Machine Learning: Rental Housing Data

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Project Overview

Objective

Explore and predict the rental prices in the private property market using machine learning algorithms on web scraped Craigslist housing data

Presentation Sections

Data Acquisition

Data Exploration & Preprocessing

Machine Learning

What I Used

Language



Libraries



Tools





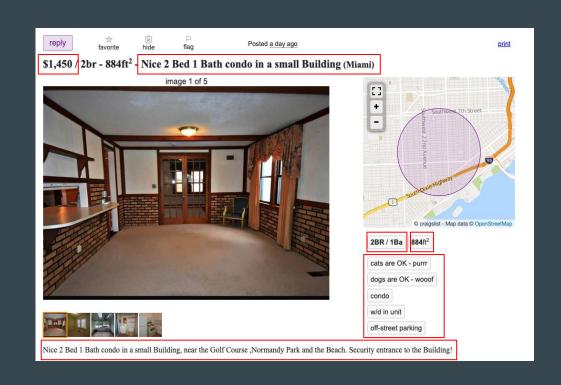
Algorithms

- LinearRegression
- Random Forest

Data Acquisition

Web Scraped Datasets

- Web Scraping code includes a splinter that opens each listing (3000) and pulls out the specific details within the post
- Code took about 1.5 hours to webscrape 3000 listings
- I web scraped Miami and San
 Francisco and used the different data sets on my ML models



Web Scraped DataFrame

	datetimes	hoods	prices	bedrooms	bathrooms	sqft	housing_type	laundry	parking	cats	dogs	furnished
0	2021-05- 30 14:02	(Dadeland 2/2)	\$1,900	2BR	2Ba	none	apartment	w/d in unit	carport	none	none	none
1	2021-05- 30 14:02	(Doral)	\$2,557	2BR	2Ba	none	apartment	w/d in unit	attached garage	none	none	none
2	2021-05- 30 14:02	(Miami)	\$2,241	2BR	2Ba	1106	apartment	w/d in unit	off-street parking	yes	yes	none
3	2021-05- 30 14:02	(Doral)	\$3,399	3BR	2Ba	none	apartment	w/d in unit	attached garage	none	none	none
4	2021-05- 30 14:01	(doral)	\$1,978	1BR	1Ba	none	apartment	w/d in unit	attached garage	none	none	none

Data Exploration

Data Exploration - ETL Process

Extract

Extract datasets using web scrape method ensuring it has all necessary information and limited null values.

Null values in sq. ft. presents a challenge

Transform

Transform data by removing duplicate listings, converting data types, replacing string values, creating separate data frames

Convert null values to 0 instead of dropping

Load

Load the data into PostgreSQL

Dataset 1: Miami Rental Listings

neighborhood	br	ba	sqft	housingType	laundry	parking	cats	dogs	furnished	rent
Dadeland	2	2.0	0.0	apartment	w/d in unit	carport	no	no	no	1900
Doral	2	2.0	0.0	apartment	w/d in unit	attached garage	no	no	no	2557
Miami	2	2.0	1106.0	apartment	w/d in unit	off-street parking	yes	yes	no	2241
Doral	3	2.0	0.0	apartment	w/d in unit	attached garage	no	no	no	3399
Doral	1	1.0	0.0	apartment	w/d in unit	attached garage	no	no	no	1978

<cla< th=""><th>ss 'pandas.cor</th><th>e.frame.DataFram</th><th>e'></th></cla<>	ss 'pandas.cor	e.frame.DataFram	e'>
Rang	eIndex: 1836 e	ntries, 0 to 183	5
Data	columns (tota	1 11 columns):	
#	Column	Non-Null Count	Dtype
0	neighborhood	1836 non-null	object
1	br	1836 non-null	int64
2	ba	1836 non-null	float64
3	sqft	1836 non-null	float64
4	housingType	1836 non-null	object
5	laundry	1836 non-null	object
6	parking	1836 non-null	object
7	cats	1836 non-null	object
8	dogs	1836 non-null	object
9	furnished	1836 non-null	object
10	rent	1836 non-null	int64
dtyp	es: float64(2)	, int64(2), obje	ct(7)
memo	ry usage: 157.	9+ KB	

	br	ba	sqft	rent
count	1836.000000	1836.00000	1836.000000	1836.000000
mean	1.735294	1.69390	342.716231	2016.338235
std	0.774721	0.55118	538.560115	799.370174
min	0.000000	1.00000	0.000000	500.000000
25%	1.000000	1.00000	0.000000	1500.000000
50%	2.000000	2.00000	0.000000	1800.000000
75%	2.000000	2.00000	750.000000	2250.000000
max	5.000000	4.50000	2921.000000	4950.000000

Dataset 2: San Francisco Rental Listings

neighborhood	br	ba	sqft	housingType	laundry	parking	cats	dogs	furnished	rent
Sunset / Parkside	4	2.0	1600.0	apartment	laundry on site	street parking	no	no	no	4200
Lower Pac Hts	0	1.0	0.0	apartment	laundry in bldg	attached garage	no	no	no	2850
SOMA / South Beach	1	1.0	598.0	apartment	w/d in unit	detached garage	yes	yes	no	3431
Lower Pac Hts	1	1.0	915.0	apartment	w/d in unit	attached garage	no	no	no	3795
Ingleside / SFSU / CCSF	1	1.0	0.0	apartment	no laundry on site	street parking	no	no	no	2000

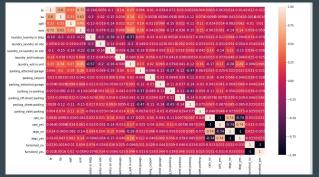
<class 'pandas.core.frame.DataFrame'> RangeIndex: 2596 entries, 0 to 2595 Data columns (total 11 columns): Column Non-Null Count Dtype neighborhood 2596 non-null object br int64 2596 non-null float64 ba 2596 non-null float64 sqft 2596 non-null housingType 2596 non-null object laundry 2596 non-null object parking 2596 non-null object 2596 non-null object cats 2596 non-null doas object furnished 2596 non-null object rent 2596 non-null int64 dtypes: float64(2), int64(2), object(7) memory usage: 223.2+ KB

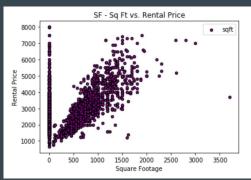
	br	ba	sqft	rent
count	2596.000000	2596.000000	2596.000000	2596.000000
mean	1.417951	1.211287	402.965331	3007.330123
std	1.095361	0.444560	508.831219	1187.119637
min	0.000000	1.000000	0.000000	650.000000
25%	1.000000	1.000000	0.000000	2190.000000
50%	1.000000	1.000000	0.000000	2795.000000
75%	2.000000	1.000000	750.000000	3688.500000
max	8.000000	4.000000	3700.000000	7995.000000

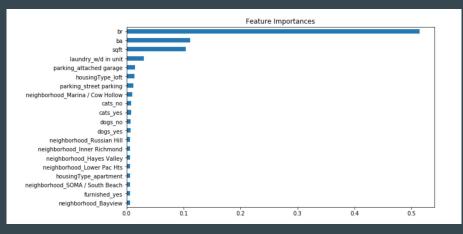
Data Pre-Processing



Heatmaps of Correlation Matrix and Scatter Plots to see if there's any obvious relationship between X variables and Rent Price





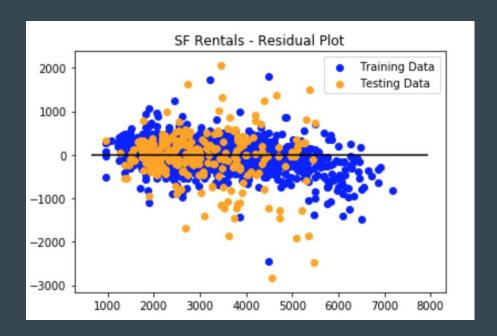


Machine Learning

Model Testing

Model Name	Data Processing	Model Parameters	Independent Variable(s) Used	RMSE	R2
LinearRegression()	80/20 train test split		sqft	\$3,286.06	0.22
LinearRegression() - Multiple	80/20 train test split		br, ba, sqft, housingType, laundry, parking, cats, dogs, furnished	\$3,285.83	0.72
Randomeoregipeoreggorii	K-fold cross validation with cv = 10 (10 90/10 splits)	(n_estimators = 1000, random_state = 42, criterion = 'mse', bootstrap=True)	neighborhood, br, ba, sqft, housingType, laundry, parking, cats, dogs, furnished	\$579.54	0.7597
RandomForestRegressor()	RandomizedSearch CV param_distribs = {'bootstrap': [True, False], 'max_depth': [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, None], 'max_features': ['auto', 'sqrt'], 'min_samples_leaf': [1, 2, 4], 'min_samples_split': [2, 5, 10], 'n_estimators': [200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800, 2000]}	best_params = 'n_estimators': 600, 'min_samples_split': 5, 'min_samples_leaf': 1, 'max_features': 'sqrt', 'max_depth': 60, 'bootstrap': False	neighborhood, br, ba, sqft, housingType, laundry, parking, cats, dogs, furnished	\$567.28	0.7703

Model Findings - Random Forest



	Predicted	Actual	Abs Error
0	1892.201528	2850	957.798472
1	4193.482500	4161	32.482500
2	3711.298333	3165	546.298333
3	2119.985278	1995	124.985278
4	4401.420417	3150	1251.420417

254	2753.233750	2295	458.233750
255	1784.722639	1550	234.722639
256	1873.075139	1895	21.924861
257	3446.631250	4595	1148.368750
258	3662.648472	4495	832.351528

Questions?