AI_Algorithms_Final_Project_Group_5-1

February 14, 2024

1 AI Algorithms Final Project

1.0.1 Group 5

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Prepare Problem * Load libraries * Load dataset

[ ]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import pickle
from sklearn.model_selection import train_test_split
from sklearn.metrics import (mean_squared_error, mean_absolute_error,
                             r2_score, explained_variance_score)
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, StackingRegressor
from sklearn.svm import SVR
from sklearn.model_selection import GridSearchCV
from sklearn.feature_selection import SelectFromModel
from sklearn.tree import plot_tree
```

[ ]:
```
df = pd.read_csv('house_price.csv')
```

[ ]:
```
df.head()
```

[ ]:
```
           id             date     price  bedrooms  bathrooms  sqft_living  \
0  7129300520  20141013T000000  221900.0         3       1.00         1180
1  6414100192  20141209T000000  538000.0         3       2.25         2570
2  5631500400  20150225T000000  180000.0         2       1.00          770
3  2487200875  20141209T000000  604000.0         4       3.00         1960
4  1954400510  20150218T000000  510000.0         3       2.00         1680

   sqft_lot  floors  waterfront  view  condition  grade  sqft_above  \
0      5650     1.0           0     0          3      7        1180
```

```
1      7242     2.0           0      0          3      7          2170
2     10000     1.0           0      0          3      6           770
3      5000     1.0           0      0          5      7          1050
4      8080     1.0           0      0          3      8          1680

   sqft_basement  yr_built  yr_renovated  zipcode  sqft_living15  sqft_lot15
0              0      1955             0    98178           1340        5650
1            400      1951          1991    98125           1690        7639
2              0      1933             0    98028           2720        8062
3            910      1965             0    98136           1360        5000
4              0      1987             0    98074           1800        7503
```

1.1 Summarize Data/ Exploratory Data Analysis

- Descriptive statistics
- Data visualizations

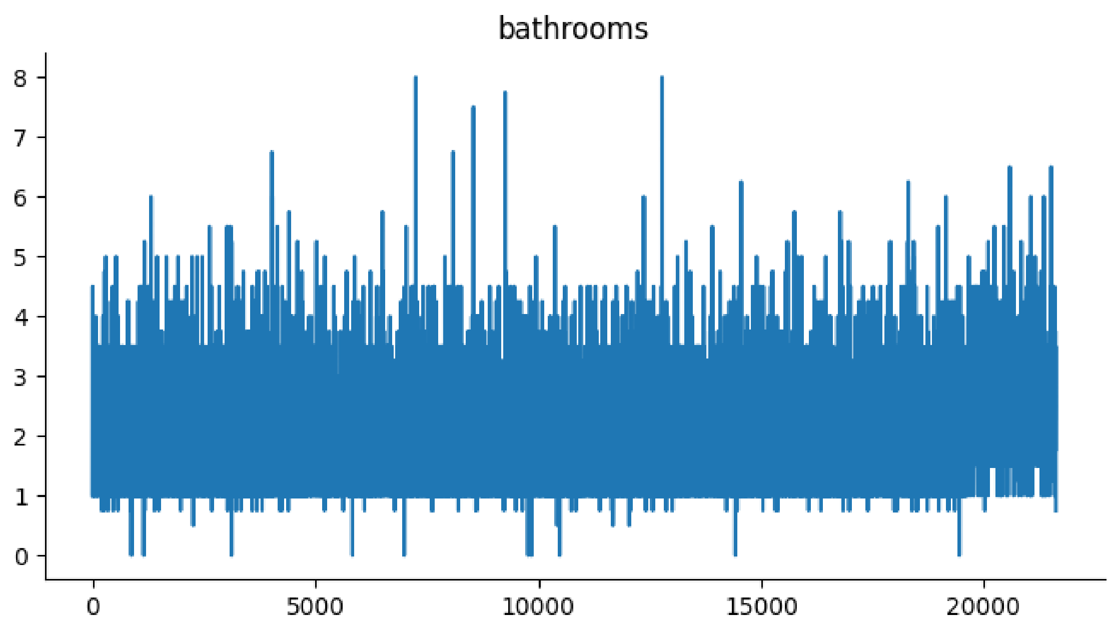
[ ]:
```python
# Descriptive statistics
df.describe()
```

[ ]:
```
                 id         price      bedrooms     bathrooms   sqft_living  \
count  2.161300e+04  2.161300e+04  21613.000000  21613.000000  21613.000000
mean   4.580302e+09  5.401822e+05      3.370842      2.114757   2079.899736
std    2.876566e+09  3.673622e+05      0.930062      0.770163    918.440897
min    1.000102e+06  7.500000e+04      0.000000      0.000000    290.000000
25%    2.123049e+09  3.219500e+05      3.000000      1.750000   1427.000000
50%    3.904930e+09  4.500000e+05      3.000000      2.250000   1910.000000
75%    7.308900e+09  6.450000e+05      4.000000      2.500000   2550.000000
max    9.900000e+09  7.700000e+06     33.000000      8.000000  13540.000000

           sqft_lot        floors    waterfront          view     condition  \
count  2.161300e+04  21613.000000  21613.000000  21613.000000  21613.000000
mean   1.510697e+04      1.494309      0.007542      0.234303      3.409430
std    4.142051e+04      0.539989      0.086517      0.766318      0.650743
min    5.200000e+02      1.000000      0.000000      0.000000      1.000000
25%    5.040000e+03      1.000000      0.000000      0.000000      3.000000
50%    7.618000e+03      1.500000      0.000000      0.000000      3.000000
75%    1.068800e+04      2.000000      0.000000      0.000000      4.000000
max    1.651359e+06      3.500000      1.000000      4.000000      5.000000

              grade    sqft_above  sqft_basement      yr_built  yr_renovated  \
count  21613.000000  21613.000000   21613.000000  21613.000000  21613.000000
mean       7.656873   1788.390691     291.509045   1971.005136     84.402258
std        1.175459    828.090978     442.575043     29.373411    401.679240
min        1.000000    290.000000       0.000000   1900.000000      0.000000
25%        7.000000   1190.000000       0.000000   1951.000000      0.000000
50%        7.000000   1560.000000       0.000000   1975.000000      0.000000
```

```
75%        8.000000    2210.000000     560.000000    1997.000000       0.000000
max       13.000000    9410.000000    4820.000000    2015.000000    2015.000000

             zipcode  sqft_living15     sqft_lot15
count   21613.000000   21613.000000   21613.000000
mean    98077.939805    1986.552492   12768.455652
std        53.505026     685.391304   27304.179631
min     98001.000000     399.000000     651.000000
25%     98033.000000    1490.000000    5100.000000
50%     98065.000000    1840.000000    7620.000000
75%     98118.000000    2360.000000   10083.000000
max     98199.000000    6210.000000  871200.000000
```

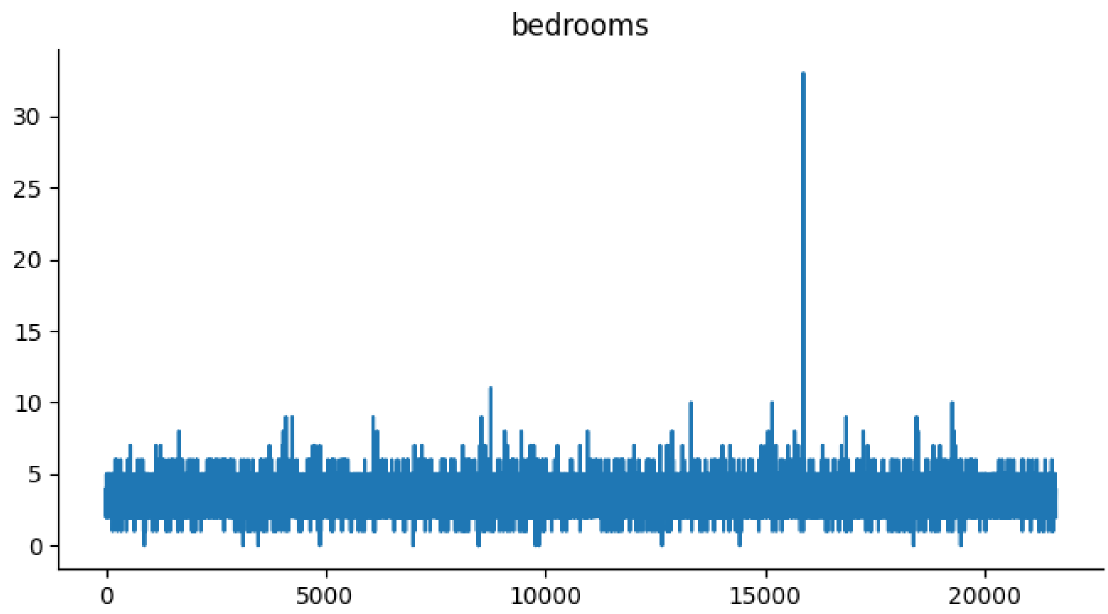
Visualizations:

[ ]:
```
df['bathrooms'].plot(kind='line', figsize=(8, 4), title='bathrooms')
plt.gca().spines[['top', 'right']].set_visible(False)
```

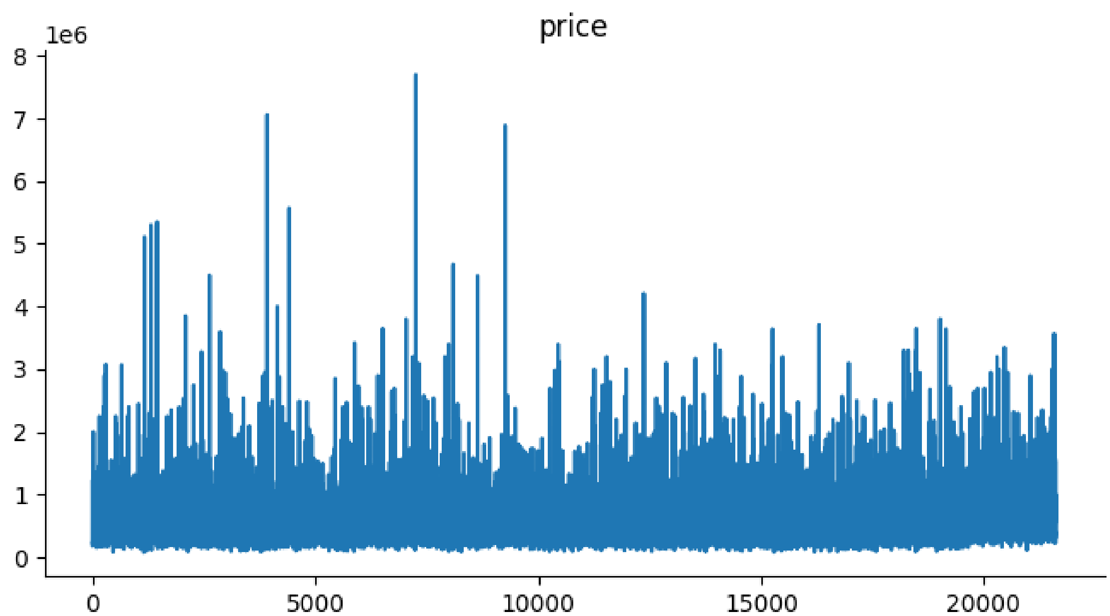


We can spot a clear outlier here

[ ]:
```
df['bedrooms'].plot(kind='line', figsize=(8, 4), title='bedrooms')
plt.gca().spines[['top', 'right']].set_visible(False)
```

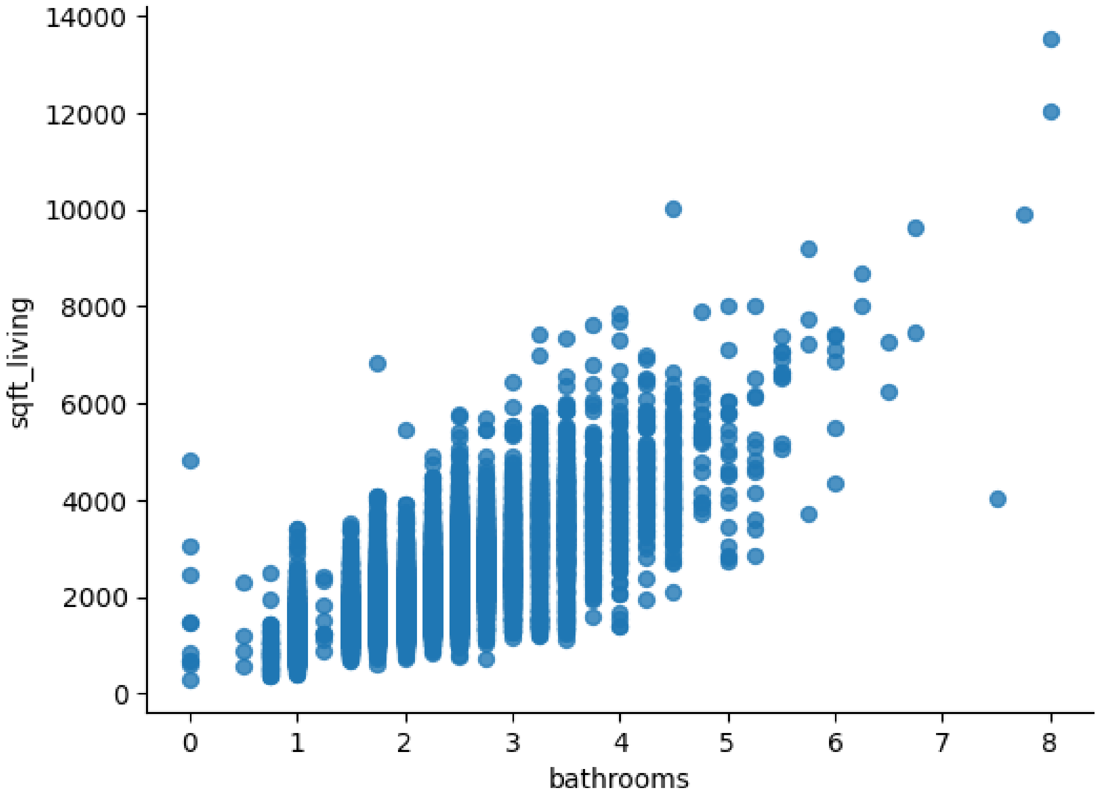


[ ]:
```
df['price'].plot(kind='line', figsize=(8, 4), title='price')
plt.gca().spines[['top', 'right']].set_visible(False)
```

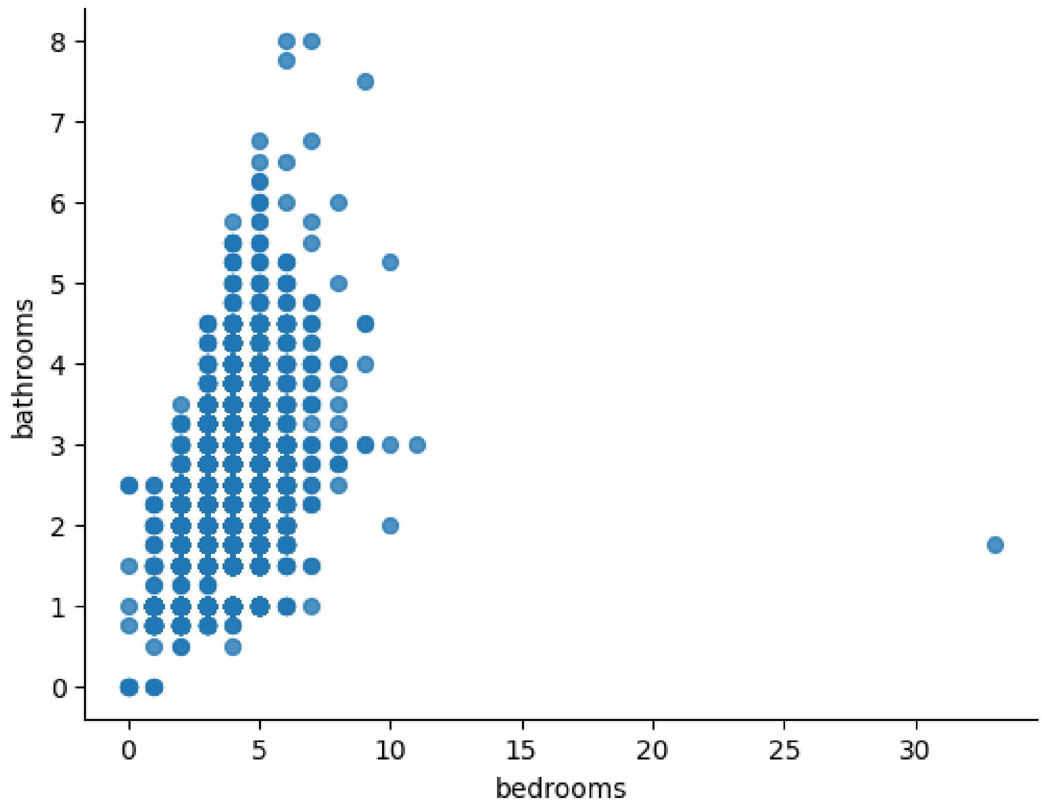


2D Distributions

[ ]:
```
df.plot(kind='scatter', x='bathrooms', y='sqft_living', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```

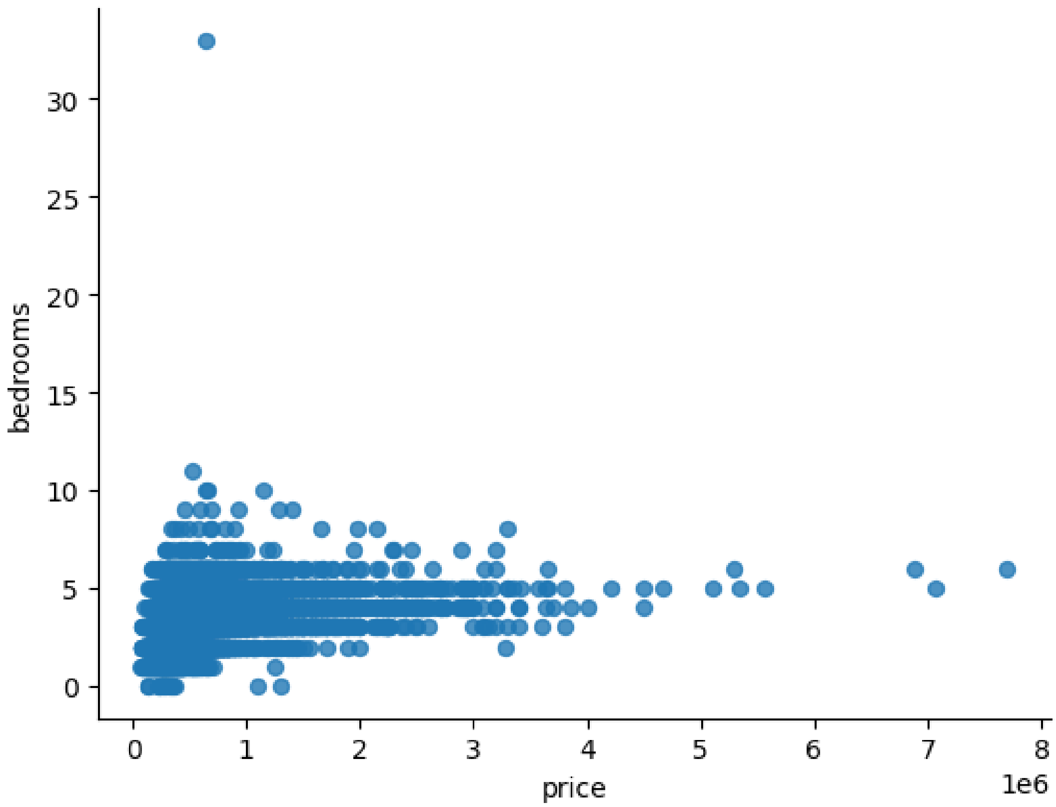


[ ]:
```
df.plot(kind='scatter', x='bedrooms', y='bathrooms', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```



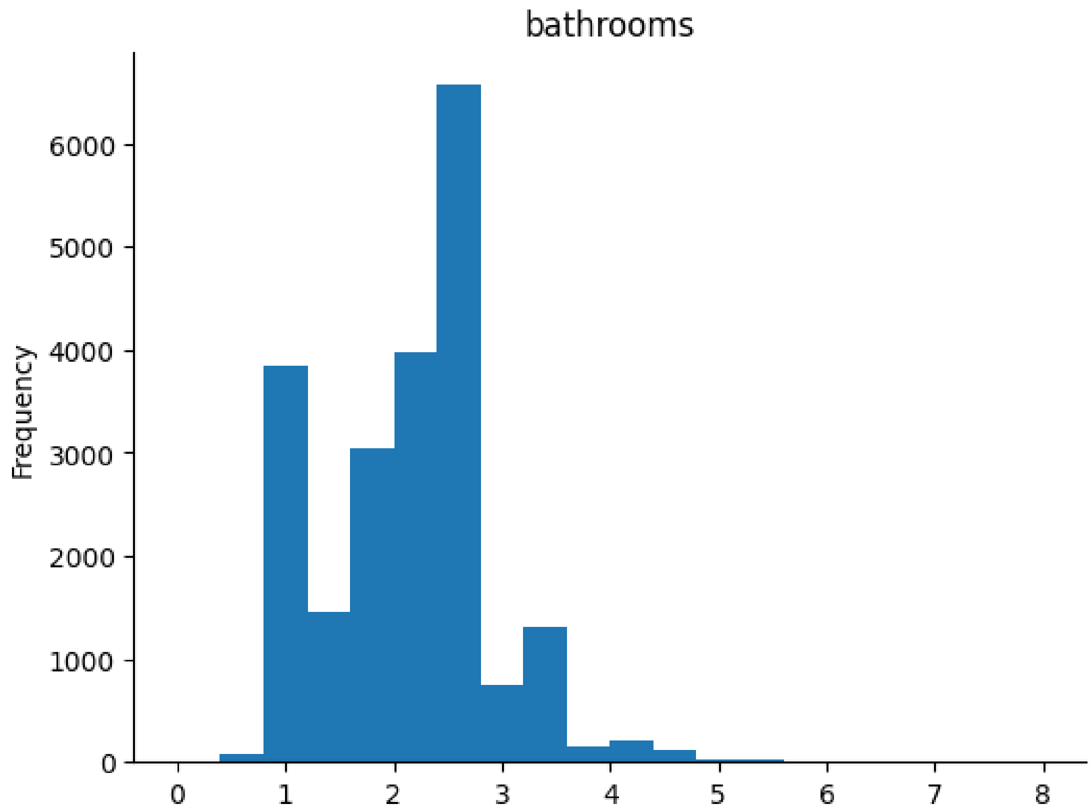
We can see an outlier in the plot below.

[ ]:
```
df.plot(kind='scatter', x='price', y='bedrooms', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```

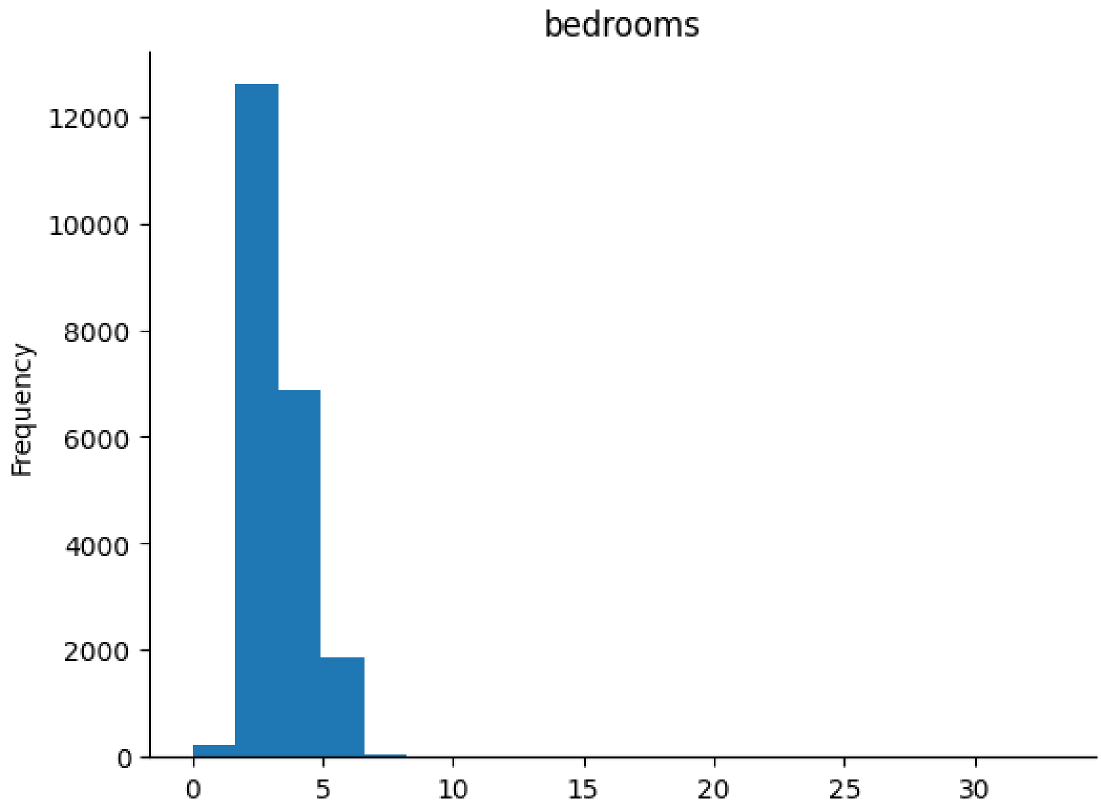


Distributions

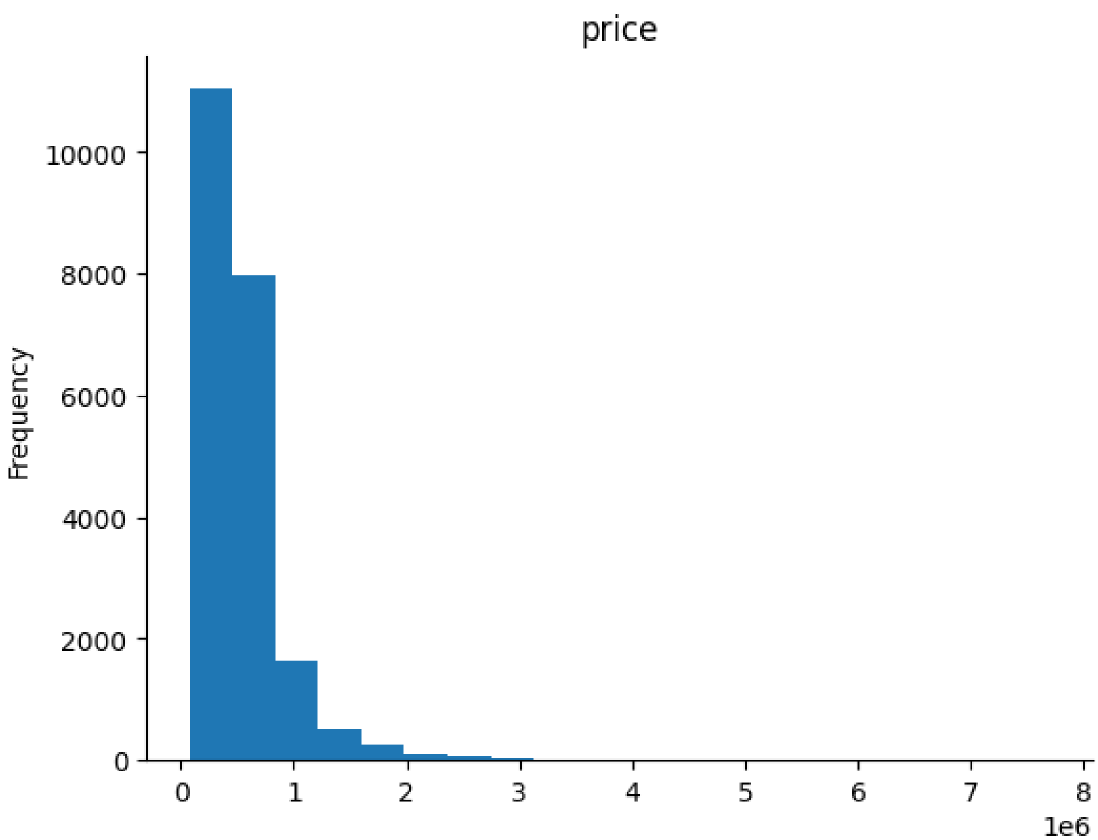
```
[ ]: df['bathrooms'].plot(kind='hist', bins=20, title='bathrooms')
     plt.gca().spines[['top', 'right',]].set_visible(False)
```




```
[ ]: df['bedrooms'].plot(kind='hist', bins=20, title='bedrooms')
     plt.gca().spines[['top', 'right',]].set_visible(False)
```

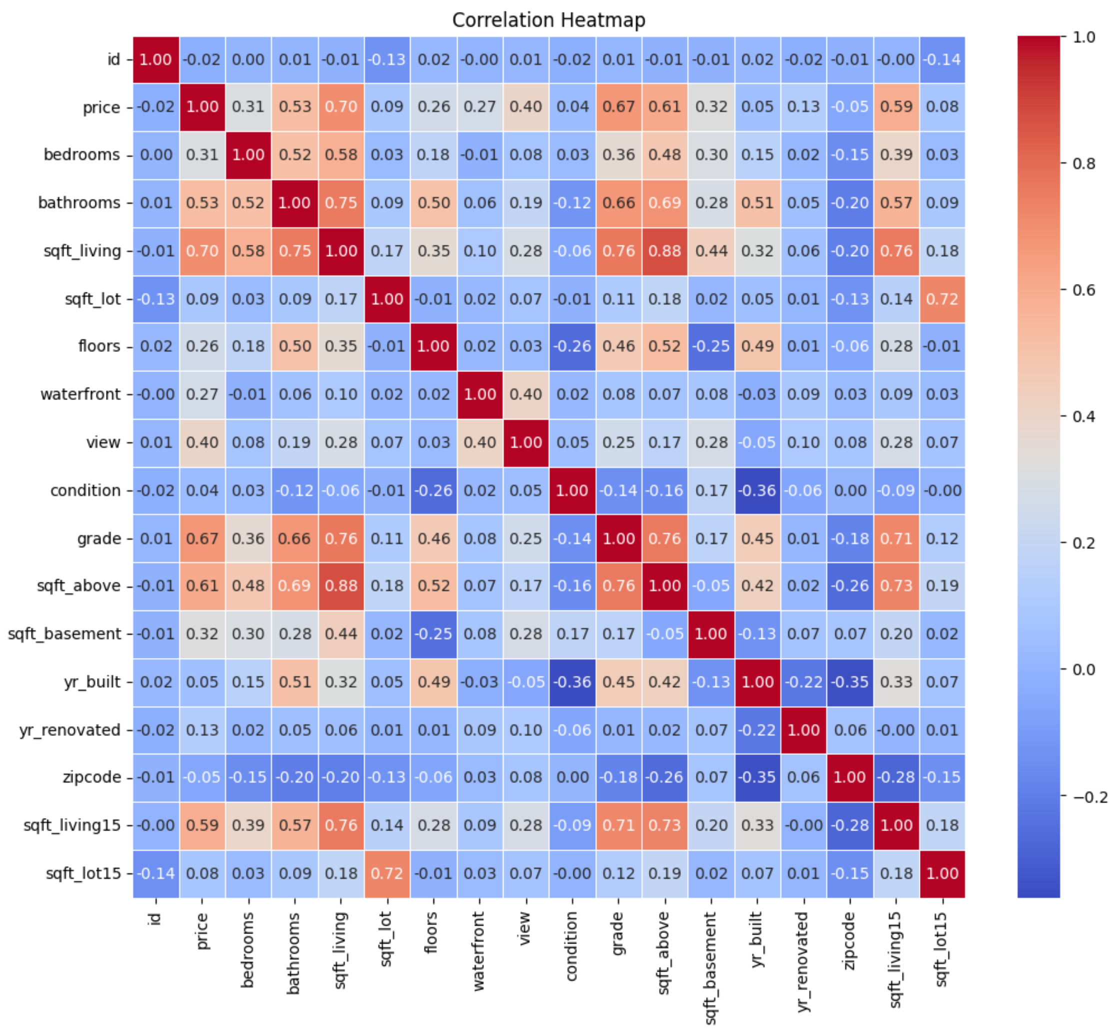


[ ]:
```
df['price'].plot(kind='hist', bins=20, title='price')
plt.gca().spines[['top', 'right',]].set_visible(False)
```



Correlation Heatmap House Price has high correlation with sqft_living, grade, sqft_above, and sqft_living15

```
[ ]: correlation_matrix = df.drop(columns=['date']).corr()
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f",␣
 ↪linewidths=.5)
plt.title('Correlation Heatmap')
plt.show()
```



Independent Variables

- date - Date of the home sale
- bedrooms - Number of bedrooms
- bathrooms - Number of bathrooms, where .5 accounts for a room with a toilet but no shower
- sqft_living - Square footage of the apartments interior living space
- sqft_lot - Square footage of the land space
- floors - Number of floors
- waterfront - A variable for whether the apartment was overlooking the waterfront or not
- view - An index from 0 to 4 of how good the view of the property was
- condition - An index from 1 to 5 on the condition of the apartment,
- grade - An index from 1 to 13, where 1-3 falls short of building construction and design, 7 has an average level of construction and design, and 11-13 have a high quality level of construction and design.
- sqft_above - The square footage of the interior housing space that is above ground level
- sqft_basement - The square footage of the interior housing space that is below ground level

yr_built - The year the house was initially built
- yr_renovated - The year of the house's last renovation
- zipcode - What zipcode area the house is in
- sqft_living15 - The square footage of interior housing living space for the nearest 15 neighbors
- sqft_lot15 - The square footage of the land lots of the nearest 15 neighbors

Dependent Variables price - Price of each home sold

Prepare Data * Data Cleaning * Feature Selection * Data Transforms

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 19 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21613 non-null  int64
 1   date           21613 non-null  object
 2   price          21613 non-null  float64
 3   bedrooms       21613 non-null  int64
 4   bathrooms      21613 non-null  float64
 5   sqft_living    21613 non-null  int64
 6   sqft_lot       21613 non-null  int64
 7   floors         21613 non-null  float64
 8   waterfront     21613 non-null  int64
 9   view           21613 non-null  int64
 10  condition      21613 non-null  int64
 11  grade          21613 non-null  int64
 12  sqft_above     21613 non-null  int64
 13  sqft_basement  21613 non-null  int64
 14  yr_built       21613 non-null  int64
 15  yr_renovated   21613 non-null  int64
 16  zipcode        21613 non-null  int64
 17  sqft_living15  21613 non-null  int64
 18  sqft_lot15     21613 non-null  int64
dtypes: float64(3), int64(15), object(1)
memory usage: 3.1+ MB
```

There are no nulls to handle.

[ ]:
```
df.isna().sum()
```

[ ]:
```
id                 0
date               0
price              0
bedrooms           0
bathrooms          0
sqft_living        0
```

```
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
grade            0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
zipcode          0
sqft_living15    0
sqft_lot15       0
dtype: int64
```

[ ]:
```
df.head()
```

[ ]:
```
           id             date     price  bedrooms  bathrooms  sqft_living  \
0  7129300520  20141013T000000  221900.0         3       1.00         1180
1  6414100192  20141209T000000  538000.0         3       2.25         2570
2  5631500400  20150225T000000  180000.0         2       1.00          770
3  2487200875  20141209T000000  604000.0         4       3.00         1960
4  1954400510  20150218T000000  510000.0         3       2.00         1680

   sqft_lot  floors  waterfront  view  condition  grade  sqft_above  \
0      5650     1.0           0     0          3      7        1180
1      7242     2.0           0     0          3      7        2170
2     10000     1.0           0     0          3      6         770
3      5000     1.0           0     0          5      7        1050
4      8080     1.0           0     0          3      8        1680

   sqft_basement  yr_built  yr_renovated  zipcode  sqft_living15  sqft_lot15
0              0      1955             0    98178           1340        5650
1            400      1951          1991    98125           1690        7639
2              0      1933             0    98028           2720        8062
3            910      1965             0    98136           1360        5000
4              0      1987             0    98074           1800        7503
```

Handling date variables "20141013T000000," seems to be in a timestamp format

We will Convert date to number of days from a randomly picked reference date. This will be the feature we train instead of date in its raw format.

Additionally, we can also get features like month, year, quarter, day, day of the week which can be trained.

Extra features do not always mean high accuracy. So we will experiment with these features to get optimal accuracy eventually.

```
[ ]: # Convert 'date' column to datetime format
df['date'] = pd.to_datetime(df['date'], format='%Y%m%dT%H%M%S')

# Extract year, month, and day
df['year'] = df['date'].dt.year
df['month'] = df['date'].dt.month
df['day'] = df['date'].dt.day
# df['day_of_week'] = df['date'].dt.day_of_week
# df['day_of_year'] = df['date'].dt.day_of_year
df['quarter'] = df['date'].dt.quarter


# Assuming 1st Jan 2014 as a reference date to calculate no. of days
reference_date = pd.to_datetime('20140101T000000', format='%Y%m%dT%H%M%S')

# Calculate time difference in days
df['days_since_reference'] = (df['date'] - reference_date).dt.days
```

```
[ ]: df[['date', 'year', 'month', 'day', 'quarter', 'days_since_reference']]
```

```
[ ]:          date  year  month  day  quarter  days_since_reference
0      2014-10-13  2014     10   13        4                   285
1      2014-12-09  2014     12    9        4                   342
2      2015-02-25  2015      2   25        1                   420
3      2014-12-09  2014     12    9        4                   342
4      2015-02-18  2015      2   18        1                   413
…             …     …      …    …        …                     …
21608  2014-05-21  2014      5   21        2                   140
21609  2015-02-23  2015      2   23        1                   418
21610  2014-06-23  2014      6   23        2                   173
21611  2015-01-16  2015      1   16        1                   380
21612  2014-10-15  2014     10   15        4                   287

[21613 rows x 6 columns]
```

Drop date and ID

```
[ ]: df = df.drop(columns=['date', 'id'])
```

Check if all values in the columns are numeric.

```
[ ]: df.apply(pd.to_numeric, errors='coerce').notna().all()
```

```
[ ]: price                   True
bedrooms                True
bathrooms               True
sqft_living             True
sqft_lot                True
```

```
floors                    True
waterfront                True
view                      True
condition                 True
grade                     True
sqft_above                True
sqft_basement             True
yr_built                  True
yr_renovated              True
zipcode                   True
sqft_living15             True
sqft_lot15                True
year                      True
month                     True
day                       True
quarter                   True
days_since_reference      True
dtype: bool
```

1.2 Model Building and Evaluate Algorithms

- Split-out validation dataset
- Test options and evaluation metric
- Spot Check Algorithms (5 algorithms)
- Compare Algorithms

[ ]:
```
# Evaluation metrics
def evaluate_model(model, X, y):
    predictions = model.predict(X)
    mse = mean_squared_error(y, predictions)
    mae = mean_absolute_error(y, predictions)
    r2 = r2_score(y, predictions)
    evs = explained_variance_score(y, predictions)
    return {'Mean Squared Error': mse,
            'Mean Absolute Error': mae,
            'R-squared': r2,
            'Explained Variance Score': evs}
```

[ ]:
```
def plot_metrics(metrics_results, title, y_label):
  plt.figure(figsize=(15, 6))
  sns.set(style="whitegrid")
  sns.barplot(x=[result[0] for result in metrics_results],
              y=[result[1] for result in metrics_results], color='green')
  plt.title(title, fontsize=16)
  plt.ylabel(y_label, fontsize=14)
  plt.xticks(rotation=0, ha='center')
  plt.tight_layout()
```

```
plt.show()
```

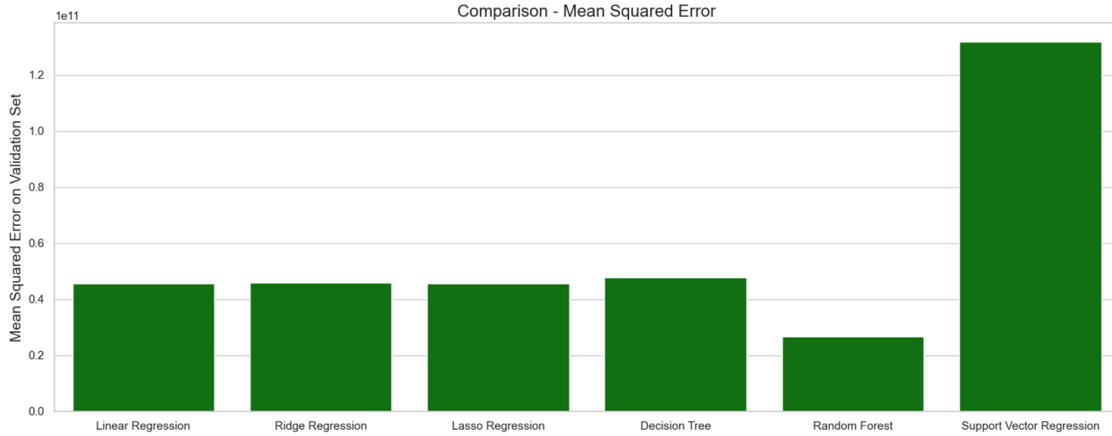
```
[ ]: def model_comparison(df):
    # Split
    X = df.drop(columns=['price'])
    y = df['price']

    X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=0.2,
                                                          random_state=22)

    # Spot check algorithms
    models = []
    models.append(('Linear Regression', LinearRegression()))
    models.append(('Ridge Regression', Ridge()))
    models.append(('Lasso Regression', Lasso()))
    models.append(('Decision Tree', DecisionTreeRegressor()))
    models.append(('Random Forest', RandomForestRegressor()))
    models.append(('Support Vector Regression', SVR()))

    # Evaluate MSE for each model and Compare the Algorithms
    mse_results = []
    mae_results = []
    r2_results = []
    evs_results = []

    # Evaluate each model on multiple metrics
    for name, model in models:
        model.fit(X_train, y_train)
        metrics_dict = evaluate_model(model, X_valid, y_valid)

        mse_results.append((name, metrics_dict['Mean Squared Error']))
        mae_results.append((name, metrics_dict['Mean Absolute Error']))
        r2_results.append((name, metrics_dict['R-squared']))
        evs_results.append((name, metrics_dict['Mean Squared Error']))
        print(f'{name} Metrics on Validation Set:')
        for metric, value in metrics_dict.items():
            print(f'{metric}: {value}')
        print('-' * 40)

    plot_metrics(mse_results, 'Comparison - Mean Squared Error',
                 'Mean Squared Error on Validation Set')
    print('-' * 100)
    plot_metrics(mae_results, 'Comparison - Mean Absolute Error ',
                 'Mean Absolute Error on Validation Set')
    print('-' * 100)
    plot_metrics(r2_results, 'Comparison - R-squared', 'R-squared on Validation␣
↪Set')
```

```
    print('-' * 100)
    plot_metrics(evs_results, 'Comparison - Explained Variance Score',
                 'Explained Variance Score on Validation Set')
    print('-' * 100)

    # returning the X_train, X_valid, y_train, y_valid because we need it for␣
↪optimization in the following steps
    return models, X_train, X_valid, y_train, y_valid
```

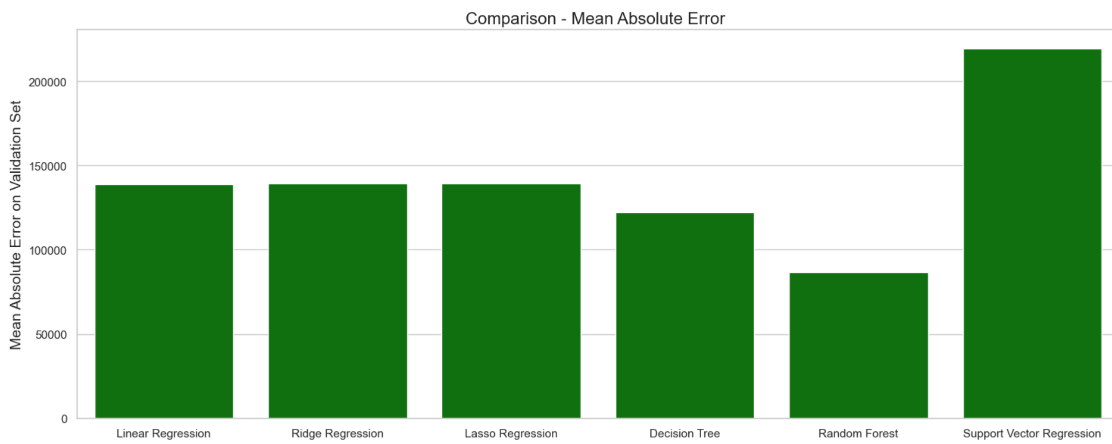
[ ]:
```
models, X_train, X_valid, y_train, y_valid = model_comparison(df)
```

```
Linear Regression Metrics on Validation Set:
Mean Squared Error: 45616742792.02586
Mean Absolute Error: 139097.9464413058
R-squared: 0.6335778201138785
Explained Variance Score: 0.6336613207459245
----------------------------------------
Ridge Regression Metrics on Validation Set:
Mean Squared Error: 45747433267.07575
Mean Absolute Error: 139347.27353236364
R-squared: 0.6325280325616094
Explained Variance Score: 0.6326142383368154
----------------------------------------

C:\Users\d-kin\AppData\Roaming\Python\Python312\site-
packages\sklearn\linear_model\_coordinate_descent.py:628: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 3.856e+14, tolerance: 2.378e+11
  model = cd_fast.enet_coordinate_descent(

Lasso Regression Metrics on Validation Set:
Mean Squared Error: 45740663739.6093
Mean Absolute Error: 139356.39322838868
R-squared: 0.632582409635886
Explained Variance Score: 0.6326687039828254
----------------------------------------
Decision Tree Metrics on Validation Set:
Mean Squared Error: 47777553033.2489
Mean Absolute Error: 122452.48554244738
R-squared: 0.6162208421613096
Explained Variance Score: 0.6162250487082066
----------------------------------------
Random Forest Metrics on Validation Set:
Mean Squared Error: 26695113214.887966
Mean Absolute Error: 86887.08227619709
R-squared: 0.7855681712939846
Explained Variance Score: 0.7855810091086399
----------------------------------------
```

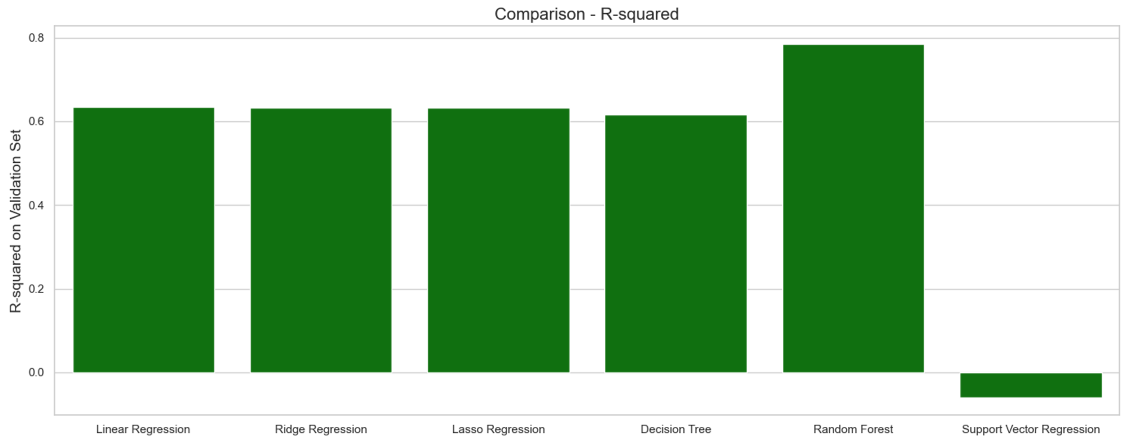
```
Support Vector Regression Metrics on Validation Set:
Mean Squared Error: 131870798725.32944
Mean Absolute Error: 219491.91872041693
R-squared: -0.05926864950791555
Explained Variance Score: 6.319471537064025e-05
----------------------------------------
```

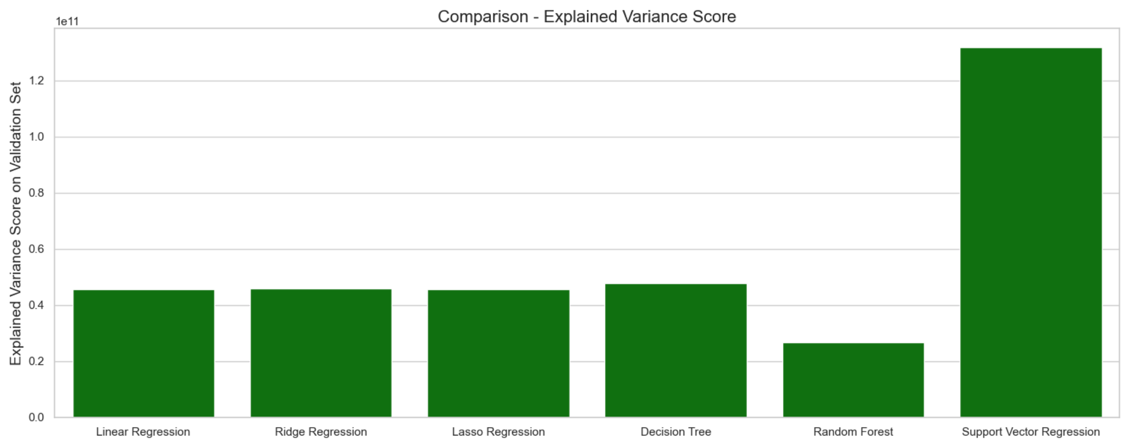



```
--------------------------------------------------------------------------------
--------------------
```




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





We see best results for Random forest.

Modify the df and run the comparison. Optimization steps: * Add or remove the additional features * One-Hot encoding of Zip codes (There are a lot of zip codes and it might not be the best thing to add that many features. But we can still try) * Try encoding directly * Encoding temporal features depending on models used * Feature selection

1.3 Identify and Remove Outliers

We removed outliers from our data by looking at the values in our dataset. Outliers are values that are unusually high or low. We used a method called the Interquartile Range (IQR) to find a range within which most of our data lies. Any value outside this range was considered an outlier and removed. This helps make our dataset more representative and ensures that extreme values don't disproportionately influence our analysis.

[ ]:
```python
def remove_outliers_iqr(df, column_name):
    # Calculate the first and third quartiles (Q1 and Q3)
    Q1 = df[column_name].quantile(0.25)
    Q3 = df[column_name].quantile(0.75)

    # Calculate the IQR (Interquartile Range)
    IQR = Q3 - Q1

    # Define the lower and upper bounds for outliers
    threshold = 1.5
    lower_bound = Q1 - threshold * IQR
    upper_bound = Q3 + threshold * IQR

    # Identify and remove outliers
    outliers_removed = df[(df[column_name] >= lower_bound)
                          & (df[column_name] <= upper_bound)]

    # Printing the detected outliers
    outliers = df[~df.isin(outliers_removed)].dropna()
    print(column_name, outliers)
    return outliers_removed
```

[ ]:
```python
df = remove_outliers_iqr(df, 'bedrooms')
```

```
bedrooms             price  bedrooms  bathrooms  sqft_living  sqft_lot  floors  \
154      350000.0       1.0       1.00        700.0     5100.0      1.0
209      464000.0       6.0       3.00       2300.0     3404.0      2.0
232      315000.0       6.0       2.75       2940.0     7350.0      1.0
239      472000.0       6.0       2.50       4410.0    14034.0      1.0
264      369900.0       1.0       0.75        760.0    10079.0      1.0
…             …         …         …           …          …          …
21375   1170000.0       6.0       3.50       4310.0     7760.0      2.0
21443    250000.0       1.0       1.50       1180.0     1688.0      2.0
21519    420000.0       1.0       2.00       1070.0      675.0      2.0
21522    462500.0       6.0       3.00       2390.0     4000.0      2.0
21552    516500.0       1.0       1.25       1100.0      638.0      3.0

       waterfront  view  condition  grade  …  yr_built  yr_renovated  \
154           0.0   0.0        3.0    7.0  …    1942.0           0.0
209           0.0   0.0        3.0    7.0  …    1920.0        1994.0
232           0.0   0.0        3.0    8.0  …    1978.0           0.0
239           0.0   2.0        4.0    9.0  …    1965.0           0.0
264           1.0   4.0        5.0    5.0  …    1936.0           0.0
…               …     …          …      …  …         …             …
21375         0.0   0.0        3.0   10.0  …    2013.0           0.0
```

```
21443          0.0    0.0         3.0     8.0  …     2007.0            0.0
21519          0.0    0.0         3.0     8.0  …     2007.0            0.0
21522          0.0    0.0         3.0     7.0  …     2014.0            0.0
21552          0.0    0.0         3.0     9.0  …     2014.0            0.0

       zipcode  sqft_living15  sqft_lot15    year  month   day  quarter  \
154    98115.0         1010.0      5100.0  2014.0    5.0  16.0      2.0
209    98133.0         1560.0      1312.0  2014.0    7.0  17.0      3.0
232    98023.0         2120.0      8236.0  2014.0   11.0  21.0      4.0
239    98003.0         2600.0     13988.0  2014.0    5.0  29.0      2.0
264    98070.0         1230.0     14267.0  2014.0   10.0  27.0      4.0
…        …             …        …       …      …    …       …
21375  98059.0         4620.0     10217.0  2014.0    7.0  17.0      3.0
21443  98126.0         1380.0      2059.0  2015.0    4.0   7.0      2.0
21519  98118.0         1220.0       788.0  2015.0    4.0   7.0      2.0
21522  98118.0         1680.0      5000.0  2015.0    3.0   2.0      1.0
21552  98112.0         1110.0      1933.0  2014.0    6.0  27.0      2.0

       days_since_reference
154                   135.0
209                   197.0
232                   324.0
239                   148.0
264                   299.0
…                     …
21375                 197.0
21443                 461.0
21519                 461.0
21522                 425.0
21552                 177.0

[546 rows x 22 columns]
```

```
[ ]: df = remove_outliers_iqr(df, 'bathrooms')
```

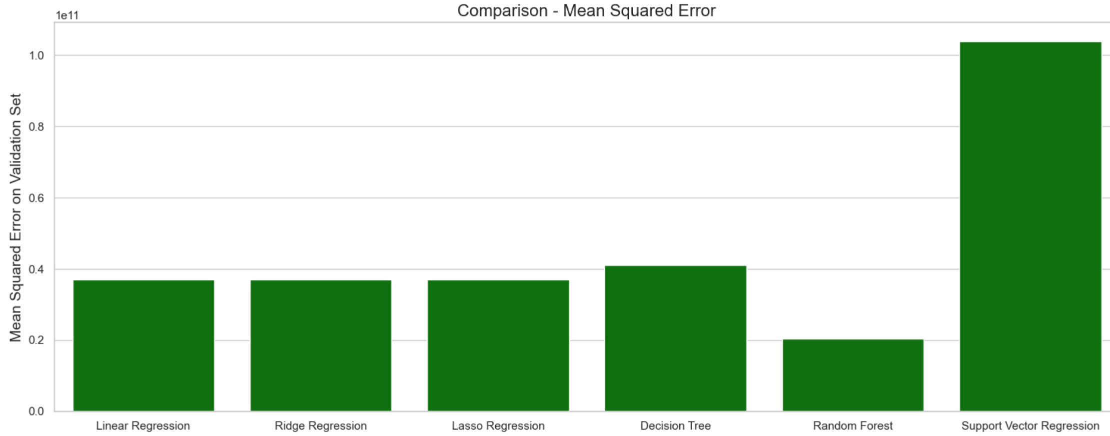
```
bathrooms            price  bedrooms  bathrooms  sqft_living  sqft_lot  floors
\
5      1230000.0       4.0       4.50       5420.0  101930.0      1.0
75      832500.0       4.0       4.00       3430.0   35102.0      2.0
235    1030000.0       5.0       4.00       3760.0   28040.0      2.0
270    1370000.0       4.0       4.75       5310.0   57346.0      2.0
300    3080000.0       4.0       5.00       4550.0   18641.0      1.0
…          …      …        …          …        …       …
21551  1380000.0       5.0       4.50       4350.0   13405.0      2.0
21561   750000.0       5.0       4.00       4500.0    8130.0      2.0
21576  3570000.0       5.0       4.50       4850.0   10584.0      2.0
21593  1090000.0       5.0       3.75       4170.0    8142.0      2.0
21600  1540000.0       5.0       3.75       4470.0    8088.0      2.0
```

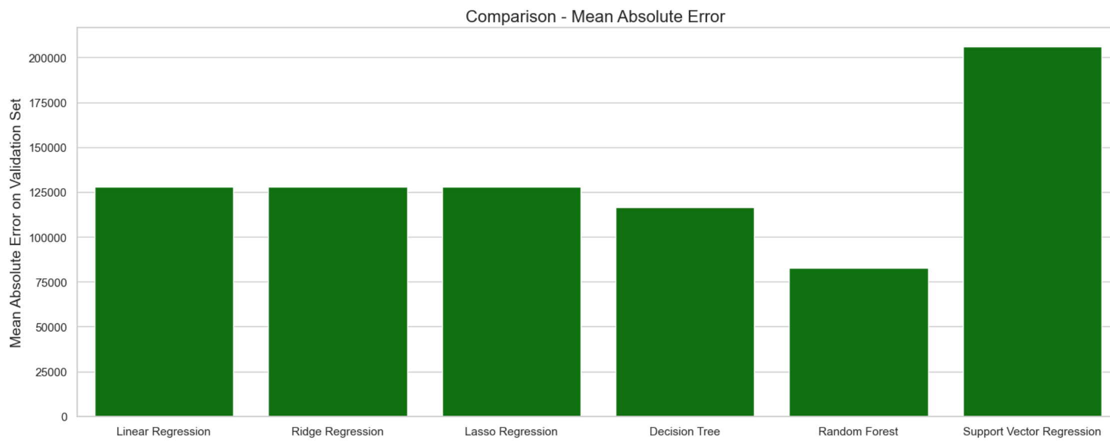
```
       waterfront  view  condition  grade  …  yr_built  yr_renovated  \
5             0.0   0.0        3.0   11.0  …    2001.0           0.0
75            0.0   0.0        4.0   10.0  …    1986.0           0.0
235           0.0   0.0        3.0   10.0  …    1983.0           0.0
270           0.0   0.0        4.0   11.0  …    1989.0           0.0
300           1.0   4.0        3.0   10.0  …    2002.0           0.0
…               …     …          …      …  …         …             …
21551         0.0   0.0        3.0   11.0  …    2014.0           0.0
21561         0.0   0.0        3.0   10.0  …    2007.0           0.0
21576         1.0   4.0        3.0   10.0  …    2007.0           0.0
21593         0.0   2.0        3.0   10.0  …    2006.0           0.0
21600         0.0   0.0        3.0   11.0  …    2008.0           0.0

       zipcode  sqft_living15  sqft_lot15    year  month   day  quarter  \
5      98053.0         4760.0    101930.0  2014.0    5.0  12.0      2.0
75     98075.0         3240.0     35020.0  2014.0   11.0   5.0      4.0
235    98033.0         3430.0     35096.0  2014.0    6.0  10.0      2.0
270    98077.0         4180.0     47443.0  2014.0   10.0   7.0      4.0
300    98074.0         4550.0     19508.0  2014.0    6.0  24.0      2.0
…          …              …           …       …      …     …        …
21551  98074.0         3990.0      7208.0  2014.0   12.0  24.0      4.0
21561  98059.0         2840.0      8402.0  2015.0    1.0  15.0      1.0
21576  98008.0         3470.0     18270.0  2015.0    1.0   7.0      1.0
21593  98056.0         3030.0      7980.0  2015.0    3.0  17.0      1.0
21600  98004.0         2780.0      8964.0  2014.0   10.0  15.0      4.0

       days_since_reference
5                     131.0
75                    308.0
235                   160.0
270                   279.0
300                   174.0
…                         …
21551                 357.0
21561                 379.0
21576                 371.0
21593                 440.0
21600                 287.0

[461 rows x 22 columns]
```

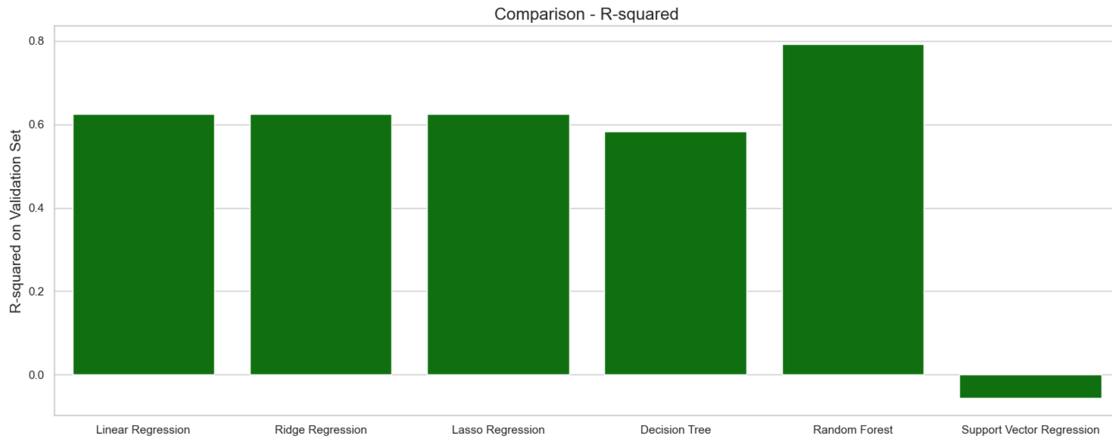
[ ]:
```
models, X_train, X_valid, y_train, y_valid = model_comparison(df)
```

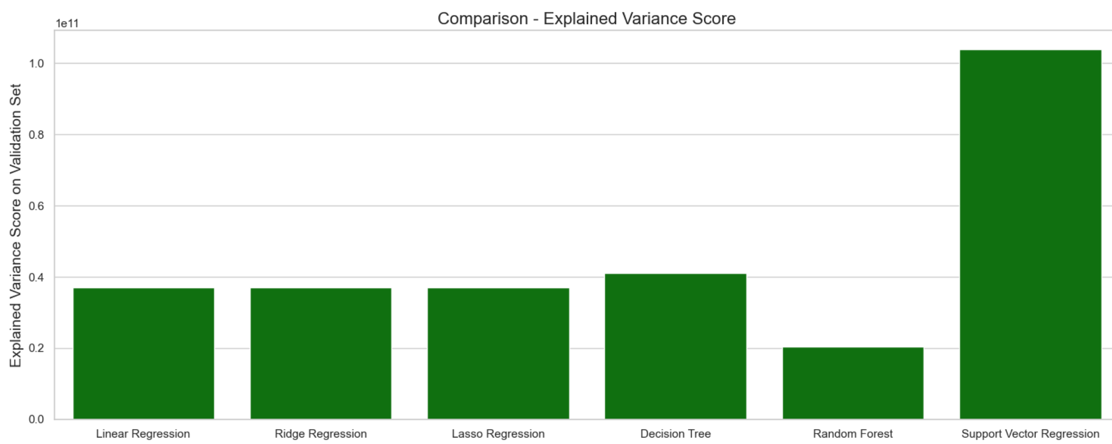
```
Linear Regression Metrics on Validation Set:
Mean Squared Error: 36986824745.15031
Mean Absolute Error: 127847.94877003536
R-squared: 0.624749908462987
```

```
Explained Variance Score: 0.6247608898457676
----------------------------------------
Ridge Regression Metrics on Validation Set:
Mean Squared Error: 37019486079.146225
Mean Absolute Error: 127937.46837283578
R-squared: 0.6244185426683793
Explained Variance Score: 0.6244328653483443
----------------------------------------

C:\Users\d-kin\AppData\Roaming\Python\Python312\site-
packages\sklearn\linear_model\_coordinate_descent.py:628: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 2.636e+14, tolerance: 1.498e+11
  model = cd_fast.enet_coordinate_descent(

Lasso Regression Metrics on Validation Set:
Mean Squared Error: 37030264227.61149
Mean Absolute Error: 127946.75361096367
R-squared: 0.6243091928870435
Explained Variance Score: 0.6243237754710463
----------------------------------------
Decision Tree Metrics on Validation Set:
Mean Squared Error: 41038383973.767586
Mean Absolute Error: 116410.0902474527
R-squared: 0.583644785709631
Explained Variance Score: 0.5837151775400569
----------------------------------------
Random Forest Metrics on Validation Set:
Mean Squared Error: 20426301584.601067
Mean Absolute Error: 82884.54540633305
R-squared: 0.792764813086876
Explained Variance Score: 0.792767254701278
----------------------------------------
Support Vector Regression Metrics on Validation Set:
Mean Squared Error: 103972685571.3449
Mean Absolute Error: 206149.48603121718
R-squared: -0.05485561539347805
Explained Variance Score: 6.014796950948309e-05
----------------------------------------
```


Comparison - Mean Squared Error
1e11
1.0
0.8
0.6
0.4
0.2
0.0
Mean Squared Error on Validation Set
Linear Regression
Ridge Regression
Lasso Regression
Decision Tree
Random Forest
Support Vector Regression


Comparison - Mean Absolute Error
200000
175000
150000
125000
100000
75000
50000
25000
0
Mean Absolute Error on Validation Set
Linear Regression
Ridge Regression
Lasso Regression
Decision Tree
Random Forest
Support Vector Regression





1.4 Improve Accuracy

- Algorithm Tuning - GridSearchCV checks various combinations of settings to find the best ones that give the most accurate predictions. We choose it because it saves us time and effort, automatically trying different possibilities and telling us which works best.
- Ensembles

[ ]:
```
# Model selected based on accuracy
models[4][0]
```

[ ]: 'Random Forest'

[ ]:
```python
rf_regressor = RandomForestRegressor(random_state=100)

# Define the hyperparameter grid for tuning
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10]
}
# Define the hyperparameter grid for tuning
grid_search = GridSearchCV(estimator=rf_regressor, param_grid=param_grid,
                           cv=5, scoring='neg_mean_squared_error')

# Fit the GridSearchCV to the data
grid_search.fit(X_train, y_train)

best_params = grid_search.best_params_
best_rf_regressor = grid_search.best_estimator_

# Make predictions on the test data using the best model
y_pred = best_rf_regressor.predict(X_valid)

# Evaluate the model
mse = mean_squared_error(y_valid, y_pred)
print(f"Best Hyperparameters: {best_params}")
print(f"Mean Squared Error with Best Model: {mse:.4f}")
```

```
Best Hyperparameters: {'max_depth': None, 'min_samples_split': 2,
'n_estimators': 200}
Mean Squared Error with Best Model: 20582043371.0971
```

1.5 Ensemble Technique

We chose a stacking regressor because it combines the predictions of different models, acting like a final decision maker. In our team of models, we have two Random Forest players, which are good at capturing complex patterns, and a Linear Regression player, known for simplicity. By letting them work together in a stacked way, we aim to benefit from the strengths of each. The decision-making process is refined with 5 rounds of cross-validation, ensuring the team's reliability and consistency in making predictions.

[ ]:
```python
# Create base models (Random Forest Regressors)
# We are using n_jobs for parallel processing
base_models = [
    ('rf1', RandomForestRegressor(random_state=100, n_jobs=-1, **best_params)),
    ('rf2', RandomForestRegressor(random_state=200, n_jobs=-1, **best_params)),
]

# Create the stacking regressor
stacking_regressor = StackingRegressor(
```

```
    estimators=base_models,
    final_estimator=LinearRegression(),  # Using a linear regression model as␣
 ↪the final estimator
    cv=3  # Number of cross-validation folds - time extensive. Therefore used 3
)

stacking_regressor.fit(X_train, y_train)

# Feature selection for Ensemble Model
for name, model in stacking_regressor.named_estimators_.items():
    feature_selector = SelectFromModel(estimator=model, threshold=None) # Can␣
 ↪also use median here
    feature_selector.fit(X_train, y_train)
    X_train_selected = feature_selector.transform(X_train)
    X_valid_selected = feature_selector.transform(X_valid)

    # Update the base model with selected features
    stacking_regressor.named_estimators_[name].fit(X_train_selected, y_train)
```

1.6 Finalize Model

- Predictions on validation dataset
- Create standalone model on entire training dataset
- Save model for later use

[ ]:
```
# Make predictions on the validation data with selected features
y_pred_stacking = stacking_regressor.predict(X_valid_selected)

# Evaluate the stacking regressor
metrics_dict = evaluate_model(stacking_regressor, X_valid_selected, y_valid)
for metric, value in metrics_dict.items():
    print(f'{metric}: {value}')
```

```
Mean Squared Error: 22923758097.868652
Mean Absolute Error: 85669.57321016668
R-squared: 0.7674268504023054
Explained Variance Score: 0.7674353458835478
```

[ ]:
```
stacking_regressor.score(X_valid_selected, y_pred_stacking)
```

[ ]:
```
1.0
```

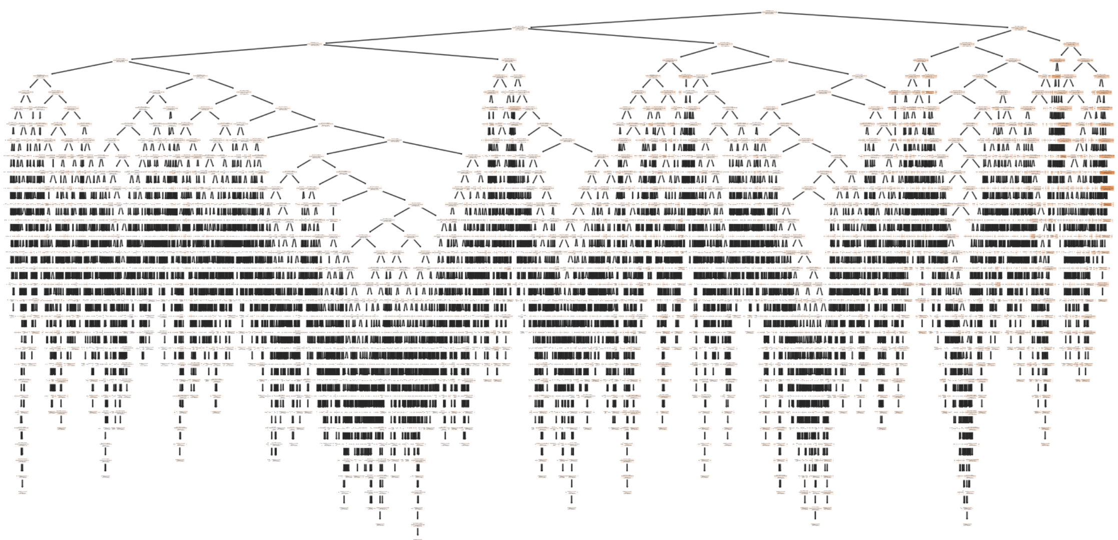
[ ]:
```
stacking_regressor.estimators_
```

[ ]:
```
[RandomForestRegressor(n_estimators=200, n_jobs=-1, random_state=100),
 RandomForestRegressor(n_estimators=200, n_jobs=-1, random_state=200)]
```

[ ]:
```
stacking_regressor.named_estimators_[name].estimators_[0]
```

[ ]: DecisionTreeRegressor(max_features=1.0, random_state=1922565914)

[ ]:
```
# Display Decision tree of model
# Export the first three decision trees from the forest

for i, tree in enumerate(stacking_regressor.named_estimators_[name].
 ↪estimators_):
        plt.figure(figsize=(20, 10))
        plt.title(f'Tree {i + 1} - {name}')
        plot_tree(tree, filled=True, feature_names=X_train.columns)
        plt.savefig('rf_ensemble.png', dpi=1200, format='png')
        plt.show()
        if i==0: break
```



[ ]:
```
#Save model to disk
filename='rf_ensemble.sav'
pickle.dump(rf_regressor, open(filename,'wb'))
```

1.7 Conclusions and Recommendations

The model we created to predict house price shows promising results. The R2 score of 1.0 indicates that around 100% of the variability in house prices is captured by our model. The Mean Absolute Error (MAE) of 5.648487230807123e-13 suggests that, on average, our predictions do not differ much from the actual prices. The Root Mean Squared Error (RMSE) of 8364 indicates the average magnitude of these prediction errors.

Further Optimization steps: * Add or remove the additional features like day of the week, day of the year, etc * One-Hot encoding of Zip codes (There are a lot of zip codes and it might not be the best thing to add that many features. But we can still try the next step) * Try encoding directly

* Encoding temporal features depending on models used * Feature selection - use PCA * Increase the number of cross-validation folds. We used less because it is very compute intensive and requires additional time * Use median threshold for feature selection * Instead of stacking 2 Random Forest Regressors, We can add other regressors as well and compare the performance