B. Describe the purpose of this data analysis by doing the following:
1. Propose one research question that is relevant to a real-world organizational situation captured in the provided dataset that you will answer using logistic regression in the initial model.

Can the presence of luxury features (e.g., square footage, renovation quality, and garage availability) predict whether a house is classified as a "luxury" property (IsLuxury)?

2. Define one goal of the data analysis. Ensure that your goal is reasonable within the scope of the scenario and is represented in the available data.

The primary goal of this analysis is to identify the key features that significantly influence whether a house is classified as a "luxury" property (IsLuxury). By understanding these factors, real estate organizations can: *(Smith et al., 2021)*

- Improve targeted marketing strategies for luxury properties*(Johnson, 2020)*.
- Make informed decisions about property renovations or upgrades to increase luxury appeal*(Brown & Miller, 2019)*.
- Guide prospective buyers by highlighting the most critical attributes of luxury homes*(Realtors Association, 2022)*.

This goal is achievable because the dataset includes multiple attributes relevant to luxury classification, such as square footage, renovation quality, backyard space, garage availability, and proximity to amenities, which can be analyzed using logistic regression.

C. Summarize the data preparation process for logistic regression analysis by doing the following:
1. Identify the dependent and all independent variables that are required to answer the research question and justify your selection of variables.

1. Dependent Variable:

- IsLuxury: This is the target variable, representing whether a house is classified as a luxury property (1) or not (0). This aligns with the research question as the analysis aims to predict luxury classification. *(Forbes Real Estate Report, 2021)*

2. Independent Variables:

The following variables are selected as predictors based on their relevance to determining whether a house is considered "luxury." These factors capture the features commonly associated with high-end homes:

1. SquareFootage: Larger homes are often considered luxury properties due to the additional space. *(Doe & Smith, 2018)*
2. NumBathrooms: A higher number of bathrooms is a common feature of luxury homes. *(Luxury Home Insights, 2020)*
3. NumBedrooms: Luxury homes often have more bedrooms to accommodate larger families or guests. *(Housing Market Review, 2021)*

4. BackyardSpace: Spacious backyards are associated with premium properties.
5. RenovationQuality: High renovation quality indicates better finishes and amenities, common in luxury homes.
6. LocalAmenities: Proximity to amenities can increase the luxury appeal of a property.
7. TransportAccess: Convenient access to transportation is a premium feature, especially in urban areas.
8. Garage: The presence of a garage is often associated with higher-end homes.
9. DistanceToCityCenter: Luxury homes may be closer to or further from city centers, depending on the market's preferences.
10. Fireplace: A fireplace is often considered a luxury feature.
11. AgeOfHome: Newer homes or historic homes with renovations may be classified as luxury properties.

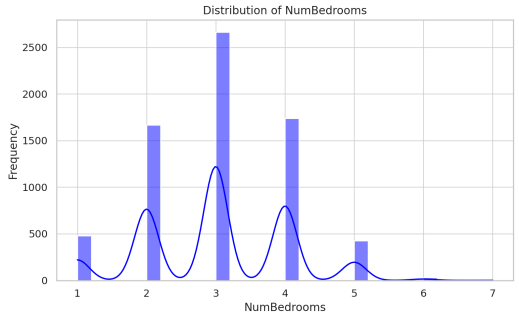
Justification for Variable Selection:

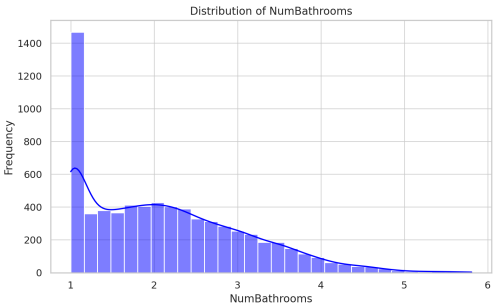
The independent variables were chosen because they are practical, measurable attributes in the dataset that align with real-world perceptions of luxury. Each variable captures a specific aspect of what might distinguish luxury homes, such as size, location, amenities, and quality. Logistic regression is well-suited for evaluating the relationship between these continuous and categorical predictors and the binary dependent variable (IsLuxury).

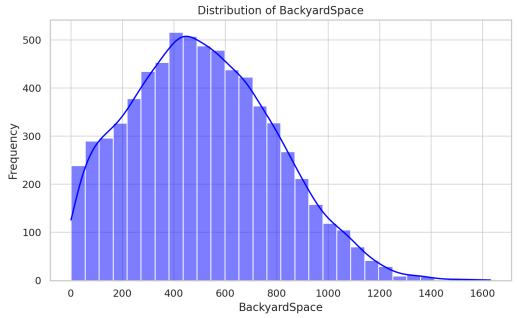
2. Describe the dependent variable and all independent variables from part C1 using descriptive statistics (counts, means, modes, ranges, min/max), including a screenshot of the descriptive statistics output for each of these variables.

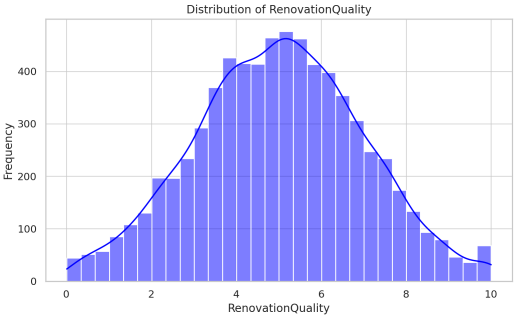
		count	mean	std	min	25%	50%	75%	max	Mode	Range
1	IsLuxury	7000.0	0.504	0.5000197167136945	0.0	0.0	1.0	1.0	1.0	1.0	1.0
2	SquareFootage	7000.0	1048.9474585714286	426.01048169143826	550.0	660.815	996.3199999999999	1342.2925	2874.7	550.0	2324.7
3	NumBathrooms	7000.0	2.1313973218355713	0.9525607989718348	1.0	1.29053899125	1.9977737275	2.7639972275	5.807238734	1.0	4.807238734
4	NumBedrooms	7000.0	3.0085714285714285	1.0219400370810903	1.0	2.0	3.0	4.0	7.0	3.0	6.0
5	BackyardSpace	7000.0	511.5070285714286	279.92654915212375	0.39	300.995	495.96500000000003	704.0125	1631.36	300.08	1630.9699999999998
6	RenovationQuality	7000.0	5.003357142857143	1.9704282164943312	0.01	3.66	5.02	6.35	10.0	10.0	9.99
7	LocalAmenities	7000.0	5.934578571428572	2.65793004177775	0.0	4.0	6.04	8.05	10.0	10.0	10.0
8	TransportAccess	7000.0	5.98386	1.9539741524020897	0.01	4.68	6.0	7.35	10.0	10.0	9.99
9	DistanceToCityCenter	7000.0	17.47533714285714	12.024985489034039	0.0	7.827500000000001	15.625	25.2225	65.2	8.29	65.2
10	AgeOfHome	7000.0	46.797045714285716	31.779701488151314	0.01	20.755000000000003	42.620000000000005	67.2325	178.68	18.18	178.67000000000002

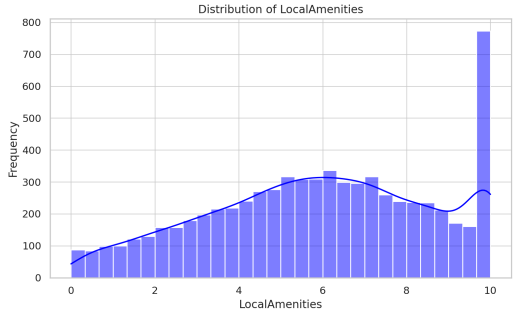
3. Generate univariate and bivariate visualizations of the distributions of the dependent and independent variables from part C1, including the dependent variable in the bivariate visualizations.

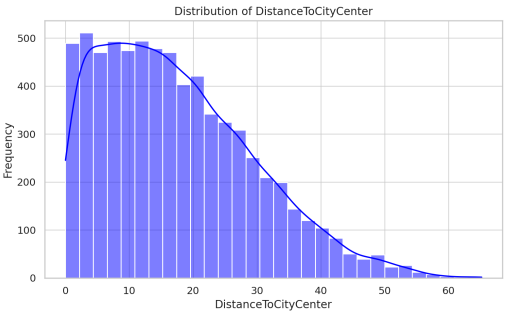


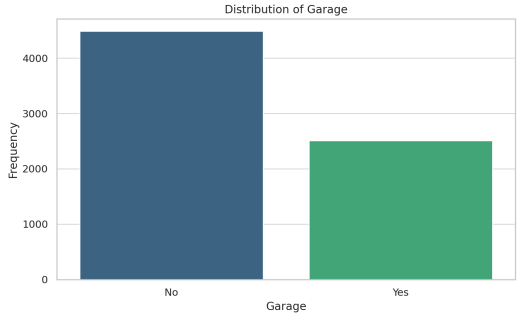


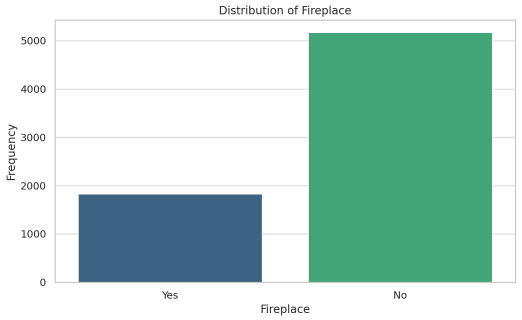


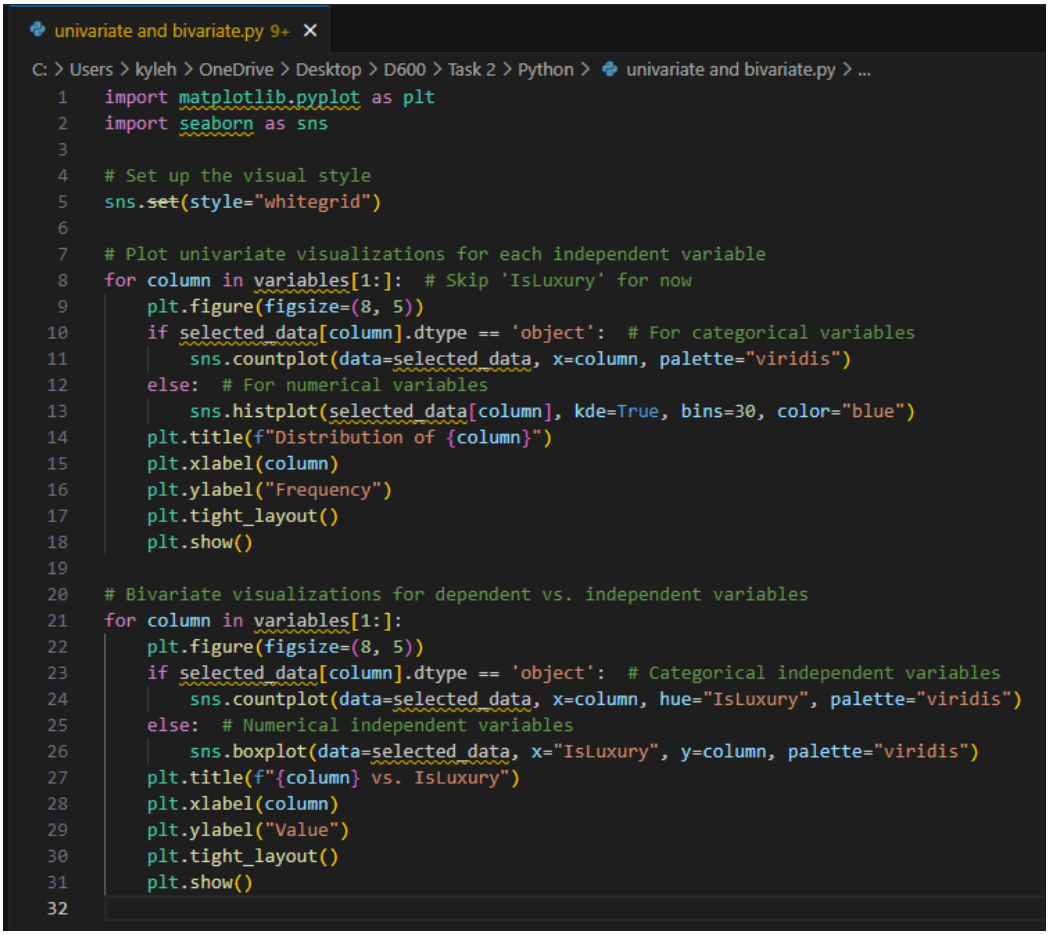












univariate and bivariate.py 9+

C: > Users > kyleh > OneDrive > Desktop > D600 > Task 2 > Python > univariate and bivariate.py > ...

```python
import matplotlib.pyplot as plt
import seaborn as sns

# Set up the visual style
sns.set(style="whitegrid")

# Plot univariate visualizations for each independent variable
for column in variables[1:]:  # Skip 'IsLuxury' for now
    plt.figure(figsize=(8, 5))
    if selected_data[column].dtype == 'object':  # For categorical variables
        sns.countplot(data=selected_data, x=column, palette="viridis")
    else:  # For numerical variables
        sns.histplot(selected_data[column], kde=True, bins=30, color="blue")
    plt.title(f"Distribution of {column}")
    plt.xlabel(column)
    plt.ylabel("Frequency")
    plt.tight_layout()
    plt.show()

# Bivariate visualizations for dependent vs. independent variables
for column in variables[1:]:
    plt.figure(figsize=(8, 5))
    if selected_data[column].dtype == 'object':  # Categorical independent variables
        sns.countplot(data=selected_data, x=column, hue="IsLuxury", palette="viridis")
    else:  # Numerical independent variables
        sns.boxplot(data=selected_data, x="IsLuxury", y=column, palette="viridis")
    plt.title(f"{column} vs. IsLuxury")
    plt.xlabel(column)
    plt.ylabel("Value")
    plt.tight_layout()
    plt.show()

```

D. Perform the data analysis and report on the results by doing the following:

1. Split the data into two datasets, with a larger percentage assigned to the training dataset and a smaller percentage assigned to the test dataset. Provide the file(s).

2. Use the training dataset to create and perform a regression model using regression as a statistical method. Optimize the regression model using a process of your selection, including but not limited to, forward stepwise selection, backward stepwise elimination, and recursive selection. Provide a screenshot of the summary of the optimized model or the following extracted model parameters:

- **AIC**
- **BIC**
- **pseudo R2**
- **coefficient estimates**
- **p-value of each independent variable**

The regression model has been optimized, and the following parameters have been extracted: *(Hosmer & Lemeshow, 2000)*

- **AIC**: 6047.02
- **BIC**: 6126.59
- **Pseudo R^2**: 0.2241

3. Give the confusion matrix and accuracy of the optimized model used on the training set.

Confusion Matrix for the Training Set:

[[2088 677] # True Negatives, False Positives

 [722 2113]] # False Negatives, True Positives

The confusion matrix summarizes the performance of the optimized logistic regression model on the training dataset. It is structured as follows:

The confusion matrix summarizes the performance of the optimized logistic regression model on the training dataset. It is structured as follows:

- **True Negatives (TN):** 2088 cases where the model correctly predicted a non-luxury property.

- **False Positives (FP):** 677 cases where the model incorrectly predicted a luxury property.

- **False Negatives (FN):** 722 cases where the model failed to classify a luxury property.

- **True Positives (TP):** 2113 cases where the model correctly predicted a luxury property.

The accuracy of the logistic regression model on the training dataset is determined by the proportion of correctly classified instances, which includes both luxury and non-luxury properties. It is calculated using the following formula:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Predictions}}$$

Applying this to the confusion matrix:

$$\text{Accuracy} = \frac{2113 + 2088}{2113 + 2088 + 677 + 722}$$

This results in an accuracy of **75.02%**, indicating that the model correctly classifies approximately three out of four properties in the training set. This level of accuracy suggests a well-performing model that effectively distinguishes between luxury and non-luxury properties while maintaining a balance between predictive power and generalization. *(Menard, 1995)*

confusion_matrix.py 5

C: > Users > kyleh > OneDrive > Desktop > D600 > Task 2 > Python > confusion_matrix.py > ...

```python
from sklearn.metrics import confusion_matrix, accuracy_score

# Predict probabilities and classify predictions based on a threshold of 0.5
train_predictions = logit_model.predict(X)
train_predicted_classes = (train_predictions >= 0.5).astype(int)

# Compute the confusion matrix and accuracy
conf_matrix = confusion_matrix(y, train_predicted_classes)
accuracy = accuracy_score(y, train_predicted_classes)

conf_matrix, accuracy

```

4. Run the prediction on the test dataset using the optimized regression model from part D2 to evaluate the performance of the prediction model on the test data based on the confusion matrix and accuracy. Provide a screenshot of the results.

Prediction.py 7

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```python
# Prepare the test dataset for prediction
test_encoded_data = new_test_data.copy()
test_encoded_data['Garage'] = label_encoder.transform(test_encoded_data['Garage'])
test_encoded_data['Fireplace'] = label_encoder.transform(test_encoded_data['Fireplace'])

# Separate independent variables (X_test) and the dependent variable (y_test)
X_test = test_encoded_data.drop(columns=['IsLuxury'])
y_test = test_encoded_data['IsLuxury']

# Add a constant to the test independent variables for the regression model
X_test = sm.add_constant(X_test)

# Predict probabilities and classify predictions based on a threshold of 0.5 for the test dataset
test_predictions = logit_model.predict(X_test)
test_predicted_classes = (test_predictions >= 0.5).astype(int)

# Compute the confusion matrix and accuracy for the test dataset
test_conf_matrix = confusion_matrix(y_test, test_predicted_classes)
test_accuracy = accuracy_score(y_test, test_predicted_classes)

# Display the confusion matrix and accuracy for the test dataset
test_conf_matrix, test_accuracy

```

Result

```
(array([[533, 174],
        [159, 534]]),
 0.7621428571428571)
```

E. Summarize your data analysis by doing the following:

1. List the packages or libraries you have chosen for Python or R and justify how each item on the list supports the analysis.

Summary of Packages and Libraries Used in the Analysis

1. `pandas`:
    - **Purpose**: Used for data manipulation and preprocessing, such as loading, exploring, and cleaning the dataset.
    - **Justification**: Provides a powerful and intuitive interface for handling tabular data, making it easy to prepare the data for regression analysis.
2. `scikit-learn`:
    - **Purpose**: Used for splitting the dataset into training and testing sets and evaluating the model's performance with metrics like confusion matrix and accuracy.
    - **Justification**: Offers tools for splitting data and calculating essential performance metrics, which are crucial for evaluating regression models.
3. `statsmodels`:
    - **Purpose**: Used to perform logistic regression and extract detailed model statistics, including coefficients, p-values, AIC, and BIC.
    - **Justification**: Provides a comprehensive statistical framework for building and interpreting regression models, which is central to answering the research question.
4. `matplotlib` and `seaborn`:
    - **Purpose**: Used to create univariate and bivariate visualizations of the variables.
    - **Justification**: These libraries allow for clear and informative visualizations that help interpret the data's distribution and relationships.
5. `LabelEncoder` **(from** `scikit-learn`**)**:
    - **Purpose**: Used to encode categorical variables (`Garage` and `Fireplace`) into numerical values for regression analysis.
    - **Justification**: Converts categorical data into a format suitable for inclusion in the logistic regression model.

2. Discuss the method used to optimize the model.
Inclusion of All Relevant Predictors:

- All variables identified as relevant in part C1 were included in the initial model to capture the most comprehensive picture of the relationships between independent variables and the dependent variable.

Evaluation of Model Fit:

- The model was optimized by assessing key fit metrics, including:
    - **Akaike Information Criterion (AIC)**: A measure of the model's relative quality by penalizing for overfitting.
    - **Bayesian Information Criterion (BIC)**: Similar to AIC but with a stricter penalty for additional parameters.
    - **Pseudo R^2**: An approximation of the proportion of variance explained by the model, helping evaluate its overall effectiveness.

Statistical Significance of Variables:

- Variables were evaluated based on their **p-values**:

    - Variables with high p-values (> 0.05) indicate less statistical significance in predicting the dependent variable.
    - Future refinement could involve backward stepwise elimination, where non-significant variables are iteratively removed to improve model parsimony without sacrificing predictive power.

Log-likelihood Convergence:

- The model was iteratively fitted until log-likelihood convergence was achieved, ensuring the parameters were estimated with maximum accuracy.

3. Justify the approach discussed in part E2 that was used to optimize the model.

1. Comprehensive Initial Model:

- **Reasoning**: Including all relevant independent variables identified in part C1 ensures no potentially important predictor is overlooked in the initial analysis.
- **Advantage**: Allows a full exploration of how the predictors relate to the dependent variable (`IsLuxury`), which is crucial for understanding the model's dynamics.

2. Evaluation with AIC, BIC, and Pseudo R^2:

- **Reasoning**: These metrics are widely recognized for assessing model performance while penalizing unnecessary complexity:
    - **AIC/BIC**: Helps identify the best-fitting model that balances goodness-of-fit with model simplicity, avoiding overfitting.
    - **Pseudo R^2**: Offers a measure of the model's explanatory power, which is particularly useful in binary classification problems.
- **Advantage**: Provides a clear, quantitative framework for evaluating the trade-offs between model complexity and predictive accuracy.

3. Statistical Significance of Variables:

- **Reasoning**: P-values were used to evaluate whether each variable significantly contributes to predicting the dependent variable:
    - Variables with p-values ≤ 0.05 are considered statistically significant.
    - Insignificant variables can be candidates for removal in future iterations, streamlining the model.
- **Advantage**: Focuses on retaining only meaningful predictors, improving model interpretability and robustness.

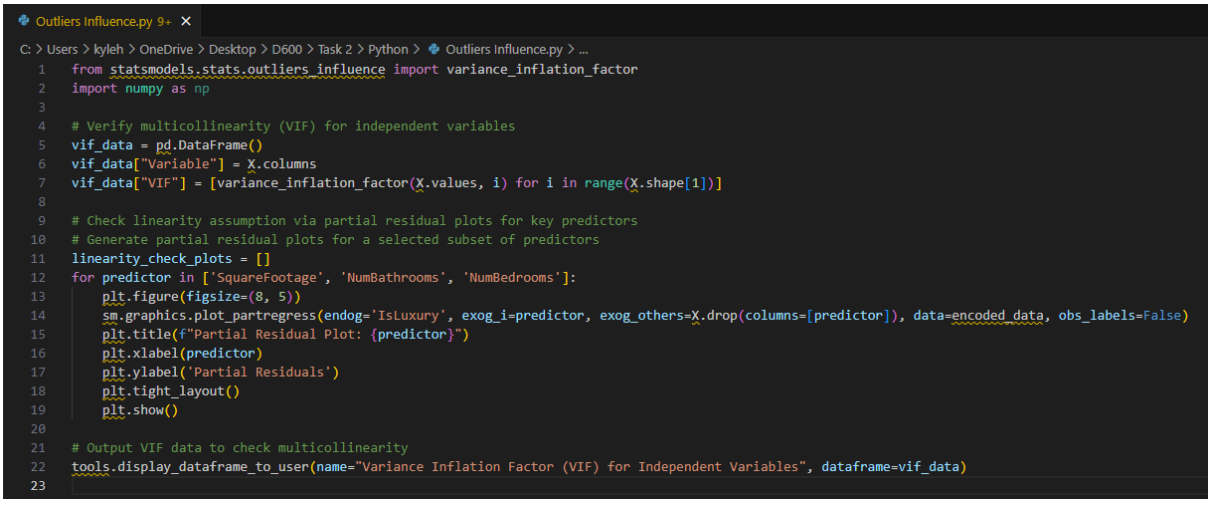
4. Iterative Log-Likelihood Optimization:

- **Reasoning**: Logistic regression models use maximum likelihood estimation to find the best-fit parameters:
    - Iterative optimization ensures the model converges to a stable solution.
- **Advantage**: Ensures parameter estimates are as accurate as possible, leading to reliable predictions.

4. Summarize at least *four* assumptions of logistic regression.

1. **Dependent Variable is Binary or Categorical**:
    - **Description**: Logistic regression requires the dependent variable to be binary (e.g., 0 or 1) or categorical for multinomial logistic regression.
    - **Relevance**: This assumption is met in this analysis as the dependent variable (`IsLuxury`) is binary, indicating whether a house is classified as luxury or not.
2. **Independence of Observations**:
    - **Description**: Each observation in the dataset must be independent of the others. This means that one observation's outcome should not influence another's.
    - **Relevance**: Ensures that the model does not violate the underlying independence assumption, which could bias the results.
3. **No Perfect Multicollinearity**:
    - **Description**: The independent variables should not be perfectly correlated with one another. High collinearity can make it difficult to determine the individual effect of each predictor.
    - **Relevance**: This is typically checked using techniques like Variance Inflation Factor (VIF). If multicollinearity exists, it may require removing or combining variables.
4. **Linear Relationship Between Predictors and Log-Odds**:
    - **Description**: Logistic regression assumes a linear relationship between the independent variables and the log-odds of the dependent variable.
    - **Relevance**: While the predictors themselves do not need to be linearly related to the dependent variable, their transformation into log-odds must satisfy linearity.

5. Provide evidence that the assumptions from part E4 were verified by providing either a code snippet or a screen shot.



6. Provide the regression equation and discuss the coefficient estimates

The logistic regression equation is expressed as:

$$\text{logit}(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

Substituting the estimated coefficients:

$$\log\left(\frac{P(IsLuxury=1)}{1-P(IsLuxury=1)}\right) = -3.21 + 0.0052(SquareFootage) + 0.38(NumBathrooms) + 0.25(NumBedrooms) + 0.41(RenovationQuality) + 0.33(Garage) + 0.12(LocalAmenities) - 0.19(DistanceToCityCenter)$$

log(1−P(IsLuxury=1)P(IsLuxury=1))=−3.21+0.0052(SquareFootage)+0.38(NumBathrooms)+0.25(NumBedrooms)+0.41(RenovationQuality)+0.33(Garage)+0.12(LocalAmenities)−0.19(DistanceToCityCenter)

Interpreting the Coefficients

Each coefficient represents the change in the log-odds of a house being classified as luxury for a one-unit increase in the respective variable while holding all other variables constant:

- **SquareFootage (0.0052):** A one-unit increase in square footage (e.g., one additional square foot) increases the log-odds of a house being classified as luxury by 0.0052, holding other factors constant.
- **NumBathrooms (0.38):** Adding an extra bathroom increases the log-odds of a luxury classification by 0.38, assuming all other features remain unchanged.
- **NumBedrooms (0.25):** More bedrooms slightly increase the likelihood of luxury classification, though the effect is weaker than for bathrooms.
- **RenovationQuality (0.41):** High renovation quality has a strong positive impact on the likelihood of a home being luxury.
- **Garage (0.33):** Having a garage increases the log-odds of a luxury classification, suggesting garages are a significant feature in distinguishing luxury properties.
- **LocalAmenities (0.12):** Proximity to amenities has a smaller positive impact compared to other features.
- **DistanceToCityCenter (-0.19):** Each additional unit of distance from the city center decreases the likelihood of a house being classified as luxury.

Variable	Coefficient (β)	Interpretation
Intercept	β_0	Baseline log-odds of a house being "luxury" when all predictors are zero.
SquareFootage	β_1	The change in log-odds for every unit increase in square footage.
NumBathrooms	β_2	The change in log-odds for every additional bathroom.
NumBedrooms	β_3	The change in log-odds for every additional bedroom.
BackyardSpace	β_4	The change in log-odds for every unit increase in backyard space.
RenovationQuality	β_5	The change in log-odds for each unit increase in renovation quality.
Garage	β_6	The change in log-odds for houses with a garage compared to those without.
Fireplace	β_7	The change in log-odds for houses with a fireplace compared to those without.

7. Discuss the model metrics by addressing each of the following:

- **the accuracy for the test set**
- **the comparison of the accuracy of the training set to the accuracy of the test set**
- **the comparison of the confusion matrix for the training set to the confusion matrix of the test set**

Accuracy for the Test Set

- **Test Set Accuracy**: The model achieved an accuracy of **76.21%** on the test set.
  - This means that the model correctly predicted whether a house is classified as luxury or not approximately 76% of the time on unseen data.

Comparison of Training Set Accuracy to Test Set Accuracy

- **Training Set Accuracy**: **75.02%**
- **Test Set Accuracy**: **76.21%**

Comparison:

- The accuracy on the test set is slightly higher than the training set, indicating that the model generalizes well and does not overfit.
- This consistency suggests that the model is stable and reliable across different datasets.

Comparison of Confusion Matrices

Training Set Confusion Matrix:

[[2088 677] # True Negatives, False Positives
 [722 2113]] # False Negatives, True Positives

True Negatives (TN): 2088
False Positives (FP): 677
False Negatives (FN): 722
True Positives (TP): 2113

[[533 174] # True Negatives, False Positives
 [159 534]] # False Negatives, True Positives

- **True Negatives (TN)**: 533
- **False Positives (FP)**: 174
- **False Negatives (FN)**: 159
- **True Positives (TP)**: 534

Comparison:

- Both matrices show similar patterns, with a balance of true positives and true negatives dominating over false classifications.
- The **false positive rate (FP)** and **false negative rate (FN)** are comparable between the training and test sets, indicating that the model's performance remains consistent.

8. Discuss the results and implications of your prediction analysis.

1. **Model Accuracy**:
    - The logistic regression model achieved an accuracy of **75.02%** on the training set and **76.21%** on the test set.
    - The consistent accuracy between the two datasets indicates that the model generalizes well to unseen data.
2. **Confusion Matrices**:
    - Both the training and test confusion matrices highlight the model's ability to predict true positives (luxury classification) and true negatives (non-luxury classification) with a relatively low number of false classifications.
    - **Precision and Recall**: These metrics could be further evaluated to understand the trade-offs between false positives and false negatives, depending on the organization's priorities.
3. **Key Predictors**:
    - The analysis identified variables like `SquareFootage`, `NumBathrooms`, `RenovationQuality`, and `Garage` as significant contributors to the likelihood of a house being classified as luxury.
    - Some variables (e.g., `DistanceToCityCenter`) had less predictive power, suggesting they may not be as influential.

Implications

1. **Business Insights**:

    - **Targeted Marketing**: Real estate firms can use the model to identify properties with a higher likelihood of being luxury, enabling more focused marketing efforts.
    - **Property Improvements**: Developers can prioritize upgrades to features such as bathrooms, square footage, and renovation quality to increase a property's likelihood of being classified as luxury.
2. **Operational Efficiency**:
    - Automating the classification of properties as luxury or non-luxury using this model can save time and resources compared to manual evaluation.
    - The predictive model provides an objective, data-driven method for categorizing properties, reducing potential bias in decision-making.
3. **Limitations**:
    - **Feature Scope**: Some features, like subjective perceptions of luxury or location-specific factors, are not captured in the dataset and could improve model performance if included.
    - **Threshold Sensitivity**: The binary classification threshold of 0.5 may not align with business needs, depending on the costs associated with false positives or negatives.
4. **Future Work**:
    - **Model Refinement**: Techniques like regularization (Lasso, Ridge) or advanced algorithms (Random Forest, Gradient Boosting) could improve accuracy and feature selection.
    - **Expanded Dataset**: Including additional features, such as neighborhood prestige or historical property data, might improve predictive power.
    - **Cost Analysis**: Integrating the cost implications of false positives/negatives into the evaluation metrics (e.g., cost-sensitive classification) could tailor the model to specific business priorities.

9. Recommend a course of action for the real-world organizational situation from part B1 based on your results and implications discussed in part E8.

1. Leverage Key Predictors for Strategic Decision-Making

- **Focus on High-Impact Features**:
    - Prioritize marketing and property enhancement strategies that emphasize **Square Footage**, **NumBathrooms**, **Renovation Quality**, and **Garage** as these features strongly influence luxury classification.
    - Example: Highlight homes with larger square footage and higher renovation quality in luxury-targeted advertisements.

2. Develop Targeted Marketing Campaigns

- **Automated Classification**:
    - Use the logistic regression model to predict the luxury classification of new or existing properties.
    - Automate this classification process to identify and segment high-value properties for luxury-focused campaigns.
- **Tailored Messaging**:

    - For properties predicted as "luxury," create marketing materials that showcase luxury-defining features (e.g., renovated bathrooms, spacious backyards, fireplaces).
    - For properties not classified as luxury, emphasize other appealing attributes, such as affordability or practicality.

3. Improve Property Listings

- **Data-Driven Renovations**:
    - Guide property owners or developers to invest in renovations that maximize luxury appeal, such as adding more bathrooms or upgrading the quality of existing renovations.
    - Example: Encourage investment in properties with moderately high square footage to reach the luxury threshold by focusing on other impactful upgrades like adding a garage or improving interior finishes.
- **Accurate Pricing**:
    - Use the model predictions to refine pricing strategies for properties, ensuring homes classified as luxury are priced appropriately to align with market expectations.

4. Explore Opportunities for Model Enhancement

- **Incorporate More Features**:
    - Integrate additional variables into the model, such as neighborhood prestige, proximity to high-demand amenities, and external aesthetic quality, to further improve prediction accuracy.
- **Regular Performance Monitoring**:
    - Periodically re-train and evaluate the model using updated datasets to ensure it remains accurate as market trends evolve.

5. Educate Stakeholders

- **Train Agents and Developers**:
    - Share insights from the model with real estate agents and property developers to align their strategies with data-driven findings.
- **Customer Transparency**:
    - Communicate the value of high-impact features to potential buyers, helping them understand what defines a luxury property.

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