Airbnb Toronto Price Prediction

Capstone Project Presentation

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Tools Used

- 1. Github (Project link)
- 2. Database PostgreSQL (<u>Database details link</u>)
- 3. Tableau (<u>Dashboard link</u>)
- 4. Python
- 5. Flask
- 6. HTML
- 7. Amazon Web Services RDS

Overview

Airbnb is an online marketplace for short term rentals. Airbnb allows people from all over the world to host their homes as someone's next stay.

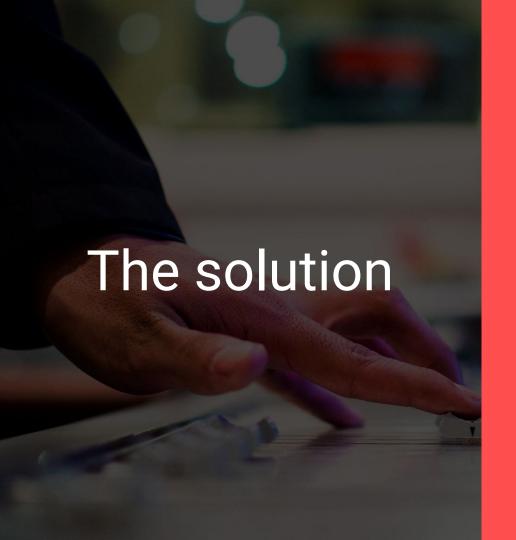
Properties can range from houses, apartments to single and shared rooms and are priced per night or per stay.



The problem

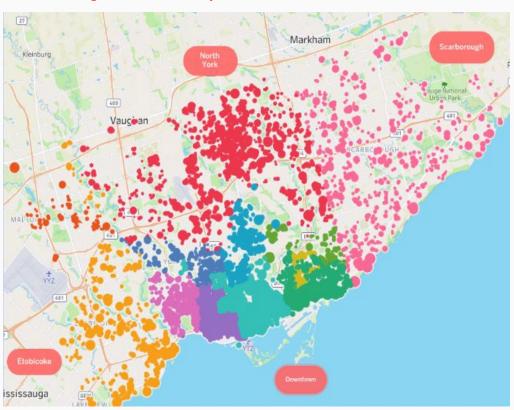
How do I determine the optimal rent price for my property?



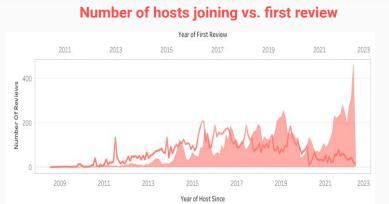


Construct a data driven solution by using machine learning to predict rental prices for each property.

Airbnb listings distribution map



- There are approx. 15, 000 Airbnb listings in Toronto
- Exploratory Data Analysis on
 - Neighbourhoods
 - Boroughs
 - Reviews
 - Host Details
 - Amenities
 - Number of guests

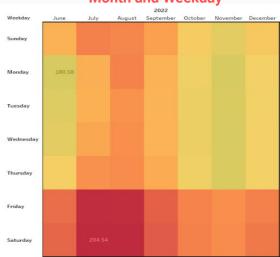








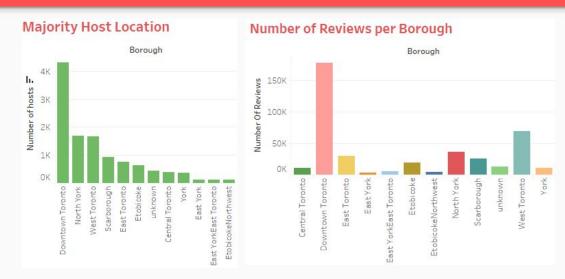
Month and Weekday



- by 75% in 2022 compared to 2010
- Summer is the most popular season for Airbnb business
- Average prices are highest in August, and during the week the highest prices are on Saturdays

Downtown Toronto is the most popular location among hosts as well as guests

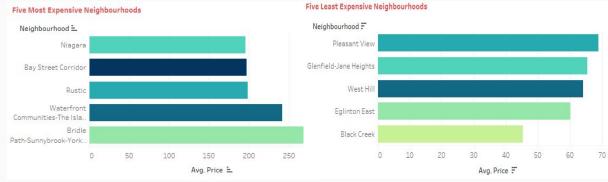


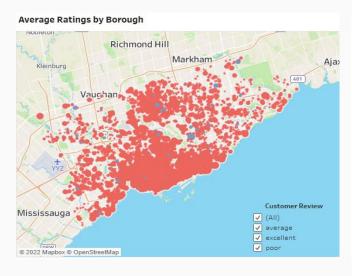


More than 50% of the Airbnb listings in Toronto are Apartments



- Renting an entire home or apartment is the most expensive in all boroughs
- In Downtown Toronto, both Apartments and entire homes can cost more than CAD \$200 per night
- Average Price by Room Type
 - Entire home CAD \$180
 - o Private room CAD \$80
 - Shared room CAD \$70
 - Hotel room CAD \$60
- Listings that accommodate 14 people are the most expensive at approx. CAD \$580
- Single guests can rent for less than CAD \$100 per night



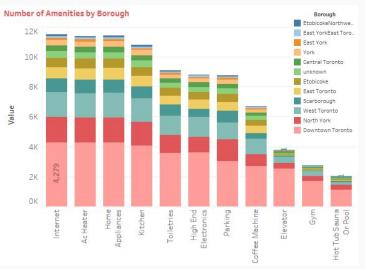




- The five most expensive neighbourhoods
 - Bridle Path-Sunnybrook-Yorkmills
 - Waterfront Communities-The Island
 - Rustic
 - Bay Street Corridor
 - Niagara
- The five least expensive neighbourhoods
 - Black Creek
 - Eglinton East
 - West Hill
 - Glenfield-Jane Heights
 - Pleasant View
- Most of the properties have "excellent" ratings
- Price benefit of 8-14% over properties with "poor" or "average" ratings









- Around 25% of hosts are superhosts. No significant impact on average price
- Around 90% hosts have verified ID.

 Average prices approx. 25% higher
- 29% of hosts allow instant booking. No significant impact on average price
- Popular Amenities Internet, AC Heater, Home Appliances, Kitchen, Toiletries, Electronics, Parking, Coffee Machines, etc.
- Higher prices are charged for amenities listed above along with some other amenities like gym, elevator, pool, etc.
- Long term stays and host greetings have lower average prices

Machine Learning Model - XGBoost

Linear Regression Model

RMSE train: 80.427 RMSE test: 79.391 R^2 train: 0.555 R^2 test: 0.550

Support Vector Regression Model

RMSE train: 101.333 RMSE test: 100.078 R^2 train: 0.294 R^2 test: 0.284

XGBoost Regressor

RMSE train: 46.833 RMSE test: 68.264 R^2 train: 0.849 R^2 test: 0.667

HistGradientBoosting Regressor

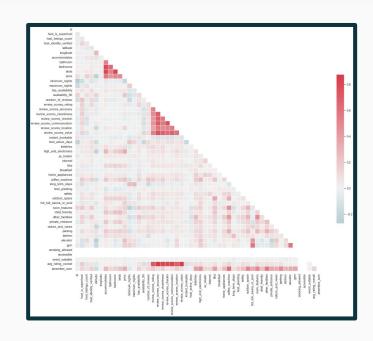
RMSE train: 67.088 RMSE test: 69.522 R^2 train: 0.690 R^2 test: 0.655

RandomForest Regressor

RMSE train: 26.395 RMSE test: 69.168 R^2 train: 0.952 R^2 test: 0.658

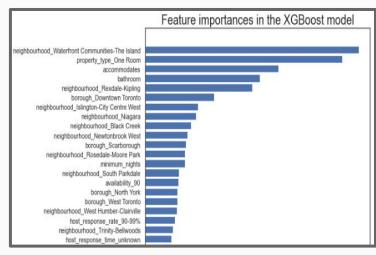
ExtraTrees Regressor

RMSE train: 0.076 RMSE test: 68.757 R^2 train: 1.000 R^2 test: 0.662



XGBoostRegressor - Hyper-parameter Tuning with GridSearchCV

Final Model After Hyper-parameter Tuning # # Test optimum values for param arid param grid = { 'n_estimators': [100,250,500,1000], 'eta':[0.05.0.1.0.2] grid search(param grid,best param) # # Run the XGBoost Regression model with optimized parameters model=xgb.XGBRegressor(random state=0, verbosity=1,**best param) model.fit(X train scaled, y train) training pred=model.predict(X_train_scaled) predictions=model.predict(X_test_scaled) r2 score(v test,predictions) rmse training=np.sqrt(mean squared error(y train,training pred)) rmse model=np.sqrt(mean squared error(y test, predictions)) print('RMSE train: %.3f' % rmse training) print('RMSE test: %.3f' % rmse model) print('R^2 train: %.3f' % (r2 score(y train, training pred))) print('R^2 test: %.3f' % (r2 score(v test, predictions))) RMSE train: 37,916 RMSE test: 67.563 R^2 train: 0.901 R^2 test: 0.672

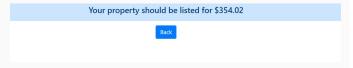


Results:

- RMSE test score: 67.35%
- R-Squared score: 67.6%
- Important features:
 - Neighbourhood
 - Property type
 - Accommodates
 - Bathroom
 - Borough
 - Minimum nights
 - Host response rate

Webpage

We created an exported machine learning model on webapp with Flask and HTML. This webapp can be used by potential Airbnb hosts to predict optimal prices for their properties.



Airbnb Toronto Price Predictor

	F	lost	Info			
	Host Since		Host Response Time			
	5-8 years	~	within a day	~		
	Host Response Rate		Number of listings			
	100%	3				
	Host Identity V	enfied	Host is Superhost			
	1	oca	ition			
	N	leighbi	ourhood			
Waterfront Communities-The Island						~
		Boro	ough			
Downtown Toronto						~
	Pro	per	ty Info			
			ty Type			
Apartment						~
	Accompdates		Bathrooms			
	Accomposites 4		sathrooms 1			
	Minimum Nights		Maximum Night	ts		
	1		90			
	☐ Instant Boo	kable	Has availability			
Nights /	Nights Available for the next 3 months		Number of reviews		verage Rating	
30		10	100		4 🗸	
	A	mei	nities			
	Toiletries High end eletror	ics 🛮	AC and Heater 2 Inter	net 🗆 I	IBQ	
□ Hom	Appliences Coffee Machine	0.10	ong term stavs. Host 0	reeting	□ Safety	
Out	door Space					
	☐ Elevator ☐ Private Entrano	0 0	lym □ Breakfast □ Chil	ld friend	ly .	
D N	ture and views D Event suitabl	e D 9	imoking allowed D Acce	essible	Other	
	1	Sub				
		SUE	11111			

Limitations and Future Improvements

- Limited data volume
- Lack of data on important factors like bookings, cancellation policy, security deposit, etc.
- No data regarding points of interests, restaurants or cafes around the property
- Have not performed sentiment analysis on customer reviews and ratings