Predicting rent price using and associated features importance using Machine Learning

1. Problem formulation

We aim to predict apartment rent prices in Texas, USA, using key features like apartment size and location. The objective is to determine the significance of each feature in influencing these prices, enabling value-based pricing which focuses on customer-centric factors.

The dataset, provided by the University of California, Irvine (UCI Machine Learning Repository, 2019), contains rent data for apartments in the USA from 2019. It includes about 100,000 rows with 21 features, such as apartment type, number of bedrooms/bathrooms, amenities, and geographic details (city, state, latitude, longitude).

The report is organized as follows: Section 1 introduces the task, Section 2 defines the problem and explains the dataset, Section 3 describes the methodology, including model hypothesis, loss function, and feature engineering. Section 4 presents the empirical results, while Section 5 concludes and discusses future directions.

2. Method

2.1. Data processing and Exploratory Data Analysis (EDA)

We started the data preprocessing by filtering the dataset to focus on apartments located in Texas. Several unnecessary columns, such as 'id', 'category', 'title', 'body', 'time', 'address', 'currency', and 'price_display', were removed to streamline the analysis. The 'price_type' column, which was heavily skewed towards monthly pricing (with only three entries for weekly pricing), was simplified by removing these three rows. To enhance the predictive power, we split the 'Amenities' column into multiple binary columns, where each amenity was represented as either 0 (not present) or 1 (present), making them usable as model features.

Next, we conducted Exploratory Data Analysis (EDA) to understand the data more thoroughly. We examined the rent prices **('rent' column in the data set)** distribution and identified outliers, particularly those where rent exceeded $2,000. These outliers were removed to maintain a cleaner dataset. The analysis was then narrowed down to apartments in Texas with rents below $2,000, including 10,759 rows with 40 features.

2.2. Feature selection

For feature selection, we generated a correlation heatmap, which revealed a high correlation (between 0.75 and 0.77) among 'bathroom', 'bedroom', and 'square_feet'. To prevent multicollinearity, we retained only 'square_feet' as a predictor. Additionally, categorical variables such as 'has_photo', 'pets_allowed', and 'city_name' were converted into binary form using OneHotEncoding to include them as predictors in the model. (Appendix A). Moreover, since the geographic location given by longitude and lattitude is on continous scale, we are more interested in having them clustered into specific distinct areas for since it is common for house prices within certain vicinity to be the same due to many reasons such as same project spaces, landlords, development companies, etc. (Vorley, 2008; UCI Machine Learning Repository, 2019). However, due to uncertainties regarding the number of clusteres, we decided to make use of DBSCAN (Appendix B) clustering algorithm with Haversine distance metrics (*Haversine formula* *to find distance between two points on a sphere*, 2018; 'DBSCAN', 2024; *DBSCAN*, no date) to have a more accurate estimation of the distance between locations within a sphere. The Harersine distance between two points can be calculated using the following formular:

$$\boldsymbol{d = 2r * \sin^{-1}\left(\sqrt{\sin^2\left(\frac{\Phi_2 - \Phi_1}{2}\right) + \cos(\Phi_1)\cos(\Phi_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right)}$$

Where:

$r\ is\ the\ radius\ of\ the\ sphere$
$\Phi_1, \Phi_2\ are\ the\ latitude\ of\ point\ 1\ and\ latitude\ of\ point\ 2$
$\lambda_1, \lambda_2\ are\ the\ longitude\ of\ point\ 1\ and\ longitude\ of\ point\ 2$

Utilizing the clustering algorithm, we were able to make 11 main clusters around Texas (Appendix A).

2.3. Model validation

We decided to split the data into Train-test-split with 60-20-20 ratios. (*train_test_split*, no date)

Training Set (60%): This set is used to train the model. It consists of 60% of the total data and is used to fit the model and optimize its parameters (such as weights in regression). The model learns patterns in the data during this phase.

Validation Set (20%): After training, the model is evaluated on the validation set, which is 20% of the data. This set is not seen by the model during training. It helps in tuning the hyperparameters (e.g., the regularization strength in Ridge or Lasso regression) and avoiding overfitting. The performance on this set is used to select the best model configuration.

Test Set (20%): Finally, the test set, which is also 20% of the data, is used to evaluate the model's generalization performance. This set is only used after the model is fully trained and validated.

2.4 Model selection:

We selected a regression model as the preferred machine learning method (*MachineLearningTheBasics/MLBasicsBook.pdf at master · alexjungaalto/MachineLearningTheBasics*, no date). Linear models were chosen for their interpretability, as the output coefficients provide insights into the importance of each feature. Additionally, for continuous predicted values, the Mean Squared Error (MSE) loss function is an effective metric for comparing model performance, as it reflects how closely predictions align with true values. Therefore, we opted to use the following regression methods:

2.4.1 Linear Regressions:

Model (*LinearRegression*, no date):

$$y = \beta_i X_i + \epsilon$$

Hypothesis Space:

$$\mathcal{H}_{Linear} = \{X_i\beta_i : \beta_i \in \mathbb{R}^p\}$$

Linear Regression is suitable for finding coefficient weights because it directly minimizes the residual sum of squares, providing easily interpretable coefficients. The simplicity of this method allows for a clear understanding of the influence of each feature on the prediction.

2.4.2 Ridge Regression (L2 regularization)

Model (*Ridge*, no date):

$$y = \beta_i X_i + \epsilon$$

Objective Function:

$$\min_{\beta}(\|y - X_i\beta_i\|^2 + \lambda\|\beta_i\|^2)$$

Where λ is the regularization parameter.
Hypothesis Space:

$$\mathcal{H}_{Ridge} = \{X_i\beta_i : \beta_i \in \mathbb{R}^p, \|\beta_i\|^2 \leq C\}$$

The hypothesis space for Ridge Regression restricts the size of the coefficients by imposing an L2 penalty, preventing large values for β. The L2 penalty helps shrink the coefficient estimates, improving the model's generalization and stability while still maintaining interpretability.

2.4.3 Lasso Regression (L1 regularization)

Model (*Lasso*, no date):

$$y = \beta_i X_i + \epsilon$$

Objective Function:

$$\min_{\beta}(\|y - X_i\beta_i\|^2 + \lambda\|\beta_i\|_1)$$

Where λ is the regularization parameter.
Hypothesis Space:

$$\mathcal{H}_{Lasso} = \{X_i\beta_i : \beta_i \in \mathbb{R}^p, \|\beta_i\|_1 \leq C\}$$

Lasso Regression is particularly useful for feature selection because the L1 penalty tends to produce models with some coefficients exactly zero, effectively eliminating less important features. This method simplifies the model, making it easier to interpret which features are most influential.

3. Results

The training and validation errors across Linear, Ridge, and Lasso regression models are nearly identical. Linear regression demonstrates an R2R2 of 0.506, while Ridge and Lasso yield 0.506 and 0.499, respectively. The Mean Squared Error (MSE) for these models is around 51,144 Euros, Root Mean Squared Error (RMSE) is approximately 226 Euros, Mean Absolute Error (MAE) is 174.5 Euros, and Mean Absolute Percentage Error (MAPE) is 0.15%. Since the performance metrics are comparable, Linear Regression is selected as the final model to optimize computational efficiency.

	LinearRegression_benchmark	Ridge_benchmark	Lasso_benchmark	Lasso_rgs	Ridge_rgs
r2	0.520202	0.519907	0.507221	0.517185	0.517185
MSE	49477.477423	49507.982314	50816.149230	49788.663310	49788.663310
RMSE	222.435333	222.503893	225.424376	223.133734	223.133734
MAE	173.568766	173.708788	175.651291	174.164254	174.164254
MAPE	0.157537	0.157719	0.160328	0.158326	0.158326

Test Error of the Chosen Model - Linear Regression is as follows:

MSE: 157,768 Euros

RMSE: 397.2 Euros

MAE: 314.3 Euros

MAPE: 0.28%

The errors on the testing dataset are significantly higher than those observed during validation, indicating possible overfitting. This suggests that the model may not generalize well to unseen data. To mitigate this, we should consider reducing the number of features used in the model, which could help lower the variance and improve generalization.

4. Conclusion

This study aims to identify important features for predicting housing prices in Texas using Linear, Ridge, and Lasso regression models. All three models exhibit similar predictive performance, with Linear Regression chosen for its simplicity and comparable results. Feature importance analysis shows that the ranking of features varies slightly between these models. However, they all show common significant features including location clusters and amenities like elevators, alarms, and TV availability. The top influential features in predicting housing prices are location (i.e. accounted for 8/10 of top 10 important features). Notably, clusters like Cluster 7 (i.e. Odessa, Midland) and Cluster 11 (i.e. Texarkana, Hooks) are among the highest-weighted features (Appendix A).

Despite hyperparameter tuning using randomized grid search and MLP Standard Scaler, no improvement in performance was achieved. The R-squared value of 0.52 for Linear Regression is considered adequate for a real-world data set.

Limitations and proposed impovement:

Although the model shows acceptable predictive ability, the significant increase in error on the testing dataset suggests that the model might be overfitting. Reducing the number of features could help to decrease the model's variance and improve its generalization to new data. Additionally, more granular data, such as socioeconomic factors or property-specific details like construction age or renovation status, could further enhance the model’s performance. Exploring advanced machine learning techniques or ensembling methods may also help in refining the model.

References:

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LinearRegression (no date) *scikit-learn*. Available at: https://scikit-learn/stable/modules/generated/sklearn.linear_model.LinearRegression.html (Accessed: 20 September 2024).

MachineLearningTheBasics/MLBasicsBook.pdf at master · alexjungaalto/MachineLearningTheBasics (no date) *GitHub*. Available at: https://github.com/alexjungaalto/MachineLearningTheBasics/blob/master/MLBasicsBook.pdf (Accessed: 20 September 2024).

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train_test_split (no date) *scikit-learn*. Available at: https://scikit-learn/stable/modules/generated/sklearn.model_selection.train_test_split.html (Accessed: 20 September 2024).

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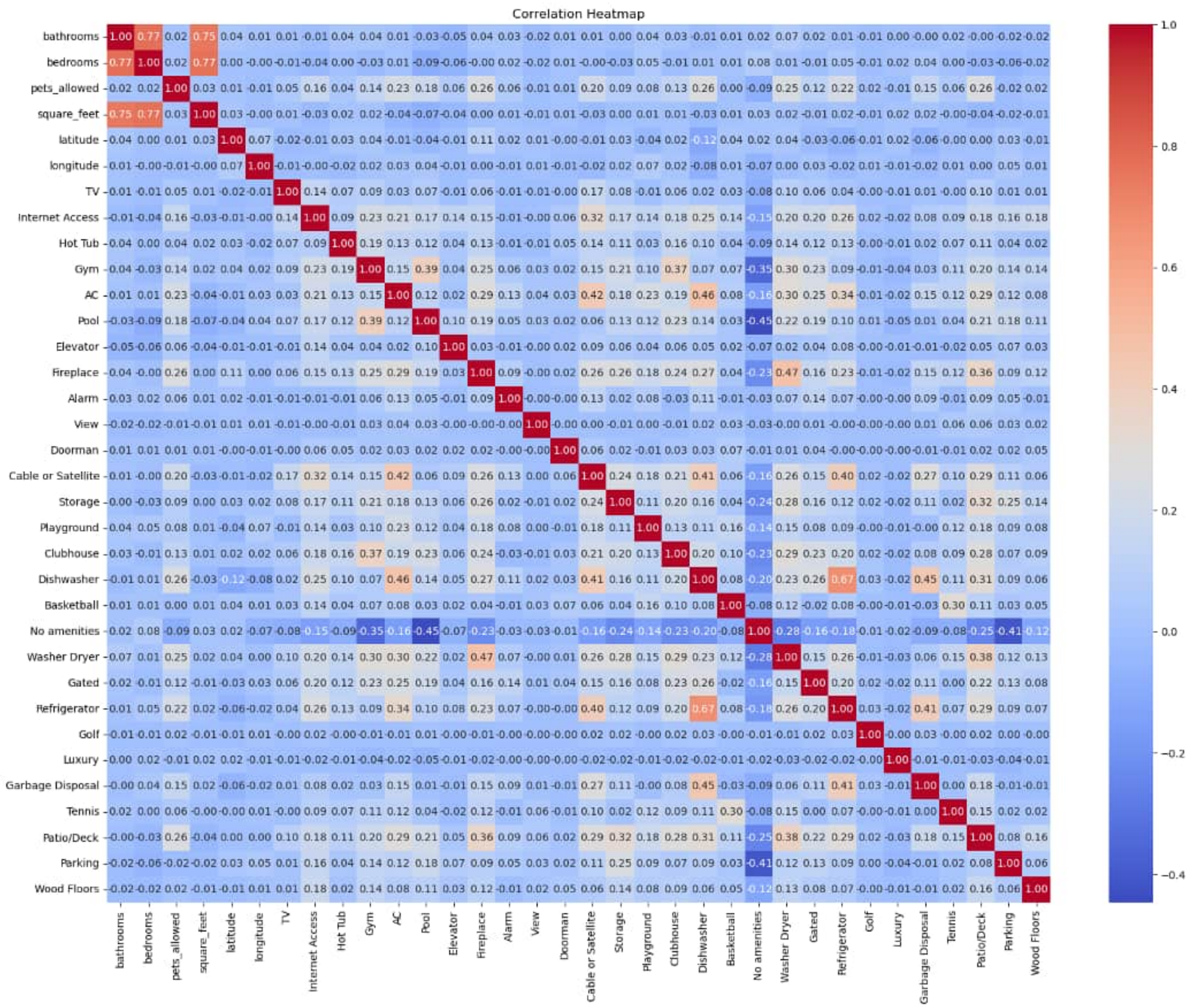
Vorley, T. (2008) ‘The Geographic Cluster: A Historical Review’, *Geography Compass*, 2(3), pp. 790–813. Available at: https://doi.org/10.1111/j.1749-8198.2008.00108.x.

Appendix A:

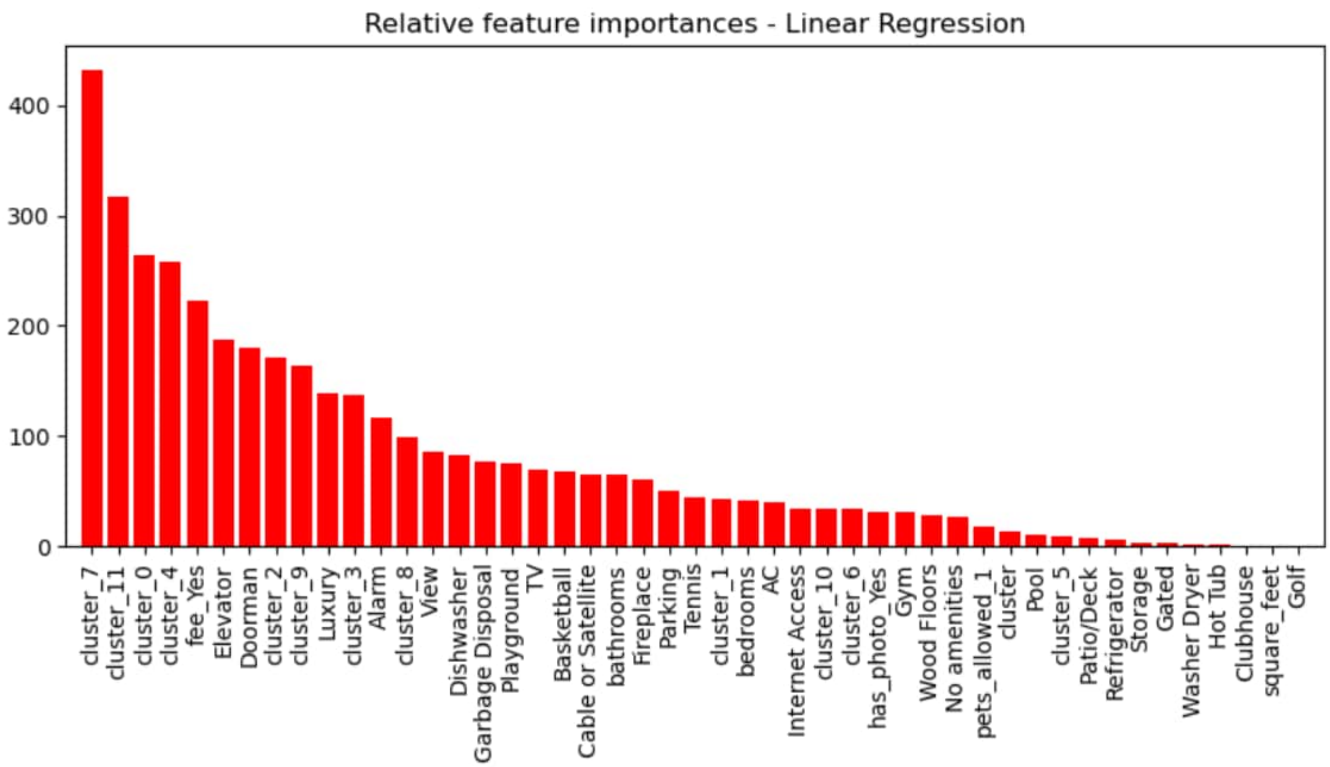
Correlation heatmap:

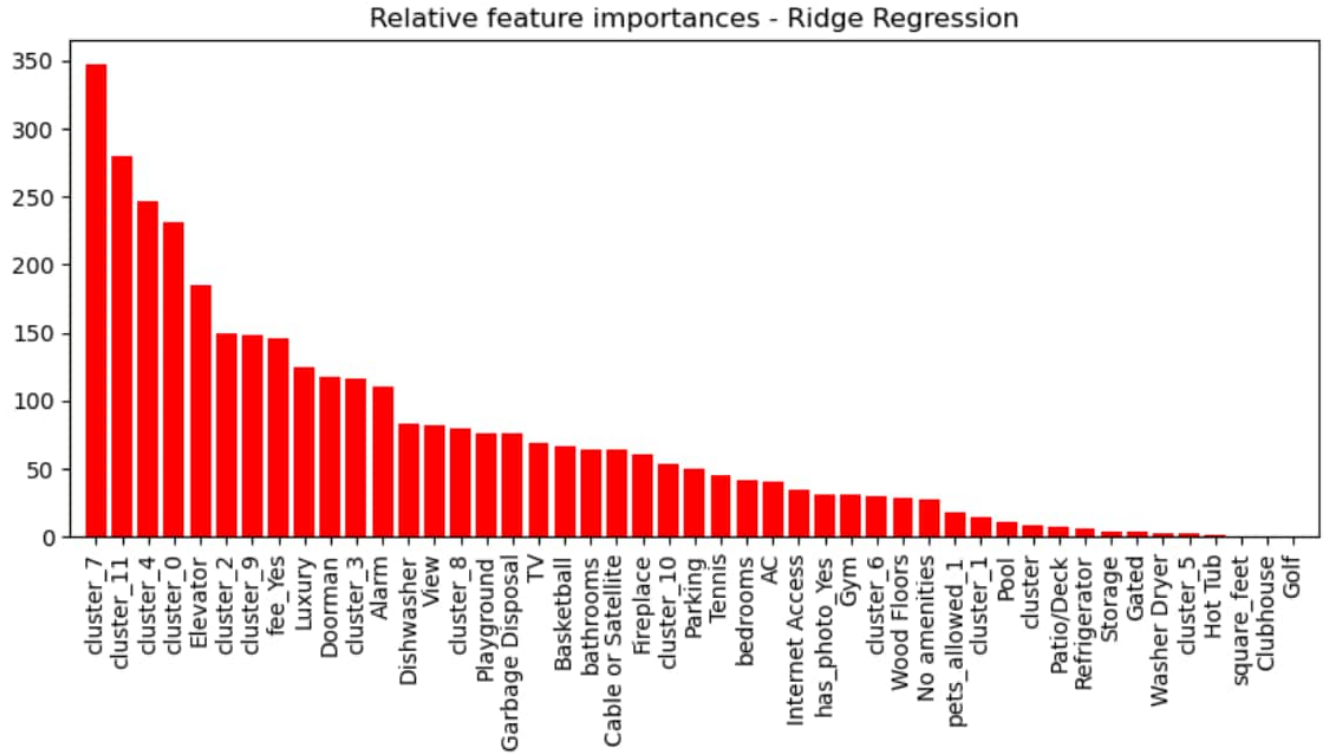


Cluster mapping:

- Cluster 0: San Antonio, Austin, Round Rock, Georgetown, Cedar Park, Blanco, etc.
- Cluster 1: Orange, Port Arthur, West Orange, Vidor, Beaumont, etc.
- Cluster 2: Houston, Pearland, Humble, Cypress, Baytown, Sugar Land, etc.
- Cluster 3: College Station, Bryan
- Cluster 4: Burleson, Fort Worth, Dallas, Grand Prairie, McKinney, etc.
- Cluster 5: Weslaco, Mission, Harlingen, McAllen, Mercedes, Edinburg
- Cluster 6: Abilene
- Cluster 7: Odessa, Midland
- Cluster 8: Lubbock

- Cluster 9: Henderson, Nacogdoches, Lufkin, Jacksonville, Longview, Tyler, etc.
- Cluster 10: Corpus Christi, Ingleside, Rockport, San Diego, Portland, etc.
- Cluster 11: Texarkana, Hooks




Relative feature importances - Ridge Regression
350
300
250
200
150
100
50
0
cluster_7
cluster_11
cluster_4
cluster_0
Elevator
cluster_2
cluster_9
fee_Yes
Luxury
Doorman
cluster_3
Alarm
Dishwasher
View
cluster_8
Playground
Garbage Disposal
TV
Basketball
bathrooms
Cable or Satellite
Fireplace
cluster_10
Parking
Tennis
bedrooms
AC
Internet Access
has_photo_Yes
Gym
cluster_6
Wood Floors
No amenities
pets_allowed_1
cluster_1
Pool
cluster
Patio/Deck
Refrigerator
Storage
Gated
Washer Dryer
cluster_5
Hot Tub
square_feet
Clubhouse
Golf

Appendix_B_Code

October 10, 2024

1 Importing libraries

[1]:
```
import pandas as pd
import numpy as np

from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.metrics import mean_absolute_error,␣
↪mean_absolute_percentage_error, mean_squared_error, r2_score
from sklearn.cluster import DBSCAN
from sklearn.metrics.pairwise import haversine_distances
from sklearn.model_selection import train_test_split, KFold, GridSearchCV,␣
↪RandomizedSearchCV
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import seaborn as sns
```

1. Data processing

[2]:
```
df = pd.read_excel("data.xlsx")
```

[3]:
```
df_copy = df.copy()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99826 entries, 0 to 99825
Data columns (total 22 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             99826 non-null  object
 1   category       99826 non-null  object
 2   title          99826 non-null  object
 3   body           99812 non-null  object
 4   amenities      83749 non-null  object
 5   bathrooms      99760 non-null  object
 6   bedrooms       99699 non-null  object
 7   currency       99822 non-null  object
 8   fee            99823 non-null  object
 9   has_photo      99823 non-null  object
```

```
 10  pets_allowed   39192 non-null  object
 11  price          99821 non-null  float64
 12  price_display  99820 non-null  object
 13  price_type     99823 non-null  object
 14  square_feet    99823 non-null  object
 15  address        7946 non-null   object
 16  cityname       99521 non-null  object
 17  state          99521 non-null  object
 18  latitude       99797 non-null  float64
 19  longitude      99795 non-null  float64
 20  source         99820 non-null  object
 21  time           99820 non-null  float64
dtypes: float64(4), object(18)
memory usage: 16.8+ MB
```

[6]:
```python
# Drop unecessary columns:
df = df.
 ↪drop(columns=["id","category","title","body","time","address","currency","price_display",␣
 ↪"source"])
```

[8]:
```python
# Fillan the 'amenities' columns with 'No amenities'
df['amenities'] =  df['amenities'].fillna("No amenities")

# Split values in the 'amenities' column:
test = set()
for value in df['amenities'].unique():
    temp = value.split(",")
    for var in temp:
        test.add(var)

# Create separate columns for each amenity: 0 = does not have that amenity, 1 =␣
 ↪has that amenity
for column in test:
    df[column] = df['amenities'].apply(lambda x: 1 if column in x else 0)

# Drop unecessary columns after splitting and creating new columns:
df = df.drop(columns=['amenities','No','USD'])
```

[9]:
```python
# Fillan the 'pets_allowed' column
df['pets_allowed'] = df['pets_allowed'].fillna("No")
df['pets_allowed'].isna().sum()
```

[9]: 0

[10]:
```python
# Drop 'NA' for all columns in the dataframe:
df = df.dropna()
```

[11]:
```
df = df[df['bathrooms']!="Thumbnail"]
df = df[df['bedrooms']!="Thumbnail"]
df = df[df['fee'].isin(["Yes", "No"])]
df = df[df['price_type'] != 'Weekly']
df['has_photo'] = df['has_photo'].replace({"Thumbnail":"No"})
df['pets_allowed'] = df['pets_allowed'].apply(lambda x: 1 if "Cats" in x or␣
↪"Dogs" in x else 0)
```

[12]:
```
# Subset data: Apartments in "Texas", less than 2000
mask_ba = df["state"].str.contains("TX")
mask_price = df["price"] < 2000
df = df[mask_ba & mask_price]
```

[13]:
```
# Create a clustering class to the dataframe
class ClusteredFeatures:

    def __init__(self, add_constant=False):
        self.add_constant=add_constant
        self.dbscan=None
        self.result = None

    def get_coor(self, df):
        return np.radians(df[['latitude', 'longitude']])

    def fit_predict(self, df, eps, min_samples):
        x = self.get_coor(df)
        self.dbscan = DBSCAN(eps = eps/6371, min_samples = min_samples,  metric␣
↪= 'haversine')
        self.result = self.dbscan.fit_predict(x)

    def transform(self, df):
        assert self.dbscan is not None, 'You have to call fit before transform!'

        # Cluster assignments from DBSCAN
        assignments = self.result

        # Add cluster assignment to the DataFrame
        df_with_clusters = df.copy()
        df_with_clusters['cluster'] = assignments

        # Print the mapping of clusters to city names
        self.map_clusters_to_cities(df_with_clusters)

        # Optionally add constant terms (dummy variables) for each cluster
        if self.add_constant:
            for cluster_id in np.unique(assignments):
                cluster_column = np.where(assignments == cluster_id, 1, 0)
```

```
                df_with_clusters[f'cluster_{cluster_id}'] = cluster_column

        df_with_clusters = df_with_clusters.drop(columns='cluster_-1')
        return df_with_clusters

    def map_clusters_to_cities(self, df_with_clusters):
        # Group by cluster and aggregate city names
        cluster_city_mapping = df_with_clusters.groupby('cluster')['cityname'].
↪apply(lambda x: ', '.join(x.unique())).reset_index()
        cluster_city_mapping.columns = ['cluster', 'cityname']

        # Print the mapping of clusters to city names
        for _, row in cluster_city_mapping.iterrows():
            print(f"Cluster {row['cluster']}: {row['cityname']}")

    def fit_transform(self, df, eps, min_samples):
        self.fit_predict(df, eps=eps, min_samples=min_samples)
        return self.transform(df)
```

[14]:
```
df_clustered = df.copy()
cluster = ClusteredFeatures(add_constant=True)
df_clustered = cluster.fit_transform(df_clustered, eps =50, min_samples = 10)
df_clustered.info()
```

```
Cluster -1: Amarillo, El Paso, Dumas, Pampa, Wichita Falls, Paris, Waco,
Henrietta, Early, Brownwood, Dalhart, Victoria, Kerrville, Laredo, Beeville
Cluster 0: San Antonio, Austin, Round Rock, Georgetown, Cedar Park, Blanco,
Leander, Pflugerville, Horseshoe Bay, Cameron, New Braunfels, San Marcos,
Converse, Bastrop, Lytle, Giddings, Helotes, Universal City, Canyon Lake, Selma,
Liberty Hill, Lakeway, Sunset Valley, Leon Valley, Castle Hills, Cibolo, Kyle,
Live Oak, Taylor, Pleasanton, Harker Heights, Lockhart, Temple, Killeen, Hutto,
Schertz, Seguin
Cluster 1: Orange, Port Arthur, West Orange, Vidor, Beaumont, Sour Lake, Bridge
City, Groves
Cluster 2: Houston, Pearland, Humble, Cypress, Baytown, Sugar Land, Missouri
City, Spring, Richmond, Crosby, Channelview, League City, Tomball, Willis,
Montgomery, Galveston, Pasadena, Porter, Katy, Kingwood, Webster, Rosenberg,
Bacliff, Angleton, Alvin, Lake Jackson, Clute, Seabrook, Bay City, Conroe,
Stafford, Huntsville, Cleveland, Freeport, Magnolia, Manvel, Dickinson, Texas
City, Shenandoah
Cluster 3: College Station, Bryan
Cluster 4: Burleson, Fort Worth, Dallas, Grand Prairie, Mckinney, Mansfield,
Irving, Glenn Heights, Plano, Mesquite, North Richland Hills, Rowlett, Denton,
Arlington, Euless, Terrell, Weatherford, Richardson, Farmers Branch, Midlothian,
Cedar Hill, Garland, Desoto, Lancaster, Crowley, Newark, Saginaw, Frisco,
Coppell, Lewisville, Springtown, Carrollton, Bedford, Grapevine, Azle, Commerce,
Greenville, Hurst, Cleburne, Granbury, Kennedale, Addison, Princeton, Aledo,
```

```
Anna, Melissa, Joshua, Mabank, Emory, Haslet, Sherman, Ennis, Forney, Kemp,
Waxahachie, The Colony, Wylie, Flower Mound, Allen, Duncanville, Rockwall, Balch
Springs, Corsicana, Wilmer, Prosper, Little Elm, Lake Dallas, Sachse, Red Oak,
Royse City
Cluster 5: Weslaco, Mission, Harlingen, Mcallen, Mercedes, Edinburg
Cluster 6: Abilene
Cluster 7: Odessa, Midland
Cluster 8: Lubbock
Cluster 9: Henderson, Nacogdoches, Lufkin, Jacksonville, Longview, Tyler,
Palestine, Lindale, Troup, Bullard, Whitehouse, Diana, Big Sandy, Marshall
Cluster 10: Corpus Christi, Ingleside, Rockport, San Diego, Portland, Kingsville
Cluster 11: Texarkana, Hooks
<class 'pandas.core.frame.DataFrame'>
Index: 10759 entries, 16 to 99821
Data columns (total 53 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   bathrooms           10759 non-null  object
 1   bedrooms            10759 non-null  object
 2   fee                 10759 non-null  object
 3   has_photo           10759 non-null  object
 4   pets_allowed        10759 non-null  int64
 5   price               10759 non-null  float64
 6   price_type          10759 non-null  object
 7   square_feet         10759 non-null  object
 8   cityname            10759 non-null  object
 9   state               10759 non-null  object
 10  latitude            10759 non-null  float64
 11  longitude           10759 non-null  float64
 12  TV                  10759 non-null  int64
 13  Internet Access     10759 non-null  int64
 14  Hot Tub             10759 non-null  int64
 15  Gym                 10759 non-null  int64
 16  AC                  10759 non-null  int64
 17  Pool                10759 non-null  int64
 18  Elevator            10759 non-null  int64
 19  Fireplace           10759 non-null  int64
 20  Alarm               10759 non-null  int64
 21  View                10759 non-null  int64
 22  Doorman             10759 non-null  int64
 23  Cable or Satellite  10759 non-null  int64
 24  Storage             10759 non-null  int64
 25  Playground          10759 non-null  int64
 26  Clubhouse           10759 non-null  int64
 27  Dishwasher          10759 non-null  int64
 28  Basketball          10759 non-null  int64
 29  No amenities        10759 non-null  int64
 30  Washer Dryer        10759 non-null  int64
```

```
 31  Gated                 10759 non-null  int64
 32  Refrigerator          10759 non-null  int64
 33  Golf                  10759 non-null  int64
 34  Luxury                10759 non-null  int64
 35  Garbage Disposal      10759 non-null  int64
 36  Tennis                10759 non-null  int64
 37  Patio/Deck            10759 non-null  int64
 38  Parking               10759 non-null  int64
 39  Wood Floors           10759 non-null  int64
 40  cluster               10759 non-null  int64
 41  cluster_0             10759 non-null  int64
 42  cluster_1             10759 non-null  int64
 43  cluster_2             10759 non-null  int64
 44  cluster_3             10759 non-null  int64
 45  cluster_4             10759 non-null  int64
 46  cluster_5             10759 non-null  int64
 47  cluster_6             10759 non-null  int64
 48  cluster_7             10759 non-null  int64
 49  cluster_8             10759 non-null  int64
 50  cluster_9             10759 non-null  int64
 51  cluster_10            10759 non-null  int64
 52  cluster_11            10759 non-null  int64
dtypes: float64(3), int64(42), object(8)
memory usage: 4.4+ MB
```

[15]:
```
# Change the datatype of individual columns
for column in df_clustered.columns:
    if column in ['bathrooms','bedrooms', 'price','latitude','longitude',␣
 ↪'square_feet']:
        df[column] = df[column].astype('float')
```

[16]:
```
df_clustered.columns
```

[16]:
```
Index(['bathrooms', 'bedrooms', 'fee', 'has_photo', 'pets_allowed', 'price',
       'price_type', 'square_feet', 'cityname', 'state', 'latitude',
       'longitude', 'TV', 'Internet Access', 'Hot Tub', 'Gym', 'AC', 'Pool',
       'Elevator', 'Fireplace', 'Alarm', 'View', 'Doorman',
       'Cable or Satellite', 'Storage', 'Playground', 'Clubhouse',
       'Dishwasher', 'Basketball', 'No amenities', 'Washer Dryer', 'Gated',
       'Refrigerator', 'Golf', 'Luxury', 'Garbage Disposal', 'Tennis',
       'Patio/Deck', 'Parking', 'Wood Floors', 'cluster', 'cluster_0',
       'cluster_1', 'cluster_2', 'cluster_3', 'cluster_4', 'cluster_5',
       'cluster_6', 'cluster_7', 'cluster_8', 'cluster_9', 'cluster_10',
       'cluster_11'],
      dtype='object')
```

2. Exploratory Data Analysis 2.1 Statistics and Distribution

[17]:
```
df.describe()
```

[17]:

	bathrooms	bedrooms	pets_allowed	price	square_feet
count	10759.000000	10759.000000	10759.000000	10759.000000	10759.000000
mean	1.379775	1.558788	0.404499	1163.117390	880.340087
std	0.502294	0.684637	0.490818	320.417962	289.490144
min	1.000000	0.000000	0.000000	300.000000	200.000000
25%	1.000000	1.000000	0.000000	920.000000	683.000000
50%	1.000000	1.000000	0.000000	1120.000000	810.000000
75%	2.000000	2.000000	1.000000	1375.000000	1041.000000
max	3.500000	5.000000	1.000000	1999.000000	3475.000000

	latitude	longitude	TV	Internet Access
count	10759.000000	10759.000000	10759.000000	10759.000000
mean	31.869706	-96.840545	0.036063	0.110977
std	1.541737	0.978930	0.186455	0.314118
min	26.159600	-106.445000	0.000000	0.000000
25%	30.305400	-97.103900	0.000000	0.000000
50%	32.782600	-96.838700	0.000000	0.000000
75%	32.918600	-96.661500	0.000000	0.000000
max	36.065600	-93.758100	1.000000	1.000000

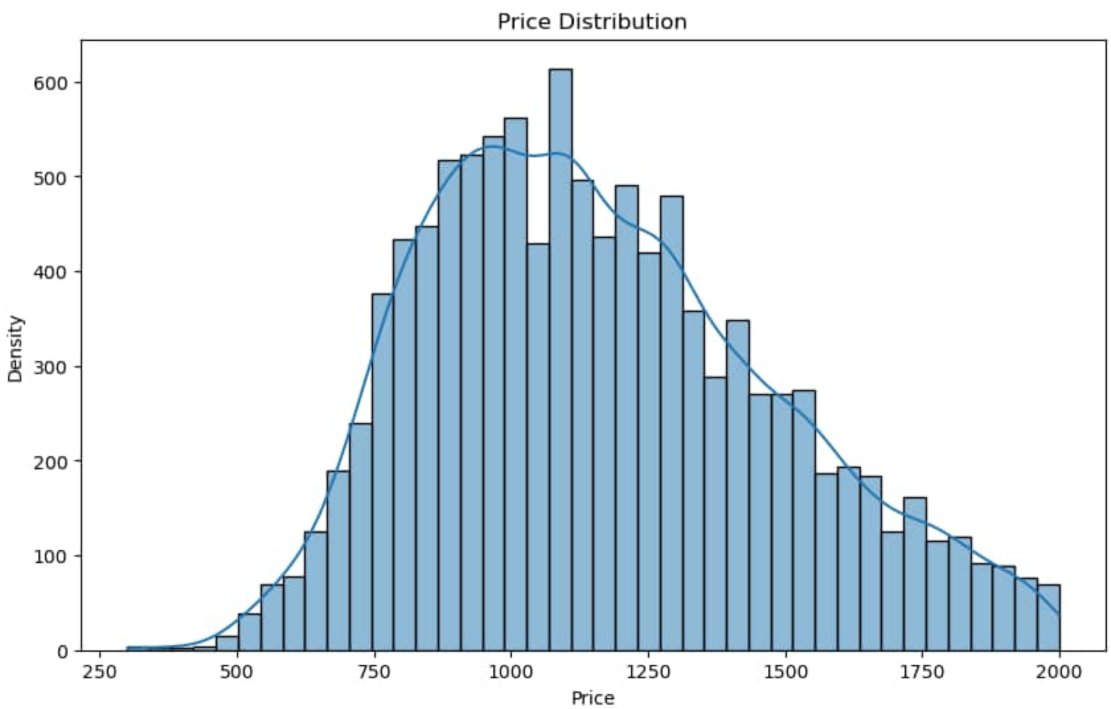
	Hot Tub	…	Washer Dryer	Gated	Refrigerator
count	10759.000000	…	10759.000000	10759.000000	10759.000000
mean	0.043127	…	0.311088	0.122130	0.160796
std	0.203152	…	0.462960	0.327451	0.367359
min	0.000000	…	0.000000	0.000000	0.000000
25%	0.000000	…	0.000000	0.000000	0.000000
50%	0.000000	…	0.000000	0.000000	0.000000
75%	0.000000	…	1.000000	0.000000	0.000000
max	1.000000	…	1.000000	1.000000	1.000000

	Golf	Luxury	Garbage Disposal	Tennis
count	10759.000000	10759.000000	10759.000000	10759.000000
mean	0.000186	0.001952	0.048796	0.038758
std	0.013634	0.044139	0.215452	0.193027
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000

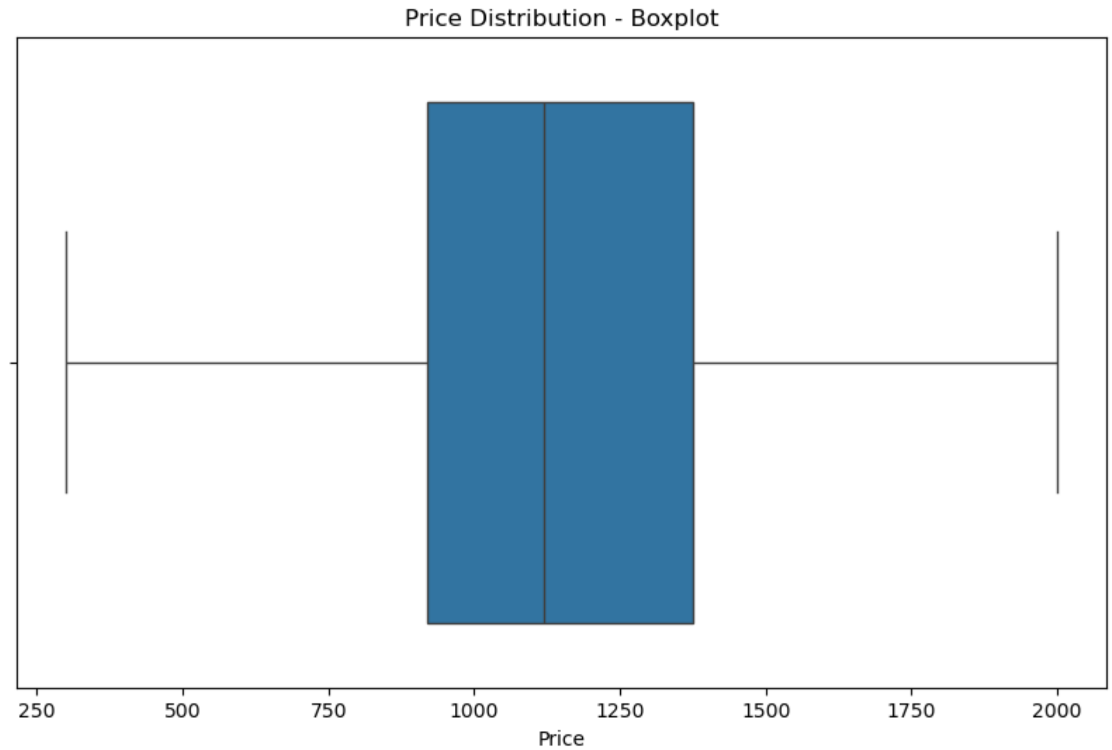
	Patio/Deck	Parking	Wood Floors
count	10759.000000	10759.000000	10759.000000
mean	0.261548	0.486755	0.081327
std	0.439498	0.499848	0.273350
min	0.000000	0.000000	0.000000

```
25%          0.000000        0.000000        0.000000
50%          0.000000        0.000000        0.000000
75%          1.000000        1.000000        0.000000
max          1.000000        1.000000        1.000000

[8 rows x 35 columns]
```

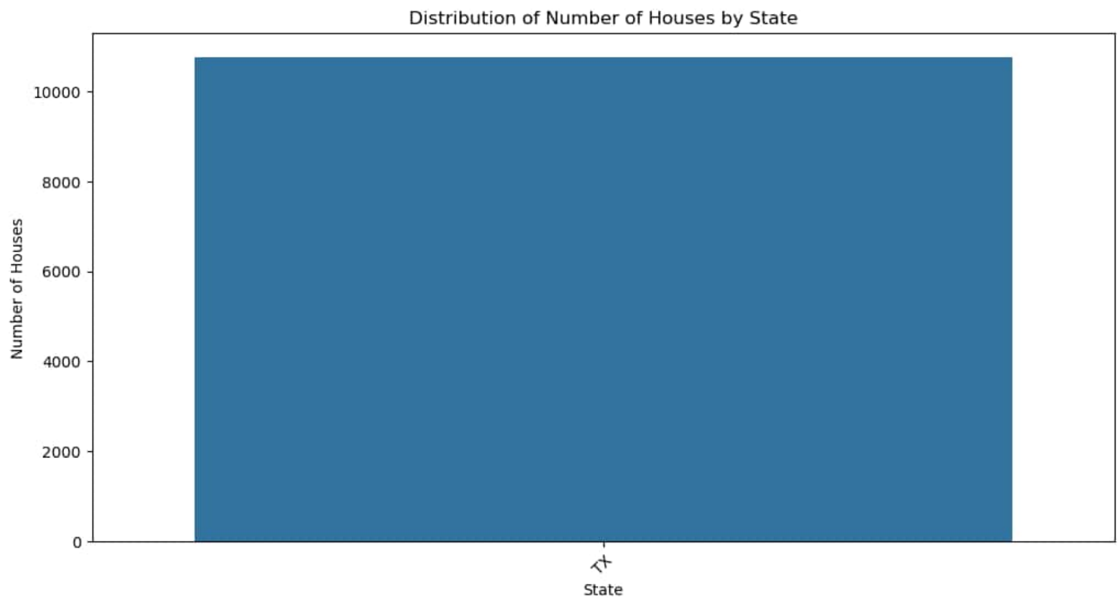
[18]:
```
# Histogram of the numerical feature 'price'
plt.figure(figsize=(10, 6))  # Adjust the figure size as needed
sns.histplot(data=df, x='price', kde=True)
plt.title('Price Distribution')
plt.xlabel('Price')
plt.ylabel('Density')
plt.show()
```



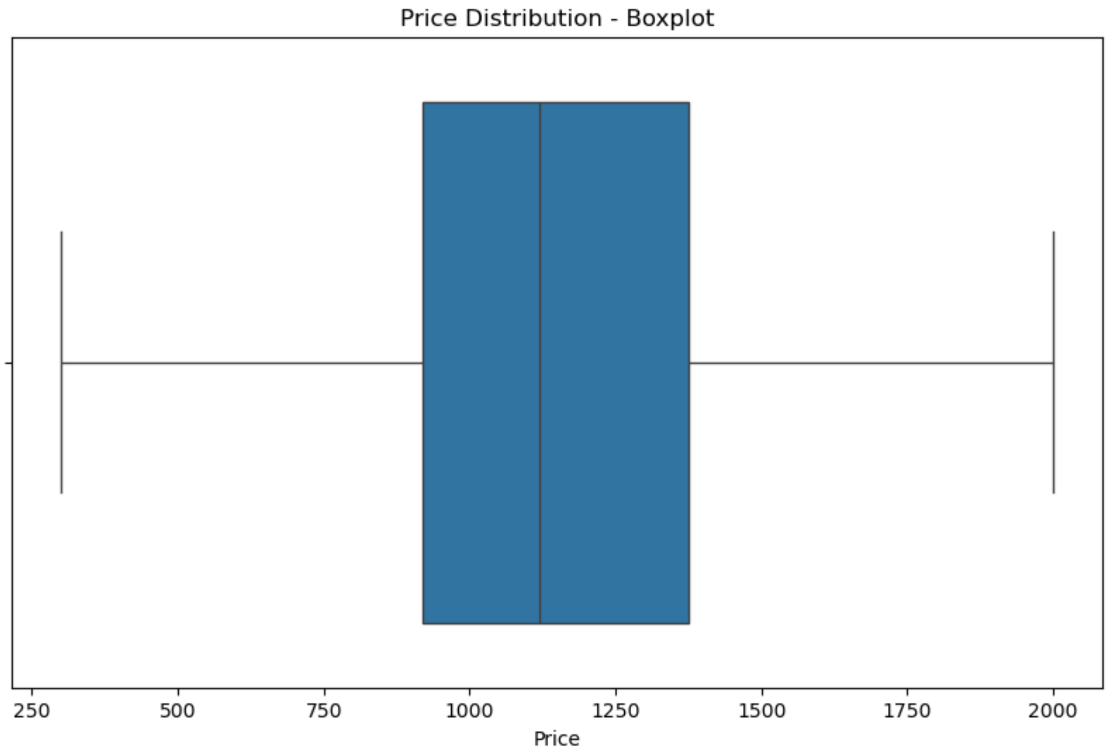
[19]:
```
# Boxplot of the numerical feature 'price'
plt.figure(figsize=(10, 6))  # Adjust the figure size as needed
sns.boxplot(data=df, x='price')
plt.title('Price Distribution - Boxplot')
plt.xlabel('Price')
plt.show()
```



[20]:
```
# Bar plot of number of houses by state
plt.figure(figsize=(12, 6))  # Adjust the figure size as needed
sns.countplot(data=df, x='state', order=df['state'].value_counts().index)
plt.title('Distribution of Number of Houses by State')
plt.xlabel('State')
plt.ylabel('Number of Houses')
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
plt.show()
```

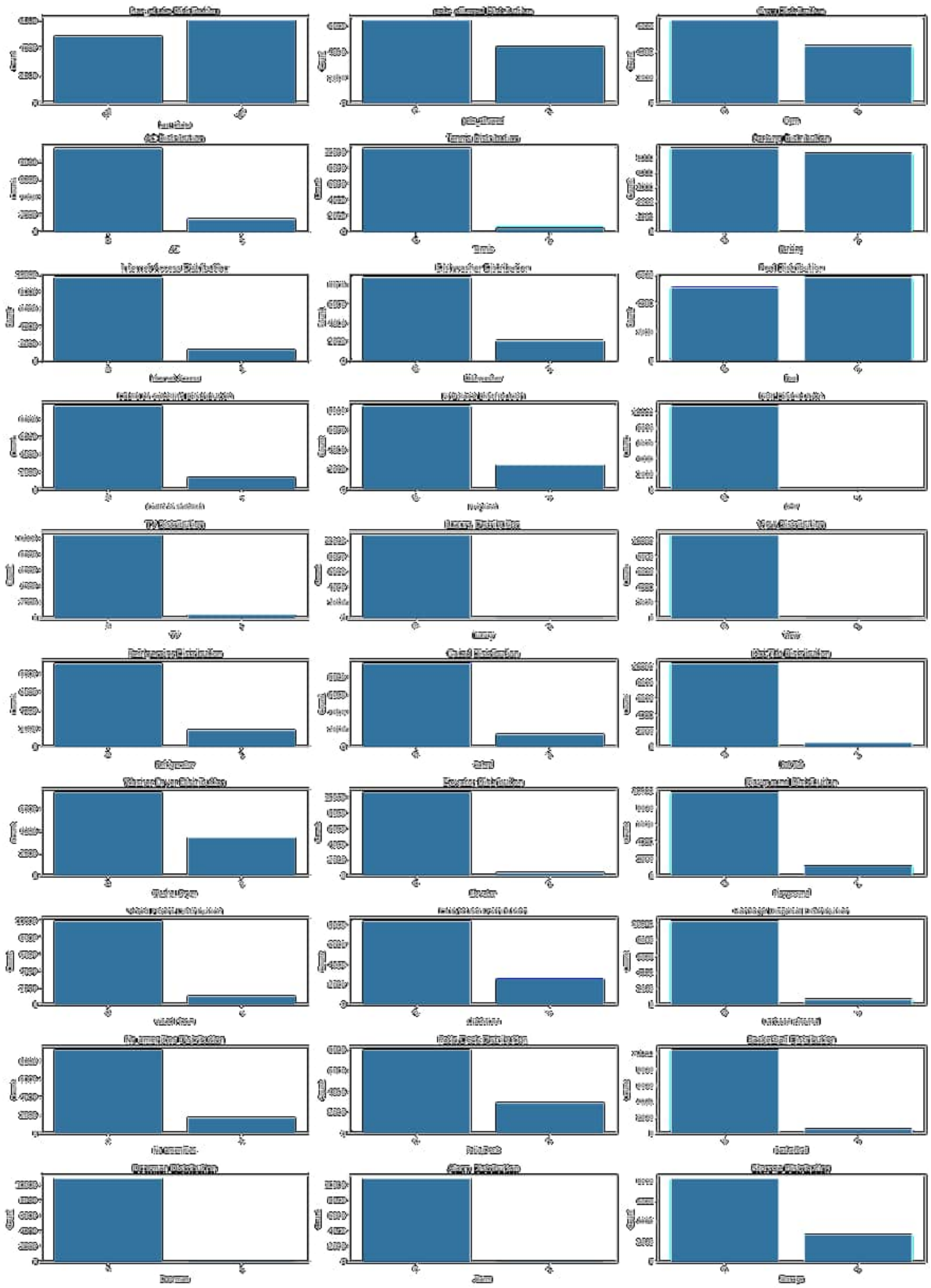


[21]:
```
# Boxplot of the 'price' in CA
data_CA = df[df['state'] == 'TX']
plt.figure(figsize=(10, 6))  # Adjust the figure size as needed
sns.boxplot(data= data_CA, x='price')
plt.title('Price Distribution - Boxplot')
plt.xlabel('Price')
plt.show()
```



[22]:
```
# Categorical columns
categorical_features = ['has_photo', 'pets_allowed', 'Gym', 'AC', 'Tennis',␣
↪'Parking',
        'Internet Access', 'Dishwasher', 'Pool', 'Cable or Satellite',
        'Fireplace', 'Golf', 'TV', 'Luxury', 'View', 'Refrigerator', 'Gated',
        'Hot Tub', 'Washer Dryer', 'Elevator', 'Playground', 'Wood Floors',
        'Clubhouse', 'Garbage Disposal', 'No amenities', 'Patio/Deck',
        'Basketball', 'Doorman', 'Alarm', 'Storage']

# Create a figure with a larger grid size
plt.figure(figsize=(20, 30))  # Adjust figure size to be large enough
total_features = len(categorical_features)

# Set up the grid size dynamically based on the number of features
for i, feature in enumerate(categorical_features, 1):
    plt.subplot((total_features // 3) + 1, 3, i)
    sns.countplot(data=df, x=feature)
    plt.title(f'{feature} Distribution')
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.xticks(rotation=45)

# Ensure the layout is adjusted for all plots to fit
```

```
plt.tight_layout()
plt.show();
```



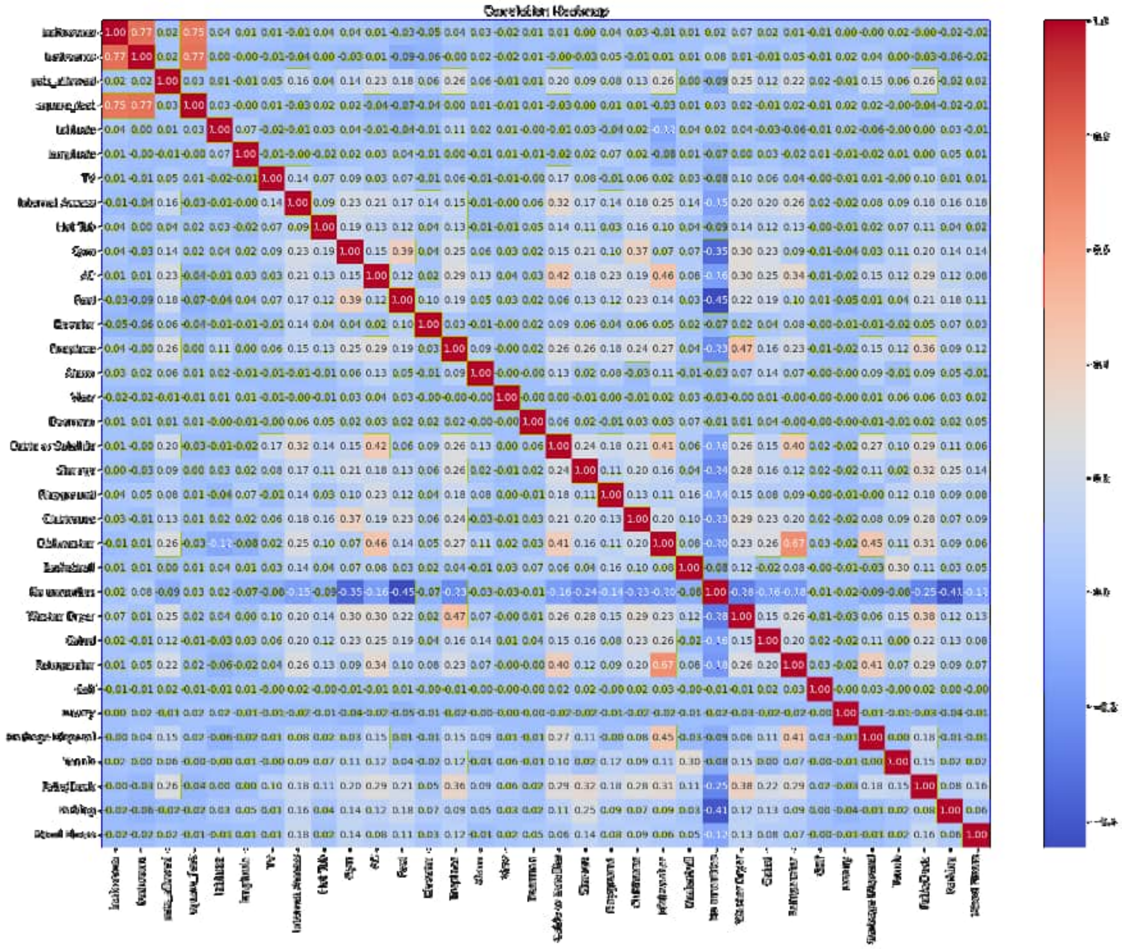
[23]:
```
'''import plotly.express as px
fig = px.scatter_mapbox(
    df,  # Our DataFrame
    lat='latitude',
    lon='longitude',
    size="price",
    center={"lat": 39.8283, "lon": -98.5795},  # Map will be centered on␣
 ↪Helsinki
    width=1000,  # Width of map
    height=700,  # Height of map
    size_max=20,
)

fig.update_layout(mapbox_style="open-street-map")

fig.show()'''
```

[23]:
```
'import plotly.express as px\nfig = px.scatter_mapbox(\n    df,  # Our
DataFrame\n    lat=\'latitude\',\n    lon=\'longitude\',\n    size="price",\n
center={"lat": 39.8283, "lon": -98.5795},  # Map will be centered on Helsinki\n
width=1000,  # Width of map\n    height=700,  # Height of map\n
size_max=20,\n)\n\nfig.update_layout(mapbox_style="open-street-
map")\n\nfig.show()'
```

2.2 Correlation heatmap

[24]:
```
corr = df.select_dtypes("number").drop(columns="price").corr()
plt.figure(figsize=(20, 15))
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Heatmap")
```

[24]:
```
Text(0.5, 1.0, 'Correlation Heatmap')
```



3. Modeling - Regression:

[25]:
```
# Splite the model into training, test and validation set
X = df_clustered.
 ↪drop(columns=['price','state','longitude','latitude','cityname']).copy()
X = pd.get_dummies(X, columns=['fee','has_photo','pets_allowed','price_type'],␣
 ↪drop_first=True)
y = df_clustered['price'].copy()

X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.6)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5)
```

[26]:
```
Regression_comparision = {}
```

[27]:
```
#Linear regression
lr_benchmark = LinearRegression()
lr_benchmark.fit(X_train, y_train)
```

```
y_pred = lr_benchmark.predict(X_val)

r2 = lr_benchmark.score(X_val, y_val)
MSE = mean_squared_error(y_val, y_pred)
RMSE = np.sqrt(MSE)
MAE = mean_absolute_error(y_val, y_pred)
MAPE = mean_absolute_percentage_error(y_val, y_pred)


Regression_comparision['LinearRegression_benchmark'] = {'r2': r2,
                                                        'MSE': MSE,
                                                        'RMSE': RMSE,
                                                        'MAE': MAE,
                                                        'MAPE': MAPE}
```

[44]:
```
# Test error with tesing data

MSE = mean_squared_error(y_test, y_pred)
RMSE = np.sqrt(MSE)
MAE = mean_absolute_error(y_test, y_pred)
MAPE = mean_absolute_percentage_error(y_test, y_pred)


Regression_comparision['LinearRegression_final'] = {'r2': r2,
                                                        'MSE': MSE,
                                                        'RMSE': RMSE,
                                                        'MAE': MAE,
                                                        'MAPE': MAPE}
```

[29]:
```
#Ridge
ridge_benchmark = Ridge()
ridge_benchmark.fit(X_train, y_train)

y_pred = ridge_benchmark.predict(X_val)

r2 = r2_score(y_val, y_pred)
MSE = mean_squared_error(y_val, y_pred)
RMSE = np.sqrt(MSE)
MAE = mean_absolute_error(y_val, y_pred)
MAPE = mean_absolute_percentage_error(y_val, y_pred)

Regression_comparision['Ridge_benchmark'] = {'r2': r2,
                                                        'MSE': MSE,
                                                        'RMSE': RMSE,
                                                        'MAE': MAE,
                                                        'MAPE': MAPE}
```

[30]:
```
#Lasso
lasso_benchmark = Lasso()
lasso_benchmark.fit(X_train, y_train)

y_pred = lasso_benchmark.predict(X_val)

r2 = r2_score(y_val, y_pred)
MSE = mean_squared_error(y_val, y_pred)
RMSE = np.sqrt(MSE)
MAE = mean_absolute_error(y_val, y_pred)
MAPE = mean_absolute_percentage_error(y_val, y_pred)

Regression_comparision['Lasso_benchmark'] = {'r2': r2,
                                                        'MSE': MSE,
                                                        'RMSE': RMSE,
                                                        'MAE': MAE,
                                                        'MAPE': MAPE}
```

4. Hyperparameter tunning

[31]:
```
# Randomized Grid Search parameters for Lasso
param_grid = {
        'alpha': np.linspace(0.01, 50, 200),
        'max_iter' : [1000,2000,3000,4000,5000],
    }

rcv = RandomizedSearchCV(Lasso(), param_grid, n_iter=100)
rcv.fit(X_train, y_train)

lasso_rgs = Lasso(**rcv.best_params_)
lasso_rgs.fit(X_train, y_train)

y_pred = lasso_rgs.predict(X_val)

r2 = r2_score(y_val, y_pred)
MSE = mean_squared_error(y_val, y_pred)
RMSE = np.sqrt(MSE)
MAE = mean_absolute_error(y_val, y_pred)
MAPE = mean_absolute_percentage_error(y_val, y_pred)

Regression_comparision['Lasso_rgs'] = {'r2': r2,
                                                        'MSE': MSE,
                                                        'RMSE': RMSE,
                                                        'MAE': MAE,
                                                        'MAPE': MAPE}
```

[32]:
```
# Randomized Grid Search parameters for Ridge
param_grid = {
        'alpha': np.linspace(0.01, 50, 200),
        'max_iter' : [1000,2000,3000,4000,5000],
    }

rcv = RandomizedSearchCV(Ridge(), param_grid, n_iter=100)
rcv.fit(X_train, y_train)

ridge_rgs = Ridge(**rcv.best_params_)
ridge_rgs.fit(X_train, y_train)

y_pred = lasso_rgs.predict(X_val)

r2 = r2_score(y_val, y_pred)
MSE = mean_squared_error(y_val, y_pred)
RMSE = np.sqrt(MSE)
MAE = mean_absolute_error(y_val, y_pred)
MAPE = mean_absolute_percentage_error(y_val, y_pred)

Regression_comparision['Ridge_rgs'] = {'r2': r2,
                                                        'MSE': MSE,
                                                        'RMSE': RMSE,
                                                        'MAE': MAE,
                                                        'MAPE': MAPE}
```

5. Model evaluation

[34]:
```
results = pd.DataFrame(Regression_comparision)
results
```

[34]:
```
      LinearRegression_benchmark  LinearRegression_final  Ridge_benchmark  \
r2                      0.506752                0.506752         0.506509
MSE                 51275.818412           157768.409370     51301.114148
RMSE                  226.441645              397.200717       226.497493
MAE                   175.925537              314.729462       175.886499
MAPE                    0.158156                0.288267         0.158185

      Lasso_benchmark     Lasso_rgs     Ridge_rgs  MLP_StandardScaler
r2           0.491831      0.497370      0.497370            0.442527
MSE      52826.910995  52251.088254  52251.088254        57952.396167
RMSE       229.841056    228.584969    228.584969          240.733039
MAE        178.041563    177.226787    177.226787          187.119868
MAPE         0.160955      0.159964      0.159964            0.167681
```

[35]:
```
coef_ridge = ridge_benchmark.coef_
```

```python
# Count non-zero coefficients
num_features_used_ridge = np.sum(coef_ridge != 0)

print(f"Number of features used in the model: {num_features_used_ridge}")
```

```
Number of features used in the model: 46
```

[36]:
```python
coef_linear = lr_benchmark.coef_

# Count non-zero coefficients
num_features_used_linear = np.sum(coef_linear != 0)

print(f"Number of features used in the model: {num_features_used_linear}")
```

```
Number of features used in the model: 47
```

[37]:
```python
coef_ridge
```

[37]:
```
array([  64.18974513,  -41.69061069,    0.64449175,   68.5369226 ,
         34.7174889 ,   -1.42998919,   30.80754769,  -40.07225841,
         10.66388426,  184.84219068,  -60.54460827,  109.86568846,
         81.70661373,  117.49615474,  -64.00969031,   -3.43566428,
        -76.21239039,    0.47373234,  -83.31686753,  -66.2800893 ,
         27.10289164,   -2.45047174,    3.32210691,    5.5697926 ,
          0.        ,  124.78589496,  -75.80637522,  -44.65575425,
          7.87757496,   49.94857839,   28.45490852,    9.04146839,
        231.31348156,   14.87010613,  149.55347265,  116.81925312,
        246.41869232,    2.07132421,  -30.16377512,  347.46907347,
        -79.7245979 , -148.56535134,   53.08505562, -280.15316183,
       -145.3762258 ,  -31.05491981,   18.28198572])
```

[38]:
```python
coef_linear
```

[38]:
```
array([ 6.45247121e+01, -4.12268468e+01,  6.43422173e-01,  6.95057516e+01,
        3.42278991e+01, -1.60970596e+00,  3.08186185e+01, -3.98766604e+01,
        1.06579949e+01,  1.86869531e+02, -6.10883517e+01,  1.16642798e+02,
        8.62403254e+01,  1.79528191e+02, -6.50169512e+01, -3.36950770e+00,
       -7.56226551e+01,  9.31733376e-01, -8.31938774e+01, -6.77988611e+01,
        2.73567342e+01, -2.10053407e+00,  2.94643459e+00,  6.50833729e+00,
       -1.27897692e-13,  1.38415253e+02, -7.68453089e+01, -4.43824412e+01,
        7.48879408e+00,  4.96469458e+01,  2.86111803e+01,  1.41730063e+01,
        2.63259705e+02,  4.24360013e+01,  1.71677138e+02,  1.37373958e+02,
        2.57882871e+02,  8.42015349e+00, -3.39628357e+01,  4.32117101e+02,
       -9.91342850e+01, -1.64217211e+02,  3.40957970e+01, -3.16524273e+02,
       -2.22202565e+02, -3.12457676e+01,  1.78850120e+01])
```

[39]:
```python
coef_linear - coef_ridge
```

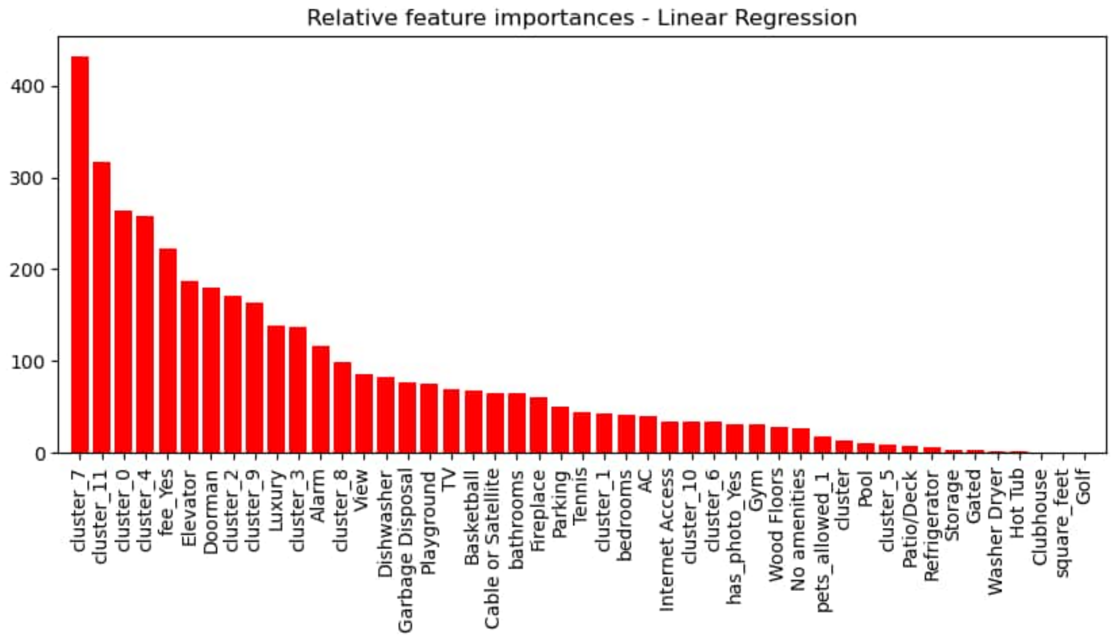
```
[39]: array([ 3.34966941e-01,  4.63763929e-01, -1.06957694e-03,  9.68829012e-01,
       -4.89589791e-01, -1.79716768e-01,  1.10708571e-02,  1.95598041e-01,
       -5.88936015e-03,  2.02734081e+00, -5.43743384e-01,  6.77710936e+00,
        4.53371166e+00,  6.20320360e+01, -1.00726088e+00,  6.61565810e-02,
        5.89735316e-01,  4.58001041e-01,  1.22990146e-01, -1.51877177e+00,
        2.53842594e-01,  3.49937666e-01, -3.75672317e-01,  9.38544694e-01,
       -1.27897692e-13,  1.36293576e+01, -1.03893373e+00,  2.73313044e-01,
       -3.88780878e-01, -3.01632584e-01,  1.56271808e-01,  5.13153791e+00,
        3.19462231e+01,  2.75658951e+01,  2.21236651e+01,  2.05547051e+01,
        1.14641783e+01,  6.34882928e+00, -3.79906056e+00,  8.46480276e+01,
       -1.94096871e+01, -1.56518596e+01, -1.89892586e+01, -3.63711108e+01,
       -7.68263390e+01, -1.90847803e-01, -3.96973764e-01])
```

```
[40]: importances1 = np.abs(lr_benchmark.coef_)  # Take the absolute value of the␣
       ↪coefficients
indices = np.argsort(importances1)[::-1]  # Sort the coefficients in descending␣
 ↪order of importance

# Get the feature names in order of importance
feature_order = np.array([X.columns.values])
i = np.argsort(importances1)[::-1]
feature_order = feature_order[:, i]

# If you want to print the features sorted by their importance
print("Features ranked by importance:")
for idx in indices:
    print(f"{X.columns[idx]}: {importances1[idx]}")
```

```
Features ranked by importance:
cluster_7: 432.11710105885976
cluster_11: 316.52427267501577
cluster_0: 263.2597046171628
cluster_4: 257.8828706053526
fee_Yes: 222.20256484445136
Elevator: 186.86953148741898
Doorman: 179.5281907609562
cluster_2: 171.6771377731783
cluster_9: 164.2172109781206
Luxury: 138.41525253521556
cluster_3: 137.3739581950266
Alarm: 116.6427978233732
cluster_8: 99.13428502065909
View: 86.2403253907662
Dishwasher: 83.19387738782866
Garbage Disposal: 76.84530894500674
Playground: 75.62265507817118
TV: 69.50575161523182
```

```
Basketball: 67.7988610753247
Cable or Satellite: 65.01695119190938
bathrooms: 64.52471206924129
Fireplace: 61.088351654118775
Parking: 49.64694580839431
Tennis: 44.38244120814629
cluster_1: 42.43600125779913
bedrooms: 41.226846757482555
AC: 39.876660370057934
Internet Access: 34.22789911193997
cluster_10: 34.09579704141177
cluster_6: 33.96283568247143
has_photo_Yes: 31.245767612468192
Gym: 30.81861854781015
Wood Floors: 28.61118032974525
No amenities: 27.35673423572701
pets_allowed_1: 17.885011961328793
cluster: 14.173006295537348
Pool: 10.657994898222608
cluster_5: 8.42015349251424
Patio/Deck: 7.488794083837774
Refrigerator: 6.5083372891893765
Storage: 3.369507701991229
Gated: 2.946434590743351
Washer Dryer: 2.1005340743649157
Hot Tub: 1.6097059555507678
Clubhouse: 0.9317333757553092
square_feet: 0.6434221731270569
Golf: 1.2789769243681803e-13
```

[41]:
```python
# Plot the feature importances
plt.figure(figsize=(10, 4))
plt.title("Relative feature importances - Linear Regression")
plt.bar(range(X.shape[1]), importances1[indices],
       color="r",  align="center")
plt.xticks(range(X.shape[1]), feature_order[0], rotation=90)
plt.xlim([-1, X.shape[1]])
plt.show()
```

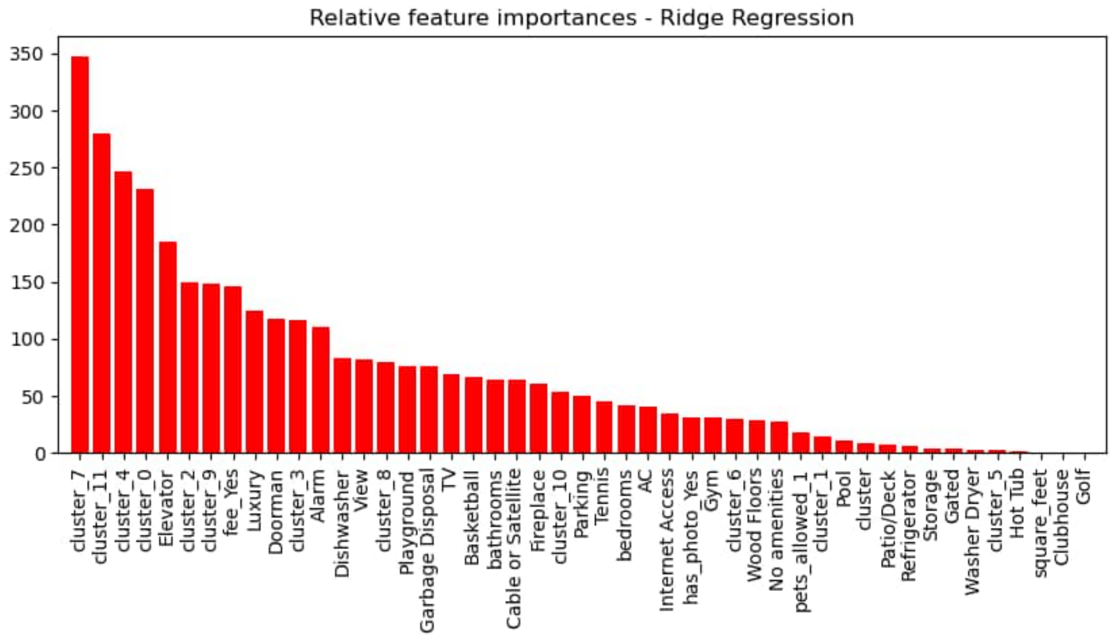


[42]:
```python
importances2 = np.abs(ridge_benchmark.coef_)  # Take the absolute value of the␣
↪coefficients
indices = np.argsort(importances2)[::-1]  # Sort the coefficients in descending␣
↪order of importance

# Get the feature names in order of importance
feature_order = np.array([X.columns.values])
i = np.argsort(importances2)[::-1]
feature_order = feature_order[:, i]

# If you want to print the features sorted by their importance
print("Features ranked by importance:")
for idx in indices:
    print(f"{X.columns[idx]}: {importances2[idx]}")
```

```
Features ranked by importance:
cluster_7: 347.46907347332115
cluster_11: 280.1531618295632
cluster_4: 246.41869231602763
cluster_0: 231.3134815617109
Elevator: 184.8421906796517
cluster_2: 149.55347265214505
cluster_9: 148.5653513385934
fee_Yes: 145.37622579714352
Luxury: 124.78589496446064
Doorman: 117.49615474128075
```

```
cluster_3: 116.81925312270253
Alarm: 109.86568846482346
Dishwasher: 83.31686753413308
View: 81.70661373373298
cluster_8: 79.7245979019962
Playground: 76.21239039431345
Garbage Disposal: 75.80637521630427
TV: 68.536922603648
Basketball: 66.28008930382178
bathrooms: 64.1897451283557
Cable or Satellite: 64.00969030710391
Fireplace: 60.544608270372265
cluster_10: 53.08505561746883
Parking: 49.94857839192022
Tennis: 44.65575425209234
bedrooms: 41.69061068664761
AC: 40.07225841127389
Internet Access: 34.71748890324036
has_photo_Yes: 31.054919809186373
Gym: 30.807547690715648
cluster_6: 30.163775119644185
Wood Floors: 28.454908521762757
No amenities: 27.102891641901262
pets_allowed_1: 18.281985724949145
cluster_1: 14.870106130854962
Pool: 10.66388425837686
cluster: 9.04146838580182
Patio/Deck: 7.877574961341456
Refrigerator: 5.569792595576981
Storage: 3.435664283034373
Gated: 3.3221069082081027
Washer Dryer: 2.4504717403284686
cluster_5: 2.0713242088060673
Hot Tub: 1.429989187187299
square_feet: 0.6444917500658675
Clubhouse: 0.4737323351338003
Golf: 0.0
```

[43]:
```python
# Plot the feature importances
plt.figure(figsize=(10, 4))
plt.title("Relative feature importances - Ridge Regression")
plt.bar(range(X.shape[1]), importances2[indices],
       color="r",  align="center")
plt.xticks(range(X.shape[1]), feature_order[0], rotation=90)
plt.xlim([-1, X.shape[1]])
plt.show()
```


Relative feature importances - Ridge Regression
350
300
250
200
150
100
50
0
cluster_7
cluster_11
cluster_4
cluster_0
Elevator
cluster_2
cluster_9
fee_Yes
Luxury
Doorman
cluster_3
Alarm
Dishwasher
View
cluster_8
Playground
Garbage Disposal
TV
Basketball
bathrooms
Cable or Satellite
Fireplace
cluster_10
Parking
Tennis
bedrooms
AC
Internet Access
has_photo_Yes
Gym
cluster_6
Wood Floors
No amenities
pets_allowed_1
cluster_1
Pool
cluster
Patio/Deck
Refrigerator
Storage
Gated
Washer Dryer
cluster_5
Hot Tub
square_feet
Clubhouse
Golf

[ ]: