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## Team Information

Team name: Team Team

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## Motivation

There are many considerations that must be made when finding temporary housing, either for vacations or business trips. Airbnb is a popular website that allows individuals or businesses to list potential places for users to choose. These users can choose where they wish to stay based on location, accommodations, how many beds they need, and price. We sought to create a model that predicts the price of an Airbnb listing based on various variables.

Airbnb data has been scraped by a team of contributors and gathered on a website [here](#). Their motivation is to show transparency in how spaces are being rented to tourists in their communities.

When coming across this dataset, we found several missing values in the price of different Airbnb listings. Of the 36111 listings we found 14783 missing prices. We believe that we can use the latitude, longitude, beds, bathrooms, and neighborhood location among other variables to impute the missing pricing data for these listings.

# Data Documentation

## Data Cleaning

### Dataset Description

#### Price

The `price` variable describes the daily price for a listing in its local currency. Since all listings in this analysis are from New York City, all prices are in \$USD.

#### Summary Statistics

Table 1: Summary Statistics of `Price`

price
Min. : 10.0
1st Qu.: 88.0
Median : 152.0
Mean : 234.5
3rd Qu.: 272.0
Max. : 10000.0
NA's : 14783

The `price` variable has a mean of \$234.53 and a median of \$152.

Due to cleaning, the max amount of price of limited to \$10000 a night. The smallest price in the dataset is \$10 a night.

There are 14783 missing values in `price`. Which means missing values make up around 41% of the observations in the dataset.

## Histogram and Price Ranges

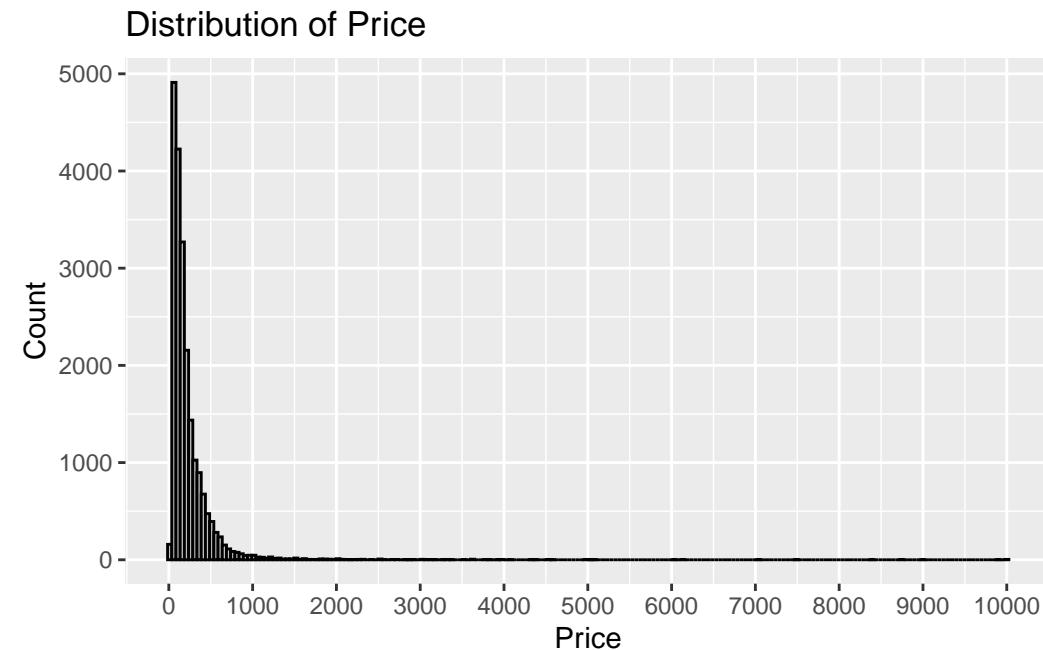


Table 2: Number of Listings in Each Price Range

price_range	n
0-1000	20755
>1000	355
N/A	14783

A histogram of `price` shows that the distribution is very right-skewed, as most of the dataset has listings in the \$0-\$1000 price range. In fact only, 1% of the dataset (including NA values) has AirBnB listings over the \$1000 price range.

## Beds

The `beds` variable describes the amount of beds an apartment/house/etc... will have for guests. This differs from `bedrooms` as there could be more than one bed in a bedroom.

## Summary Statistics

Table 3: Summary Statistics of Beds

beds
Min. : 0.000
1st Qu.: 1.000
Median : 1.000
Mean : 1.634
3rd Qu.: 2.000
Max. : 40.000
NA's : 14468

## Model Construction

The next step in the analysis will be to build a model with price as the response variable. The predictors will be values that are suspected to be indicators of price such as beds, lat and long, accommodates, bathrooms, etc. This model will then be run and coefficients values and significance will be documented. This will all be done without imputation.

### Matrix Plot to Assess Variable Correlation

### Model Building

The airbnb model that will be used for this study will be attempting to predict the price variable. The predictors are beds, bathrooms, latitude, longitude, accommodates, and bedrooms. The final model was developed from a variety of model building techniques, along with understanding our predictors of interest. This model will create a basis for comparing imputation methods with different coordinate points.

$$\log(\text{Price}) = \beta_0 + \beta_1 \cdot \text{bedrooms} + \beta_2 \cdot \text{beds} + \beta_3 \cdot \text{latitude} + \beta_4 \cdot \text{longitude} + \beta_5 \cdot \text{latitude} * \text{longitude} + \beta_6 \cdot \text{accomodates} + \beta_7 \cdot \text{beds}$$

### Coefficient Estimates for Airbnb Model

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	1.300198e+05	3167.1630953	41.052448	0
bedrooms	-8.017570e-02	0.0057295	-13.993592	0
beds	4.220580e-02	0.0054763	7.706955	0
latitude	-3.202096e+03	77.8232893	-41.145733	0

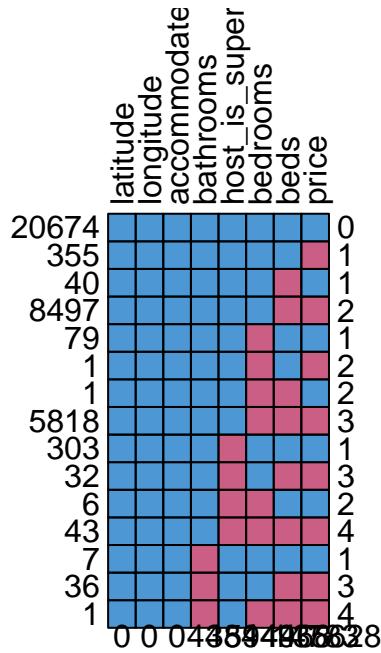
	Estimate	Std. Error	t value	Pr(> t )
longitude	1.759253e+03	42.8374615	41.068097	0
accommodates	1.993121e-01	0.0031530	63.214307	0
bathrooms	5.594000e-02	0.0090677	6.169126	0
latitude:longitude	-4.332788e+01	1.0525988	-41.162769	0

The coefficient estimate table above shows that all variables are significant predictors of price. This will then allow us to test the differences in imputation when using geographic coordinates versus Universal Transverse Mercator (UTM).

The overall goal of this study is to test the imputive quality of different distance based metrics on the price variable from the airbnb dataset. This analysis will then provide information regarding the potential use of UTM more consistently over geographic coordinates.

Geographic coordinates are based on a spherical Earth model and uses degrees to measure distance. This can create issues with interpretation as degrees are not uniform in distance and can add necessary complications to a model. Geographic coordinates are usually measured in latitude and longitude. UTM is a projected coordinate system which is based on 60 zones across the Earth. These coordinates are more easily interpreted on a linear scale. UTM is usually measured on a x and y scale. The hypothesis on this study is that if UTM is in the predictor set the imputation will have more accuracy than if geographic coordinates are in the predictor set. The first step is to analyze the missing value patterns of our price variable.

## Missing Values of Price



	latitude	longitude	accommodates	bathrooms	host_is_superhost	bedrooms	beds	price
20674	1	1	1	1	1	1	1	0
355	1	1	1	1	1	1	1	1
40	1	1	1	1	1	1	1	1
8497	1	1	1	1	1	1	1	1
79	1	1	1	1	1	1	1	0
1	1	1	1	1	1	1	1	0
1	1	1	1	1	1	1	1	0
5818	1	1	1	1	1	1	1	0
303	1	1	1	1	1	0	1	1
32	1	1	1	1	1	0	1	1
6	1	1	1	1	1	0	0	0
43	1	1	1	1	1	0	0	0
7	1	1	1	0	1	1	1	1
36	1	1	1	0	1	1	1	1
1	1	1	1	0	1	0	1	0
0	0	0	0	44	384	5949		
	beds	price						
20674	1	1	0					
355	1	0	1					

40	0	1	1
8497	0	0	2
79	1	1	1
1	1	0	2
1	0	1	2
5818	0	0	3
303	1	1	1
32	0	0	3
6	1	1	2
43	0	0	4
7	1	1	1
36	0	0	3
1	0	0	4
	14468	14783	35628

We know there are 14783 missing values in `price`. There are 355 occurrences when `price` is the only missing value. It looks like `price` is missing the most when `beds` is also missing. The second most time `price` is missing is when `beds` AND `bedrooms` are missing. Note that, `latitude`, `longitude`, and `accomodates` are the only variables of interest that do not have any missing values.

### Imputing Missing Values with Geographic Coordinates

The imputation process throughout this study will be using the `mice` package in R. The `mice` package contains a variety of methods for imputation for this analysis predictive mean matching (pmm) will be used. The `price` variable and the entire predictor set are all quantitative variables for which pmm is the recommended method of imputation.

The table above shows the estimates for the airbnb model with the `price` variable imputed. The coefficient estimates for the model are slightly different from the original model showing that imputation does have an impact in this data set and model. The next step of the analysis to replace geographic coordinates (`latitude` and `longitude`) with UTM based distance measurements.

### Imputing Missing Values with Universal Transverse Mercator

term	estimate	std.error	statistic	df	p.value
(Intercept)	4.4337415	0.0102707	431.690343	84.276261	0.0000000
bedrooms	-0.0664399	0.0064109	-10.363582	23.811081	0.0000000
bathrooms	0.1292279	0.0083531	15.470649	354.923050	0.0000000

term	estimate	std.error	statistic	df	p.value
beds	0.0137633	0.0072911	1.887691	10.916969	0.0859201
accommodates	0.1977896	0.0039064	50.632007	14.007389	0.0000000
X	-0.2750749	0.0044886	-61.282494	40.484154	0.0000000
Y	0.0993012	0.0068342	14.530062	7.307948	0.0000012
X:Y	-0.1112607	0.0038699	-28.750012	23.889664	0.0000000

The coefficient estimates above show the imputed model for price with UTM distance variables. This model shows a drastic difference from the previous two models. This shows that not only imputation but which distance based metric used impacts coefficient estimates. The only way to truly see model performance of each model is to compare AIC and BIC measurements for each of the models constructed.

### Comparing Model Accuracy Between Predictor Sets

	mean_AIC	mean_BIC
Geographic	70677.62	70754.02
UTM	70911.21	70987.61

The table above shows the mean AIC and BIC measurements for each imputation predictor set. The AIC and BIC measurements are lower for the geographic coordinates suggesting that they represent the relationship better than UTM. The model comparison give the idea that geographic coordinates could be a better fit in the model when compared to UTM. This difference can truly be tested by comparing the imputation quality of each method. This will be done by calculating the RMSE for each imputation method.

### Comparing Imputation Methods with RMSE

Predictor_Set	Mean_RMSE	Min_RMSE	Max_RMSE	SE	CI_lower	CI_upper	
UTM	456.0150	56.90380	356.7984	547.1487	17.99456	420.7457	491.2844
Geographic	457.9202	54.40467	361.9025	543.0629	17.20427	424.1998	491.6405

It can be seen in the table above the the predictor set containing UTM as the slightly lower RMSE signifying that it could have higher imputation accuracy. The predictor set with the geographic coordinates does have the lower SE. These results do not give any conclusions. The results in the table above will need to be statistically tested. This can be done with a anova

model, with RMSE as the response variable and the “predictor sets” (UTM vs. Geographic) as the predictor variable.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
predictors	1	18.14782	18.14782	0.0058561	0.9398454
Residuals	18	55781.19654	3098.95536	NA	NA

The anova summary above shows that we fail to reject the null hypothesis that the group means are equal. This means that there is no statistical difference in using the predictor set with geographic coordinates or UTM in regards to imputation quality. This shows that overall for the airbnb data set neither the imputation or the model would directly benefit from using UTM over geographic coordinates.