color='k'). The keyword argument will take precedence.
  plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)],
'k--', lw=2, color='red')
```



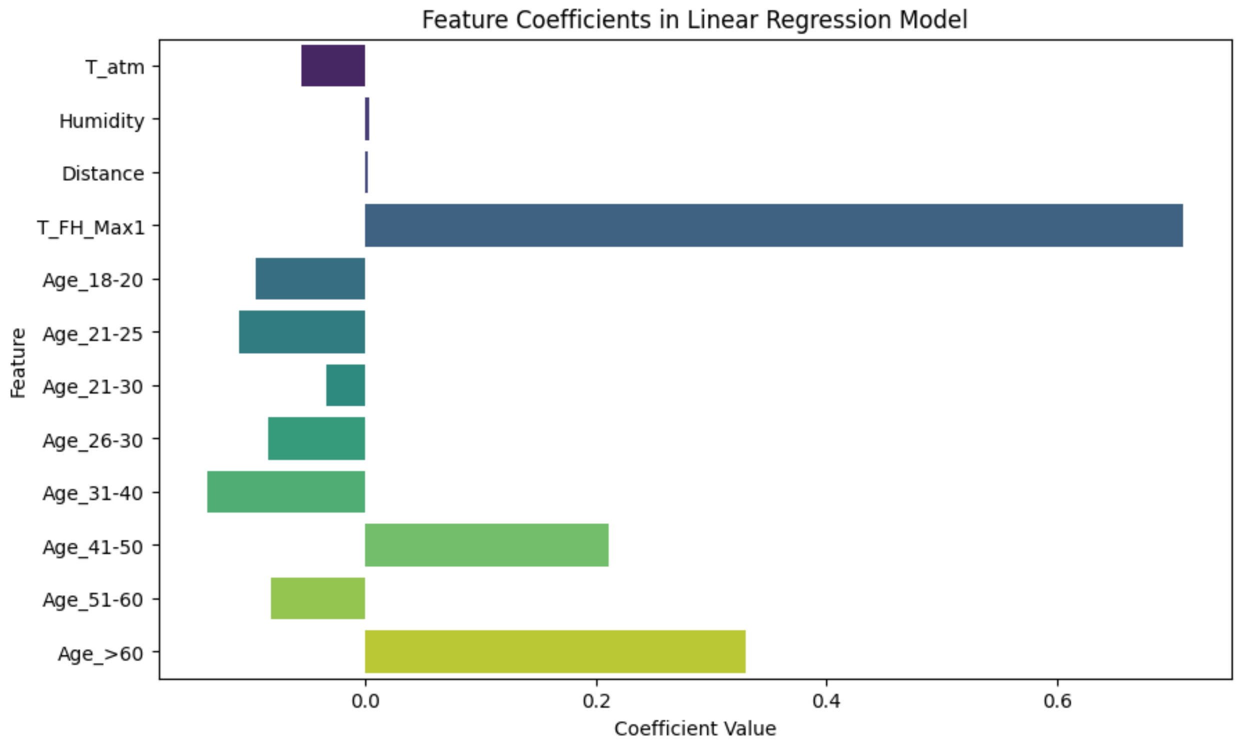
3.8.

By looking at the coefficient we can see T_FH_Max1 got the maximum value which mean T_FH_Max1 contributes highly for the dependent feature

```
# Plotting the coefficients
!pip install seaborn # install seaborn
import seaborn as sns
plt.figure(figsize=(10, 6))
sns.barplot(x='Coefficient', y='Feature', data=coeff_df,
palette='viridis')
plt.title('Feature Coefficients in Linear Regression Model')
plt.xlabel('Coefficient Value')
plt.ylabel('Feature')
plt.show()
```

```
Requirement already satisfied: seaborn in
/usr/local/lib/python3.10/dist-packages (0.13.1)
Requirement already satisfied: numpy!=1.24.0,>=1.20 in
/usr/local/lib/python3.10/dist-packages (from seaborn) (1.26.4)
Requirement already satisfied: pandas>=1.2 in
/usr/local/lib/python3.10/dist-packages (from seaborn) (2.1.4)
Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in
/usr/local/lib/python3.10/dist-packages (from seaborn) (3.7.1)
```

```
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (1.3.0)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (4.53.1)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (1.4.5)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (24.1)
Requirement already satisfied: pillow>=6.2.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (3.1.4)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=1.2->seaborn)
(2024.1)
Requirement already satisfied: tzdata>=2022.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=1.2->seaborn)
(2024.1)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7-
>matplotlib!=3.6.1,>=3.4->seaborn) (1.16.0)

<ipython-input-23-843087b86571>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x='Coefficient', y='Feature', data=coeff_df,
palette='viridis')
```



3.9.

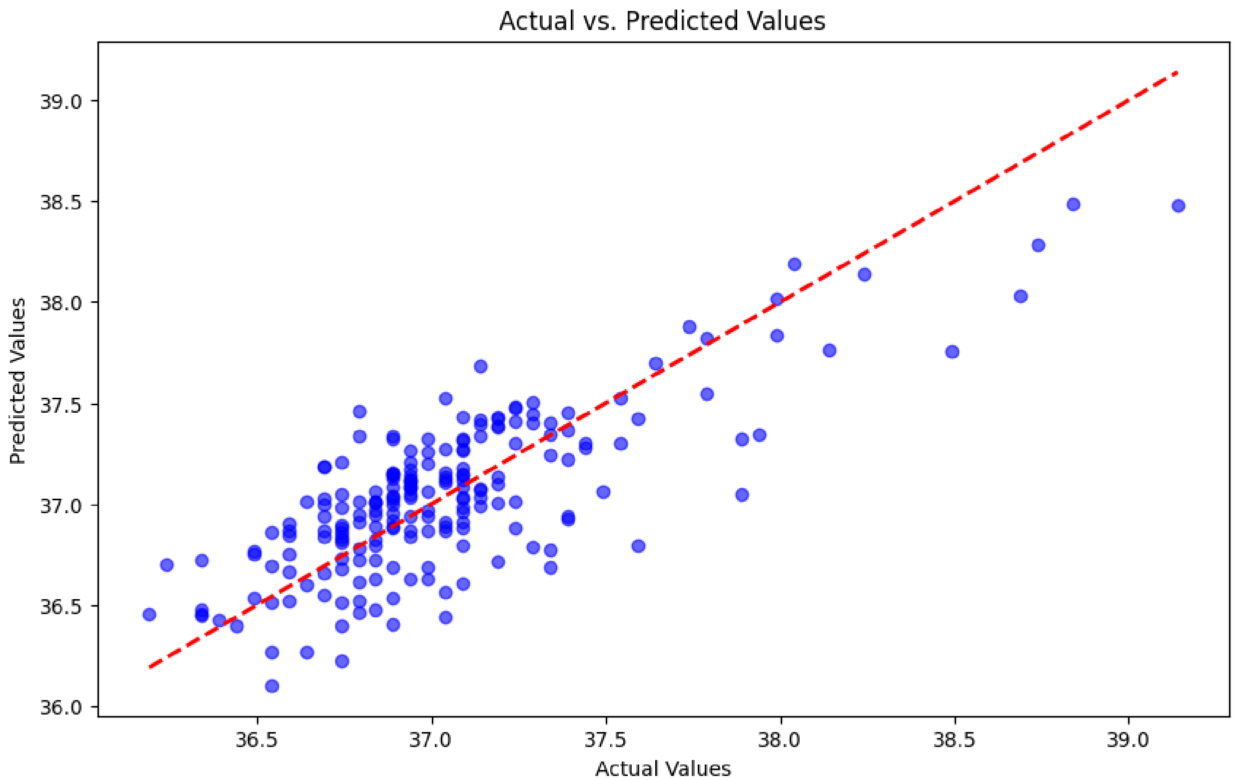
```
# Select the dependent and independent variables
dependent_feature_n = data_set['aveOralM']
independent_features_n = data_set[['T_OR1', 'T_OR_Max1', 'T_FHC_Max1',
'T_FH_Max1'] ]
# Combine into a new DataFrame for modeling
model_data_n = pd.concat([independent_features_n,
dependent_feature_n], axis=1)

# Display the prepared dataset
print("Prepared dataset:")
#independent_features_n.head()

X_train,X_test, y_train, y_test =
train_test_split(independent_features_n, dependent_feature_n,
test_size=0.2, random_state=42)

from sklearn import datasets, linear_model
from sklearn.metrics import mean_squared_error, r2_score

model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions using the testing set
y_pred = model.predict(X_test)
```

```python
# Creating the DataFrame with features and their coefficients
coeff_df = pd.DataFrame({'Feature': X_train.columns, 'Coefficient':
model.coef_})

# Displaying the DataFrame as a table
print("Intercept:", model.intercept_)
print("Estimated features vs coefficients:")
print(tabulate(coeff_df, headers='keys', tablefmt='pretty'))
```

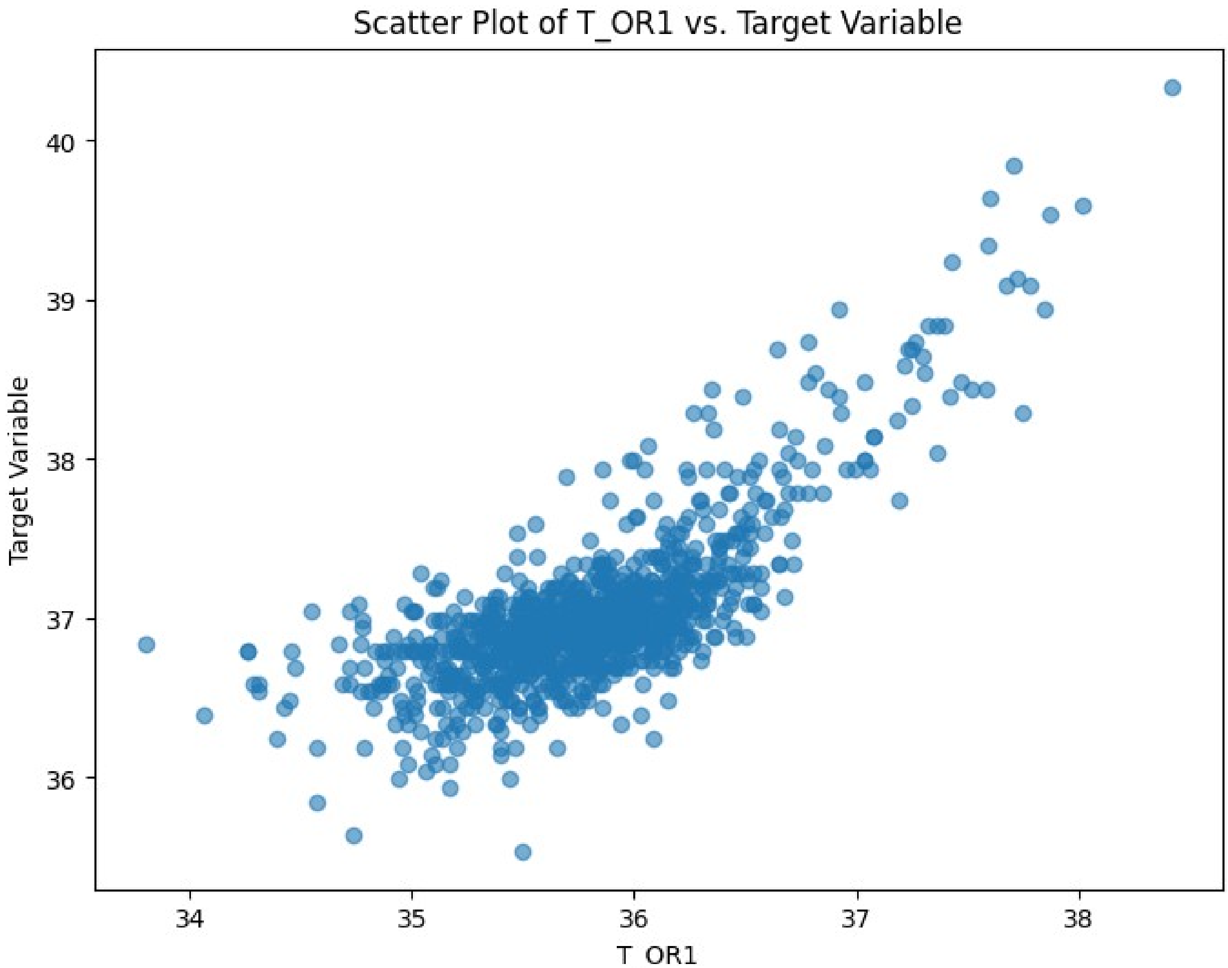
```
Prepared dataset:
Intercept: 6.79355629984887
Estimated features vs coefficients:
+---+------------+---------------------+
|   |  Feature   |     Coefficient     |
+---+------------+---------------------+
| 0 |   T_OR1    | 0.20545776323994563 |
| 1 | T_OR_Max1  | 0.34819684316002775 |
| 2 | T_FHC_Max1 | -0.08371846705362093 |
| 3 | T_FH_Max1  |  0.376564342065323  |
+---+------------+---------------------+
```

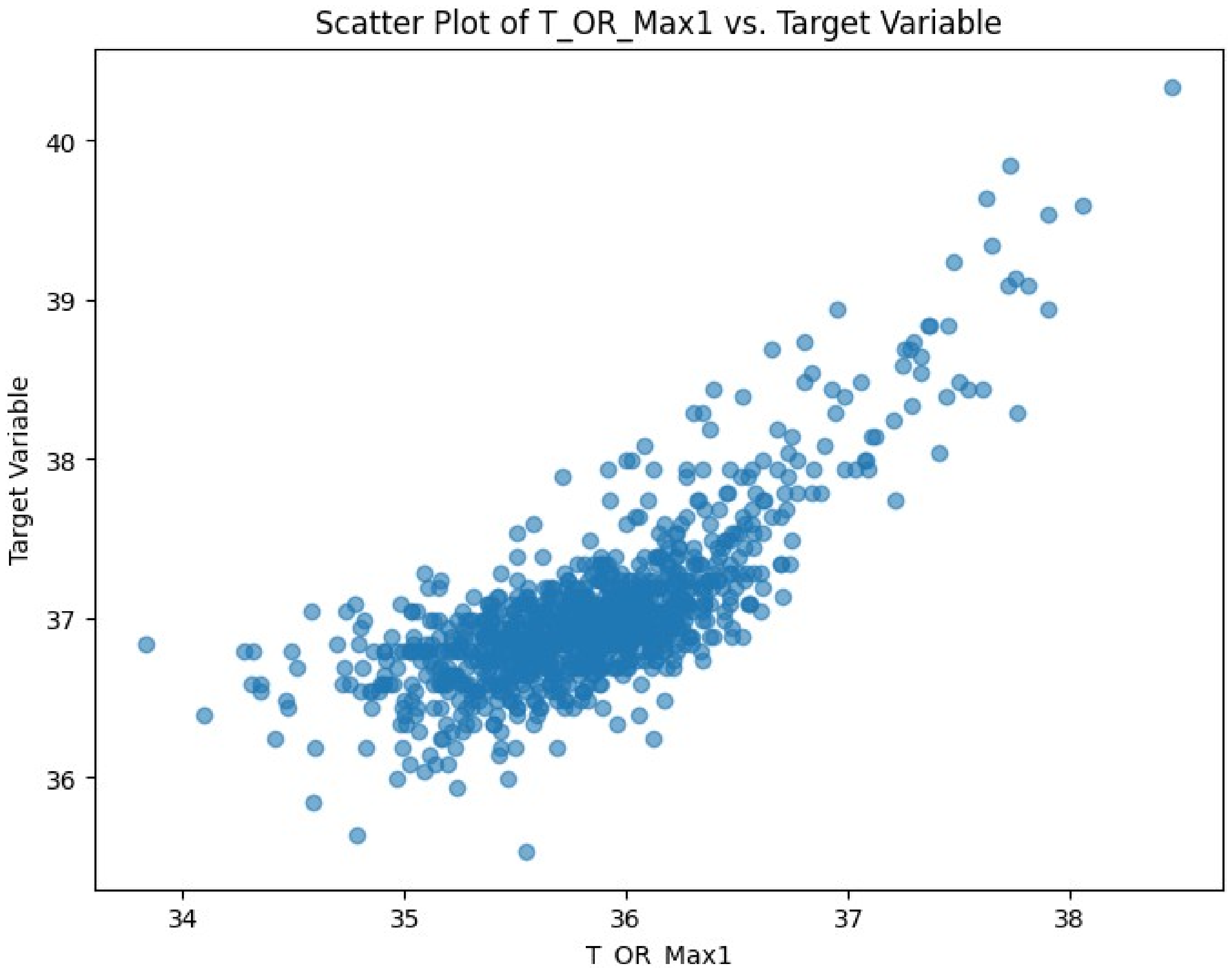
```python
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, alpha=0.6, color='blue')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)],
'k--', lw=2, color='red')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs. Predicted Values')
plt.show()
```

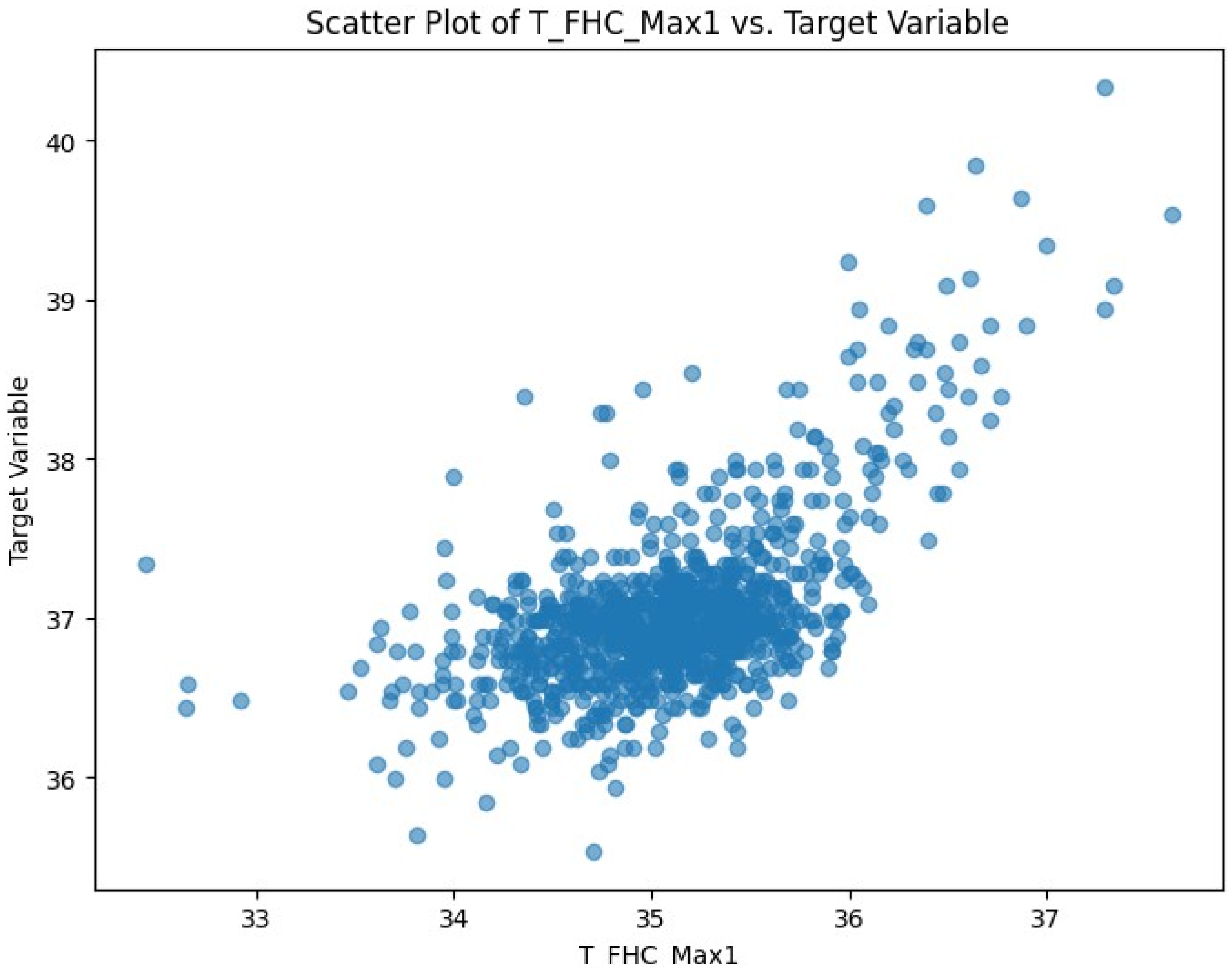
```
<ipython-input-25-53a471df34c0>:3: UserWarning: color is redundantly
defined by the 'color' keyword argument and the fmt string "k--" (->
color='k'). The keyword argument will take precedence.
  plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)],
'k--', lw=2, color='red')
```

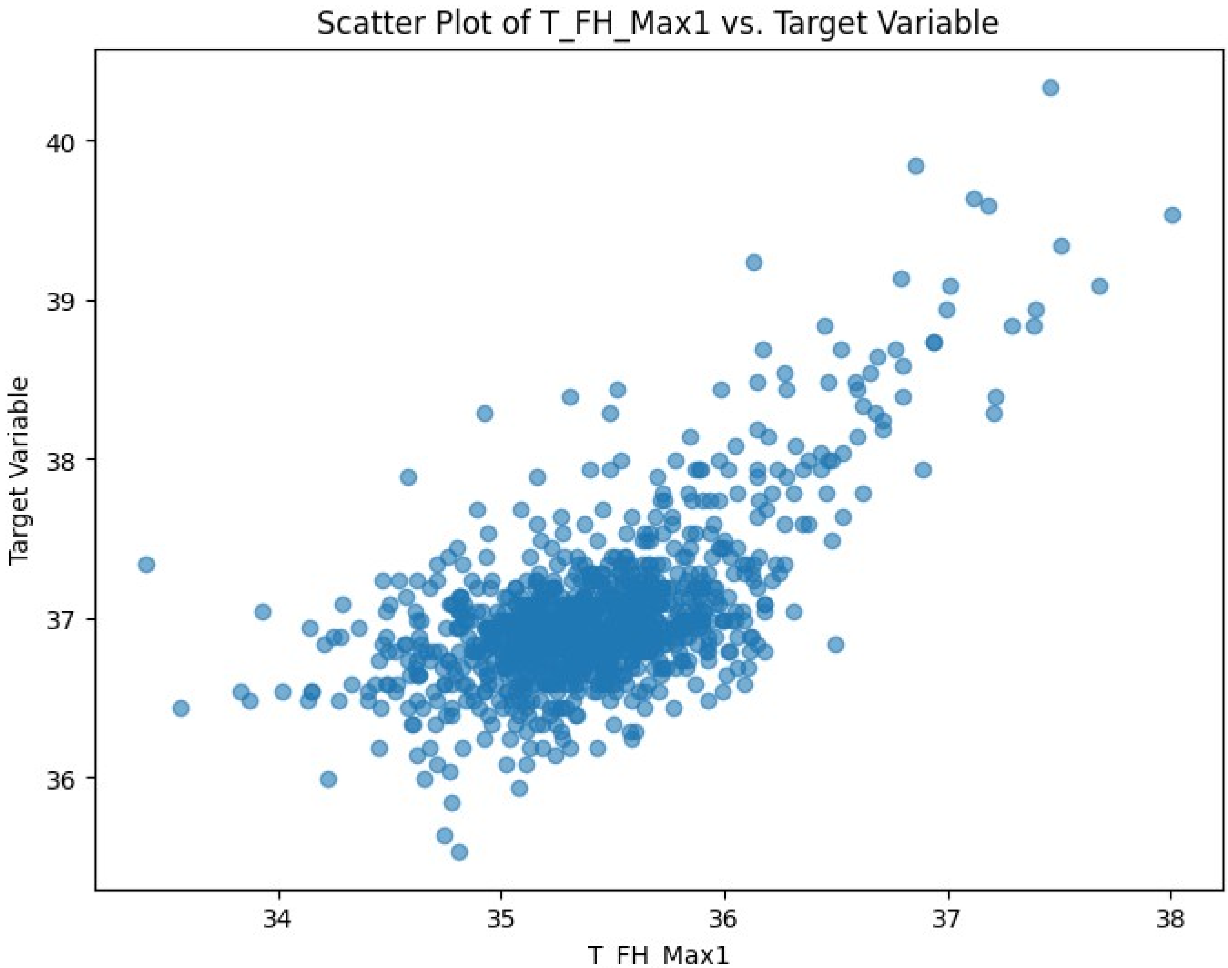



```
import matplotlib.pyplot as plt

# Assuming 'independent_features_n' is your DataFrame with independent
features
# and 'dependent_feature_n' is your Series with the target variable
for col in independent_features_n.columns:
  plt.figure(figsize=(8, 6))
  plt.scatter(independent_features_n[col], dependent_feature_n,
alpha=0.6)
  plt.xlabel(col)  # Label with the independent variable name
  plt.ylabel('Target Variable')
  plt.title(f'Scatter Plot of {col} vs. Target Variable')
  plt.show()
```


Scatter Plot of T_OR1 vs. Target Variable
Target Variable
T_OR1
40
39
38
37
36
34
35
36
37
38


Scatter Plot of T_OR_Max1 vs. Target Variable
Target Variable
T_OR_Max1
34
35
36
37
38
36
37
38
39
40


Scatter Plot of T_FHC_Max1 vs. Target Variable
Target Variable
40
39
38
37
36
33
34
35
36
37
T_FHC_Max1




```
yhat=model.predict(X_train)
d = independent_features_n.shape[1]
print('d:',d)

# Residual Sum of Sqaures (RSS)
RSS = np.sum((yhat - y_train)**2)
print('RSS=', RSS)

N=len(y_train)
#print('Number of Datapoints=',N)

# Residual Standard Error (RSE)
RSE = np.sqrt(1/(N-d-1)*RSS)
print('RSE=', RSE)

# Mean squre error(MSE)
#predictions = lm.predict(X_train)

newX =
pd.DataFrame({"Constant":np.ones(len(X_train))}).join(pd.DataFrame(X_t
```

```
rain))
MSE = (sum((y_train-yhat)**2))/(len(newX)-len(newX.columns))
print('MSE=', MSE)

# Total Sum of Squares (TSS)
TSS = np.sum((y_train- np.mean(y_train))**2)
print('TSS=', TSS)

# R2

R2 = (TSS - RSS)/TSS
print('R² (from direct calculations)=', R2)

# Calculation of R2 using sklearn
R2 = model.score(X_train,y_train)

print('R² (from sklearn module)=', R2)

d: 4
RSS= 77.97449082857881
RSE= 0.31045739777400483
MSE= 0.09638379583260669
TSS= 223.63911855036855
R² (from direct calculations)= 0.6513378726673116
R² (from sklearn module)= 0.6513378726673116

from scipy.stats import t
import numpy as np
import scipy.stats as stats
#samples size
SN = len(X_train)

features = ['T_OR1', 'T_OR_Max1', 'T_FHC_Max1', 'T_FH_Max1']
w_0 = model.intercept_
w_1 = model.coef_

NF = len(features)

#Calculate Standard error
standard_error = []
for feature in features:
  SE2 = RSS/(SN-NF-1) / np.sum((X_train[feature] -
np.mean(X_train[feature]))**2)
  standard_error.append(np.sqrt(SE2))

#calculate t values
t_values = []
for i in range(NF):
  t_values.append(w_1[i]/standard_error[i])

#calculate p-values
```

```python
p_values = []
for i in range(NF):
  p_values.append(2 * (1 - stats.t.cdf(abs(t_values[i]), SN-NF-1)))


# Create a DataFrame to display the values in a table
results_df = pd.DataFrame({
    'Feature': features,
    'Standard Error': standard_error,
    't-value': t_values,
    'p-value': p_values
})

# Print the table
print(results_df)

# Save the table to a CSV file (optional)
results_df.to_csv('model_statistics.csv', index=False)
```

```
      Feature  Standard Error    t-value  p-value
0       T_OR1        0.019226  10.686208  0.00000
1   T_OR_Max1        0.019219  18.117535  0.00000
2  T_FHC_Max1        0.018810  -4.450810  0.00001
3   T_FH_Max1        0.020771  18.129689  0.00000
```