

House Price Prediction

Machine Learning for Advanced Regression

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Overview:

- **Problem to be solved and Audience:**

Financial media focus most of their attention on stocks and bonds, but the world's biggest asset class is actually residential property. With an estimated value of about \$200trn, homes are collectively worth about three times as much as all publicly traded shares (cited from '*The Economics*'). According to Zillow and Redfin data, house prices almost doubled globally during the past five years in USA. Houses could not only mean your dream home, but also could be valuable investments in this fast growing economic era.

What variables/parameters are most important in determining house price is very hard to predict manually due to too many features should be taken into consideration. For example, intuitively, we would assume house size, how old is the house, neighborhood, house style, quality, etc, they are all valuable attributes, and the house price would be an overall reflection of all those values. Correctly predict/evaluate the house price would be necessary to make wise investment for investors, or to generate maximum revenue for real estate developers.

This project would provide data evidence for home-buyer and real estate investors to evaluate house price, and provide insightful information for real estate developers to form designing and

marketing strategies. And would attract interests of companies like Zillow and Redfin to better collect house information for further improved modeling purpose.

- **Data:**

This project would use 'Ames Housing Dataset' from kaggle competition as training and testing data. [Data from here.](#)

Explanation:

The dataset contains 79 explanatory variables, with 44 categorical variables and 35 numerical variables.

Detailed explanation of each variable and its categorical groups is uploaded into github ([info from here](#)).

- **Solution:**

After cleaning and wrangling data to fit machine learning,

We first used exploratory data analysis (EDA) to investigate correlations between different variables/features and house prices, to generate insight of interesting features.

Second, we used Xgboost algorithm for machine learning modeling, and extract the feature importance level, to extract insight of feature importance and to predict new data.

Third, we used hypothesis driven study to investigate causal or correlation/association relationship of features with house prices, and then used Monte Carlo simulation using best model from machine learning to validate hypothesis.

Deliverables:

- Github repository
 - Data cleaning, wrangling, processing protocol
 - Machine learning with parameter fine tuning
 - Statistical analysis and storytelling
 - Prediction of new data

- Final report and presentation

Additional investigations:

It would be nice to compare different machine learning algorithms, and compare how feature importance features are varied for different algorithms.

Data Wrangling:

- **Data Cleaning:**

First, load data to pandas dataframe. Fill missing values (NA) with appropriate value according to explanatory of variables, for example, NA could be filled either with a 0 or a string indicate for a category.

Deal with abnormal data if any.

- **Data Wrangling:**

- ❖ Change year to age
- ❖ Convert selling year and month data to datetime object, and set 'datetime' to index for 'timeseries' analysis
- ❖ Re-organize data with categorical data grouped together and numeric data grouped together
- ❖ Preprocess categorical data using LabelEncoder() and OneHotEncoder(), save mapping dictionaries for standardized data processing protocol
- ❖ Use MinMaxScaler to normalize data
- ❖ Split data to training and testing set for standardized data input for different machine learning algorithms
- ❖ Save training and testing input into csv files for future load
- ❖ Standardize data processing of new data for future prediction

Exploratory Data Analysis and Statistical Inference:

- **Distribution plot:**

In this section, I first explored the data distribution to get a general idea of data complexity. Track features which doesn't have enough complexity, they could be potentially not important due to not enough diversity or variance generated to contribute to difference. Store these columns in 'single_columns' list.

Generally speaking, the features that are in 'single_columns' are prone to be miscellaneous, key words can be summarized as:

- ❖ Porch
- ❖ Fence
- ❖ Pool
- ❖ Utility
- ❖ Outside condition

- **Correlation plot:**

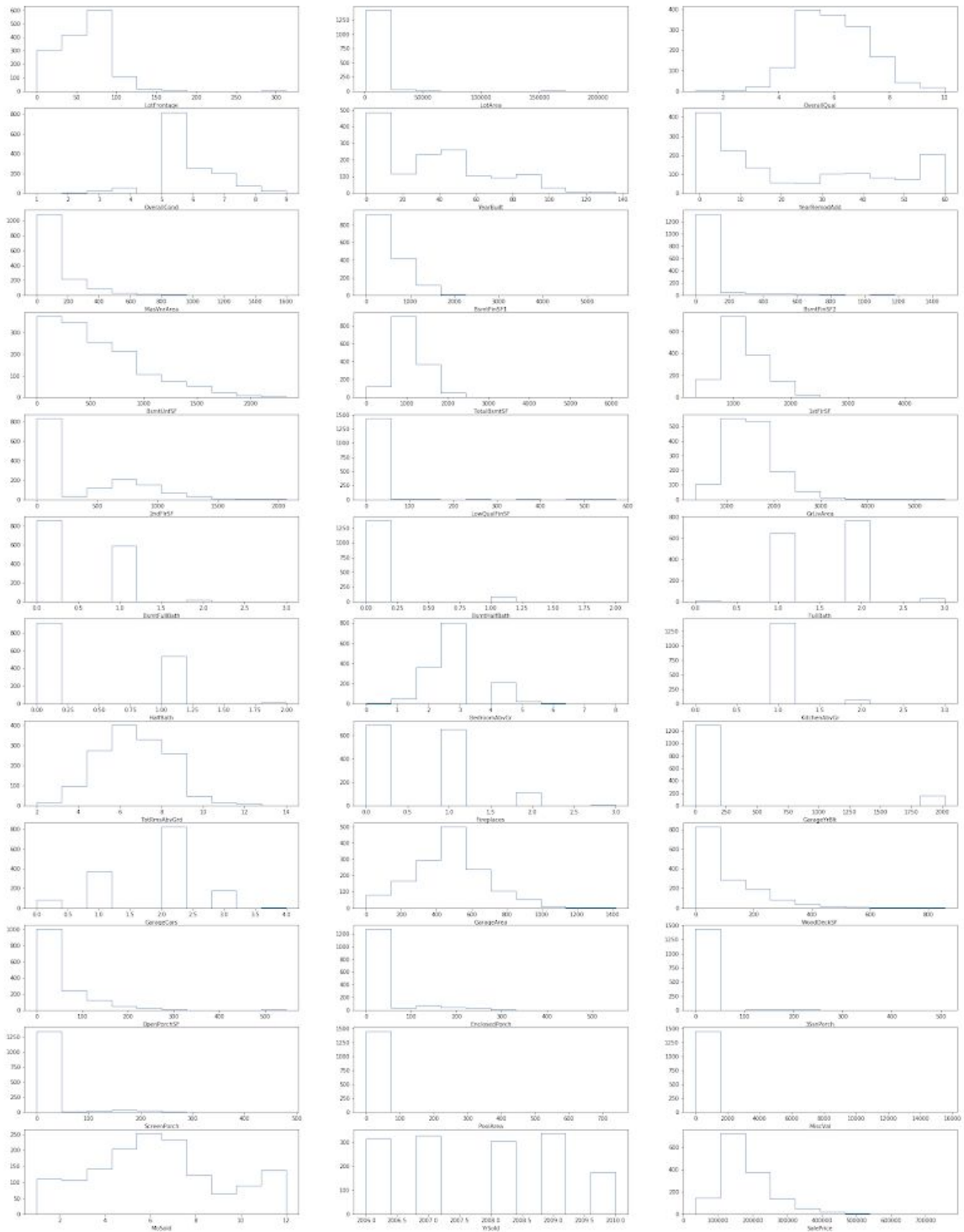
In this section, I plotted the relationship between 'SalePrice' and each feature, track the interesting columns that have noticeable correlation with 'SalePrice', those are potential important features to be analyzed. Store the information in 'interesting_columns' list.

There are four key words can be summarized to describe the common attributes of features in 'interesting_columns':

- ❖ Quality
- ❖ Age
- ❖ Size
- ❖ Neighborhood

Fig1: Distribution of variables. For categorical data, mean and standard deviation were drawn for each category, and for continuous data, histogram was used.

Fig1



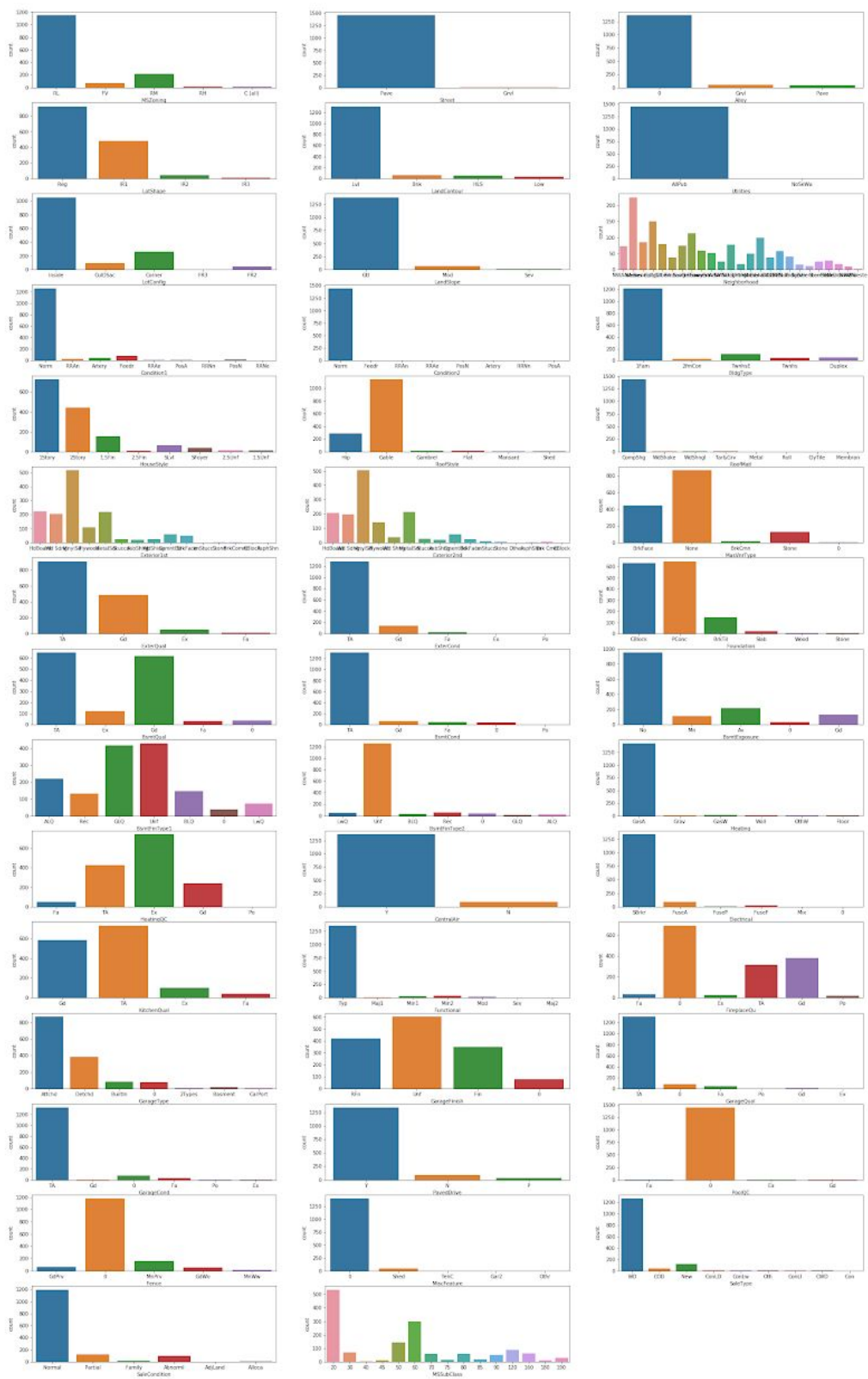
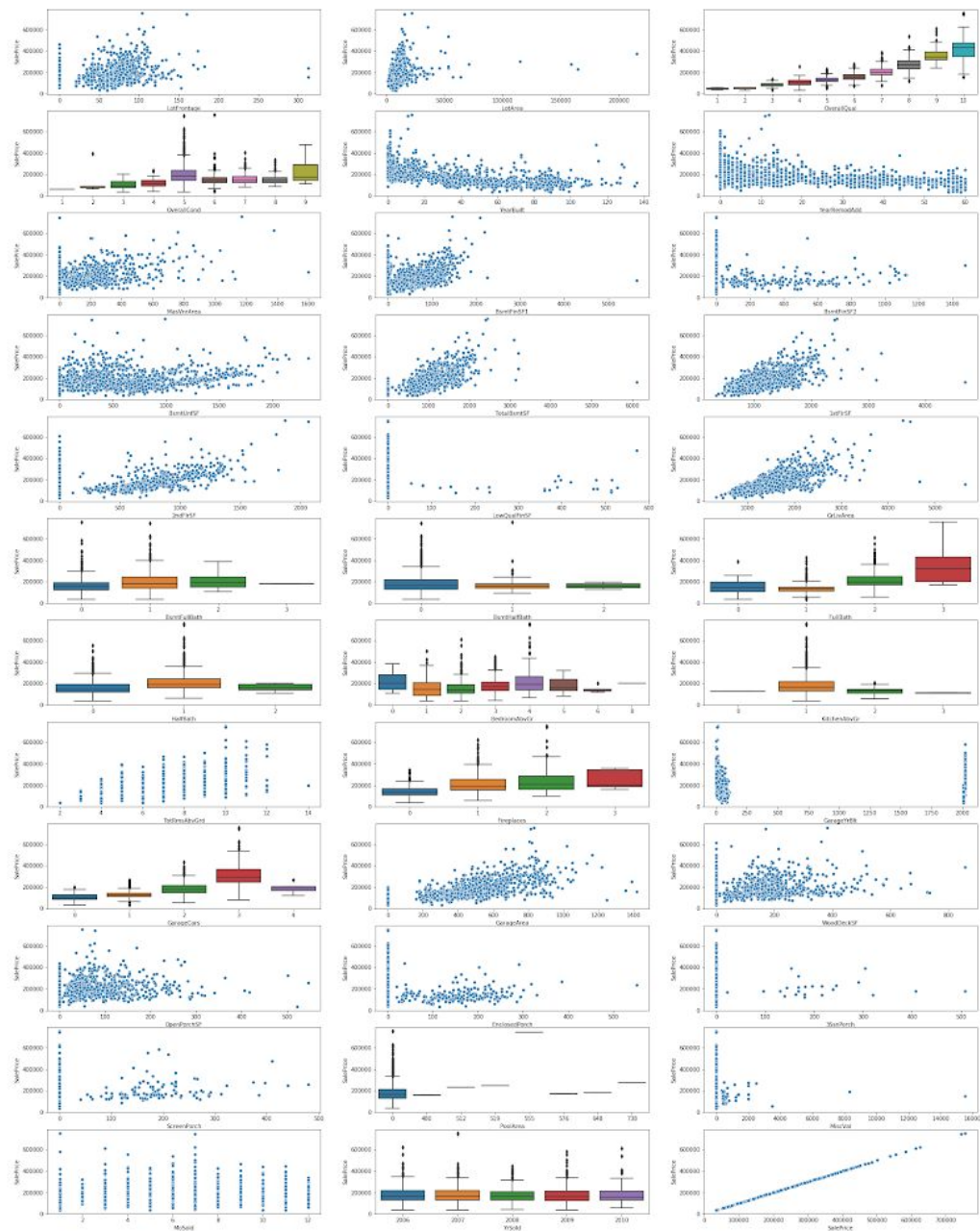


Fig2: Correlation plot of variables. For more discrete data (unique values ≤ 10), box plots of median and percentiles were used, and for more continuous data, scatter plots were used.





Machine Learning:

In this section, I used Xgboost as model to train data, and fine tuned parameters to reach maximum testing accuracy power.

- **Random grid search to get a reasonable starting point:**

```
model = xgb.XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
    colsample_bynode=1, colsample_bytree=1, gamma=0,
    importance_type='gain', learning_rate=0.15000000000000002,
    max_delta_step=0, max_depth=4, min_child_weight=1, missing=None,
    n_estimators=50*n, n_jobs=1, nthread=None,
    objective='reg:squarederror', random_state=0, reg_alpha=0,
    reg_lambda=1, scale_pos_weight=1, seed=None, silent=None,
    subsample=0.8500000000000001, verbosity=1)
```

- **Fine tune parameters:**

- ❖ I plotted accuracy curve to find best value for the following parameters:

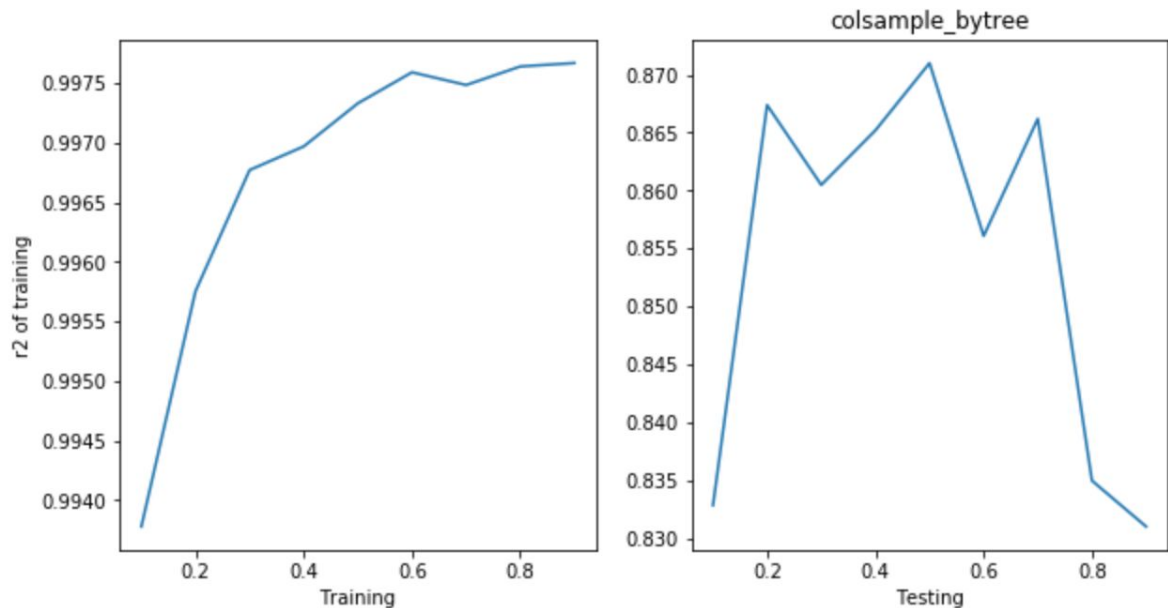
- N_estimator
- Learning_rate
- Maximum tree depth
- Min tree nodes
- subsample/colsample
- Base score

- ❖ Experiment outcome was documented into a dataframe, and saved as '.csv' file.

	parameter_name	best_parameter(train,test)	best_score(train,test)
0	n_estimators	(400, 350)	(0.999807244639819, 0.8621939187139758)
1	Learning Rate	(0.16, 0.06)	(0.9997778081287881, 0.8630069628715896)
2	max_depth	(7, 2)	(0.999982526524428, 0.8579016329547222)
3	subsample	(0.64, 0.56)	(0.9979672879949777, 0.8571673758577336)
4	colsample_bytree	(0.8, 0.4)	(0.997669999620488, 0.8710150491582573)
5	min_child_weight	(0.0, 0.2)	(0.9970036828809768, 0.8691081680526537)

❖ Plotting accuracy performance example:

Fig3. y axis is accuracy score r-square, x axis is colsample_bytree value.
Left panel is training process, right panel is testing process.



● **Conclusion: The best model found is:**

```
# Best model for testing accuracy:
model = xgb.XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
    colsample_bynode=1, colsample_bytree=0.4, gamma=0,
    importance_type='gain', learning_rate=0.2,
    max_delta_step=0, max_depth=3, min_child_weight=1, missing=None,
    n_estimators= 350, n_jobs=1, nthread=None,
    objective='reg:squarederror', random_state=0, reg_alpha=0,
    reg_lambda=1, scale_pos_weight=1, seed=None, silent=None,
    subsample=0.65, verbosity=1)
```

Saved model to 'best_xgb_model.dat' for future prediction.

Prediction of new data:

- Preprocess new data accordingly as training data
- Load best model and predict
- Scale final sale price back to real number as original input
- Save results in dataframe and '.csv' file

Case Study Story:

In this section, I chose one feature from each interesting feature keywords (Quality, age, size) to investigate causal relationships: House overall quality, age, living area. I also investigated a more ambiguous feature, the bedroom number, since intuitively we would think it is important.

- **Time Series View:**

Fig4. Age of house and Sale Price correlation trends over time.

Y axis is average house sale price (red, SalePrice) or average home age (black, YearBuilt) of sold houses within a month. X axis is Sold Time with precision of a month.

We see a negative correlation along time between the two.

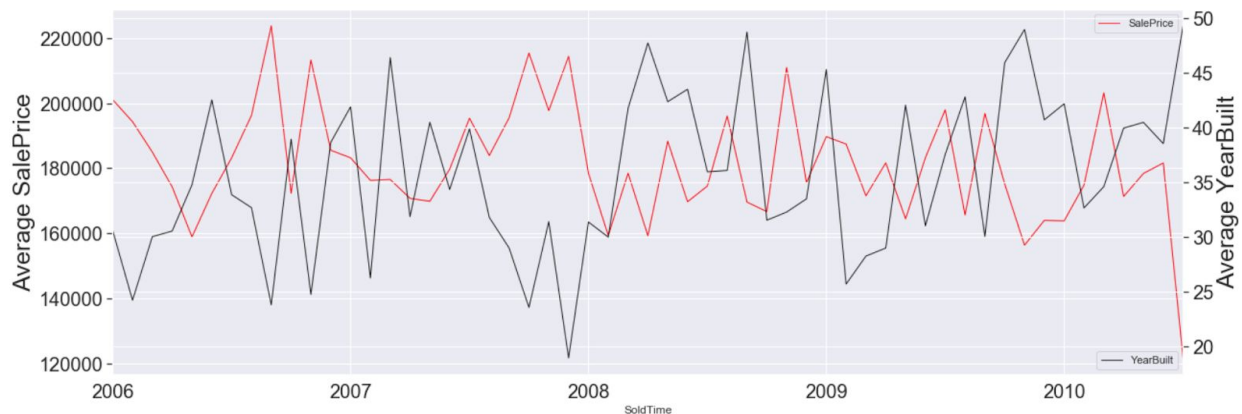


Fig5. House quality and Sale Price correlation trends over time.

Y axis is average house sale price (red, SalePrice) or average home quality (black, OverallQual) of sold houses within a month. X axis is Sold Time with precision of a month.

We see a positive correlation along time between the two.

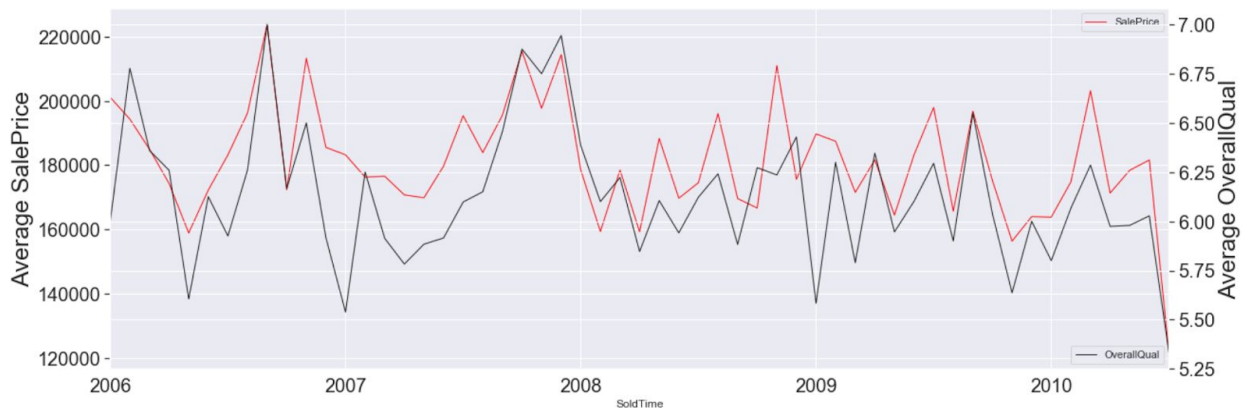
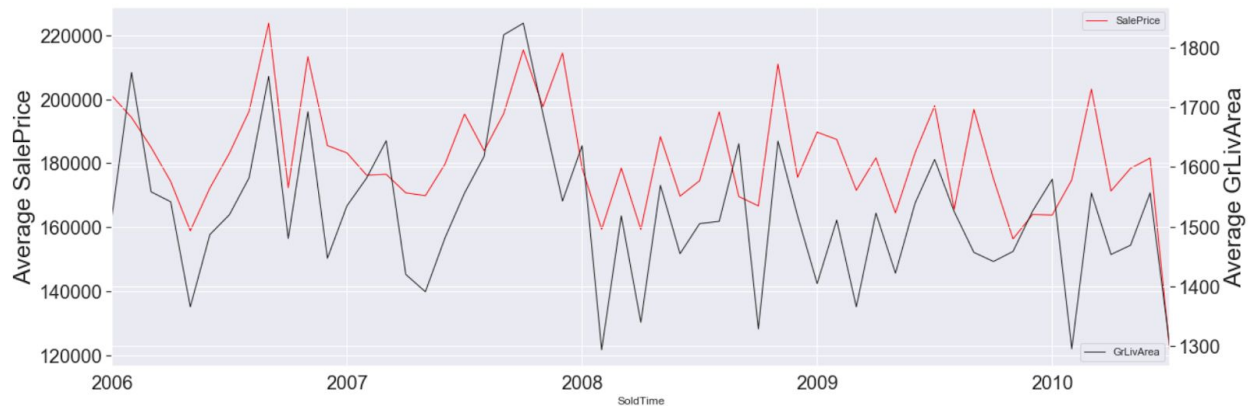


Fig5. Living area and Sale Price correlation trends over time.

Y axis is average house sale price (red, SalePrice) or average living area (black, GrLivArea) of sold houses within a month. X axis is Sold Time with precision of a month.

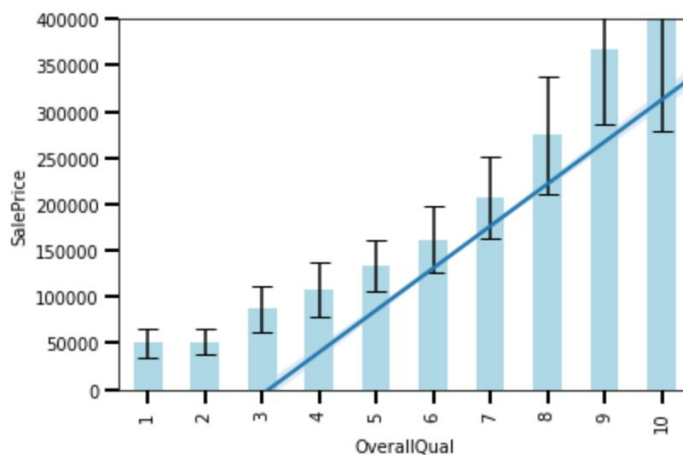
The correlation is harder to predict, most times are positively correlated, but sometimes see negative effect.



- **Statistical inference:**

Time series are most suitable for us to draw a trend insight, which unfortunately, from this dataset, we didn't see a trend pattern, therefore, more suitable way to visualize correlation is to use mean and standard deviation plot, and fit data using regression. I also used ANOVA test difference and confidence interval between groups.

Fig6. plot the mean and standard deviation of house prices grouped by overall quality of house. Fit with linear regression.



```

=====
                        OLS Regression Results
=====
Dep. Variable:          OverallQual      R-squared (uncentered):          0.928
Model:                  OLS              Adj. R-squared (uncentered):      0.928
Method:                 Least Squares    F-statistic:                     1.879e+04
Date:                   Wed, 04 Sep 2019  Prob (F-statistic):              0.00
Time:                   10:30:10          Log-Likelihood:                  -2828.1
No. Observations:      1460              AIC:                             5658.
Df Residuals:          1459              BIC:                             5663.
Df Model:               1
Covariance Type:        nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
SalePrice	3.049e-05	2.22e-07	137.068	0.000	3.01e-05	3.09e-05

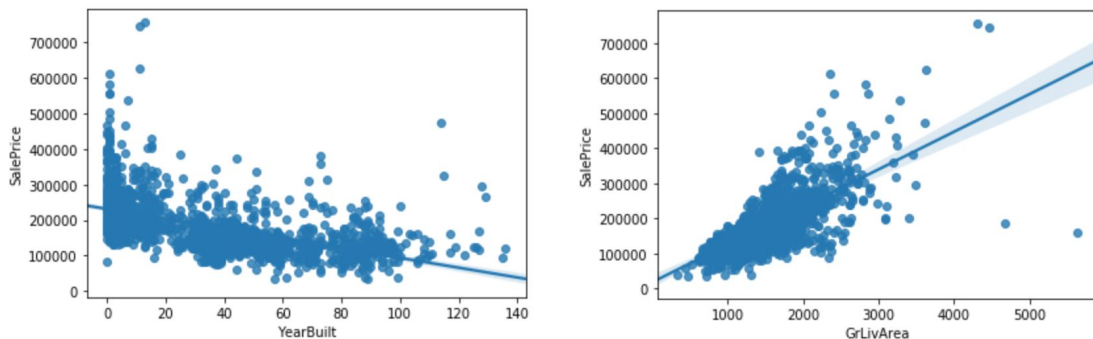
```

=====
Omnibus:                812.455      Durbin-Watson:                1.794
Prob(Omnibus):           0.000      Jarque-Bera (JB):             10480.098
Skew:                    -2.319      Prob(JB):                     0.00
Kurtosis:                15.278      Cond. No.:                    1.00
=====

```

The above statistics showed strong correlation of x, y in data, r-squared = 0.928, and the probability to get this statistics given the null hypothesis that x,y is not related is 0.00 (Prob of F-statistic). The coefficient (line slope) within 95% confidence interval is [3.01e-5, 3.09e-5].

Fig7. Correlation for house age and house size with sale price:



We now can have a good sense of the positive and negative correlation of features and sale prices.

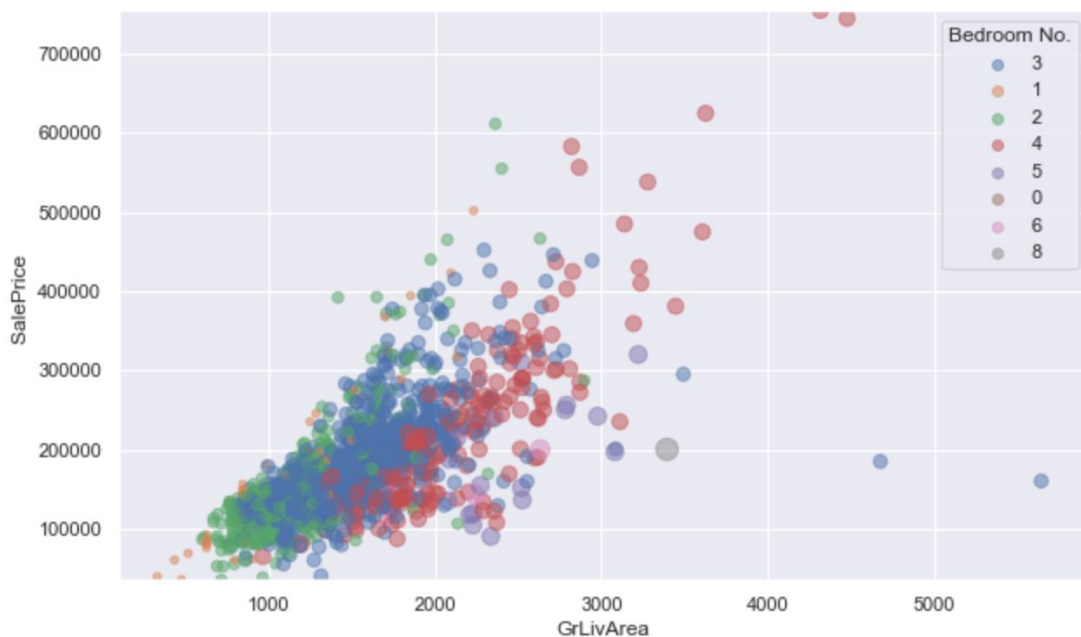
- **Investigate the relationship between bedroom number and sale price.**

Intuitively, we would think bedroom numbers could affect house prices a lot, due to the market impression that renting a 3 bedroom house is much more expensive than renting a 2 bedroom or 1 bedroom house. Is that true in metadata?

EDA:

We used scatter plot to show this information with bedroom numbers in different colors:

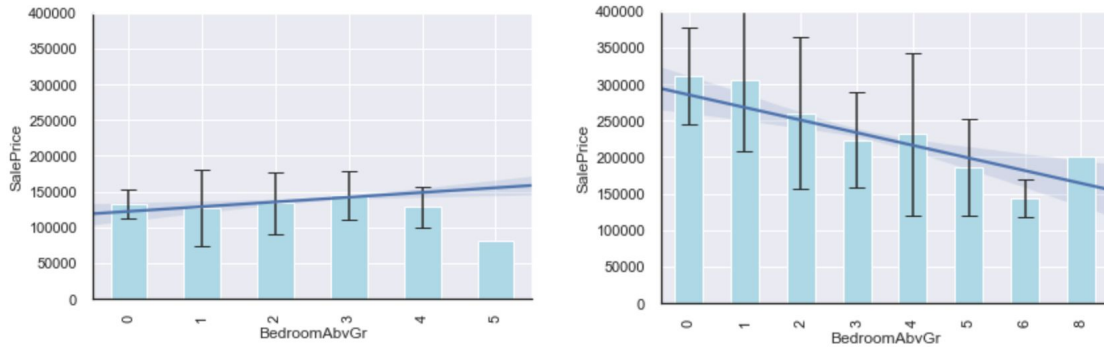
Fig8.



Surprisingly, we would see that generally speaking, bedroom numbers negatively correlated with SalePrice, especially after living area bigger than 1500 square feet.

We separate the data for two parts, df1500U contain house data with living area more than 1500 square feet, and df1500L contain house data with living area less than 1500 square feet.

Fig9. left: df1500L, right: df1500U.



We can see, for smaller houses, bedroom number slightly positively correlated with house price, but the effect is very subtle, but for bigger rooms, bedroom number strongly negatively correlated with house price. ANOVA analysis with post Tukey Hsd analysis showed significant group difference, with p value smaller than 0.002.

Multiple Comparison of Means - Tukey HSD, FWER=0.03						
group1	group2	meandiff	p-adj	lower	upper	reject
0	1	-5463.3333	0.9	-183353.6785	172427.0118	False
0	2	-50298.0145	0.9	-214094.9474	113498.9185	False
0	3	-86825.1878	0.6258	-247820.3807	74170.0052	False
0	4	-79340.5218	0.7199	-240943.0847	82262.041	False
0	5	-124523.3333	0.2594	-296477.6105	47430.9438	False
0	6	-166554.3333	0.0873	-358207.0777	25098.4111	False
0	8	-110333.3333	0.9	-431029.7138	210363.0471	False
1	2	-44834.6812	0.6362	-128806.8547	39137.4924	False
1	3	-81361.8544	0.0167	-159728.5747	-2995.1342	True
1	4	-73877.1885	0.0511	-153484.2171	5729.8401	False
1	5	-119060.0	0.0023	-218005.2582	-20114.7418	True
1	6	-161091.0	0.0015	-291293.4006	-30888.5994	True
1	8	-104870.0	0.9	-393085.2999	183345.2999	False
2	3	-36527.1733	0.0242	-72938.7536	-115.593	True
2	4	-29042.5073	0.227	-68051.985	9966.9703	False
2	5	-74225.3188	0.0143	-144756.3365	-3694.3012	True
2	6	-116256.3188	0.0138	-226424.9417	-6087.696	True

Question: Correlation or Causation?

Is this a random association or actually driven by other factors or the bedroom number is a driven force to drag down house price for bigger rooms?

To answer this question, we would take advantage of machine learning models, to do a Monte Carlo simulation, which is to use random simulation to randomly assign bedroom numbers to houses, and then predict the house price to see whether altering bedroom number alone would drive the house price to change, or say whether more rooms really can drag the house price down.

We need a clean background to show the difference, otherwise since house price is a multi-factor driven outcome, we don't want other features to bother the outcome and bury the signal in background.

Keep in mind, the negative correlation only happens in bigger houses

Simulation Algorithm:

- ❖ Choose a random house with living area bigger than 1500 as a simulation base input
- ❖ Keep all other features the same with the chosen house, assign bedroom numbers randomly to house data
- ❖ Predict house price after processing data accordingly to protocol
- ❖ Draw mean and standard deviation and plot linear regression to visualize the data

Results:

- ❖ Results showed random trend. We don't see a strong correlation between bedroom number with house price.

Fig10. Simulation results of 3 independent simulation experiments.



Question:

Then what caused this observation that bedroom number is negatively correlated with house price, which is very counter-intuitive.

Hypothesis:

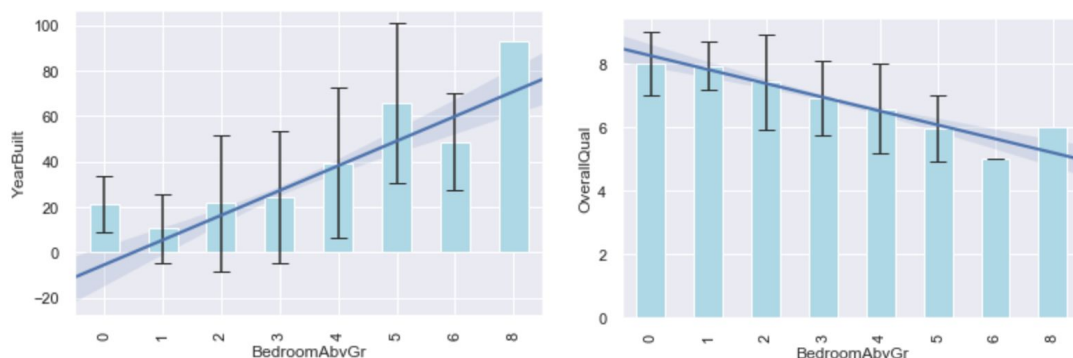
Bedroom number is actually correlated with other more important features, for example: house age. It could be possible that older houses tend to have more bedrooms, because family size is generally bigger in older times, and nowadays, family sizes get smaller because people tend to have fewer kids in the more modern era (This should be supported by other data), therefore, newer houses tend to have fewer bedrooms.

Another more important feature is: house quality. Bedroom number might be negatively correlated with house quality, because it's easier to maintain or fix for fewer bedrooms, house quality could also correlate with house age because older rooms tend to have worse condition than newer rooms.

Testing:

First of all, we need to see whether bedroom numbers are correlated with house age or overall quality.

Fig11. Plot of mean and standard deviation with linear regression of bedroom number and Yearbuilt or OverallQual.



	coef	std err	t	P> t	[0.025	0.975]
YearBuilt	0.0545	0.002	26.296	0.000	0.050	0.059
Omnibus:		89.762	Durbin-Watson:			1.005
Prob(Omnibus):		0.000	Jarque-Bera (JB):			123.564
Skew:		-1.023	Prob(JB):			1.47e-27
Kurtosis:		3.458	Cond. No.			1.00
	coef	std err	t	P> t	[0.025	0.975]
OverallQual	0.4488	0.006	69.923	0.000	0.436	0.461
Omnibus:		26.071	Durbin-Watson:			1.921
Prob(Omnibus):		0.000	Jarque-Bera (JB):			61.411
Skew:		0.139	Prob(JB):			4.62e-14
Kurtosis:		4.451	Cond. No.			1.00

The answer is yes! Bedroom number is positively correlated with house age, which is negatively correlated with house price. Bedroom number is also negatively correlated with house quality, which is positively correlated with house price.

Question:

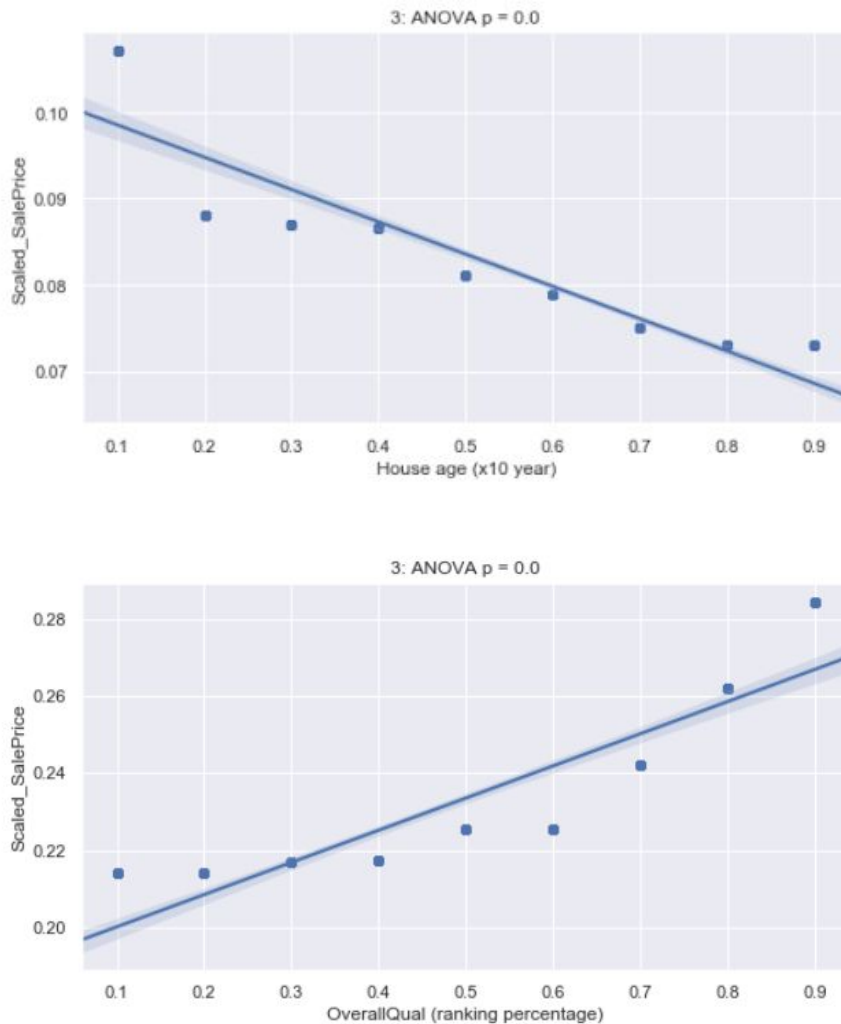
Are house age and quality driven forces to affect house age?

Testing:

We used the same simulation algorithm and change bedroom number to 'Yearbuilt' or 'OverallQual'.

The Answer is Yes!

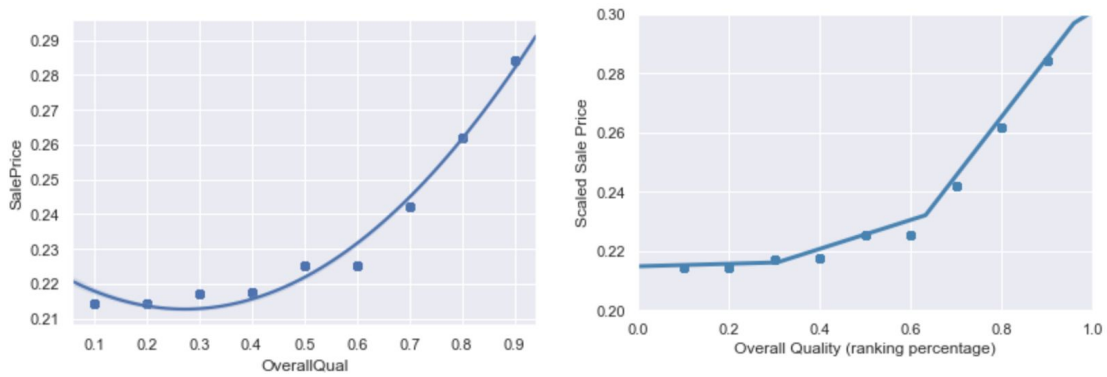
Fig12. Simulation results examples.



House price is strongly correlated with house age and Overall quality, although the correlation might not be linear, it showed the house prices would be capped to some point. It also gave us insight that house age would only affect house prices within a certain range, and overall quality below a certain point would also not contribute too much to house price difference.

We could use other functions to better fit with the simulation data. For example, higher order of polynomial regression (Fig13 left) or sigmoid curve (Fig13 right).

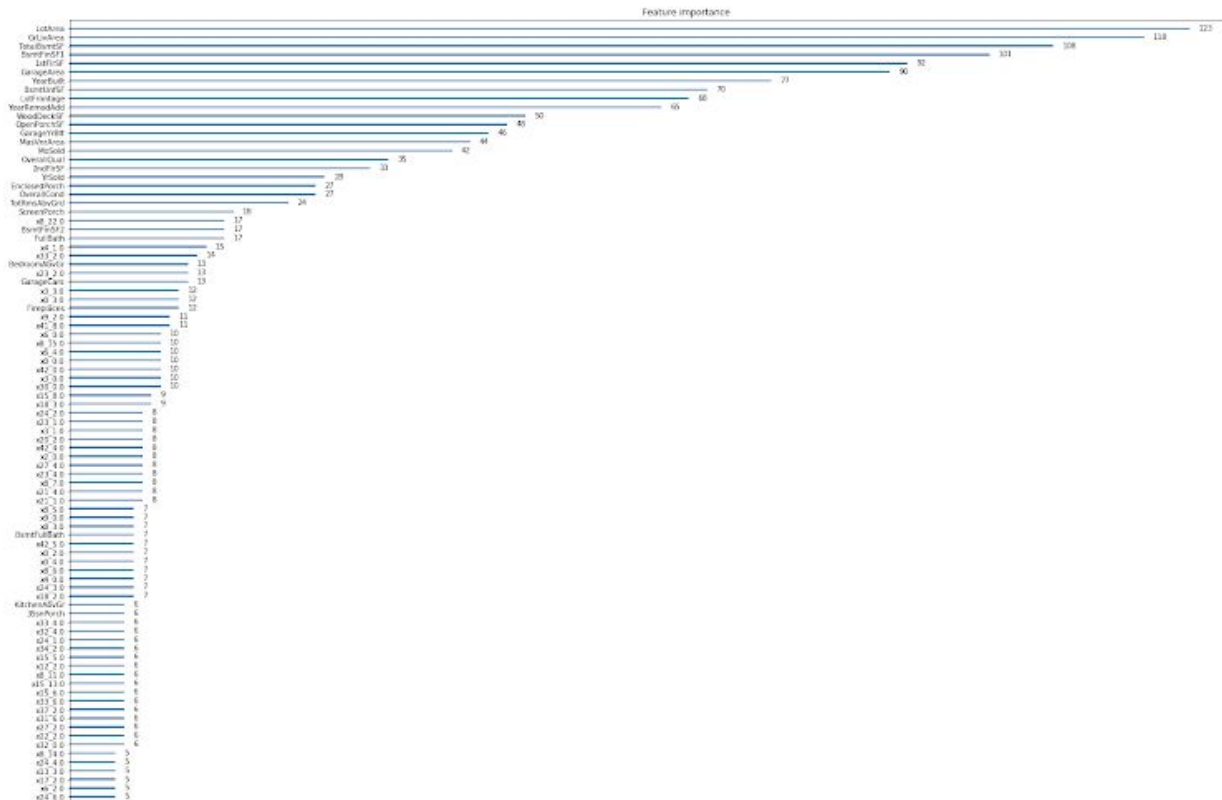
Fig13. Other regression to fit simulation results for better fitting. Left: order of 2 polynomial regression. Right: sigmoid curve regression.



Conclusion:

House ages and House quality are two driving forces to determine house prices, and bedroom number is not, it is just correlated with the important features therefore correlated with the house price, but is not a driving force or causal feature. Actually, with machine learning, we could extract the importance hierarchy precisely.

Fig14. Importance score of each feature: (partial)



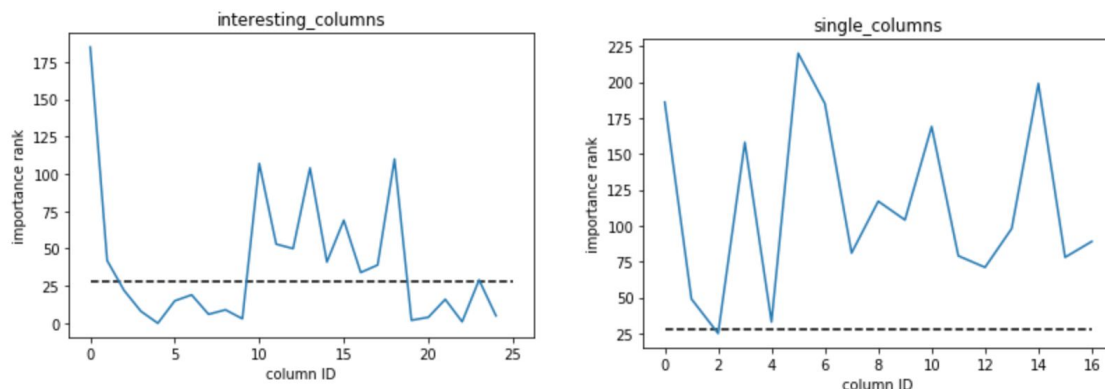
According to the importance score, bedroom number is one of the least considered features during the modeling (score =13, ranked 28), while living area, house quality and age are among the top 20 important features (score > 30). This is a very good explanation of what is causally correlated with outcome, and what correlation is not a cause at all due to much less important to affect the outcome.

Let's also verify whether our initial hypothesis is right:

Initially we thought the features in 'single_column' tend to be not important because not enough variance could be introduced, and in 'interesting_columns' tend to be important, because they showed correlation with sale price. We plotted the importance score (the lower the more important), and set 28 as a threshold, which is equal to the importance of bedroom number.

The results supported our hypothesis. Although in 'interesting columns', some features pop out to be not important(features with rank above threshold), but indeed many of them are important, while in 'single columns', almost all of them are not important. Machine learning helped us to make unbiased conclusion.

Fig15. Plot importance of each column in single_columns(right) or interesting_columns(left).



● Discussion and insights:

House price regression represents one type of problem that share the following essences:

- ❖ Only one outcome (observation) feature, could be either categorical (discrete) or numeric (continuous).
- ❖ The parameters/features/attributes which could affect the outcome are too many to fit human predictable model or function with manageable estimators (10 is already a lot if manually).
- ❖ The parameter/feature number to affect the outcome should be less than the training sample number.
- ❖ There are a mix of categorical and numeric features.

This project is an example of attribution analysis to extract importance of attributes, and understand the causal or correlation relationship between attribute and outcome.

This project also showed the power of machine learning in extracting important attributes among hundreds of attributes. Without machine learning algorithm, we could easily mistakenly thought some features are important due to seeing a strong correlation of the feature and the outcome.

Similar problems could be applied to (not limited to):

- ❖ Clinical data with patient background (genetic and environmental) as attributes/features, and patient's disease or drug response as outcome.
- ❖ Multi-channel marketing with multiple marketing/advertising strategies as attributes and sales as outcome.
- ❖ Stock price and attributing reasons.

Successfully solving a problem and provide the correct data-driven solution includes at least three parts of work:

- ❖ Deep understanding of problems, perform careful investigation to gather enough information to make sure the driving forces are all included in the dataset for machine learning to mine them out. These require people to form all possible hypotheses for data curation.
- ❖ Deep understanding of machine learning algorithms and choose the best model.
- ❖ Careful validation and interpretation of data, distinguish the difference of causal reason and correlation.

As investigated in this project, bedroom number showed association with house prices, with an inner connection of house age, living area and house quality, etc, and is not a causal attribute to drag down house prices (as shown a negative correlation in the raw data), and didn't contribute much to increase house value. Therefore, for real estate developers, there is no need to design houses with more bedrooms (this also could be verified by market research), fewer rooms are easier to design and could cut down budget. And for investors, if two houses in the market with similar prices, then buy the newer or bigger one, fewer bedrooms? Doesn't matter.