DC Properties

Catalin Banu

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Abstract

In this paper I try to predict the prices of houses for Washington DC residential Area based on the records that are public on Kaggle.com

The Data Set

The residential property descriptions and address point information is current as of July 2018 and is provided by D.C. Geographic Information System

The main columns of the data are

- ID
- BATHRM - Number of Full Bathrooms
- HF_BATHRM - Number of Half Bathrooms (no bathtub or shower)
- HEAT - Heating
- AC - Cooling
- NUM_UNITS - Number of Units
- ROOMS - Number of Rooms
- BEDRM - Number of Bedrooms
- AYB - The earliest time the main portion of the building was built
- YR_RMDL - Year structure was remodeled
- EYB - The year an improvement was built more recent than actual year built
- STORIES Number of stories in primary dwelling
- SALEDATE - Date of most recent sale
- PRICE - Price of most recent sale
- QUALIFIED - Qualified
- SALE_NUM - Sale Number
- GBAG - ross building area in square feet
- BLDG_NUM - Building Number on Property
- STYLE - Style
- STRUCT - Structure
- GRADE - Grade
- CNDTN - Condition
- EXTWALL - Extrerior wall
- ROOF - Roof type
- INTWALL - Interior wall

Eda

At first look:

- there are some columns that can't be used directly : FULLADRESS, CENSUS_BLOCK, SQUARE, X, Y (the last two are the same with latitude and longitude)
- Some fields need processing. Like SALEDATE into year and zipcode into categorical
- few colummns have `NA` VALUEs

Types of data

```
table(sapply(df, class))
```

factor	integer	numeric
23	11	15

Data analysis

From 158957 properties, only 98216 had price so all the analysis was made starting with this subset of data

Missing Values

We are looking to the columns that are missing most of the values

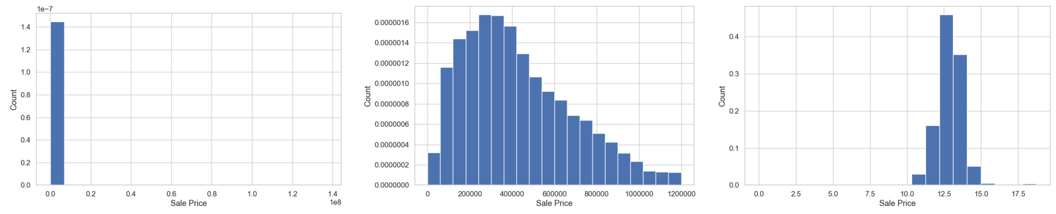
Column	Percentage
NUM_UNITS	**41.048**
AYB	**0.114**
YR_RMDL	**41.278**
STORIES	41.082
SALEDATE	**0.001**
GBA	41.048
STYLE	41.048
STRUCT	41.048
GRADE	41.048
CNDTN	41.048
EXTWALL	41.048
ROOF	41.048
INTWALL	41.048
KITCHENS	**41.049**
CMPLX_NUM	58.952
LIVING_GBA	58.952
CITY	41.385
STATE	41.385
NATIONALGRID	41.385
ASSESSMENT_SUBNBHD	20.623
QUADRANT	**0.103**

From the columns with missed values I will keep only the following columns:

- AYB, SALEDATE, QUADRANT (they miss only few values and I can drop the rows)
- KITCHEN,NUM_UNITS - can be imputed
- YR_RMDL - can be calculated from AYB
- LIVING_GBA - can be imputed from GBA
- GBA - can be imputed from LIVING_GBA

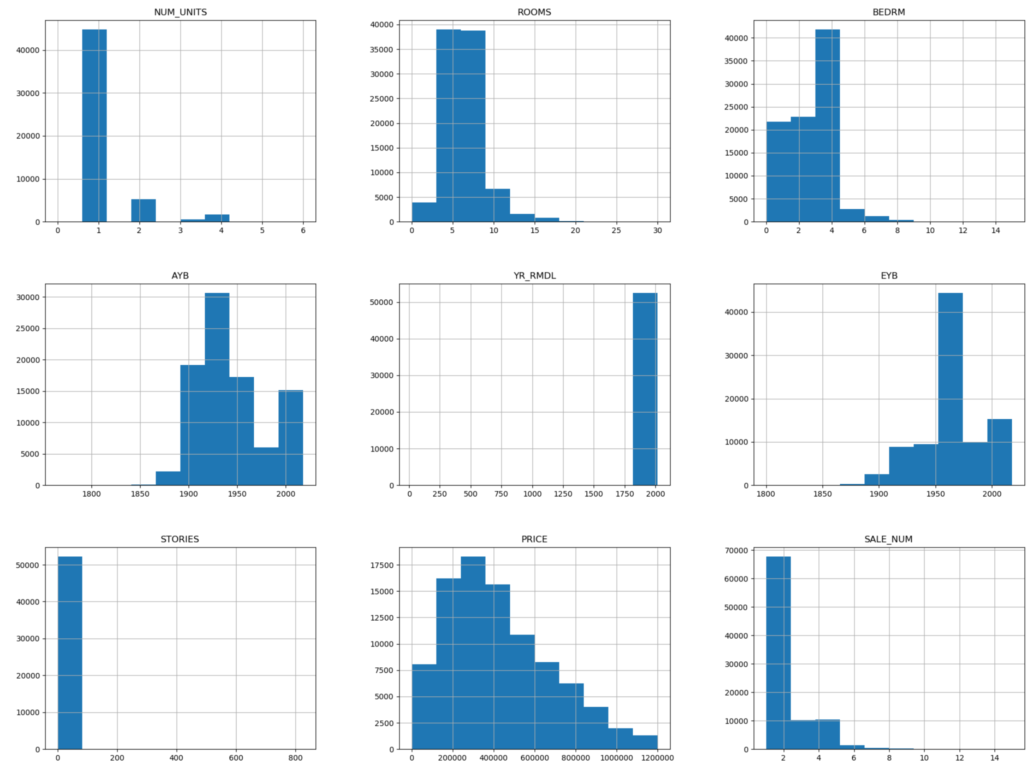
What type of variation occurs within my variables?

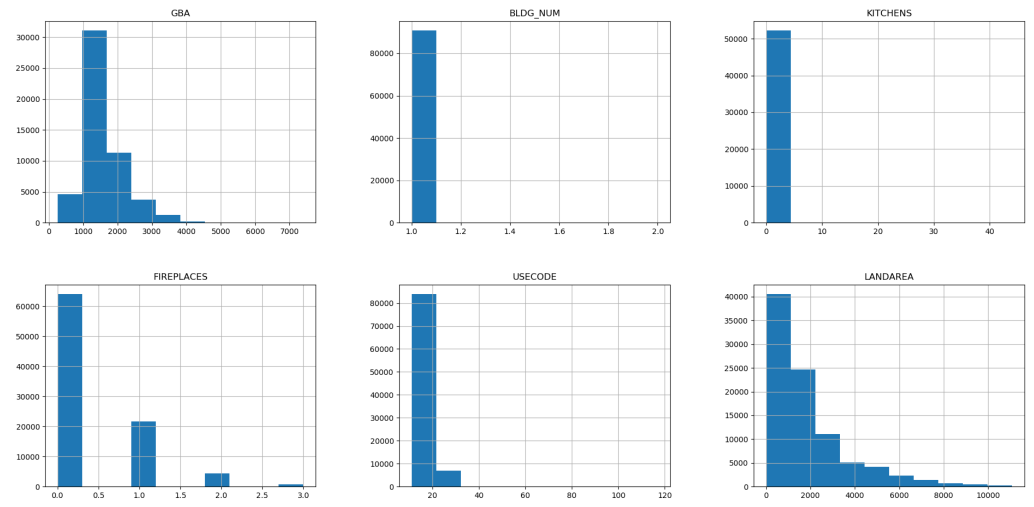
First we look at the price column, the value that I try to predict.



The `PRICE` column has 4655 outlier values. An option would be removed them as they represent less than 5% of data

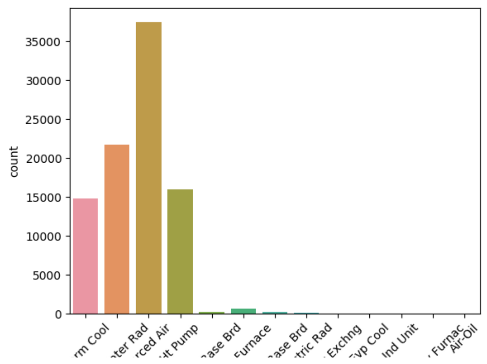
Numerical

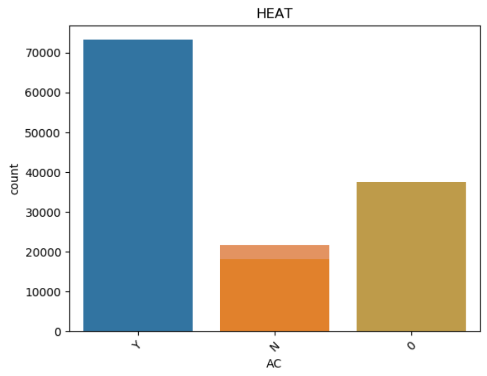


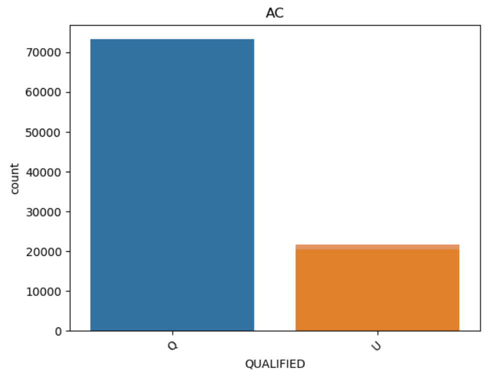


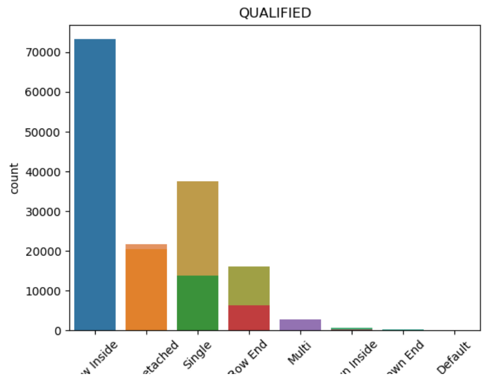
A couple of feature have large outliers

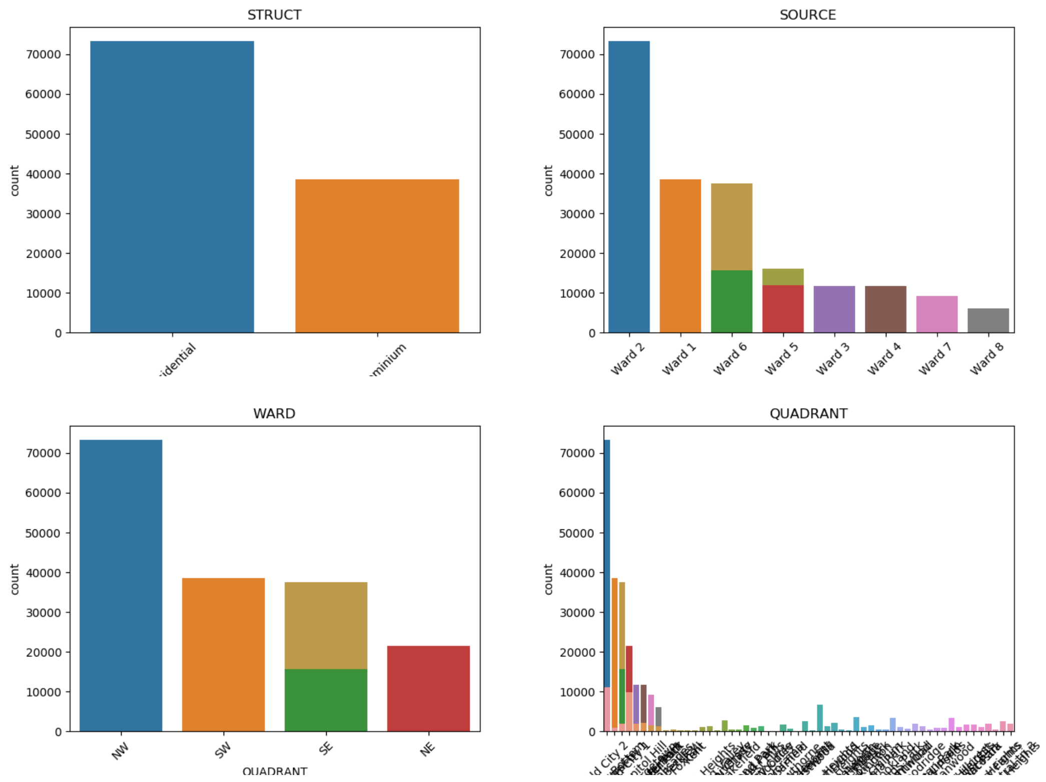
Categorical









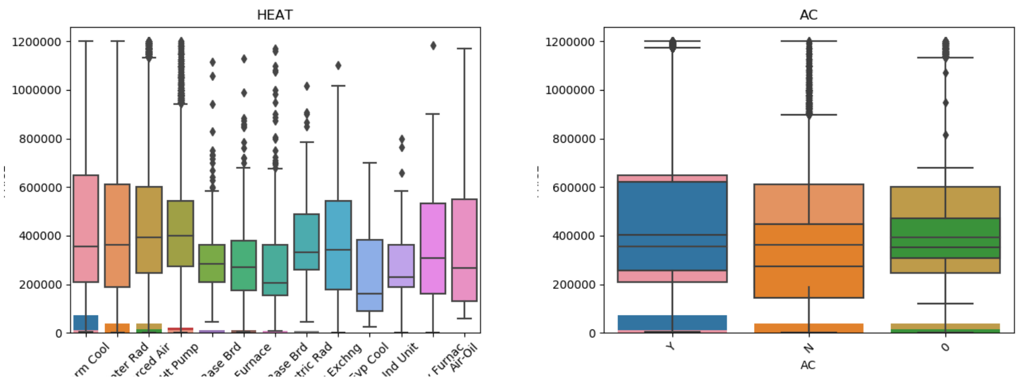


What type of covariation occurs between my variables?

Variation between columns can be seen in the figure below

Choosing most important features would show us in detail how these features relate to each other:

Let's see how categorical columns coralate with PRICE column



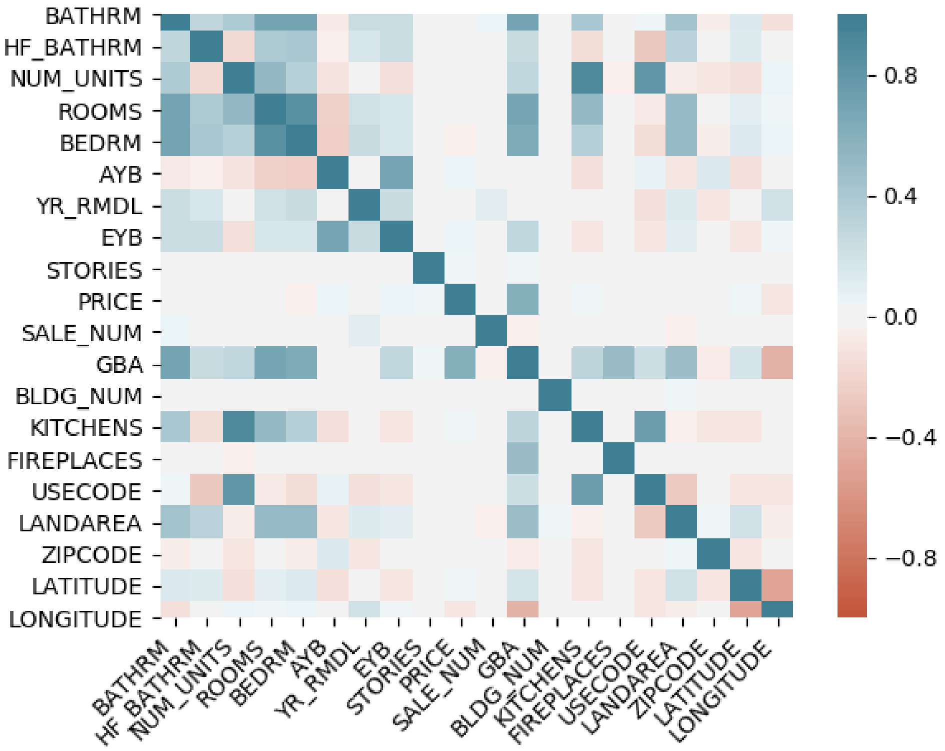


Figure 1: corr

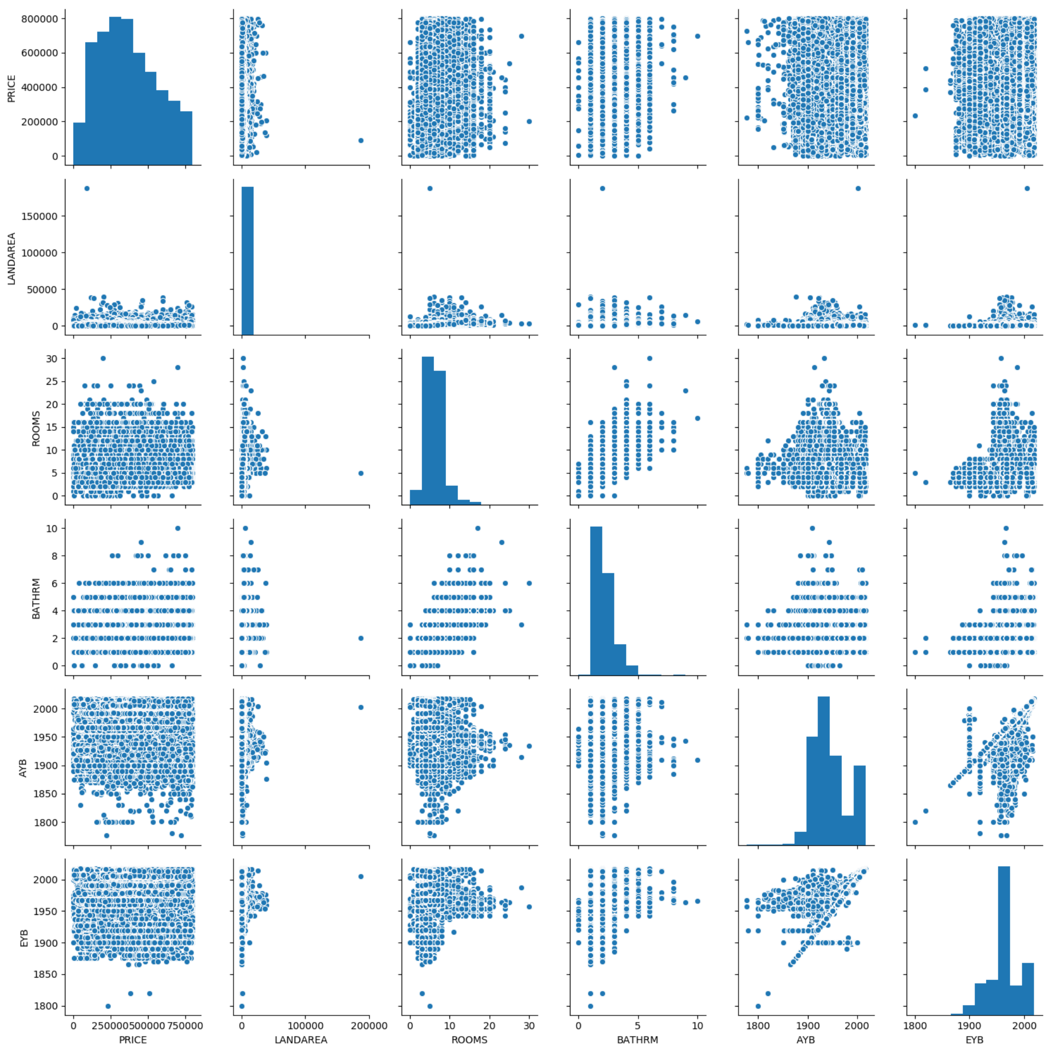
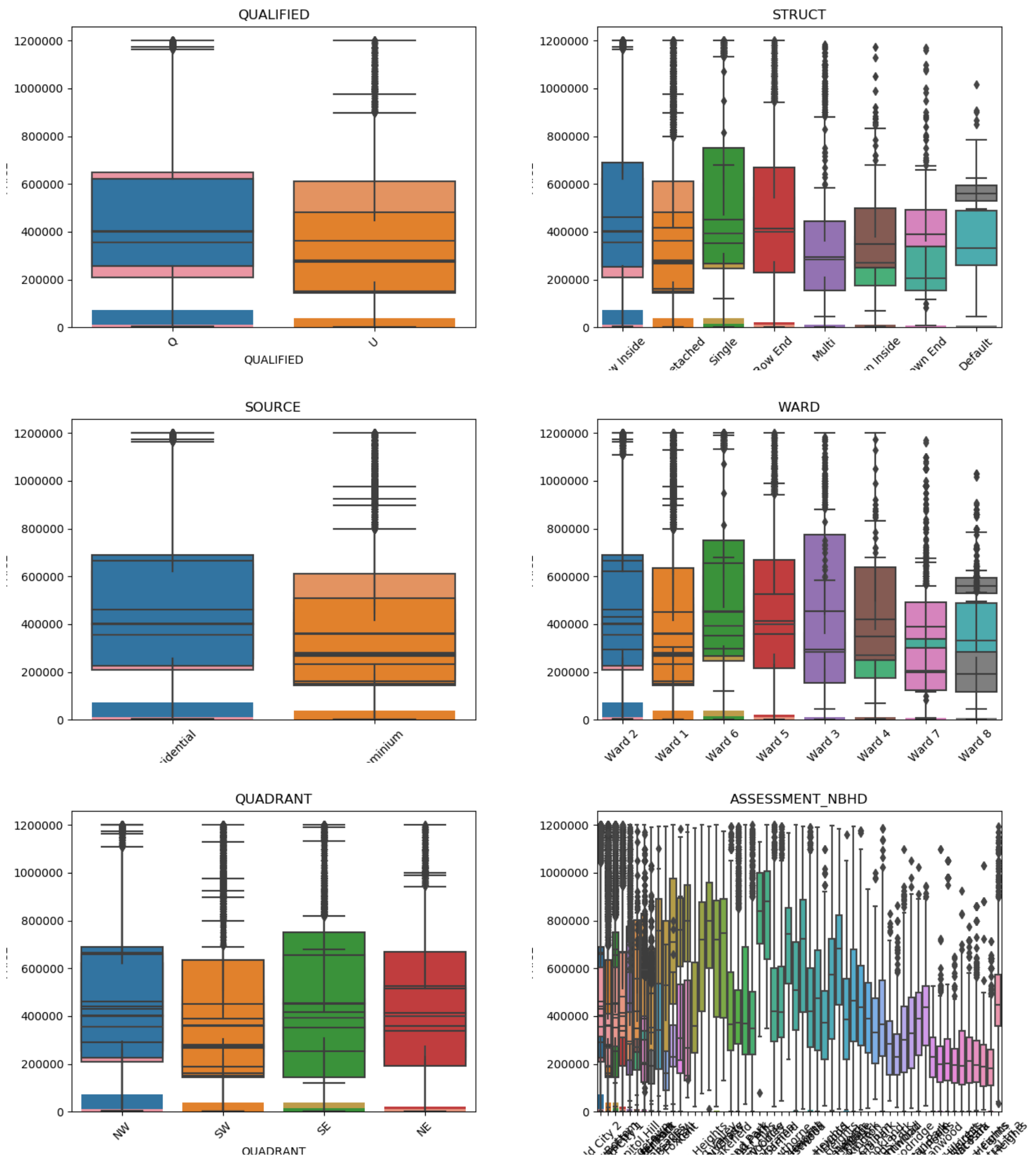


Figure 2: numerical pairwise



We can see that per neighbourhod price range differs so we we zoom it a little bit per median price

##PCA

From numerical features only 4 components explain 99% of the variance

Some intesting plot: plot Map

plot on map

Observation: we can see that North-West has expensive houses

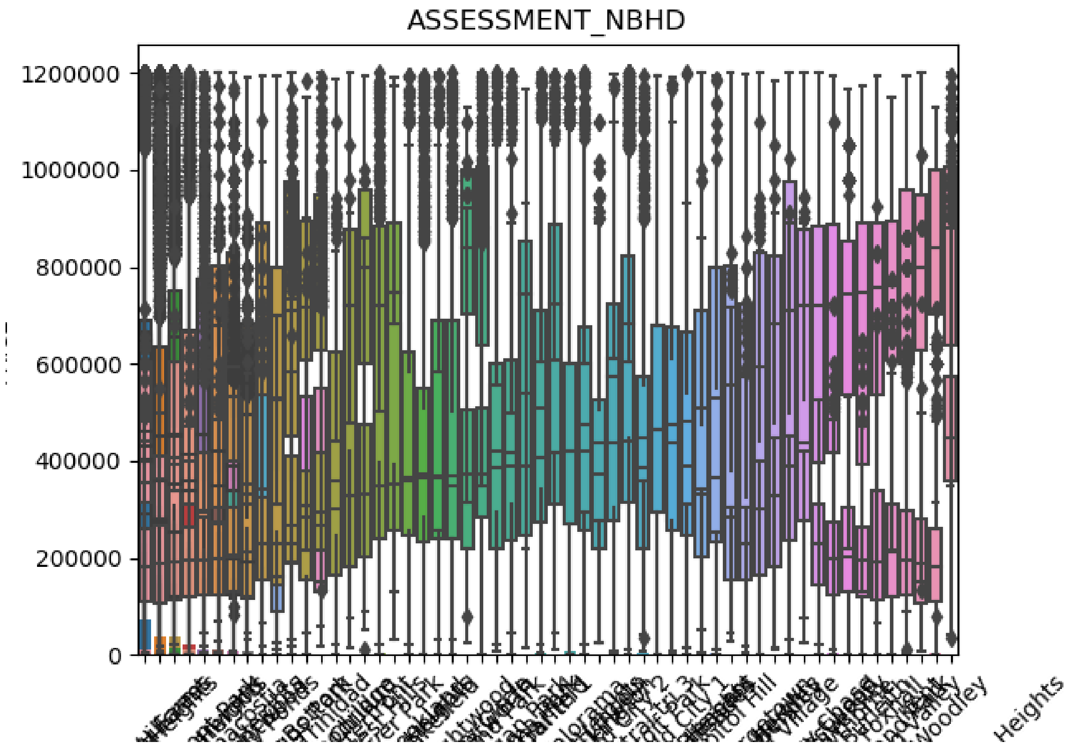


Figure 3: Meian price per neighbourhood

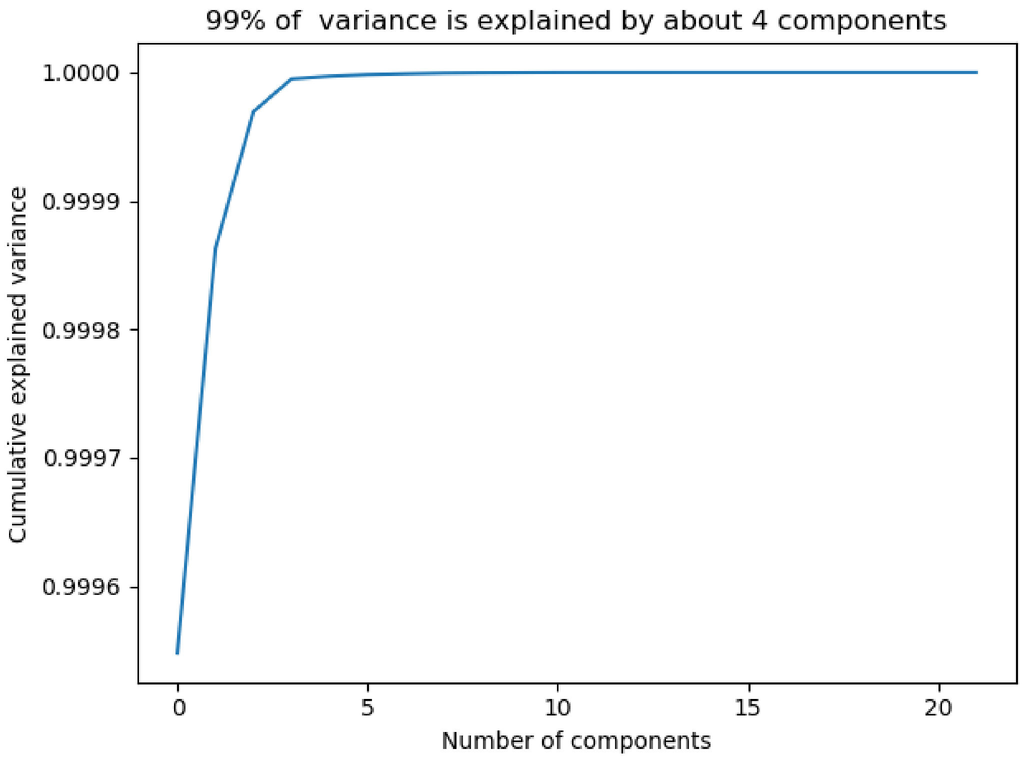

99% of variance is explained by about 4 components
Cumulative explained variance
1.0000
0.9999
0.9998
0.9997
0.9996
0
5
10
15
20
Number of components

Figure 4: PCA

Data processing

After EDA some data processing is required - remove columns with no variation - remove outliers regarding columns PRICE, FIREPLACES, LANDAREA - add a couple feature engineering columns: ratio between bedrooms and rooms, stories and living area, years of house since build , yeards of house since remodeled

Regression Models

Linear Regression

Different combinations of features and feature price tranformations, but this model is too simple for such data

name	EV	MAE	r2	RMSE	max_error
lin_simple	0.55	97268.36	0.55	127492.14	2458603.92
lin_log10	0.53	0.13	0.53	0.17	1.61
lin_sqrt	0.55	81.21	0.55	105.79	1457.71
lin______log	0.53	0.3	0.53	0.4	3.7
lin_comb0	0.24	125093.19	0.24	165680.56	5743210.07
lin_comb1	-0.14	137774.93	-0.14	202373.04	12692410.06
lin_comb2	0.31	122764.38	0.31	157340.08	3997288.0
lin_comb3	0.43	110459.09	0.43	142531.27	675468.0
lin_comb4	0.26	129887.61	0.26	163364.18	3291952.0
lin_comb5	0.46	107613.75	0.46	139188.01	1176272.28

GradientBoost

Gradient boosting is a machine learning technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees.

name	EV	MAE	r2	RMSE	max_error
gradsimple	0.7	77878.03	0.7	104299.53	663640.63
gradlog10	0.65	0.11	0.65	0.15	0.9
gradsqrt	0.69	66.52	0.69	88.92	532.51
xg_400_log	0.65	0.25	0.65	0.34	2.08
grad_comb0	0.47	107406.77	0.47	137976.15	530732.41
grad_comb1	0.45	109735.75	0.45	140046.31	553400.78
grad_comb2	0.5	103469.16	0.5	133469.4	558932.02
grad_comb3	0.55	97318.09	0.55	127395.34	557618.39
grad_comb4	0.54	98072.06	0.54	127839.75	540362.36
grad_comb5	0.55	97247.4	0.55	126860.91	542116.1

RandomForest

Random forest is a Supervised Learning algorithm which uses ensemble learning method for classification and regression. Random forest is a bagging technique and not a boosting technique. The trees in random forests are run in parallel.

Running simple classifiers we get these results

name	MAE	r2	RMSE	max_error

After trying different hyper parameters and running a randomized search on hyper parameters we get:

name	MAE	r2	RMSE	max_error
rf	156709.45	-0.14	210002.65	635000.0
rf400	151426.89	-0.07	203276.95	629172.0
rftune	137795.46	0.31	163011.09	490026.72
rf_100_log10	0.14	0.31	0.18	0.9
rf_400_log10	0.14	0.31	0.18	0.91
rf_400_log	0.32	0.31	0.42	2.08

Feature selection

Different combinations were used to test the algorithm

```
comb = [
["LANDAREA", "BEDRM", "ROOMS", "BATHRM", "HF_BATHRM", "AYB", "EYB", "FIREPLACES", "STORIES"],

["BATHRM", "HF_BATHRM", "AYB", "EYB", "FIREPLACES", "STORIES", "QUALIFIED", "CNDTN"],

["BATHRM", "HF_BATHRM", "ROOMS", "AYB", "EYB", "STORIES", "QUALIFIED", "CNDTN", "QUADRANT"],

["ATHRM", "HF_BATHRM", "ROOMS", "AYB", "STORIES", "QUALIFIED", "CNDTN", "WARD"],

["BATHRM", "HF_BATHRM", "ROOMS", "AYB", "EYB", "STORIES", " QUALIFIED", "CNDTN", "ZIPCODE"],

["BATHRM", "HF_BATHRM", "ROOMS", "AYB", "EYB", "STORIES", " QUALIFIED", "CNDTN", "ASSESSMENT_NBH
]
```

Although different subset combinations were tried there was no clear improvement

name	MAE	r2	RMSE	max_error
rf	156709.45	-0.14	210002.65	635000.0
rf400	151426.89	-0.07	203276.95	629172.0
rftune	137795.46	0.31	163011.09	490026.72
rf_100_log10	0.14	0.31	0.18	0.9
rf_400_log10	0.14	0.31	0.18	0.91

name	MAE	r2	RMSE	max_error
rf_400_log	0.32	0.31	0.42	2.08
rf_comb0	149579.1	0.19	177480.72	492658.65
rf_comb1	149252.42	0.19	177435.91	493537.32
rf_comb2	145243.66	0.23	172223.76	513858.18
rf_comb3	145997.44	0.23	172099.83	507289.36
rf_comb4	145259.06	0.23	172484.53	517800.21
rf_comb5	145922.58	0.23	172585.49	504692.43

Tuning hypermaters

For tuning parameters different parameters were tried

```
{
    'max_features': ['auto', 'sqrt', 'log2'],
    'min_samples_split': array([0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1. ]),
    'max_depth': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19]
}
```

And got the final version of:

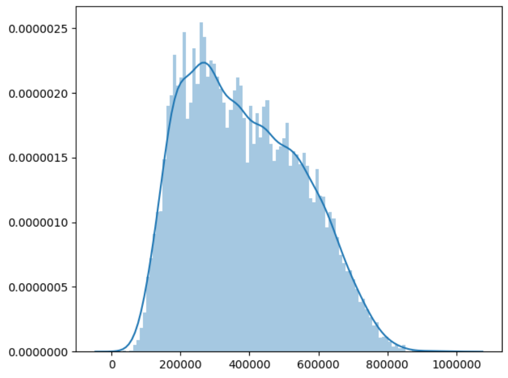
```
{'min_samples_split': 0.1, 'max_features': 'sqrt', 'max_depth': 18}
```

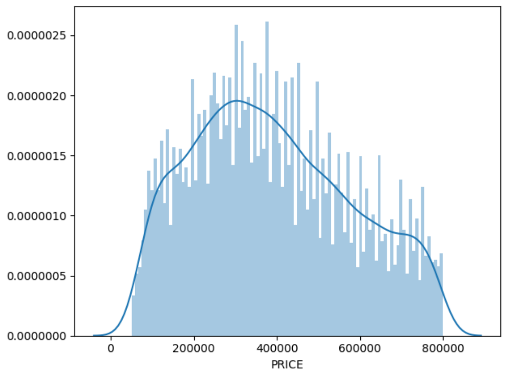
XGBoost

XGBoost is an optimized distributed gradient boosting library designed to be highly efficient, flexible and portable. It implements machine learning algorithms under the Gradient Boosting framework. XGBoost provides a parallel tree boosting (also known as GBDT, GBM) that solve many data science problems in a fast and accurate way.

name	EV	MAE	r2	RMSE	max_error
xgb	0.43	160083.13	-0.09	197846.36	554660.23
xgb20	0.65	86530.85	0.64	113248.39	545448.81
xgb100	0.7	75181.37	0.7	103808.83	570595.81
xgb100sqrt	0.68	64.89	0.68	89.02	517.86
xg_100_log10	0.65	0.11	0.65	0.15	1.02
xg_400_log10	0.63	0.11	0.63	0.15	0.93
xg_400_log	0.63	0.25	0.63	0.35	2.41
xg_comb0	0.45	105287.45	0.45	140907.3	679083.19
xg_comb1	0.43	108694.64	0.43	143113.26	638272.56
xg_comb2	0.49	101872.58	0.49	135876.38	655555.44
xg_comb3	0.52	97480.49	0.52	131858.26	668339.5
xg_comb4	0.51	97535.55	0.51	132096.97	651970.25
xg_comb5	0.53	95647.39	0.53	129583.88	669786.51

Pred vs Test set





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Conclusions

- Houses with high prices were predicted poorer
- XGBOOST And Gradient Boosting performed very well
- more CPU power would be needed in order to hyper tune parameters. Some RandomisedSearchCV took more than 12 hours