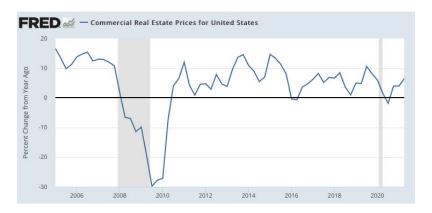
# Predicting NY Real Estate Prices

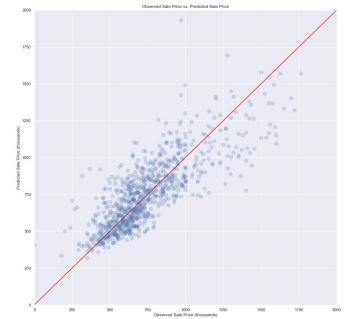
Using web scraping, geocoding, sentiment analysis, topic modeling, random forests, and the command line to create an automated data pipeline

#### 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: 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)

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

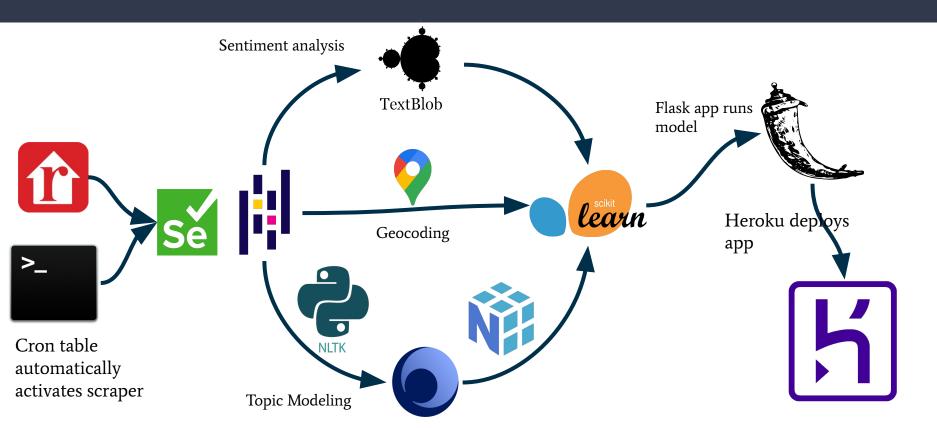
## Data cleaning

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 | <br>Commercial | Condo | Multi-<br>Family<br>Home | Other | Single-<br>Family<br>Home | Bronx |
|----|------|-------|-----------|--------|---------|-------|--------------|----------|----------|------------|----------------|-------|--------------------------|-------|---------------------------|-------|
| 3  | 3.0  | 3.0   | 665000.0  | 1350.0 | 3.0     | 6.0   | 19.0         | 0.417532 | 0.530519 | 0.009693   | <br>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   | <br>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   | <br>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   | <br>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   | <br>0.0        | 1     | 0                        | 0     | 0                         | 0.0   |
|    |      |       | 2         |        |         |       |              |          |          | 11.2       | <br>           |       |                          |       |                           |       |
| 72 | 1.0  | 1.0   | 725000.0  | 786.0  | 32.0    | 3.0   | 36.0         | 0.133917 | 0.482117 | 0.019385   | <br>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   | <br>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   | <br>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   | <br>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   | <br>0.0        | 0     | 1                        | 0     | 0                         | 0.0   |

2375 rows × 83 columns

## Data Pipeline - Tools



Model:

Random Forest Regressor

256 trees

Train-Test 85-15 split

Train: 2000 listings

Test: 353 listings

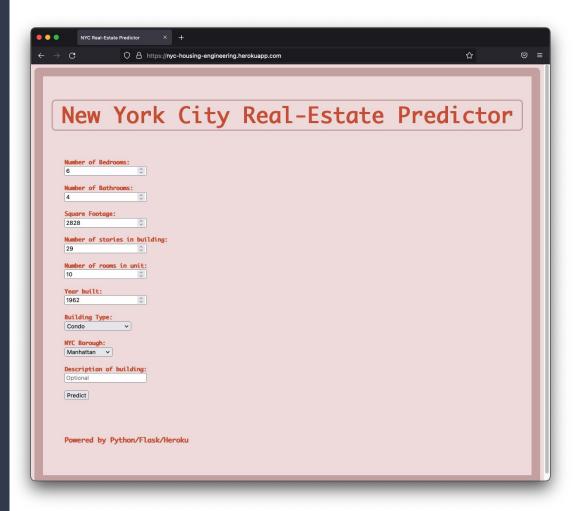
Training data r<sup>2</sup>: 0.88

Test data r<sup>2</sup>: 0.57

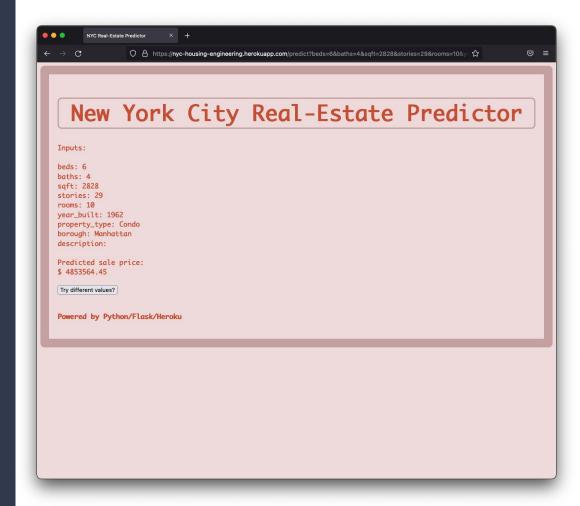
As the pipeline acquires more and more data, the problems caused by overfitting will diminish.

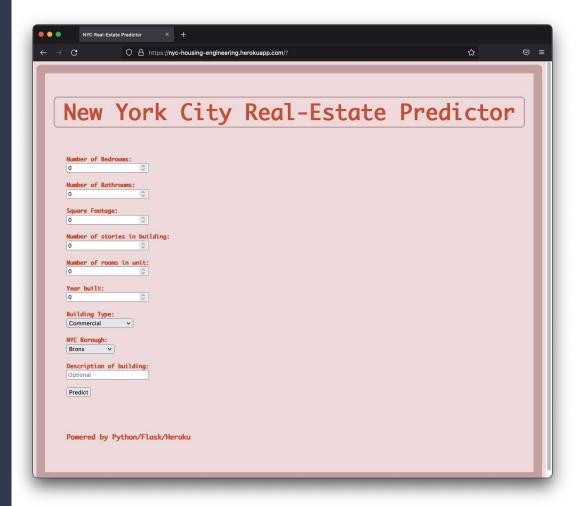
The model can be used and tested at:

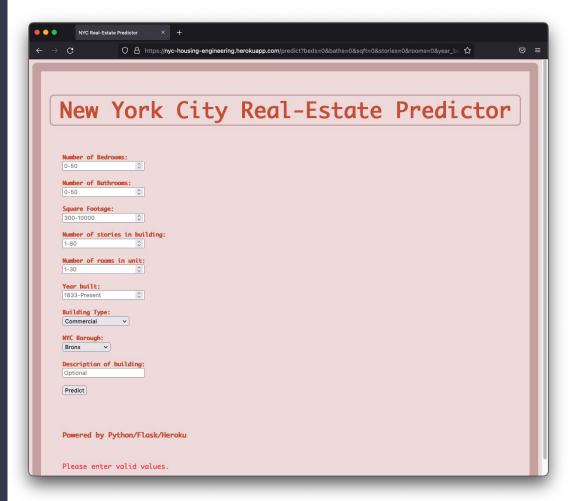
<u> https://nyc-housing-engineering.herokuapp.com</u>

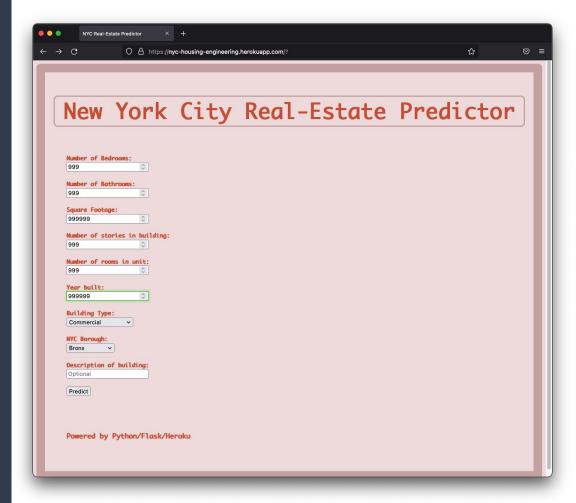


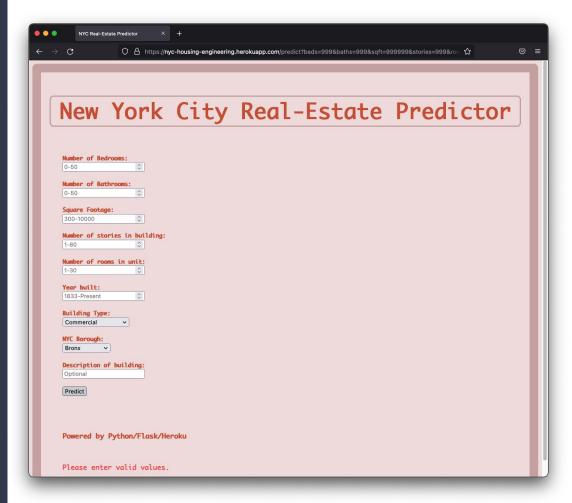
The app takes several real-estate features and a written description (optional), then predicts the predicted sale price.



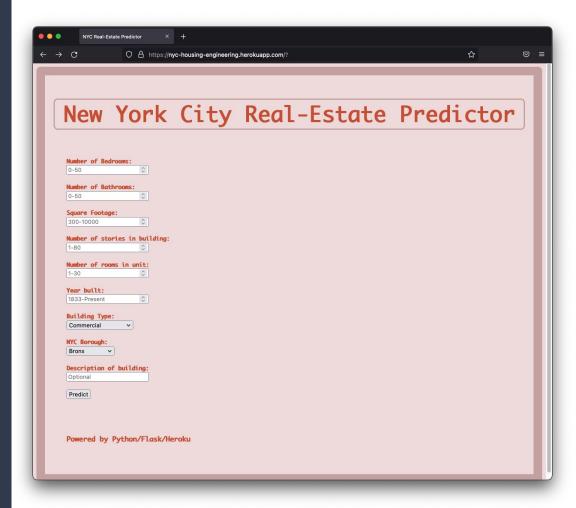




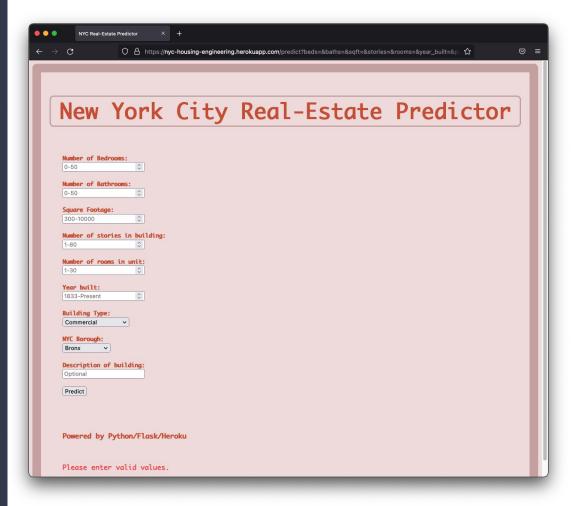




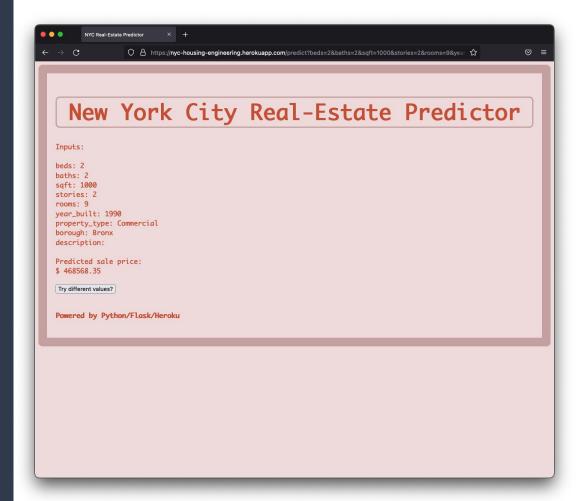
So does leaving values blank.



So does leaving values blank.

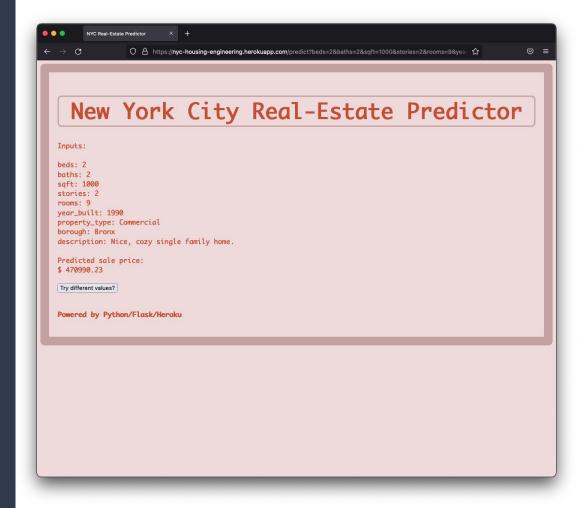


Writing a positive description can help increase your property's sale price!



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

- Refine website; make it better looking and more user-friendly

- 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?