Leap_Assignment2_Task2

August 18, 2025

1 Apartment Rent Dataset Classification

1.1 Objective

Implement a data mining project using the Python machine learning library Spark MLlib to predict rental prices (`price`).
Only Spark MLlib can be used for machine learning tasks, but non-ML libraries are allowed for other purposes.

1.2 Data Source

Kaggle: Apartment Rent Data This dataset comprises detailed information on apartment rentals

This dataset comprises detailed information on apartment rentals:

- **Identifiers & Location:**
  - Unique identifiers (`id`)
  - Geographic details (`address`, `cityname`, `state`, `latitude`, `longitude`)
  - Source of the classified listing (`source`)
- **Property Details:**
  - Category (`category`)
  - Title (`title`)
  - Description (`body`)
  - Amenities (`amenities`)
  - Number of bathrooms (`bathrooms`)
  - Number of bedrooms (`bedrooms`)
  - Size of the apartment (`square_feet`)
- **Pricing Information:**
  - Rental price (`price`)
  - Displayed price (`price_display`)
  - Price type (`price_type`)
  - Fee (`fee`)
- **Additional Features:**
  - Photo availability (`has_photo`)
  - Pets allowed (`pets_allowed`)
  - Currency (`currency`)
  - Time of listing creation (`time`)

1.3 Project Phases

1. **Discover and visualize the data**

2. **Prepare the data for machine learning algorithms**

3. **Select and train models**

4. **Fine-tune the model**

5. **Evaluate the outcomes**

   Note:
   You must repeat phases 3, 4, and 5 for at least three different models.

[1]:
```
#!/usr/bin/env python3
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
pd.set_option('display.float_format', lambda x: f'{x:,.2f}')

# Load dataset
DATA_PATH = "./data/apartments_for_rent_classified_100K.csv"
df = pd.read_csv(DATA_PATH, delimiter=';', encoding='ISO-8859-1')
df.shape
```

```
/tmp/ipykernel_110/1453841023.py:11: DtypeWarning: Columns (15) have mixed
types. Specify dtype option on import or set low_memory=False.
  df = pd.read_csv(DATA_PATH, delimiter=';', encoding='ISO-8859-1')
```

[1]:
```
(99492, 22)
```

2 (a) Discover and Visualize the Data

2.1 Dataset Structure Analysis

Objective: Understand data characteristics to inform preprocessing strategies.

2.1.1 Key Analysis Areas

- **Data types and structure** - Feature characteristics and distributions
- **Missing data patterns** - Identify incomplete records and percentages

- **Feature cardinality** - Assess uniqueness and dimensionality issues
- **Correlation analysis** - Examine relationships between numerical variables
- **Data quality issues** - Detect duplicates, outliers, and inconsistencies

[2]:
```python
# Understand structure and type of the data
# ------------------------------------------------------------------
summary = []
for col in df.columns:
    value_counts = df[col].value_counts().head(10)
    top_values = [str(x)[:50] for x in value_counts.index]  # Truncate long␣
↪values
    summary.append({
        "Column": col,
        "Data Type": str(df[col].dtype),
        "Unique Values": df[col].nunique(),
        "Top 10 frequent Values (desc)": " | ".join(top_values)
    })

summary_df = pd.DataFrame(summary)
summary_df
```

[2]:
```
           Column Data Type  Unique Values  \
0              id     int64          99408
1        category    object              7
2           title    object          58503
3            body    object          94503
4       amenities    object           9827
5       bathrooms   float64             16
6        bedrooms   float64             10
7        currency    object              1
8             fee    object              2
9       has_photo    object              3
10   pets_allowed    object              4
11          price   float64           3687
12  price_display    object           3718
13     price_type    object              3
14    square_feet     int64           2538
15        address    object           7771
16       cityname    object           2979
17          state    object             51
18       latitude   float64           7212
19      longitude   float64           7270
20         source    object             25
21           time     int64          75360

                        Top 10 frequent Values (desc)
0   5197858885 | 5197859052 | 5197859695 | 5197860…
1   housing/rent/apartment | housing/rent/commerci…
2   Apartment in great location | Apartment in pri…
3   When searching for a pet-friendly One-, Two- a…
4   Parking | Parking,Storage | Gym,Pool | Pool | …
```

```
5   1.0 | 2.0 | 1.5 | 2.5 | 3.0 | 3.5 | 4.0 | 4.5 …
6   2.0 | 1.0 | 3.0 | 4.0 | 0.0 | 5.0 | 6.0 | 7.0 …
7                                                   USD
8                                              No | Yes
9                                  Yes | Thumbnail | No
10           Cats,Dogs | Cats | Dogs | Cats,Dogs,None
11  1350.0 | 850.0 | 1200.0 | 950.0 | 1100.0 | 150…
12  $1,350 | $850 | $1,200 | $950 | $1,100 | $1,50…
13                  Monthly | Weekly | Monthly|Weekly
14  1000 | 900 | 700 | 800 | 750 | 1100 | 850 | 65…
15  8215 S.W 72nd Avenue | 2647 Eastgate Road | 90…
16  Dallas | Denver | Los Angeles | Las Vegas | Ar…
17    TX | CA | VA | NC | CO | FL | MD | MA | OH | GA
18  42.328 | 30.3054 | 40.722 | 38.9118 | 33.7848 …
19  -71.071 | -97.7497 | -74.0644 | -77.0132 | -84…
20  RentDigs.com | RentLingo | ListedBuy | GoSecti…
21  1568754048 | 1577359251 | 1577359489 | 1568753…
```

[3]:
```
# Missing data %
# -------------------------------------------------------------------
pd.set_option('display.float_format', lambda x: f'{x:,.4f}')
missing_values = (df.isnull().sum())/ (df.shape[0]) * 100
missing_values.loc[missing_values > 0].sort_values(ascending=False)
```

[3]:
```
address          92.0164
pets_allowed     60.7325
amenities        16.1259
state             0.3035
cityname          0.3035
bedrooms          0.1246
bathrooms         0.0633
latitude          0.0251
longitude         0.0251
price_display     0.0010
price             0.0010
dtype: float64
```

[4]:
```
# Determine cardinality of features (i.e the effective uniqueness)
# -------------------------------------------------------------------
import builtins
categorical_cols = [col for col in df.columns if col not in␣
↪['id','longitude','latitude','price','time','title','body','address','square_feet','price_d
max_len = builtins.max([len(c) for c in categorical_cols])
for col in categorical_cols:
    print(f"{col.ljust(max_len)} :{str(df[col].dtype).ljust(10)} : {str(df[col].
↪nunique()).rjust(10)} unique values")
```

```
category     :object     :          7 unique values
amenities    :object     :       9827 unique values
bathrooms    :float64    :         16 unique values
bedrooms     :float64    :         10 unique values
currency     :object     :          1 unique values
fee          :object     :          2 unique values
has_photo    :object     :          3 unique values
pets_allowed :object     :          4 unique values
price_type   :object     :          3 unique values
cityname     :object     :       2979 unique values
state        :object     :         51 unique values
source       :object     :         25 unique values
```

[5]:

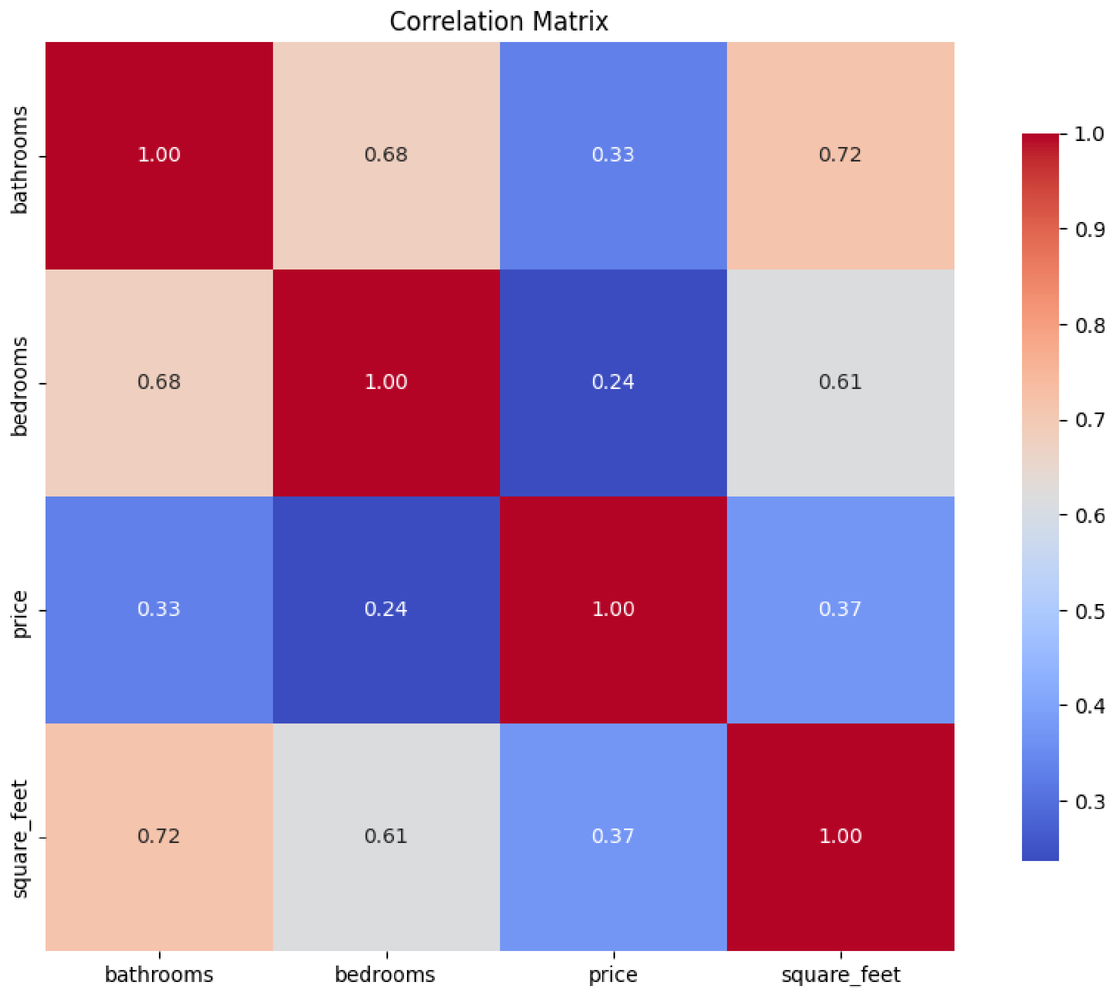
```python
# Check if identifier has duplicates
# ------------------------------------------------------------------
print(f"id has duplicates: {df['id'].duplicated().any()}")
```

```
id has duplicates: True
```

[6]:

```python
# Correlation analysis
# ------------------------------------------------------------------
correlation_matrix = df[['bathrooms', 'bedrooms', 'price', 'square_feet']].
 ↪corr()
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='coolwarm',␣
 ↪square=True, cbar_kws={"shrink": .8})
plt.title('Correlation Matrix')
```

[6]: Text(0.5, 1.0, 'Correlation Matrix')



2.2 Results of Analysis of the Structure and Content of Each Column

2.2.1 Missing Values Analysis

There are missing values in the dataset, most notably for `address` where **92% of the values are missing**.

2.2.2 Cardinality Assessment

We define **high cardinality** as a feature having more than 20 unique values. Looking at categorical features, we encounter significant cardinality issues:

Feature	Unique Values	Category	Issue Level
`amenities`	9,827	Very High	Critical
`cityname`	2,979	Very High	Critical
`source`	~50+	High	Moderate
`state`	~50	High	Moderate

Impact: High cardinality features can lead to: - Sparse feature matrices after one-hot encoding
- Overfitting due to too many dimensions
- Poor model generalization

2.2.3 Duplicate Values Detection

Duplicate values found in:
- **Identifiers**: `id` field has duplicates
- **Free text fields**: Both `title` and `body` contain duplicates

2.3 Analyzing The Distribution Of Values in The Dataset

2.3.1 Analysis Methods

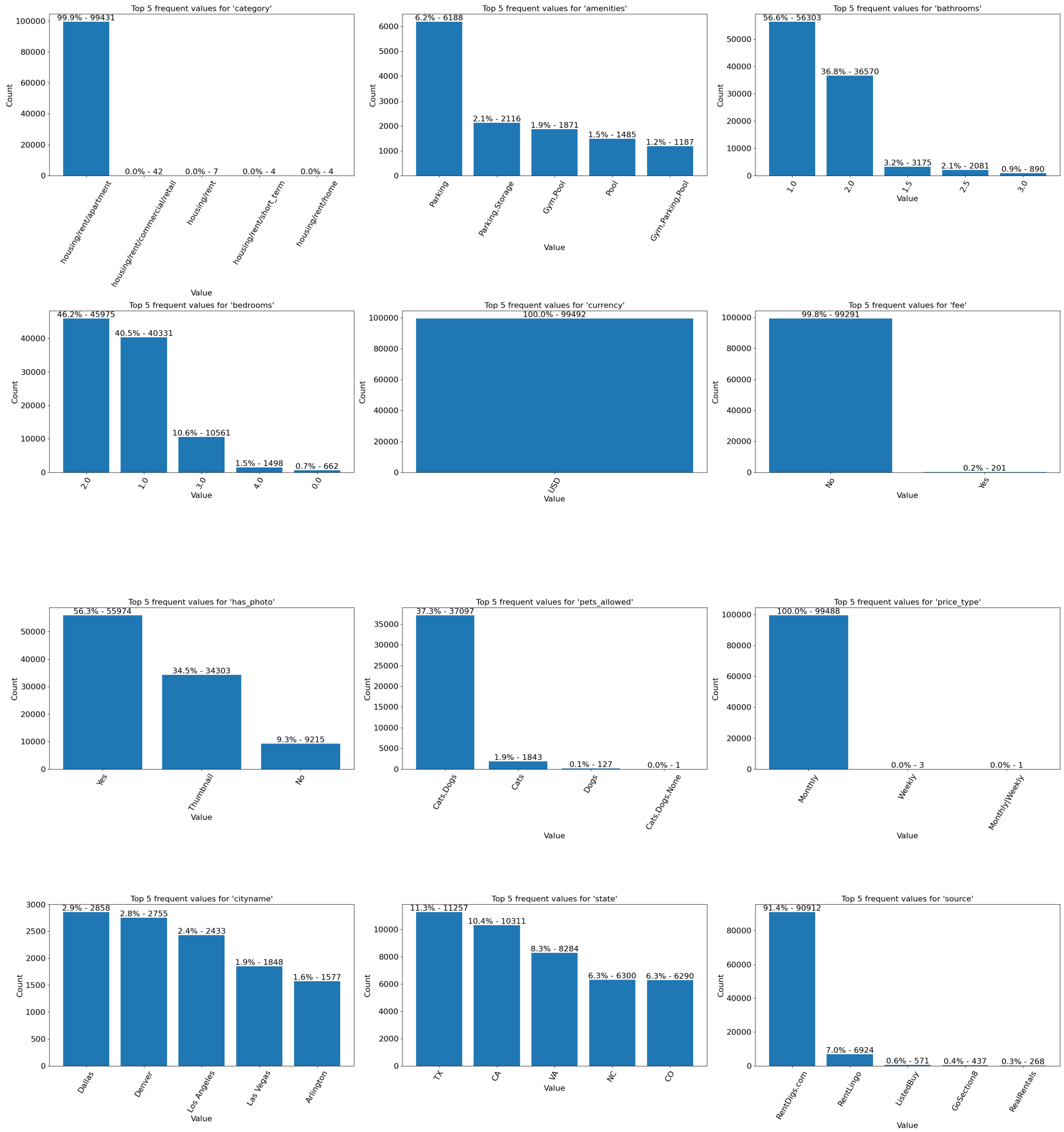
- **Bar graphs** of categorical features
- **Box plots** of numeric features
- **Histograms** of numeric features

2.3.2 Objectives

- **Identify outliers** in numerical data
- **Examine statistics** of numerical features (ranges, min/max values)
- **Assess data distribution** - determine if values are well-spread or skewed

[7]:
```
"""
Visualize the distribution of features in the dataset.
Also shows the percentage of the dataset that each value represents.
Only the top 5 most frequent values for each feature are plotted.
**This ignores null values, there are features where most of the values are null
"""

import math
# The following columns are ignored
columns_to_plot = [col for col in df.columns if col not in [
    'id', # Unique identifier, not useful for plotting
    'body', 'title', 'address', # Free text field
    'latitude', 'longitude', # GPS exact values, not useful for plotting
    'time','square_feet','price','price_display' # Numeric fields, not␣
↪categorical
    ]]
num_cols = len(columns_to_plot)
cols_per_row = 3  # Fewer columns per row for more space
num_rows = math.ceil(num_cols / cols_per_row)
```

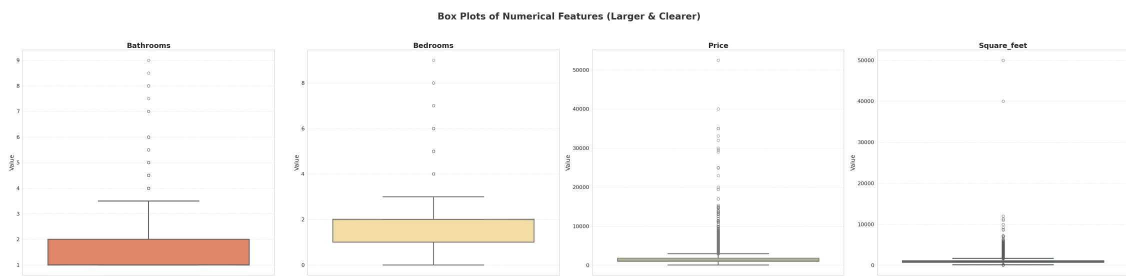
```
fig, axes = plt.subplots(num_rows, cols_per_row, figsize=(cols_per_row*10,␣
↪num_rows*8))
axes = axes.flatten()

for i, col in enumerate(columns_to_plot):
    value_counts = df[col].value_counts().head(5)
    total = len(df)
    unique_count = df[col].nunique()
    # Use a colormap for more colorful bars
    bars = axes[i].bar(value_counts.index.astype(str), value_counts.values)
    axes[i].set_title(f"Top 5 frequent values for '{col}'", fontsize=16)
    axes[i].set_xlabel("Value",fontsize=16)
    axes[i].set_ylabel("Count", fontsize=16)
    axes[i].tick_params(axis='x', rotation=60, labelsize=16)
    axes[i].tick_params(axis='y', labelsize=16)
    for bar, count in zip(bars, value_counts.values):
        percent = 100 * count / total
        axes[i].text(bar.get_x() + bar.get_width()/2, bar.get_height(),␣
↪f"{percent:.1f}% - {count}",
                     ha='center', va='bottom', fontsize=16, color='black')

# Hide any unused subplots
for j in range(i+1, len(axes)):
    fig.delaxes(axes[j])

plt.tight_layout()
```



[8]:

```
# Identifying outliers with larger, clearer boxplots

import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)

float_cols = ["bathrooms", "bedrooms", "price", "square_feet"]

sns.set(style="whitegrid", font_scale=1.5)
num_cols = len(float_cols)
```

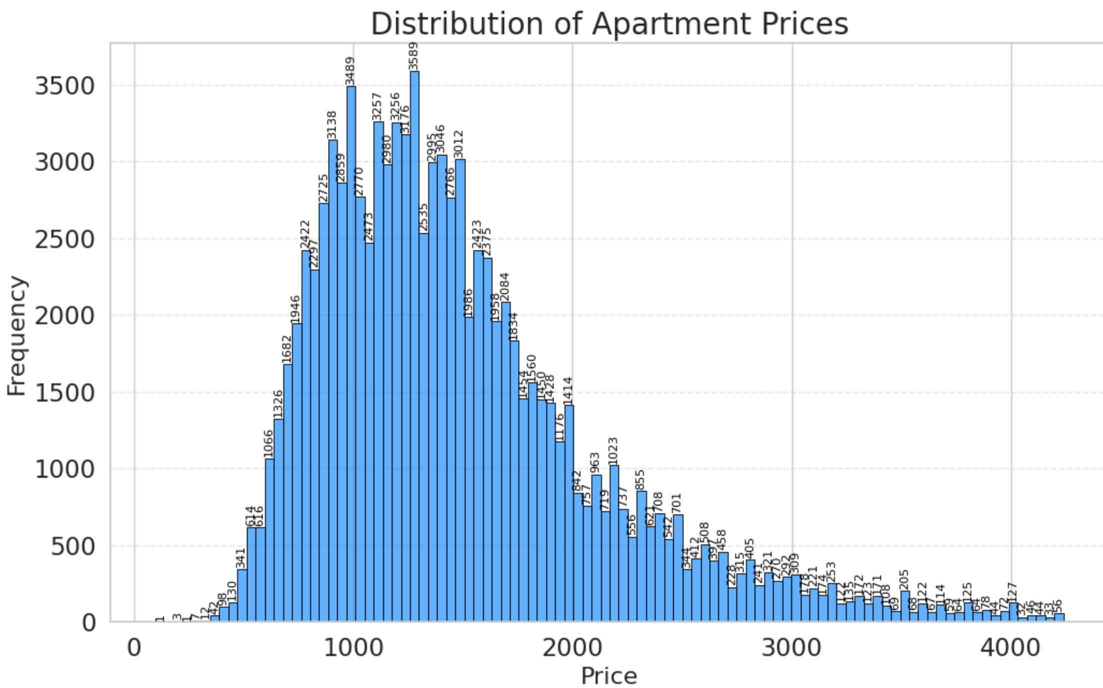
```python
fig, axes = plt.subplots(1, num_cols, figsize=(12*num_cols, 12), sharey=False)

for i, col in enumerate(float_cols):
    sns.boxplot(
        y=df[col],
        ax=axes[i],
        color=sns.color_palette("Spectral", num_cols)[i],
        notch=True,
        linewidth=3,
        fliersize=8,
        boxprops=dict(alpha=0.9)
    )
    axes[i].set_title(f"{col.capitalize()}", fontsize=22, weight='bold')
    axes[i].set_xlabel("")
    axes[i].set_ylabel("Value", fontsize=18)
    axes[i].grid(axis='y', linestyle='--', alpha=0.5)
    axes[i].tick_params(axis='y', labelsize=16)
    axes[i].tick_params(axis='x', labelsize=16)

plt.suptitle("Box Plots of Numerical Features (Larger & Clearer)", fontsize=28, weight='bold', color='#333333')
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```



[9]:

```python
# Histogram for price excluding outliers
pd.set_option('display.float_format', lambda x: f'{x:,.2f}')
# Exclude outliers (5 std from mean)
mean_price = df['price'].mean()
std_price = df['price'].std()
lower_bound = mean_price - 3 * std_price
upper_bound = mean_price + 3 * std_price
price_histogram = df[(df['price'] >= lower_bound) & (df['price'] <= upper_bound)].copy(deep=True)


plt.figure(figsize=(12, 7))
```

```python
ax = sns.histplot(
    price_histogram['price'].dropna(),
    bins=100,
    color='dodgerblue',
    edgecolor='black',
    alpha=0.7
)
ax.set_title('Distribution of Apartment Prices', fontsize=20)
ax.set_xlabel('Price', fontsize=16)
ax.set_ylabel('Frequency', fontsize=16)
ax.grid(axis='y', linestyle='--', alpha=0.5)

# Annotate each bin with its count
for patch in ax.patches:
    if patch.get_height() > 0:
        ax.annotate(
            f'{int(patch.get_height())}',
            (patch.get_x() + patch.get_width() / 2, patch.get_height() +10),
            ha='center', va='bottom', fontsize=8, color='black', rotation=90
        )

plt.show()

print(f"Price histogram: {len(price_histogram)} rows, {price_histogram['price'].
 ↪nunique()} unique prices")
print('-' * 50)
print(f"Price Statistics")
print(df['price'].describe())
```

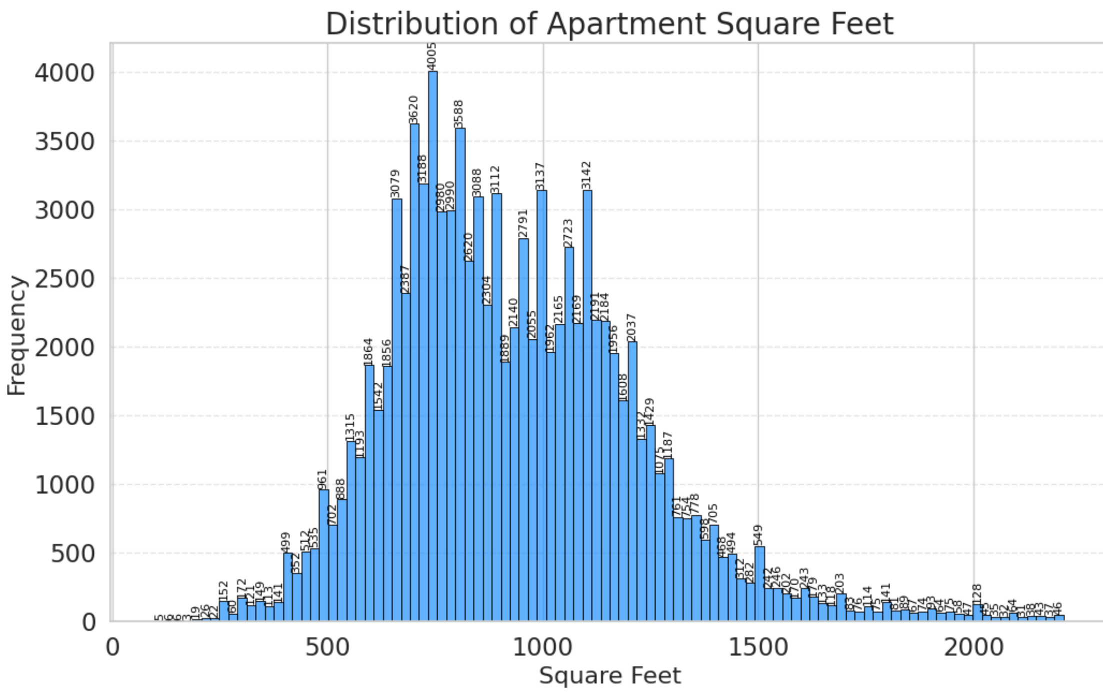



```
Price histogram: 98482 rows, 3298 unique prices
--------------------------------------------------
Price Statistics
count    99,491.00
mean      1,527.06
std         904.25
min         100.00
25%       1,013.00
50%       1,350.00
75%       1,795.00
max      52,500.00
Name: price, dtype: float64
```

[10]:

```
# Histogram for square feet excluding outliers

# Exclude outliers (3 std from mean)
mean_sqft = df['square_feet'].mean()
std_sqft = df['square_feet'].std()
lower_bound = mean_sqft - 3 * std_sqft
upper_bound = mean_sqft + 3 * std_sqft
square_feet_histogram = df[(df['square_feet'] >= lower_bound) &
  ↪(df['square_feet'] <= upper_bound)].copy(deep=True)

# graph
plt.figure(figsize=(12, 7))
```

```
ax = sns.histplot(
    square_feet_histogram['square_feet'].dropna(),
    bins=100,
    color='dodgerblue',
    edgecolor='black',
    alpha=0.7
)
ax.set_title('Distribution of Apartment Square Feet', fontsize=20)
ax.set_xlabel('Square Feet', fontsize=16)
ax.set_ylabel('Frequency', fontsize=16)
ax.grid(axis='y', linestyle='--', alpha=0.5)

# Annotate each bin with its count, with more vertical separation
for patch in ax.patches:
    if patch.get_height() > 0:
        ax.annotate(
            f'{int(patch.get_height())}',
            (patch.get_x() + patch.get_width() / 2, patch.get_height() + 5),
            ha='center', va='bottom', fontsize=8, color='black', rotation=90
        )

plt.show()

# stats
print(f"Square feet histogram: {len(square_feet_histogram)} rows,␣
 ↪{square_feet_histogram['square_feet'].nunique()} unique square feet values")
print('-' * 50)
print(f"Square Feet Statistics")
print(df['square_feet'].describe())
```




```
Square feet histogram: 98420 rows, 1875 unique square feet values
--------------------------------------------------
Square Feet Statistics
count   99,492.00
mean       956.43
std        417.57
min        101.00
25%        729.00
50%        900.00
75%      1,115.00
max     50,000.00
Name: square_feet, dtype: float64
```

2.4 Summary of Data Quality Issues and Preprocessing Concerns

2.4.1 Duplicate Data Issues

- **`id`** - Contains duplicate identifiers that need investigation
- **`title`, `body`** - Free text fields with duplicates; need to determine if these are legitimate listings or cross-platform duplicates from different `source` sites

2.4.2 Highly Skewed Features (Low Information Value)

Features dominated by a single value (~90%+ of data):
- **`category`** - 99.4% are "housing/rent/apartment"

- `currency` - 100% are USD
- `fee` - 99.8% are "No"
- `price_type` - 99.9% are "Monthly"
- `source` - 91.4% are from "RentDigs.com"

Impact: These features provide minimal predictive power due to lack of variance

2.4.3 Extreme Outliers

Numerical features with extreme values requiring treatment:
- `price` - Rental prices with unrealistic extremes
- `square_feet` - Property sizes with outliers
- `bedrooms` - Bedroom counts with extreme values
- `bathrooms` - Bathroom counts with extreme values

2.4.4 High Cardinality Features

Features requiring dimensionality reduction:
- `amenities` - 9,827 unique values (combinatorial explosion)
- `cityname` - 2,979 unique cities

2.4.5 Missing Data

Features with significant missing values:
- `address` - 92% missing (can be safely dropped)
- `pets_allowed` - 60.7% missing
- `amenities` - 16% missing

2.4.6 Processing Requirements

- `price_display` - Redundant formatting of `price`, safe to drop
- `currency` - All USD, safe to drop
- `title, body` - Text features need processing or exclusion
- `latitude, longitude` - Raw coordinates require transformation for usefulness
- **Categorical features** - Require multi-value binarization (one-hot encoding)

2.4.7 Rare Categories

- `price_type`, `pets_allowed` - Contain single-occurrence values that may cause issues

2.5 Key Dataset Insights

Exploring geographic patterns, pricing trends, and market distribution across the US apartment rental market.

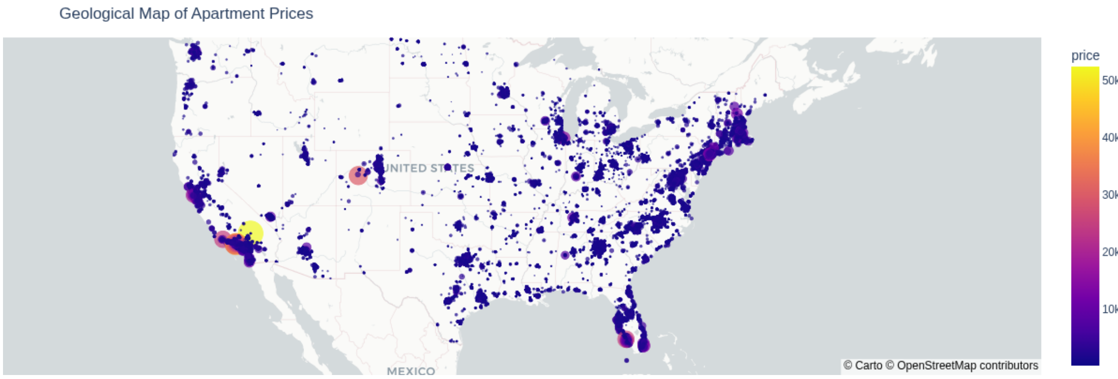
[ ]:
```python
# Imports for displaying graph images
import plotly.io as pio
from IPython.display import Image
```

[12]:
```python
# Geographical map
# Prepare data for mapping
geo_df = df.copy(deep=True)
geo_df = geo_df.dropna(subset=['latitude', 'longitude', 'price'])
geo_df["address"] = geo_df["address"].fillna('Not available')



fig = px.scatter_mapbox(
    geo_df,
    lat="latitude",
    lon="longitude",
    color="price",
    size="price",
    hover_name="title",
    hover_data=["address", "category", "source","state","cityname"],
    mapbox_style="carto-positron",
    zoom=3,
    color_continuous_scale=px.colors.sequential.Plasma,
    title="Geological Map of Apartment Prices"
)

fig.update_layout(margin={"r":0,"t":40,"l":0,"b":0})
fig.show()
```

```
/tmp/ipykernel_110/2639109610.py:8: DeprecationWarning: *scatter_mapbox* is
deprecated! Use *scatter_map* instead. Learn more at:
https://plotly.com/python/mapbox-to-maplibre/
  fig = px.scatter_mapbox(
```

[13]:
```python
# Save the figure as an image & Display in report
# Note: This is done so the plotly graph is displayed in the exported pdf
# ------------------------------------------------------------------------
pio.write_image(fig,"./images/geo_map_apartment_prices.png",width=1200,␣
↪height=400)
Image("./images/geo_map_apartment_prices.png")
```

[13]:



[14]:
```python
state_names = {
    'AL': 'Alabama', 'AK': 'Alaska', 'AZ': 'Arizona', 'AR': 'Arkansas', 'CA': 'California',
    'CO': 'Colorado', 'CT': 'Connecticut', 'DE': 'Delaware', 'FL': 'Florida', 'GA': 'Georgia',
    'HI': 'Hawaii', 'ID': 'Idaho', 'IL': 'Illinois', 'IN': 'Indiana', 'IA': 'Iowa',
    'KS': 'Kansas', 'KY': 'Kentucky', 'LA': 'Louisiana', 'ME': 'Maine', 'MD': 'Maryland',
    'MA': 'Massachusetts', 'MI': 'Michigan', 'MN': 'Minnesota', 'MS': 'Mississippi', 'MO': 'Missouri',
    'MT': 'Montana', 'NE': 'Nebraska', 'NV': 'Nevada', 'NH': 'New Hampshire', 'NJ': 'New Jersey',
    'NM': 'New Mexico', 'NY': 'New York', 'NC': 'North Carolina', 'ND': 'North Dakota', 'OH': 'Ohio',
    'OK': 'Oklahoma', 'OR': 'Oregon', 'PA': 'Pennsylvania', 'RI': 'Rhode Island', 'SC': 'South Carolina',
    'SD': 'South Dakota', 'TN': 'Tennessee', 'TX': 'Texas', 'UT': 'Utah', 'VT': 'Vermont',
    'VA': 'Virginia', 'WA': 'Washington', 'WV': 'West Virginia', 'WI': 'Wisconsin', 'WY': 'Wyoming'
}

# Calculate median price per state
state_prices = df.groupby('state')['price'].median().sort_values()

# Get top 5 least and top 5 most expensive states
least_expensive = state_prices.head(5)
most_expensive = state_prices.tail(5)

# Combine for plotting
contrast_states = pd.concat([least_expensive, most_expensive]).reset_index()
contrast_states['State Name'] = contrast_states['state'].map(state_names)
```

```
contrast_states['Group'] = ['Least Expensive']*5 + ['Most Expensive']*5

fig = px.bar(
    contrast_states,
    x='price',
    y='State Name',
    color='Group',
    orientation='h',
    text='price',
    color_discrete_map={'Least Expensive': 'teal', 'Most Expensive': 'red'},
    title='Top 5 Least vs Most Expensive States (Median Apartment Price)'
)
fig.update_traces(texttemplate='$%{text:,.0f}', textposition='inside')
fig.update_layout(
    xaxis_title='Median Price (USD)',
    yaxis_title='State',
    yaxis=dict(categoryorder='total ascending'),
    legend_title='',
    font=dict(size=14),
)
fig.show()
```

[15]:
```
# Save the figure as an image & Display in report
# Note: This is done so the plotly graph is displayed in the exported pdf
# ----------------------------------------------------------------------
pio.write_image(fig,"./images/top5_least_vs_most_expensive.png",width=1200,␣
↪height=400)
Image("./images/top5_least_vs_most_expensive.png")
```

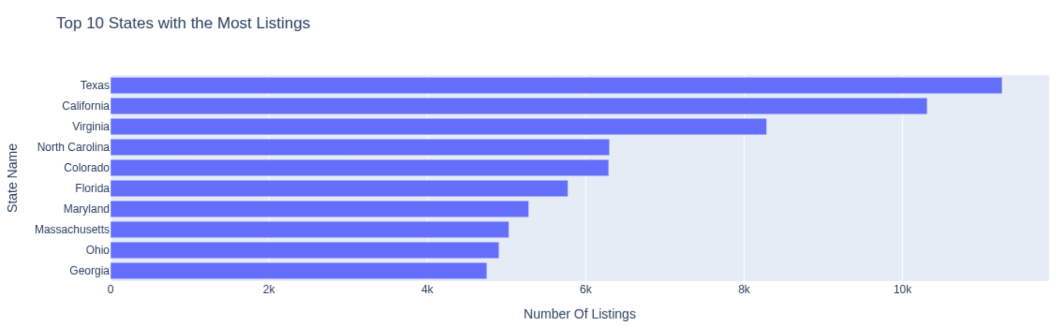
[15]:

[16]:
```
# Get visualization of top 10 states with the most listings
top_states = df["state"].value_counts().head(10).reset_index()
top_states.columns = ['state', 'count']  # Rename columns for clarity
top_states["state_name"] = top_states["state"].map(state_names)
```

```
fig = px.bar(
    top_states,
    x='count',
    y='state_name',
    orientation='h',
    title='Top 10 States with the Most Listings'
)
fig.update_layout(
    xaxis_title='Number Of Listings',
    yaxis_title='State Name',
    yaxis=dict(categoryorder='total ascending')
)
fig.show()
```

[17]:
```
# Save the figure as an image & Display in report
# Note: This is done so the plotly graph is displayed in the exported pdf
# -----------------------------------------------------------------------
pio.write_image(fig,"./images/top10_states_with_the_most_listings.
↪png",width=1200, height=400)
Image("./images/top10_states_with_the_most_listings.png")
```

[17]:



[18]:
```
# Analysing how prices change over time per state (time intervals are in months)
df["time_readable"] = pd.to_datetime(df["time"], unit='s')
df["month"] = df["time_readable"].dt.to_period("M").astype(str)
top_states = df['state'].value_counts().head(10).index

# Group by state and month, get median price and count
plot_df = (
    df[df['state'].isin(top_states)]
    .groupby(['state', 'month'])
    .agg(price=('price', 'median'), count=('price', 'size'))
    .reset_index()
)
```

```python
fig = px.line(
    plot_df,
    x='month',
    y='price',
    color='state',
    markers=True,
    title='Median Apartment Price by Month (Top 10 States)',
    labels={'month': 'Month', 'price': 'Median Price', 'state': 'State'},
    custom_data=['count']  # Set custom data here for hovertemplate
)

# Add sample count as hover info
fig.update_traces(
    hovertemplate=''
    '<b>%{x}</b>'
    '<br>Median Price: $%{y:,.0f}'
    '<br>Samples: %{customdata[0]}'
)

fig.update_layout(xaxis_tickangle=-45)
fig.show()
# Investigating why california rose so much in this month
print(f"Sudden Spike in November for CA:")
print(
    df.loc[
        (df["month"] == "2019-11") &
        (df["state"] == "CA")
    ]["price"]
)


df.drop(["time_readable","month"],axis=1,inplace=True)
# Conclusion:
# State prices are mostly stable throughout the year in which this data was␣
 ↪recorded
```

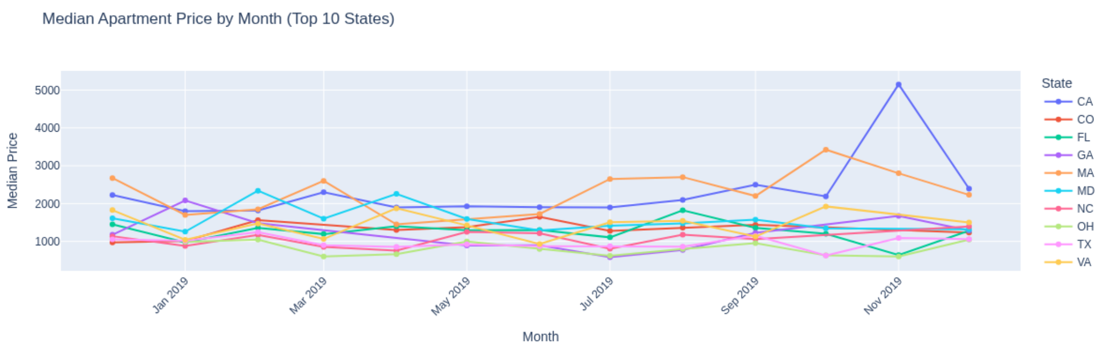
```
Sudden Spike in November for CA:
7123    9,450.00
51779     850.00
Name: price, dtype: float64
```

[19]:

```python
# Save the figure as an image & Display in report
# Note: This is done so the plotly graph is displayed in the exported pdf
# ----------------------------------------------------------------------
pio.write_image(fig,"./images/median_price_by_month_top_10_states.
 ↪png",width=1200, height=400)
```

```
Image("./images/median_price_by_month_top_10_states.png")
```

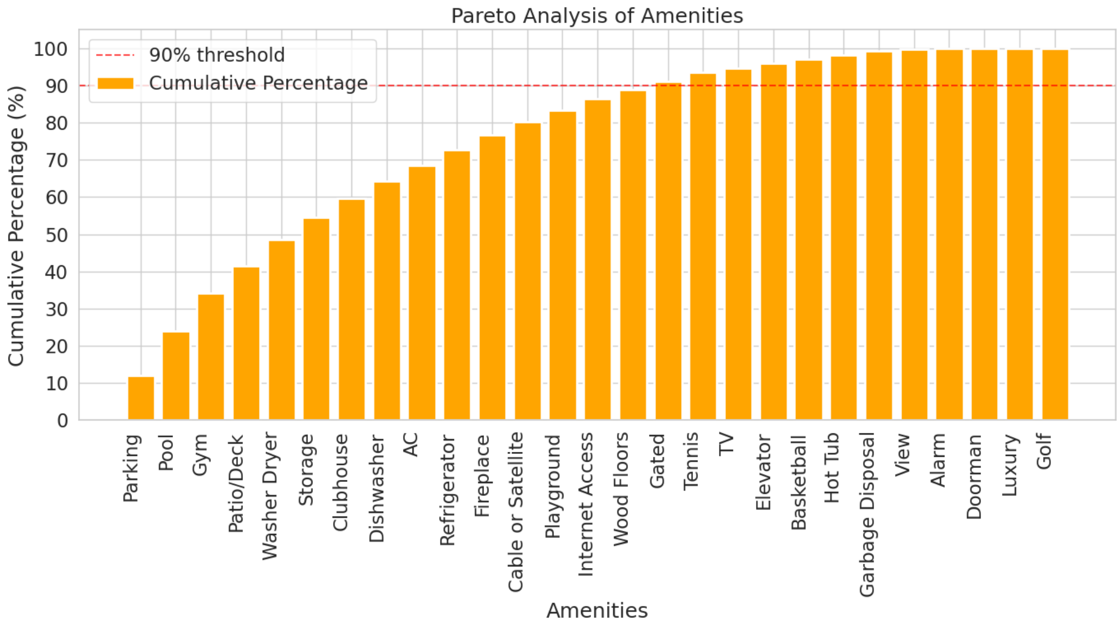
[19]:



[20]:

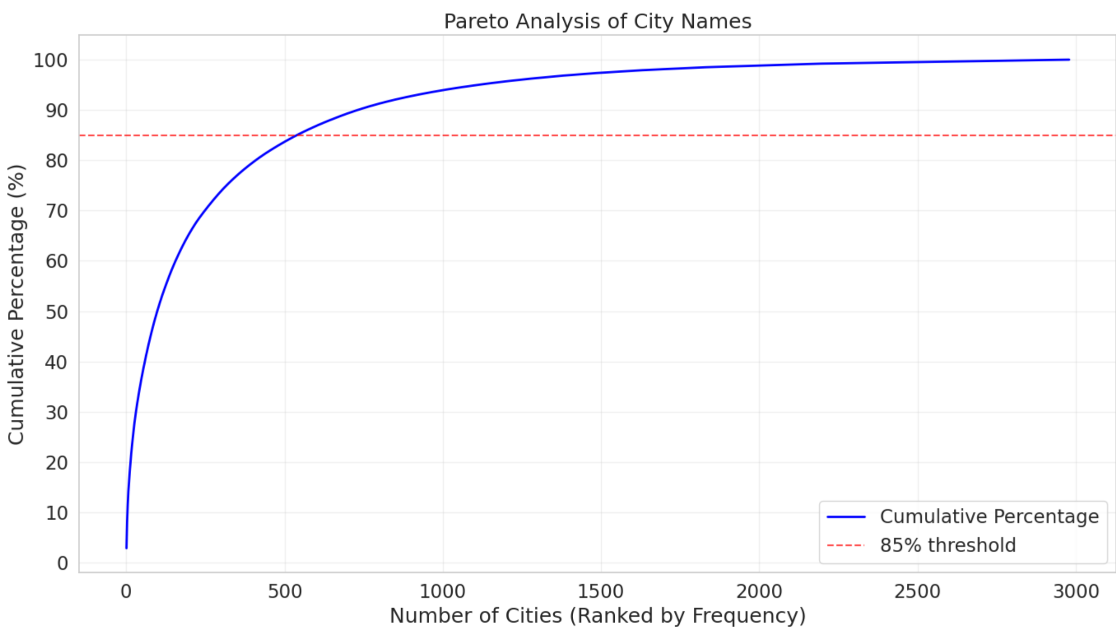
```
# Pareto analysis of amenities to identify the most common amenities
# -------------------------------------------------------------------
amenity_value_counts = df["amenities"].str.split(',').explode().value_counts()
amenity_value_counts = amenity_value_counts.reset_index()
amenity_value_counts["cumulative_count"] = amenity_value_counts["count"].
    ↪cumsum().astype(int)
amenity_value_counts["cumulative_pct"] =␣
    ↪(amenity_value_counts["cumulative_count"] / amenity_value_counts["count"].
    ↪sum()) * 100
amenity_value_counts

# Plotting the Pareto chart for amenities
plt.figure(figsize=(14, 8))
plt.bar(
    amenity_value_counts["amenities"],
    amenity_value_counts["cumulative_pct"],
    color='orange',
    label='Cumulative Percentage',
    linewidth=2
)
plt.xlabel('Amenities')
plt.ylabel('Cumulative Percentage (%)')
plt.title('Pareto Analysis of Amenities')
plt.xticks(rotation=90, ha='right')

# Set y-axis to show in tens (10, 20, 30, etc.)
plt.yticks(range(0, 101, 10))  # 0, 10, 20, 30, ..., 100

# Add horizontal line at 90%
plt.axhline(y=90, color='red', linestyle='--', alpha=0.7, label='90% threshold')
```

```
plt.legend()
plt.tight_layout()
plt.show()
```



[21]:
```
# Pareto analysis of cityname to identify the most common cities
# ------------------------------------------------------------------
cityname_counts = df["cityname"].value_counts().reset_index()
cityname_counts["cumulative_count"] = cityname_counts["count"].cumsum().
↪astype(int)
cityname_counts["cumulative_pct"] = (cityname_counts["cumulative_count"] /␣
↪cityname_counts["count"].sum()) * 100
cityname_counts.reset_index(inplace=True)
cityname_counts.columns = ["num_cities","cityname", "count",␣
↪"cumulative_count", "cumulative_pct"]
cityname_counts["num_cities"] = cityname_counts["num_cities"] + 1  # Adjust␣
↪index to start from 1


# Plotting the Pareto chart for city names as LINE PLOT
plt.figure(figsize=(14, 8))
plt.plot(
    cityname_counts["num_cities"],
    cityname_counts["cumulative_pct"],
    color='blue',
    markersize=3,
    linewidth=2,
```

```
    label='Cumulative Percentage'
)

plt.xlabel('Number of Cities (Ranked by Frequency)')
plt.ylabel('Cumulative Percentage (%)')
plt.title('Pareto Analysis of City Names')

# Set x-axis to show in ranges/intervals instead of individual city names
max_cities = len(cityname_counts)

# Set y-axis to show in tens (10, 20, 30, etc.)
plt.yticks(range(0, 101, 10))  # 0, 10, 20, 30, ..., 100

# Add horizontal line at 90%
plt.axhline(y=85, color='red', linestyle='--', alpha=0.7, label='85% threshold')

# Add grid for better readability
plt.grid(True, alpha=0.3)

plt.legend()
plt.tight_layout()
plt.show()
```



3 (b) Prepare the data for machine learning algorithms

Data preprocessing pipeline implemented using Spark MLlib to transform raw apartment rental data into ML-ready format.

3.1 Data Cleaning & Quality Issues

- **Removed low-variance features**: Dropped columns with >90% single values (currency, category, fee, etc.)
- **Handled missing data**: Addressed 92% missing addresses and 60% missing pet policies

- **Eliminated duplicates**: Cleaned duplicate IDs and redundant listings
- **Outlier treatment**: Applied IQR-based filtering to remove extreme values in price, bedrooms, bathrooms, and square footage

3.2 Feature Engineering

- **Geographic transformation**: Converted lat/lon coordinates into regional categories (northwest, northeast, southwest, southeast, central)
- **High cardinality reduction**:
  - Amenities: Applied Pareto analysis (90% coverage) + one-hot encoding for top amenities
  - Cities: Reduced 2,979 cities to top 80% coverage + "other" category
- **New features**: Created `sqft_per_room` and interaction terms using RFormula
- **Text processing**: Excluded free-text fields (title, body) from current implementation

3.3 ML Pipeline Preparation

- **Feature vectorization**: Used RFormula to create feature vectors with interaction terms:
  - `bedrooms:bathrooms`, `bedrooms:square_feet`, `bathrooms:square_feet`
- **Data scaling**: Applied StandardScaler for linear models while preserving tree-based model compatibility
- **Train/test split**: 80/20 split with both scaled and unscaled versions
- **Data persistence**: Saved preprocessed data as Parquet format for efficient reuse

[22]:
```
# Initialize spark
from pyspark.sql import SparkSession
import psutil
import builtins

total_memory = psutil.virtual_memory().total // (1024**3)  # GB
cpu_cores = psutil.cpu_count()
print(f"Specs: {total_memory}GB RAM, {cpu_cores} CPU cores")

spark = SparkSession.builder \
    .appName("CSCI316-Task2-Optimized") \
    .config("spark.driver.memory", f"{builtins.min(total_memory-4, 20)}g") \
    .config("spark.driver.maxResultSize", "4g") \
    .config("spark.executor.memory", f"{builtins.min(total_memory-6, 16)}g") \
    .config("spark.executor.cores", str(builtins.min(cpu_cores-2, 6))) \
```

```
    .config("spark.default.parallelism", str(cpu_cores * 2)) \
    .config("spark.sql.adaptive.enabled", "true") \
    .config("spark.sql.adaptive.coalescePartitions.enabled", "true") \
    .config("spark.serializer", "org.apache.spark.serializer.KryoSerializer") \
    .config('spark.kryoserializer.buffer.max', '512m') \
    .getOrCreate()
# Check Spark UI URL and enable logging
print(f"Spark UI URL: {spark.sparkContext.uiWebUrl}")
print(f"Spark App ID: {spark.sparkContext.applicationId}")
print(f"Spark Master: {spark.sparkContext.master}")

# Enable more verbose logging for better progress tracking
spark.sparkContext.setLogLevel("INFO")
```

```
Specs: 19GB RAM, 16 CPU cores
Spark UI URL: http://4d0d670895c4:4040
Spark App ID: local-1755542630058
Spark Master: local[*]
```

[23]:
```
from pyspark.ml import Pipeline, Transformer
from pyspark.ml.param.shared import HasInputCol, HasOutputCol, Param
from pyspark.ml.util import DefaultParamsReadable, DefaultParamsWritable
from pyspark.sql import DataFrame
from pyspark.sql.functions import *
from pyspark.sql.types import *
from pyspark.ml.feature import RFormula, StandardScaler
from pyspark.sql.window import Window
from pyspark.ml import Estimator
import os
```

[24]:
```
# Drop redundant columns, dominated/uninformative features
# --------------------------------------------------------
class DataCleaningTransformer(Transformer, HasInputCol, HasOutputCol,␣
 ↪DefaultParamsReadable, DefaultParamsWritable):
    """Custom transformer for data cleaning operations"""

    def __init__(self,verbose=False):
        super(DataCleaningTransformer, self).__init__()
        self.verbose = verbose

    def _transform(self, dataset: DataFrame) -> DataFrame:
        if self.verbose:
            print(f"Starting data cleaning transformation with dataset shape:␣
 ↪({dataset.count()}, {len(dataset.columns)})")

        # Handle duplicate IDs first
        # --------------------------------------------------------
```

```
        if self.verbose:
            print("Removing duplicate IDs...")

        # If 'id' column exists, remove duplicates based on 'id', keeping the␣
↪first
        if "id" in dataset.columns:
            # Remove duplicates based on 'id', keeping the first occurrence
            if self.verbose:
                print(f"Initial dataset size: {dataset.count()} rows")

            dataset = dataset.dropDuplicates(["id"])

            if self.verbose:
                print(f"Dataset size after removing duplicates by 'id':␣
↪{dataset.count()} rows")

        # Ensure that all listings are unique based on content
        # --------------------------------------------------------
        content_columns = [col for col in dataset.columns if col not in␣
↪["id","source"]]

        if self.verbose:
            print(f"Removing duplicates based on content columns:␣
↪{content_columns}")

        dataset = dataset.dropDuplicates(content_columns)

        if self.verbose:
            print(f"Dataset size after removing duplicates based on content:␣
↪{dataset.count()} rows")


        # Drop redundant columns
        # --------------------------------------------------------
        columns_to_drop = []
        # Same information as price
        if "price_display" in dataset.columns:
            columns_to_drop.append("price_display")

        # All rows are in USD
        if "currency" in dataset.columns:
            columns_to_drop.append("currency")

        # We will assume that all listings have category housing/rent/apartment␣
↪for this implementation, will ignore every other data that has otherwise
        if "category" in dataset.columns:
```

```python
            dataset = dataset.filter(dataset["category"] == "housing/rent/
↪apartment")
            columns_to_drop.append("category")

        # We will assume that all listings do not have a fee for this␣
↪implementation, will ignore every other data that has otherwise
        if "fee" in dataset.columns:
            dataset = dataset.filter(dataset["fee"] == "No")
            columns_to_drop.append("fee")

        # 91.4% of all sources are RentDigs.com, we can just drop this column␣
↪then check if there are duplicate listings later on
        if "source" in dataset.columns:
            columns_to_drop.append("source")

        # We will assume that all price_types are monthly for this␣
↪implementation, will ignore every other data that has otherwise
        if "price_type" in dataset.columns:
            dataset = dataset.filter(dataset["price_type"] == "Monthly")
            columns_to_drop.append("price_type")

        # time just shows when the listing was made, all the listings were␣
↪recorded in the span of ~1 year
        if "time" in dataset.columns:
            columns_to_drop.append("time")

        # has_photo shows if listing has photos attached, will ignore this␣
↪feature
        if "has_photo" in dataset.columns:
            columns_to_drop.append("has_photo")

        # address is a free text field that contains the address of the␣
↪listing, we will ignore this feature as we are using other features for␣
↪geographical information. FUrthermore, 92% of values do not have a populated␣
↪address.
        if "address" in dataset.columns:
            columns_to_drop.append("address")

        # The body and title are free text fields, we will ignore them for this␣
↪implementation
        if "body" in dataset.columns:
            columns_to_drop.append("body")

        if "title" in dataset.columns:
            columns_to_drop.append("title")
```

```
        if self.verbose:
            print(f"Dropping columns: {columns_to_drop}")
        dataset = dataset.drop(*columns_to_drop)

        # Handle missing values
        # --------------------------------------------------------
        if self.verbose:
            print("Handling missing values in pets_allowed and amenities...")

        dataset = dataset.fillna({"pets_allowed": "none", "amenities": "none␣
↪provided"})
        dataset = dataset.replace("NaN", "none", subset=["pets_allowed"])
        dataset = dataset.replace("", "none provided", subset=["amenities"])
        dataset = dataset.replace("NaN", "none provided", subset=["amenities"])

        # Other features have less than 1% of values missing we can drop these

        if self.verbose:
            print("Dropping rows with missing values in other features...")
            print(f"Initial dataset size before dropping missing values:␣
↪{dataset.count()} rows")

        dataset = dataset.na.drop()

        if self.verbose:
            print(f"Final dataset size after cleaning: {dataset.count()} rows")
        if self.verbose:
            print(f"Final dataset shape after data cleaning transformation:␣
↪({dataset.count()}, {len(dataset.columns)})")
        return dataset
```

[25]:
```
# Geographic Transformer
# --------------------------------------------------------
class GeographicTransformer(Estimator, DefaultParamsReadable,␣
↪DefaultParamsWritable):
    """Custom transformer for geographic data processing"""

    def __init__(self, verbose=False):
        super(GeographicTransformer, self).__init__()
        self.verbose = verbose

    def _fit(self, dataset: DataFrame):
        """Fit method to calculate geographic boundaries from training data"""
        if self.verbose:
            print(f"Starting geographic fitting with dataset shape: ({dataset.
↪count()}, {len(dataset.columns)})")
            print("Calculating geographic boundaries from training data...")
```

```
        # Calculate boundaries from training data only
        lat_bounds = dataset.select(
            expr("percentile_approx(latitude, 0.33)").alias('lat_33'),
            expr("percentile_approx(latitude, 0.67)").alias('lat_67')
        ).collect()[0]

        lon_bounds = dataset.select(
            expr("percentile_approx(longitude, 0.33)").alias('lon_33'),
            expr("percentile_approx(longitude, 0.67)").alias('lon_67')
        ).collect()[0]

        if self.verbose:
            print(f"Fitted latitude bounds: 33rd percentile = {lat_bounds['lat_33']}, 67th percentile = {lat_bounds['lat_67']}")
            print(f"Fitted longitude bounds: 33rd percentile = {lon_bounds['lon_33']}, 67th percentile = {lon_bounds['lon_67']}")

        # Return a fitted model
        return GeographicTransformerModel(lat_bounds, lon_bounds, self.verbose)

class GeographicTransformerModel(Transformer, DefaultParamsReadable, DefaultParamsWritable):
    """Fitted Geographic Transformer Model"""

    def __init__(self, lat_bounds, lon_bounds, verbose=False):
        super(GeographicTransformerModel, self).__init__()
        self.lat_bounds = lat_bounds
        self.lon_bounds = lon_bounds
        self.verbose = verbose

    def _transform(self, dataset: DataFrame) -> DataFrame:
        if self.verbose:
            print(f"Transforming geographic data using fitted boundaries...")

        lat_33, lat_67 = self.lat_bounds['lat_33'], self.lat_bounds['lat_67']
        lon_33, lon_67 = self.lon_bounds['lon_33'], self.lon_bounds['lon_67']

        # Create regional features using fitted boundaries
        dataset = dataset.withColumn(
            "resides_in",
            when((col("latitude") >= lat_67) & (col("longitude") <= lon_33), "northwest")
            .when((col("latitude") >= lat_67) & (col("longitude") >= lon_67), "northeast")
            .when((col("latitude") <= lat_33) & (col("longitude") <= lon_33), "southwest")
```

```
            .when((col("latitude") <= lat_33) & (col("longitude") >= lon_67),␣
↪"southeast")
            .otherwise("central")
        )

        # Drop original latitude and longitude columns
        if self.verbose:
            print("Dropping original latitude and longitude columns...")
        dataset = dataset.drop("latitude", "longitude")

        if self.verbose:
            print(f"Final dataset shape after geographical transformation:␣
↪({dataset.count()}, {len(dataset.columns)})")
        return dataset
```

[26]:

```
# Pets Transformer
# -------------------------------------------------------
class PetsTransformer(Estimator, DefaultParamsReadable, DefaultParamsWritable):
    """Custom transformer for pets_allowed feature processing"""

    def __init__(self, verbose=False):
        super(PetsTransformer, self).__init__()
        self.verbose = verbose

    def _fit(self, dataset: DataFrame):
        """Fit method to determine pet types from training data"""
        if self.verbose:
            print(f"Starting pets_allowed fitting with dataset shape: ({dataset.
↪count()}, {len(dataset.columns)})")
            print("Determining unique pet types from training data...")

        # Get unique pet types from training data
        pets_allowed_list = (
            dataset.select(explode(split(dataset.pets_allowed, ",")).
↪alias("pet"))
            .distinct()
            .rdd.flatMap(lambda x: x)
            .collect()
        )
        pets_allowed_list = [pet.lower().strip() for pet in pets_allowed_list␣
↪if pet.lower().strip() != "none"]

        if self.verbose:
            print(f"Fitted pet types: {pets_allowed_list}")
            print(f"Total unique pet types: {len(pets_allowed_list)}")

        return PetsTransformerModel(pets_allowed_list, self.verbose)
```

```
class PetsTransformerModel(Transformer, DefaultParamsReadable,␣
↪DefaultParamsWritable):
    """Fitted Pets Transformer Model"""

    def __init__(self, pets_allowed_list, verbose=False):
        super(PetsTransformerModel, self).__init__()
        self.pets_allowed_list = pets_allowed_list
        self.verbose = verbose

    def _transform(self, dataset: DataFrame) -> DataFrame:
        if self.verbose:
            print(f"Transforming pets_allowed using fitted pet types...")

        # Create binary columns for each pet type from fitted list
        for pet in self.pets_allowed_list:
            if pet != "none":
                dataset = dataset.withColumn(
                    f"allows_{pet}",
                    when(col("pets_allowed").contains(pet.strip()), 1).
↪otherwise(0)
                )

        # Drop the original pets_allowed column
        if self.verbose:
            print("Dropping original pets_allowed column...")
        dataset = dataset.drop("pets_allowed")

        if self.verbose:
            print(f"Final dataset shape after pets_allowed transformation:␣
↪({dataset.count()}, {len(dataset.columns)})")
        return dataset
```

[27]:
```
# Amenities Transformer
# --------------------------------------------------------
class AmenitiesTransformer(Estimator, DefaultParamsReadable,␣
↪DefaultParamsWritable):
    """Custom transformer for amenities feature processing"""

    def __init__(self, verbose=False):
        super(AmenitiesTransformer, self).__init__()
        self.verbose = verbose

    def _fit(self, dataset: DataFrame):
        """Fit method to determine amenities from training data"""
        # explode amenities and count them
```

```
        amenities_exploded = dataset.select(explode(split(dataset.amenities,␣
↪",")).alias('amenity'))
        amenity_counts = (
            amenities_exploded
            .filter(col('amenity') != "None provided")
            .groupBy('amenity')
            .agg(count("*").alias("count"))
            .orderBy('count', ascending=False)
        )

        # Pareto analysis
        total_count = amenity_counts.agg(sum("count")).collect()[0][0]
        window_spec = Window.orderBy(col("count").desc()).rowsBetween(Window.
↪unboundedPreceding, Window.currentRow)
        amenity_counts_with_cumsum = amenity_counts\
            .withColumn("cumulative_count", sum("count").over(window_spec))\
            .withColumn("cumulative_pct", (col("cumulative_count") /␣
↪total_count) * 100)

        # Get amenities that account for 90% of all mentions
        amenities_90pct = amenity_counts_with_cumsum.
↪filter(col("cumulative_pct") <= 90)

        # Store the amenity list for consistent transformation
        amenity_list = [row['amenity'] for row in amenities_90pct.
↪select("amenity").collect() if row['amenity'] != "none provided"]

        if self.verbose:
            print(f"Fitted amenities transformer with {len(amenity_list)}␣
↪amenities")

        return AmenitiesTransformerModel(amenity_list, self.verbose)

class AmenitiesTransformerModel(Transformer, DefaultParamsReadable,␣
↪DefaultParamsWritable):
    """Fitted Amenities Transformer Model"""

    def __init__(self, amenity_list, verbose=False):
        super(AmenitiesTransformerModel, self).__init__()
        self.amenity_list = amenity_list
        self.verbose = verbose

    def _transform(self, dataset: DataFrame) -> DataFrame:
        if self.verbose:
            print(f"Transforming amenities using fitted amenity list: {self.
↪amenity_list}")
```

```
        # Create binary columns for each amenity in the fitted list
        for amenity in self.amenity_list:
            dataset = dataset.withColumn(
                f"has_{amenity.lower().strip()}",
                when(col("amenities").contains(amenity.strip()), 1).otherwise(0)
            )

        # Create "other" amenities column
        amenity_set = set([a.lower().strip() for a in self.amenity_list])
        def has_other_amenities(amenities_str):
            if amenities_str == "None provided":
                return 0
            items = [a.lower().strip() for a in amenities_str.split(",")]
            return int(any(a not in amenity_set for a in items))

        has_other_udf = udf(has_other_amenities, IntegerType())
        dataset = dataset.withColumn("has_other",␣
↪has_other_udf(col("amenities")))

        dataset = dataset.drop("amenities")
        return dataset
```

[28]:
```
# City Transformer
# --------------------------------------------------------
class CityTransformer(Estimator, DefaultParamsReadable, DefaultParamsWritable):
    """Custom transformer for cityname feature processing"""

    def __init__(self, verbose=False):
        super(CityTransformer, self).__init__()
        self.verbose = verbose

    def _fit(self, dataset: DataFrame):
        """Fit method for cityname"""
        if self.verbose:
            print(f"Starting cityname transformation with dataset shape:␣
↪({dataset.count()}, {len(dataset.columns)})")
            print("Performing Pareto analysis on city names...")

        # Get city counts and apply pareto analysis
        city_counts = dataset.groupBy('cityname').count().orderBy('count',␣
↪ascending=False)
        total_count = city_counts.agg(sum("count")).collect()[0][0]
        window_spec = Window.orderBy(col("count").desc()).rowsBetween(Window.
↪unboundedPreceding, Window.currentRow)
        city_counts_with_cumsum = city_counts\
            .withColumn("cumulative_count", sum("count").over(window_spec))\
```

```
            .withColumn("cumulative_pct", (col("cumulative_count") /␣
↪total_count) * 100)

        # Get cities that account for 85% of all mentions
        cities_85pct = city_counts_with_cumsum.filter(col("cumulative_pct") <=␣
↪85)

        if self.verbose:
            print(f"Total cities accounting for 85% of mentions: {cities_85pct.
↪count()}")
        # Collect the city list
        city_list = [row['cityname'] for row in cities_85pct.select("cityname").
↪collect()]

        return CityTransformerModel(city_list, self.verbose)

class CityTransformerModel(Transformer, DefaultParamsReadable,␣
↪DefaultParamsWritable):
    """Fitted City Transformer Model"""

    def __init__(self, city_list, verbose=False):
        super(CityTransformerModel, self).__init__()
        self.city_list = city_list
        self.verbose = verbose

    def _transform(self, dataset: DataFrame) -> DataFrame:
        if self.verbose:
            print(f"Changing cities not in the top 85% to 'other'...")
        dataset = dataset.withColumn(
            "cityname",
            when(col("cityname").isin(self.city_list), col("cityname")).
↪otherwise("other")
        )
        if self.verbose:
            print(f"Final dataset shape after cityname transformation:␣
↪({dataset.count()}, {len(dataset.columns)})")
        return dataset
```

[29]:
```
# Fix OutlierRemovalTransformer to properly implement Estimator interface
class OutlierRemovalTransformer(Estimator, DefaultParamsReadable,␣
↪DefaultParamsWritable):
    """Custom transformer for outlier removal based on IQR"""

    def __init__(self, verbose=False):
        super(OutlierRemovalTransformer, self).__init__()
        self.verbose = verbose
```

```python
    def _fit(self, dataset: DataFrame):
        """Fit method to calculate outlier bounds from training data"""
        if self.verbose:
            print(f"Starting outlier bounds fitting with dataset shape: ({dataset.count()}, {len(dataset.columns)})")
            print("Calculating outlier bounds from training data...")

        outlier_cols = ["bathrooms", "bedrooms", "price", "square_feet"]
        bounds = {}

        for col_name in outlier_cols:
            quantiles = dataset.select(
                expr(f"percentile_approx({col_name}, 0.25)").alias('Q1'),
                expr(f"percentile_approx({col_name}, 0.75)").alias('Q3')
            ).collect()[0]

            Q1 = quantiles['Q1']
            Q3 = quantiles['Q3']
            IQR = Q3 - Q1

            lower_bound = Q1 - 3 * IQR
            upper_bound = Q3 + 3 * IQR

            bounds[col_name] = {'lower': lower_bound, 'upper': upper_bound}

            if self.verbose:
                print(f"Fitted bounds for {col_name}: [{lower_bound:.2f}, {upper_bound:.2f}]")

        return OutlierRemovalTransformerModel(bounds, self.verbose)

class OutlierRemovalTransformerModel(Transformer, DefaultParamsReadable, DefaultParamsWritable):
    """Fitted Outlier Removal Transformer Model"""

    def __init__(self, outlier_bounds, verbose=False):
        super(OutlierRemovalTransformerModel, self).__init__()
        self.outlier_bounds = outlier_bounds
        self.verbose = verbose

    def _transform(self, dataset: DataFrame) -> DataFrame:
        if self.verbose:
            print(f"Removing outliers using fitted bounds...")

        # Apply fitted bounds to remove outliers
        for col_name, bounds in self.outlier_bounds.items():
```

```
            if self.verbose:
                print(f"Filtering {col_name} with bounds [{bounds['lower']:.
↪2f}, {bounds['upper']:.2f}]")

            dataset = dataset.filter(
                (col(col_name) >= bounds['lower']) &
                (col(col_name) <= bounds['upper'])
            )

        if self.verbose:
            print(f"Final dataset shape after outlier removal: ({dataset.
↪count()}, {len(dataset.columns)})")
        return dataset
```

[30]:
```
class FeatureEngineeringTransformer(Transformer, DefaultParamsReadable,␣
↪DefaultParamsWritable):
    """
    Custom transformer for feature engineering.
    Purely deterministic transformation that creates new features.
    """

    def __init__(self, verbose=False):
        super(FeatureEngineeringTransformer, self).__init__()
        self.verbose = verbose

    def _transform(self, dataset: DataFrame) -> DataFrame:
        if self.verbose:
            print(f"Starting feature engineering transformation with dataset␣
↪shape: ({dataset.count()}, {len(dataset.columns)})")
            print("Creating new features...")


        # Create a new feature: sqft_per_room
        if self.verbose:
            print("Creating sqft_per_room feature...")
        dataset = dataset.withColumn(
            "sqft_per_room",
            when(col("bedrooms") > 0, col("square_feet") / col("bedrooms")).
↪otherwise(0)
        )

        if self.verbose:
            print(f"Dropping id column if it exists...")
        if "id" in dataset.columns:
            dataset = dataset.drop("id")
```

```
        if self.verbose:
            print(f"Final dataset shape after feature engineering␣
↪transformation: ({dataset.count()}, {len(dataset.columns)})")
        return dataset
```

[31]:
```
def create_safe_preprocessing_pipeline():
    """
    Create a preprocessing pipeline with transformers that do not use any of␣
↪the data statistics.
    This is a measure for preventing data leakage.
    """

    pipeline = Pipeline(stages=[
        DataCleaningTransformer(verbose=True)
        ])
    return pipeline

def create_preprocessing_pipeline():
    """
    Create a preprocessing pipeline with the custom transformers that use data␣
↪statistics.
    This is a measure for preventing data leakage.
    """
    return Pipeline(stages=[
        GeographicTransformer(verbose=True),
        PetsTransformer(verbose=True),
        AmenitiesTransformer(verbose=True),
        CityTransformer(verbose=True),
        OutlierRemovalTransformer(verbose=True),
        FeatureEngineeringTransformer(verbose=True)
    ])
```

[32]:
```
def preprocess_data(spark,df):
    """
    Run the preprocessing pipeline on the given DataFrame.
    This function will apply the preprocessing steps defined in the pipeline.
    """
    # Create a Spark DataFrame from the pandas DataFrame
    data = spark.createDataFrame(df)

    # Clean the data: Apply transformers that do not use statistics
    clean_data = create_safe_preprocessing_pipeline().fit(data).transform(data)

    # Split the data
    train_data, test_data = clean_data.randomSplit([0.8, 0.2], seed=170121)

    # Preprocess the data: Apply transformers that use statistics
```

```python
preprocess_pipeline = create_preprocessing_pipeline()
print(f"\n\nFitting Preprocessing Pipeline on Train data...")
fitted_pipeline = preprocess_pipeline.fit(train_data)
print(f"\n\nTransforming Train data...")
processed_train_data = fitted_pipeline.transform(train_data)
print(f"\n\nTransforming Test data...")
processed_test_data = fitted_pipeline.transform(test_data)

# Apply RFormula to create features and label
rformula = RFormula(
    formula="""price ~ . +
    bedrooms:bathrooms +
    bedrooms:square_feet +
    bathrooms:square_feet
    """,
    featuresCol="features",
    labelCol="label"
)

# Fit RFormula
print(f"\n\nFitting RFormula on Train data...")
rformula_model = rformula.fit(processed_train_data)
print(f"Transforming Train data with RFormula...")
processed_train_data = rformula_model.transform(processed_train_data)
print(f"Transforming Test data with RFormula...")
processed_test_data= rformula_model.transform(processed_test_data)

# Scale the features
scaler = StandardScaler(
    inputCol="features",
    outputCol="scaled_features",
    withMean=True,
    withStd=True
)
print(f"\n\nFitting StandardScaler on Train data...")
scaler_model = scaler.fit(processed_train_data)
print(f"Transforming Train data with StandardScaler...")
processed_scaled_train_data = scaler_model.transform(processed_train_data)
print(f"Transforming Test data with StandardScaler...")
processed_scaled_test_data = scaler_model.transform(processed_test_data)

# Cache for performance
print(f"\n\nCaching processed and scaled data for performance...")
processed_scaled_train = processed_scaled_train_data.cache()
processed_scaled_test = processed_scaled_test_data.cache()

# Save models and data
```

```
    os.makedirs("./models", exist_ok=True)
    os.makedirs("./data", exist_ok=True)

    print(f"Saving RFormula and StandardScaler models...")
    rformula_model.write().overwrite().save("./models/rformula_model")
    scaler_model.write().overwrite().save("./models/scaler_model")

    print(f"Saving processed and scaled data to Parquet files...")
    processed_scaled_train.write.mode("overwrite").parquet("./data/
↪scaled_train_data.parquet")
    processed_scaled_test.write.mode("overwrite").parquet("./data/
↪scaled_test_data.parquet")

    print(f"\n\nPreprocessing complete. Processed and scaled data is saved to␣
↪Parquet files.")
    return {
        "train_data": processed_scaled_train_data,
        "test_data": processed_scaled_test_data
    }
```

[33]:
```
processed_data = preprocess_data(spark,df)
print(f"Processed train data shape: {processed_data['train_data'].count()},␣
↪{len(processed_data['train_data'].columns)}")
print(f"Processed test data shape: {processed_data['test_data'].count()},␣
↪{len(processed_data['test_data'].columns)}")
```

```
Starting data cleaning transformation with dataset shape: (99492, 22)
Removing duplicate IDs…
Initial dataset size: 99492 rows
Dataset size after removing duplicates by 'id': 99408 rows
Removing duplicates based on content columns: ['category', 'title', 'body',
'amenities', 'bathrooms', 'bedrooms', 'currency', 'fee', 'has_photo',
'pets_allowed', 'price', 'price_display', 'price_type', 'square_feet',
'address', 'cityname', 'state', 'latitude', 'longitude', 'time']
Dataset size after removing duplicates based on content: 99408 rows
Dropping columns: ['price_display', 'currency', 'category', 'fee', 'source',
'price_type', 'time', 'has_photo', 'address', 'body', 'title']
Handling missing values in pets_allowed and amenities…
Dropping rows with missing values in other features…
Initial dataset size before dropping missing values: 99142 rows
Final dataset size after cleaning: 98936 rows
Final dataset shape after data cleaning transformation: (98936, 11)


Fitting Preprocessing Pipeline on Train data…
Starting geographic fitting with dataset shape: (79211, 11)
Calculating geographic boundaries from training data…
```

```
Fitted latitude bounds: 33rd percentile = 34.0809, 67th percentile = 39.3302
Fitted longitude bounds: 33rd percentile = -96.8499, 67th percentile = -80.8103
Transforming geographic data using fitted boundaries…
Dropping original latitude and longitude columns…
Final dataset shape after geographical transformation: (79211, 10)
Starting pets_allowed fitting with dataset shape: (79211, 10)
Determining unique pet types from training data…
Fitted pet types: ['dogs', 'cats']
Total unique pet types: 2
Transforming pets_allowed using fitted pet types…
Dropping original pets_allowed column…
Final dataset shape after pets_allowed transformation: (79211, 11)
Fitted amenities transformer with 15 amenities
Transforming amenities using fitted amenity list: ['Parking', 'Pool', 'Gym',
'Patio/Deck', 'Washer Dryer', 'Storage', 'Clubhouse', 'Dishwasher', 'AC',
'Fireplace', 'Refrigerator', 'Cable or Satellite', 'Playground', 'Internet
Access', 'Wood Floors']
Starting cityname transformation with dataset shape: (79211, 26)
Performing Pareto analysis on city names…
Total cities accounting for 85% of mentions: 536
Changing cities not in the top 85% to 'other'…
Final dataset shape after cityname transformation: (79211, 26)
Starting outlier bounds fitting with dataset shape: (79211, 26)
Calculating outlier bounds from training data…
Fitted bounds for bathrooms: [-2.00, 5.00]
Fitted bounds for bedrooms: [-2.00, 5.00]
Fitted bounds for price: [-1319.00, 4127.00]
Fitted bounds for square_feet: [-426.00, 2269.00]
```

```
Transforming Train data…
Transforming geographic data using fitted boundaries…
Dropping original latitude and longitude columns…
Final dataset shape after geographical transformation: (79211, 10)
Transforming pets_allowed using fitted pet types…
Dropping original pets_allowed column…
Final dataset shape after pets_allowed transformation: (79211, 11)
Transforming amenities using fitted amenity list: ['Parking', 'Pool', 'Gym',
'Patio/Deck', 'Washer Dryer', 'Storage', 'Clubhouse', 'Dishwasher', 'AC',
'Fireplace', 'Refrigerator', 'Cable or Satellite', 'Playground', 'Internet
Access', 'Wood Floors']
Changing cities not in the top 85% to 'other'…
Final dataset shape after cityname transformation: (79211, 26)
Removing outliers using fitted bounds…
Filtering bathrooms with bounds [-2.00, 5.00]
Filtering bedrooms with bounds [-2.00, 5.00]
Filtering price with bounds [-1319.00, 4127.00]
Filtering square_feet with bounds [-426.00, 2269.00]
```

```
Final dataset shape after outlier removal: (77733, 26)
Starting feature engineering transformation with dataset shape: (77733, 26)
Creating new features…
Creating sqft_per_room feature…
Dropping id column if it exists…
Final dataset shape after feature engineering transformation: (77733, 26)


Transforming Test data…
Transforming geographic data using fitted boundaries…
Dropping original latitude and longitude columns…
Final dataset shape after geographical transformation: (19725, 10)
Transforming pets_allowed using fitted pet types…
Dropping original pets_allowed column…
Final dataset shape after pets_allowed transformation: (19725, 11)
Transforming amenities using fitted amenity list: ['Parking', 'Pool', 'Gym',
'Patio/Deck', 'Washer Dryer', 'Storage', 'Clubhouse', 'Dishwasher', 'AC',
'Fireplace', 'Refrigerator', 'Cable or Satellite', 'Playground', 'Internet
Access', 'Wood Floors']
Changing cities not in the top 85% to 'other'…
Final dataset shape after cityname transformation: (19725, 26)
Removing outliers using fitted bounds…
Filtering bathrooms with bounds [-2.00, 5.00]
Filtering bedrooms with bounds [-2.00, 5.00]
Filtering price with bounds [-1319.00, 4127.00]
Filtering square_feet with bounds [-426.00, 2269.00]
Final dataset shape after outlier removal: (19321, 26)
Starting feature engineering transformation with dataset shape: (19321, 26)
Creating new features…
Creating sqft_per_room feature…
Dropping id column if it exists…
Final dataset shape after feature engineering transformation: (19321, 26)


Fitting RFormula on Train data…
Transforming Train data with RFormula…
Transforming Test data with RFormula…


Fitting StandardScaler on Train data…
Transforming Train data with StandardScaler…
Transforming Test data with StandardScaler…


Caching processed and scaled data for performance…
Saving RFormula and StandardScaler models…
Saving processed and scaled data to Parquet files…
```

```
Preprocessing complete. Processed and scaled data is saved to Parquet files.
Processed train data shape: 77733, 29
Processed test data shape: 19321, 29
```

4 (c) & (d) Select and Train model

Pipeline - Load the data - Split the data into train_data and test_data - Define a scaler and fit scaler to train_data - Use scaler to transform both train_data and test_data to create scaled_train_data and scaled_test_data

We will have a non-scaled and scaled train_data and test_data as some of the models do not require scaled data whereas, others perform better when fitted to scaled data.

[34]:
```python
from pyspark.ml.feature import StandardScaler, VectorAssembler
from pyspark.ml import Pipeline
import os

# Load data
train_data = spark.read.parquet("./data/scaled_train_data.parquet")
test_data = spark.read.parquet("./data/scaled_test_data.parquet")
```

4.1 Model 1: Gradient Boosted Trees (GBT)

4.1.1 Hyperparameter Fine-tuning

Parameter	Options	Description
maxIter	200	Number of boosting iterations (trees) in the ensemble
maxDepth	6, 8	Maximum depth of each individual tree
stepSize	0.1, 0.15	Learning rate; how much each tree contributes to the final prediction

Parameter Details

- **maxIter**: Number of boosting iterations (trees) in the ensemble.
  Higher values increase model complexity and training time significantly, but may improve accuracy.
- **maxDepth**: Maximum depth of each individual tree.
  Deeper trees can capture more complex patterns but risk overfitting.
- **stepSize**: Learning rate, controlling how much each tree contributes to the final prediction.
  Lower values make learning more gradual and stable, but require more iterations.
- **subsamplingRate**: Fraction of training data randomly sampled for each tree.
  Lower values introduce more randomness, which can help prevent overfitting and improve generalization.

  Note: This grid search will train 4 (1x2x2) parameter combinations. With 3-fold cross-validation, a total of 12 models will be trained.

4.1.2 3-Fold Cross Validation

- The dataset is split into 3 equal folds.
- For each run, the model is trained on 2 folds and tested on the remaining fold.
- This process repeats 3 times, each time with a different fold as the test set.
- The final performance metric is the average of the 3 test results.

[35]:
```
from pyspark.ml.regression import GBTRegressor, GBTRegressionModel
from pyspark.ml.evaluation import RegressionEvaluator
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator,␣
↪CrossValidatorModel
import builtins

# GBT with hyperparameter tuning
gbt = GBTRegressor(
    featuresCol="features",
    labelCol="label",
    predictionCol="prediction",
    subsamplingRate=0.7,  # Use 70% of data for each tree
    seed=42
)

# Hyperparameter grid
param_grid = ParamGridBuilder() \
    .addGrid(gbt.maxIter, [200]) \
    .addGrid(gbt.maxDepth, [6,8]) \
    .addGrid(gbt.stepSize, [0.1,0.15]) \
    .build()

# Cross validation
cv = CrossValidator(
    estimator=gbt,
    estimatorParamMaps=param_grid,
    evaluator=RegressionEvaluator(labelCol="label", predictionCol="prediction",␣
↪metricName="rmse"),
    numFolds=3,
    parallelism=builtins.min(cpu_cores-1, 6),
    seed=42
)

model_path = "./models/gbt_regressor"
retrain=False
if not os.path.exists(os.path.join(model_path,"gbt_best_model")) or retrain:
    print("Training GBT with Cross Validation...")
    cv_model = cv.fit(train_data)
    gbt_best_model = cv_model.bestModel
```

```
    print(f"Best parameters found: ")
else:
    print("Loading best pre-trained GBT model...")
    gbt_best_model = GBTRegressionModel.load(os.path.
 ↪join(model_path,"gbt_best_model"))
    print(f"Loaded model with paremeters: ")


print(f"maxIter: {gbt_best_model.getMaxIter()}")
print(f"maxDepth: {gbt_best_model.getMaxDepth()}")
print(f"stepSize: {gbt_best_model.getStepSize()}")
print(f"subsamplingRate: {gbt_best_model.getSubsamplingRate()}")

gbt_train_predictions = gbt_best_model.transform(train_data)
gbt_test_predictions = gbt_best_model.transform(test_data)

# Evaluate the model
evaluator = RegressionEvaluator(labelCol="label", predictionCol="prediction")

# Calculate train metrics
train_rmse = evaluator.evaluate(gbt_train_predictions, {evaluator.metricName:␣
 ↪"rmse"})
train_mae = evaluator.evaluate(gbt_train_predictions, {evaluator.metricName:␣
 ↪"mae"})
train_r2 = evaluator.evaluate(gbt_train_predictions, {evaluator.metricName:␣
 ↪"r2"})
# Calculate test metrics
test_rmse = evaluator.evaluate(gbt_test_predictions, {evaluator.metricName:␣
 ↪"rmse"})
test_mae = evaluator.evaluate(gbt_test_predictions, {evaluator.metricName:␣
 ↪"mae"})
test_r2 = evaluator.evaluate(gbt_test_predictions, {evaluator.metricName: "r2"})

# Show metrics
performance_data = {
    'Metric': ['RMSE', 'MAE', 'R²', "Sample Size"],
    'Train': [f'{train_rmse:.2f}', f'{train_mae:.2f}', f'{train_r2:.
 ↪4f}',f'{train_data.count()}'],
    'Test': [f'{test_rmse:.2f}', f'{test_mae:.2f}', f'{test_r2:.
 ↪4f}',f'{test_data.count()}']
}
performance_df_gbt = pd.DataFrame(performance_data)
print(f"\nGBT Model Performance (Best Parameters):")
print(performance_df_gbt)

# Save the model if doesnt exist
```

```
if not os.path.exists(os.path.join(model_path,"gbt_best_model")) or retrain:
    print(f"Saving the best GBT model to {os.path.
 ↪join(model_path,'gbt_best_model')}")
    gbt_best_model.write().overwrite().save(os.path.
 ↪join(model_path,"gbt_best_model"))
if not os.path.exists(os.path.join(model_path,"cv_model")) or retrain:
    print(f"Saving the CrossValidator model to {os.path.
 ↪join(model_path,'cv_model')}")
    cv_model.write().overwrite().save(os.path.join(model_path,"cv_model"))
```

```
Loading best pre-trained GBT model…
Loaded model with paremeters:
maxIter: 200
maxDepth: 8
stepSize: 0.15
subsamplingRate: 0.7

GBT Model Performance (Best Parameters):
        Metric   Train    Test
0         RMSE  239.54  292.43
1          MAE  166.42  197.84
2           R²  0.8566  0.7940
3  Sample Size   77733   19321
```

4.2 Model 2: Linear Regression

4.2.1 Hyperparameter Fine-tuning

Parameter	Options	Description
regParam	0.01, 0.05, 0.1	L2 regularization parameter (Ridge penalty)
elasticNetParam	0.1, 0.5, 1.0	Elastic net mixing parameter (0=L2, 1=L1, 0.5=balanced)
maxIter	100, 200, 500, 600	Maximum number of iterations for optimization

Parameter Details

- **regParam**: L2 regularization parameter to prevent overfitting.
  Higher values add more penalty to large coefficients, reducing model complexity.
- **elasticNetParam**: Controls the balance between L1 (Lasso) and L2 (Ridge) regularization.
  0.5 = balanced elastic net, 1.0 = pure Lasso regression (L1 only).
- **maxIter**: Maximum iterations for the optimization algorithm.
  Higher values allow more time for convergence but increase training time.

  Note: Linear regression benefits greatly from feature scaling. We use the scaled features for optimal performance.

4.2.2 3-Fold Cross Validation

- Uses scaled features for better convergence and performance
- Tests different regularization strategies to prevent overfitting
- Evaluates on RMSE metric to select the best hyperparameter combination
- This grid search will train 36 parameter combinations (3x3x4) with 3-fold CV = 108 models total

[36]:
```
from pyspark.ml.regression import LinearRegression, LinearRegressionModel
from pyspark.ml.evaluation import RegressionEvaluator
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator,␣
↪CrossValidatorModel
import builtins

# Define model
lr = LinearRegression(
    featuresCol = "scaled_features",
    labelCol="label",
    predictionCol="prediction"
)

param_grid = ParamGridBuilder() \
    .addGrid(lr.regParam, [0.01, 0.05 ,0.1]) \
    .addGrid(lr.elasticNetParam,[0.1,0.5,1.0])\
    .addGrid(lr.maxIter, [100,200,500,600]) \
    .build()

# Cross validation
cv = CrossValidator(
    estimator=lr,
    estimatorParamMaps = param_grid,
    evaluator = RegressionEvaluator(labelCol="label",␣
↪predictionCol="prediction", metricName="rmse"),
    numFolds =3,
    parallelism=builtins.min(cpu_cores-1, 6),
    seed = 24
)

model_path = "./models/linear_regressor"
retrain=False
if not os.path.exists(os.path.join(model_path,"lr_best_model")) or retrain:
    print("Training Linear Regression with Cross Validation...")
    cv_model = cv.fit(train_data)
    lr_best_model = cv_model.bestModel
    print(f"Best parameters found: ")
else:
    print("Loading best pre-trained LR model ...")
```

```
    lr_best_model = LinearRegressionModel.load(os.path.
 ↪join(model_path,"lr_best_model"))

if os.path.exists(os.path.join(model_path,"cv_model")):
    print("Loading CV model...")
    cv_model = CrossValidatorModel.load(os.path.join(model_path,"cv_model"))
    print("Loaded CV model.")

print(f"regParam (L2 penalty): {lr_best_model.getRegParam()}")
print(f"elasticNetParam (L1/L2 mix): {lr_best_model.getElasticNetParam()}")
print(f"maxIter: {lr_best_model.getMaxIter()}")

lr_train_predictions = lr_best_model.transform(train_data)
lr_test_predictions = lr_best_model.transform(test_data)

# Evaluate the model
evaluator = RegressionEvaluator(labelCol="label", predictionCol="prediction")

# Calculate train metrics
train_rmse = evaluator.evaluate(lr_train_predictions, {evaluator.metricName:␣
 ↪"rmse"})
train_mae = evaluator.evaluate(lr_train_predictions, {evaluator.metricName:␣
 ↪"mae"})
train_r2 = evaluator.evaluate(lr_train_predictions, {evaluator.metricName:␣
 ↪"r2"})
# Calculate test metrics
test_rmse = evaluator.evaluate(lr_test_predictions, {evaluator.metricName:␣
 ↪"rmse"})
test_mae = evaluator.evaluate(lr_test_predictions, {evaluator.metricName:␣
 ↪"mae"})
test_r2 = evaluator.evaluate(lr_test_predictions, {evaluator.metricName: "r2"})

# Show metrics
performance_data = {
    'Metric': ['RMSE', 'MAE', 'R²', "Sample Size"],
    'Train': [f'{train_rmse:.2f}', f'{train_mae:.2f}', f'{train_r2:.
 ↪4f}',f'{train_data.count()}'],
    'Test': [f'{test_rmse:.2f}', f'{test_mae:.2f}', f'{test_r2:.
 ↪4f}',f'{test_data.count()}']
}
performance_df_lr = pd.DataFrame(performance_data)
print(f"\nLR Model Performance (Best Parameters):")
print(performance_df_lr)

# Save the model if doesnt exist
if not os.path.exists(os.path.join(model_path,"lr_best_model")) or retrain:
```

```
    print(f"Saving the best lr model to {os.path.
  ↪join(model_path,'lr_best_model')}")
    lr_best_model.write().overwrite().save(os.path.
  ↪join(model_path,"lr_best_model"))
if not os.path.exists(os.path.join(model_path,"cv_model")) or retrain:
    print(f"Saving the CrossValidator model to {os.path.
  ↪join(model_path,'cv_model')}")
    cv_model.write().overwrite().save(os.path.join(model_path,"cv_model"))
```

```
Loading best pre-trained LR model …
Loading CV model…
Loaded CV model.
regParam (L2 penalty): 0.05
elasticNetParam (L1/L2 mix): 1.0
maxIter: 500

LR Model Performance (Best Parameters):
        Metric   Train    Test
0         RMSE  334.63  342.90
1          MAE  236.86  241.70
2           R²  0.7202  0.7168
3  Sample Size   77733   19321
```

4.3 Model 3: Random Forest Regression

4.3.1 Hyperparameter Fine-tuning

Parameter	Options	Description
numTrees	150	Number of trees in the random forest ensemble
maxDepth	8,15	Maximum depth of each individual tree
featureSubsetStrategy	"auto"	Number of features to consider at each split (auto = sqrt(total features))

Parameter Details

- **numTrees**: Number of trees in the random forest ensemble.
  More trees generally improve performance but increase computational cost and training time.
- **maxDepth**: Maximum depth allowed for each individual tree in the forest.
  Deeper trees can capture more complex patterns but may lead to overfitting.
- **featureSubsetStrategy**: Strategy for selecting features at each split.
  "auto" uses sqrt(total_features) which provides good balance between performance and randomness.
- **subsamplingRate**: Fraction of training data used for each tree (set to 0.9).
  Introduces randomness to improve generalization and reduce overfitting.

- **minInstancesPerNode**: Minimum instances per leaf node (uses default value). *Prevents overfitting by ensuring meaningful sample sizes at leaf nodes.*

  Note: Random Forest is an ensemble method that combines multiple decision trees. It's particularly effective at handling non-linear relationships and feature interactions without requiring feature scaling.

4.3.2 3-Fold Cross Validation

- Uses original features (not scaled) as Random Forest handles different feature scales naturally
- Tests different tree depth configurations to find optimal complexity
- Evaluates on RMSE metric to select the best hyperparameter combination
- This grid search will train 2 parameter combinations (1x2) with 3-fold CV = 12 models total

[44]:
```
from pyspark.ml.regression import RandomForestRegressor,␣
↪RandomForestRegressionModel
from pyspark.ml.evaluation import RegressionEvaluator
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator,␣
↪CrossValidatorModel
import builtins

# Define model
rf = RandomForestRegressor(
    featuresCol="features",
    labelCol="label",
    predictionCol="prediction",
    featureSubsetStrategy="auto",
    seed=42,
    subsamplingRate=0.8
)

# Build hyperparameter grid
param_grid = ParamGridBuilder() \
    .addGrid(rf.maxDepth, [8,15]) \
    .addGrid(rf.numTrees, [150]) \
    .build()

# cross validation
cv = CrossValidator(
    estimator=rf,
    estimatorParamMaps=param_grid,
    evaluator=RegressionEvaluator(labelCol="label", predictionCol="prediction",␣
↪metricName="rmse"),
    numFolds=3,
    parallelism=builtins.min(cpu_cores-1, 6),
    seed=42
)
```

```python
model_path = "./models/random_forest_regressor"
retrain=False
if not os.path.exists(os.path.join(model_path,"rf_best_model")) or retrain:
    print("Training RF with Cross Validation...")
    cv_model = cv.fit(train_data)
    rf_best_model = cv_model.bestModel
    print(f"Best parameters found: ")
else:
    print("Loading best pre-trained FM model ...")
    rf_best_model = RandomForestRegressionModel.load(os.path.
 ↪join(model_path,"rf_best_model"))
    print(f"Loaded model with paremeters: ")

print(f"numTrees: {rf_best_model.getNumTrees}")
print(f"maxDepth: {rf_best_model.getMaxDepth()}")
print(f"featureSubsetStrategy: {rf_best_model.getFeatureSubsetStrategy()}")
print(f"minInstancesPerNode: {rf_best_model.getMinInstancesPerNode()}")
print(f"subsamplingRate: {rf_best_model.getSubsamplingRate()}")
rf_train_predictions = rf_best_model.transform(train_data)
rf_test_predictions = rf_best_model.transform(test_data)

# Evaluate the model
evaluator = RegressionEvaluator(labelCol="label", predictionCol="prediction")

# Calculate train metrics
train_rmse = evaluator.evaluate(rf_train_predictions, {evaluator.metricName:␣
 ↪"rmse"})
train_mae = evaluator.evaluate(rf_train_predictions, {evaluator.metricName:␣
 ↪"mae"})
train_r2 = evaluator.evaluate(rf_train_predictions, {evaluator.metricName:␣
 ↪"r2"})

# Calculate test metrics
test_rmse = evaluator.evaluate(rf_test_predictions, {evaluator.metricName:␣
 ↪"rmse"})
test_mae = evaluator.evaluate(rf_test_predictions, {evaluator.metricName:␣
 ↪"mae"})
test_r2 = evaluator.evaluate(rf_test_predictions, {evaluator.metricName: "r2"})

# Show metrics
performance_data = {
    'Metric': ['RMSE', 'MAE', 'R²', "Sample Size"],
    'Train': [f'{train_rmse:.2f}', f'{train_mae:.2f}', f'{train_r2:.
 ↪4f}',f'{train_data.count()}'],
```

```
    'Test': [f'{test_rmse:.2f}', f'{test_mae:.2f}', f'{test_r2:.
 ↪4f}',f'{test_data.count()}']
}
performance_df_rf = pd.DataFrame(performance_data)
print(f"\nRF Model Performance (Best Parameters):")
print(performance_df_rf)

# Save the model if doesnt exist
if not os.path.exists(os.path.join(model_path,"rf_best_model")) or retrain:
    print(f"Saving the best RF model to {os.path.
 ↪join(model_path,'rf_best_model')}")
    rf_best_model.write().overwrite().save(os.path.
 ↪join(model_path,"rf_best_model"))
if not os.path.exists(os.path.join(model_path,"cv_model")) or retrain:
    print(f"Saving the CrossValidator model to {os.path.
 ↪join(model_path,'cv_model')}")
    cv_model.write().overwrite().save(os.path.join(model_path,"cv_model"))
```

```
Training RF with Cross Validation…
Best parameters found:
numTrees: 150
maxDepth: 15
featureSubsetStrategy: auto
minInstancesPerNode: 1
subsamplingRate: 0.8

RF Model Performance (Best Parameters):
        Metric   Train    Test
0         RMSE  298.47  335.90
1          MAE  219.22  241.31
2           R²  0.7774  0.7283
3  Sample Size   77733   19321
Saving the best RF model to ./models/random_forest_regressor/rf_best_model
Saving the CrossValidator model to ./models/random_forest_regressor/cv_model
```

5 (e) Evaluate the outcomes

[45]:
```
performance_dfs = [performance_df_rf, performance_df_gbt, performance_df_lr]
model_names = ["Random Forest", "Gradient Boosted Trees", "Linear Regression"]
eval_df = pd.DataFrame({
    'Model': model_names,
    'RMSE': [p['Test'][0] for p in performance_dfs],
    'MAE': [p['Test'][1] for p in performance_dfs],
    'R²': [p['Test'][2] for p in performance_dfs],
    'Sample Size': [p['Test'][3] for p in performance_dfs]
}).sort_values(by="R²",ascending=False)
```

```python
print("\nModel Evaluation Summary:")
print(eval_df)
```

```
Model Evaluation Summary:
                    Model    RMSE     MAE      R²  Sample Size
1  Gradient Boosted Trees  292.43  197.84  0.7940        19321
0           Random Forest  335.90  241.31  0.7283        19321
2       Linear Regression  342.90  241.70  0.7168        19321
```

5.1 Evaluation

- Gradient Boosted Trees performed the best overall with the highest R^2 score with the lowest MAE and RMSE
- Random Forest performed well but not as well as Gradient Boosted Trees
- Linear Regression performed the worst compared to the other two models

5.2 Comparison of models

5.2.1 Training Time

Linear Regression: Despite the fact that the grid search space for the linear regression was the largest compared to the three models, it still was the easiest and fastest to train. This is likely because it is the simplest model out of the three and assumes linear relationships. It however, performed the worst as it is unable to capture non-linear relationships in the apartment rental data.

Random Forest: Random Forest performed better than the linear regressor as it is able to capture non-linear relationships and feature interactions through its ensemble of decision trees. However, it required more computational resources and training time due to building multiple trees all of which are meant to be good learners/models (150 trees in our hyperparameter grid). The model generalized better than the linear regressor but was outperformed by GBT.

Gradient Boosted Trees: GBT achieved the best performance but required the longest training time among all models. This is because it builds trees sequentially, with each tree learning from the errors of previous trees. The boosting process is computationally intensive but results in superior predictive accuracy. The model effectively captured complex patterns in the apartment rental data.

5.2.2 Model Characteristics

Feature Scaling Requirements: - Linear Regression required scaled features for optimal performance - Tree-based models (RF and GBT) worked directly with original features without scaling

Overfitting Resistance: - Linear Regression: Regularization (L1/L2) helped prevent overfitting
- Random Forest: Bootstrap sampling and feature randomness provided natural overfitting protection
- GBT: Required careful tuning of learning rate and tree depth to avoid overfitting

Interpretability: - Linear Regression: Most interpretable with clear coefficient meanings - Random Forest: Moderate interpretability through feature importance - GBT: Least interpretable due to complex sequential tree interactions

5.2.3 Why Ensemble Methods Outperformed Linear Regression

The apartment rental dataset contains complex, non-linear relationships between features that Linear Regression cannot capture due to its linear assumption. Ensemble methods like Random Forest and GBT excel at:

1. **Capturing Non-linear Patterns**: Tree-based models naturally handle non-linear relationships
2. **Feature Interactions**: Automatically detect interactions between features (e.g., bedrooms × bathrooms)
3. **Handling Mixed Data Types**: Effectively process both categorical and numerical features
4. **Robustness to Outliers**: Tree splits are less sensitive to extreme values

The sequential learning approach in GBT, where each tree corrects previous errors, made it particularly effective for this regression task, achieving the highest R^2 score.

[ ]:
```
# Export notebook to PDF
!jupyter nbconvert --to pdf --output-dir="./deliverables/" --output␣
↪"leap-csci316-task2" Leap_Assignment2_Task2.ipynb
```