Airbnb Price Prediction in London

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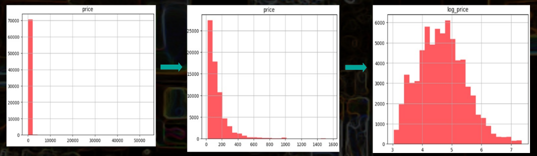
INTRODUCTION

Airbnb offers a "smart pricing" tool but the current smart pricing tool has received mixed reviews from hosts, who claim it doesn't accurately reflect their property's true market value, lacking specificity in its calculations. In response, Our team has created a transparent model that uses a combination of machine learning, convolutional neural network, and deep learning methods, including a score for listing images, amenities, proximity to public transportation, crime rates, and other factors. The goal is to provide more accurate pricing recommendations and help hosts attract more guests.

EXPLORATORY DATA ANALYSIS



A log transformation was applied to the prices to produce a Gaussian distribution, which reduces the effect of outliers on model performance when using log(price) as the target variable in price prediction models.

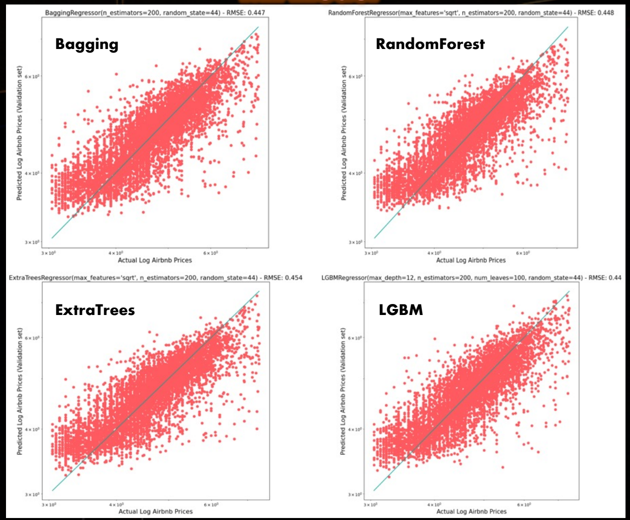
DATASET

- Airbnb Listings dataset : property id, description, amenities, listing picture url, location, and other features

- AVA dataset : contains over 250,000 images along with a rich variety of meta-data including a large number of aesthetic scores for each image, semantic labels for over 60 categories

METHODS

ML model



Scatterplot results of predicted vs actual for each tuned model

Four models, including BaggingRegressor, RandomForestRegressor, ExtraTreesRegressor, and LGBMRegressor, were selected for hyperparameter tuning to improve their performance. Overall, RMSE and R-square metrics were used to evaluate the regression techniques and ensemble methods for Airbnb price prediction.

CNN + ML model

Predicted images scores for each model and a rank ()

Our team developed an aesthetic scoring model to rate visually appealing Airbnb listing images using two ImageNet-based CNN models, MobileNet and InceptionV3. The InceptionV3 model was found to be aligned with human judgment, while the MobileNet model trained only on "interior" data diverged from human judgment. However, the MobileNet model trained on the entire AVA dataset was closer to human rankings. The scores from both models were averaged, normalized, and used as a new feature for an ML model, which was re-evaluated using various metrics.

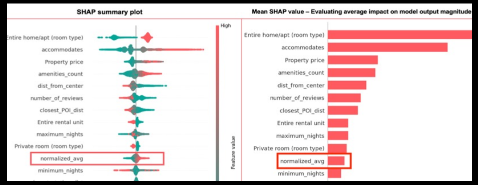
CNN+BERT + ML model

Our team developed a deep learning model using features from a machine learning model and image scores from a CNN, plus word embeddings as a new feature. They were created using GloVe and BERT to represent amenities. The feed-forward network model consisted of an input layer, an output layer, and multiple hidden layers. The model was evaluated using mean squared error and R-squared, with hyperparameters optimized through a manual search. The model was trained on the Train set and evaluated on the independent Test set after hyperparameter tuning.

RESULT

Model Names	RMSE	RMSE (Image score included)	R-Square	R-square (Image score included)
LinearRegression (Base Model)	0.234618	0.219991	0.624174	0.638390
BaggingRegressor	0.464274	0.429387	0.646498	0.702149
RandomForestRegressor	0.442907	0.429209	0.678286	0.702396
ExtraTreesRegressor	0.449795	0.436603	0.668202	0.692053
LGMBRegressor	0.44458	0.419599	0.675852	0.715573
Deep Learning (with GloVe)	0.479887	0.465522	0.672094	0.691432
Deep Learning (with BERT)	0.473098	0.454505	0.681306	0.705863

The LGBMRegressor model with image scores performed significantly better than any other model, with a lower RMSE and an improved R-squared value. The study suggests that incorporating image scores can improve the accuracy of Airbnb price-prediction models.



The SHAP showed that the impact of the "image score" feature on model output was found to be substantially stronger than other important features.

CONCLUSION

Our team developed an effective and transparent Airbnb pricing model incorporating listing images, which explained 71% of the variation in price. CNN models were used to replicate human aesthetic judgment to assist hosts in setting the right price. Factors affecting the price included "entire home" feature, maximum occupancy limit, and aesthetic appeal of the listing. Suggestions for improvement include feature selection, increasing training data, using a more powerful model, and employing ensemble methods for the future iterations

Neon edition