```
#Import drive
from google.colab import drive
dr = drive.mount('/content/drive')
# Data Manipulation
import pandas as pd
import numpy as np
import re
# Visualization
import matplotlib.pyplot as plt
import seaborn as sns
# Preprocessing
from sklearn.model selection import train test split
# Machine Learning Models
from sklearn.linear model import LinearRegression, Ridge, Lasso
from sklearn.tree import DecisionTreeRegressor
# Model Evaluation
from sklearn.metrics import mean squared error, r2 score
# Feature Selection
from sklearn.feature selection import SelectKBest, chi2
from sklearn.metrics import accuracy score, precision score,
recall score
# Cross-validation
from sklearn.model selection import cross val score
# Hyperparameter Tuning
from sklearn.model selection import GridSearchCV
#Intialize encoder
Drive already mounted at /content/drive; to attempt to forcibly
remount, call drive.mount("/content/drive", force_remount=True).
drive path = '/content/drive/MyDrive/Final Project Computer Science
2023/project/'
df file = 'final stock file.csv'
df = pd.read csv(drive path+df file)
df
         transaction date trade date ticker
company_name \
      2022-01-12 16:53:26 2022-01-11
                                        ADSK
Autodesk, Inc.
      2022-01-11 19:26:43 2022-01-07
                                        IBKR Interactive Brokers
```

Group, Inc. 2 2022-01-03 10:01:05	2021-12-30 LLY	Eli		
Lilly & Co 3 2022-01-10 16:09:20		LCI		
Hershey Co 4 2022-01-31 16:15:08				
Safehold Inc.				
2057 2023-01-09 16:38:38 Heska Corp	2023-01-06 HSKA			
2058 2023-01-13 16:20:21 Atlassian Corp	2023-01-12 TEAM			
2059 2023-01-31 16:04:58 Holding Corp	2023-01-27 F0XF Fox Fac	tory		
2060 2023-01-26 19:48:32 Atlassian Corp	2023-01-25 TEAM			
2061 2023-01-19 16:39:34 Jabil Inc	2023-01-17 JBL			
owner_name	Title			
	VP, Chief Accounting Officer	S -		
Sale 1 Frank Thomas Aj	CIO	S -		
Sale 2 Lilly Endowment Inc	10%	S -		
	SVP Chief Supply Chain Officer	S -		
Sale 4 Istar Inc. Purchase	10%	Р -		
	•••			
2057 Wilson Kevin S.	CEO, Pres	Р -		
Purchase 2058 Farquhar Scott	Co-CEO, Co-Founder, 10% S			
Sale 2059 Dennison Michael C.	CEO	S -		
Sale 2060 Farquhar Scott	Co-CEO, Co-Founder, 10%	S -		
Sale 2061 Sansone Thomas A Sale	Dir	S -		
last_price Qty	shares_held Owned Value s	tock_value		
0 260.47 -197	3,755 -5% -\$51,313	270.630005		
1 76.51 -32,897	394,861 -8% -\$2,516,911	76.679276		

```
2
          279.55
                   -3,614
                           107,463,810
                                           0%
                                                -$1,010,276
                                                               272.629761
3
          196.45
                      - 150
                                 12,740
                                           - 1%
                                                   -$29,468
                                                               191.524307
4
           59.09 +16,920
                             36,739,336
                                           0%
                                                  +$999,859
                                                                57.652042
. . .
             . . .
                       . . .
                                           . . .
                                                        . . .
                                     . . .
                                                                      . . .
2057
           58.62
                                477,578
                                                  +$645,926
                 +11,018
                                           +2%
                                                                62.169998
2058
          144.00
                   -8,614
                                465,156
                                           - 2%
                                               -$1,240,432
                                                               146.479996
2059
          115.00
                   -7,500
                                 62,701
                                          - 11%
                                                  -$862,500
                                                               114.279999
2060
          148.18
                   -8,614
                                396,244
                                          - 2%
                                               -$1,276,438
                                                               151.929993
2061
           78.75 -20,000
                              1,416,245
                                           -1% -$1,575,000
                                                                78.330002
      30_days_later
         251.339996
0
1
          72.449654
2
         241.015518
3
         198.301239
4
          60.336269
2057
          88.480003
2058
         172.229996
2059
         112.139999
2060
         170.630005
2061
          84.089996
[2062 rows x 14 columns]
# Infer the data types of the columns
df = df.infer objects()
# Check the data types of the columns
print(df.dtypes)
transaction date
                      object
```

trade date

owner name

company name

transaction type

ticker

Title

object

object

object

object

object

object

```
float64
last price
                     object
Qty
shares held
                     object
0wned
                     object
Value
                     object
stock value
                     float64
30 days later
                     float64
dtype: object
train_data, test_data = train_test_split(df, test_size=0.2)
train data
         transaction date
                            trade date ticker
      2022-08-26 20:20:47
                            2022-08-25
1336
                                         CTLT
622
      2022-04-28 21:46:49
                           2022-04-27
                                         TSLA
1250
      2022-08-04 16:24:34
                            2022-08-03
                                          SAM
      2023-01-24 16:37:51
1718
                            2023-01-23
                                         AKAM
661
      2022-04-05 16:33:53
                           2022-04-04
                                          RMD
                                           . . .
. . .
723
      2022-04-27 18:23:32
                           2022-04-25
                                         SMAR
      2022-09-08 14:09:34
                            2022-09-07
1464
                                          SXI
      2022-05-25 16:23:28
1015
                            2022-05-24
                                          IART
1259
      2022-08-02 20:45:40
                            2022-07-19
                                         CNXC
334
      2022-01-06 18:07:57
                            2022-01-06
                                          MAA
                                 company name
owner name \
1336
                               Catalent, Inc.
                                                          Maselli
Alessandro
622
                                  Tesla, Inc.
                                                                    Musk
Elon
1250
                           Boston Beer Co Inc
                                                          0'Boyle
Carolyn L.
1718
                     Akamai Technologies Inc
                                                          Leighton F
Thomson
661
                                   Resmed Inc
                                                             Pendarvis
David
. . .
. . .
                               Smartsheet Inc
                                                           Barker
723
Geoffrey T
              Standex International Corp/de/
1464
                                                             Sarcevic
Ademir
          Integra Lifesciences Holdings Corp
1015
                                                                   Evoli
Lisa
1259
                              Concentrix Corp Silver Star Developments
Ltd
      Mid America Apartment Communities Inc.
334
                                                            Bolton H
Eric Jr
```

```
Title transaction_type last_price
Qty \
1336
                          Pres, CEO
                                             S - Sale
                                                            103.04
4,646
                           CEO, 10%
                                             S - Sale
                                                            898.00
622
345,601
1250
              Chief People Officer
                                             S - Sale
                                                            381.73
251
                                         P - Purchase
1718
                                 CE0
                                                             87.79
+571
                                             S - Sale
661
      Chief Administrative Officer
                                                            246,60
1,544
. . .
. . .
723
                                 Dir
                                             S - Sale
                                                             50.44
2,250
1464
                 VP, CFO, Treasurer
                                             S - Sale
                                                             85.89
1,592
1015
                           EVP, CHRO
                                             S - Sale
                                                             59.85
250
1259
                                             S - Sale
                                 10%
                                                            125.00
524,691
                          Pres, CEO
334
                                             S - Sale
                                                            223.64
1,461
      shares held Owned
                                                        30 days later
                                   Value
                                          stock value
           41,190
1336
                    - 10%
                               -$478,724
                                           104.199997
                                                            76.070000
622
      168,193,251
                      0%
                          -$310,350,358
                                           293.836670
                                                           235.910004
1250
            2,593
                     - 9%
                                -$95,814
                                           378.329987
                                                           337,290009
1718
        2,355,858
                      0%
                               +$50,131
                                            89.190002
                                                            76.400002
                               -$380,750
661
          111,403
                     - 1%
                                           245.710007
                                                           196.419998
. . .
                     . . .
               . . .
723
          349,006
                               -$113,479
                                            50.810001
                                                            33.470001
                     - 1%
           17,575
1464
                     -8%
                               -$136,741
                                            86.860001
                                                            86.059998
1015
           20,811
                     - 1%
                               -$14,963
                                            60.099998
                                                            54.220001
1259
        4,415,535
                    - 11%
                           -$65,586,375
                                           129.210007
                                                           133.630005
334
          282,650
                     - 1%
                               -$326,738
                                           219.791565
                                                           212.529999
[1649 rows x 14 columns]
def check null values(df):
    # Get the names of columns that have null values
    null cols = df.columns[df.isnull().any()]
    # If any columns have null values, print their names
    if len(null cols) > 0:
        print("The following columns contain null values:")
        for col in null cols:
            print(col)
    # If no columns have null values, print a message indicating this
```

```
else:
        print("No columns contain null values.")
def check empty values(df):
    # Get the names of columns that have empty values
    empty cols = [col for col in df.columns if
df[col].astype(str).str.strip().empty]
    # If any columns have empty values, print their names
    if len(empty cols) > 0:
        print("The following columns contain empty values:")
        for col in empty_cols:
            print(col)
    # If no columns have empty values, print a message indicating this
    else:
        print("No columns contain empty values.")
def check nan values(df):
    # Check if each column is numerical
    num cols = [col for col in df.columns if
pd.api.types.is numeric dtype(df[col])]
    # Get the names of columns that have NaN values
    nan cols = [col for col in num cols if pd.to numeric(df[col],
errors='coerce').isnull().any()]
    # If any columns have NaN values, print their names
    if len(nan cols) > 0:
        print("The following numerical columns contain NaN values:")
        for col in nan cols:
            print(col)
    # If no columns have NaN values, print a message indicating this
    else:
        print("No numerical columns contain NaN values.")
def replace_missing_values(df):
    Replace missing (NaN) values in a DataFrame with appropriate
values based on data type of the column.
    Parameters:
        - df (pd.DataFrame): Input DataFrame
    Returns:
        - pd.DataFrame: DataFrame with missing values replaced
    null columns = df.columns[df.isnull().sum() > 0]
    for column in null columns:
        if df[column].dtype == 'float64' or df[column].dtype ==
'int64':
            df[column].fillna(df[column].mean(), inplace=True)
```

```
else:
            df[column].fillna(df[column].mode().iloc[0], inplace=True)
    return df
def encode values(column dict,column):
    unique values = column.unique() # Get unique values in the column
    num variants = len(unique values) # Get the number of unique
values
    unique values = list(enumerate(unique values))
    for number, value in unique values:
        column dict[value]=number
    return column dict
def replace items(column, dictionary):
    return column.replace(dictionary)
encoded values ticker= encode values(dict(),df['ticker'])
encoded values owner name = encode values(dict(),df['owner name'])
check null values(train data)
check empty values(train data)
check nan values(train data)
No columns contain null values.
No columns contain empty values.
No numerical columns contain NaN values.
# Function to replace 'P' with 1 and 'S' with 0 in a string column
def replace p s with 1 0(value):
    if 'P' in value:
        return 1
    elif 'S' in value:
        return 0
# Define a function for hashing the company names
def hash trick binary(s, num bits=16):
    Hashing trick function to encode company names to binary
representation
   Args:
        s (str): Company name
        num bits (int): Number of bits for the binary representation
(default: 16)
    Returns:
        str: Binary representation of the hashed company name
    hashed value = hash(s) # Use the built-in hash function to hash
the company name
    binary value = format(hashed value, '0{}b'.format(num bits)) #
```

```
Convert to binary representation
    return binary value
def one hot encode column(df, col name):
    This function takes a pandas dataframe and a column name, one hot
encodes the column, and returns the resulting dataframe.
    Arguments:
    df -- pandas dataframe
    col_name -- string, the name of the column to be one hot encoded
    Returns:
    pandas dataframe -- the original dataframe with the one hot
encoded column added and the original column removed
    # Select the column to be one hot encoded
    col = df[col name]
    # Apply one hot encoding to the column
    one hot encoded col = pd.get dummies(col, prefix=col name)
    # Concatenate the original dataframe with the one hot encoded
column
    df = pd.concat([df, one hot encoded col], axis=1)
    # Remove the original column
    df.drop(col name, axis=1, inplace=True)
    return df
df['Title']
          VP, Chief Accounting Officer
1
                                   CIO
2
                                    10%
3
        SVP Chief Supply Chain Officer
4
                                   10%
2057
                             CEO, Pres
2058
               Co-CEO, Co-Founder, 10%
2059
2060
               Co-CEO, Co-Founder, 10%
2061
Name: Title, Length: 2062, dtype: object
def clean array(arr):
    return [word.strip().replace('co-', '') for word in arr]
```

```
def find initials(s):
    return ''.join([x[0] for x in s.split(' ')])
#It's for a series object NOT for array
def replace with initials(s,in string):
    new s = s.copy()
    for i, string in s.items():
            if in string in string:
                new s[i] = find initials(string)
    return new s
def replace_to_cob(s):
    new s = s.copy()
    for i, string in s.items():
    # Check if string contains "chair, exec cob" (case insensitive)
       if 'chair' in string or 'cob' in string:
               new s[i] = 'cob'
    return new s
# Split the strings on commas and create a list of values for each
cell
train data['Title'] = train data['Title'].str.lower()
train_data['Title'] = train_data['Title'].str.split(',')
#Clean array will remove the co- start from each title
train data['Title'] = train data['Title'].apply(clean array)
unique values = train data['Title'].explode()
print(len(unique values.value counts()))
unique values = replace with initials(unique values, 'chief')
unique values = replace to cob(unique values)
unique values = unique values.value counts()
print(unique values[:50])
299
                                 449
dir
cob
                                 216
                                 202
ceo
10%
                                 184
                                 162
evp
                                 130
pres
                                 122
cfo
                                 94
svp
qc
                                  86
                                  75
cao
COO
                                  65
                                  38
qν
founder
                                  36
                                  28
cto
                                  22
cro
                                  22
CCO
                                  21
secretary
```

```
21
see remarks
                                   21
cmo
сро
                                   20
clo
                                   19
                                   16
treasurer
chro
                                   16
                                   15
CSO
cio
                                   15
cl
                                   14
controller
                                   11
d
                                    8
                                    7
hr
                                    7
cbo
principal accounting officer
                                    6
cdo
                                    6
sales
                                    6
                                    5
qm
                                    5
marketing
                                    5
exec officer
                                    5
CSCO
                                    4
r
                                    4
md
                                    4
gen. counsel
core technologies
                                    3 3 3 3 3 3 3 3
cea
tax
coo t
systems
cr
control
operations
fin plan
                                    3
group pres
Name: Title, dtype: int64
def replace to initials for array(string, df):
    # Loop through the columns of the DataFrame
    for i, value in df.items():
        new array = []
        # Loop through the values in the column
        for v in value:
            if string in v:
                 # Replace string with initials using the
find_initials() function
                 new array.append(find initials(v))
            else:
                 new array.append(v)
        # Update the column in the DataFrame with the modified values
        df[i] = new array
```

```
def replace to string for array(string, df, optional=None,
not optional=None):
    if optional is None and not optional is None:
        # If neither optional nor not optional are provided, replace
strina with strina
        # in all values of the DataFrame
        for i, value in df.items():
            df = df.apply(lambda v: string if string in v else v)
    elif not optional is None:
        # If not optional is not provided, replace string with string
in values that
        # contain either string or optional
        for i, value in df.items():
            new array = []
            # Loop through the values in the column
            for v in value:
                if string in v or optional in v:
                    new array.append(string)
                else:
                    new array.append(v)
            # Update the column in the DataFrame with the modified
values
            df[i] = new array
    elif optional is None:
        # If optional is not provided, replace string with string in
values that
        # contain string but not not optional
        for i, value in df.items():
            new array = []
            # Loop through the values in the column
            for v in value:
                if string in v and not optional != v:
                    new array.append(string)
                else:
                    new array.append(v)
            # Update the column in the DataFrame with the modified
values
            df[i] = new array
replace to string for array('cob',df=train data['Title'],optional='cha
replace to string for array('pres',df=train data['Title'])
replace_to_string_for_array('vp',df=train_data['Title'],not_optional='
replace to initials for array('chief',train data['Title'])
<ipython-input-57-756befde8387>:33: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation:
```

```
https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#
returning-a-view-versus-a-copy
  df[i] = new array
<ipython-input-57-756befde8387>:46: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df[i] = new array
<ipython-input-57-756befde8387>:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#
returning-a-view-versus-a-copy
  df[i] = new array
ranks = {
    'founder': 1.
    'cob': 2,
    'ceo': 2,
    'president':3,
    'pres': 3,
    'evp': 3,
    'coo': 4.
    'cfo': 4,
    'cto': 4,
    'cio': 4,
    'chro': 4,
    'gc': 4,
    'vp': 5,
    'controller': 5.
    'cmo': 5,
    'cao': 5.
    'treasurer': 5,
    'secretary': 5,
    '10%': 5,
    'dir':5
    }
# Function to replace titles in an array with their corresponding
ranks from the dictionary,
# and return the minimum rank among them. If title not found in
dictionary, default rank is 5.
def replace title with rank(title array):
   return min([ranks.get(title, 5) if title in ranks else 5 for title
in title array]) # Use 5 as default value if title not found in
dictionary
```

```
train data['Title'] =
train data['Title'].apply(replace title with rank)
train data['transaction type'] =
train data['transaction_type'].apply(replace_p_s_with_1_0)
train data['ticker'] =
replace_items(train_data['ticker'],encoded_values_ticker)
train data['owner name'] =
replace items(train data['owner name'],encoded values owner name)
columns to drop = ['transaction date', 'trade date', 'company name']
train data=train data.drop(columns_to_drop, axis=1)
train data['Qty']= train data['Qty'].str.replace(",",
"").astype(float)
train data['shares held']= train data['shares held'].str.replace(",",
"").astype(int)
train data["0wned"] = train data["0wned"].str.replace("%",
"").replace("New",0)
train data['Owned'] =
train data['Owned'].str.replace('>',"").astype(float)
# Divide by 100
train data["Owned"] = train data["Owned"]/100
train data['Value'] = train data['Value'].str.replace("$", "")
train data['Value'] = train data['Value'].str.replace(",",
"").astype(int)
<ipython-input-64-72f3c9a12d17>:7: FutureWarning: The default value of
regex will change from True to False in a future version. In addition,
single character regular expressions will *not* be treated as literal
strings when regex=True.
  train data['Value'] = train data['Value'].str.replace("$", "")
train data
      ticker
              owner name
                          Title transaction type
                                                   last price
Qty \
1336
                     918
                              2
                                                 0
                                                        103.04
         173
4646.0
                              2
                                                 0
                                                        898.00 -
622
          11
                     461
345601.0
                              5
                                                 0
                                                        381.73
1250
         492
                     859
251.0
1718
         151
                              2
                                                 1
                                                         87.79
                    1063
571.0
661
         295
                     486
                              5
                                                 0
                                                        246.60
1544.0
. . .
                                                           . . .
723
                     355
                              5
                                                 0
                                                         50.44
         115
2250.0
```

1464 542 1592.0		992	4	0	85.89 -	
1015 250.0	403	682	3	0	59.85	-
1259 52469	202 1 0	864	5	0	125.00 -	
334 1461.0	15	272	2	Θ	223.64 -	
	shares_held	0wned	Value	stock_value	30_days_later	
1336	41190	-0.10	-478724	104.199997	76.070000	
622	168193251	0.00	-310350358	293.836670	235.910004	
1250	2593	-0.09	-95814	378.329987	337.290009	
1718	2355858	0.00	50131	89.190002	76.400002	
661	111403	-0.01	-380750	245.710007	196.419998	
 723	349006	-0.01	 -113479	50.810001	33.470001	
1464	17575	-0.08	-136741	86.860001	86.059998	
1015	20811	-0.01	- 14963	60.099998	54.220001	
1259	4415535	-0.11	-65586375	129.210007	133.630005	
		-				
334	282650	-0.01	-326738	219.791565	212.529999	

[1649 rows x 11 columns]

check_null_values(train_data)
check_empty_values(train_data)
check_nan_values(train_data)

The following columns contain null values:

0wned

No columns contain empty values.

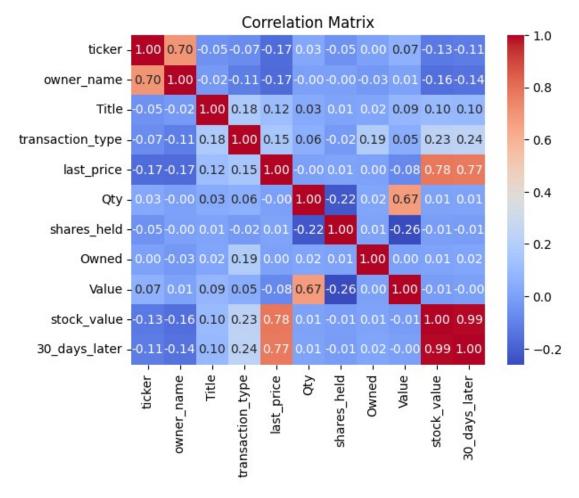
The following numerical columns contain NaN values: Owned

train_data = replace_missing_values(train_data)
train_data

ti	.cker	owner_name	Title	transaction_type	last_price	
Qty \ 1336 4646.0	173	918	2	0	103.04	-
622	11	461	2	0	898.00	-
345601.0						
1250	492	859	5	0	381.73	-
251.0 1718 571.0	151	1063	2	1	87.79	
661 1544.0	295	486	5	0	246.60	-
• • •						• •

.

```
50.44
723
         115
                      355
                                5
                                                   0
2250.0
1464
                                4
                                                            85.89
         542
                      992
                                                   0
1592.0
1015
         403
                      682
                                3
                                                   0
                                                            59.85
250.0
                      864
                                5
                                                           125.00 -
1259
         202
                                                   0
524691.0
334
          15
                      272
                                2
                                                   0
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      shares held
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                                        378.329987
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1250
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                                          89.190002
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                              -380750
                                        245.710007
           111403
                    -0.01
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. . .
723
           349006
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                                          50.810001
                                                          33.470001
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             17575
                    -0.08
                              -136741
                                         86.860001
                                                          86.059998
1015
                    -0.01
                                         60.099998
                                                          54.220001
            20811
                               -14963
1259
                    -0.11
                                         129.210007
                                                         133.630005
          4415535
                            -65586375
                              -326738
334
                    -0.01
                                        219.791565
                                                         212.529999
           282650
[1649 rows x 11 columns]
# Compute the correlation matrix
corr matrix = train data.corr()
# Create a heatmap of the correlation matrix
sns.heatmap(corr matrix, cmap='coolwarm', annot=True, fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```



train_data

	cker	owner_name	Title	transaction_type	last_price		
Qty \ 1336	173	918	2	0	103.04	-	
4646.0 622	11	461	2	0	898.00	-	
345601.0 1250 251.0	492	859	5	Θ	381.73	-	
1718 571.0	151	1063	2	1	87.79		
661 1544.0	295	486	5	0	246.60	-	
723 2250.0	115	355	5	Θ	50.44	-	
1464 1592.0	542	992	4	0	85.89	-	
1015 250.0	403	682	3	0	59.85	-	

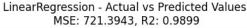
```
1259
         202
                     864
                              5
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                                                0
524691.0
                                                        223.64
334
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                     272
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1336
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                            -478724
                                      104.199997
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622
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                                      293.836670
                                                      235.910004
1250
             2593
                  -0.09
                             -95814
                                      378.329987
                                                      337.290009
1718
          2355858
                    0.00
                              50131
                                       89.190002
                                                       76,400002
661
           111403
                   -0.01
                            -380750
                                      245.710007
                                                      196.419998
. . .
              . . .
723
           349006
                   -0.01
                            -113479
                                       50.810001
                                                       33,470001
                   -0.08
1464
            17575
                            -136741
                                       86.860001
                                                       86.059998
1015
            20811
                   -0.01
                             - 14963
                                       60.099998
                                                       54.220001
1259
          4415535
                   -0.11 -65586375
                                      129.210007
                                                      133.630005
334
           282650
                  -0.01
                            -326738
                                      219.791565
                                                      212.529999
[1649 rows x 11 columns]
# Define the parameter grid for grid search for Ridge and Lasso
regression
param grid ridge = {'alpha': np.logspace(-3, 3, 7)} # alpha values
ranging from 0.001 to 1000
param grid lasso = {'alpha': np.logspace(-3, 3, 7)} # alpha values
ranging from 0.001 to 1000
X = train data.drop('30 days later', axis=1) # Replace 'target' with
the column name of your target variable
y = train data['30 days later'] # Replace 'target' with the column
name of your target variable
# Create an array of regression models
models = [LinearRegression(), Ridge(),
Lasso(), DecisionTreeRegressor()]
# Define different test sizes
test sizes = [0.10, 0.15, 0.2, 0.25]
# Create a dictionary to store model information
model info = {}
# Loop through each test size
for test size in test sizes:
    X_train, X_test, y_train, y_test = train_test_split(X, y,
test size=test size, random state=42)
    print('Test size:', test size)
    # Loop through each model
    for model in models:
```

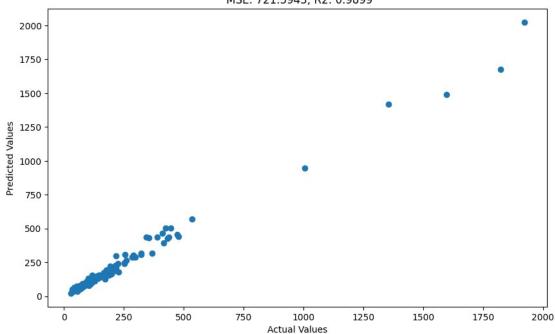
```
model_name = model.__class__._name__
        # Perform grid search with cross-validation
        if model name == 'LinearRegression':
            param grid = \{\}
        elif model name == 'Ridge':
            param grid = param grid ridge
        elif model name == 'Lasso':
            param grid = param grid lasso
        elif model name == 'DecisionTreeRegressor':
          param grid = {}
        grid_search = GridSearchCV(model, param_grid, cv=5)
        grid search.fit(X train, y train)
        # Get the best hyperparameters
        best params = grid search.best params
        best alpha = best params['alpha'] if 'alpha' in best params
else None
        # Train the model with the best hyperparameters
        model best = model. class (**best params) if best alpha else
model. class ()
        trained model=model best.fit(X train, y train)
        # Make predictions on the test set
        y pred = model best.predict(X test)
        # Calculate metrics
        mse = mean_squared_error(y_test, y_pred)
        r2 = r2 score(y test, y pred)
        # Store model information in the dictionary
        model info[model name] = {
            'best params': best params,
            'best_alpha': best_alpha,
            'trained model':trained model,
            'model': model best,
            'X_train': X_train,
            'y train': y train,
            'X_test': X_test,
            'y_test': y_test,
            'y_pred': y_pred,
            'mse': mse,
            'r2': r2
        }
        # Plot the results
        plt.figure(figsize=(10, 6))
        plt.scatter(y test, y pred)
```

```
plt.xlabel('Actual Values')
    plt.ylabel('Predicted Values')
    plt.title('{} - Actual vs Predicted Values\n MSE: {:.4f}, R2:
{:.4f}'.format(model_name, mse, r2))
    plt.show()

# Access model information from the dictionary
# Example usage:
# best_params_ridge = model_info['Ridge']['best_params']
```

Test size: 0.1





/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/
_ridge.py:216: LinAlgWarning: Ill-conditioned matrix (rcond=9.1921e18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.52635e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.58972e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.25785e-18): result may not be accurate.

/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.32093e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=9.1928e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.52686e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.58984e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.25835e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.32142e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=9.19982e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.532e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.59102e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.26337e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.32631e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=9.26998e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py:
216: LinAlgWarning: Ill-conditioned matrix (rcond=7.58336e-18): result

may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.6028e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.31357e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.37521e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=9.97222e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.09785e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.72075e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.81642e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.86512e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.70451e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.33114e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=2.90592e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.29083e-17): result may not be accurate.

/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.28292e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=9.34976e-17): result may not be accurate.

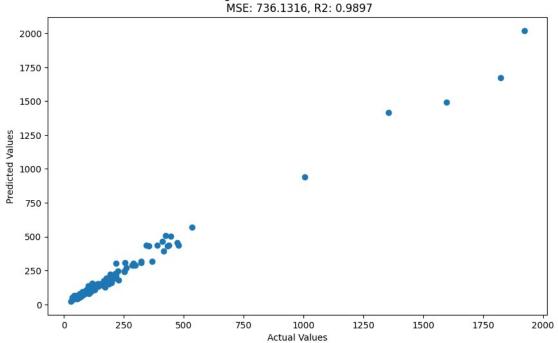
return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.75499e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.56962e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.45294e-17): result may not be accurate.

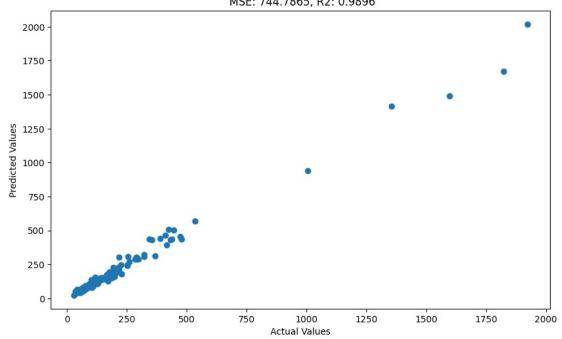
return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.46587e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.46587e-17): result may not be accurate.

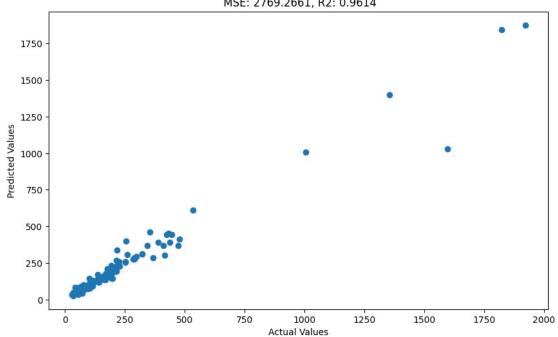


Ridge - Actual vs Predicted Values

Lasso - Actual vs Predicted Values MSE: 744.7865, R2: 0.9896

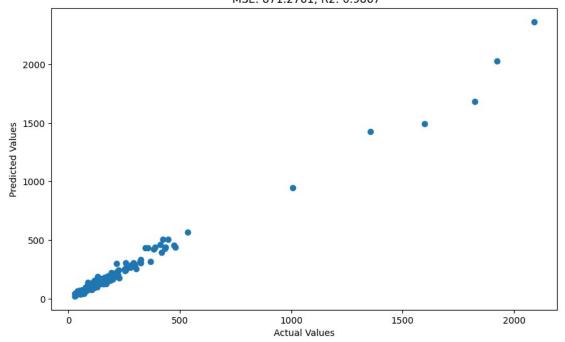


DecisionTreeRegressor - Actual vs Predicted Values MSE: 2769.2661, R2: 0.9614



Test size: 0.15

LinearRegression - Actual vs Predicted Values MSE: 871.2761, R2: 0.9867



/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/
_ridge.py:216: LinAlgWarning: Ill-conditioned matrix (rcond=8.79884e18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.0156e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.82335e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.91709e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.88759e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.79956e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.01568e-17): result may not be accurate.

/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.82399e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.91759e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.88807e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.80671e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.01647e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.83042e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.9226e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.89295e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.87829e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.02432e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.89476e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.97266e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py:
216: LinAlgWarning: Ill-conditioned matrix (rcond=6.94176e-18): result

may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=9.59506e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.10296e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=9.53928e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.47416e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.43076e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.68316e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.89574e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.60769e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.25576e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.23905e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=9.10377e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.05174e-16): result may not be accurate.

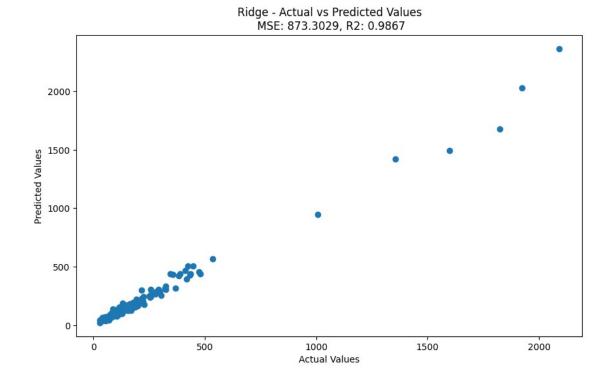
/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.42578e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.5422e-17): result may not be accurate.

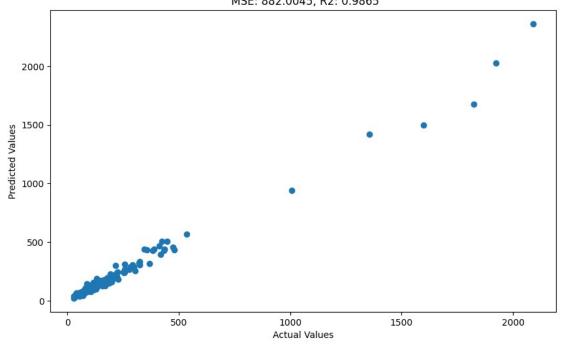
return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.42e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.35632e-17): result may not be accurate.

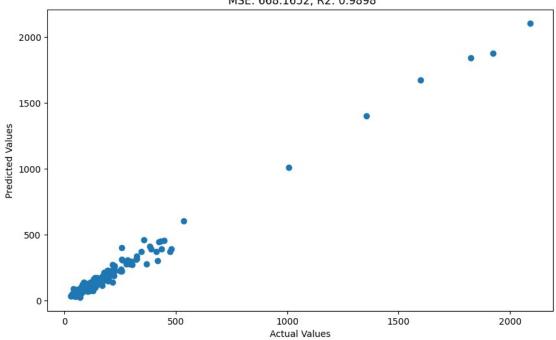
return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.35632e-17): result may not be accurate.



Lasso - Actual vs Predicted Values MSE: 882.0045, R2: 0.9865

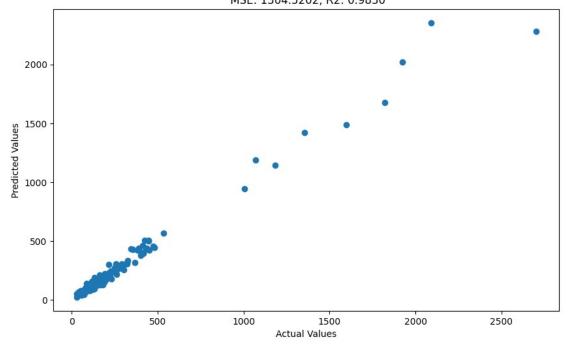


DecisionTreeRegressor - Actual vs Predicted Values MSE: 668.1652, R2: 0.9898



Test size: 0.2

LinearRegression - Actual vs Predicted Values MSE: 1304.5202, R2: 0.9830



/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/
_ridge.py:216: LinAlgWarning: Ill-conditioned matrix (rcond=8.33997e18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=9.5553e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.2572e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.56183e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.45069e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.34068e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=9.55631e-18): result may not be accurate.

/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.25784e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.56233e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.45118e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.34781e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=9.56417e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.26427e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.56734e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.45606e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.41915e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=9.64272e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.32857e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.61736e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py:
216: LinAlgWarning: Ill-conditioned matrix (rcond=6.5049e-18): result

may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=9.13367e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.04294e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.97285e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.11855e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.99427e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.63601e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.83747e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.55131e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.22038e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.19617e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=9.06579e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.00106e-16): result may not be accurate.

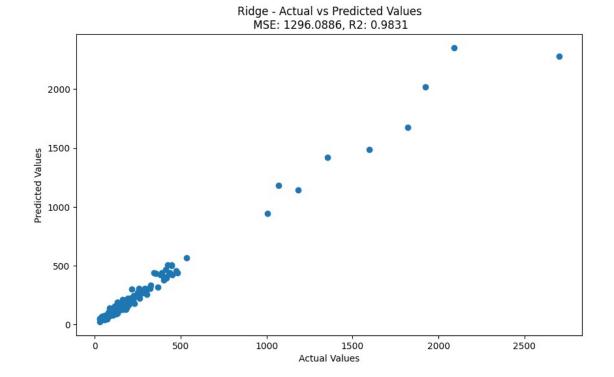
/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.38873e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.52187e-17): result may not be accurate.

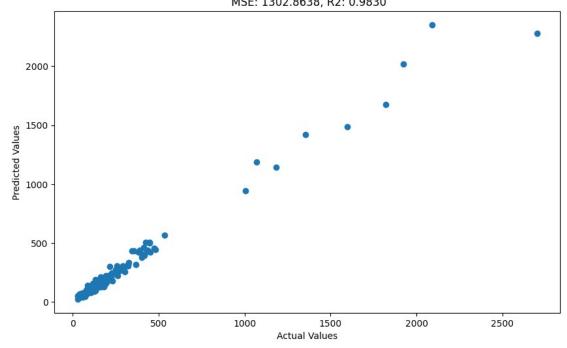
return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.39472e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.30975e-17): result may not be accurate.

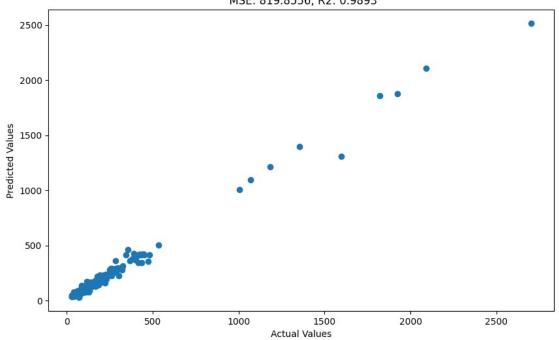
return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.30975e-17): result may not be accurate.



Lasso - Actual vs Predicted Values MSE: 1302.8638, R2: 0.9830

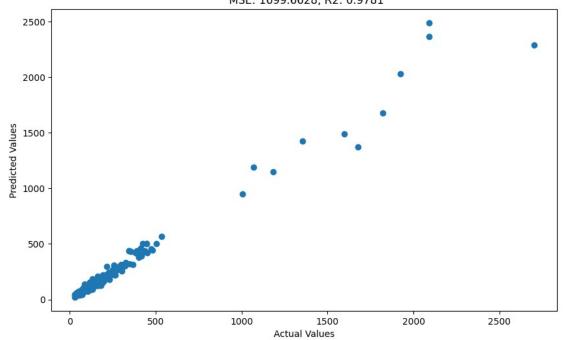


DecisionTreeRegressor - Actual vs Predicted Values MSE: 819.8556, R2: 0.9893



Test size: 0.25

LinearRegression - Actual vs Predicted Values MSE: 1699.6628, R2: 0.9781



/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/
_ridge.py:216: LinAlgWarning: Ill-conditioned matrix (rcond=7.97284e18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.22669e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=5.55779e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=5.74054e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=5.83503e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.97355e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.22801e-18): result may not be accurate.

/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=5.55828e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=5.74106e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=5.83553e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.98069e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.24116e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=5.56319e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=5.74625e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=5.84056e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.05207e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=7.37277e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=5.6123e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=5.79822e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py:
216: LinAlgWarning: Ill-conditioned matrix (rcond=5.89085e-18): result

may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.76718e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=8.69518e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.10424e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.31831e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.39451e-18): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.60085e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=2.22898e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.10824e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.15477e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=1.1488e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=9.06236e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.24462e-17): result may not be accurate.

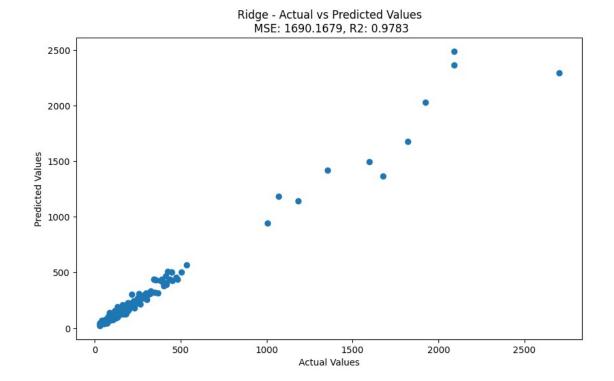
/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.74473e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.78903e-17): result may not be accurate.

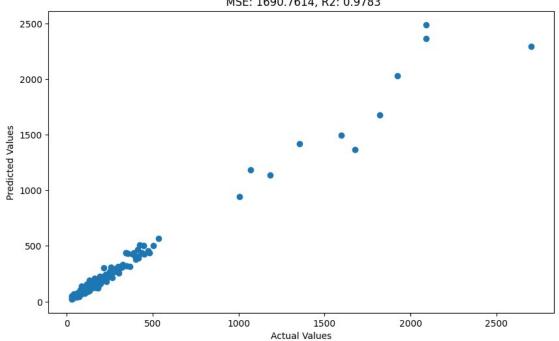
return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.65023e-17): result may not be accurate.

return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T /usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_ridge.py: 216: LinAlgWarning: Ill-conditioned matrix (rcond=6.65023e-17): result may not be accurate.

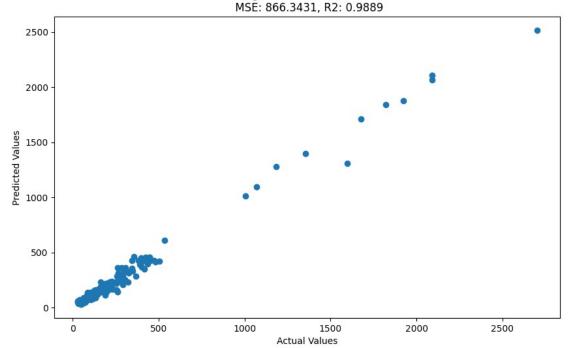
return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T



Lasso - Actual vs Predicted Values MSE: 1690.7614, R2: 0.9783



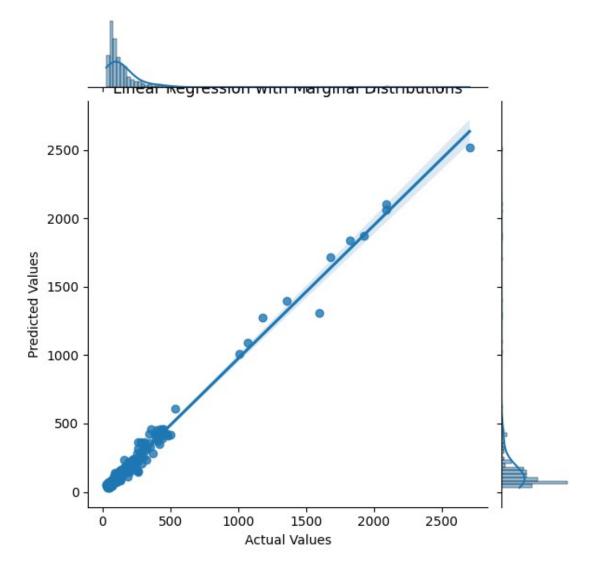
DecisionTreeRegressor - Actual vs Predicted Values



data = {'Actual': y_test, 'Predicted': y_pred}
prediction = pd.DataFrame(data)

sns.jointplot(x='Actual', y='Predicted', data=prediction, kind='reg')

```
# Set labels and title
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Linear Regression with Marginal Distributions')
# Show the plot
plt.show()
```

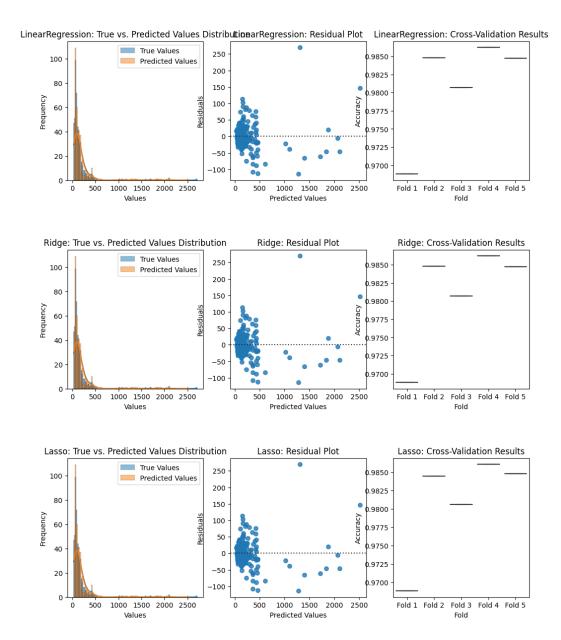


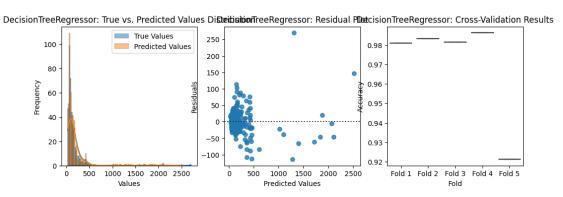
```
# Set up the subplots
n_models = len(models) # Replace 'models' with your array of models
fig, axes = plt.subplots(n_models, 3, figsize=(12, n_models*5)) # 3
columns for histograms, residual plots, and boxplots
fig.subplots_adjust(hspace=0.5) # Add vertical space between subplots
```

Loop over the models and create plots
for i, model in enumerate(models): # Replace 'models' with your array
of models

```
model name = type(model). name
    # Create histogram of true and predicted values
    sns.histplot(y test, kde=True, label='True Values', ax=axes[i, 0])
    sns.histplot(y_pred, kde=True, label='Predicted Values',
ax=axes[i, 0])
    axes[i, 0].set xlabel('Values')
    axes[i, 0].set ylabel('Frequency')
    axes[i, 0].set title(f'{model name}: True vs. Predicted Values
Distribution')
    axes[i, 0].legend()
    # Create residual plot
    sns.residplot(x=y_pred, y=y_test, ax=axes[i, 1])
    axes[i, 1].set xlabel('Predicted Values')
    axes[i, 1].set_ylabel('Residuals')
    axes[i, 1].set title(f'{model name}: Residual Plot')
    # Perform cross-validation and get results
    scores = cross val score(model, X, y, cv=5) # Replace 'model',
'X', and 'y' with your specific model, features, and target variable
    fold_labels = [f"Fold {i+1}" for i in range(len(scores))]
    # Create boxplot to visualize cross-validation results
    sns.boxplot(x=fold_labels, y=scores, ax=axes[i, 2])
    axes[i, 2].set_xlabel("Fold")
    axes[i, 2].set ylabel("Accuracy") # Replace with appropriate
evaluation metric
    axes[i, 2].set title(f'{model name}: Cross-Validation Results')
# Show the plots
plt.show()
/usr/local/lib/python3.9/dist-packages/sklearn/linear model/
ridge.py:216: LinAlgWarning: Ill-conditioned matrix (rcond=3.62174e-
18): result may not be accurate.
  return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
/usr/local/lib/python3.9/dist-packages/sklearn/linear model/ ridge.py:
216: LinAlgWarning: Ill-conditioned matrix (rcond=6.92413e-18): result
may not be accurate.
  return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
/usr/local/lib/python3.9/dist-packages/sklearn/linear model/ ridge.py:
216: LinAlqWarning: Ill-conditioned matrix (rcond=9.20821e-18): result
may not be accurate.
  return linalg.solve(A, Xy, assume a="pos", overwrite a=True).T
/usr/local/lib/python3.9/dist-packages/sklearn/linear model/ ridge.py:
216: LinAlgWarning: Ill-conditioned matrix (rcond=1.08241e-17): result
may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/usr/local/lib/python3.9/dist-packages/sklearn/linear model/ ridge.py:
```

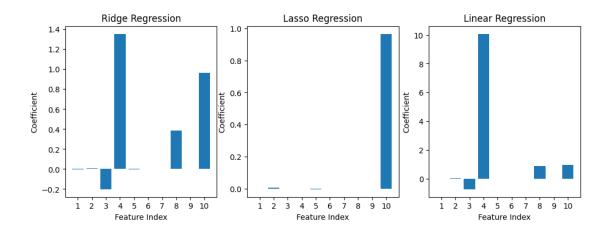
216: LinAlgWarning: Ill-conditioned matrix (rcond=1.09699e-17): result may not be accurate.
 return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T





Create a figure with subplots for each model
fig, axes = plt.subplots(1, 3, figsize=(12, 4))

```
model info['Ridge']['coefficients'] = model info['Ridge']
['model'].coef
model info['Lasso']['coefficients'] = model info['Lasso']
['model'].coef
model info['LinearRegression']['coefficients'] =
model info['LinearRegression']['model'].coef
# Plot coefficients for Ridge model
ridge coefs = model info['Ridge']['coefficients']
axes[0].bar(range(len(ridge coefs)), ridge coefs)
axes[0].set xticks(range(len(ridge coefs)))
axes[0].set xticklabels(range(1, len(ridge coefs)+1))
axes[0].set xlabel('Feature Index')
axes[0].set ylabel('Coefficient')
axes[0].set title('Ridge Regression')
# Plot coefficients for Lasso model
lasso coefs = model info['Lasso']['coefficients']
axes[1].bar(range(len(lasso coefs)), lasso coefs)
axes[1].set xticks(range(len(lasso coefs)))
axes[1].set xticklabels(range(1, len(lasso coefs)+1))
axes[1].set xlabel('Feature Index')
axes[1].set ylabel('Coefficient')
axes[1].set title('Lasso Regression')
# Plot coefficients for Linear model
linear coefs = model info['LinearRegression']['coefficients']
axes[2].bar(range(len(linear coefs)), linear coefs)
axes[2].set xticks(range(len(linear coefs)))
axes[2].set xticklabels(range(1, len(linear coefs)+1))
axes[2].set xlabel('Feature Index')
axes[2].set ylabel('Coefficient')
axes[2].set title('Linear Regression')
Text(0.5, 1.0, 'Linear Regression')
```

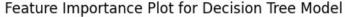


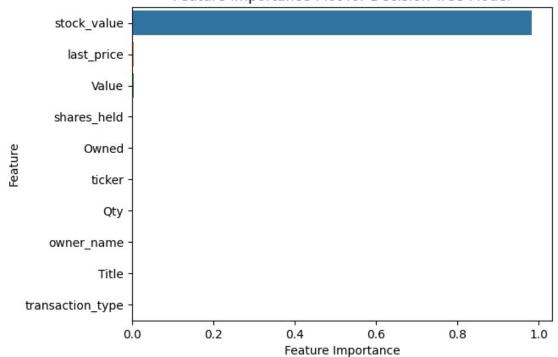
```
# Get feature importances from the model
feature_importances = model_info['DecisionTreeRegressor']
['model'].feature_importances_

# Create a DataFrame to store feature importances
feature_df = pd.DataFrame({'Feature': X_train.columns, 'Importance': feature_importances})

# Sort the DataFrame by feature importances
feature_df = feature_df.sort_values('Importance', ascending=False)

# Create a bar plot to visualize feature importances
sns.barplot(x='Importance', y='Feature', data=feature_df)
plt.xlabel('Feature Importance')
plt.ylabel('Feature Importance Plot for Decision Tree Model')
plt.show()
```





```
# Create a dictionary to store the performance metrics of each model
model_performance = {
    'Linear Regression': {'R2': model_info['LinearRegression']['r2'],
'MSE': model_info['LinearRegression']['mse']},
    'Ridge Regression': {'R2': model_info['Ridge']['r2'], 'MSE':
model_info['Ridge']['mse']},
    'Lasso Regression': {'R2': model_info['Lasso']['r2'], 'MSE':
model_info['Lasso']['mse']},
    'Decision Tree': {'R2': model_info['DecisionTreeRegressor']
```

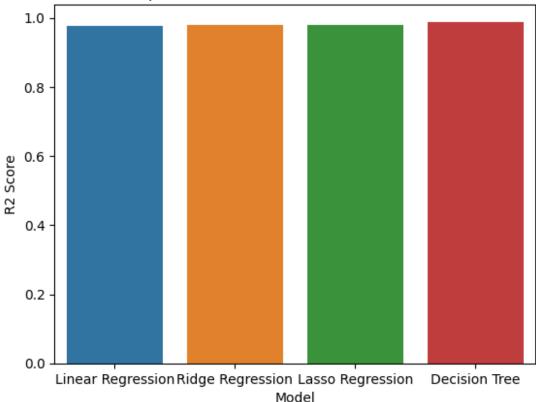
```
['r2'], 'MSE': model_info['DecisionTreeRegressor']['mse']}

# Convert the dictionary to a DataFrame
model_df = pd.DataFrame(model_performance).T

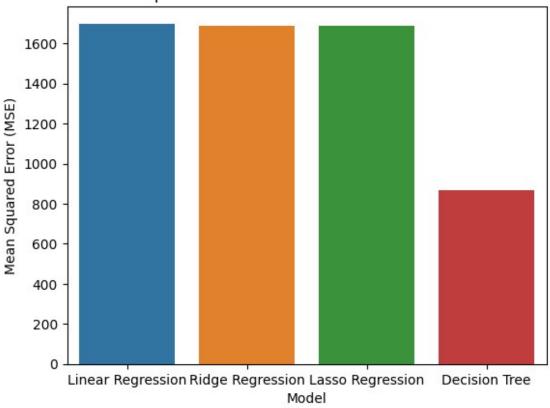
# Create a bar plot to compare R2 scores
sns.barplot(x=model_df.index, y=model_df['R2'])
plt.xlabel('Model')
plt.ylabel('R2 Score')
plt.title('Comparison of R2 Scores for Different Models')
plt.show()

# Create a bar plot to compare MSE values
sns.barplot(x=model_df.index, y=model_df['MSE'])
plt.xlabel('Model')
plt.ylabel('Mean Squared Error (MSE)')
plt.title('Comparison of MSE Values for Different Models')
plt.show()
```

Comparison of R2 Scores for Different Models



Comparison of MSE Values for Different Models



```
check null values(test data)
check empty values(test data)
check nan values(test data)
No columns contain null values.
No columns contain empty values.
No numerical columns contain NaN values.
# Split the strings on commas and create a list of values for each
cell
test data['Title'] = test data['Title'].str.lower()
test data['Title'] = test data['Title'].str.split(',')
#Clean array will remove the co- start from each title
test data['Title'] = test data['Title'].apply(clean array)
replace to string for array('cob',df=test data['Title'],optional='chai
replace to string for array('pres',df=test data['Title'])
replace to string for array('vp',df=test data['Title'],not optional='e
vp')
replace_to_initials_for_array('chief',test_data['Title'])
test data['Title'] = test data['Title'].apply(replace title with rank)
<ipython-input-57-756befde8387>:33: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

```
See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#
returning-a-view-versus-a-copy
  df[i] = new array
<ipython-input-57-756befde8387>:46: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#
returning-a-view-versus-a-copy
  df[i] = new_array
<ipython-input-57-756befde8387>:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#
returning-a-view-versus-a-copy
  df[i] = new array
test data['Qty']= test data['Qty'].str.replace(",", "").astype(float)
test data['shares held'] = test data['shares held'].str.replace(",",
"").astvpe(int)
test data["Owned"] = test data["Owned"].str.replace("%",
"").replace("New",0)
test data['Owned'] =
test_data['Owned'].str.replace('>',"").astype(float)
# Divide by 100
test data["Owned"] = test data["Owned"]/100
test data['Value'] = test data['Value'].str.replace("$", "")
test data['Value'] = test data['Value'].str.replace(",",
"").astype(int)
<ipython-input-78-fa3b1365255d>:7: FutureWarning: The default value of
regex will change from True to False in a future version. In addition,
single character regular expressions will *not* be treated as literal
strings when regex=True.
  test data['Value'] = test data['Value'].str.replace("$", "")
test data['transaction type'] =
test data['transaction type'].apply(replace p s with 1 0)
test data['ticker'] =
replace items(test data['ticker'],encoded values ticker)
test data['owner name'] =
replace_items(test_data['owner_name'],encoded_values_owner_name)
test data=test data.drop(columns to drop, axis=1)
test data
      ticker owner name Title transaction type last price
                                                                   Qty
```

1846	579	1184	2		0	145.94	-6500.0
1435	35	167	5		0	98.60	-300.0
10	10	10	3		0	147.72	-1442.0
11	11	11	5		0	1160.85	-1100.0
264	161	217	2		0	140.22	-2000.0
1183	468	807	3		0	80.00	-3164.0
1724	542	992	4		0	109.38	-846.0
788	31	31	5		0	50.31	-10200.0
1295	343	889	5		0	71.53	-5412.0
1269	499	871	4		0	220.00	-2000.0
1846 1435 10 11 264	shares_held 143790 36440 77300 22905 157617	Owned -0.04 -0.01 -0.02 -0.05 -0.01	Value -948597 -29580 -213017 -1276940 -280440	stock_value 146.309998 98.809998 141.789993 362.706665 133.220001	30	_days_later 162.559998 104.930000 118.089996 297.046661 122.980003	
1183 1724 788 1295 1269	49303 12275 2123999 65132 37187	-0.06 -0.06 0.00 -0.08 -0.05	-253120 -92535 -513162 -387131 -440000	81.010002 109.750000 49.34998 71.680000 212.559998		66.709999 116.400002 47.180000 61.680000 219.710007	

[413 rows x 11 columns]

check_null_values(test_data)
check_empty_values(test_data)
check_nan_values(test_data)

No columns contain null values. No columns contain empty values. No numerical columns contain NaN values.

test_data = replace_missing_values(test_data)
test_data

```
owner name Title transaction type
      ticker
                                                      last price
                                                                        0tv
1846
                     1184
         579
                                2
                                                   0
                                                           145.94
                                                                   -6500.0
1435
                                5
          35
                      167
                                                   0
                                                            98.60
                                                                    -300.0
10
          10
                       10
                                3
                                                   0
                                                           147.72
                                                                   -1442.0
11
          11
                       11
                                5
                                                   0
                                                          1160.85
                                                                    -1100.0
                                2
264
         161
                      217
                                                   0
                                                           140.22
                                                                   -2000.0
          . . .
         468
                      807
                                3
                                                   0
                                                            80.00
                                                                   -3164.0
1183
1724
         542
                      992
                                4
                                                   0
                                                           109.38
                                                                     -846.0
788
          31
                       31
                                5
                                                   0
                                                            50.31 -10200.0
1295
         343
                      889
                                5
                                                   0
                                                            71.53
                                                                   -5412.0
                                4
1269
         499
                      871
                                                   0
                                                           220.00
                                                                   -2000.0
      shares held
                    0wned
                                                   30 days later
                              Value
                                     stock value
           143790
                    -0.04
                            -948597
                                      146.309998
                                                       162.559998
1846
1435
            36440
                    -0.01
                             -29580
                                       98.809998
                                                       104.930000
            77300
                    -0.02
                                      141.789993
10
                            -213017
                                                       118.089996
                    -0.05 -1276940
                                      362.706665
11
            22905
                                                       297.046661
                    -0.01
264
           157617
                            -280440
                                      133.220001
                                                       122.980003
                      . . .
. . .
               . . .
1183
            49303
                    -0.06
                            -253120
                                       81.010002
                                                        66.709999
1724
            12275
                    -0.06
                            -92535
                                      109.750000
                                                       116.400002
788
          2123999
                     0.00
                           -513162
                                       49.349998
                                                        47.180000
                    -0.08
                            -387131
                                       71.680000
1295
            65132
                                                        61.680000
                            -440000
                                      212.559998
                                                       219.710007
1269
            37187
                    -0.05
[413 rows x 11 columns]
test_X = test_data.drop('30_days_later', axis=1)
test y = test data['30 days later']
for model name, model in model info.items():
    model obj = model['model']
    y pred = model obj.predict(test X)
    mse = mean_squared_error(test_y, y_pred)
```

```
rmse = np.sqrt(mse)
    print("Model: {}".format(model name))
    print("Mean Squared Error (MSE) on Test Data: {:.2f}".format(mse))
    print("Root Mean Squared Error (RMSE) on Test Data:
{:.2f}".format(rmse))
    print("---")
Model: LinearRegression
Mean Squared Error (MSE) on Test Data: 1335.66
Root Mean Squared Error (RMSE) on Test Data: 36.55
Model: Ridge
Mean Squared Error (MSE) on Test Data: 1304.55
Root Mean Squared Error (RMSE) on Test Data: 36.12
Model: Lasso
Mean Squared Error (MSE) on Test Data: 1304.20
Root Mean Squared Error (RMSE) on Test Data: 36.11
Model: DecisionTreeRegressor
Mean Squared Error (MSE) on Test Data: 1295.98
Root Mean Squared Error (RMSE) on Test Data: 36.00
import joblib
import os
# Loop through the models in 'model info' dictionary
for model name, model in model info.items():
    # Extract the model from the dictionary
    model obj = model['model']
    # Save the model to a binary file
    file name = "{}.joblib".format(model name) # File name for the
model
    file path = os.path.join(drive path[:-1], file name)
    joblib.dump(model obj, file name) # Save the model to file
    print("Model '{}' saved as {}".format(model_name, file_name))
Model 'LinearRegression' saved as LinearRegression.joblib
Model 'Ridge' saved as Ridge.joblib
Model 'Lasso' saved as Lasso.joblib
Model 'DecisionTreeRegressor' saved as DecisionTreeRegressor.joblib
import pickle
def save_dicts_to_file(dict1, dict2, file_path):
```

```
with open(file_path, 'wb') as f:
    pickle.dump([dict1, dict2], f)

save_dicts_to_file(encoded_values_owner_name,encoded_values_ticker,'encoded_dicts')
```