San Francisco Housing

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Inspiration

- Living in the Bay Area is expensive
- Understand what factors drive the renting/housing cost in Bay Area
- **Main Problem:** How do various factors such as the location and square footage affect and influence the renting prices in San Francisco?
- Identify ways for renters to get the best value and investors to optimize purchases

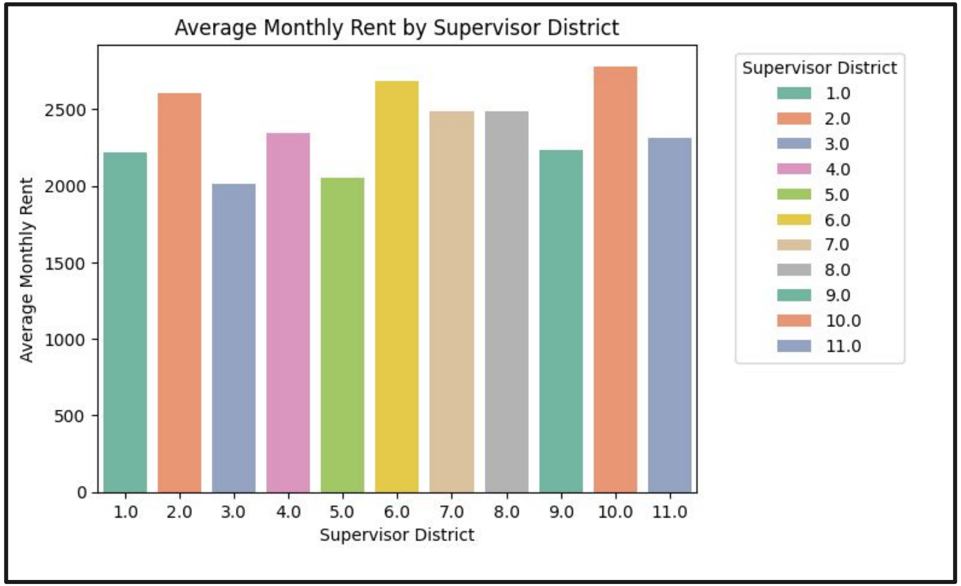
Dataset

- Utilized SF Apartment Rental Inventory dataset from April 8th, 2025
- Information obtained from the submissions of apartment owners
- Over 186K apartment records
- Key variables include (monthly rent, number of bedrooms, number of bathrooms, etc.)

Problem Background (Q1)

How does location influence rental price?

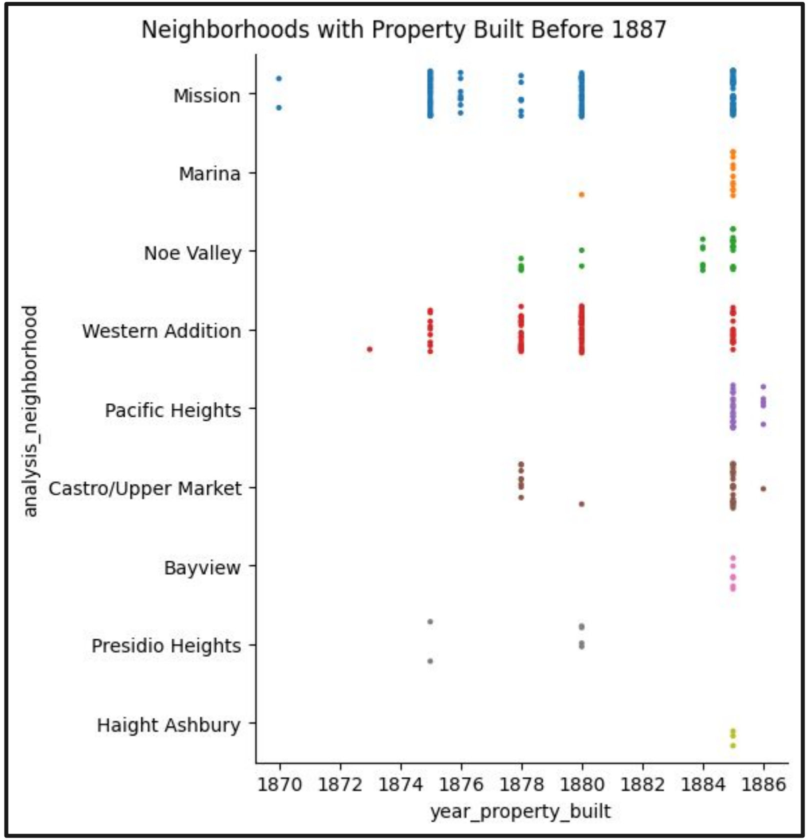
- Used a barplot
- District 3 and 5 are the most affordable
- Districts 2, 6, and 10 are the most expensive



Problem Background (Q2)

Which neighborhood has the oldest buildings (built before 1886)?

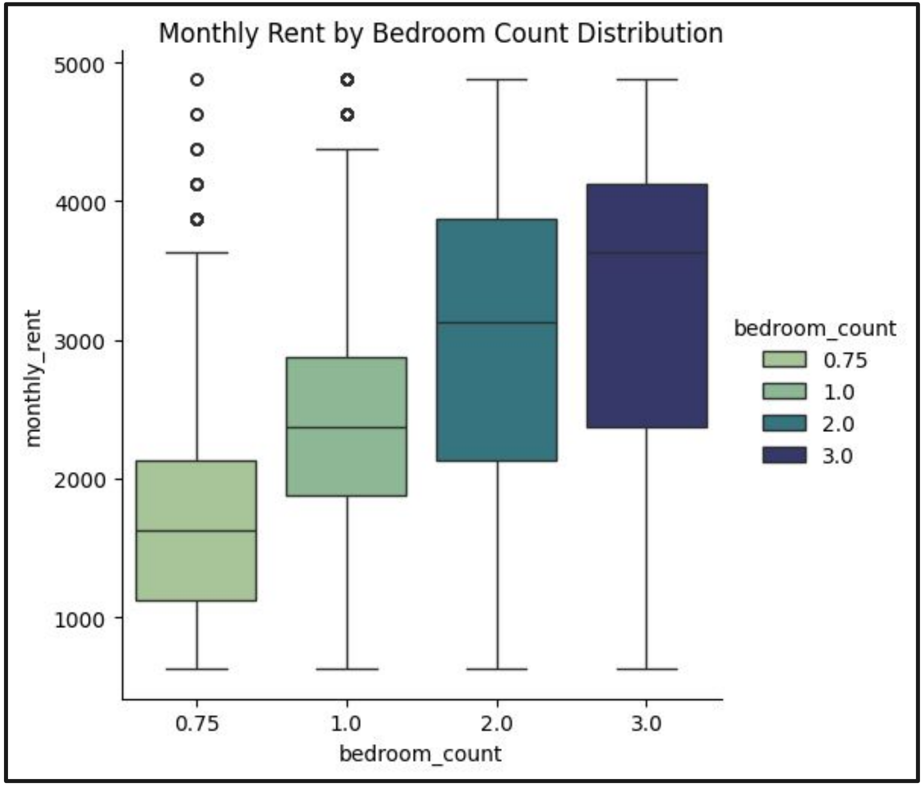
- Used a strip plot
- Mission and Western Addition have the most oldest buildings
- Other neighborhoods have considerably fewer old buildings



Problem Background (Q3)

How does bedroom count influence rent?

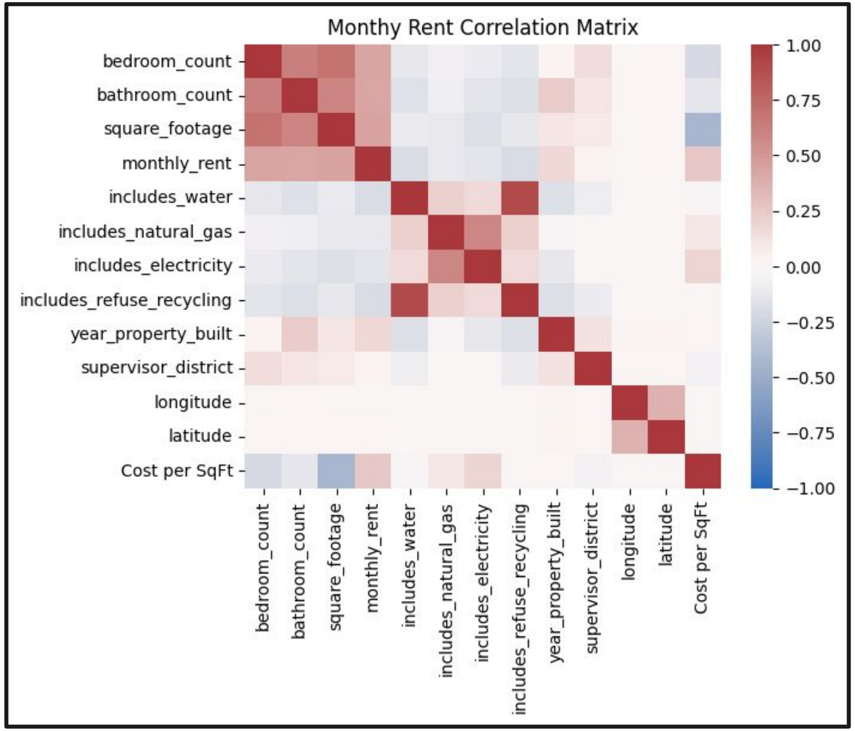
- Used a box plot
- Rent increases as bedroom count increases
- Large increase from one to two bedrooms, but a smaller increase from two to three bedrooms



Problem Background (Q4)

Which factor has the biggest impact on rent?

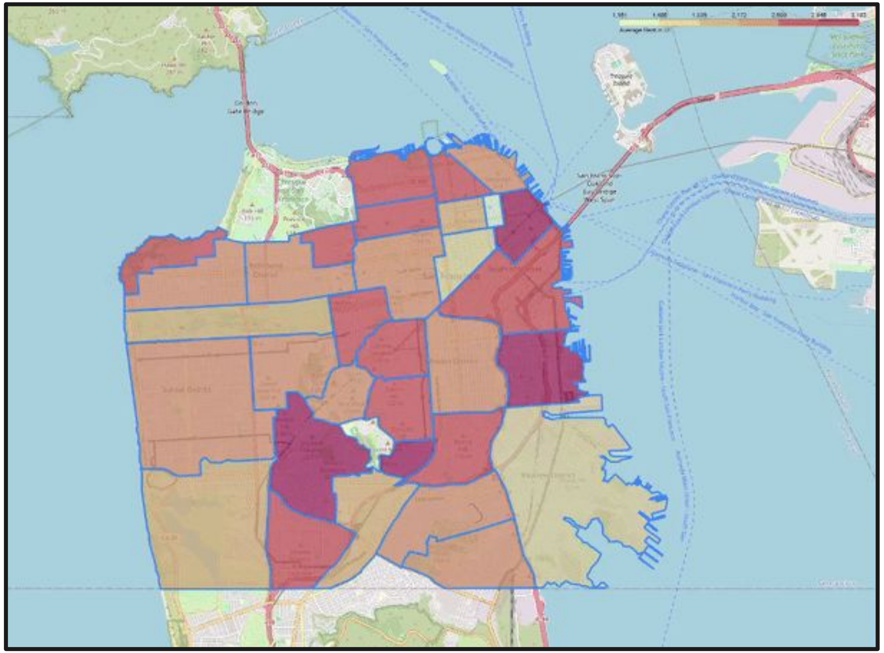
- Used a correlation matrix
- Square footage has the largest positive effect on monthly rent.
- Includes natural gas and includes refuse recycling has the largest negative impact on monthly rent.



Problem Background (Q5)

How do rental attributes differ among neighborhoods?

- Used a choropleth / folium map
- The Financial District has the highest average rent for only a small footage
- Bayview has a balance of high square footage and low average rent (best value)
- Chinatown has the lowest average rent but has very low square footage



Data Cleaning and Preprocessing (Pt 1)

- Imported necessary libraries including Matplotlib, Pandas, Seaborn as well as machine learning related libraries from sklearn
- Drop missing values for important features
- Drop unnecessary columns

```python
##imports
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import re
import folium
import geopy
import numpy as np
%matplotlib inline
```

```python
##ml imports
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import cross_val_score
```

Data Cleaning and Preprocessing (Pt 2)

- Standardize inconsistent types and values
  - Map functions to correct non-numeric data
  - Define boolean values
- New columns were added to engineer new features
  - Created cost per square foot, longitude, and latitude

```
##map bedrooms to ints
def mapBed(x):
  if x == "One-Bedroom" or x == "One-bedroom" or x == "1 b
    return 1
  if x == "Two-Bedroom" or x == "Two-bedroom" or x == "2 b
    return 2
  if x == "Three-Bedroom" or x == "3 bedroom" or x == "3":
    return 3
  if x == "Four-Bedroom":
    return 4
  if x == "Studio" or x == "studio" or x == "0" or x == "0
    return 0.75
  if x == "5+" or x == "Five-Bedroom":
    return 5
  if x == "Vacant":
    return None

rent["bedroom_count"] = rent["bedroom_count"].map(mapBed)
```

Map function

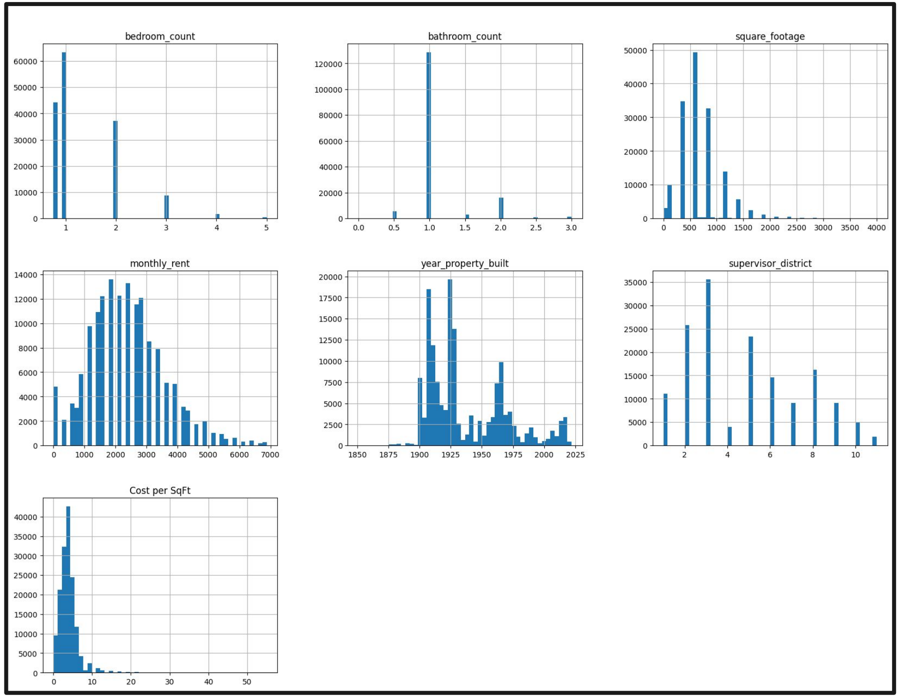
Data Exploration

To identify important features and relationships for our ML Model, we used:

- Histogram
- Choropleth Map
- Correlation Matrix
- Pairplot

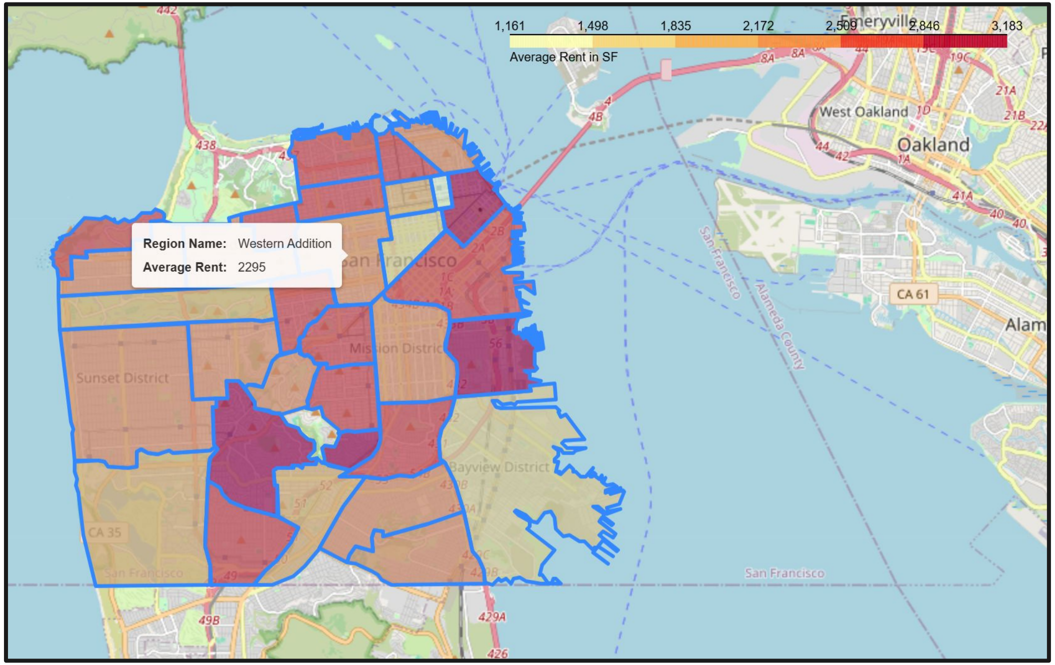
Data Exploration - Histogram

- Gives a sense of the distribution across each numeric category.
    - Allows us to better understand the spread and shape of the data.
- Identify outliers so that we can drop to improve ML model.
    - Ensures that extreme values don't disproportionately influence the analysis.

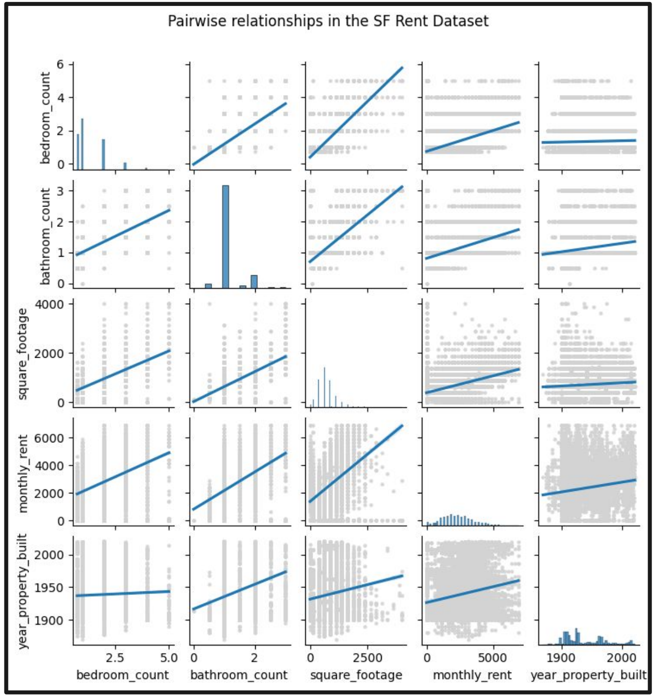


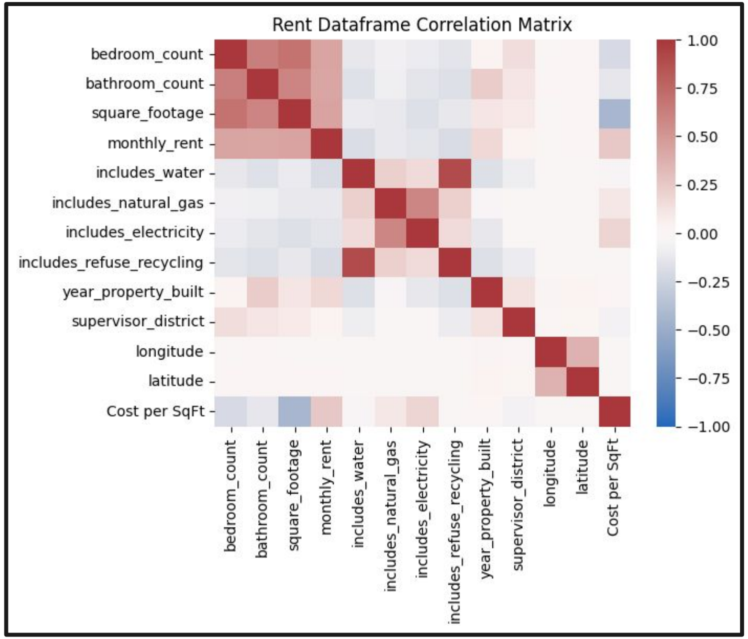
Data Exploration - Choropleth / Folium Map

- Neighborhood (a categorical variable) appears to influence rent prices.
- Legend shows the mean rent in different neighborhoods. Yellow indicates low rent, red indicates high rent.



Data Exploration - Pairplot and Correlation Matrix





Machine Learning Strategies (Pt 1)

- **Target Variable:** Monthly Rent
- Apply ML techniques to estimate rent based on property features
- Results benefit future and current homeowners

Machine Learning Strategies (Pt 2)

- Split 90-10 into a training set and a test set stratified by year property built.
- Preprocessed the dataset by applying one-hot encoding to the categorical features.
- Used median imputation and ordinal standardization for numerical features.
- Both numerical and categorical features were integrated using a Column Transformer.

```
# convert categorical values into one-hot vectors
cat_encoder = OneHotEncoder()
rent_cat_1hot = cat_encoder.fit_transform(rent_cat)
rent_cat_1hot

cat_attr = ["analysis_neighborhood"]
rent_num = rent.drop('analysis_neighborhood', axis=1)
num_attr = list(rent_num)

num_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy="median")),
    ('std_scaler', StandardScaler())
    ])

rent_num_tr = num_pipeline.fit_transform(rent_num)
```

```
full_pipeline = ColumnTransformer([
        ("num", num_pipeline, num_attr),
        ("cat", OneHotEncoder(), cat_attr)
    ])

rent_prepared = full_pipeline.fit_transform(rent)
cols=list(rent_num) + cat_encoder.categories_[0].tolist()

## Convert the 2D array into Pandas DataFrame
rent_prep_df = pd.DataFrame.sparse.from_spmatrix(
    rent_prepared,
    columns=cols,
    index=rent.index)
rent_prep_df.head()
```

ML Model Fine Tuning (Pt 1)

- Performing 10 cross validation for each chosen machine learning model and using RMSE, MAE, & R^2 as the evaluation metrics, we found the following:

	Linear Regression	Decision Tree Regression	Random Forest Regression
RMSE	747.99	658.88	639.68
MAE	466.02	465.30	464.92
R^2	0.43	0.56	0.58

- Random Forest Regression achieved the best performance, with the lowest RMSE (score = 639.68), lowest MAE (score = 464.92), and highest R^2 value (0.58) among the models tested.

ML Model Fine Tuning (Pt 2)

- Random forest was then fine-tuned with Grid Search and Random Search. We obtained the following results:

	Grid Search	Random Search
RMSE	541.86	541.39
MAE	394.66	394.27
R^2	0.7011	0.7016

- Grid Search performed slightly better on the test data compared to Random Search, however the R^2 value was slightly lower than the Random Search

ML Model Results (Pt 1)

- To collect our model results, the fine-tuned Random Forest Regression model was run on our test data set after applying the preprocessing pipeline.
- Results were assessed through RMSE, MAE values, R^2, confusion matrix, and line graph.

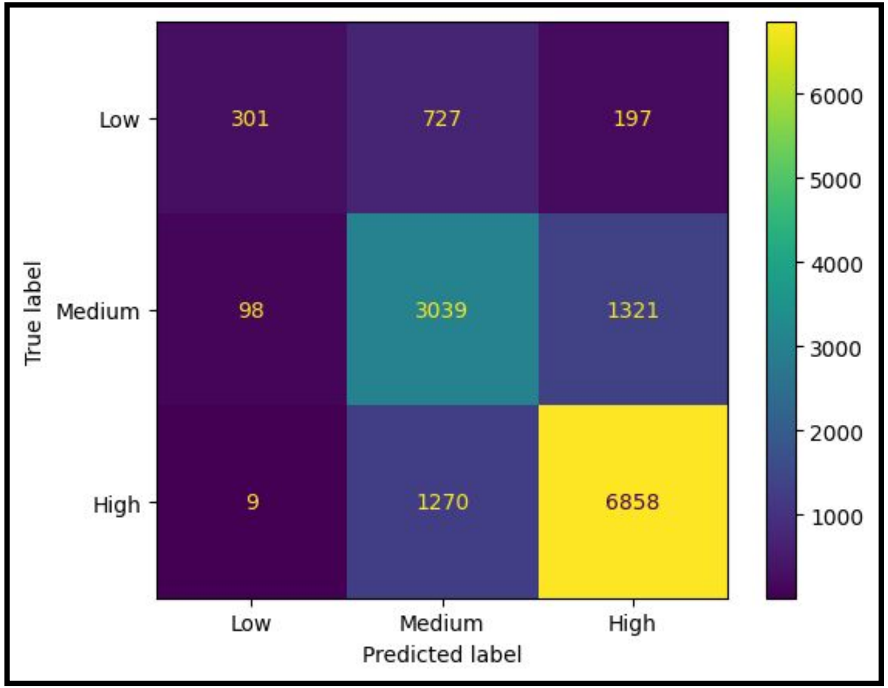
ML Model Results (Pt 2)

	Random Forest Regression
RMSE	621.53
MAE	455.27
R^2	0.6115

- Large margin of error apparent in the RMSE, MAE, and R^2 value.
- Although there were many attempts made at fine-tuning the model to achieve a better result, these scores were ultimately determined to be a consequence of the data supplied.

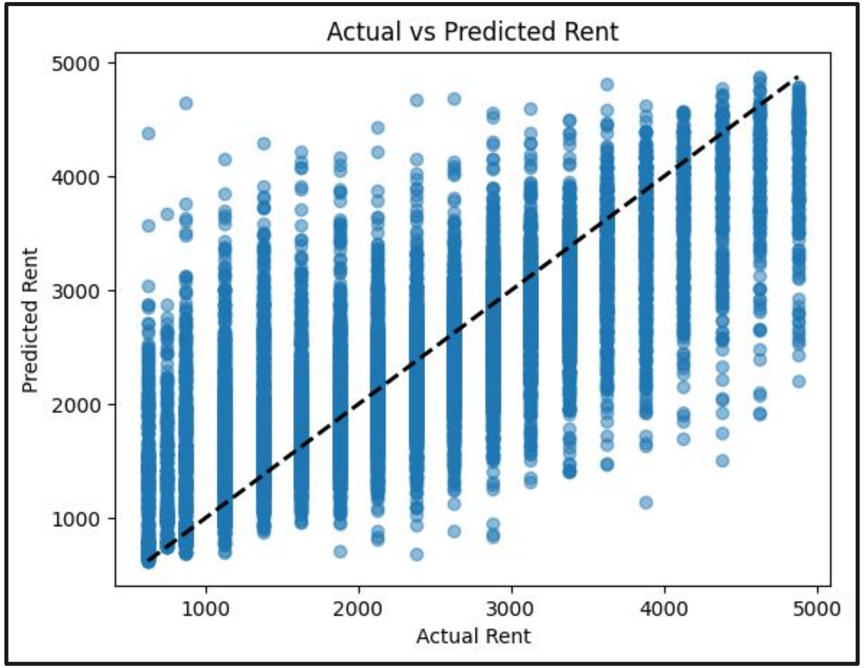
ML Model Results (Pt 3)

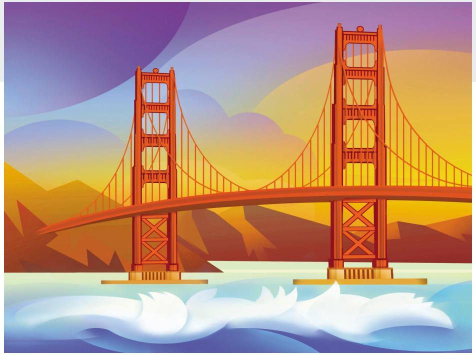
- The model correctly classified 84% of high-cost, 68% of medium-cost, and 24% of low-cost apartments.
- While accurate for high-cost units, it tends to overestimate rent for lower-cost apartments.



ML Model Results (Pt 4)

- The black dashed line represents the ideal predictions
- Upward trend represents positive correlation
- Wide spread data indicates high variability, suggesting a lack of precision





Conclusion

- Our project demonstrates how machine learning can assist in estimating rent but also underscores the limits of purely data-driven approaches in real estate.

- The final evaluation of the model on the test set yielded an RMSE of 621.53, an MAE of 455.27, and an R^2 value of 0.6115, reflecting moderate accuracy and acceptable generalization.

- While the model can reasonably predict rental prices, it is not highly precise, emphasizing the inherent complexity of rental pricing.

- Model improvements may be available through collecting more data (walkability, transit, etc), and exploring advanced models like gradient boosting.

Thank you for listening!