Homestays Data analysis and price prediction

Step 1: Please find the dataset required for the following tasks at this link: [Homestays_Data.zip](https://cerinaco-my.sharepoint.com/:u:/g/personal/omkar_cerina_co/ETARwr3mqEtAoZFmWmYKnOIBtPhRtBczH9svOQ1gIGqxUg?e=3NwzrD) [https://cerinaco-my.sharepoint.com/:u:/g/personal/omkar_cerina_co/ETARwr3mqEtAoZFmWmYKnOIBtPhRtBczH9svOQ1gIGqxUg?e=3NwzrD]

Download the "Homestays_Data.zip" file and find the "Homestays_Data.csv" which contains the dataset.

Note: The entire dataset has multiple columns and has more than 70,000 rows. Processing the following tasks on a Jupyter notebook on your local environment (your personal computer) might be time consuming due to limited processing power. We encourage you to use cloud-based tools such as Google Colab or AWS Sagemaker or anything that you prefer.

Step 2: Complete the following tasks.

Objective: Build a robust predictive model to estimate the `log_price` of homestay listings based on comprehensive analysis of their characteristics, amenities, and host information.

First make sure that the entire dataset is clean and ready to be used.

1. Feature Engineering:

Task: Enhance the dataset by creating actionable and insightful features. Calculate `Host_Tenure` by determining the number of years from `host_since` to the current date, providing a measure of host experience. Generate `Amenities_Count` by counting the items listed in the `amenities` array to quantify property offerings. Determine `Days_Since_Last_Review` by calculating the days between `last_review` and today to assess listing activity and relevance.

2. Exploratory Data Analysis (EDA):

Task: Conduct a deep dive into the dataset to uncover underlying patterns and relationships. Analyze how pricing (`log_price`) correlates with both categorical (such as `room_type` and `property_type`) and numerical features (like `accommodates` and `number_of_reviews`). Utilize statistical tools and visualizations such as correlation matrices, histograms for distribution analysis, and scatter plots to explore relationships between variables.

3. Geospatial Analysis:

Task: Investigate the geographical data to understand regional pricing trends. Plot listings on a map using `latitude` and `longitude` data to visually assess price distribution. Examine if certain neighbourhoods or proximity to city centres influence pricing, providing a spatial perspective to the pricing strategy.

4. Sentiment Analysis on Textual Data:

Task: Apply advanced natural language processing techniques to the `description` texts to extract sentiment scores. Use sentiment analysis tools to determine whether positive or negative descriptions influence listing prices, incorporating these findings into the predictive model being trained as a feature.

5. Amenities Analysis:

Task: Thoroughly parse and analyse the `amenities` provided in the listings. Identify which amenities are most associated with higher or lower prices by applying statistical tests to determine correlations, thereby informing both pricing strategy and model inputs.

6. Categorical Data Encoding:

Task: Convert categorical data into a format suitable for machine learning analysis. Apply one-hot encoding to variables like `room_type`, `city`, and `property_type`, ensuring that the model can interpret these as distinct features without any ordinal implication.

7. Model Development and Training:

Task: Design and train predictive models to estimate `log_price`. Begin with a simple linear regression to establish a baseline, then explore more complex models such as RandomForest and GradientBoosting to better capture non-linear relationships and interactions between features. Document (briefly within Jupyter notebook itself) the model-building process, specifying the choice of algorithms and rationale.

8. Model Optimization and Validation:

Task: Systematically optimize the models to achieve the best performance. Employ techniques like grid search to experiment with different hyperparameters settings. Validate model choices through techniques like k-fold cross-validation, ensuring the model generalizes well to unseen data.

9. Feature Importance and Model Insights:

Task: Analyze the trained models to identify which features most significantly impact `log_price`. Utilize model-specific methods like feature importance scores for tree-based models and SHAP values for an in-depth understanding of feature contributions.

10. Predictive Performance Assessment:

Task: Critically evaluate the performance of the final model on a reserved test set. Use metrics such as Root Mean Squared Error (RMSE) and R-squared to assess accuracy and goodness of fit. Provide a detailed analysis of the residuals to check for any patterns that might suggest model biases or misfit.

Final Deliverables:

Comprehensive Jupyter notebook (PDF File/ PDF Export): Contains all codes, analytical steps, visualizations, and detailed commentary explaining each action and decision.