Real Estate Price Prediction

with MLS and Redfin Data

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Harvard CS209b Data Science Final Project

AGENDA

- Problem Statement & Motivation
- Data Description
- Exploratory Data Analysis
- Approach
- Results
- Conclusions
- Future Work

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To accurately predict real estate prices / DOM ...

- Curate historical real estate transaction data with an emphasis on property images
- Develop feature extraction methods and identify key factors that determine property prices
- Build predictive models for sold price and number of days on market (DOM)

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Data Description

MLS Data (Provided)

- MLSNUM
- STATUS
- LISTDATE
- SOLDPRICE*
- DOM*
- ADDRESS
- CITY, STATE, ZIP
- LOTSIZE
- AGE
- GARAGE
- REMARKS

Redfin Data (Scraped)

- MLSNUM
- beds, baths
- sqft_finished, sqft_unfinished
- year_built, year_renovated
- parking_space, garage_space
- hoa_fee
- school_ratings, school_distances
- walk_score, transit_score, bike_score
- num_photo
- photos posted on Redfin

* : response variable

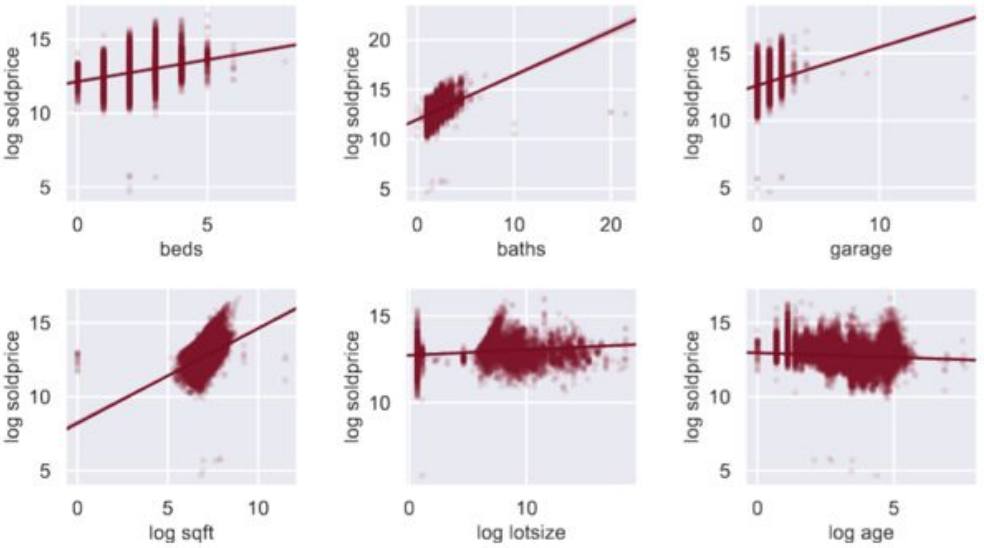
Exploratory Data Analysis I - Response Variable

Sold-Price is very right skewed
Single log-transformation makes it more symmetrical

Response: Log(sold-price)

Exploratory Data Analysis II - Selected MLS Predictors

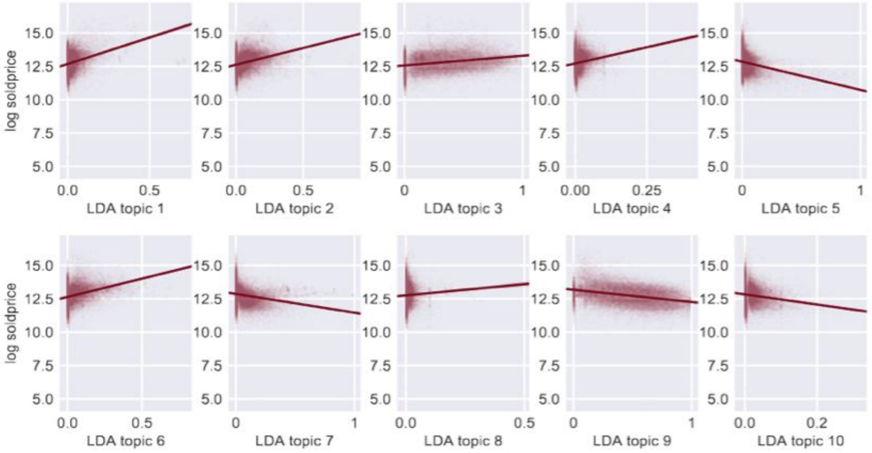
Log Sold-Price vs. Selected MLS Predictors



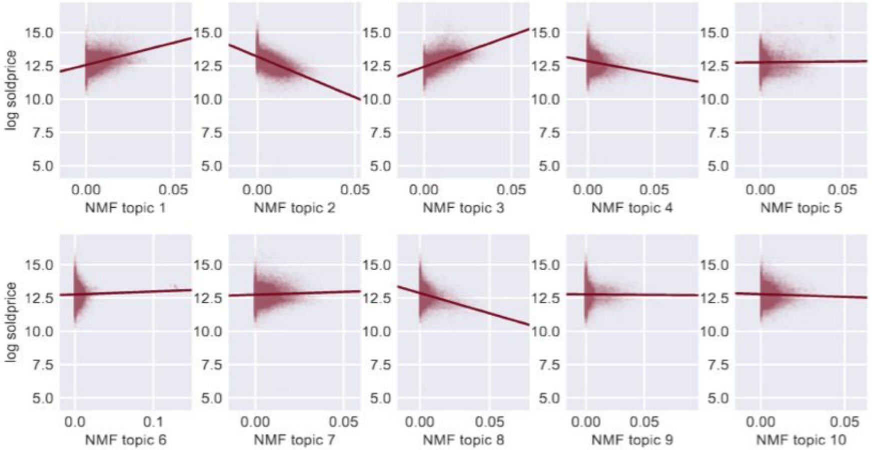
- Beds, baths, number of parking spaces, square footage and lot size positively correlate with the response
- Property age negatively correlates with the response

Exploratory Data Analysis III - MLS Remarks Topics

LDA topics



NMF topics



- Features extracted from remarks appear to have strong correlation with the response variable

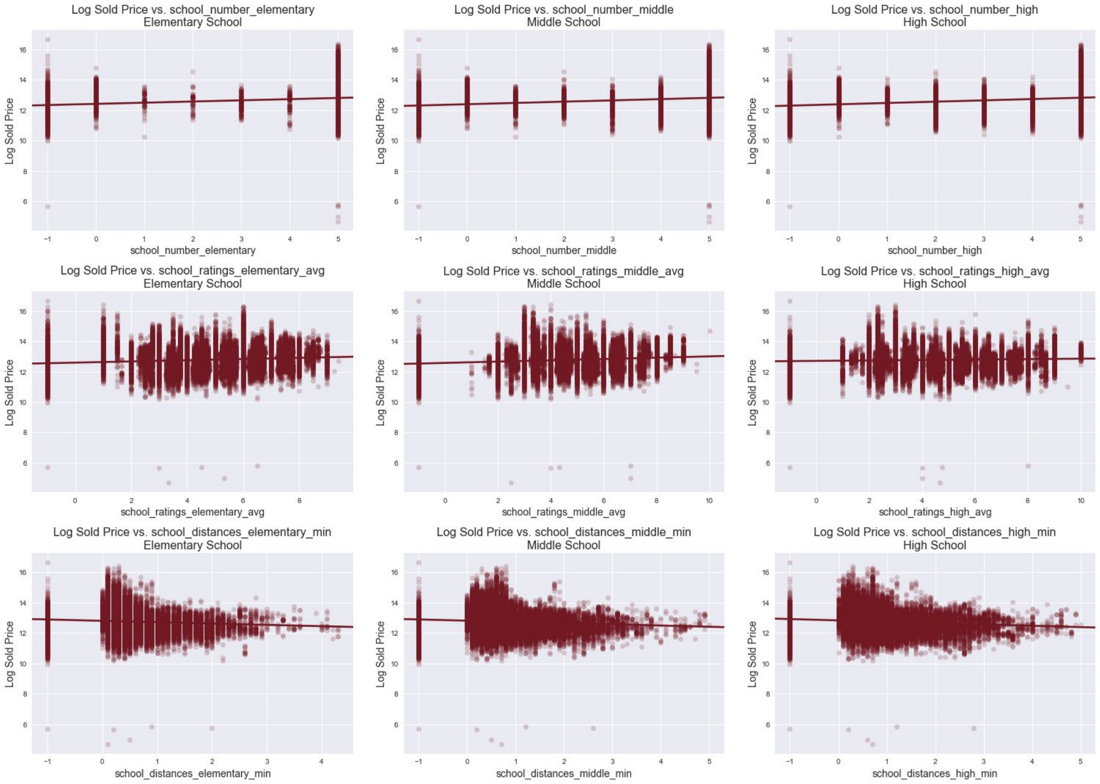
Exploratory Data Analysis IV - Educational Resources

Elementary School | Middle School | High School

Number of Schools

Avg School Rating

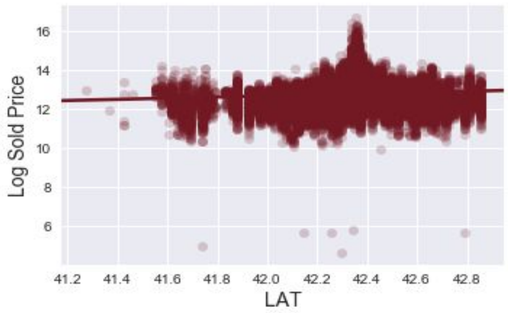
Min Distance to School



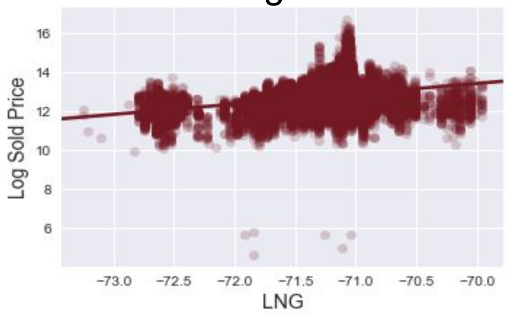
Exploratory Data Analysis V - Geographic Location

Log Sold-Price vs. Latitude/Longitude

Latitude

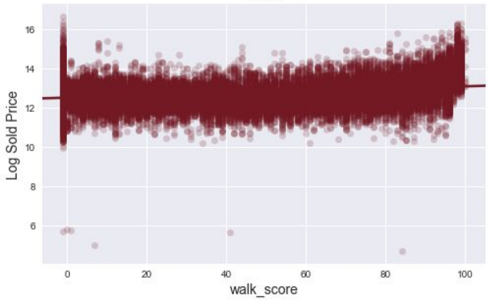


Longitude

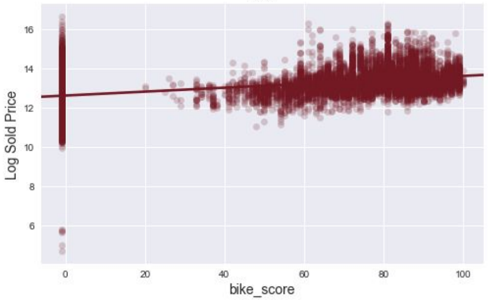


Log Sold-Price vs. Convenience Scores

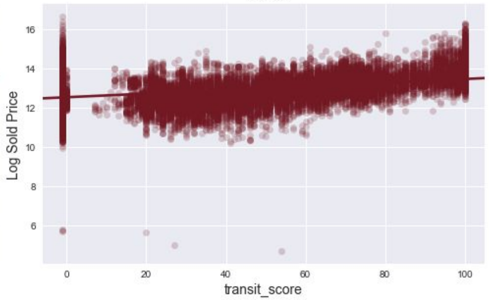
Walk score



Bike score



Transit score



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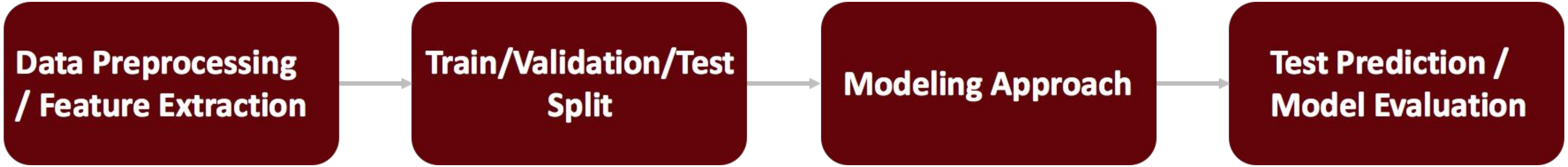
Approach Overview



Data Preprocessing / Feature Extraction

MLS Numeric

- Convert Zip to lat/lng
- Get Month from list date
- Drop non-MA rows
- Fill -1 for NA’s

Beds
Baths
Sqft
Age
etc.

10 Numeric Features

MLS Remarks

NLP - Topic Modeling

- LDA : Fit-transform TF
- NMF: Fit-transform TF-IDF

Topics

20 Numeric Features

Redfin Numeric

- Get avg school ratings
- Get # closest schools
- Get min/max school distance
- Fill -1 for NA’s

School Ratings
School Distances
walk/bike/transit scores

20 Numeric Features

Redfin Images

CV – Image Modeling

- Use the output of ResNet50 last pooling layer to represent each image
- Take avg of all its image features for each house

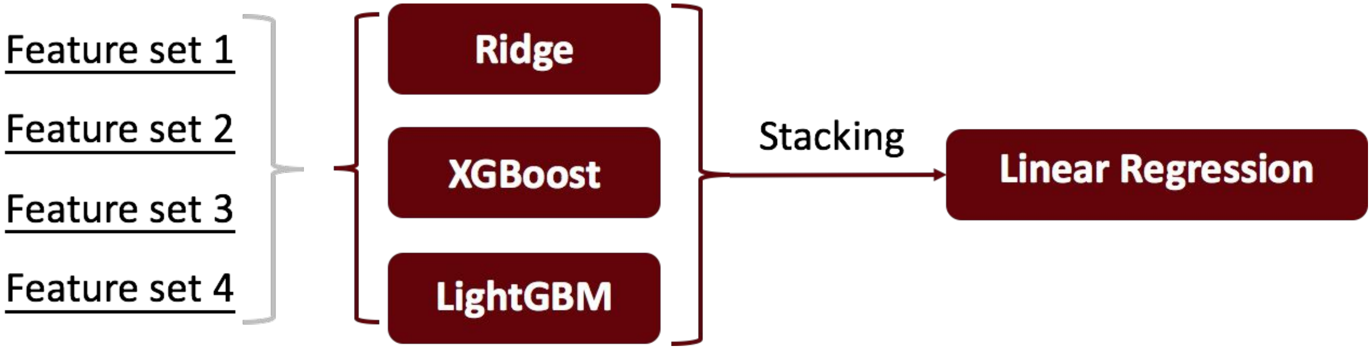
Image Features

2048 Numeric Features

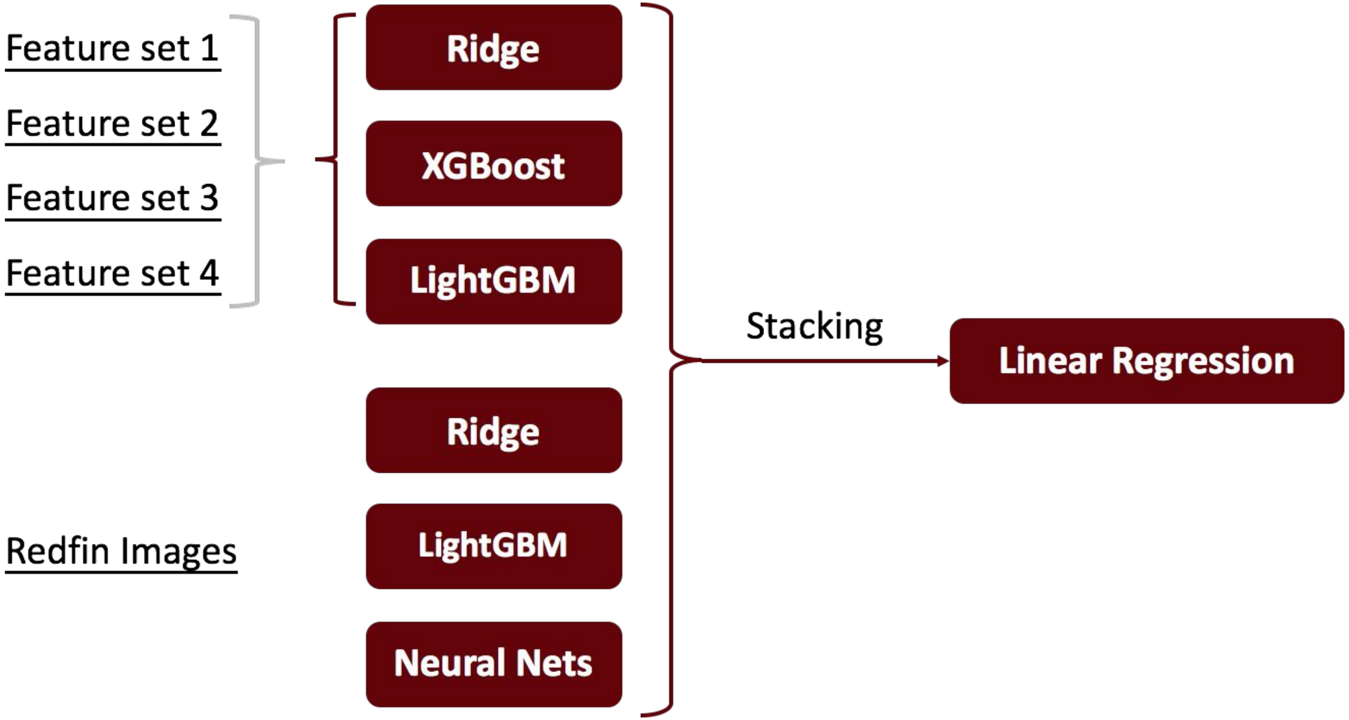
Feature Sets

Type	**Source**	**Feature Set**					
		Set 1	Set 2	Set 3	Set 4	Set 5	Set 6
Non-image	MLS numerical	X	X	X	X	X	X
	MLS remarks		X		X		X
	Redfin numerical			X	X	X	X
Image	Redfin images					X	X
Total # of features		10	30	30	50	2078	2098

Modeling Approach I



Modeling Approach II



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Results

Condo: **Price** R^2 (Ensemble Model)			
	Training	Validation	Test
MLS	0.977	0.936	0.884
MLS + Remarks	0.990	0.942	0.899
MLS + Redfin	0.987	0.947	0.893
MLS + Redfin + Remarks	0.989	0.947	0.907
MLS + Redfin + Images	0.988	0.949	0.898
MLS + Redfin + Remarks + Images	0.990	0.948	0.911

Multi-family: Price R^2 (Ensemble Model)			
	Training	Validation	Test
MLS	0.903	0.782	0.718
MLS + Remarks	0.956	0.841	0.801
MLS + Redfin	0.930	0.807	0.736
MLS + Redfin + Remarks	0.961	0.849	0.803
MLS + Redfin + Images	0.947	0.777	0.724
MLS + Redfin + Remarks + Images	0.967	0.837	0.800

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Conclusions

- Developed
  - topic feature extraction methods using NMF and LDA
  - a method to scrape property data and images from Redfin
  - a method to extract visual features from property images (the average 2048-dimensional ResNet final average pooling layer output)

- Found
  - that both transformed remark topic features and information from Redfin are useful features for predicting the sold price
  - that our current method of extracting images is likely sub-optimal

Future Work

- Curate more multi-family observations to reduce overfitting and improve model generalizability.
- Curate additional features from external sources to try to capture market temperature and the overall economy.
- Develop a better method of incorporating image features.