COE 379L - Project 4
James Grant Robinett (jgr2722) - Hung-Yi Tseng (ht7796)

Introduction

The ability to accurately estimate rental prices for properties listed on platforms like Airbnb is valuable for both hosts and guests. Hosts can optimize their pricing strategy to maximize revenue, while guests can ensure they are getting fair value for their booking. However, pricing a rental property is a complex task that depends on various factors beyond just the property's location and size. Visual elements like the decor, amenities, and overall aesthetic can significantly influence perceived value and demand. Additionally, the textual descriptions provided in the listing play a crucial role in attracting potential guests and shaping expectations. To tackle this multifaceted problem, we propose the development of a multimodal machine learning model that leverages both image and text data from Airbnb listings to predict rental prices more accurately. By combining convolutional neural networks for image analysis with natural language processing techniques for text, our model aims to capture the nuanced interplay between visual and descriptive elements that shape a property's perceived value and pricing. This report details our methodology, experimental results, and insights gained from this innovative multimodal approach to the rental price prediction challenge.

Data Source and Preprocessing

Our data source comes from MongoDB, provided by Hugging Face, and includes scraped data from AirBnb listings. This dataset includes important listing data, such as listing id, description of listing, price per night and other location descriptions. To download this data, we used a MongoDB connection key to download the .json file locally, and sent requests to download all images and stored them within the ‘imagesData’ directory. For the sake of price prediction, we used only the most important columns, which turned out to be: [‘description’, 'accommodates', 'bedrooms', 'beds', 'bathrooms', 'review_scores_rating', 'review_scores_value',’property_type’,’price’]. We were then able to preprocess the data accordingly.

For preprocessing, we cleaned the data by removing listings with incomplete data (NaN or zero) and filtering out images that failed to download. Additionally, to have a good price prediction, we limited the price per night to be $500 or below, giving our model better predictive power. All numerical data were normalized, and categorical data were one-hot encoded. Text data from descriptions was vectorized using the tfidfVectorizer, and images were standardized to a fixed size and format. The final dataframe looked like so:
Original DataFrame size: (5555, 43)
Filtered DataFrame size: (4610, 43)
Number of remaining folders in 'imagesData': 4611

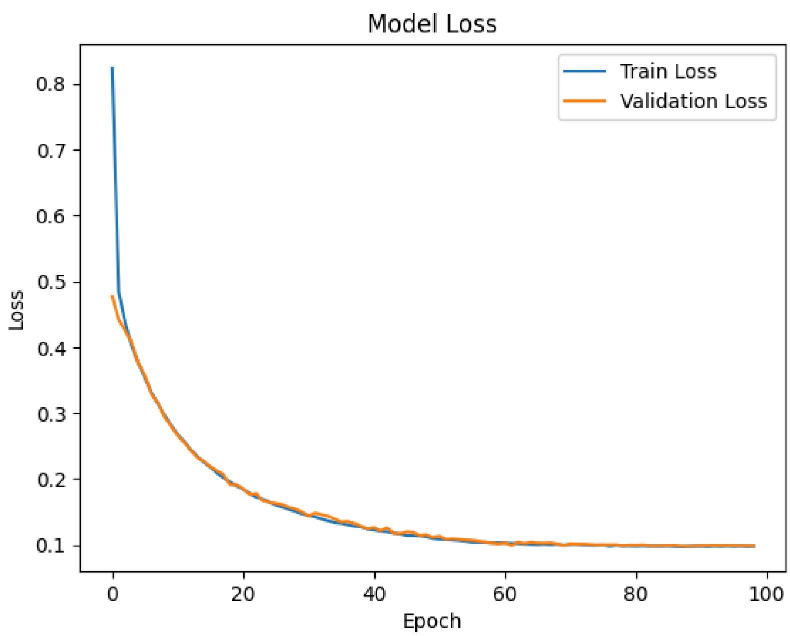
Methodology

To create this neural network, we used python and tensorflow, as well as Scikit learn for easy train test split. In addition, we used pandas to convert the json data to a dataframe, and used this as our main training dataframe.

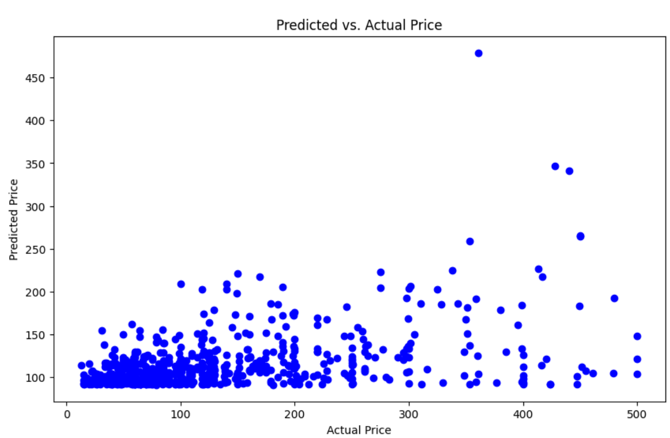
For our model, we used a multi-model chaining method, that included:

- A Dense network for structured numerical and categorical data.
- A Convolutional Neural Network for image data processing.
- An integration layer that merges features from both networks for final prediction.

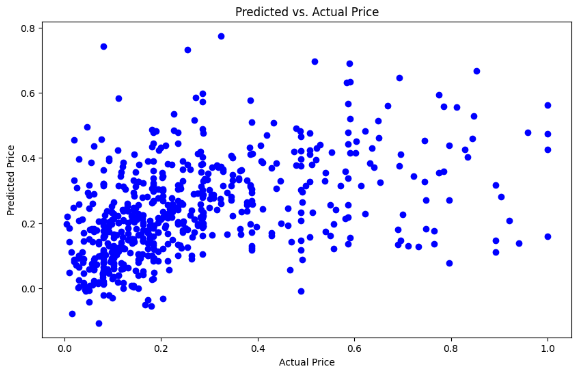
Model Evaluation



Training on just an ANN based on columns, no image evaluation used.



Previous Model with no images used



With images used, model accuracy increases.

Final Metrics:
Mean Squared Error: 0.04
Mean Absolute Error: 0.14
R^2 Score: 0.12

Conclusions and Future Work
In conclusion, we developed a model that leverages both image and text data from Airbnb listings to predict rental prices. By combining convolutional neural networks for image analysis and natural language processing techniques for text, our model aimed to capture the nuanced interplay between visual and descriptive elements that shape a property's perceived value and pricing.

While our model demonstrated promising results in predicting rental prices, we acknowledged that the accuracy deteriorated for higher pricing ranges. To address this issue, we experimented with adding or dropping key variables in the model, which provided marginal improvements. However, further enhancements are necessary to achieve the desired level of accuracy across all price ranges.

For future work, we plan to explore alternative model architectures and different layer configurations to improve the model's performance, particularly in the higher pricing ranges. Additionally, we are interested in investigating a classification-based approach, where we segment the pricing into discrete categories rather than treating it as a regression problem. By separating the pricing into categories, we may be able to leverage the strengths of classification models and potentially improve the overall accuracy of our predictions.
Furthermore, we recognize the importance of continually updating and fine-tuning our model as new data becomes available. The rental market is dynamic, and factors influencing pricing may evolve over time. By incorporating mechanisms for continuous learning and adaptation, our model can stay relevant and accurate, reflecting the ever-changing trends and preferences in the rental market.
Overall, while our current model represents a promising step towards accurately predicting Airbnb rental prices, there is still room for improvement. We remain committed to exploring new

techniques, architectures, and approaches to enhance the model's performance and deliver increasingly reliable and valuable insights to hosts and guests alike.

References

- https://huggingface.co/datasets/MongoDB/airbnb_embeddings