VANCOUVER, BC 2025

# RENTAL PRICE PREDICTION

Leveraging <u>machine learning</u> to analyze Vancouver's rental market.

## Hi, I'm Pam!

- Business Engineering > Data Science Co-Op
- 5 year Experience in Digital Marketing & Analysis for Startups, SaaS, Service, Retail Industries.
  - Tech Stack: Python, SQL, PostgreSQL, BigQuery
    - Project: Python for ML, Looker

# WHY?

## RENTING A PLACE IN VANCOUVER IS A CHALLENGE

- Landlords are increasing rents by 23.5% when apartments become vacant.
- Vancouver's rental market has a **0.8% vacancy rate** in purpose-built rentals.
- CMHC's Fall 2024 Rental Market Report shows that rising rents and low vacancy rates discourage tenant mobility in Vancouver.

<sup>1 -</sup> CBC | https://www.cbc.ca/news/canada/british-columbia/rent-hike-23-per-cent-1.7295152

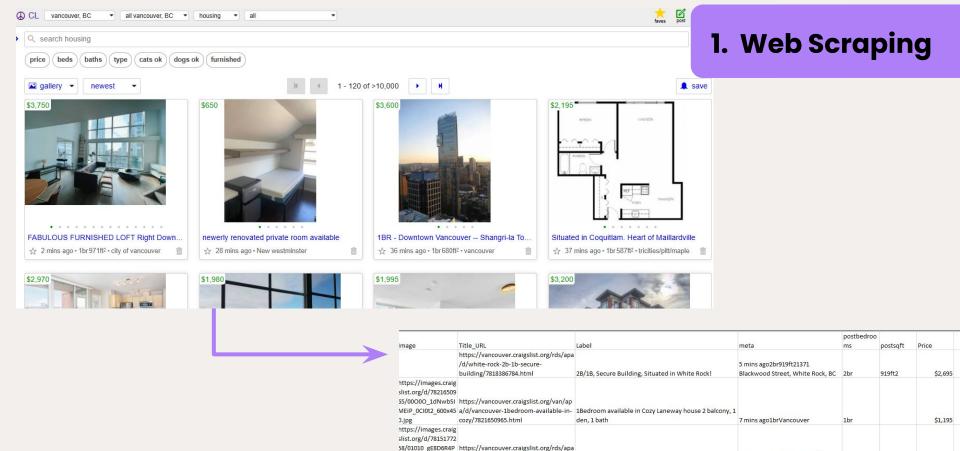
<sup>2 -</sup> CMHC | 2024-02-12-memo-updated-rental-market-data-from-cmhc-for-2024 3 - Fall 2024 Rental Market Report | CMHC - Fall 2024 Rental Market Report | CMHC

## Where are you looking for rentals?

### GOAL

## Predict rent prices in Vancouver using Machine Learning.

# HOW?



dZP 0CI0pO 600x45 /d/port-coquitlam-house-

https://images.craig

rent/7815177258.html

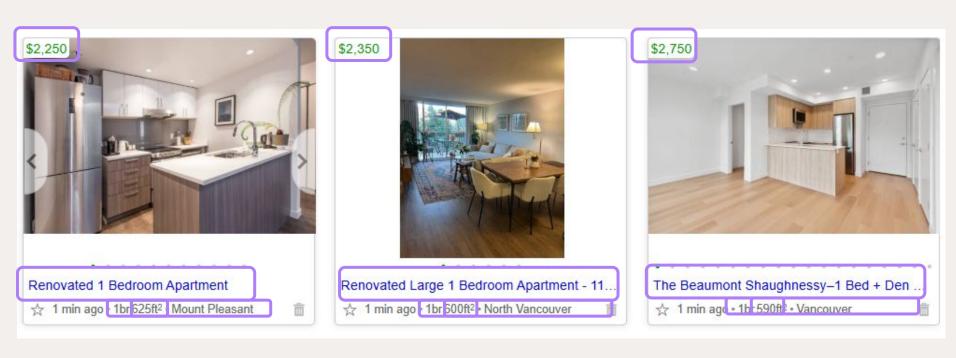
HOUSE RENT

9 mins ago4br1250ft2Port

1250ft2

Coquitlam

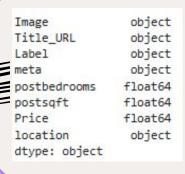
### Data



```
# Lower case the "location" column to clean it.
df['location'] = df['location'].str.lower()
# Replace al strings that have a "Vancouver" with just "Vancouver"
df['location'] = df['location'].str.replace(r'.*surrey.*', 'surrey', regex=True)
df['location'] = df['location'].str.replace(r'.*\b(burnaby|brentwood|metrotown)\b.*', 'burnaby', regex=True)
df['location'] = df['location'].str.replace(r'.*richmond.*', 'richmond', regex=True)
df['location'] = df['location'].str.replace(r'.*delta.*', 'delta', regex=True)
df['location'] = df['location'].str.replace(r'.*maple ridge.*', 'maple ridge', regex=True)
df['location'] = df['location'].str.replace(r'.*pitt meadows.*', 'pitt meadows', regex=True)
df['location'] = df['location'].str.replace(r'.*white rock.*', 'white rock', regex=True)
df['location'] = df['location'].str.replace(r'.*langley.*', 'langley', regex=True)
df['location'] = df['location'].str.replace(r'.*coquitlam.*', 'coquitlam', regex=True)
df['location'] = df['location'].str.replace(r'.*tsawwassen.*', 'tsawwassen', regex=True)
df['location'] = df['location'].str.replace(r'.*port moody.*', 'port moody', regex=True)
df['location'] = df['location'].str.replace(r'.*new westminster.*', 'port moody', regex=True)
df['location'] = df['location'].str.replace(
   r'.*\b(north|west) vancouver\b.*', r'\1 vancouver', regex=True # Preserve special cases
# Replace remaining patterns containing "Vancouver" with "Vancouver"
df['location'] = df['location'].str.replace(
   r'.*vancouver.*', 'vancouver', regex=True)
# If the value is not then turn into vancouver
df['location'] = df['location'].apply(lambda x: x if x in [
    'surrey', 'burnaby', 'richmond', 'delta', 'maple ridge', 'pitt meadows', 'white rock', 'langley', 'coquitlam'
    , 'tsawwassen', 'port moody', 'vancouver'] else 'vancouver')
df['location'].unique()
```

#### 2. Data Cleanup

Image object object Title URL Label object meta object postbedrooms object object postsqft Price object object zone name dtype: object



#### 2. Data Cleanup

```
# find empty values
df.isnull().sum()

Image 333
Title_URL 0
Label 0
meta 0
postbedrooms 391
postsqft 971
Price 1
dtype: int64
```

The <u>null values</u> appear because the user left these sections of the ad on Craigslist unfilled.

# EDA Exploratory Data Analysis

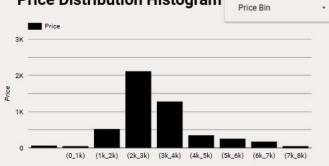




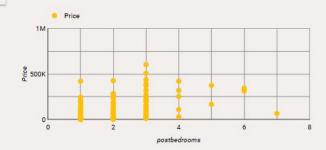


Price 3.3K postbedrooms 2.06

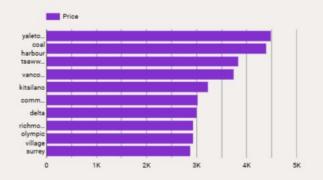
#### **Price Distribution Histogram**



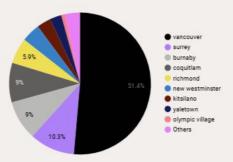
#### Price vs. Square Footage Scatter Plot



#### **Price by Location Bar Chart:**



#### **Listings by Location Pie Chart**



#### Let's go to:



#### 4. Encoding

Vancouver is priority.

#### **Label Encoding**

5. Feature Scaling

Test\_size = 0.2 means 80% of the data will be used for training and 20% for testing.

#### 5. Feature Scaling

```
# Initialize StandardScaler
scaler = StandardScaler()

scaler = StandardScaler()

X_train[["postbedrooms", "postsqft"]] = scaler.fit_transform(X_train[["postbedrooms", "postsqft"]])

X_test[["postbedrooms", "postsqft"]] = scaler.transform(X_test[["postbedrooms", "postsqft"]])
```

Scaling ensures all the features contribute equally to the model.

# MODEL

#### 6. Machine Learning

#### RandomForestRegressor model

```
# Train a Random Forest Regressor
rf model = RandomForestRegressor(random state=42, n estimators=100)
rf_model.fit(X_train, y_train)
v pred rf = rf model.predict(X test)
# Fualuate the model
mse rf = mean_squared_error(y_test, y_pred_rf)
r2 rf = r2 score(y test, y pred rf)
print(f'Mean Squared Error (Random Forest): {mse_rf}')
print(f'R-squared (Random Forest): {r2_rf}')
Mean Squared Error (Random Forest): 998824.9979292797
R-squared (Random Forest): 0.7226820599458545
```

MSE = 998824

 $R^2 = 0.72$ 

# RESULTS

```
# Create new data for prediction
new_data = pd.DataFrame({
    "postbedrooms": [2, 2, 2],
    "postsqft": [800, 800, 800],
    "location": ["vancouver", "burnaby", "coquitlam"]
})
```

#### evaluation\_results

```
{'Random Forest MSE': 998824.9979292797,
'Random Forest R<sup>2</sup>': 0.7226820599458545,
'Predicted Rental Prices (Random Forest)': [2751, 2173, 2032]}
```

#### **Predicted Rental Prices (RandomForest)**

Vancouver: \$ 2751

**Burnaby:** \$ 2173

Coquitlam: \$ 2032

#### **CONCLUSIONS**

#### **HOT RENTALS**

1 - 3 bedroom houses / apartments.

#### **VANCOUVER**

Can have the <u>lowest price</u>
but also the <u>highest price</u>
for the same amount of
bedrooms.

#### **OPTIONS**

Affordable rents in cities nearby.

#### TO LOOK FORWARD

2025 New research(CIBC): Growth in Unit compilations well outpaced **population growth.** 

- International student permits cap (newcomers)
- 45% less (fall of 2024) University in-person enrollments.

2025 might be a good year to look around for rents.

## **Further Projects:**

More data

Effect of new regulations



Github repository





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