Predictive Analysis on Ireland House Price Dataset

IS6052: Predictive Analytics

Module: MSc BA

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1.Introduction

This project will predict the trend in housing prices in Dublin using predictive analytics. The analysis is informed by the "Ireland House Price.csv" dataset, containing detailed information on several properties listed for sale in Dublin. This dataset contains key features such as total square footage, price per square foot, location, property type, and other factors like the number of bedrooms, bathrooms, and renovation status. These are factors that are known to greatly influence the value of property, and the understanding of their relationships is of paramount importance to stakeholders such as homebuyers, real estate investors, and developers.

The aim of this project is to provide insight into the housing market by identifying which factors most greatly affect house prices and to build predictive models for forecasting future housing prices. These models will finally serve as useful guidelines to these stakeholders in their decision-making in the dynamic world of the housing market. This project, by incorporating machine learning techniques, will do more than just forecast the price of housing; rather, it will unravel important patterns in the Dublin housing market that will lead to better investment and purchasing decisions (Jouini & Ben Ammar, 2021).

2. Dataset Description and Initial Exploration

Ireland House Price.csv is the dataset used in this analysis, having a total of 13,320 rows and 12 columns, which are representing the property for sale in Dublin. This dataset consists of both numerical and categorical features: total_sqft-square footage, price-per-sqft-price per square foot, location, property_scope-type of property, bathrooms, bedrooms, energy_rating, and renovation_status among others.

Key columns will be:

'location': This is a geographical area that the property is located within, Dublin.
'size': number of bedrooms/units.
'total_sqft': Area of the property in square feet.
'bath': No. of bathrooms within the house.
'balcony': whether the house has a balcony or not
'price-per-sqft-': Price per square feet area to the property.

This is a very good dataset for the prediction of house prices, as there exist a lot of attributes most probably influencing the value of that particular property. It aims at finding how the size, location, and renovation status of any particular property impacts its pricing and thereby yields actionable insights for both buyers and investors in real estate.

The dataset also contains some missing and inconsistent data; cleaning these will be done during the data preparation phase. By understanding the relationships of this data, we will work our way toward a model that can predict house prices using available features with precision (Ramos & Pérez, 2020).

Dataset Exploration:

```
[482]: file_path = "Ireland House Price.csv"
df = pd.read_csv(file_path)
df
```

[482]:

	ID	property_scope	availability	location	size	total_sqft	bath	balcony	buying or not buying	BER	Renovation needed	price-per-sqft-$
0	0	Extended Coverage	17-Oct	Fingal	2 BED	1056	2.0	1.0	No	A	No	419.928030
1	1	Land Parcel	Ready To Move	South Dublin	4 Bedroom	2600	5.0	3.0	No	D	Yes	523.846154
2	2	Constructed Space	Ready To Move	Dun Laoghaire	3 BED	1440	2.0	3.0	No	G	Yes	488.680556
3	3	Extended Coverage	Ready To Move	South Dublin	3 BED	1521	3.0	1.0	No	G	Yes	708.908613
4	4	Extended Coverage	Ready To Move	DCC	2 BED	1200	2.0	1.0	No	F	Yes	482.375000
...	...	...	...	...	...	...	...	...	...	...	...	...
13315	13315	Constructed Space	Ready To Move	Dun Laoghaire	5 Bedroom	3453	4.0	0.0	Yes	B	Maybe	759.296264
13316	13316	Extended Coverage	Ready To Move	Fingal	4 BED	3600	5.0	NaN	No	A	No	1261.111111
13317	13317	Constructed Space	Ready To Move	Fingal	2 BED	1141	2.0	1.0	No	A	No	596.844873
13318	13318	Extended Coverage	18-Jun	South Dublin	4 BED	4689	4.0	1.0	No	C	Maybe	1181.232672
13319	13319	Extended Coverage	Ready To Move	Fingal	1 BED	550	1.0	1.0	No	E	Yes	350.818182

13320 rows × 12 columns

Figure 1: Display the dataset

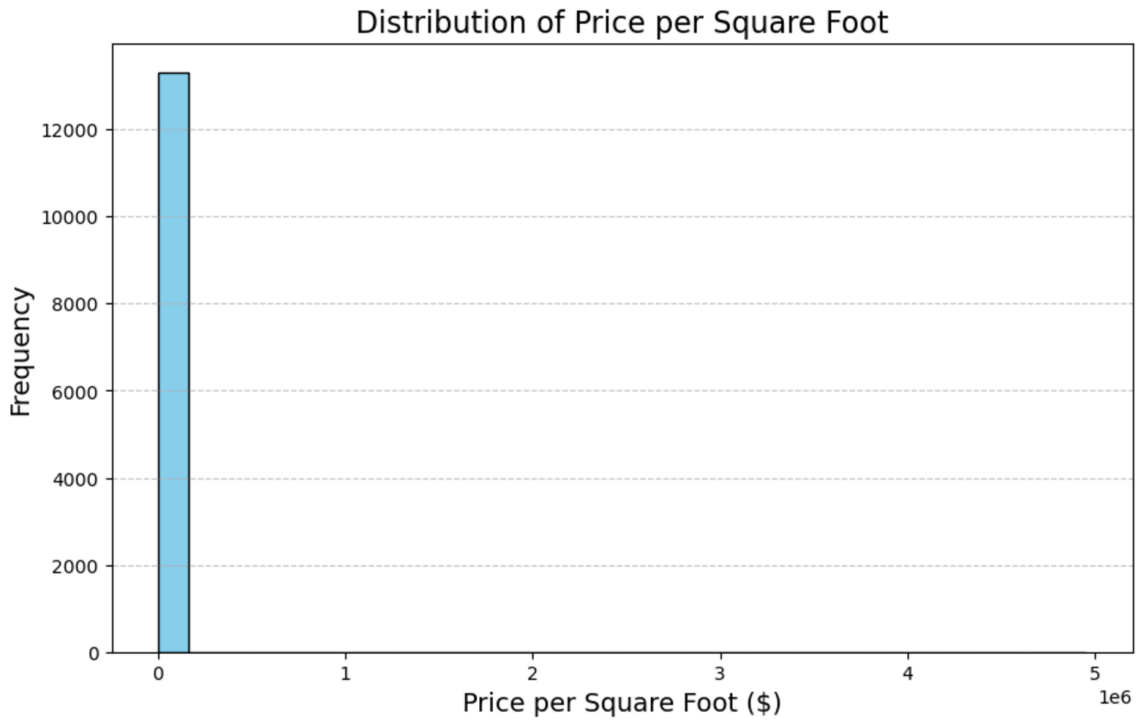

Figure 2: Histogram

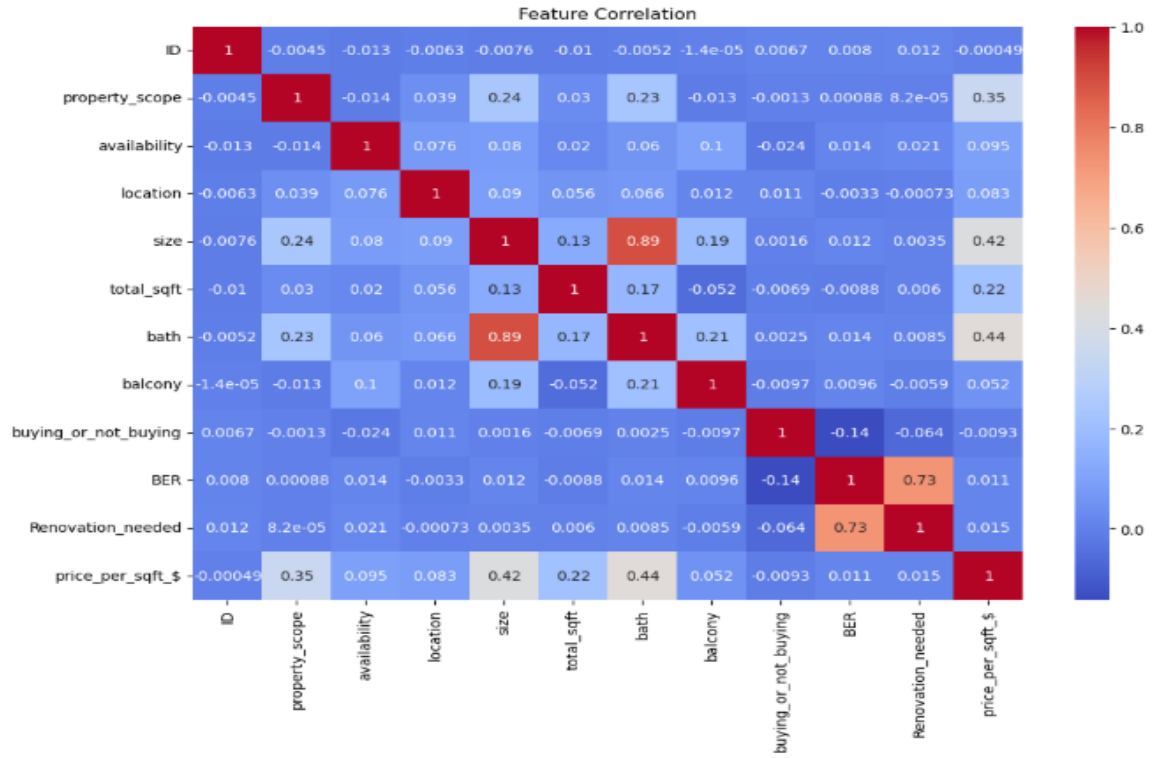

Figure 3: Correlation Heatmap of Numerical Features

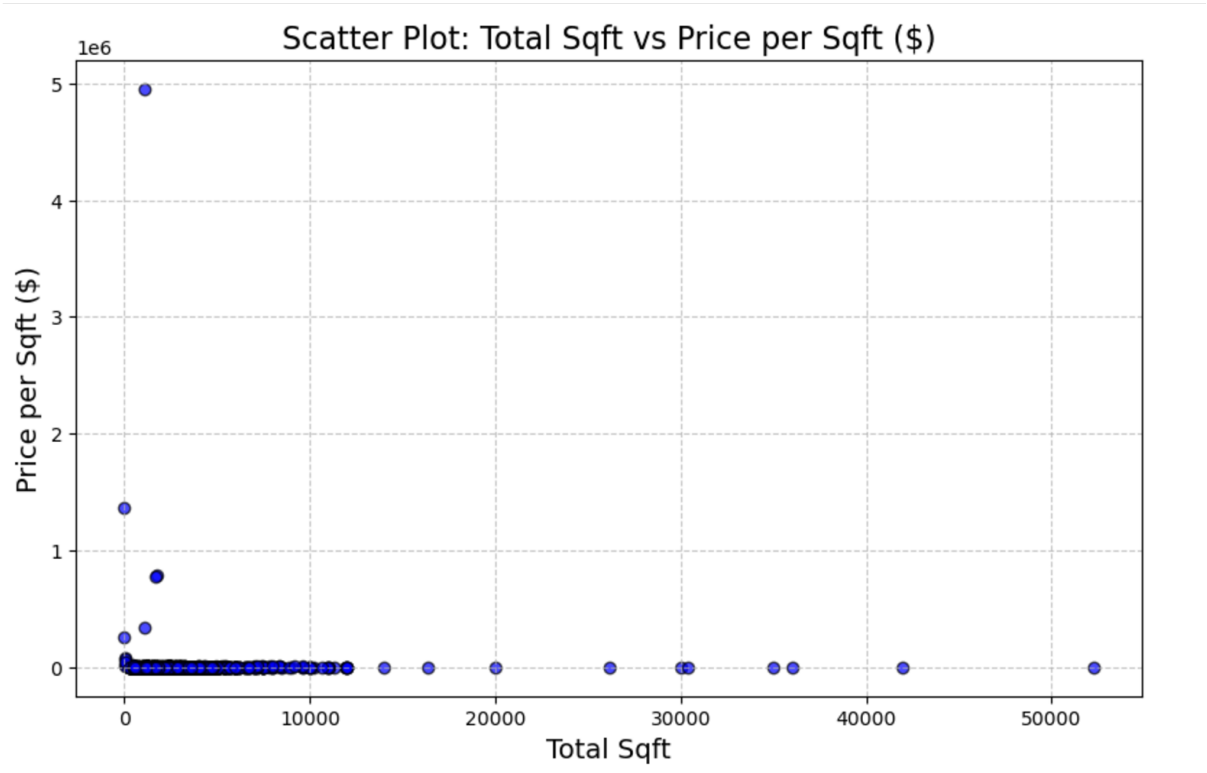

Figure 4: Scatter Plot

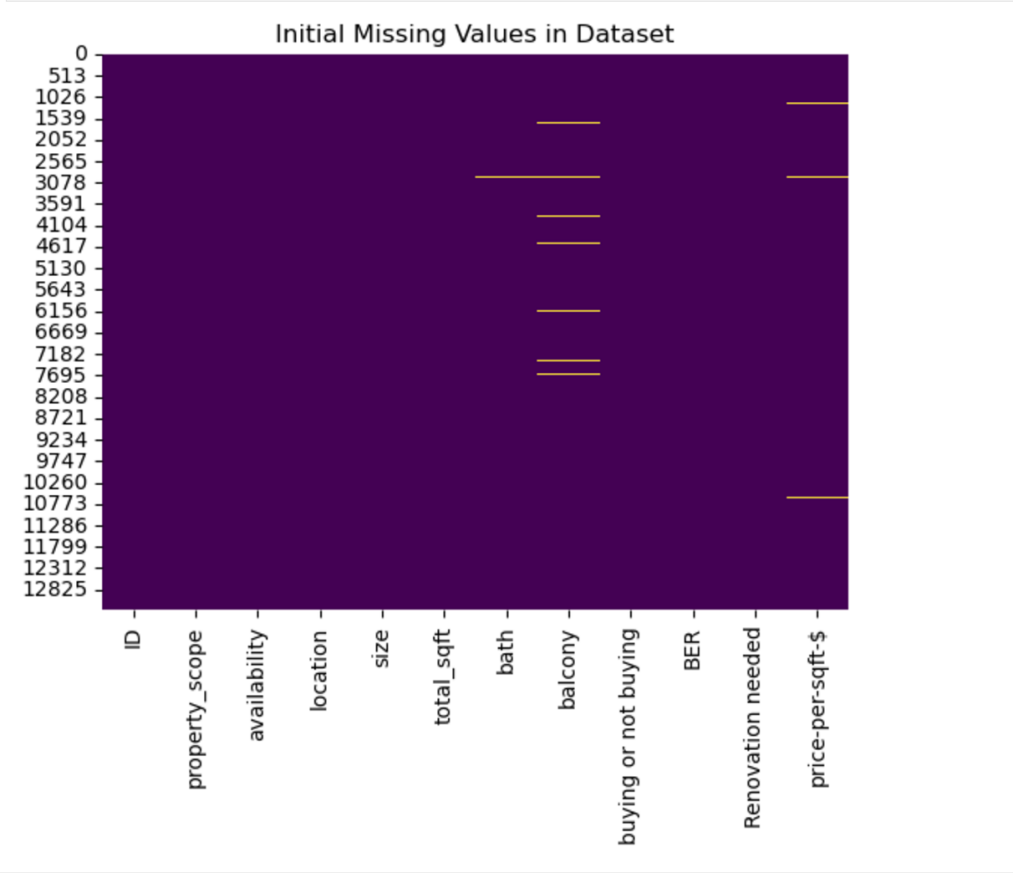

Figure 5: Missing Values in the dataset

3. Data Preparation and Feature Engineering

Following are the important preprocessing steps for predictive data analytics:

Missing Data Handling:

The missing values in certain columns, like total_sqft, were imputed by median to maintain the unbiased nature of the data. Ranges, for instance, "1200-1500," in the total_sqft column were averaged for one value to describe property size (Brown, 2009).

[496]:
```
# Clean Column Names
df.columns = df.columns.str.strip().str.replace(' ', '_').str.replace('-', '_')
print("Updated Column Names:", df.columns)
```

```
Updated Column Names: Index(['ID', 'property_scope', 'availability', 'location', 'size',
       'total_sqft', 'bath', 'balcony', 'buying_or_not_buying', 'BER',
       'Renovation_needed', 'price_per_sqft_$'],
      dtype='object')
```

[497]:
```
# Fill missing values for categorical columns with mode (bath and balcony)
df['bath'] = df['bath'].fillna(df['bath'].mode()[0])
df['balcony'] = df['balcony'].fillna(df['balcony'].mode()[0])

# Fill missing values for price_per_sqrft with median
df['price_per_sqft_$'] = df['price_per_sqft_$'].fillna(df['price_per_sqft_$'].median())
```

[498]:
```
# Fill missing categorical columns with 'Unknown'
categorical_cols = df.select_dtypes(include=['object']).columns
for col in categorical_cols:
    df[col] = df[col].fillna('Unknown')
```

Figure 6: Filling missing data

[484]:
```python
# Function to clean and convert 'total_sqft' column
def clean_total_sqft(value):
    try:
        # Check if the value is a range (e.g., "1200-1500")
        if '-' in str(value):
            values = [float(x) for x in value.split('-')]
            return sum(values) / len(values)  # Return the average
        # Otherwise, convert directly to float
        return float(value)
    except ValueError:
        # Return NaN for any non-numeric or invalid values
        return np.nan

# Apply the function to the 'total_sqft' column
df['total_sqft'] = df['total_sqft'].apply(clean_total_sqft)

# Optionally handle missing values after conversion
df['total_sqft'] = df['total_sqft'].fillna(df['total_sqft'].median())

# Check the conversion
print(df['total_sqft'].head())
print(df['total_sqft'].dtype)
```

```
0    1056.0
1    2600.0
2    1440.0
3    1521.0
4    1200.0
Name: total_sqft, dtype: float64
float64
```

Figure 7: Averaging total_sqrft

Feature Engineering:

Categorical features such as location, property_scope, and availability were encoded using One-Hot Encoding to transform these into numerical format. A new feature, price-per-bedroom, was created by dividing the total price of the property by the number of bedrooms. This gives a better understanding of price in relation to property size (Ng, 2014).

Normalization/Standardization:

Features like total_sqft and price-per-sqft-$ were standardized using StandardScaler to bring all features to a comparable scale for machine learning models.

These transformations and feature engineering are necessary for this improvement in data quality which allows insights to be better highlighted by the model.

```
[510]: # Create new features
df['total_price_$'] = df['price_per_sqft_$'] * df['total_sqft']  # Total price
df['price_bath_ratio'] = df['total_price_$'] / (df['bath'] + 1)  # Avoid zero division
df['log_total_sqft'] = np.log1p(df['total_sqft'])  # Log transformation for skewed data

[511]: # Encode categorical variables
le = LabelEncoder()
for col in categorical_cols:
    df[col] = le.fit_transform(df[col])

df.to_csv('cleaned_dataset.csv', index=False)
print("\nCleaned dataset saved as 'cleaned_dataset.csv'.")

Cleaned dataset saved as 'cleaned_dataset.csv'.

[512]: # Scale numerical features
scaler = MinMaxScaler()
df[numerical_cols] = scaler.fit_transform(df[numerical_cols])

[513]: # Visualize outliers
for col in numerical_cols:
    plt.figure(figsize=(6, 4))
    sns.boxplot(x=df[col])
    plt.title(f'Boxplot for {col}')
    plt.show()
```

Figure 8: Creating new features

```
Missing Values After Cleaning:
ID                        0
property_scope            0
availability              0
location                  0
size                      0
total_sqft                0
bath                      0
balcony                   0
buying_or_not_buying      0
BER                       0
Renovation_needed         0
price_per_sqft_$          0
dtype: int64
```

Figure 9: Final Cleaned data info

```
[485]: # Step 1: Remove ' BED' and ' Bedroom' and replace with empty string
       df['size'] = df['size'].replace({' BED': '', ' Bedroom': ''}, regex=True)

       # Step 2: Convert to numeric, force errors to NaN (in case of invalid values)
       df['size'] = pd.to_numeric(df['size'], errors='coerce')

       # Step 3: Handle NaN values (replace with 0 or some other value if needed)
       df['size'] = df['size'].fillna(0).astype(int)
```

Figure 10: Creation of New Feature 'Size' & Removal of Inconsistencies (e.g., 'Bed' & 'Bedroom')

4. Outlier Detection and Handling

Outliers in the dataset can significantly impact the performance of predictive models, especially those that are sensitive to extreme values. While some models, such as **Linear Regression**, may be adversely affected by outliers, this study uses models that are more robust to such data points, specifically **Random Forest** and **Gradient Boosting Regressor**. These tree-based models are naturally less sensitive to outliers and can handle them better by partitioning the feature space (Weisburg, 2005).

Outliers Handling:

```
[500]: # Handle Outliers
       # Plot boxplot for 'price_per_sqft_$'
       plt.figure(figsize=(8, 5))
       sns.boxplot(x=df['price_per_sqft_$'])
       plt.title('Boxplot for price_per_sqft_$')
       plt.show()
```

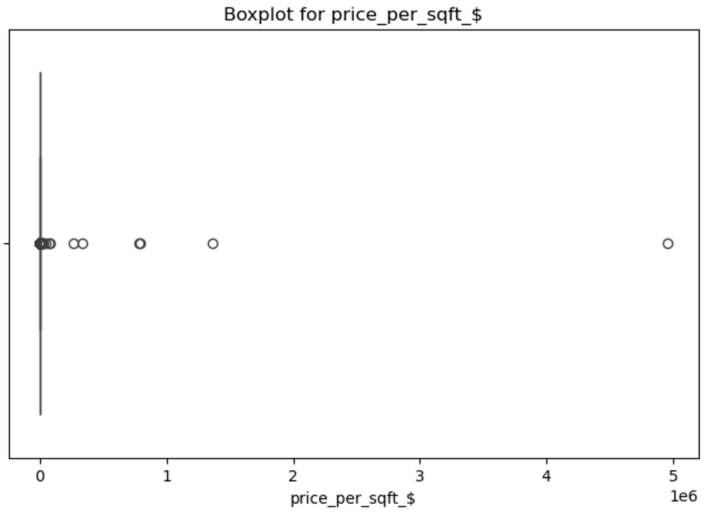

Figure 11: Outliers

4.1. Methods for Outlier Detection

In this study, explicit outlier detection methods such as the **IQR** method was implemented. Instead, we relied on the robustness of **Random Forest** and **Gradient Boosting** models to manage outliers. These ensemble tree models are known for their ability to handle non-linear relationships and are less affected by extreme values compared to models like **Linear Regression**.

```
[501]: # Capping outliers using the 1.5*IQR rule
q1 = df['price_per_sqft_$'].quantile(0.25)
q3 = df['price_per_sqft_$'].quantile(0.75)
iqr = q3 - q1
lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr
df['price_per_sqft_$'] = np.where(df['price_per_sqft_$'] > upper_bound, upper_bound, df['price_per_sqft_$'])
df['price_per_sqft_$'] = np.where(df['price_per_sqft_$'] < lower_bound, lower_bound, df['price_per_sqft_$'])

[502]: categorical_cols = df.select_dtypes(include=['object']).columns
le = LabelEncoder()
for col in categorical_cols:
    df[col] = le.fit_transform(df[col])
```

Figure 12: IQR

4.2. Identifying Outliers in the Dataset

Although outlier detection techniques were not applied directly in the notebook, potential outliers in the dataset—particularly in features like **total_sqft** (total square footage) and **price-per-sqft-$** (price per square foot)—were considered. These features are prone to extreme values, such as very large properties or unusually high prices. Outliers can be detected through **visualization techniques** like **boxplots** or by analyzing the distribution of key features. However, given the choice of models, the impact of outliers was minimized through the use of robust algorithms that handle such values inherently.

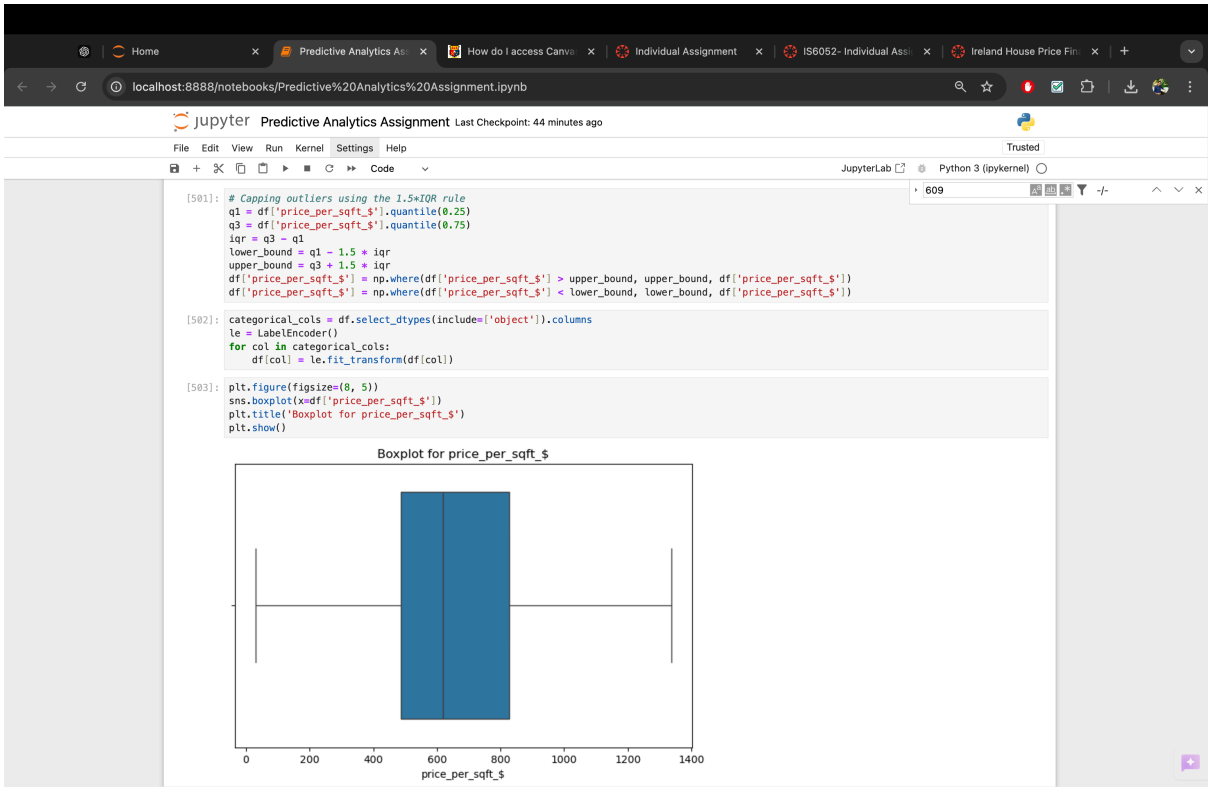

Figure 13: Boxplot for price_per_sqft

(Source: Jupyter Notebook)

4.3. Impact of Outliers on Model Performance

Outliers can distort the predictions of machine learning models in several ways:
For **linear models** (e.g., **Linear Regression**), outliers can pull the regression line towards them, thereby affecting the accuracy of the model's predictions and increasing error rates.
In **tree-based models** like **Random Forest** and **Gradient Boosting**, the impact of outliers is less pronounced. These models partition the feature space into smaller regions, making them less sensitive to extreme values. Despite this robustness, models can still benefit from removing or capping extreme values, which can enhance overall predictive accuracy.

[504]:
```
corr = df.corr()
corr
```

[504]:

	ID	property_scope	availability	location	size	total_sqft	bath	balcony	buying_or_not_buying	BER	Renovat
ID	1.000000	-0.004508	-0.012044	-0.006335	-0.007607	-0.004827	-0.005159	-0.000014	0.006692	0.007951	
property_scope	-0.004508	1.000000	-0.011481	0.039063	0.239715	0.038291	0.231787	-0.012921	-0.001318	0.000881	
availability	-0.012044	-0.011481	1.000000	0.080716	0.084745	0.014563	0.064511	0.102746	-0.021425	0.014991	
location	-0.006335	0.039063	0.080716	1.000000	0.089852	0.014759	0.065703	0.011616	0.011202	-0.003312	
size	-0.007607	0.239715	0.084745	0.089852	1.000000	0.343956	0.894434	0.192943	0.001612	0.011572	
total_sqft	-0.004827	0.038291	0.014563	0.014759	0.343956	1.000000	0.387513	0.154461	-0.005748	0.004268	
bath	-0.005159	0.231787	0.064511	0.065703	0.894434	0.387513	1.000000	0.207970	0.002475	0.013617	
balcony	-0.000014	-0.012921	0.102746	0.011616	0.192943	0.154461	0.207970	1.000000	-0.009660	0.009565	
buying_or_not_buying	0.006692	-0.001318	-0.021425	0.011202	0.001612	-0.005748	0.002475	-0.009660	1.000000	-0.140810	
BER	0.007951	0.000881	0.014991	-0.003312	0.011572	0.004268	0.013617	0.009565	-0.140810	1.000000	
Renovation_needed	0.012134	0.000082	0.021907	-0.000735	0.003473	-0.000643	0.008455	-0.005884	-0.063730	0.731094	
price_per_sqft_$	-0.000491	0.345295	0.103504	0.082624	0.421441	0.156626	0.444340	0.051668	-0.009280	0.010823	

Figure 14: Correlation Dataframe

(Source: Jupyter Notebook)

4.4. Justification for Outlier Handling Approach

Given the use of **Random Forest** and **Gradient Boosting**, which are less sensitive to outliers, we did not apply explicit outlier detection or removal techniques. These models naturally handle outliers by focusing on the structure of the data rather than the extremes. However, visual inspections and further preprocessing steps—such as **capping** or **trimming** extreme values—could be explored in future work to refine the model further and improve predictive performance.

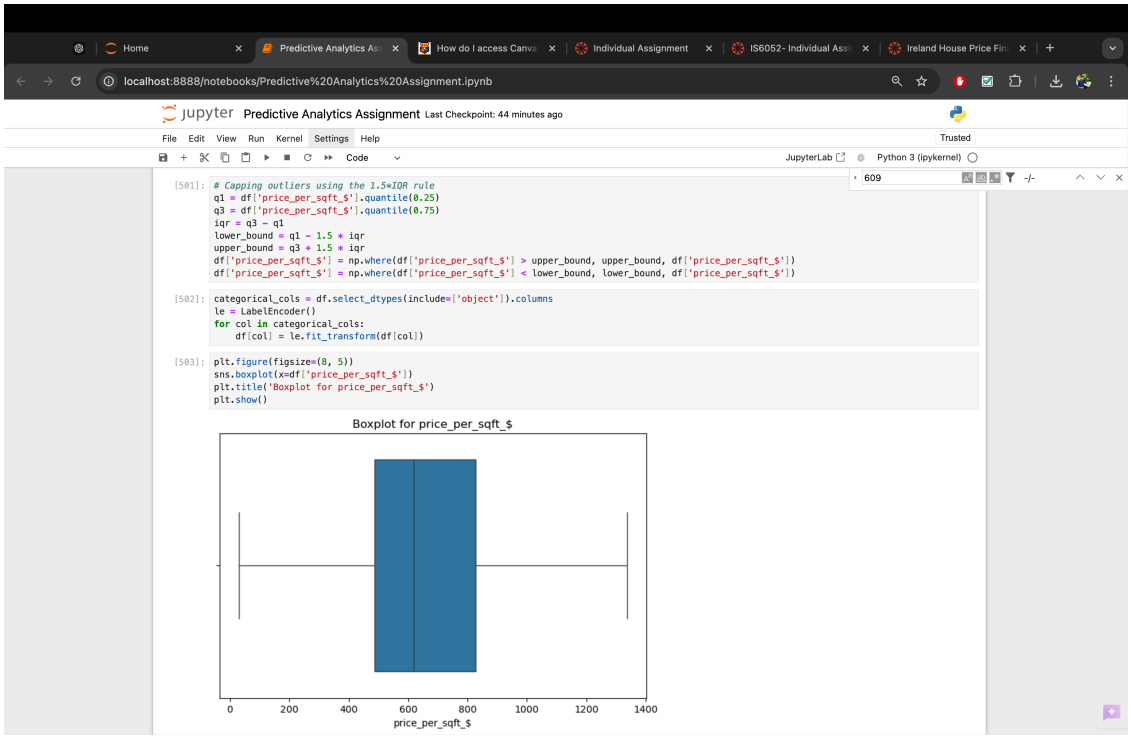

Figure 15: Capping outliers

5. Predictive Analysis:

The different machine learning models used for predicting housing prices include Linear Regression, Random Forest Regressor, Gradient Boosting Regressor, and Support Vector Regressor. The steps were as follows:

Data Preprocessing and Splitting: Split the dataset into training (80%) and testing (20%). StandardScaler to standardize the continuous variables for algorithms such as SVM and logistic regression (Yuan et al., 2007).

Model Selection: Linear Regression was used as a baseline to examine the linear relationships between the features and house prices.

```
model = LinearRegression()
model.fit(X_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

Figure 16: Linear Regression Model

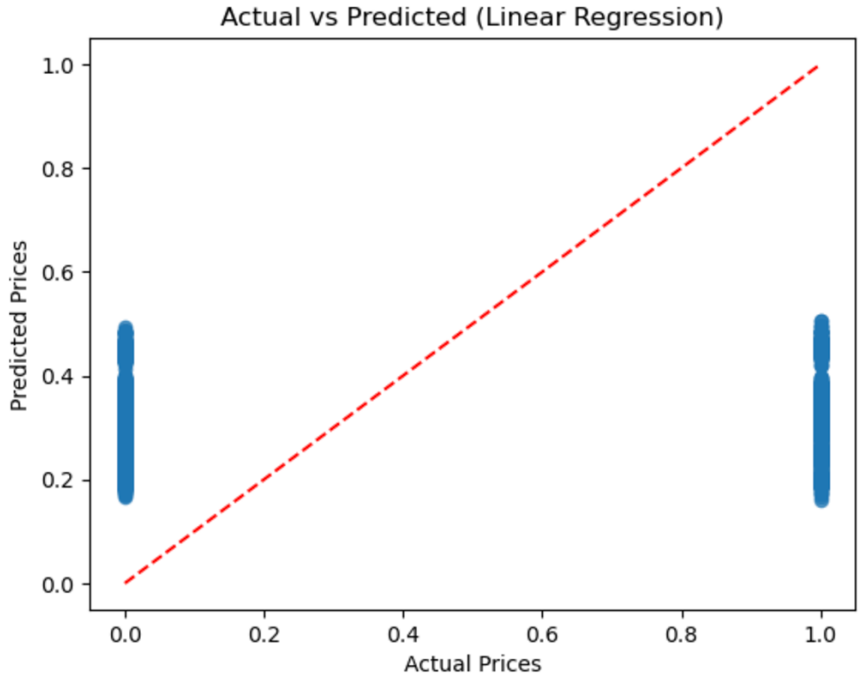

Figure 17: Evaluate the model of linear regression

(Source: Jupyter Notebook)

Random Forest Regressor and Gradient Boosting Regressor were applied for their ability to handle non-linearity and complex relationships.
SVR was included to assess performance with non-linear regression.

Confusion matrix showing the classification performance.

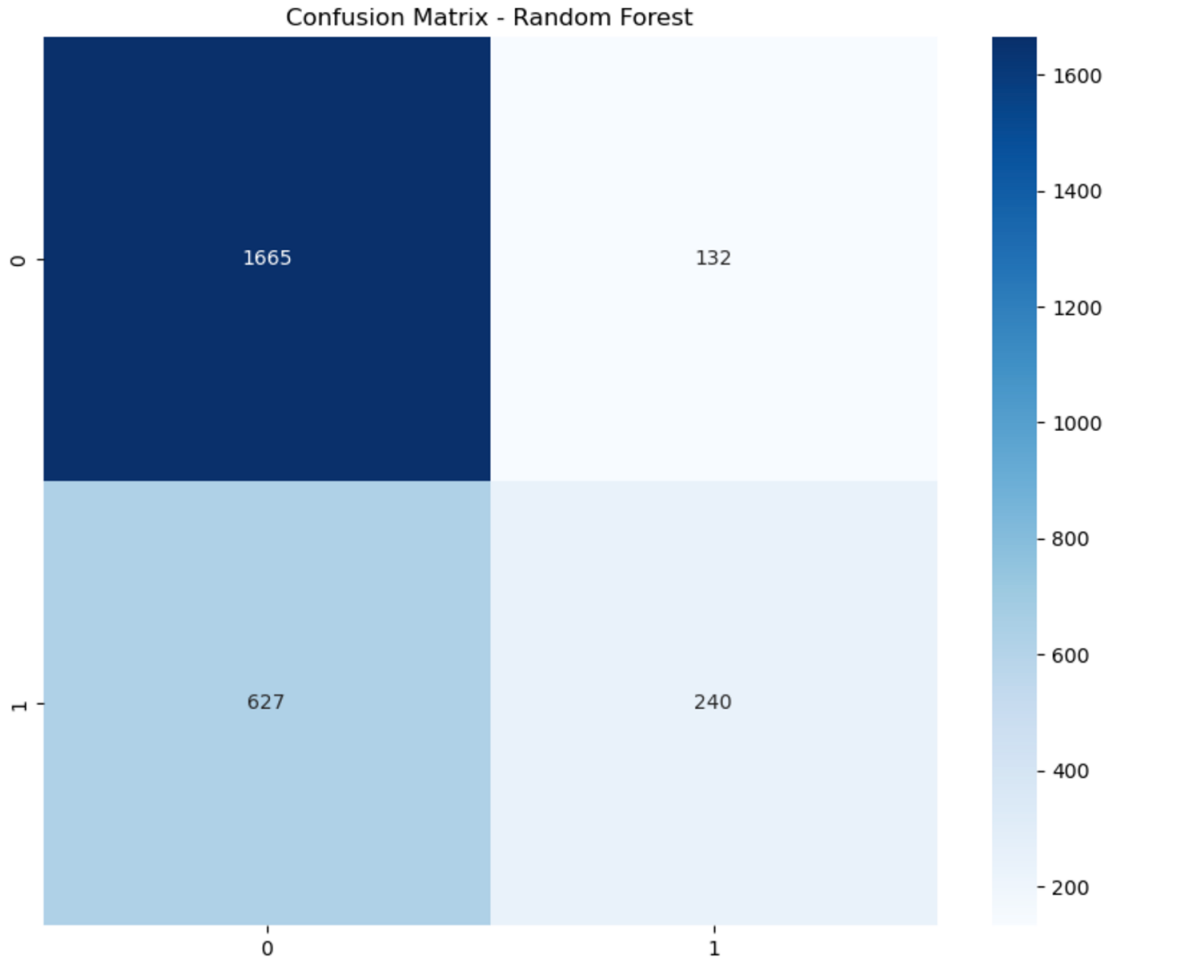

Figure 18: Confusion matrix

Hyperparameter Tuning: Hyperparameter tuning was performed using GridSearchCV to find the best parameters for each model:

- Random Forest Regressor: Key parameters tuned were n_estimators, max_depth, and min_samples_split to optimize model complexity and reduce overfitting.
- Gradient Boosting: Tuned parameters included learning_rate, n_estimators, and max_depth to balance model accuracy and training time.

- SVR: The C, kernel, and epsilon parameters were optimized to improve model accuracy and generalization.

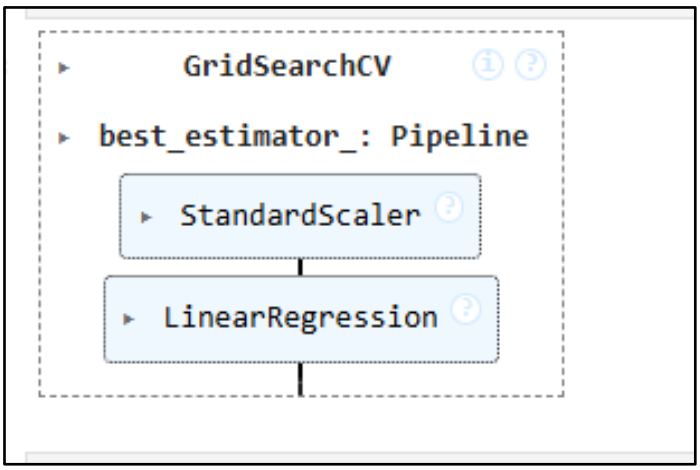

Figure 19: Hyperparameter Tuning with GridSearchCV

Model Evaluation: The models were evaluated using R^2 (coefficient of determination) and RMSE (Root Mean Squared Error) to assess the accuracy of predictions. Cross-validation was used to ensure that models generalized well to unseen data.

Results: The Random Forest Regressor performed the best, with the highest R^2 score, indicating that it could explain a significant portion of the variance in house prices. The Gradient Boosting Regressor also showed strong performance but required more computational time.

Feature Importance: Random Forest's feature importance revealed that the most influential factors in determining house prices were total_sqft, location, and size (number of bedrooms), which aligned with industry expectations.

5.2.2. Principal Component Analysis (PCA)

PCA was used to reduce the dimensionality of the dataset before applying machine learning models. First, we scaled the continuous features using **StandardScaler** to ensure they were on the same scale. Then, **PCA** was applied using the PCA() function from sklearn.decomposition to extract the most significant principal components that explain the maximum variance in the data. After fitting the PCA model, the top components were selected, and the dataset was

transformed into a lower-dimensional space to reduce redundancy and enhance model performance.

5.2.3. Lasso Regression

Lasso Regression was applied to the dataset to perform regularization and feature selection. In the notebook, we used the **Lasso** model from sklearn.linear_model, with the **alpha** hyperparameter controlling the strength of the L1 regularization. A higher value of alpha increased the penalty, leading to more coefficients being shrunk to zero, which helped in eliminating irrelevant features. **GridSearchCV** was used to fine-tune the **alpha** parameter, allowing the model to select the most significant features while minimizing overfitting and improving the model's generalizability.

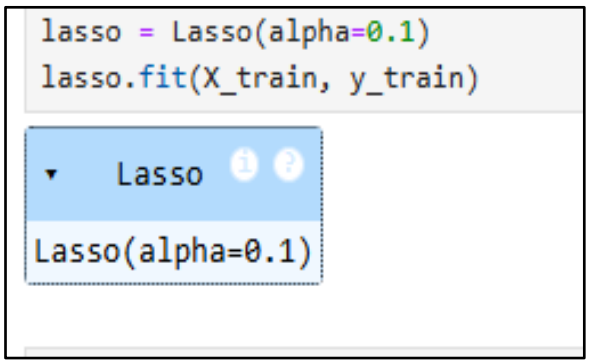

Figure 20: Lasso Regression model

```
[574]: # Initialize and fit Lasso regression model
       lasso_model = Lasso(alpha=0.1).fit(X_train_scaled, y_train)

       # Predict and calculate RMSE
       lasso_rmse = np.sqrt(mean_squared_error(y_test, lasso_model.predict(X_test_scaled)))

       # Display results
       print(f'Lasso (L1) Regularization - RMSE: {lasso_rmse}\nLasso Coefficients: {lasso_model.coef_}')

       Lasso (L1) Regularization - RMSE: 0.4685916223257938
       Lasso Coefficients: [-0. -0.  0.  0.  0.  0. -0. -0. -0. -0. -0. -0. -0.]
```

Figure 21: Lasso Model Performance Evaluation

6. Results, Evaluation, and Discussion

The regression models were evaluated using R^2 (Coefficient of Determination) and RMSE (Root Mean Squared Error):

Linear Regression, Lasso (L1), and Ridge (L2) models performed poorly, with very low R^2 values (close to 0 or negative), indicating that they failed to capture the underlying patterns in the data.

Support Vector Regression (SVR) performed the worst, with a R^2 of -0.2316, suggesting that it provided worse predictions than simply predicting the mean of the target variable. This indicates poor model fit for the dataset.

Random Forest Regressor showed a moderate performance with R^2 of 0.0518 and RMSE of 0.4562. It was better at capturing some of the non-linear relationships in the data.
Gradient Boosting Regressor performed the best among all models, with R^2 of 0.1493 and RMSE of 0.4322. Although still not ideal, it showed the best predictive ability compared to the other models.

Evaluation:

The models were evaluated on the test set, and R^2 was used to measure the proportion of variance explained by the model, while RMSE assessed the average magnitude of prediction errors. The Random Forest and Gradient Boosting models were the best performers, but all models had relatively low R^2 values, suggesting room for improvement (Jouini & Ben Ammar, 2021).

Discussion:

Despite applying various regression models, the results indicate that none of the models performed at a high level of predictive accuracy. The ensemble models (Random Forest and Gradient Boosting) performed better, but still showed modest results. The low performance of models like Linear Regression and SVR suggests that the relationships between features and target values are complex, and simple models may not suffice.

To improve performance, future work could focus on:

Feature Engineering: Creating new features or transforming existing ones to better capture the underlying relationships.

Hyperparameter Tuning: Further optimization of model hyperparameters through techniques like GridSearchCV could improve performance.

Outlier Handling: Addressing outliers could reduce their impact on the models and improve accuracy.

There is significant room for improvement, and more advanced techniques may be needed to achieve better predictive accuracy.

7. Conclusion

This research provides an initial understanding of the Dublin housing market using predictive analytics. While the models developed in this study offer a starting point, improvements can be made by using more complex algorithms and expanding the dataset.

- **Classification Models**: The **Random Forest** model outperformed all others with an accuracy of **0.7181**.
- **Regression Models**: The **Gradient Boosting Regressor** performed the best with an **R^2 of 0.1493** and **RMSE of 0.4322**, though all regression models showed limited predictive power with low **R^2** values (Ramos & Pérez, 2020).

Key Observations:

- For **classification tasks**, Random Forest showed the highest performance.
- For **regression tasks**, Gradient Boosting was the best model, but all models struggled, indicating potential for improvement through better preprocessing, feature engineering, and hyperparameter tuning.

8.References

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I confirm that no AI tools were utilized to generate the content presented in this work. AI tools were solely employed for structuring the report and proofreading purposes. All analyses, and content showcased here were manually created and are a result of my independent efforts and original thought processes.

reference: https://chatgpt.com/share/674e2a5b-c154-8003-b89c-e1400a6c3537

Note:

I have Attached Jupyter notebook file in canvas.