```python
# Data Manipulation and Model Visualization
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.tree import plot_tree

# Supervised Learning

# Regression
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor

# Classification
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB

# Unsupervised Learning
from sklearn.cluster import KMeans # Kmeans

# Data Preprocessing & Feature Engineering
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler

# Dimensionality Reduction
from sklearn.decomposition import PCA

# Model Selection
from sklearn.model_selection import train_test_split

# Evaluation Metrics for Classification
from sklearn import metrics

# Evaluation Metrics for Regression
from sklearn.metrics import root_mean_squared_error,
mean_absolute_error
```

# *Supervised*

*ApplyingRegression*

## 1. Linear Regression

```
# read file
df_linear_regression = pd.read_csv(r"path\Real estate.csv")

# get the first five rows of you data
df_linear_regression.head()
```

```
   No  X1 transaction date  X2 house age  \
0   1             2012.917          32.0
1   2             2012.917          19.5
2   3             2013.583          13.3
3   4             2013.500          13.3
4   5             2012.833           5.0

   X3 distance to the nearest MRT station  X4 number of convenience
stores  \
0                                84.87882
10
1                               306.59470
9
2                               561.98450
5
3                               561.98450
5
4                               390.56840
5

   X5 latitude  X6 longitude  Y house price of unit area
0     24.98298     121.54024                        37.9
1     24.98034     121.53951                        42.2
2     24.98746     121.54391                        47.3
3     24.98746     121.54391                        54.8
4     24.97937     121.54245                        43.1
```

```
df_linear_regression.shape # check the shape row & columns of your
data
```

```
(414, 8)
```

```
df_linear_regression.info() # check basic info of you data
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 414 entries, 0 to 413
Data columns (total 8 columns):
 #   Column                                  Non-Null Count  Dtype
```

```
---  ------                                  --------------  -----
 0   No                                      414 non-null    int64
 1   X1 transaction date                     414 non-null    float64
 2   X2 house age                            414 non-null    float64
 3   X3 distance to the nearest MRT station  414 non-null    float64
 4   X4 number of convenience stores         414 non-null    int64
 5   X5 latitude                             414 non-null    float64
 6   X6 longitude                            414 non-null    float64
 7   Y house price of unit area              414 non-null    float64
dtypes: float64(6), int64(2)
memory usage: 26.0 KB
```

```
df_linear_regression.isnull().sum() # check the null values of your data
```

```
No                                        0
X1 transaction date                       0
X2 house age                              0
X3 distance to the nearest MRT station    0
X4 number of convenience stores           0
X5 latitude                               0
X6 longitude                              0
Y house price of unit area                0
dtype: int64
```

```
df_linear_regression.drop(columns=['No'], axis=1, inplace=True) # drop column since i wasn't required
df_linear_regression.head() # again check head of your data
```

```
   X1 transaction date  X2 house age  X3 distance to the nearest MRT station  \
0             2012.917          32.0
84.87882
1             2012.917          19.5
306.59470
2             2013.583          13.3
561.98450
3             2013.500          13.3
561.98450
4             2012.833           5.0
390.56840

   X4 number of convenience stores  X5 latitude  X6 longitude  \
0                               10     24.98298     121.54024
1                                9     24.98034     121.53951
2                                5     24.98746     121.54391
3                                5     24.98746     121.54391
4                                5     24.97937     121.54245

   Y house price of unit area
```

```
0                        37.9
1                        42.2
2                        47.3
3                        54.8
4                        43.1
```

```
df_linear_regression.describe() # check basic statitics of you data
```

```
       X1 transaction date  X2 house age  \
count           414.000000    414.000000
mean           2013.148971     17.712560
std               0.281967     11.392485
min            2012.667000      0.000000
25%            2012.917000      9.025000
50%            2013.167000     16.100000
75%            2013.417000     28.150000
max            2013.583000     43.800000

       X3 distance to the nearest MRT station  \
count                              414.000000
mean                              1083.885689
std                               1262.109595
min                                 23.382840
25%                                289.324800
50%                                492.231300
75%                               1454.279000
max                               6488.021000

       X4 number of convenience stores  X5 latitude  X6 longitude  \
count                       414.000000   414.000000    414.000000
mean                          4.094203    24.969030    121.533361
std                           2.945562     0.012410      0.015347
min                           0.000000    24.932070    121.473530
25%                           1.000000    24.963000    121.528085
50%                           4.000000    24.971100    121.538630
75%                           6.000000    24.977455    121.543305
max                          10.000000    25.014590    121.566270

       Y house price of unit area
count                  414.000000
mean                    37.980193
std                     13.606488
min                      7.600000
25%                     27.700000
50%                     38.450000
75%                     46.600000
max                    117.500000
```

```
df_linear_regression.corr() # check the correlation of you data
```

```
                                        X1 transaction date  X2 house
age  \
X1 transaction date                                1.000000
0.017549
X2 house age                                       0.017549
1.000000
X3 distance to the nearest MRT station             0.060880
0.025622
X4 number of convenience stores                    0.009635
0.049593
X5 latitude                                        0.035058
0.054420
X6 longitude                                      -0.041082     -
0.048520
Y house price of unit area                         0.087491     -
0.210567

                                        X3 distance to the nearest MRT
station  \
X1 transaction date
0.060880
X2 house age
0.025622
X3 distance to the nearest MRT station
1.000000
X4 number of convenience stores                                      -
0.602519
X5 latitude                                                          -
0.591067
X6 longitude                                                         -
0.806317
Y house price of unit area                                           -
0.673613

                                        X4 number of convenience
stores  \
X1 transaction date
0.009635
X2 house age
0.049593
X3 distance to the nearest MRT station                        -
0.602519
X4 number of convenience stores
1.000000
X5 latitude
0.444143
X6 longitude
0.449099
Y house price of unit area
0.571005
```

```
                                              X5 latitude  X6 longitude  \
X1 transaction date                              0.035058     -0.041082
X2 house age                                     0.054420     -0.048520
X3 distance to the nearest MRT station          -0.591067     -0.806317
X4 number of convenience stores                  0.444143      0.449099
X5 latitude                                      1.000000      0.412924
X6 longitude                                     0.412924      1.000000
Y house price of unit area                       0.546307      0.523287

                                              Y house price of unit area
X1 transaction date                                             0.087491
X2 house age                                                   -0.210567
X3 distance to the nearest MRT station                         -0.673613
X4 number of convenience stores                                 0.571005
X5 latitude                                                     0.546307
X6 longitude                                                    0.523287
Y house price of unit area                                      1.000000
```

```
x_linear_regression = df_linear_regression.drop(columns=['Y house
price of unit area']) # make independent variables (here drop your
target varible)
x_linear_regression.head() # check head of your in independent
variables
```

```
   X1 transaction date  X2 house age  X3 distance to the nearest MRT
station  \
0              2012.917          32.0
84.87882
1              2012.917          19.5
306.59470
2              2013.583          13.3
561.98450
3              2013.500          13.3
561.98450
4              2012.833           5.0
390.56840

   X4 number of convenience stores  X5 latitude  X6 longitude
0                               10     24.98298     121.54024
1                                9     24.98034     121.53951
2                                5     24.98746     121.54391
3                                5     24.98746     121.54391
4                                5     24.97937     121.54245
```

```
y_linear_regression = df_linear_regression['Y house price of unit
area']# make dependent variables (here just select your target
varible)
y_linear_regression.head() # check head of your in dependent variable
```

```
0    37.9
1    42.2
2    47.3
3    54.8
4    43.1
Name: Y house price of unit area, dtype: float64
```

```
print("x=",x_linear_regression.shape,"\ny=",
y_linear_regression.shape) # check the shape of you x and y varibales
```

```
x= (414, 6)
y= (414,)
```

```
from sklearn.model_selection import train_test_split # import train
test split
```

```
# Apply train_test_split and make your training and testinig x and y
x_train_linear_regression, x_test_linear_regression,
y_train_linear_regression, y_test_linear_regression =
train_test_split(x_linear_regression, y_linear_regression,
test_size=0.3, random_state=42)
```

```
# check the shape of you training and testinig x and y
print("\nx train shape: ", x_train_linear_regression.shape,"\nx test
shape: ", x_test_linear_regression.shape)
print("\ny train shape: ", y_train_linear_regression.shape, "\ny test
shape: ", y_test_linear_regression.shape)
```

```

x train shape:  (289, 6)
x test shape:  (125, 6)

y train shape:  (289,)
y test shape:  (125,)
```

```
from sklearn.linear_model import LinearRegression # import Linear
Regression
```

```
linear_regression = LinearRegression() # call LinearRegression
```

```
linear_regression.fit(x_train_linear_regression,
y_train_linear_regression) # fit you training x and y in
LinearRegression
```

```
LinearRegression()
```

```
linear_regression.coef_ # check the Coedicients
```

```
array([ 5.84779706e+00, -2.42545813e-01, -5.13873381e-03,
1.07449530e+00,
        2.39096949e+02, -5.22351591e+01])
```

```python
pd.DataFrame(linear_regression.coef_, x_linear_regression.columns,
columns=["Coedicients"]) # making dataframe of Coedicients
```

| | Coedicients |
|---|---|
| X1 transaction date | 5.847797 |
| X2 house age | -0.242546 |
| X3 distance to the nearest MRT station | -0.005139 |
| X4 number of convenience stores | 1.074495 |
| X5 latitude | 239.096949 |
| X6 longitude | -52.235159 |

```python
y_pred_linear_regression =
linear_regression.predict(x_test_linear_regression) # predict values
by linear regression using x test
y_pred_linear_regression[:5] # just to see first five prrdicted values
(no necessary)
```

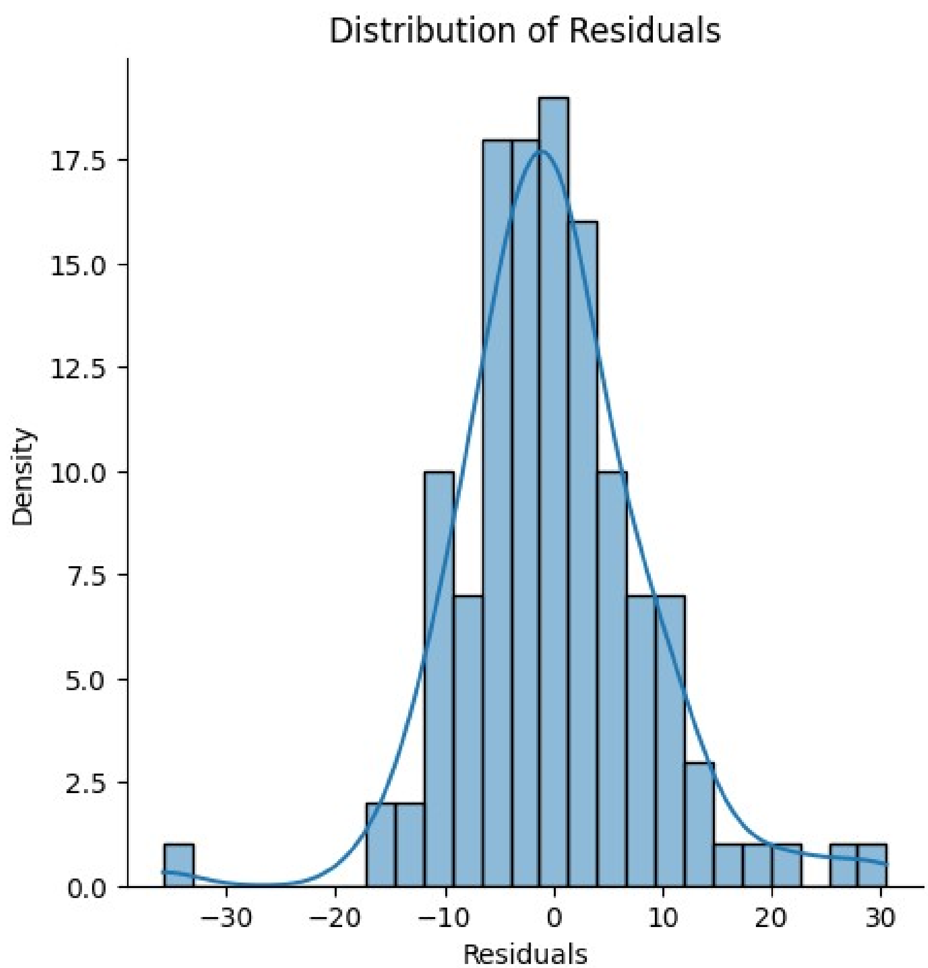
```
array([47.55430212, 41.08372744, 44.25551663, 40.51685112,
27.43467608])
```

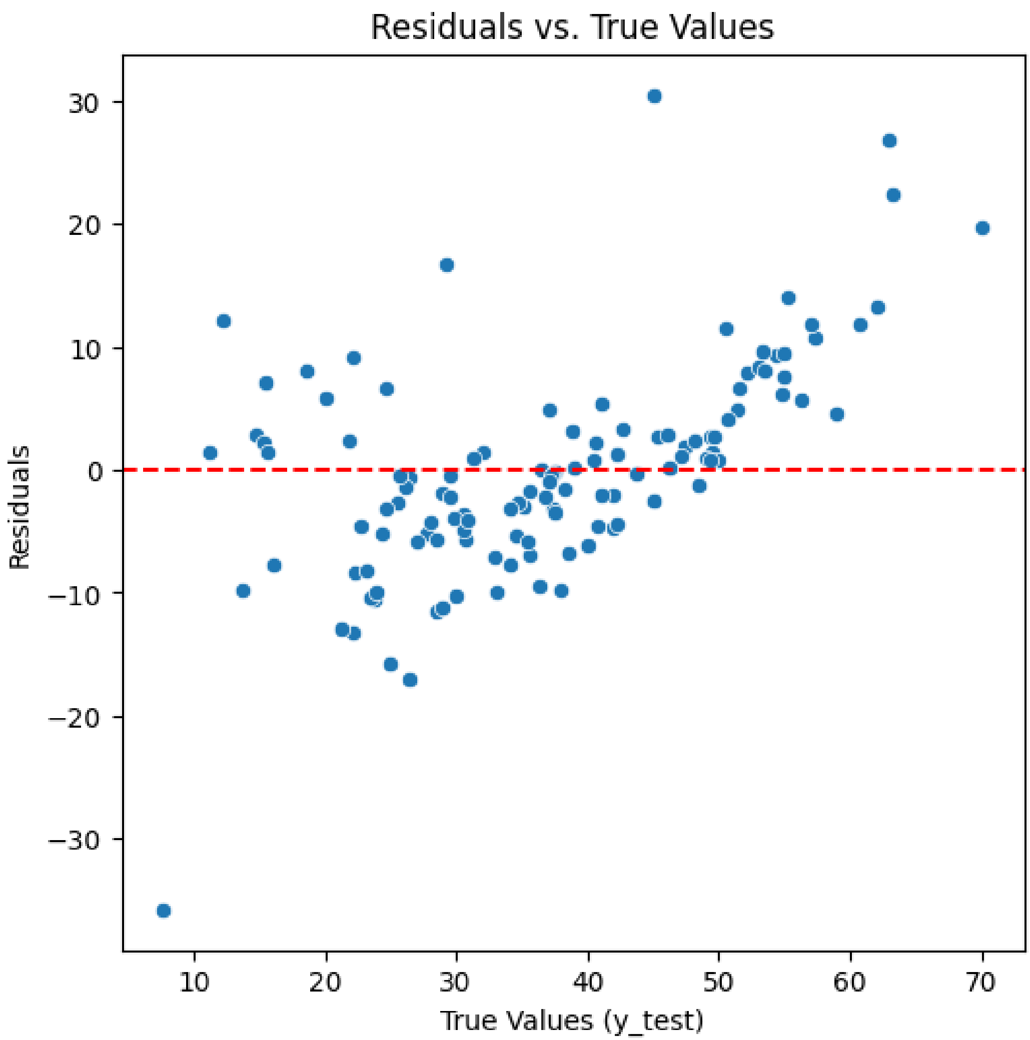
```python
from sklearn import metrics # import metrics

# check error by placing y test and and y predicted in comparsion
MAE_linear_regression =
metrics.mean_absolute_error(y_test_linear_regression,
y_pred_linear_regression)
MSE_linear_regression =
metrics.mean_squared_error(y_test_linear_regression,
y_pred_linear_regression)
RMSE_linear_regression =
metrics.root_mean_squared_error(y_test_linear_regression,
y_pred_linear_regression)

print("Logistic Regression MAE", MAE_linear_regression)
print("Logistic Regression MSE", MSE_linear_regression)
print("Logistic Regression RMSE", RMSE_linear_regression)
```

```
Logistic Regression MAE 6.1848363400971085
Logistic Regression MSE 73.5683793285023
Logistic Regression RMSE 8.577201136064275
```

```python
test_residual_linear_regression = y_test_linear_regression -
y_pred_linear_regression # check test residual

import seaborn as sns  # Import seaborn
import matplotlib.pyplot as plt  # Import matplotlib

# Plot 1: Distribution of residuals (displot)
plt.figure(figsize=(6, 6))  # Increase figure size for clarity
sns.displot(test_residual_linear_regression, bins=25, kde=True)  #
Displot with KDE
```

```
plt.title("Distribution of Residuals")  # Add title for clarity
plt.xlabel("Residuals")  # Label the x-axis
plt.ylabel("Density")  # Label the y-axis
plt.show()  # Display the plot

# Plot 2: Scatterplot of residuals vs. true values (y_test)
plt.figure(figsize=(6, 6))  # Increase figure size
sns.scatterplot(x=y_test_linear_regression,
y=test_residual_linear_regression)  # Scatter plot
plt.axhline(y=0, color='r', ls='--')  # Red dashed line at y=0
plt.title("Residuals vs. True Values")  # Add title for clarity
plt.xlabel("True Values (y_test)")  # Label the x-axis
plt.ylabel("Residuals")  # Label the y-axis
plt.show()  # Display the plot

<Figure size 600x600 with 0 Axes>
```






---

## 2. Decision Tree

```
# read file
df_decision_tree = pd.read_csv(r"path\Real estate.csv")

df_decision_tree.head() # see first five rows
```

```
   No  X1 transaction date  X2 house age  \
0   1             2012.917          32.0
1   2             2012.917          19.5
2   3             2013.583          13.3
3   4             2013.500          13.3
4   5             2012.833           5.0

   X3 distance to the nearest MRT station  X4 number of convenience 
stores  \
0                                84.87882
```

```
10
1                                306.59470
9
2                                561.98450
5
3                                561.98450
5
4                                390.56840
5

   X5 latitude  X6 longitude  Y house price of unit area
0     24.98298     121.54024                        37.9
1     24.98034     121.53951                        42.2
2     24.98746     121.54391                        47.3
3     24.98746     121.54391                        54.8
4     24.97937     121.54245                        43.1
```

```
df_decision_tree.shape # check the shape (rows and columns)
```

```
(414, 8)
```

```
df_decision_tree.info() # check the basic info
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 414 entries, 0 to 413
Data columns (total 8 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                  --------------  -----
 0   No                                      414 non-null    int64
 1   X1 transaction date                     414 non-null    float64
 2   X2 house age                            414 non-null    float64
 3   X3 distance to the nearest MRT station  414 non-null    float64
 4   X4 number of convenience stores         414 non-null    int64
 5   X5 latitude                             414 non-null    float64
 6   X6 longitude                            414 non-null    float64
 7   Y house price of unit area              414 non-null    float64
dtypes: float64(6), int64(2)
memory usage: 26.0 KB
```

```
df_decision_tree.drop(columns=['No'], axis=1, inplace=True) # drop
`No` bcz its not req.
df_decision_tree.head() # check head after droping `No`
```

```
   X1 transaction date  X2 house age  X3 distance to the nearest MRT
station  \
0             2012.917          32.0
84.87882
1             2012.917          19.5
306.59470
2             2013.583          13.3
561.98450
```

```
3             2013.500          13.3
561.98450
4             2012.833           5.0
390.56840

   X4 number of convenience stores  X5 latitude  X6 longitude  \
0                               10     24.98298     121.54024
1                                9     24.98034     121.53951
2                                5     24.98746     121.54391
3                                5     24.98746     121.54391
4                                5     24.97937     121.54245

   Y house price of unit area
0                        37.9
1                        42.2
2                        47.3
3                        54.8
4                        43.1
```

```
df_decision_tree.isnull().sum() # check any null value
```

```
X1 transaction date                       0
X2 house age                              0
X3 distance to the nearest MRT station    0
X4 number of convenience stores           0
X5 latitude                               0
X6 longitude                              0
Y house price of unit area                0
dtype: int64
```

```
df_decision_tree.describe() # check the basic statitcts
```

```
       X1 transaction date  X2 house age  \
count           414.000000    414.000000
mean           2013.148971     17.712560
std               0.281967     11.392485
min            2012.667000      0.000000
25%            2012.917000      9.025000
50%            2013.167000     16.100000
75%            2013.417000     28.150000
max            2013.583000     43.800000

       X3 distance to the nearest MRT station  \
count                              414.000000
mean                              1083.885689
std                               1262.109595
min                                 23.382840
25%                                289.324800
50%                                492.231300
75%                               1454.279000
```

```
max                                   6488.021000

       X4 number of convenience stores  X5 latitude  X6 longitude  \
count                       414.000000   414.000000    414.000000
mean                          4.094203    24.969030    121.533361
std                           2.945562     0.012410      0.015347
min                           0.000000    24.932070    121.473530
25%                           1.000000    24.963000    121.528085
50%                           4.000000    24.971100    121.538630
75%                           6.000000    24.977455    121.543305
max                          10.000000    25.014590    121.566270

       Y house price of unit area
count                  414.000000
mean                    37.980193
std                     13.606488
min                      7.600000
25%                     27.700000
50%                     38.450000
75%                     46.600000
max                    117.500000
```

```
df_decision_tree.corr() # check the corr relation
```

```
                                        X1 transaction date  X2 house
age  \
X1 transaction date                                1.000000
0.017549
X2 house age                                       0.017549
1.000000
X3 distance to the nearest MRT station             0.060880
0.025622
X4 number of convenience stores                    0.009635
0.049593
X5 latitude                                        0.035058
0.054420
X6 longitude                                      -0.041082     -
0.048520
Y house price of unit area                         0.087491     -
0.210567

                                        X3 distance to the nearest MRT
station  \
X1 transaction date
0.060880
X2 house age
0.025622
X3 distance to the nearest MRT station
1.000000
X4 number of convenience stores                                     -
```

```
0.602519
X5 latitude                                                                    -
0.591067
X6 longitude                                                                   -
0.806317
Y house price of unit area                                                     -
0.673613

                                        X4 number of convenience
stores  \
X1 transaction date
0.009635
X2 house age
0.049593
X3 distance to the nearest MRT station                              -
0.602519
X4 number of convenience stores
1.000000
X5 latitude
0.444143
X6 longitude
0.449099
Y house price of unit area
0.571005

                                        X5 latitude  X6 longitude  \
X1 transaction date                        0.035058     -0.041082
X2 house age                               0.054420     -0.048520
X3 distance to the nearest MRT station    -0.591067     -0.806317
X4 number of convenience stores            0.444143      0.449099
X5 latitude                                1.000000      0.412924
X6 longitude                               0.412924      1.000000
Y house price of unit area                 0.546307      0.523287

                                        Y house price of unit area
X1 transaction date                                       0.087491
X2 house age                                             -0.210567
X3 distance to the nearest MRT station                   -0.673613
X4 number of convenience stores                           0.571005
X5 latitude                                               0.546307
X6 longitude                                              0.523287
Y house price of unit area                                1.000000

x_decision_tree = df_decision_tree.drop(columns=['Y house price of
unit area']) # make you independent varibles by droping target varible
in them
x_decision_tree.head() # see the head of your independent varibles

   X1 transaction date  X2 house age  X3 distance to the nearest MRT
station  \
```

```
0               2012.917          32.0
84.87882
1               2012.917          19.5
306.59470
2               2013.583          13.3
561.98450
3               2013.500          13.3
561.98450
4               2012.833           5.0
390.56840

   X4 number of convenience stores  X5 latitude  X6 longitude
0                                10     24.98298     121.54024
1                                 9     24.98034     121.53951
2                                 5     24.98746     121.54391
3                                 5     24.98746     121.54391
4                                 5     24.97937     121.54245
```

```
y_decision_tree = df_decision_tree['Y house price of unit area'] #
select your target variable by picking it up this way
y_decision_tree.head() # check the head of ur dep_var.
```

```
0    37.9
1    42.2
2    47.3
3    54.8
4    43.1
Name: Y house price of unit area, dtype: float64
```

```
from sklearn.model_selection import train_test_split # import
train_test_split

# split you data in x and y in from of training and testing data
x_train_decision_tree, x_test_decision_tree, y_train_decision_tree,
y_test_decsion_tree = train_test_split(x_decision_tree,
y_decision_tree, test_size=0.3, random_state=42)

# check the shape of your training and testing data
print("Training data shape: ", x_train_decision_tree.shape,
y_train_decision_tree.shape)
print("Testing data shape: ", x_test_decision_tree.shape,
y_test_decsion_tree.shape)
```

```
Training data shape:  (289, 6) (289,)
Testing data shape:  (125, 6) (125,)
```

```
from sklearn.tree import DecisionTreeRegressor # import decision tre

decision_tree = DecisionTreeRegressor(random_state=42) # call decision
tree in a varible
```

```
decision_tree.fit(x_train_decision_tree, y_train_decision_tree) # fit
ur training data
```

```
DecisionTreeRegressor(random_state=42)
```

```
y_pred_decision_tree = decision_tree.predict(x_test_decision_tree) #
predict values by decision tree by using `x_test_decision_tree`
y_pred_decision_tree[:5] # just to see first five predicted values
```

```
array([48.6, 38.9, 43.5, 29.3, 25.7])
```

```
from sklearn import metrics # import metrics
```

```
# check the eroor value
MAE_decision_tree = metrics.mean_absolute_error(y_test_decsion_tree,
y_pred_decision_tree)
MSE_decision_tree = metrics.mean_squared_error(y_test_decsion_tree,
y_pred_decision_tree)
RMSE_decision_tree =
metrics.root_mean_squared_error(y_test_decsion_tree,
y_pred_decision_tree)
```

```
# print error values
print("Decision Tree MAE", MAE_decision_tree)
print("Decision Tree MSE", MSE_decision_tree)
print("Decision Tree RMSE", RMSE_decision_tree)
```

```
Decision Tree MAE 5.6076
Decision Tree MSE 73.4509
Decision Tree RMSE 8.570350051193943
```

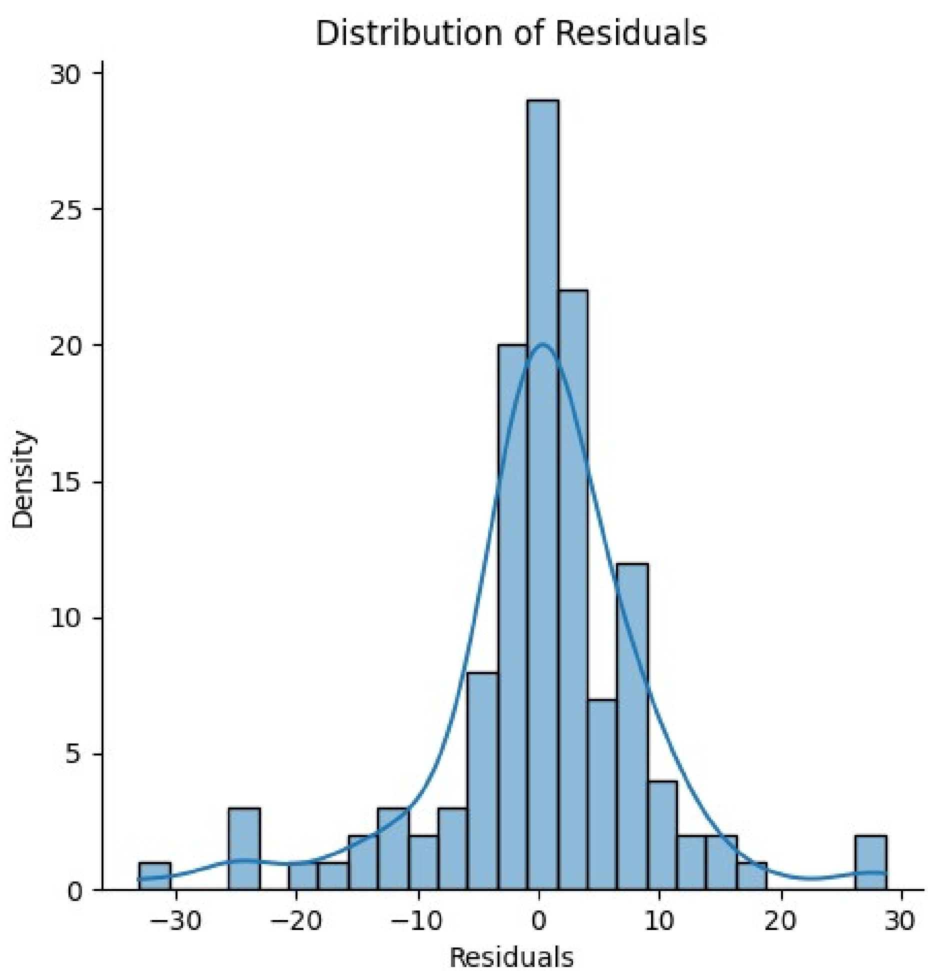
```
test_residual_decision_tree = y_test_decsion_tree -
y_pred_decision_tree
test_residual_decision_tree
```

```
358    -3.5
350     3.4
373     8.7
399     8.0
369    -2.9
       ...
268    -0.5
148    26.9
16      0.4
66     -3.7
341    -9.4
Name: Y house price of unit area, Length: 125, dtype: float64
```

```
import seaborn as sns  # Import seaborn
import matplotlib.pyplot as plt  # Import matplotlib
```

```python
# Plot 1: Distribution of residuals (displot)
plt.figure(figsize=(6, 6))  # Increase figure size for clarity
sns.displot(test_residual_decision_tree, bins=25, kde=True)  # Displot with KDE
plt.title("Distribution of Residuals")  # Add title for clarity
plt.xlabel("Residuals")  # Label the x-axis
plt.ylabel("Density")  # Label the y-axis
plt.show()  # Display the plot

# Plot 2: Scatterplot of residuals vs. true values (y_test)
plt.figure(figsize=(6, 6))  # Increase figure size
sns.scatterplot(x=y_test_decsion_tree, y=test_residual_decision_tree)  # Scatter plot
plt.axhline(y=0, color='r', ls='--')  # Red dashed line at y=0
plt.title("Residuals vs. True Values")  # Add title for clarity
plt.xlabel("True Values (y_test)")  # Label the x-axis
plt.ylabel("Residuals")  # Label the y-axis
plt.show()  # Display the plot
```

```
<Figure size 600x600 with 0 Axes>
```




things are approxly same I will not use comment and and not repeat same steps

---

## 3. Random Foest

```
df_random_forest = pd.read_csv(r"path\Real estate.csv")
df_random_forest.head()

   No  X1 transaction date  X2 house age  \
0   1              2012.917          32.0
1   2              2012.917          19.5
2   3              2013.583          13.3
3   4              2013.500          13.3
4   5              2012.833           5.0

   X3 distance to the nearest MRT station  X4 number of convenience 
stores  \
0                                 84.87882
10
```

```
1                                306.59470
9
2                                561.98450
5
3                                561.98450
5
4                                390.56840
5
```

```
   X5 latitude  X6 longitude  Y house price of unit area
0     24.98298     121.54024                        37.9
1     24.98034     121.53951                        42.2
2     24.98746     121.54391                        47.3
3     24.98746     121.54391                        54.8
4     24.97937     121.54245                        43.1
```

```
df_random_forest.drop(columns=['No'], axis=True, inplace=True)
x_random_forest = df_random_forest.drop(columns=['Y house price of
unit area'])
y_random_forest = df_random_forest['Y house price of unit area']

x_train_random_forest, x_test_random_forest, y_train_random_forest,
y_test_random_forest = train_test_split(x_random_forest,
y_random_forest, test_size=0.3, random_state=42)

random_forest = RandomForestRegressor(random_state=42)
random_forest.fit(x_train_random_forest, y_train_random_forest)
```

```
RandomForestRegressor(random_state=42)
```

```
y_pred_random_forest = random_forest.predict(x_test_random_forest)
y_pred_random_forest[:5]
```

```
array([49.153  , 38.522  , 53.18325, 35.144  , 25.453  ])
```

```
print("MAE Random Froest",
metrics.mean_absolute_error(y_test_random_forest,
y_pred_random_forest))
print("MSE Random Froest",
metrics.mean_squared_error(y_test_random_forest,
y_pred_random_forest))
print("RMSE Random Froest",
metrics.root_mean_squared_error(y_test_random_forest,
y_pred_random_forest))
```

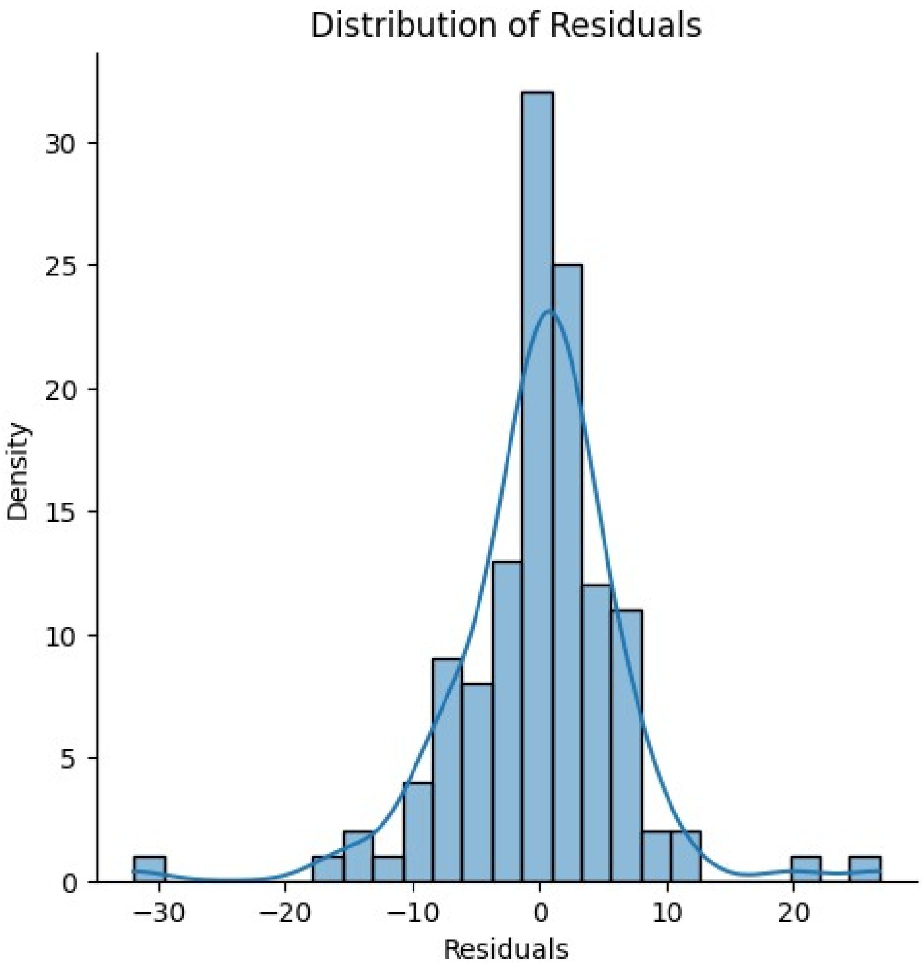
```
MAE Random Froest 4.397113295238097
MSE Random Froest 42.75048519970811
RMSE Random Froest 6.538385519354767
```

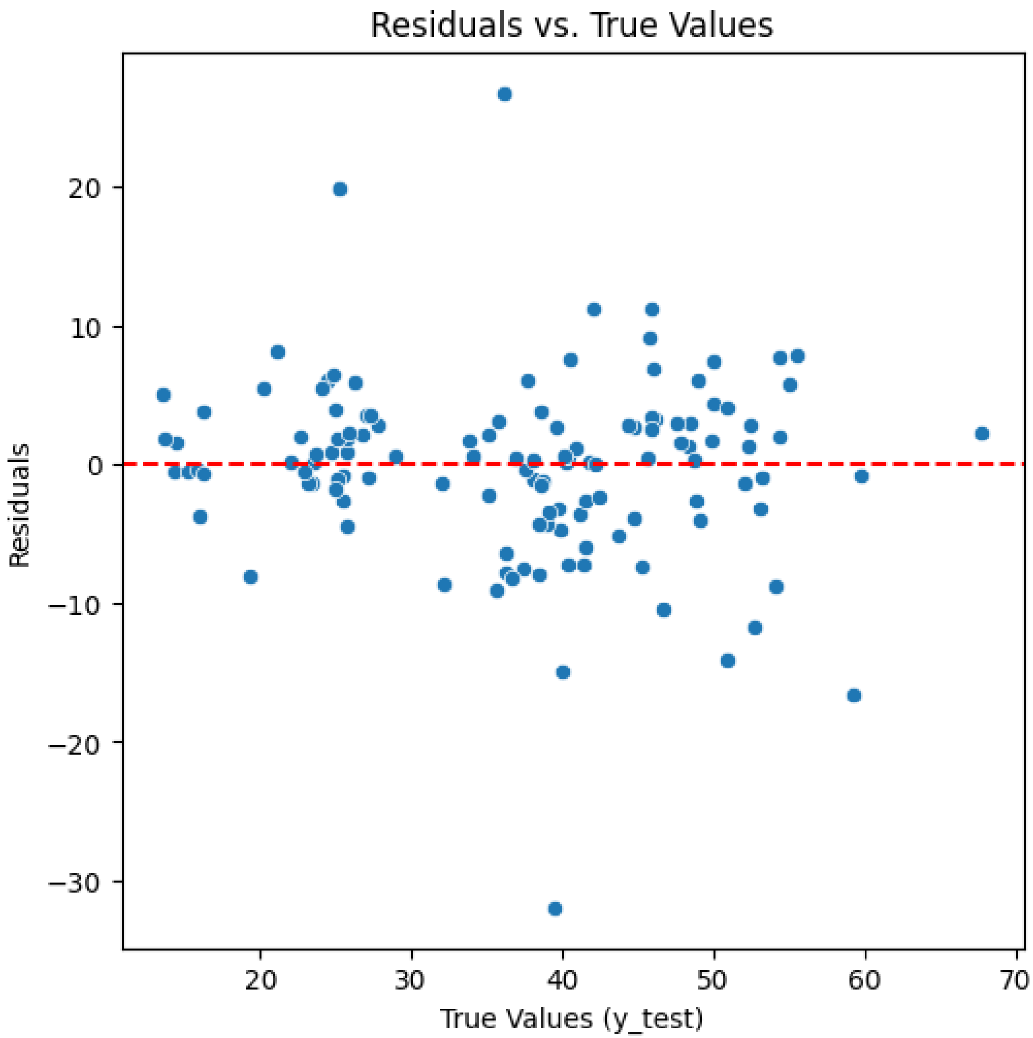
```python
test_residual_random_forest = y_test_random_forest -
y_pred_random_forest
test_residual_random_forest
```

```
358    -4.05300
350     3.77800
373    -0.98325
399     2.15600
369    -2.65300
         ...
268    -2.35360
148    19.87900
16      2.31025
66     -1.42950
341    -1.53900
Name: Y house price of unit area, Length: 125, dtype: float64
```

```python
import seaborn as sns  # Import seaborn
import matplotlib.pyplot as plt  # Import matplotlib

# Plot 1: Distribution of residuals (displot)
plt.figure(figsize=(6, 6))  # Increase figure size for clarity
sns.displot(test_residual_random_forest, bins=25, kde=True)  # Displot
with KDE
plt.title("Distribution of Residuals")  # Add title for clarity
plt.xlabel("Residuals")  # Label the x-axis
plt.ylabel("Density")  # Label the y-axis
plt.show()  # Display the plot

# Plot 2: Scatterplot of residuals vs. true values (y_test)
plt.figure(figsize=(6, 6))  # Increase figure size
sns.scatterplot(x=y_pred_random_forest, y=test_residual_random_forest)
# Scatter plot
plt.axhline(y=0, color='r', ls='--')  # Red dashed line at y=0
plt.title("Residuals vs. True Values")  # Add title for clarity
plt.xlabel("True Values (y_test)")  # Label the x-axis
plt.ylabel("Residuals")  # Label the y-axis
plt.show()  # Display the plot
```

```
<Figure size 600x600 with 0 Axes>
```


Distribution of Residuals
Density
Residuals
30
25
20
15
10
5
0
−30
−20
−10
0
10
20




---

## 4. SVM

```
df_svm = pd.read_csv(r"path\Real estate.csv")
df_svm.head()

   No  X1 transaction date  X2 house age  \
0   1             2012.917          32.0
1   2             2012.917          19.5
2   3             2013.583          13.3
3   4             2013.500          13.3
4   5             2012.833           5.0

   X3 distance to the nearest MRT station  X4 number of convenience
stores  \
0                                84.87882
10
1                               306.59470
```

```
9
2                                   561.98450
5
3                                   561.98450
5
4                                   390.56840
5
```

```
   X5 latitude  X6 longitude  Y house price of unit area
0     24.98298     121.54024                        37.9
1     24.98034     121.53951                        42.2
2     24.98746     121.54391                        47.3
3     24.98746     121.54391                        54.8
4     24.97937     121.54245                        43.1
```

```
df_svm.drop(columns=['No'], axis=1, inplace=True)
```

```
x_svm = df_svm.drop(columns=['Y house price of unit area'])
y_svm = df_svm['Y house price of unit area']
```

```
x_train_svm, x_test_svm, y_train_svm, y_test_svm =
train_test_split(x_svm, y_svm, test_size=0.3, random_state=42)
```

```
svm = SVR()
svm.fit(x_train_svm, y_train_svm)
```

```
SVR()
```

```
y_pred_svm = svm.predict(x_test_svm)
y_pred_svm[:5]
```

```
array([43.90987572, 41.32920139, 43.27836755, 44.0793227 ,
25.17732503])
```

```
print("MAE SVM: ", metrics.mean_absolute_error(y_test_svm,
y_pred_svm))
print("MSE SVM: ", metrics.mean_squared_error(y_test_svm, y_pred_svm))
print("RMSE SVM: ", metrics.root_mean_squared_error(y_test_svm,
y_pred_svm))
```

```
MAE SVM:  6.882396075217186
MSE SVM:  85.34235717951594
RMSE SVM:  9.23809272412417
```

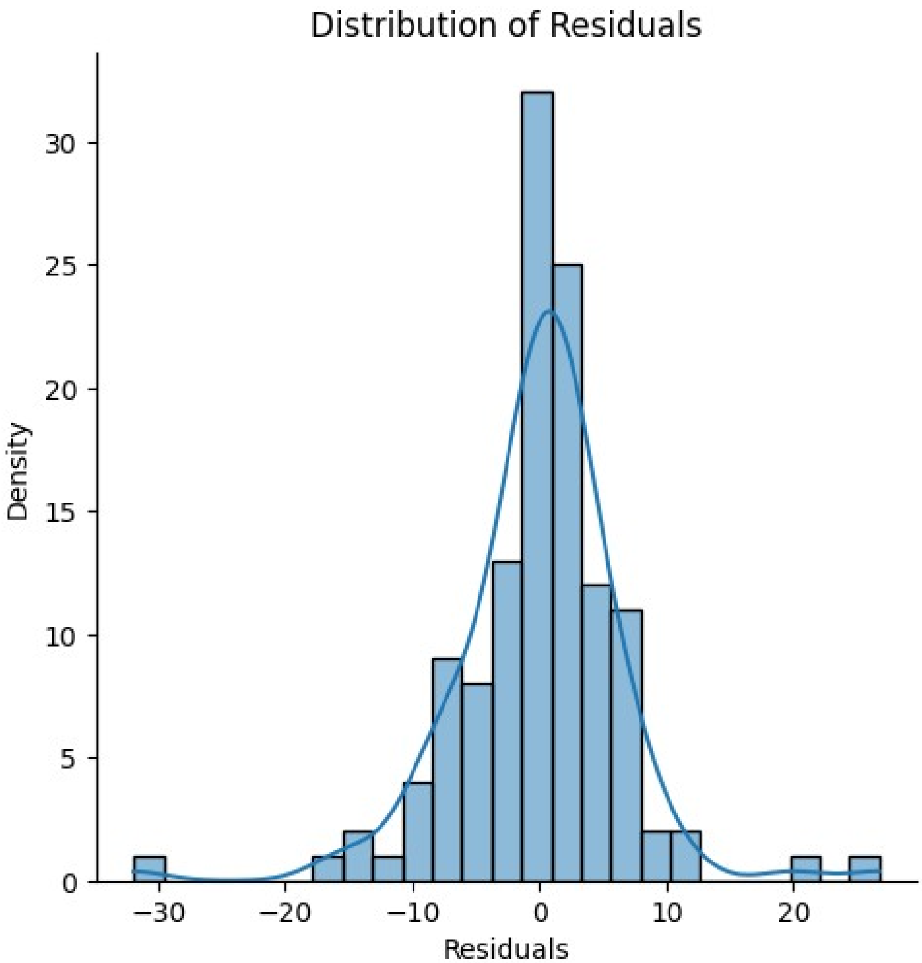
```
test_residual_svm = y_test_svm - y_pred_svm
test_residual_svm
```

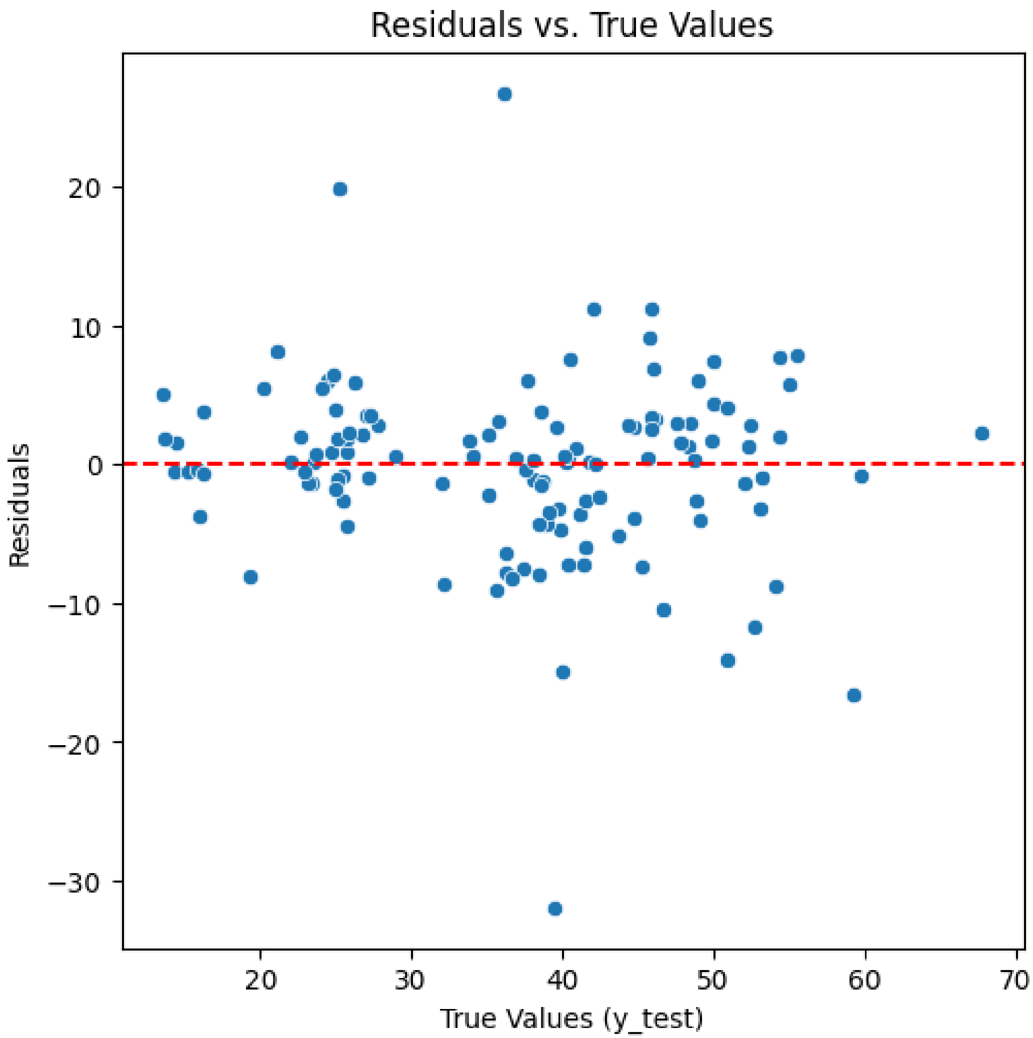
```
358     1.190124
350     0.970799
373     8.921632
399    -6.779323
369    -2.377325
```

```
           ...
268    -2.171528
148    24.718366
16     26.977536
66      6.790088
341    -1.707198
Name: Y house price of unit area, Length: 125, dtype: float64
```

```
plt.figure(figsize=(6, 6))
sns.displot(test_residual_random_forest, bins=25, kde=True)
plt.title("Distribution of Residuals")
plt.xlabel("Residuals")
plt.ylabel("Density")
plt.show()

plt.figure(figsize=(6, 6))
sns.scatterplot(x=y_pred_random_forest, y=test_residual_random_forest)
plt.axhline(y=0, color='r', ls='--')
plt.title("Residuals vs. True Values")
plt.xlabel("True Values (y_test)")
plt.ylabel("Residuals")
plt.show()
```

```
<Figure size 600x600 with 0 Axes>
```


Distribution of Residuals
Density
Residuals
30
25
20
15
10
5
0
−30
−20
−10
0
10
20




---

## 5. KNN

```
df_knn = pd.read_csv(r"path\Real estate.csv")
df_knn.head()

   No  X1 transaction date  X2 house age  \
0   1              2012.917         32.0
1   2              2012.917         19.5
2   3              2013.583         13.3
3   4              2013.500         13.3
4   5              2012.833          5.0

   X3 distance to the nearest MRT station  X4 number of convenience
stores  \
0                                84.87882
10
1                               306.59470
```

```
9
2                                561.98450
5
3                                561.98450
5
4                                390.56840
5
```

```
   X5 latitude  X6 longitude  Y house price of unit area
0     24.98298     121.54024                        37.9
1     24.98034     121.53951                        42.2
2     24.98746     121.54391                        47.3
3     24.98746     121.54391                        54.8
4     24.97937     121.54245                        43.1
```

```
df_knn.drop(columns=['No'], axis=1, inplace=True)
x_knn = df_knn.drop(columns=['Y house price of unit area'])
y_knn = df_knn['Y house price of unit area']

x_train_knn, x_test_knn, y_train_knn, y_test_knn =
train_test_split(x_knn, y_knn, test_size=0.3, random_state=42)

knn = KNeighborsRegressor()
knn.fit(x_train_knn, y_train_knn)
```

```
KNeighborsRegressor()
```

```
y_pred_knn = knn.predict(x_test_knn)
y_pred_knn[:5]
```

```
array([49.82, 39.16, 46.06, 38.98, 26.3 ])
```

```
print("MAE KNN: ", metrics.mean_absolute_error(y_test_knn,
y_pred_knn))
print("MSE KNN: ", metrics.mean_squared_error(y_test_knn, y_pred_knn))
print("RMSE KNN: ", metrics.root_mean_squared_error(y_test_knn,
y_pred_knn))
```

```
MAE KNN:  5.45248
MSE KNN:  62.8123712
RMSE KNN:  7.925425616331277
```

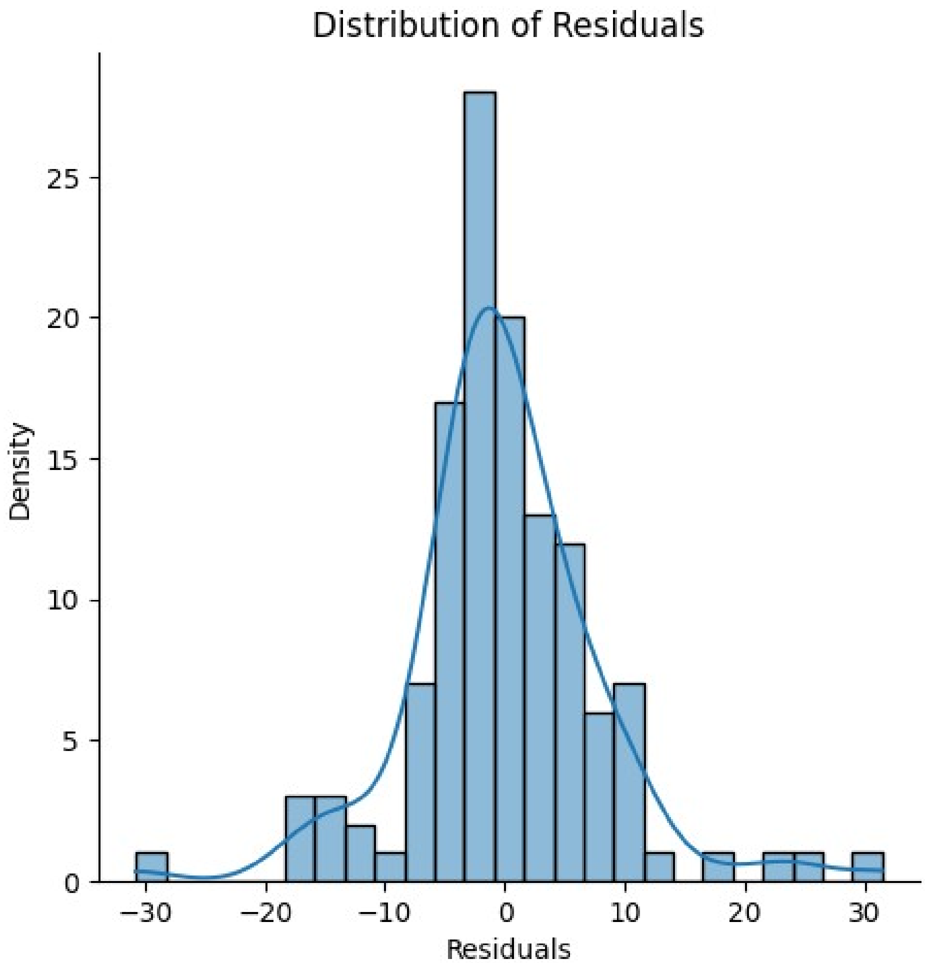
```
test_residual_knn = y_test_knn - y_pred_knn
test_residual_knn
```

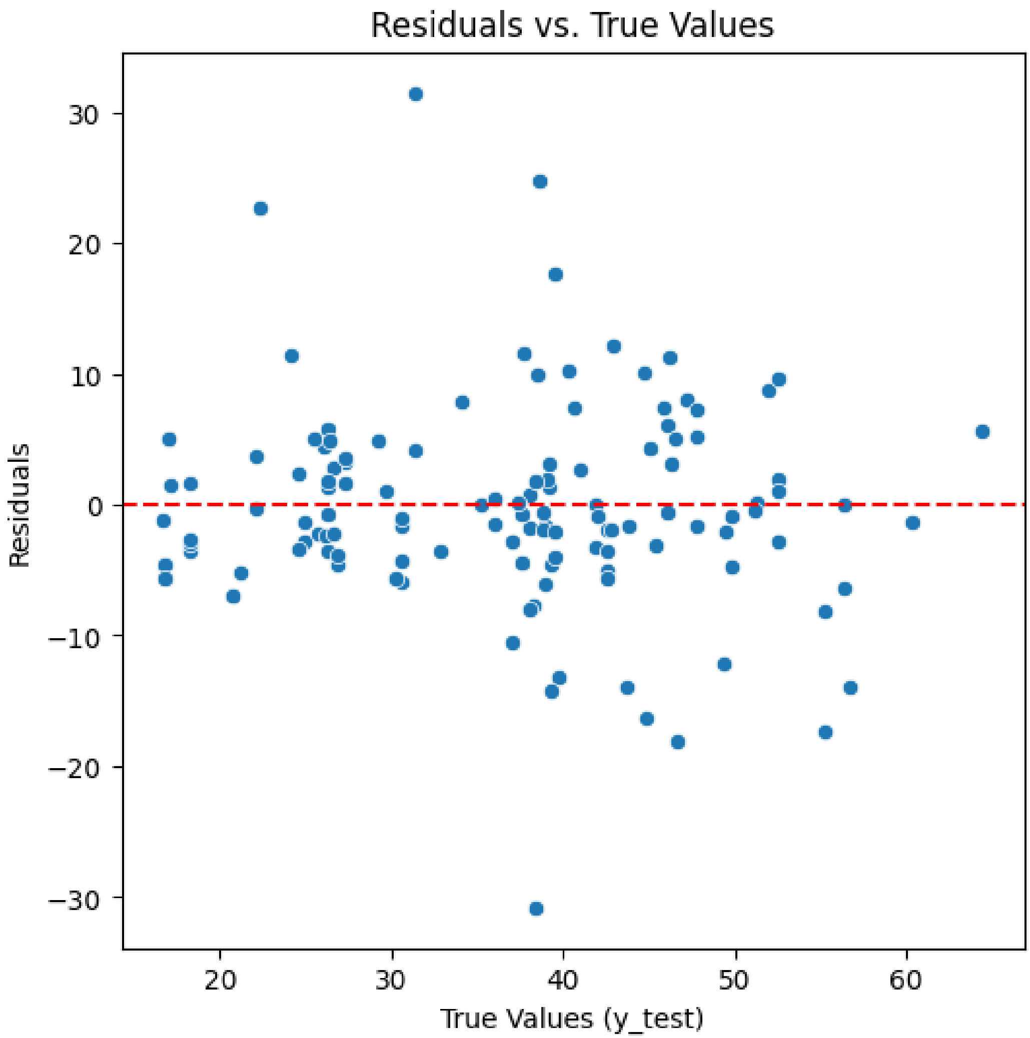
```
358    -4.72
350     3.14
373     6.14
399    -1.68
369    -3.50
       ...
```

```
268     1.72
148    22.74
16      5.68
66     -0.46
341    -5.56
Name: Y house price of unit area, Length: 125, dtype: float64
```

```
plt.figure(figsize=(6, 6))
sns.displot(test_residual_knn, bins=25, kde=True)
plt.title("Distribution of Residuals")
plt.xlabel("Residuals")
plt.ylabel("Density")
plt.show()

plt.figure(figsize=(6, 6))
sns.scatterplot(x=y_pred_knn, y=test_residual_knn)
plt.axhline(y=0, color='r', ls='--')
plt.title("Residuals vs. True Values")
plt.xlabel("True Values (y_test)")
plt.ylabel("Residuals")
plt.show()
```

```
<Figure size 600x600 with 0 Axes>
```


Distribution of Residuals
Density
Residuals
0
5
10
15
20
25
−30
−20
−10
0
10
20
30

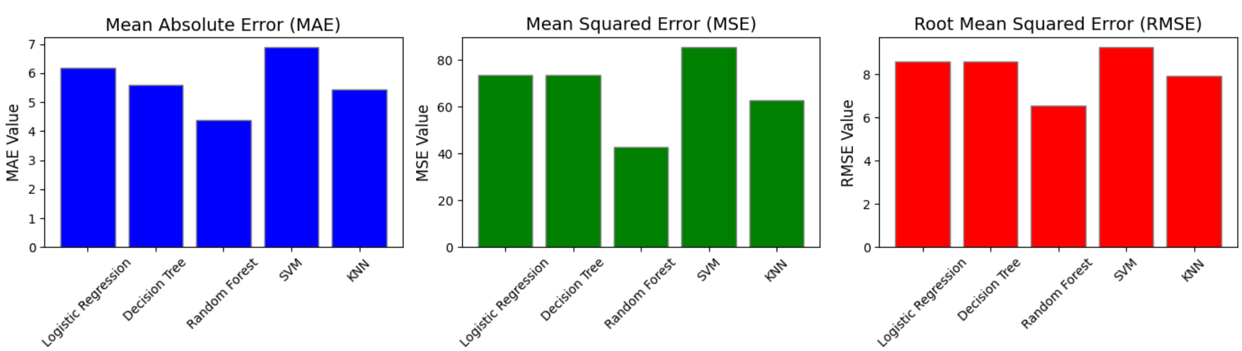



---

# Comparison

```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

# Create a dictionary with the results for each model and each metric
data = {
    'Model': ['Logistic Regression', 'Decision Tree', 'Random Forest',
'SVM', 'KNN'],
    'MAE': [6.1848363400971085, 5.6076, 4.397113295238097,
6.882396075217186, 5.45248],
    'MSE': [73.5683793285023, 73.4509, 42.75048519970811,
85.34235717951594, 62.8123712],
    'RMSE': [8.577201136064275, 8.570350051193943, 6.538385519354767,
```

```
9.23809272412417, 7.925425616331277]
}

# Convert the dictionary to a pandas DataFrame
df = pd.DataFrame(data)

# Create a figure and axis with 3 subplots (1 row, 3 columns)
fig, axes = plt.subplots(1, 3, figsize=(14, 4))

# Plot MAE, MSE, and RMSE in separate subplots

# MAE subplot
axes[0].bar(df['Model'], df['MAE'], color='b', edgecolor='grey')
axes[0].set_title('Mean Absolute Error (MAE)', fontsize=14)
axes[0].set_ylabel('MAE Value', fontsize=12)
axes[0].tick_params(axis='x', rotation=45)  # Rotate x-axis labels for
better readability

# MSE subplot
axes[1].bar(df['Model'], df['MSE'], color='g', edgecolor='grey')
axes[1].set_title('Mean Squared Error (MSE)', fontsize=14)
axes[1].set_ylabel('MSE Value', fontsize=12)
axes[1].tick_params(axis='x', rotation=45)

# RMSE subplot
axes[2].bar(df['Model'], df['RMSE'], color='r', edgecolor='grey')
axes[2].set_title('Root Mean Squared Error (RMSE)', fontsize=14)
axes[2].set_ylabel('RMSE Value', fontsize=12)
axes[2].tick_params(axis='x', rotation=45)

# Adjust layout for better spacing
plt.tight_layout()

# Show the plot
plt.show()
```




---

---

---

*ApplyingClassification*

Making one df and x and y and training and testing data

# 1. Logistic Regression

```
import pandas as pd
df = pd.read_csv(r"path\bank.csv")
df.head()
```

```
   age         job  marital  education default  balance housing loan
contact  \
0   59      admin.  married  secondary      no     2343     yes   no
unknown
1   56      admin.  married  secondary      no       45      no   no
unknown
2   41  technician  married  secondary      no     1270     yes   no
unknown
3   55    services  married  secondary      no     2476     yes   no
unknown
4   54      admin.  married   tertiary      no      184      no   no
unknown

   day month  duration  campaign  pdays  previous poutcome deposit
0    5   may      1042         1     -1         0  unknown     yes
1    5   may      1467         1     -1         0  unknown     yes
2    5   may      1389         1     -1         0  unknown     yes
3    5   may       579         1     -1         0  unknown     yes
4    5   may       673         2     -1         0  unknown     yes
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11162 entries, 0 to 11161
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   age        11162 non-null  int64
 1   job        11162 non-null  object
 2   marital    11162 non-null  object
 3   education  11162 non-null  object
 4   default    11162 non-null  object
 5   balance    11162 non-null  int64
 6   housing    11162 non-null  object
 7   loan       11162 non-null  object
 8   contact    11162 non-null  object
 9   day        11162 non-null  int64
 10  month      11162 non-null  object
 11  duration   11162 non-null  int64
```

```
 12  campaign   11162 non-null  int64
 13  pdays      11162 non-null  int64
 14  previous   11162 non-null  int64
 15  poutcome   11162 non-null  object
 16  deposit    11162 non-null  object
dtypes: int64(7), object(10)
memory usage: 1.4+ MB
```

```
df.isnull().sum()
```

```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
deposit      0
dtype: int64
```

```
categorical_columns = df.select_dtypes(object).columns

label_encoder = LabelEncoder()
df1 = df.copy()

for column in categorical_columns:
    df1[column] = label_encoder.fit_transform(df[column])

df1
```

```
       age  job  marital  education  default  balance  housing  loan
contact  \
0       59    0        1          1        0     2343        1     0
2
1       56    0        1          1        0       45        0     0
2
2       41    9        1          1        0     1270        1     0
2
3       55    7        1          1        0     2476        1     0
2
4       54    0        1          2        0      184        0     0
```

```
2
...      ...   ...       ...         ...       ...       ...       ...   ...
...
11157     33     1         2           0         0         1         1     0
0
11158     39     7         1           1         0       733         0     0
2
11159     32     9         2           1         0        29         0     0
0
11160     43     9         1           1         0         0         0     1
0
11161     34     9         1           1         0         0         0     0
0

       day  month  duration  campaign  pdays  previous  poutcome
deposit
0        5      8      1042         1     -1         0         3
1
1        5      8      1467         1     -1         0         3
1
2        5      8      1389         1     -1         0         3
1
3        5      8       579         1     -1         0         3
1
4        5      8       673         2     -1         0         3
1
...    ...    ...       ...       ...    ...       ...       ...
...
11157   20      0       257         1     -1         0         3
0
11158   16      6        83         4     -1         0         3
0
11159   19      1       156         2     -1         0         3
0
11160    8      8         9         2    172         5         0
0
11161    9      5       628         1     -1         0         3
0

[11162 rows x 17 columns]

x = df1.drop(columns=['deposit'])
y = df1['deposit']

x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.3, random_state=42)

logistic_regression = LogisticRegression()

logistic_regression.fit(x_train, y_train)
```

```
C:\Users\Dell\AppData\Roaming\Python\Python313\site-packages\sklearn\
linear_model\_logistic.py:469: ConvergenceWarning: lbfgs failed to
converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(

LogisticRegression()
```

```
y_pred_logistic_regression = logistic_regression.predict(x_test)
y_pred_logistic_regression[:5]
```

```
array([0, 1, 1, 1, 0])
```

```
print("Logistic Regression Classification Report: \n",
metrics.classification_report(y_test, y_pred_logistic_regression))
print("\n\nLogistic Regression Confusion Matrix: \n",
metrics.confusion_matrix(y_test, y_pred_logistic_regression))
print("\n\n\nLogistic Regression Accuracy Score: \n",
metrics.accuracy_score(y_test, y_pred_logistic_regression))
```

```
Logistic Regression Classification Report:
               precision    recall  f1-score   support

           0       0.74      0.80      0.77      1742
           1       0.76      0.69      0.72      1607

    accuracy                           0.75      3349
   macro avg       0.75      0.75      0.75      3349
weighted avg       0.75      0.75      0.75      3349



Logistic Regression Confusion Matrix:
 [[1393  349]
 [ 496 1111]]



Logistic Regression Accuracy Score:
 0.7476858763810093
```

## 2. Decision Tree

```
decision_tree = DecisionTreeClassifier()

decision_tree.fit(x_train, y_train)

DecisionTreeClassifier()

y_pred_decision_tree = decision_tree.predict(x_test)
y_pred_decision_tree[:5]

array([0, 1, 0, 1, 0])

print("Decision Tree Classification Report: \n",
metrics.classification_report(y_test, y_pred_decision_tree))
print("\n\nDecision Tree Confusion Matrix: \n",
metrics.confusion_matrix(y_test, y_pred_decision_tree))
print("\n\nDecision Tree Accuracy Score: \n",
metrics.accuracy_score(y_test, y_pred_decision_tree))

Decision Tree Classification Report:
               precision    recall  f1-score   support

           0       0.78      0.79      0.79      1742
           1       0.77      0.76      0.77      1607

    accuracy                           0.78      3349
   macro avg       0.78      0.78      0.78      3349
weighted avg       0.78      0.78      0.78      3349



Decision Tree Confusion Matrix:
 [[1379  363]
 [ 380 1227]]


Decision Tree Accuracy Score:
 0.7781427291728874
```

---

## 3. Random Forest

```
random_forest = RandomForestClassifier()

random_forest.fit(x_train, y_train)

RandomForestClassifier()

y_pred_random_forest = random_forest.predict(x_test)
y_pred_random_forest[:5]
```

```
array([1, 1, 1, 1, 0])
```

```
print("Random Forest Classification Report: \n",
metrics.classification_report(y_test, y_pred_random_forest))
print("\n\nRandom Forest Confusion Matrix: \n",
metrics.confusion_matrix(y_test, y_pred_random_forest))
print("\n\nRandom Forest Accuracy Score: \n",
metrics.accuracy_score(y_test, y_pred_random_forest))
```

```
Random Forest Classification Report:
               precision    recall  f1-score   support

           0       0.87      0.81      0.84      1742
           1       0.81      0.87      0.84      1607

    accuracy                           0.84      3349
   macro avg       0.84      0.84      0.84      3349
weighted avg       0.84      0.84      0.84      3349



Random Forest Confusion Matrix:
 [[1418  324]
 [ 213 1394]]


Random Forest Accuracy Score:
 0.8396536279486414
```

---

## 4. SVM

```
svm = RandomForestClassifier()

svm.fit(x_train, y_train)
```

```
RandomForestClassifier()
```

```
y_pred_svm = svm.predict(x_test)
y_pred_svm[:5]
```

```
array([1, 1, 1, 1, 0])
```

```
print("SVM Classification Report: \n",
metrics.classification_report(y_test, y_pred_svm))
print("\n\nSVM Confusion Matrix: \n", metrics.confusion_matrix(y_test,
y_pred_svm))
print("\n\nSVM Accuracy Score: \n", metrics.accuracy_score(y_test,
y_pred_svm))
```

```
SVM Classification Report:
               precision    recall  f1-score   support

           0       0.87      0.82      0.84      1742
           1       0.81      0.87      0.84      1607

    accuracy                           0.84      3349
   macro avg       0.84      0.84      0.84      3349
weighted avg       0.84      0.84      0.84      3349



SVM Confusion Matrix:
 [[1423  319]
 [ 214 1393]]


SVM Accuracy Score:
 0.8408480143326366
```

---

## 6. KNN

```
knn = KNeighborsClassifier()

knn.fit(x_train, y_train)

KNeighborsClassifier()

y_pred_knn = knn.predict(x_test)
y_pred_knn[:5]

array([0, 1, 1, 1, 0])

print("KNN Classification Report: \n", 
metrics.classification_report(y_test, y_pred_knn))
print("\n\nKNN Confusion Matrix: \n", metrics.confusion_matrix(y_test, 
y_pred_knn))
print("\n\nKNN Accuracy Score: \n", metrics.accuracy_score(y_test, 
y_pred_knn))

KNN Classification Report:
               precision    recall  f1-score   support

           0       0.75      0.76      0.76      1742
           1       0.74      0.72      0.73      1607

    accuracy                           0.74      3349
   macro avg       0.74      0.74      0.74      3349
weighted avg       0.74      0.74      0.74      3349
```

```
KNN Confusion Matrix:
 [[1330  412]
 [ 445 1162]]


KNN Accuracy Score:
 0.7441027172290235
```

---

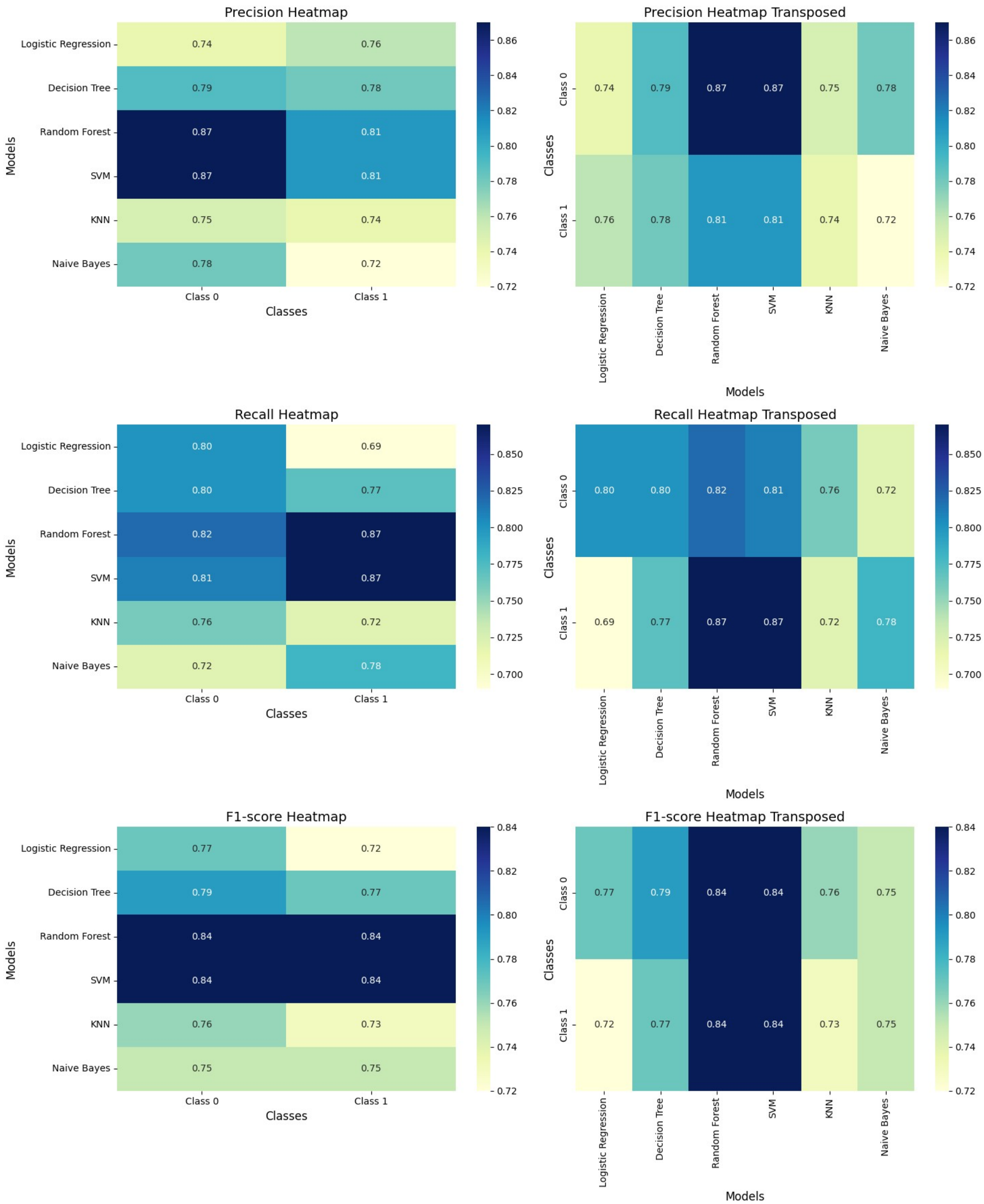
## 7. Navie Bayes

```
nb = GaussianNB()

nb.fit(x_train, y_train)

GaussianNB()

y_pred_nb = nb.predict(x_test)
y_pred_nb[:5]

array([1, 1, 1, 1, 0])

print("NB Classification Report: \n",
metrics.classification_report(y_test, y_pred_nb))
print("\n\nNB Confusion Matrix: \n", metrics.confusion_matrix(y_test,
y_pred_nb))
print("\n\nNB Accuracy Score: \n", metrics.accuracy_score(y_test,
y_pred_nb))

NB Classification Report:
               precision    recall  f1-score   support

           0       0.78      0.72      0.75      1742
           1       0.72      0.78      0.75      1607

    accuracy                           0.75      3349
   macro avg       0.75      0.75      0.75      3349
weighted avg       0.75      0.75      0.75      3349



NB Confusion Matrix:
 [[1256  486]
 [ 353 1254]]


NB Accuracy Score:
 0.7494774559570021
```

## Comparison

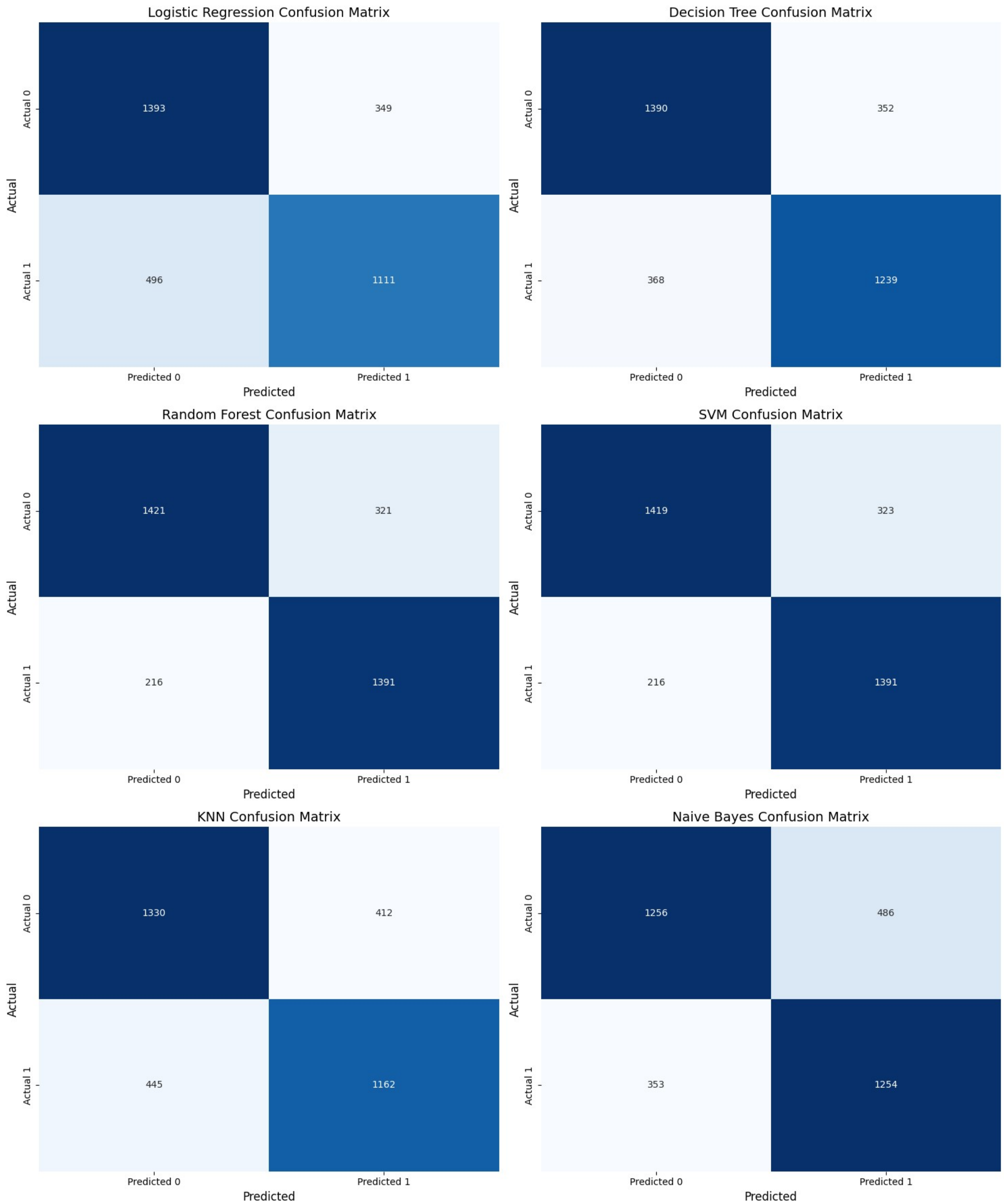
```
# Sample classification report strings for each model
classification_reports = {
    'Logistic Regression': {
        'precision': [0.74, 0.76],
        'recall': [0.80, 0.69],
        'f1-score': [0.77, 0.72],
    },
    'Decision Tree': {
        'precision': [0.79, 0.78],
        'recall': [0.80, 0.77],
        'f1-score': [0.79, 0.77],
    },
    'Random Forest': {
        'precision': [0.87, 0.81],
        'recall': [0.82, 0.87],
        'f1-score': [0.84, 0.84],
    },
    'SVM': {
        'precision': [0.87, 0.81],
        'recall': [0.81, 0.87],
        'f1-score': [0.84, 0.84],
    },
    'KNN': {
        'precision': [0.75, 0.74],
        'recall': [0.76, 0.72],
        'f1-score': [0.76, 0.73],
    },
    'Naive Bayes': {
        'precision': [0.78, 0.72],
        'recall': [0.72, 0.78],
        'f1-score': [0.75, 0.75],
    },
}

# Create a figure with 3 rows and 2 columns (for precision, recall,
f1-score)
fig, axes = plt.subplots(3, 2, figsize=(15, 18))

# Define the metrics labels (precision, recall, f1-score)
metrics = ['precision', 'recall', 'f1-score']

# Loop through each metric and plot the heatmap for each model
for i, metric in enumerate(metrics):
    # Prepare a list of model names and corresponding metric values
    values = []
```

```
    for model in classification_reports:
        values.append(classification_reports[model][metric])

    # Convert the values into a DataFrame
    df = pd.DataFrame(values, columns=['Class 0', 'Class 1'],
index=classification_reports.keys())

    # Plot the heatmap in the corresponding subplot
    sns.heatmap(df, annot=True, cmap="YlGnBu", cbar=True, fmt=".2f",
ax=axes[i][0])
    axes[i][0].set_title(f'{metric.capitalize()} Heatmap',
fontsize=14)
    axes[i][0].set_ylabel('Models', fontsize=12)
    axes[i][0].set_xlabel('Classes', fontsize=12)

    # Now move to next column (to keep the layout of each model in a
new column)
    sns.heatmap(df.T, annot=True, cmap="YlGnBu", cbar=True, fmt=".2f",
ax=axes[i][1])
    axes[i][1].set_title(f'{metric.capitalize()} Heatmap Transposed',
fontsize=14)
    axes[i][1].set_ylabel('Classes', fontsize=12)
    axes[i][1].set_xlabel('Models', fontsize=12)

# Adjust layout for better spacing
plt.tight_layout()

# Show the plot
plt.show()
```




```python
# Confusion matrices for each model
confusion_matrices = {
    'Logistic Regression': np.array([[1393, 349], [496, 1111]]),
    'Decision Tree': np.array([[1390, 352], [368, 1239]]),
```

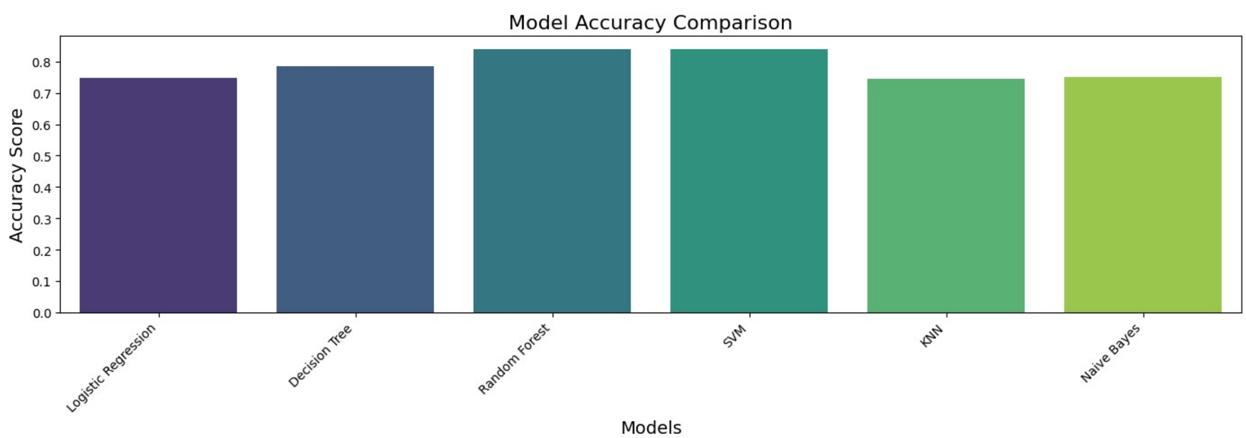
```
    'Random Forest': np.array([[1421, 321], [216, 1391]]),
    'SVM': np.array([[1419, 323], [216, 1391]]),
    'KNN': np.array([[1330, 412], [445, 1162]]),
    'Naive Bayes': np.array([[1256, 486], [353, 1254]])
}

# Create a figure with 3 rows and 2 columns (for 6 models)
fig, axes = plt.subplots(3, 2, figsize=(15, 18))

# Loop through each confusion matrix and plot the heatmap
for i, (model, matrix) in enumerate(confusion_matrices.items()):
    row, col = divmod(i, 2)  # Determine the row and column for
subplot

    # Plot the heatmap for the confusion matrix
    sns.heatmap(matrix, annot=True, fmt='d', cmap="Blues", cbar=False,
ax=axes[row][col],
                xticklabels=['Predicted 0', 'Predicted 1'],
yticklabels=['Actual 0', 'Actual 1'])

    # Set the title and labels for the subplot
    axes[row][col].set_title(f'{model} Confusion Matrix', fontsize=14)
    axes[row][col].set_xlabel('Predicted', fontsize=12)
    axes[row][col].set_ylabel('Actual', fontsize=12)

# Adjust layout for better spacing
plt.tight_layout()

# Show the plot
plt.show()
```




```
# Data: Models and their corresponding accuracy scores
models = ['Logistic Regression', 'Decision Tree', 'Random Forest',
'SVM', 'KNN', 'Naive Bayes']
accuracy_scores = [0.7476858763810093, 0.78501045088086,
0.8396536279486414,
```

```
                   0.8390564347566438, 0.7441027172290235,
0.7494774559570021]

# Create a bar chart
plt.figure(figsize=(14, 5))
sns.barplot(x=models, y=accuracy_scores, palette='viridis')

# Set titles and labels
plt.title('Model Accuracy Comparison', fontsize=16)
plt.xlabel('Models', fontsize=14)
plt.ylabel('Accuracy Score', fontsize=14)

# Rotate x-axis labels for better visibility
plt.xticks(rotation=45, ha='right')

# Display the plot
plt.tight_layout()
plt.show()
```

```
C:\Users\Dell\AppData\Local\Temp\ipykernel_19280\2162836733.py:8:
FutureWarning:

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

  sns.barplot(x=models, y=accuracy_scores, palette='viridis')
```

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# THE END @:-)

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