

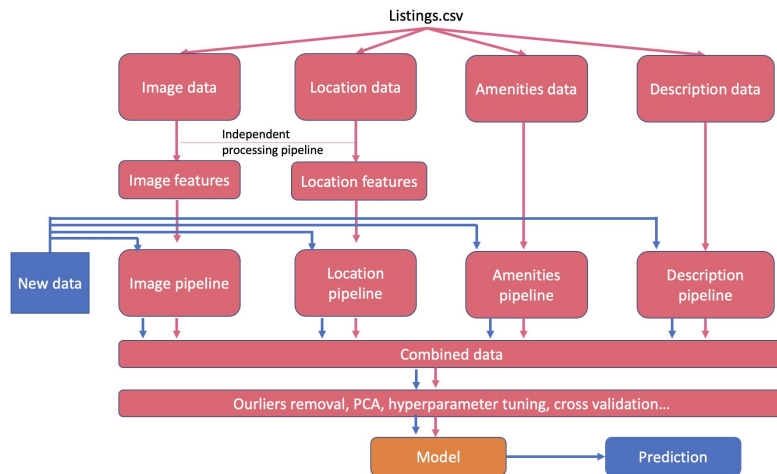
# Price Recommender Web Application for New Properties on Airbnb

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## Project Overview

How should I charge my Airbnb listing? Owners typically consider several factors including prices around the neighborhood, the configuration of the property, and the cost of owning and listing the unit. While some systems have provided solutions to a reasonable pricing recommendation, they are either less comprehensive in features input or did not mention the “competitiveness” at that price. This project aims to create a web application to allow users to figure out the optimal price point that is competitive with the market while not undervaluing the property for new property owners looking to list on Airbnb. Besides that, we aim to provide users with further helpful information about why they should charge at this range and what additional features they can include improving their pricing power.

## Workflow



## Data Sources

- Airbnb Listings data in Los Angeles (<http://insideairbnb.com/get-the-data/>)
- “Amenity Universe” dataset
- COCO128 dataset (<https://github.com/ultralytics/yolov5>)
- RealEstate dataset (<https://www.redfin.com/news/data-center/>)

## Key methodology

### Image pipeline

- CNN: extracting price related image features
- Aesthetic features: brightness, contrast, etc.
- Object detection: common daily object identified
- Rule of third: structural values in photography

### Amenity pipeline

- Binary encoding of Airbnb standard amenities
- Bathrooms, bedrooms, property types & counts encoding.

### Location pipeline

- Summary of neighborhood average prices with similar conditions
- Real estate pricing by zipcode
- Count & distance of facilities in the neighborhood
- Distance to the famous tourist attractions

### Description pipeline

- Named entities recognition from host descriptions
- Whole Sentence embedding using transformers

### Modeling

- Five quantile regression models with LightGBM
- Outlier removal and dimensionality reduction
- Fine-tuning using GridSearchCV

### Interpretation

- Feature importance interpretation with SHAP package beewarm plot
- prediction result explanation using waterfall plot
- Learning curve, sensitivity analysis and failure analysis with matplotlib & seaborn presentation

### Application

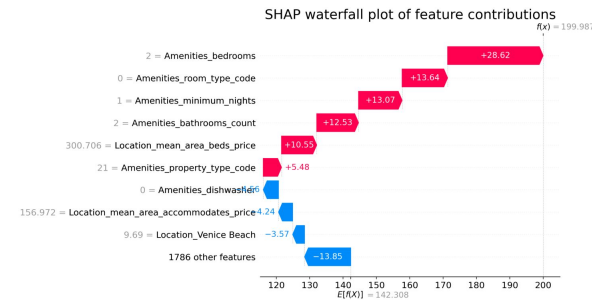
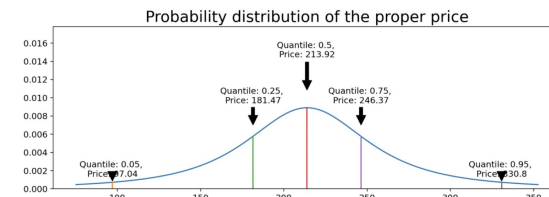
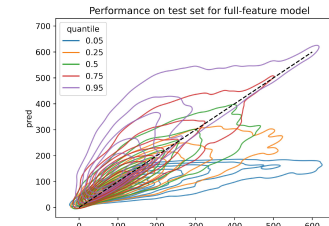
- Web application: Streamlit

## Results

Overall good model fitting with **R2 around 0.64** for the 0.5 quantile model. Web application generate prediction report within 10 seconds.

Suggested price: \$ 213

Quantiles	Price (\$)
0	0.05 97.0399
1	0.25 181.4735
2	0.5 213.9194
3	0.75 246.3652
4	0.95 330.7988



### Project Resources:

Web application: [http://18.205.39.151:8502/my\\_app](http://18.205.39.151:8502/my_app)

GitHub: [https://github.com/foye501/Capstone\\_GMT89](https://github.com/foye501/Capstone_GMT89)

Report: <https://docs.google.com/document/d/161fEv0t4Ops9SG5NPMAXZgnTigGPNvgPrR8gCyeM7x0/>

Video explanation: <https://www.youtube.com/playlist?list=PL-lh8lEqwhvFGjCMphHh4x3e4OoW4smu>

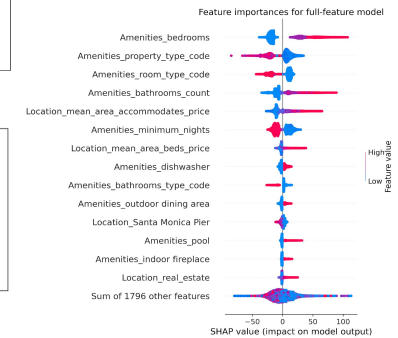
Medium

blog: [https://medium.com/@chenyk\\_80392/beyond-a-single-price-pricing-range-improvement-suggestions-for-new-airbnb-hosts-a33ffa718fbb](https://medium.com/@chenyk_80392/beyond-a-single-price-pricing-range-improvement-suggestions-for-new-airbnb-hosts-a33ffa718fbb)



## Feature importances

As “hardware”, House property, amenities and location determined the most percentages of price variance, with description and image as decoration effects. Other unexplained price variance could be due to complexity, dynamism and subjectivity in Airbnb pricing.



On the web application side, our product successfully provide insightful information on instructing the hosts to price their listing properly, with further model interpretation to facilitate the understanding of pricing mechanism. This is how we “go beyond a single price”.