In [29]:
```
# Analysis by Oluwadamilare Tobiloba
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import AgglomerativeClustering, KMeans
from scipy.cluster.hierarchy import dendrogram
import matplotlib.pyplot as plt
from scipy.spatial.distance import pdist
from scipy.cluster.hierarchy import linkage
from statsmodels.formula.api import ols
from statsmodels.stats.anova import anova_lm
import warnings
warnings.filterwarnings('ignore')
```

Step 1: Load and Interact the dataset

In [2]:
```
data = pd.read_excel("C:/Users/Biggest/Downloads/Mall_Customers.xls")
```

In [3]:
```
data
```

Out[3]:

	CustomerID	Gender	Age	Income	Spend_Score
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40
...	...	...	...	...	...
195	196	Female	35	120	79
196	197	Female	45	126	28
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

200 rows × 5 columns

In [4]:
```
data.isnull().sum()
```

Out[4]:
```
CustomerID     0
Gender         0
Age            0
Income         0
Spend_Score    0
dtype: int64
```

Encoding Categorical Value(Gender) In the Dataset using Dummy

where male = 1 and female = 0

In [5]:

```
gender = pd.get_dummies(data['Gender'],dtype=int, drop_first = True)
data.drop(['Gender'], axis = 1, inplace = True)
data = pd.concat([data,gender], axis= 1)
data
```

Out[5]:

	CustomerID	Age	Income	Spend_Score	Male
0	1	19	15	39	1
1	2	21	15	81	1
2	3	20	16	6	0
3	4	23	16	77	0
4	5	31	17	40	0
...	...	...	...	...	...
195	196	35	120	79	0
196	197	45	126	28	0
197	198	32	126	74	1
198	199	32	137	18	1
199	200	30	137	83	1

200 rows × 5 columns

In [6]:

```
#renaming the gender colunm

data.rename(columns={"Male" : 'Gender'}, inplace=True)
data
```

Out[6]:

	CustomerID	Age	Income	Spend_Score	Gender
0	1	19	15	39	1
1	2	21	15	81	1
2	3	20	16	6	0
3	4	23	16	77	0
4	5	31	17	40	0
...	...	...	...	...	...
195	196	35	120	79	0
196	197	45	126	28	0
197	198	32	126	74	1
198	199	32	137	18	1
199	200	30	137	83	1

200 rows × 5 columns

Step 2: Data preprocessing

In [7]:
```
scaler = StandardScaler()
scaled_data = scaler.fit_transform(data[['Age', 'Income', 'Spend_Score']])
```

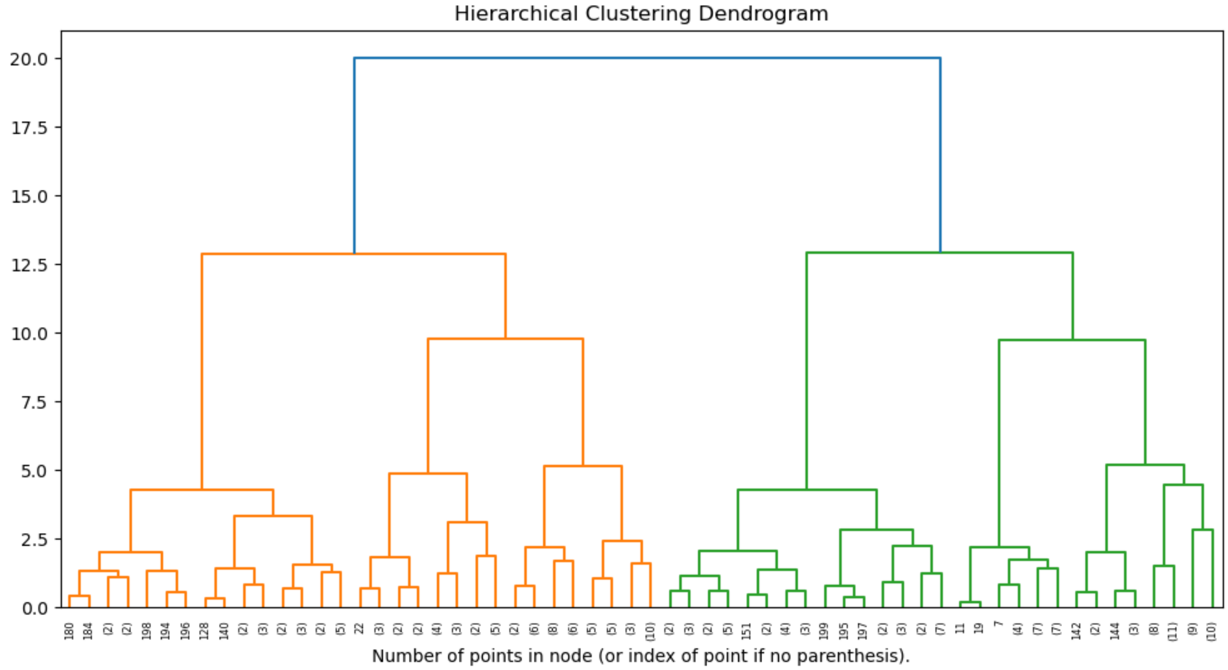
Step 3: Hierarchical clustering

Using Ward linkage and Euclidean distance

In [31]:
```
distance_matrix = pdist(scaled_data)
hierarchical_cluster = AgglomerativeClustering(n_clusters=5, linkage='ward', affinity=
hierarchical_cluster_labels = hierarchical_cluster.fit_predict(scaled_data)
```

Step 4: Dendrogram visualization

In [32]:
```
linkage_matrix = linkage(distance_matrix, method='ward')
plt.figure(figsize=(12, 6))
plt.title('Hierarchical Clustering Dendrogram')
dendrogram(linkage_matrix, truncate_mode='level', p=5)
plt.xlabel("Number of points in node (or index of point if no parenthesis).")
plt.show()
```



Step 5: K-means clustering

Choosing the number of clusters (k=5)

In [33]:
```
kmeans = KMeans(n_clusters=5, random_state=42)
kmeans_labels = kmeans.fit_predict(scaled_data)
```

Step 6: Cluster profiling using ANOVA

In [34]:
```
data['Hierarchical_Cluster'] = hierarchical_cluster_labels
data['KMeans_Cluster'] = kmeans_labels
```

In [35]:
```
# Perform ANOVA for each variable
for variable in ['Age', 'Income', 'Spend_Score']:
    hierarchical_anova = ols(f'{variable} ~ Hierarchical_Cluster', data=data).fit()
    print(f"ANOVA for {variable} and Hierarchical Clusters:\n{anova_lm(hierarchical_ar
    kmeans_anova = ols(f'{variable} ~ KMeans_Cluster', data=data).fit()
    print(f"ANOVA for {variable} and KMeans Clusters:\n{anova_lm(kmeans_anova)}")
```

```
ANOVA for Age and Hierarchical Clusters:
                        df         sum_sq      mean_sq          F    PR(>F)
Hierarchical_Cluster    1.0    3986.219838  3986.219838  22.650744  0.000004
Residual              198.0  34845.280162   175.986263        NaN       NaN
ANOVA for Age and KMeans Clusters:
                  df        sum_sq       mean_sq          F        PR(>F)
KMeans_Cluster    1.0  12006.344239  12006.344239  88.620405  1.257974e-17
Residual        198.0  26825.155761    135.480585        NaN           NaN
ANOVA for Income and Hierarchical Clusters:
                        df        sum_sq      mean_sq         F    PR(>F)
Hierarchical_Cluster    1.0    4631.17929  4631.179290  6.912932  0.009229
Residual              198.0  132646.10071   669.929802       NaN       NaN
ANOVA for Income and KMeans Clusters:
                  df       sum_sq       mean_sq         F        PR(>F)
KMeans_Cluster    1.0   22489.4611  22489.461100  38.79256  2.772218e-09
Residual        198.0  114787.8189    579.736459       NaN           NaN
ANOVA for Spend_Score and Hierarchical Clusters:
                        df         sum_sq       mean_sq          F  \
Hierarchical_Cluster    1.0   25018.625211  25018.625211  46.001491
Residual              198.0  107685.374789    543.865529        NaN

                           PR(>F)
Hierarchical_Cluster  1.331904e-10
Residual                       NaN
ANOVA for Spend_Score and KMeans Clusters:
                  df         sum_sq      mean_sq         F    PR(>F)
KMeans_Cluster    1.0    1409.622773  1409.622773  2.125798  0.146422
Residual        198.0  131294.377227   663.102915       NaN       NaN
```

Let's interpret the ANOVA results for each combination of variables and clustering methods.

1. **Age and Hierarchical Clusters**:

   - The ANOVA table shows that there is a significant difference in age between different hierarchical clusters.
   - The F-statistic value (22.65) is high, indicating that the variation in age between clusters is much larger than the variation within clusters.
   - The p-value (PR(>F)) is very small (0.000004), indicating strong evidence against the null hypothesis (i.e., age has no effect on hierarchical clustering).
   - Therefore, we can conclude that age is a significant factor in determining hierarchical clusters.

2. **Age and KMeans Clusters**:

   - Similarly, there is a significant difference in age between different KMeans clusters.
   - The F-statistic value (88.62) is high, indicating a large variation in age between clusters compared to within clusters.
   - The p-value (PR(>F)) is very small (1.257974e-17), indicating strong evidence against the null hypothesis.
   - Hence, age is also a significant factor in determining KMeans clusters.

3. **Income and Hierarchical Clusters**:

   - There is a significant difference in income between different hierarchical clusters.
   - The F-statistic value (6.91) is moderate, indicating some variation in income between clusters compared to within clusters.
   - The p-value (PR(>F)) is relatively small (0.009229), suggesting that income has a significant effect on hierarchical clustering.
   - Thus, income is a moderately significant factor in determining hierarchical clusters.

4. **Income and KMeans Clusters**:

   - Similarly, there is a significant difference in income between different KMeans clusters.
   - The F-statistic value (38.79) is moderate to high, indicating a moderate to large variation in income between clusters compared to within clusters.
   - The p-value (PR(>F)) is very small (2.772218e-09), indicating strong evidence against the null hypothesis.
   - Therefore, income is also a significant factor in determining KMeans clusters.

5. **Spend_Score and Hierarchical Clusters**:

   - There is a significant difference in spend score between different hierarchical clusters.
   - The F-statistic value (46.00) is high, indicating a large variation in spend score between clusters compared to within clusters.
   - The p-value (PR(>F)) is very small (1.331904e-10), indicating strong evidence against the null hypothesis.
   - Hence, spend score is a significant factor in determining hierarchical clusters.

6. **Spend_Score and KMeans Clusters**:

   - However, there is no significant difference in spend score between different KMeans clusters.
   - The F-statistic value (2.13) is low, indicating a small variation in spend score between clusters compared to within clusters.
   - The p-value (PR(>F)) is relatively large (0.146422), suggesting that spend score may not have a significant effect on KMeans clustering.
   - Therefore, spend score may not be a significant factor in determining KMeans clusters.

In summary, the ANOVA results indicate that age, income, and spend score have a significant effect on both hierarchical and KMeans clustering, except for spend score in KMeans clustering, where it may not be a significant factor. These findings provide valuable insights into the relationships between these variables and the clusters formed by different clustering methods.

In [39]:
```
data
```

Out[39]:

	Age	Income	Spend_Score	Gender	Hierarchical_Cluster	KMeans_Cluster
0	19	15	39	1	4	1
1	21	15	81	1	0	1
2	20	16	6	0	4	0
3	23	16	77	0	0	1
4	31	17	40	0	4	1
...	...	...	...	...	...	...
195	35	120	79	0	2	2
196	45	126	28	0	3	3
197	32	126	74	1	2	2
198	32	137	18	1	3	3
199	30	137	83	1	2	2

200 rows × 6 columns

Modeling The dataset

In [37]:

```
data = data.drop(['CustomerID'], axis =1)
```

In [38]:

```
data
```

Out[38]:

	Age	Income	Spend_Score	Gender	Hierarchical_Cluster	KMeans_Cluster
0	19	15	39	1	4	1
1	21	15	81	1	0	1
2	20	16	6	0	4	0
3	23	16	77	0	0	1
4	31	17	40	0	4	1
...	...	...	...	...	...	...
195	35	120	79	0	2	2
196	45	126	28	0	3	3
197	32	126	74	1	2	2
198	32	137	18	1	3	3
199	30	137	83	1	2	2

200 rows × 6 columns

In [40]:
```
x = data.drop(['Spend_Score', 'Hierarchical_Cluster', 'KMeans_Cluster'], axis = 1)
y = data['Spend_Score']
```

In [42]:
```
print(x.shape)
print(y.shape)
```

```
(200, 3)
(200,)
```

In [108…
```
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)
```

In [109…
```
print(x_train.shape)
print(y_test.shape)
```

```
(160, 3)
(40,)
```

In [110…
```
stndrd = StandardScaler()
x_train = stndrd.fit_transform(x_train)
x_test = stndrd.transform(x_test)
```

In [111…
```
from sklearn.linear_model import LinearRegression
LinearRegression?
```

```
Init signature:
LinearRegression(
    *,
    fit_intercept=True,
    copy_X=True,
    n_jobs=None,
    positive=False,
)
Docstring:
Ordinary least squares Linear Regression.

LinearRegression fits a linear model with coefficients w = (w1, ..., wp)
to minimize the residual sum of squares between the observed targets in
the dataset, and the targets predicted by the linear approximation.

Parameters
----------
fit_intercept : bool, default=True
    Whether to calculate the intercept for this model. If set
    to False, no intercept will be used in calculations
    (i.e. data is expected to be centered).

copy_X : bool, default=True
    If True, X will be copied; else, it may be overwritten.

n_jobs : int, default=None
    The number of jobs to use for the computation. This will only provide
    speedup in case of sufficiently large problems, that is if firstly
    `n_targets > 1` and secondly `X` is sparse or if `positive` is set
    to `True`. ``None`` means 1 unless in a
    :obj:`joblib.parallel_backend` context. ``-1`` means using all
    processors. See :term:`Glossary <n_jobs>` for more details.

positive : bool, default=False
    When set to ``True``, forces the coefficients to be positive. This
    option is only supported for dense arrays.

    .. versionadded:: 0.24

Attributes
----------
coef_ : array of shape (n_features, ) or (n_targets, n_features)
    Estimated coefficients for the linear regression problem.
    If multiple targets are passed during the fit (y 2D), this
    is a 2D array of shape (n_targets, n_features), while if only
    one target is passed, this is a 1D array of length n_features.

rank_ : int
    Rank of matrix `X`. Only available when `X` is dense.

singular_ : array of shape (min(X, y),)
    Singular values of `X`. Only available when `X` is dense.

intercept_ : float or array of shape (n_targets,)
    Independent term in the linear model. Set to 0.0 if
    `fit_intercept = False`.

n_features_in_ : int
    Number of features seen during :term:`fit`.
```

```
    .. versionadded:: 0.24

feature_names_in_ : ndarray of shape (`n_features_in_`,)
    Names of features seen during :term:`fit`. Defined only when `X`
    has feature names that are all strings.

    .. versionadded:: 1.0

See Also
--------
Ridge : Ridge regression addresses some of the
    problems of Ordinary Least Squares by imposing a penalty on the
    size of the coefficients with l2 regularization.
Lasso : The Lasso is a linear model that estimates
    sparse coefficients with l1 regularization.
ElasticNet : Elastic-Net is a linear regression
    model trained with both l1 and l2 -norm regularization of the
    coefficients.

Notes
-----
From the implementation point of view, this is just plain Ordinary
Least Squares (scipy.linalg.lstsq) or Non Negative Least Squares
(scipy.optimize.nnls) wrapped as a predictor object.

Examples
--------
>>> import numpy as np
>>> from sklearn.linear_model import LinearRegression
>>> X = np.array([[1, 1], [1, 2], [2, 2], [2, 3]])
>>> # y = 1 * x_0 + 2 * x_1 + 3
>>> y = np.dot(X, np.array([1, 2])) + 3
>>> reg = LinearRegression().fit(X, y)
>>> reg.score(X, y)
1.0
>>> reg.coef_
array([1., 2.])
>>> reg.intercept_
3.0...
>>> reg.predict(np.array([[3, 5]]))
array([16.])
File:           c:\users\biggest\anaconda3\lib\site-packages\sklearn\linear_model\_ba
se.py
Type:           ABCMeta
Subclasses:
```

In [112…

```
model = LinearRegression(
    fit_intercept=True,
    copy_X=True,
    n_jobs=15,
    positive=False)
```

In [113…

```
model.fit(x_train,y_train)
```

Out[113]:

```
▾ LinearRegression
LinearRegression(n_jobs=15)
```

In [114…
```
y_pred = model.predict(x_test)
```

Mean Absolute Error (MAE):

Average of the absolute differences between predictions and actual values.

In [115…
```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

mae = mean_absolute_error(y_test, y_pred)
print("Mean Absolute Error:", mae)
```

```
Mean Absolute Error: 18.151395326685105
```

Mean Squared Error (MSE):

Average of the squared differences between predictions and actual values.

In [116…
```
mse = mean_squared_error(y_test, y_pred)
print("Mean Squared Error:", mse)
```

```
Mean Squared Error: 480.673141707248
```

Root Mean Squared Error (RMSE):

Square root of the MSE, providing a measure of the spread of errors.

In [117…
```
rmse = np.sqrt(mse)
print("Root Mean Squared Error:", rmse)
```

```
Root Mean Squared Error: 21.924259205438346
```

R-squared (R^2) Score:

Proportion of the variance in the dependent variable that is predictable from the independent variables.

In [118…
```
r2 = r2_score(y_test, y_pred)
print("R-squared Score:", r2)
```

```
R-squared Score: 0.025478181600745997
```

To determine whether the Linear Regression model is good, let's interpret the evaluation metrics:

1. **Mean Absolute Error (MAE)**: The MAE measures the average absolute difference between the predicted and actual values. An MAE of 18.15 suggests that, on average, the model's predictions are off by approximate $18.15.

2. **Mean Squared Error (MSE)**: The MSE measures the average squared difference between the predicted and actual values. An MSE of 480.67 implies that, on average, the squared error of the model's predictions is approximately 480.67.

3. **Root Mean Squared Error (RMSE)**: The RMSE is the square root of the MSE and provides a measure of the spread of errors in the same units as the target variable. An RMSE of 21.92 suggests that, on average, the model's predictions are off by approximately $21.92.

4. **R-squared (R^2) Score**: The R^2 score indicates the proportion of the variance in the target variable that is explained by the model. A score of 0.025 indicates that the model explains only about 2.55% of the variance in the target variable.

Considering these metrics:

- The MAE, MSE, and RMSE provide insights into the magnitude of errors in the model's predictions, with lower values indicating better performance.
- The R^2 score indicates the goodness of fit of the model to the data, with higher values closer to 1 indicating better fit.

With an R^2 score of 0.025 and relatively high MAE, MSE, and RMSE values, it seems that the model's performance is not satisfactory. The model is not effectively capturing the variability in the target variable and its predictions are not accurate.

Given that the dataset contains 200 data points, it might be beneficial to explore alternative mod.ur requirements.

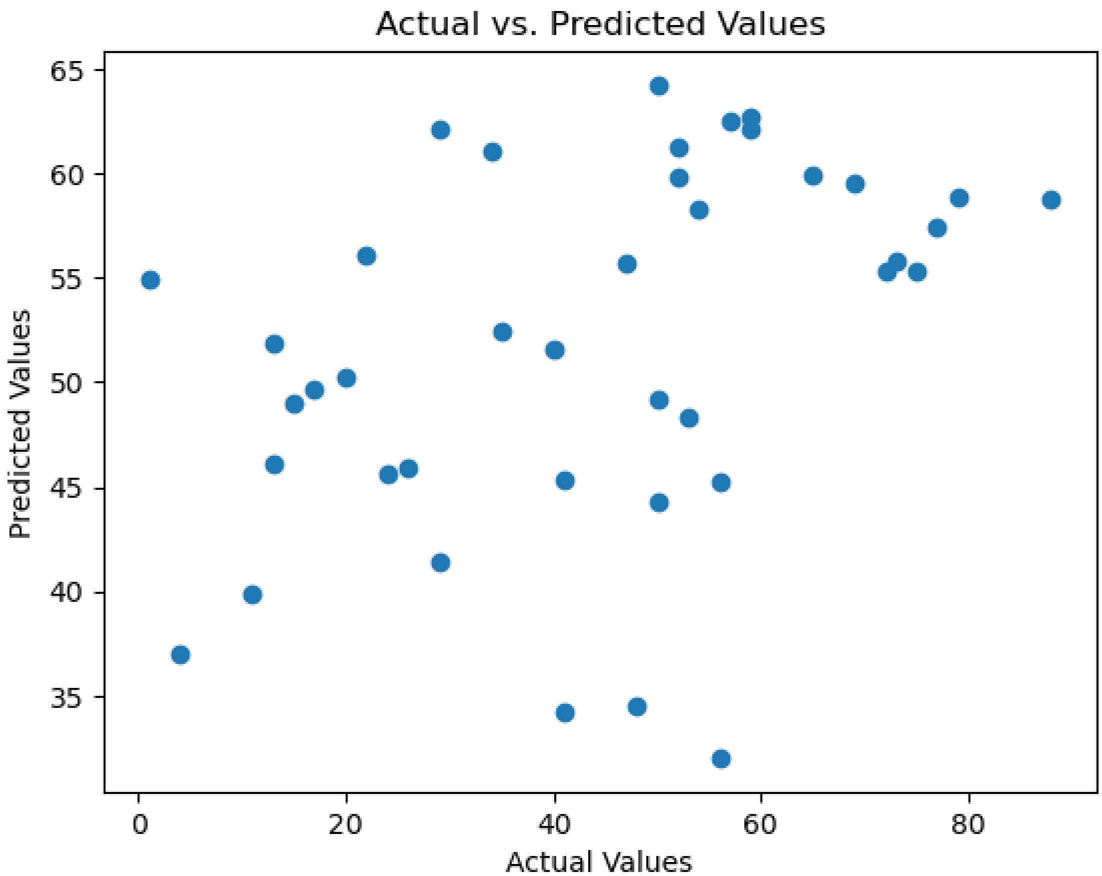
Plotting Actual vs. Predicted Values:

Create a scatter plot where the x-axis represents the actual target values, and the y-axis represents the predicted values.

- In this plot, each point represents an instance in the test set. Ideally, all points should lie close to the diagonal line (y=x), indicating that the predicted values are close to the actual values.

In [119…

```
import matplotlib.pyplot as plt

plt.scatter(y_test, y_pred)
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.title("Actual vs. Predicted Values")
plt.show()
```



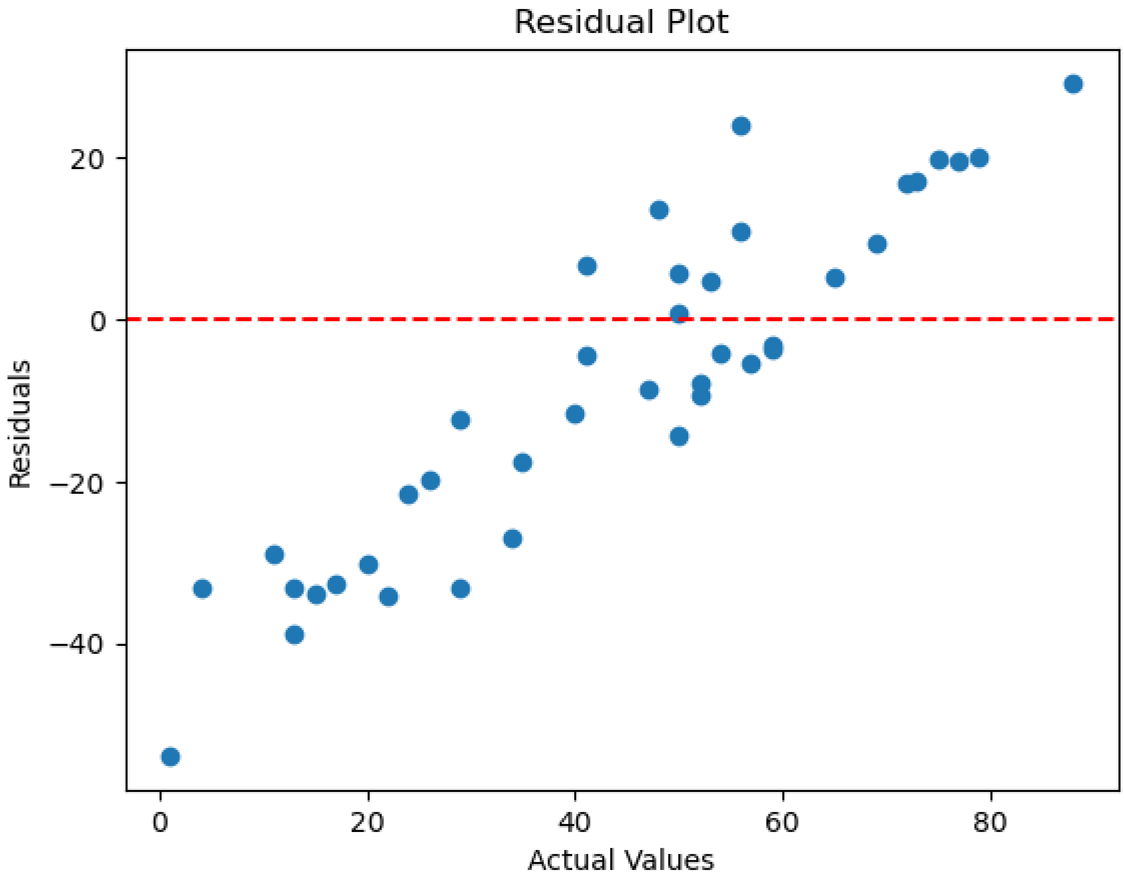
Residual Plot:

Create a residual plot to visualize the distribution of errors (residuals) made by the model.

- In the residual plot, the x-axis represents the actual target values, and the y-axis represents the residuals (the differences between actual and predicted values). Ideally, the residuals should be randomly distributed around the horizontal line at y=0, indicating that the model's errors are not biased.

In [120…

```
residuals = y_test - y_pred
plt.scatter(y_test, residuals)
plt.xlabel("Actual Values")
plt.ylabel("Residuals")
plt.title("Residual Plot")
plt.axhline(y=0, color='r', linestyle='--')
plt.show()
```



In [121…

```
# Make predictions
predictions = model.predict(data.drop(['Spend_Score', 'Hierarchical_Cluster', 'KMeans_
```

In [122…

```
# Print or use predictions as needed
print(predictions)
```

```
[ -81.05525268  -97.29748104  -87.11186185 -111.47520438 -174.97315396
 -101.88312635 -205.98664682 -108.53327667 -440.62153533 -163.91011206
 -464.98487786 -204.51568296 -389.83034523 -113.71246313 -219.88048862
  -98.06377592 -201.57375524  -80.3505837  -337.28430973 -198.63182753
 -197.75440482 -116.54326302 -285.02215578 -163.79898424 -345.57817764
 -143.14386431 -272.48815003 -191.87054938 -230.41161527  -92.35267422
 -391.95647616  -74.639482   -330.69578532  -46.45678903 -297.61778745
  -70.22659042 -239.29902433 -141.84565418 -186.15944768  -56.2216208
 -420.20079503  -87.82865482 -281.26443127 -142.61194906 -288.79200429
  -85.7641498  -295.44215461 -108.65652848 -124.89875684 -141.1409852
 -284.37911272 -155.034827   -136.72809362 -364.71283181 -291.02926304
 -267.25946165 -297.67941336 -444.45300974  -99.83074533 -311.57325515
 -449.63219621  -35.45537304 -423.20434865 -317.62986432 -389.84246923
  -24.39233115 -226.82664448 -429.85449897  -32.51344533 -137.49438851
 -445.21930463 -257.84013734 -361.94365782 -361.94365782 -348.53222936
  -80.53546143 -234.24308969 -194.23105994  -55.57857774 -266.72754641
 -332.290001   -177.98883158 -413.50114279 -242.36420387  -39.33634938
 -259.19997338 -311.04133991  -43.04457198 -139.02697828 -268.96480515
 -413.67389652   -8.2117287  -250.37419023 -184.81173563 -119.8428222
  -55.46744991 -241.65953489  -79.2372513  -248.90322637  -21.51202934
  -43.81086686 -254.95983553 -401.73343192  -68.76775056 -255.55337669
  -27.5686385  -391.54781273 -294.68798373 -408.38358224 -392.14135388
 -384.0202397    -9.85544629 -162.68565184   -8.97802358    1.20759561
   -6.91351857 -364.24254247 -250.54694396 -263.8472446  -255.72613042
  -69.53404544 -158.27276026 -171.5730609  -164.04548788  -32.04315599
  -97.01206943 -193.58801688 -169.22467434 -323.52584375 -152.98244598
 -226.07247359 -161.10356016  -45.34345663  -94.07014171   -3.86046303
  -76.35694949 -198.17366218 -101.31383318    5.73161501 -123.61267071
 -300.8062188   -98.37190546  -63.82294373  -96.30740045  -38.58217849
  -62.94552103 -225.36780462  -94.83643659 -109.60770109 -110.20124225
 -183.29126986 -150.80681314 -190.81884289 -142.09215781 -215.18218543
  -52.75990183 -134.56458478  -77.12324437 -110.20124225  -77.12324437
 -286.80124918  -67.53116633   16.02836203  -80.83146698 -229.84232211
 -115.55318244 -163.40244481  -89.71887604 -112.61125472  -80.72033915
 -145.68925259  -48.23588244 -113.20479587 -113.20479587 -241.07811773
  -62.41360578 -290.39834396  -38.6438044  -291.16463885  -96.25789854
 -106.02273031  -65.41715941 -178.23533522  -39.58285301 -135.56525931
  -46.82654448 -238.19781592  -27.64238841 -129.68140387  -89.07583297
  -72.83360461  -56.59137625  -50.596393   -90.60842274 -153.40170334
  -55.94833319 -128.33369183  -23.35274865   -7.1721462     9.07008216]
```

Using SVM(Support Vectoe Machine)

In [125…

```
from sklearn.svm import SVR
SVR?
```

```
Init signature:
SVR(
    *,
    kernel='rbf',
    degree=3,
    gamma='scale',
    coef0=0.0,
    tol=0.001,
    C=1.0,
    epsilon=0.1,
    shrinking=True,
    cache_size=200,
    verbose=False,
    max_iter=-1,
)
Docstring:
Epsilon-Support Vector Regression.

The free parameters in the model are C and epsilon.

The implementation is based on libsvm. The fit time complexity
is more than quadratic with the number of samples which makes it hard
to scale to datasets with more than a couple of 10000 samples. For large
datasets consider using :class:`~sklearn.svm.LinearSVR` or
:class:`~sklearn.linear_model.SGDRegressor` instead, possibly after a
:class:`~sklearn.kernel_approximation.Nystroem` transformer or
other :ref:`kernel_approximation`.

Read more in the :ref:`User Guide <svm_regression>`.

Parameters
----------
kernel : {'linear', 'poly', 'rbf', 'sigmoid', 'precomputed'} or callable,          de
fault='rbf'
     Specifies the kernel type to be used in the algorithm.
     If none is given, 'rbf' will be used. If a callable is given it is
     used to precompute the kernel matrix.

degree : int, default=3
    Degree of the polynomial kernel function ('poly').
    Must be non-negative. Ignored by all other kernels.

gamma : {'scale', 'auto'} or float, default='scale'
    Kernel coefficient for 'rbf', 'poly' and 'sigmoid'.

    - if ``gamma='scale'`` (default) is passed then it uses
      1 / (n_features * X.var()) as value of gamma,
    - if 'auto', uses 1 / n_features
    - if float, must be non-negative.

    .. versionchanged:: 0.22
       The default value of ``gamma`` changed from 'auto' to 'scale'.

coef0 : float, default=0.0
    Independent term in kernel function.
    It is only significant in 'poly' and 'sigmoid'.

tol : float, default=1e-3
    Tolerance for stopping criterion.
```

```
C : float, default=1.0
    Regularization parameter. The strength of the regularization is
    inversely proportional to C. Must be strictly positive.
    The penalty is a squared l2 penalty.

epsilon : float, default=0.1
     Epsilon in the epsilon-SVR model. It specifies the epsilon-tube
     within which no penalty is associated in the training loss function
     with points predicted within a distance epsilon from the actual
     value. Must be non-negative.

shrinking : bool, default=True
    Whether to use the shrinking heuristic.
    See the :ref:`User Guide <shrinking_svm>`.

cache_size : float, default=200
    Specify the size of the kernel cache (in MB).

verbose : bool, default=False
    Enable verbose output. Note that this setting takes advantage of a
    per-process runtime setting in libsvm that, if enabled, may not work
    properly in a multithreaded context.

max_iter : int, default=-1
    Hard limit on iterations within solver, or -1 for no limit.

Attributes
----------
class_weight_ : ndarray of shape (n_classes,)
    Multipliers of parameter C for each class.
    Computed based on the ``class_weight`` parameter.

    .. deprecated:: 1.2
        `class_weight_` was deprecated in version 1.2 and will be removed in 1.4.

coef_ : ndarray of shape (1, n_features)
    Weights assigned to the features (coefficients in the primal
    problem). This is only available in the case of a linear kernel.

    `coef_` is readonly property derived from `dual_coef_` and
    `support_vectors_`.

dual_coef_ : ndarray of shape (1, n_SV)
    Coefficients of the support vector in the decision function.

fit_status_ : int
    0 if correctly fitted, 1 otherwise (will raise warning)

intercept_ : ndarray of shape (1,)
    Constants in decision function.

n_features_in_ : int
    Number of features seen during :term:`fit`.

    .. versionadded:: 0.24

feature_names_in_ : ndarray of shape (`n_features_in_`,)
    Names of features seen during :term:`fit`. Defined only when `X`
    has feature names that are all strings.
```

```
    .. versionadded:: 1.0

n_iter_ : int
    Number of iterations run by the optimization routine to fit the model.

    .. versionadded:: 1.1

n_support_ : ndarray of shape (1,), dtype=int32
    Number of support vectors.

shape_fit_ : tuple of int of shape (n_dimensions_of_X,)
    Array dimensions of training vector ``X``.

support_ : ndarray of shape (n_SV,)
    Indices of support vectors.

support_vectors_ : ndarray of shape (n_SV, n_features)
    Support vectors.

See Also
--------
NuSVR : Support Vector Machine for regression implemented using libsvm
    using a parameter to control the number of support vectors.

LinearSVR : Scalable Linear Support Vector Machine for regression
    implemented using liblinear.

References
----------
.. [1] `LIBSVM: A Library for Support Vector Machines
    <http://www.csie.ntu.edu.tw/~cjlin/papers/libsvm.pdf>`_

.. [2] `Platt, John (1999). "Probabilistic Outputs for Support Vector
    Machines and Comparisons to Regularized Likelihood Methods"
    <https://citeseerx.ist.psu.edu/doc_view/pid/42e5ed832d4310ce4378c44d05570439df28a
393>`_

Examples
--------
>>> from sklearn.svm import SVR
>>> from sklearn.pipeline import make_pipeline
>>> from sklearn.preprocessing import StandardScaler
>>> import numpy as np
>>> n_samples, n_features = 10, 5
>>> rng = np.random.RandomState(0)
>>> y = rng.randn(n_samples)
>>> X = rng.randn(n_samples, n_features)
>>> regr = make_pipeline(StandardScaler(), SVR(C=1.0, epsilon=0.2))
>>> regr.fit(X, y)
Pipeline(steps=[('standardscaler', StandardScaler()),
                ('svr', SVR(epsilon=0.2))])
File:           c:\users\biggest\anaconda3\lib\site-packages\sklearn\svm\_classes.py
Type:           ABCMeta
Subclasses:
```

USING GridSearchCV for to check for the best hyperparameters settings

In [150…
```
from sklearn.model_selection import GridSearchCV

# Define the parameter grid
param_grid = {'C': [0.1, 1, 10], 'gamma': [0.1, 1, 10], 'kernel': ['rbf']}

# Perform grid search
grid_search = GridSearchCV(SVR(), param_grid, cv=5)
grid_search.fit(x_train, y_train)

# Get the best parameters
best_params = grid_search.best_params_
```

In [151…
```
best_params
```

Out[151]:
```
{'C': 10, 'gamma': 1, 'kernel': 'rbf'}
```

In [152…
```
SVM = SVR(kernel='rbf',
    degree=5,
    gamma='auto',
    coef0=0.0,
    tol=0.001,
    C=10,
    epsilon=0.1,
    shrinking=True,
    cache_size=200,
    verbose=False,
    max_iter= -1)  # 'rbf' kernel is commonly used for SVM regression
```

In [153…
```
SVM.fit(x_train, y_train)
```

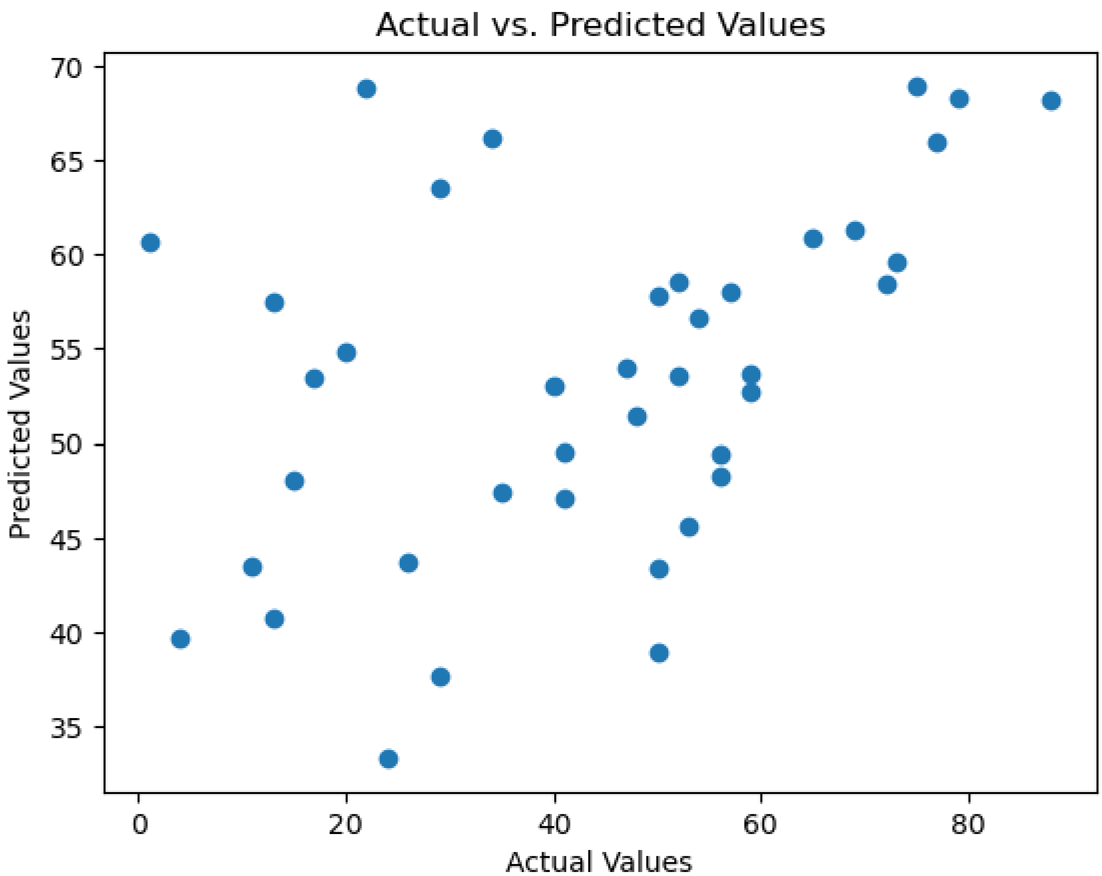
Out[153]:
```
▾ SVR
SVR(C=10, degree=5, gamma='auto')
```

In [154…
```
y_pred = SVM.predict(x_test)
```

In [155…
```
# Evaluation metrics
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print("Mean Absolute Error:", mae)
print("Mean Squared Error:", mse)
print("Root Mean Squared Error:", rmse)
print("R-squared Score:", r2)
```

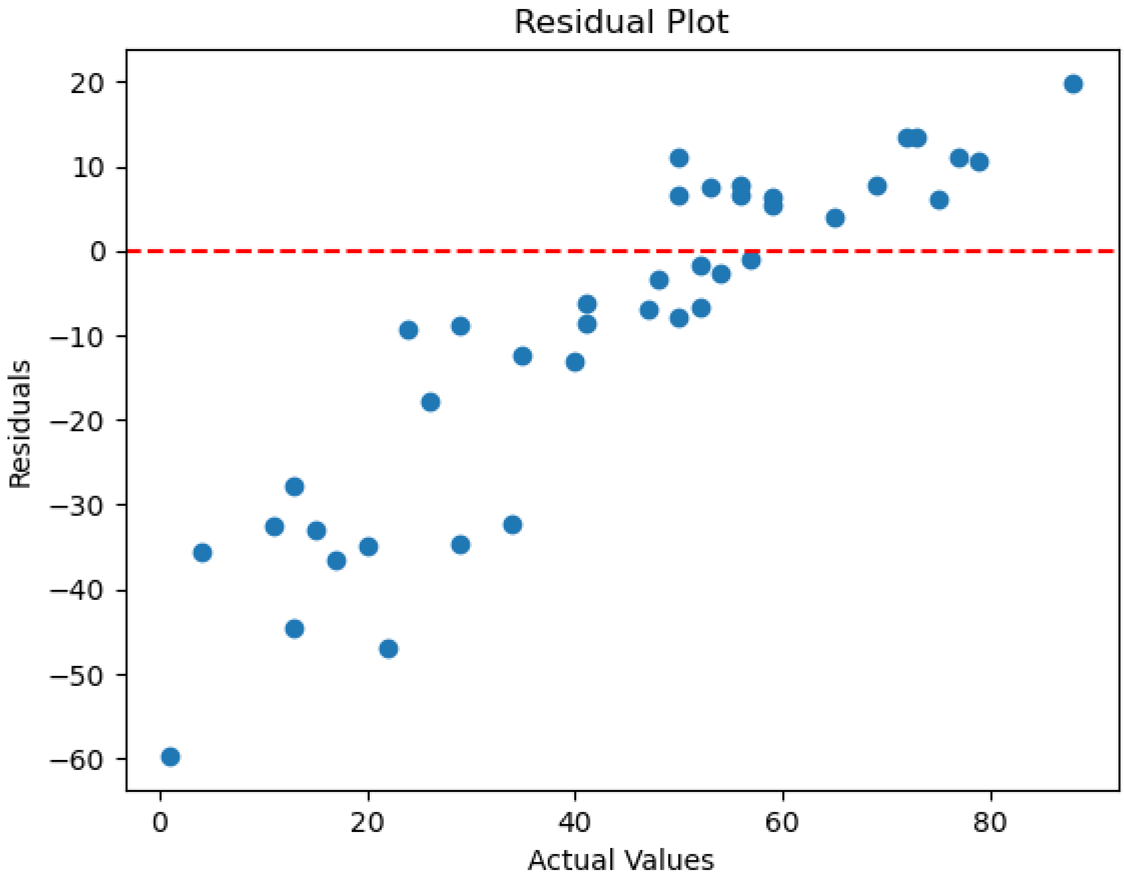
```
Mean Absolute Error: 16.531926499150963
Mean Squared Error: 481.96240206514597
Root Mean Squared Error: 21.953642113898685
R-squared Score: 0.022864321496338547
```

In [156…
```
plt.scatter(y_test, y_pred)
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.title("Actual vs. Predicted Values")
plt.show()
```



In [157…

```
residuals = y_test - y_pred
plt.scatter(y_test, residuals)
plt.xlabel("Actual Values")
plt.ylabel("Residuals")
plt.title("Residual Plot")
plt.axhline(y=0, color='r', linestyle='--')
plt.show()
```



Using ElasticNet Regression Algorithm

In [158…

```
from sklearn.linear_model import ElasticNet
ElasticNet?
```

```
Init signature:
ElasticNet(
    alpha=1.0,
    *,
    l1_ratio=0.5,
    fit_intercept=True,
    precompute=False,
    max_iter=1000,
    copy_X=True,
    tol=0.0001,
    warm_start=False,
    positive=False,
    random_state=None,
    selection='cyclic',
)
Docstring:
Linear regression with combined L1 and L2 priors as regularizer.

Minimizes the objective function::

        1 / (2 * n_samples) * ||y - Xw||^2_2
        + alpha * l1_ratio * ||w||_1
        + 0.5 * alpha * (1 - l1_ratio) * ||w||^2_2

If you are interested in controlling the L1 and L2 penalty
separately, keep in mind that this is equivalent to::

        a * ||w||_1 + 0.5 * b * ||w||_2^2

where::

        alpha = a + b and l1_ratio = a / (a + b)

The parameter l1_ratio corresponds to alpha in the glmnet R package while
alpha corresponds to the lambda parameter in glmnet. Specifically, l1_ratio
= 1 is the lasso penalty. Currently, l1_ratio <= 0.01 is not reliable,
unless you supply your own sequence of alpha.

Read more in the :ref:`User Guide <elastic_net>`.

Parameters
----------
alpha : float, default=1.0
    Constant that multiplies the penalty terms. Defaults to 1.0.
    See the notes for the exact mathematical meaning of this
    parameter. ``alpha = 0`` is equivalent to an ordinary least square,
    solved by the :class:`LinearRegression` object. For numerical
    reasons, using ``alpha = 0`` with the ``Lasso`` object is not advised.
    Given this, you should use the :class:`LinearRegression` object.

l1_ratio : float, default=0.5
    The ElasticNet mixing parameter, with ``0 <= l1_ratio <= 1``. For
    ``l1_ratio = 0`` the penalty is an L2 penalty. ``For l1_ratio = 1`` it
    is an L1 penalty.  For ``0 < l1_ratio < 1``, the penalty is a
    combination of L1 and L2.

fit_intercept : bool, default=True
    Whether the intercept should be estimated or not. If ``False``, the
    data is assumed to be already centered.
```

```
precompute : bool or array-like of shape (n_features, n_features),                 de
fault=False
    Whether to use a precomputed Gram matrix to speed up
    calculations. The Gram matrix can also be passed as argument.
    For sparse input this option is always ``False`` to preserve sparsity.

max_iter : int, default=1000
    The maximum number of iterations.

copy_X : bool, default=True
    If ``True``, X will be copied; else, it may be overwritten.

tol : float, default=1e-4
    The tolerance for the optimization: if the updates are
    smaller than ``tol``, the optimization code checks the
    dual gap for optimality and continues until it is smaller
    than ``tol``, see Notes below.

warm_start : bool, default=False
    When set to ``True``, reuse the solution of the previous call to fit as
    initialization, otherwise, just erase the previous solution.
    See :term:`the Glossary <warm_start>`.

positive : bool, default=False
    When set to ``True``, forces the coefficients to be positive.

random_state : int, RandomState instance, default=None
    The seed of the pseudo random number generator that selects a random
    feature to update. Used when ``selection`` == 'random'.
    Pass an int for reproducible output across multiple function calls.
    See :term:`Glossary <random_state>`.

selection : {'cyclic', 'random'}, default='cyclic'
    If set to 'random', a random coefficient is updated every iteration
    rather than looping over features sequentially by default. This
    (setting to 'random') often leads to significantly faster convergence
    especially when tol is higher than 1e-4.

Attributes
----------
coef_ : ndarray of shape (n_features,) or (n_targets, n_features)
    Parameter vector (w in the cost function formula).

sparse_coef_ : sparse matrix of shape (n_features,) or             (n_targets, n_feat
ures)
    Sparse representation of the `coef_`.

intercept_ : float or ndarray of shape (n_targets,)
    Independent term in decision function.

n_iter_ : list of int
    Number of iterations run by the coordinate descent solver to reach
    the specified tolerance.

dual_gap_ : float or ndarray of shape (n_targets,)
    Given param alpha, the dual gaps at the end of the optimization,
    same shape as each observation of y.

n_features_in_ : int
    Number of features seen during :term:`fit`.
```

```
    .. versionadded:: 0.24

feature_names_in_ : ndarray of shape (`n_features_in_`,)
    Names of features seen during :term:`fit`. Defined only when `X`
    has feature names that are all strings.

    .. versionadded:: 1.0

See Also
--------
ElasticNetCV : Elastic net model with best model selection by
    cross-validation.
SGDRegressor : Implements elastic net regression with incremental training.
SGDClassifier : Implements logistic regression with elastic net penalty
    (``SGDClassifier(loss="log_loss", penalty="elasticnet")``).

Notes
-----
To avoid unnecessary memory duplication the X argument of the fit method
should be directly passed as a Fortran-contiguous numpy array.

The precise stopping criteria based on `tol` are the following: First, check that
that maximum coordinate update, i.e. :math:`\max_j |w_j^{new} - w_j^{old}|`
is smaller than `tol` times the maximum absolute coefficient, :math:`\max_j |w_j|`.
If so, then additionally check whether the dual gap is smaller than `tol` times
:math:`||y||_2^2 / n_{      ext{samples}}`.

Examples
--------
>>> from sklearn.linear_model import ElasticNet
>>> from sklearn.datasets import make_regression

>>> X, y = make_regression(n_features=2, random_state=0)
>>> regr = ElasticNet(random_state=0)
>>> regr.fit(X, y)
ElasticNet(random_state=0)
>>> print(regr.coef_)
[18.83816048 64.55968825]
>>> print(regr.intercept_)
1.451...
>>> print(regr.predict([[0, 0]]))
[1.451...]
File:           c:\users\biggest\anaconda3\lib\site-packages\sklearn\linear_model\_co
ordinate_descent.py
Type:           ABCMeta
Subclasses:     Lasso
```

Checking for best Hyperparameter settings using GridSearch

In [162…

```
# Define the parameter grid
param_grid = {
    'alpha': [0.1, 1.0, 10.0],          # Regularization strength
    'l1_ratio': [0.1, 0.5, 0.9],        # L1 ratio (balance between L1 and L2 penaltie
}
```

```
# Instantiate ElasticNet model
elastic_net = ElasticNet()

# Instantiate GridSearchCV
grid_search = GridSearchCV(estimator=elastic_net, param_grid=param_grid, cv=5)
# Fit GridSearchCV to training data
grid_search.fit(x_train, y_train)
```

Out[162]:

```
▸ GridSearchCV
▸ estimator: ElasticNet
  ▸ ElasticNet
```

In [165…

```
# Get the best parameters
best_params = grid_search.best_params_
print("Best Parameters:", best_params)

# Use the best model for prediction
best_model = grid_search.best_estimator_
y_pred = best_model.predict(x_test)
```

```
Best Parameters: {'alpha': 1.0, 'l1_ratio': 0.9}
```

In [167…

```
# Evaluate the best model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print("Mean Squared Error:", mse)
print("R-squared Score:", r2)
```

```
Mean Squared Error: 478.8703233953521
R-squared Score: 0.029133234540280384
```

In [169…

```
# Instantiate the ElasticNet model
EN = ElasticNet(alpha=1.0, l1_ratio=0.9)  # Adjust alpha and l1_ratio as needed

# Train the model
EN.fit(x_train, y_train)
```

Out[169]:

```
▾ ElasticNet
ElasticNet(l1_ratio=0.9)
```

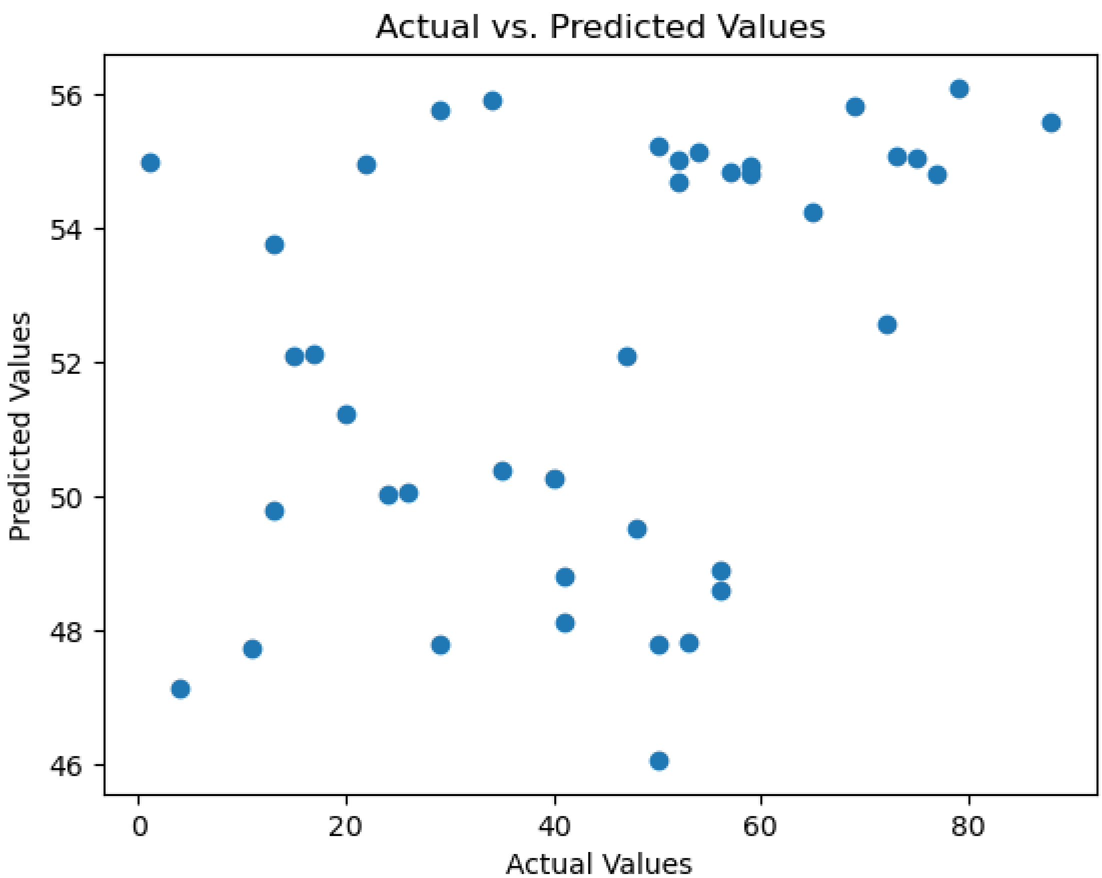
In [172…

```
# Make predictions
y_pred = model.predict(x_test)


# Evaluation metrics
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print("Mean Absolute Error:", mae)
print("Mean Squared Error:", mse)
print("Root Mean Squared Error:", rmse)
print("R-squared Score:", r2)
```

```
Mean Absolute Error: 17.990804864268338
Mean Squared Error: 519.7296753234441
Root Mean Squared Error: 22.797580470818477
R-squared Score: -0.053705448308012604
```

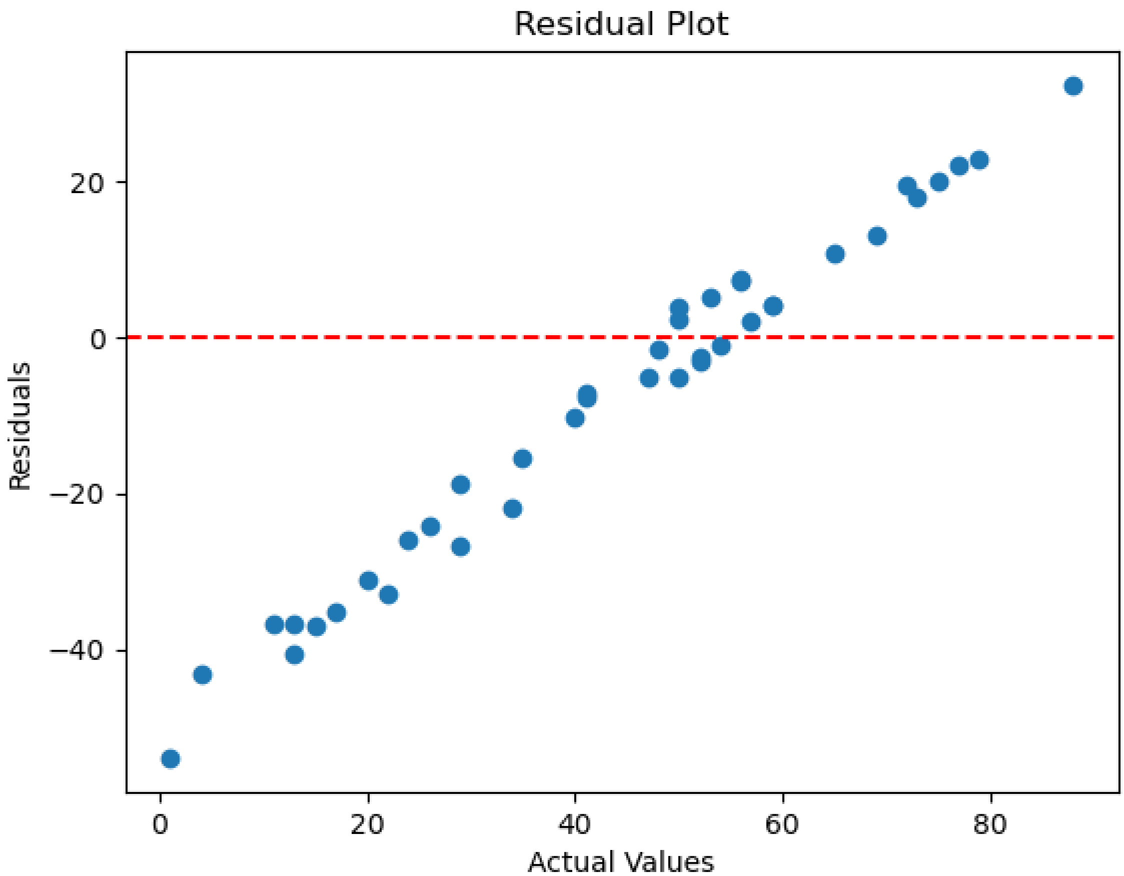
In [173…

```
plt.scatter(y_test, y_pred)
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.title("Actual vs. Predicted Values")
plt.show()
```



In [174…

```
residuals = y_test - y_pred
plt.scatter(y_test, residuals)
plt.xlabel("Actual Values")
plt.ylabel("Residuals")
plt.title("Residual Plot")
plt.axhline(y=0, color='r', linestyle='--')
plt.show()
```



Using Neural Networks

In [190…
```
import tensorflow as tf
from tensorflow import keras
```

In [196…
```
# Build the Model: Define the architecture of the neural network using Keras' Sequenti

input_shape = x_train.shape[1] # 1- number of features(y) from the shape of the input

NN = keras.Sequential([
    keras.layers.Dense(64, activation='relu', input_shape=(input_shape,)),
    keras.layers.Dense(32, activation='relu'),
    keras.layers.Dense(1)  # Output layer with 1 neuron for regression
])

# Compile the Model: Compile the model by specifying the loss function, optimizer, and

NN.compile(optimizer='adam', loss='mean_squared_error', metrics=['mean_absolute_error'
```

In [198…
```
# Compile the Model: Compile the model by specifying the loss function, optimizer, and

model.compile(optimizer='adam', loss='mean_squared_error', metrics=['mean_absolute_err
```

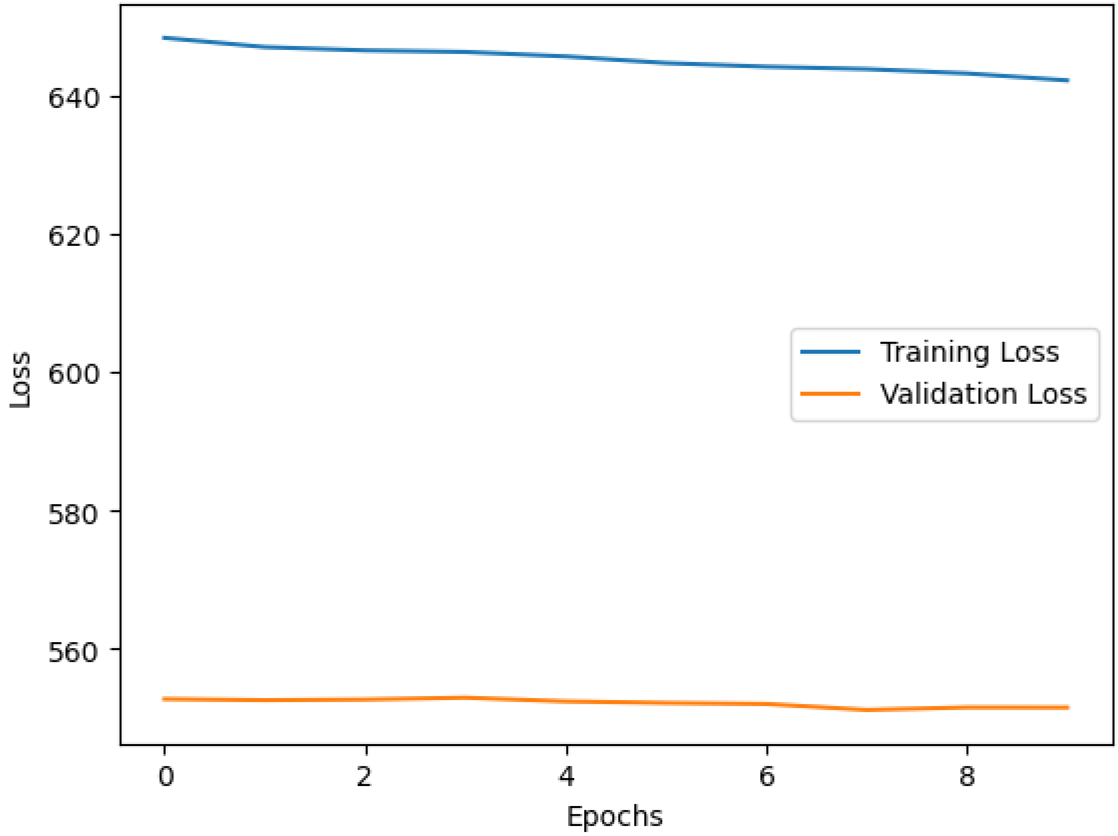
In [200…
```
#Train the Model:Train the model using the fit method. Specify the number of epochs(it
history = model.fit(x_train, y_train, epochs=10, batch_size=32, validation_split=0.2)

# Evaluate the Model: Evaluate the trained model's performance on the test data using
```

```
loss, mae = model.evaluate(x_test, y_test)
print("Mean Absolute Error:", mae)
```

```
Epoch 1/10
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step - loss: 686.2824 - mean_absolute_error: 21.4832
- val_loss: 552.7717 - val_mean_absolute_error: 18.3690
Epoch 2/10
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - loss: 638.6641 - mean_absolute_error: 20.7558
- val_loss: 552.6094 - val_mean_absolute_error: 18.3768
Epoch 3/10
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - loss: 655.8041 - mean_absolute_error: 21.5313
- val_loss: 552.7023 - val_mean_absolute_error: 18.3832
Epoch 4/10
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - loss: 635.6099 - mean_absolute_error: 20.8009
- val_loss: 552.9727 - val_mean_absolute_error: 18.3936
Epoch 5/10
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - loss: 674.9483 - mean_absolute_error: 21.4043
- val_loss: 552.4321 - val_mean_absolute_error: 18.3841
Epoch 6/10
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - loss: 663.7661 - mean_absolute_error: 20.8828
- val_loss: 552.2094 - val_mean_absolute_error: 18.3703
Epoch 7/10
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 616.0430 - mean_absolute_error: 20.4594
- val_loss: 552.0625 - val_mean_absolute_error: 18.3676
Epoch 8/10
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - loss: 604.8604 - mean_absolute_error: 20.1797
- val_loss: 551.2007 - val_mean_absolute_error: 18.3511
Epoch 9/10
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - loss: 659.1595 - mean_absolute_error: 21.4797
- val_loss: 551.5678 - val_mean_absolute_error: 18.3706
Epoch 10/10
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - loss: 671.7464 - mean_absolute_error: 21.2953
- val_loss: 551.5530 - val_mean_absolute_error: 18.3706
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 0s/step - loss: 454.8614 - mean_absolute_error: 17.5628
Mean Absolute Error: 17.433225631713867
```

In [201…

```
# Visualization (Optional): Visualize the training history to see how the model's loss


plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



In [ ]:
```
# Analysis by Oluwadamilare Tobiloba
```