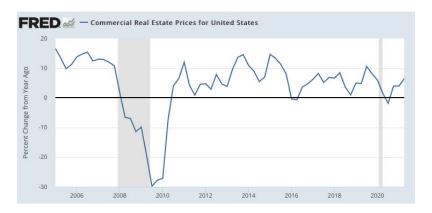
Predicting NY Real Estate Prices

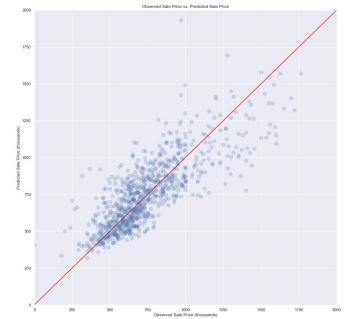
Using web scraping, geocoding, sentiment analysis, topic modeling, random forests, and the command line to create an automated data pipeline

Motivation

A few months ago, I took on this problem with only basic data analysis skills - and created a linear model for the data.

However, the housing market is far too complicated to be predicted by a single line.





Objective: Create an easily-accessible web application for predicting real-estate prices in New York City.

Methodology

Data source: realtor.com

Initial scraping: 9000 listings; ~2400 usable

Daily updates: ~100 new listings/day

From raw HTML, 9 features (2 categorical, 1 text)

After processing/topic clustering: 83 features (9 numerical, 10 dummies, 64 NLP topics)

Target variable: Sale Price

Data cleaning

Step 1: Raw HTML

Step 2: Pull data into Pandas dataframe

		beds	baths	price	description	address	sqft	sale_date	lot_size	year_built	stories	rooms	property_type	neighborhood	borough
	0	6	2	1810000	- 2 family home in the Heart of Willia	129 Devoe St, Ny, NY 11211	N/A	November 8, 2021	2500	1901	2	Total Rooms: 13	Single Family Home	Williamsburg	Brooklyn, NY
ξ,	1	1	2	N/A	- Primary residence only, no pied-a-te	160 Bleecker St Apt 10LE, New York City, NY 10012	N/A	November 2, 2021	N/A	1896	10	Total Rooms: 4	N/A	SoHo	Manhattan, NY
	2	2	3	2190000	- Presenting 110 Summit Street; a coll	110 Summit St Apt 1, New York City, NY 11231	2008	October 25, 2021	N/A	1899	3	Total Rooms: 5	N/A	others	Brooklyn, NY
	3	3	3	665000	- Beautiful 2 family home on a 30' x 1	109 Station Ave, Staten Island, NY 10309	1350	November 10, 2021	3270	2002	3	Total Rooms: 6	Single Family Home	others	N/A
ξ,	4	3	2	508000	- Prime Arden Heights. Well Kept Singl	92 Carlyle Grn, Staten Island, NY 10312	1080	November 16, 2021	2697	1975	2	N/A	Condo	others	BROOKLYN, NY

Data cleaning

Step 3: Cluster descriptions with topic model, create dummy variables, conduct sentiment analysis!

	beds	baths	price	sqft	stories	rooms	building_age	pol	sub	lda_topic0	 Commercial	Condo	Multi- Family Home	Other	Single- Family Home	Bronx
3	3.0	3.0	665000.0	1350.0	3.0	6.0	19.0	0.417532	0.530519	0.009693	 0.0	0	0	0	1	0.0
8	1.0	1.0	459000.0	532.0	4.0	2.0	5.0	0.122857	0.495714	0.009472	 0.0	1	0	0	0	0.0
15	5.0	5.0	1999999.0	3114.0	3.0	12.0	122.0	0.262141	0.528006	0.056832	 0.0	1	0	0	0	0.0
18	6.0	5.0	1190000.0	3700.0	3.0	12.0	51.0	0.330556	0.701190	0.006829	 0.0	0	1	0	0	0.0
20	2.0	1.0	849000.0	1200.0	6.0	5.0	104.0	0.303194	0.571307	0.066964	 0.0	1	0	0	0	0.0
			2							11.2	 					
72	1.0	1.0	725000.0	786.0	32.0	3.0	36.0	0.133917	0.482117	0.019385	 0.0	1	0	0	0	0.0
75	2.0	3.0	379000.0	1354.0	3.0	6.0	25.0	0.356746	0.542659	0.011675	 0.0	0	0	0	1	0.0
79	2.0	2.0	1695000.0	2000.0	7.0	4.0	109.0	0.296512	0.593700	0.032381	 0.0	1	0	0	0	0.0
80	2.0	1.0	760750.0	793.0	6.0	4.0	122.0	0.151384	0.348802	0.028637	 0.0	1	0	0	0	0.0
81	7.0	2.0	1470000.0	1100.0	2.0	12.0	101.0	0.116667	0.275000	0.009032	 0.0	0	1	0	0	0.0

2375 rows × 83 columns

Methodology

Tools (a lot!):

Selenium for data scraping

Pandas and NumPy for data storage and formatting

Google Maps Geocoding API for filling in missing location data

NLTK for tokenization of listing descriptions

TextBlob for sentiment analysis of descriptions

Gensim for topic modeling descriptions in order to perform soft clustering

Scikit-Learn for regression models

TensorFlow's Keras module for constructing a MLP Regressor

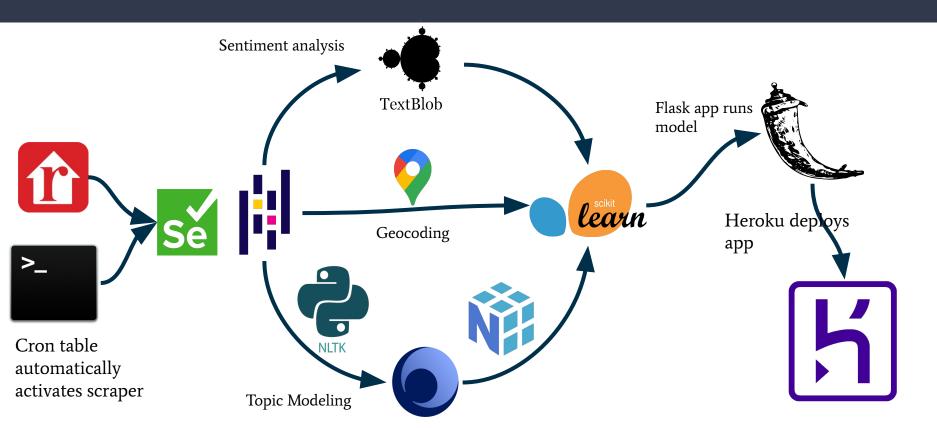
MacOS Command Line scripts (cron) for automated data collection and model updates

GitHub API for automatically pushing the Random Forest model to a backup repository

Flask for creating web app

Heroku for deploying Flask app

Data Pipeline - Tools



Model:

Random Forest Regressor

256 trees

Train-Test 85-15 split

Train: 2000 listings

Test: 353 listings

Training data r²: 0.88

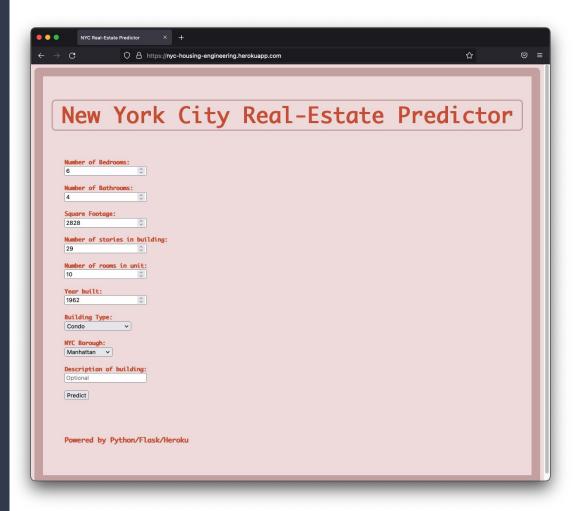
Test data r²: 0.57

MAE: \$164608

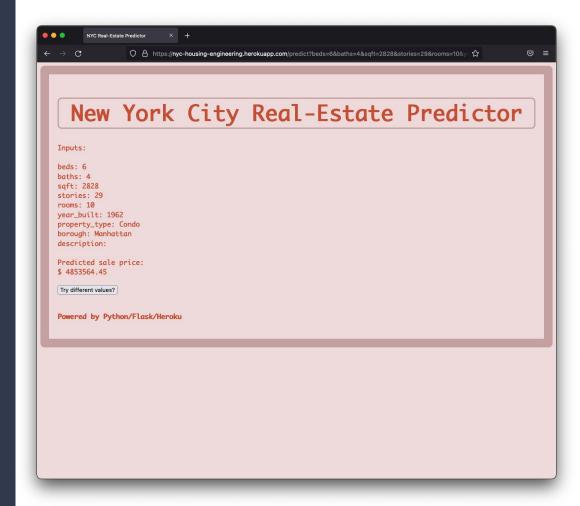
As the pipeline acquires more and more data, the problems caused by overfitting will diminish.

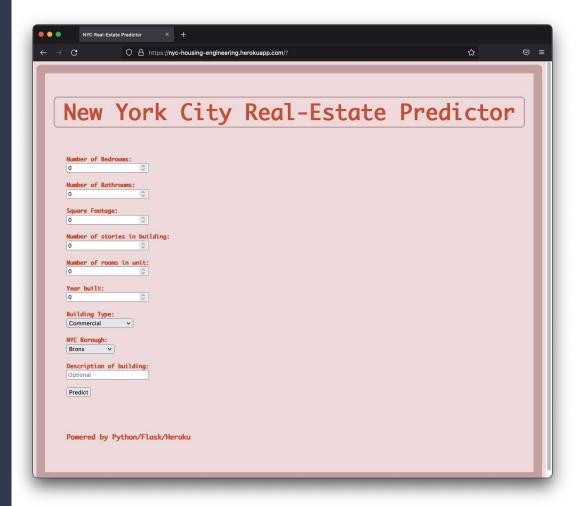
The model can be used and tested at:

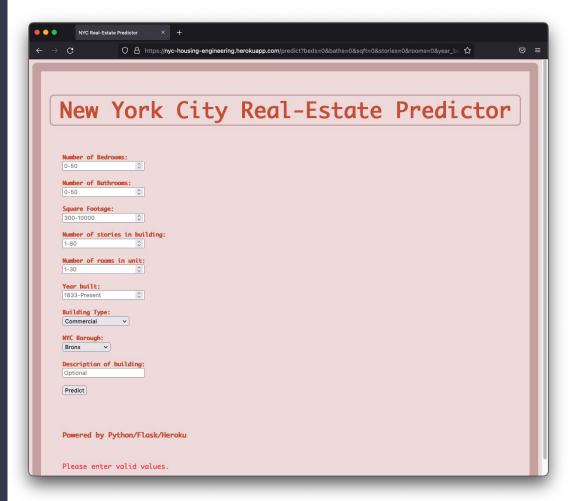
<u> https://nyc-housing-engineering.herokuapp.com</u>

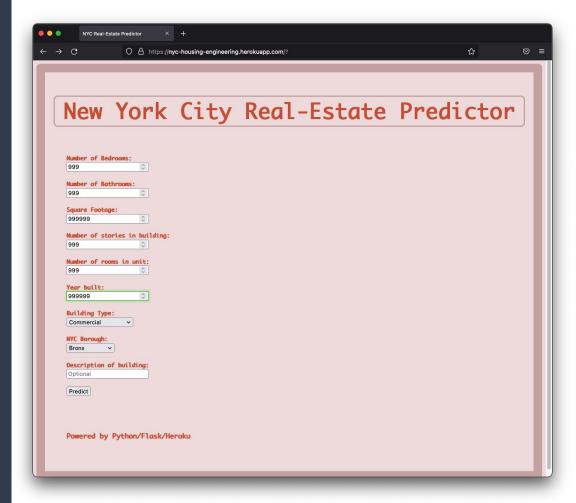


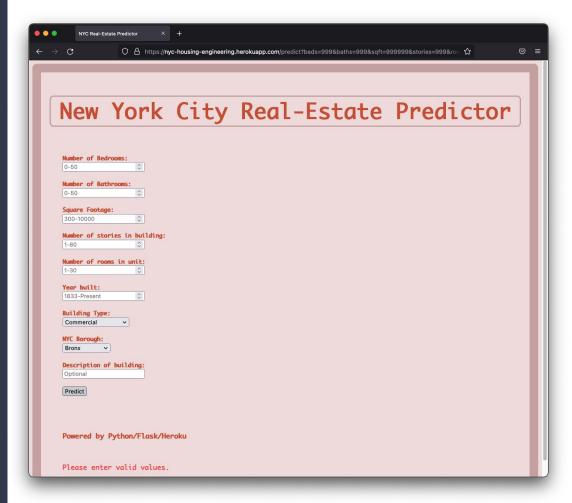
The app takes several real-estate features and a written description (optional), then predicts the predicted sale price.



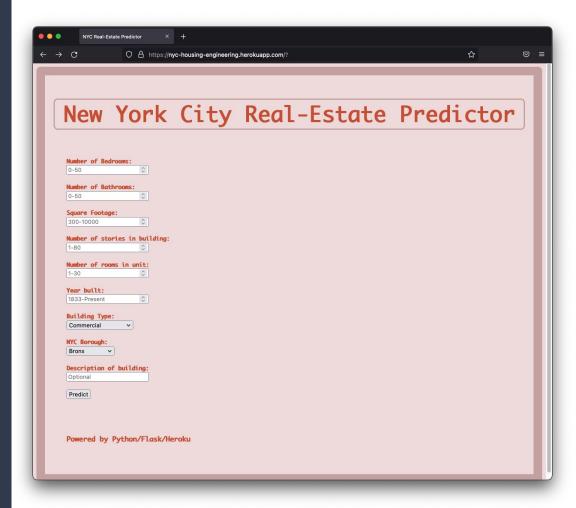




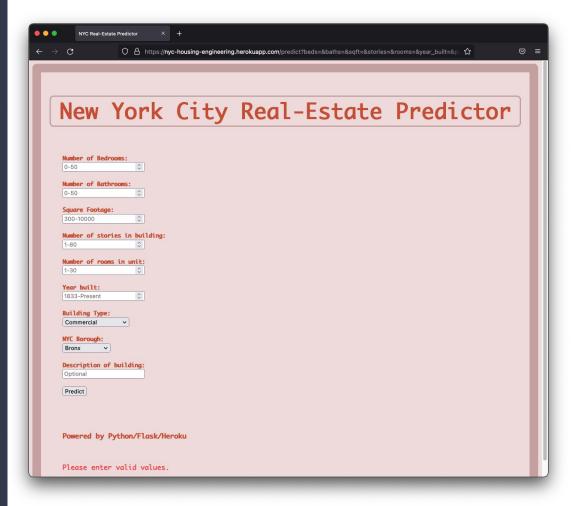




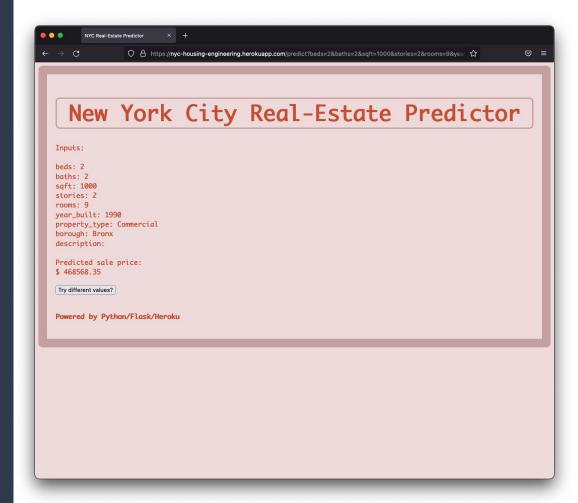
So does leaving values blank.



So does leaving values blank.

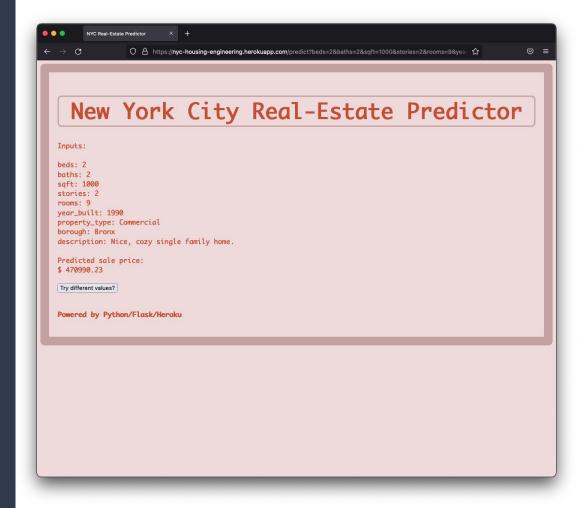


Writing a positive description can help increase your property's sale price!



Writing a positive description can help increase your property's sale price!

Disclaimer: Writing this exact sentence may not increase your home's price by \$2,000.



Future Work

Create different webpages that run different models for different boroughs

- Create an API that can process more than one listing per user at a time

Migrate away from Pandas,
which is not scalable for large data sets

Questions?