Two Sigma Connect: Rental Listing Inquiries

https://www.kaggle.com/c/two-sigma-connect-rental-listing-inquiries

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Outline

1. Problem description
2. Train Data analysis
3. Machine Learning Outline
4. Feature engineering
5. Machine learning Results Summary
6. Take-home message

1. Problem Description

- Predict the popularity of an apartment rental listing.
- Figure out key features responsible for the popularity of apartment rental listings.

training dataset:
9352 entries, 15 columns (with interest_level as target)
testing dataset:
74659 entries, 14 columns (without interest_level).

15 features

1. bathrooms: number of bathrooms, float
2. bedrooms: number of bedrooms, int
3. building_id: the id of the building, string
4. created: date and time when the post is created, string
5. description: description of the apartment, string
6. display_address: display address of the apartment in the posting, string
7. features: a list of features about this apartment, string
8. latitude: latitude of the apartment, float
9. listing_id: listing id of the apartment, int
10. longitude: longitude of the apartment, float
11. manager_id: id of the manager of the apartment, string
12. photos: a list of photo links. string
13. price: in USD, int
14. street_address: street address of the apartment, string
15. interest_level: this is the target variable. It has 3 categories: 'high', 'medium', 'low'

2. Train Data Analysis

Interest level

Numerical features:

bathrooms: [0, 10], mean = 1.2

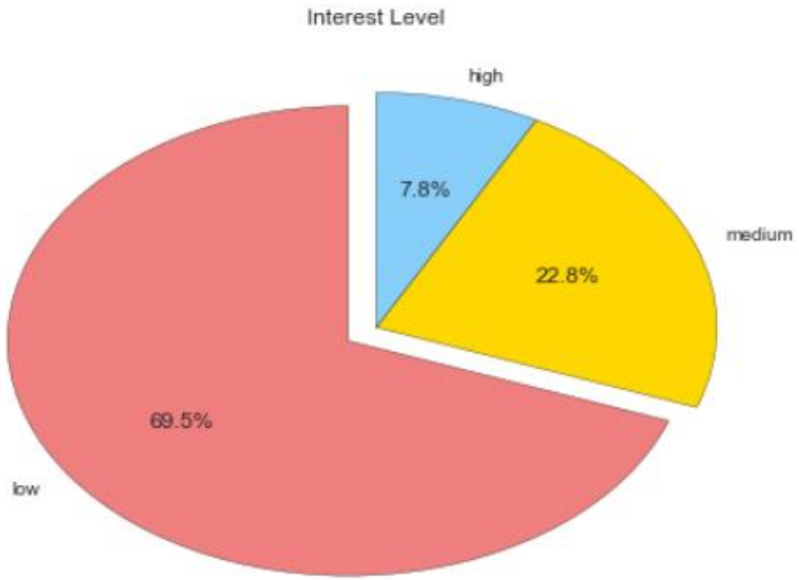
bedrooms:[0, 8.0], mean = 1.5

latitude:[0.000000, 44.883500]

longitude:[-118.271000, 0.00000]

listing_id:[6811957, 7753784], unique for each listing

price:[43, 4490000]



Texts:

created → extract day, hour, week of day

photos → extract number of photos

features → extract length of features or key words

description → extract length or key words

building_id: there’re multiple listings with the same building_id

manager_id: there’re multiple listings with the same manager_id

display_address: there’re multiple listings with the same display_address

street_address: there’re multiple listings with the same street_address

interest_level: distribution shown above

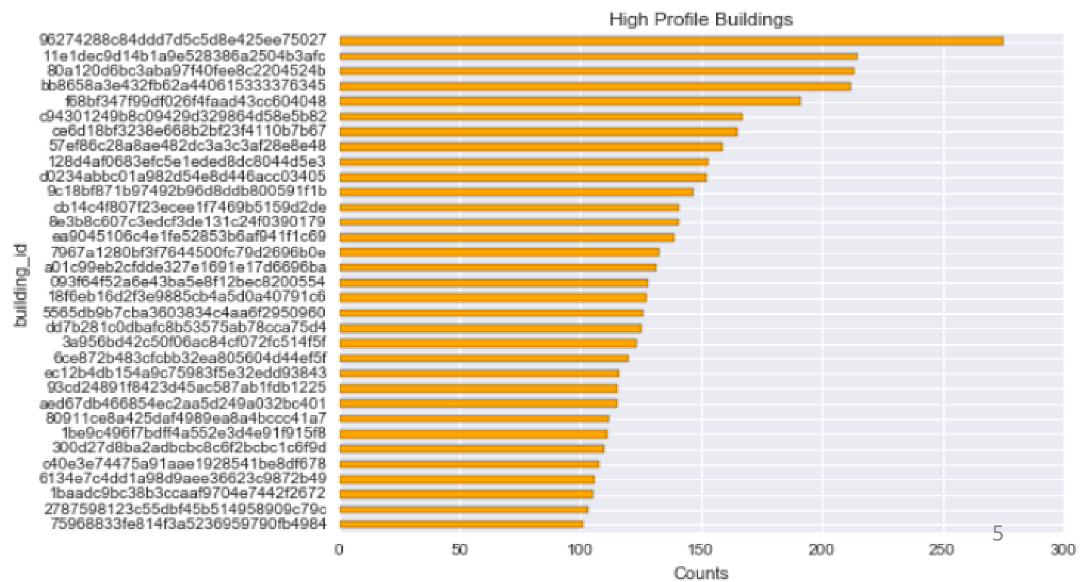
The distribution of different classes are imbalanced. Thus classification accuracy is not a good metric for evaluating the performance of different machine learning algorithms. Instead, Log Loss, which is based on probability of each predicted class is prefered as the evaluation metric.

Building id and Manager id

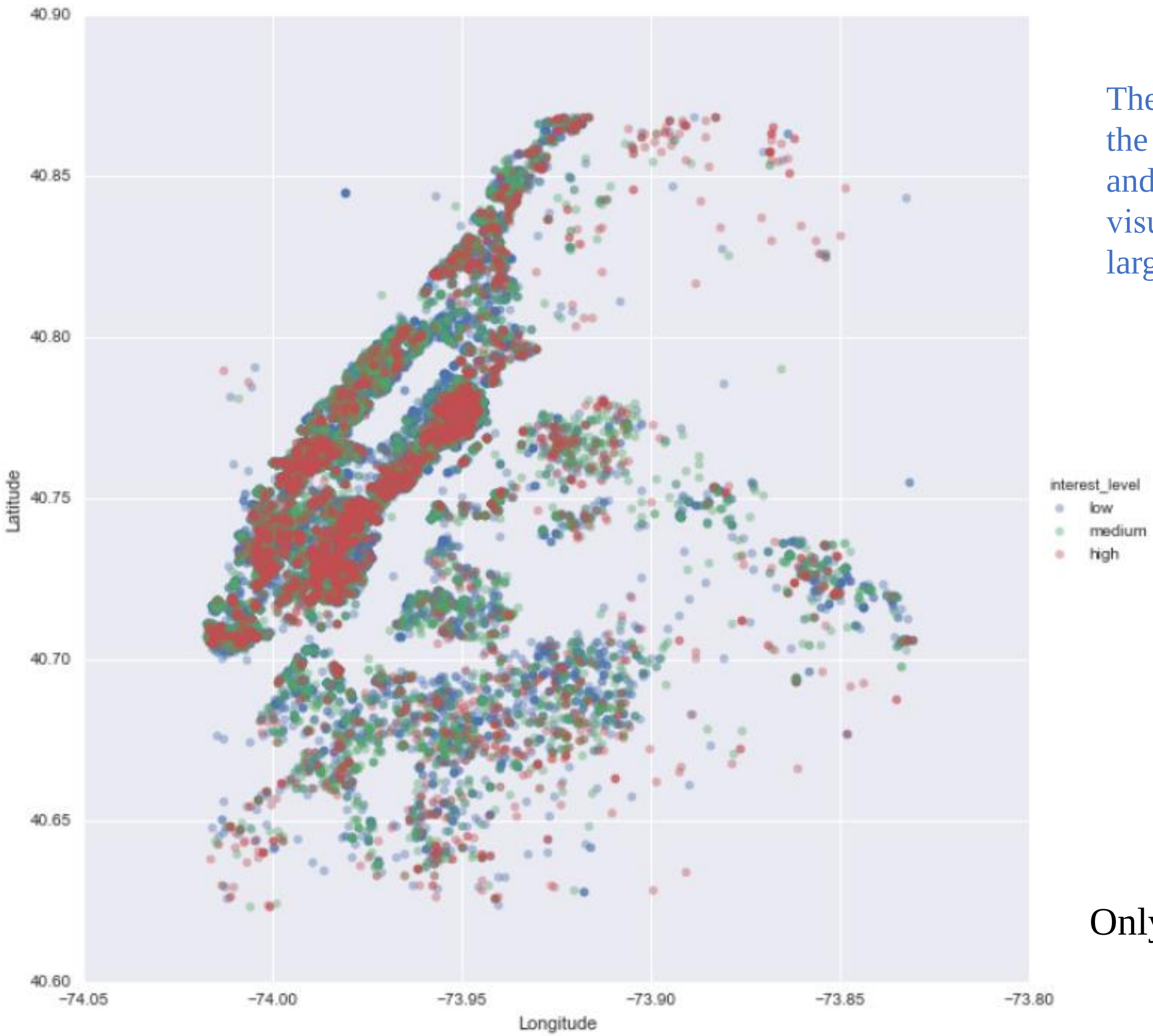
manager_id with counts over 200

building_id with counts over 100

Keep in mind that the apartment posting may attract consistent interest level depending on the manager who posted it and its location (building_id, street address, longitude, latitude etc).



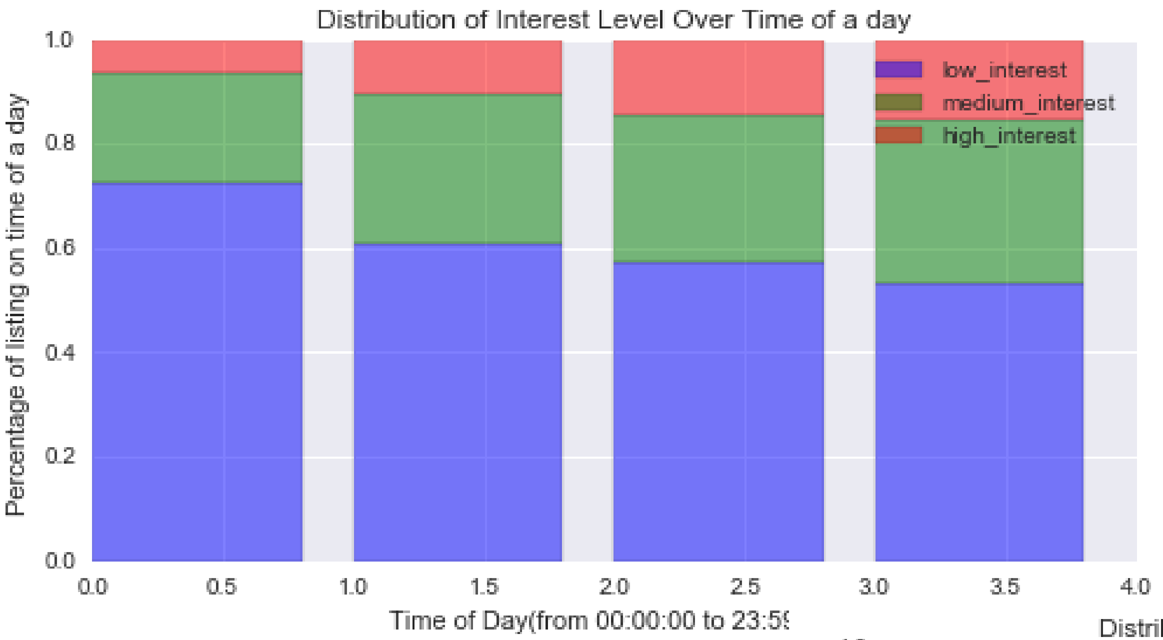
Geographic Distribution

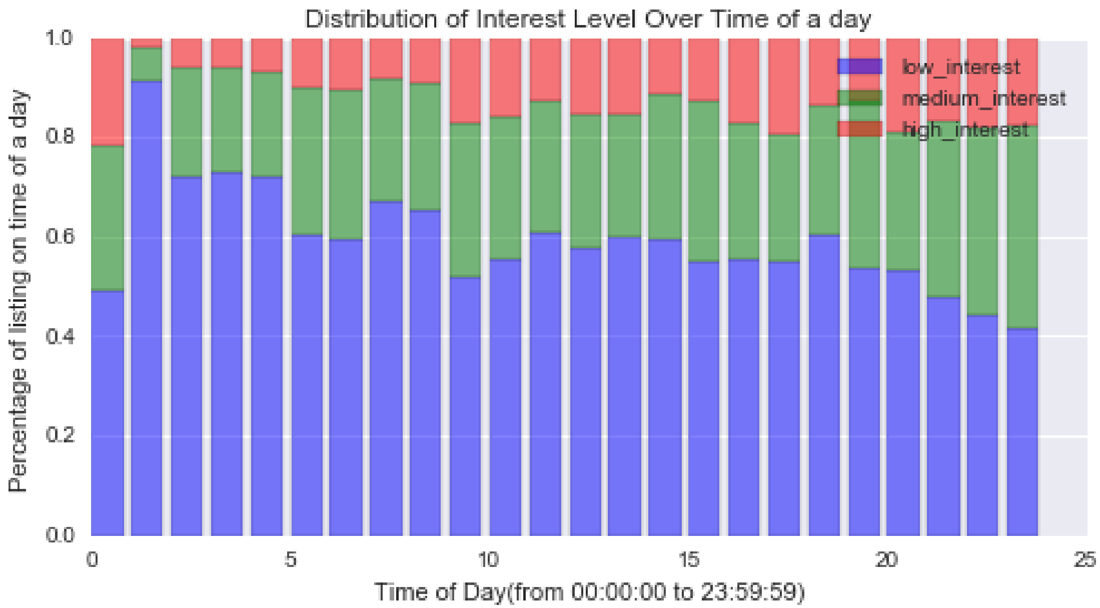


There is no obvious correlation between the geographic location of the apartments and their interest level. (Or there is, but visually it's hard to tell because of the large amount of data.

Only 99.5% data are shown.

Posting Time



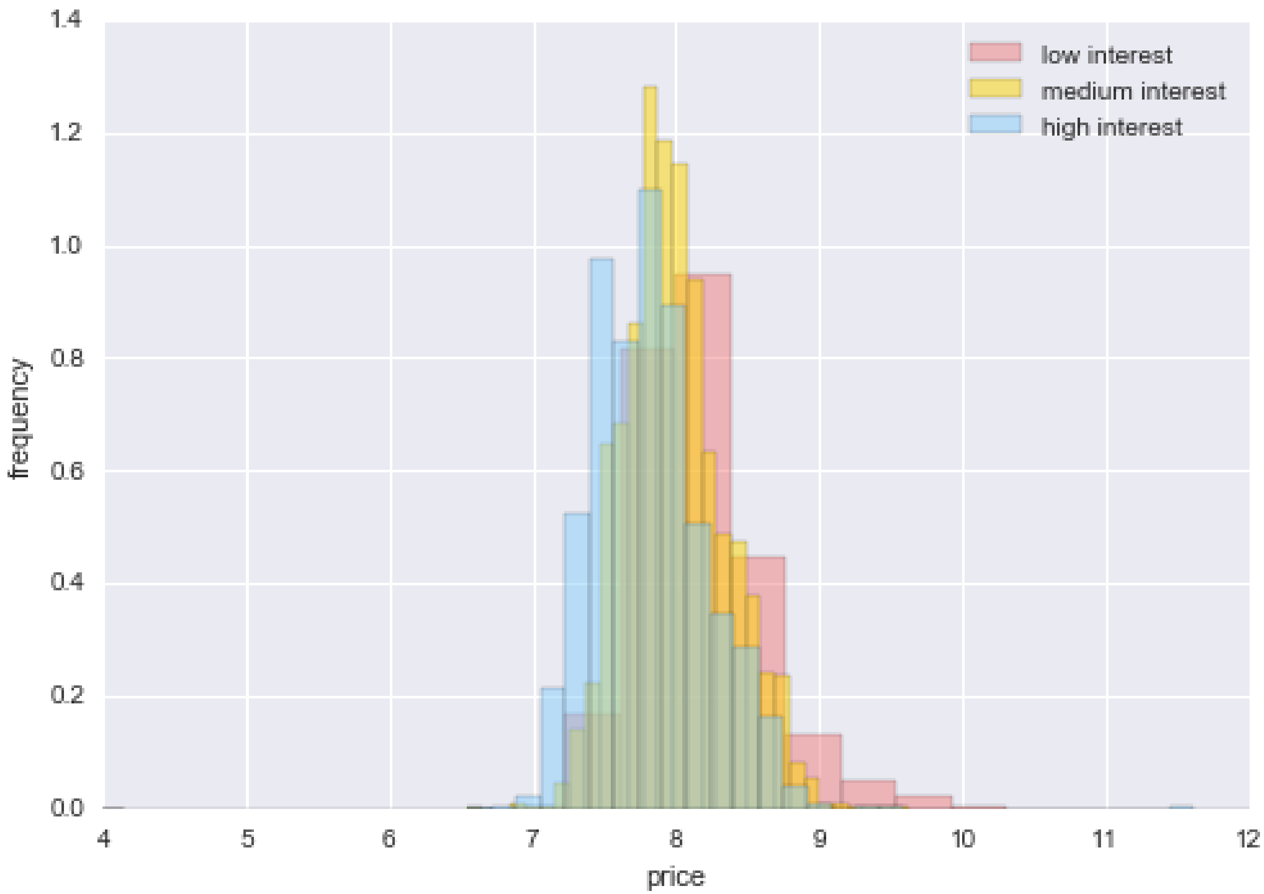


Apartment rental lists posted at different time of day indeed have attracted different interest. This may be related to people's daily schedule/activities and energy cycles. There is no obvious pattern though.

Price

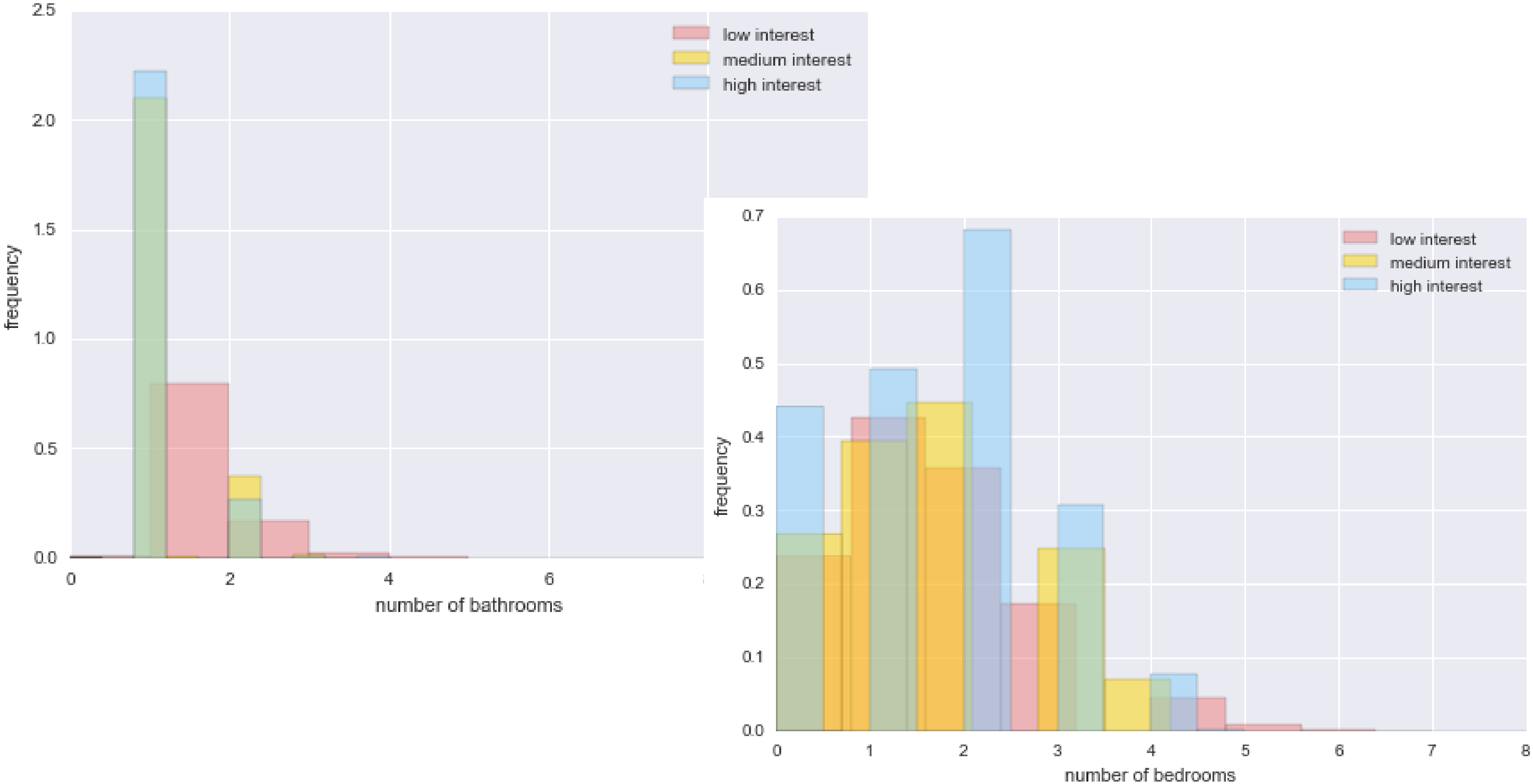
The distribution of price is skewed and doesn't follow normal distribution. Log transformation may be needed to make it normal.

Price



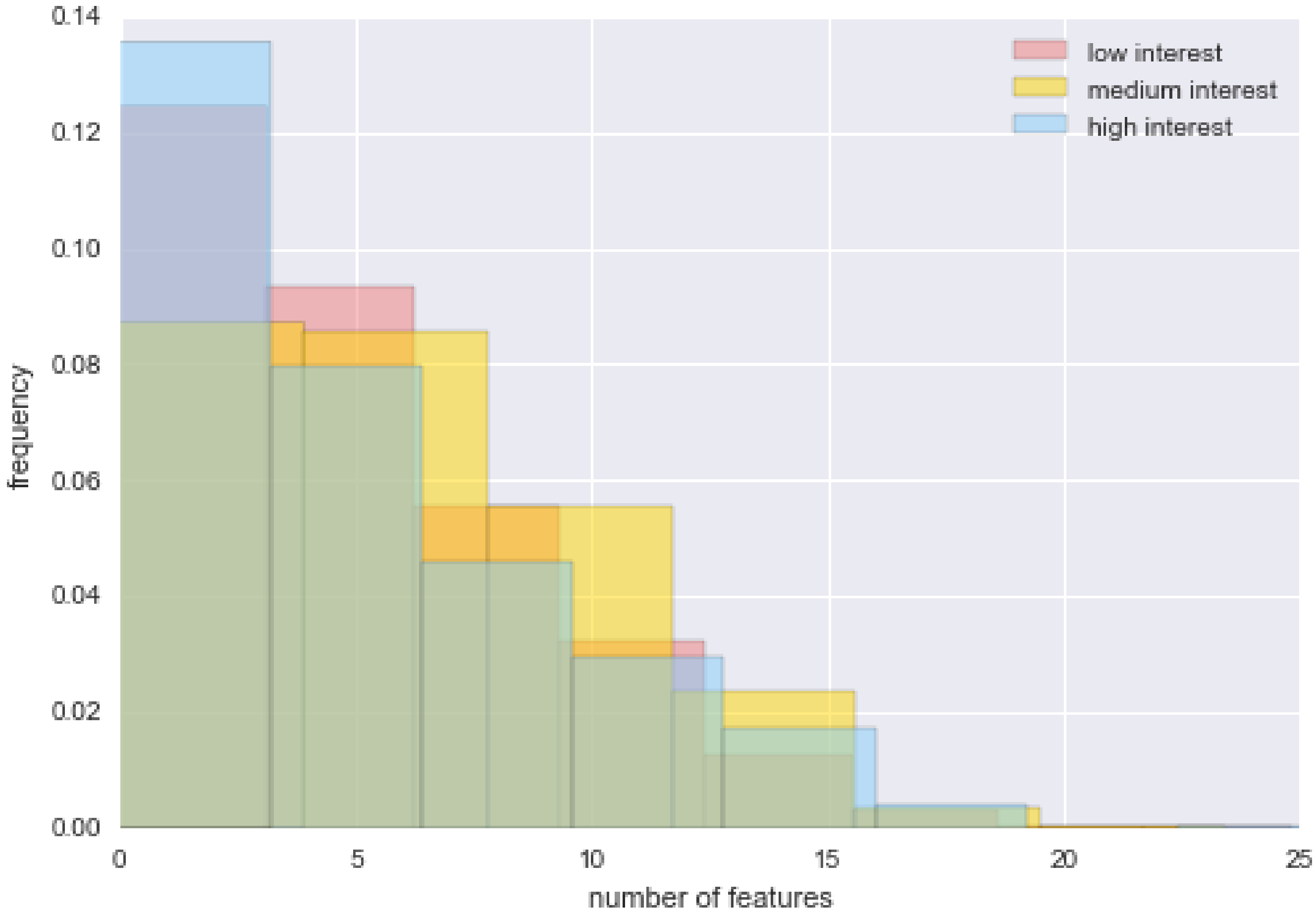
At a significance level of 0.05, we have enough evidence to reject the null hypothesis and conclude that ***the price of apartments with low interest level and high interest level are statistically significant.***

Number of Bedroom & Bathroom



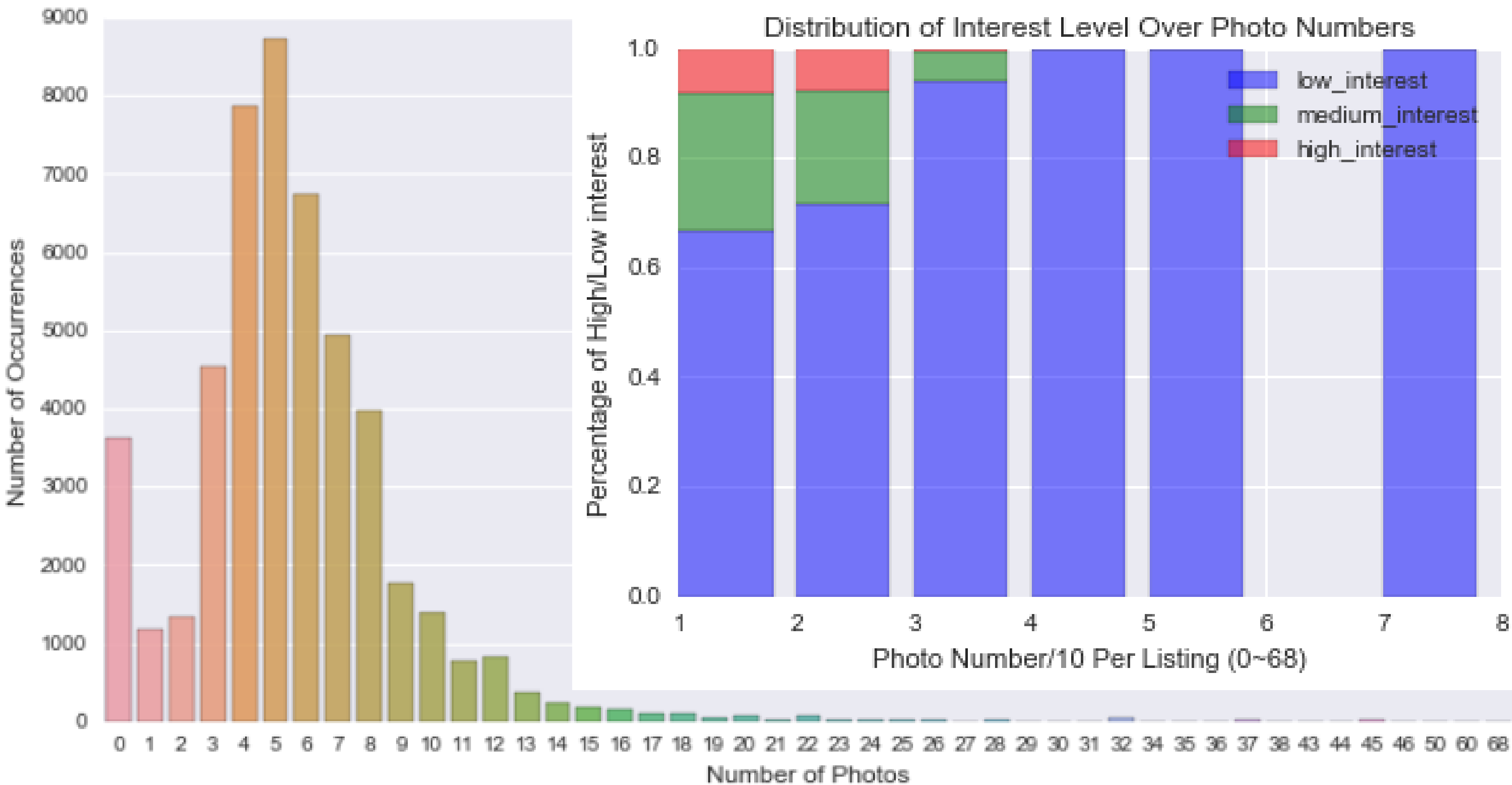
The number of bedrooms and bathrooms for apartments with different interest level are not statistically significant.

Number of features



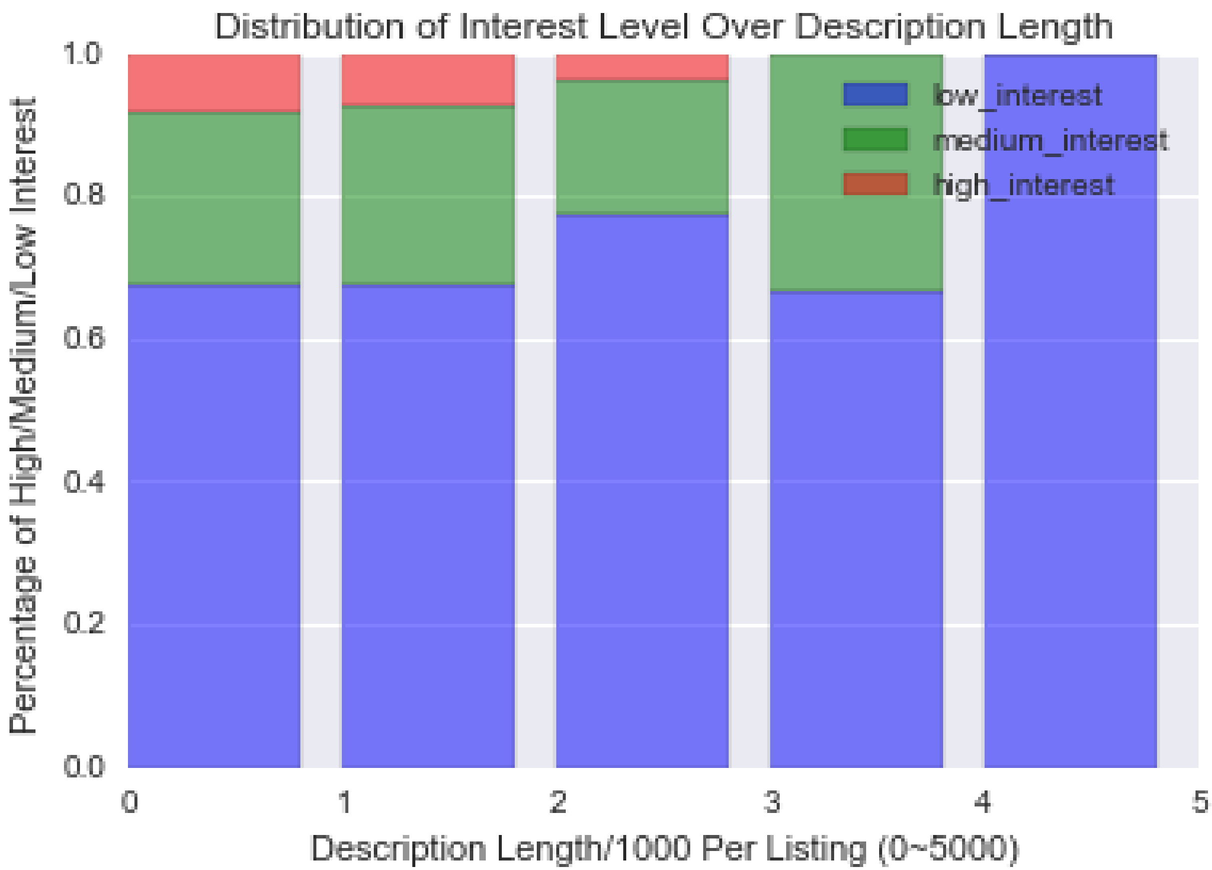
ANOVA test (or F test) verified that the number of features for listings with low, medium, high interest level are statistically significant at a significance level of 0.05.

Number of Photos



Posts with 0 ~ 20 photos has the highest percentage of attracting high interest, while posts with over 30 photos mostly attracts low interest.

Length of Descriptions



Description length of 0~1000 shows the highest proportion of posts that attract the highest interest level while this value decreases with increasing description length.

3. Machine Learning Outline

Data Cleaning

- Remove outliers(ML_0)
- Do nothing *(similar results as ML_0)*

Feature Engineering

- Naïve feature engineering (FE_0)
- get_statistics (FE_1, FE_4, FE_5)
- CV_statistics (FE_2)
- Clustering (FE_3)
- Factorization (FE_6)

Machine Learning

- Logistic regression
- Random Forests
- XGBoost
- LightGBM

4. Feature Engineering

- Naïve feature engineering
  - total number of rooms
  - average price per room
  - number of photos
  - length of features
  - number of words in description
  - created day, month, hour

- get_statistics

  group the dataframe by group column (manager_id, building_id), then calculate the count, mean, std, median, max, min of the target column (bathrooms, bedrooms, latitude, longitude, price etc) feature

- cv_statistics

  calculate building_level = {manager_id: low_count, medium_count, high_count} Then update three new features: low_count%, medium_count% and high_count% for both train_df and test_df. If this manager_id only shows up in train_df but not test_df, nan is added.

  encode categorical values into numerical values between 0 and n_classes - 1

- Clustering

  categorize 'features' by the top ten features

  separate Friday from the rest of the days and clustering the time of day into four categories

- Factorization

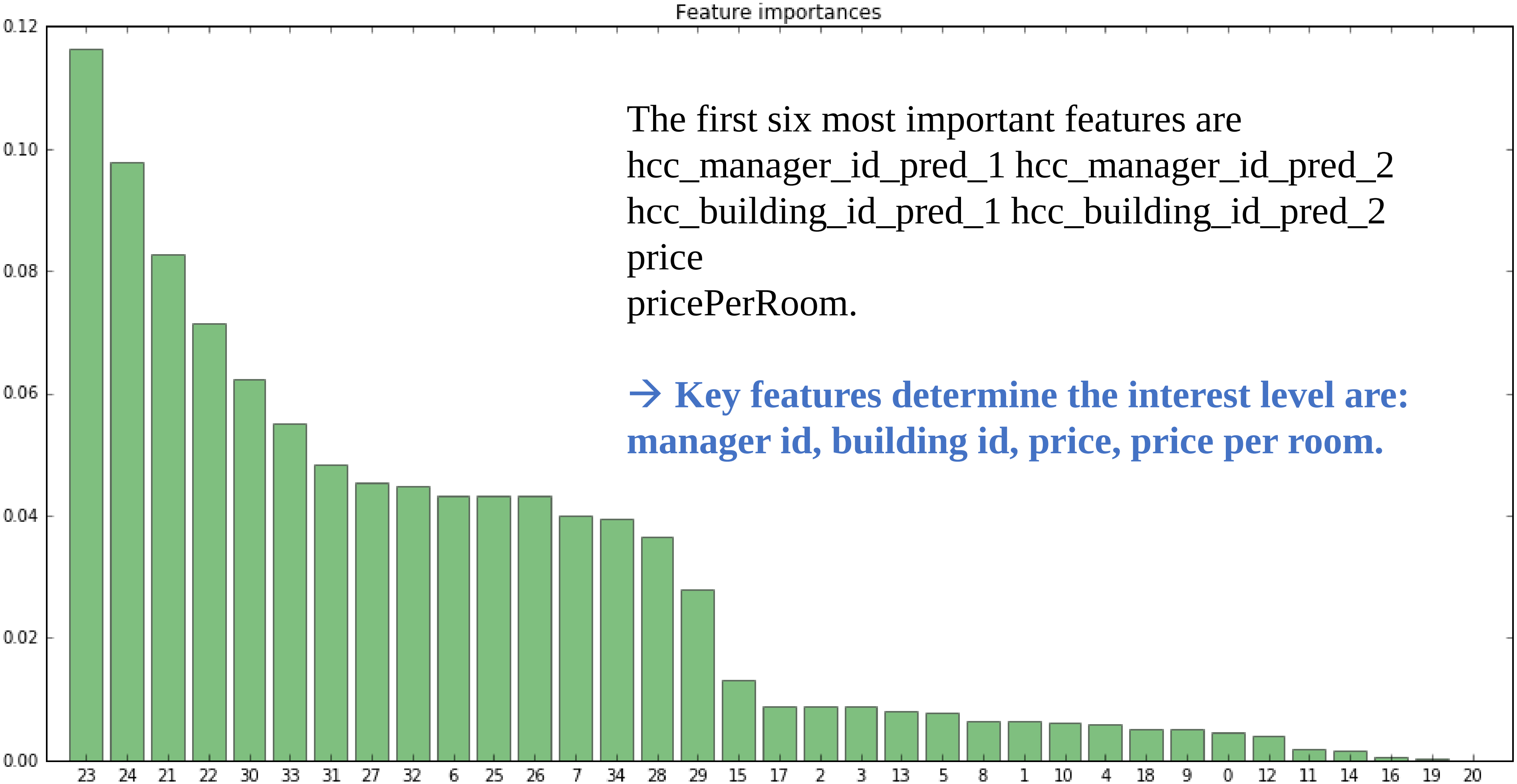
  Encode input values as an enumerated type or categorical variable (i.e., 0, 1, 2,…..) and return the unique values

5. Machine learning Results Summary

Ref on logloss: http://www.exegetic.biz/blog/2015/12/making-sense-logarithmic-loss/

Log loss on X_validation/lb	Logistic Regression	Random Forests	XGBoost (without NAN)	XGBoost (withNAN)	LightGBM (withnan)	Notes
FE_0	0.70304 /0.72024	0.62085 /0.63383	0.631709 /0.62627	0.628339 /0.62627	0.6068221 /0.60777	Too simple FE
FE_1	0.667379 /1.00415	0.6153 /1.4447	0.572166 /1.15843	0.582721 /1.07354	0.550506 /1.16804	Overfitting?? Or data leaking
FE_2	0.459439 /test data contain NAN	0.4482 /test data contain NAN	0.408885 /0.87942	0.407328 /0.87324	0.40023587 /0.86359	Data leaking??
FE_3	0.795639/0 .82395	0.8112 /0.82395	0.796590 /0.79797	0.796626 /0.796626	0.79183 /0.79195	Bad performance
FE_4	0.70040 /0.94479	0.61523 /1.35541	0.603335 /1.02034	0.600084 /0.94132	0.5619336 /1.17163	Overfitting?? Or data leaking
FE_5	N.A.	N.A.	N.A.	0.592260 /1.05636	0.534319 /1.27489	Overfitting?? Or data leaking
FE_6 (with listing_id)	0.646260 /0.64718	0.57552 /0.58216		0.550675 /0.55800	0.538097 /0.54073 0.53814(replace NAN with -1)/0.54114	**Best result**

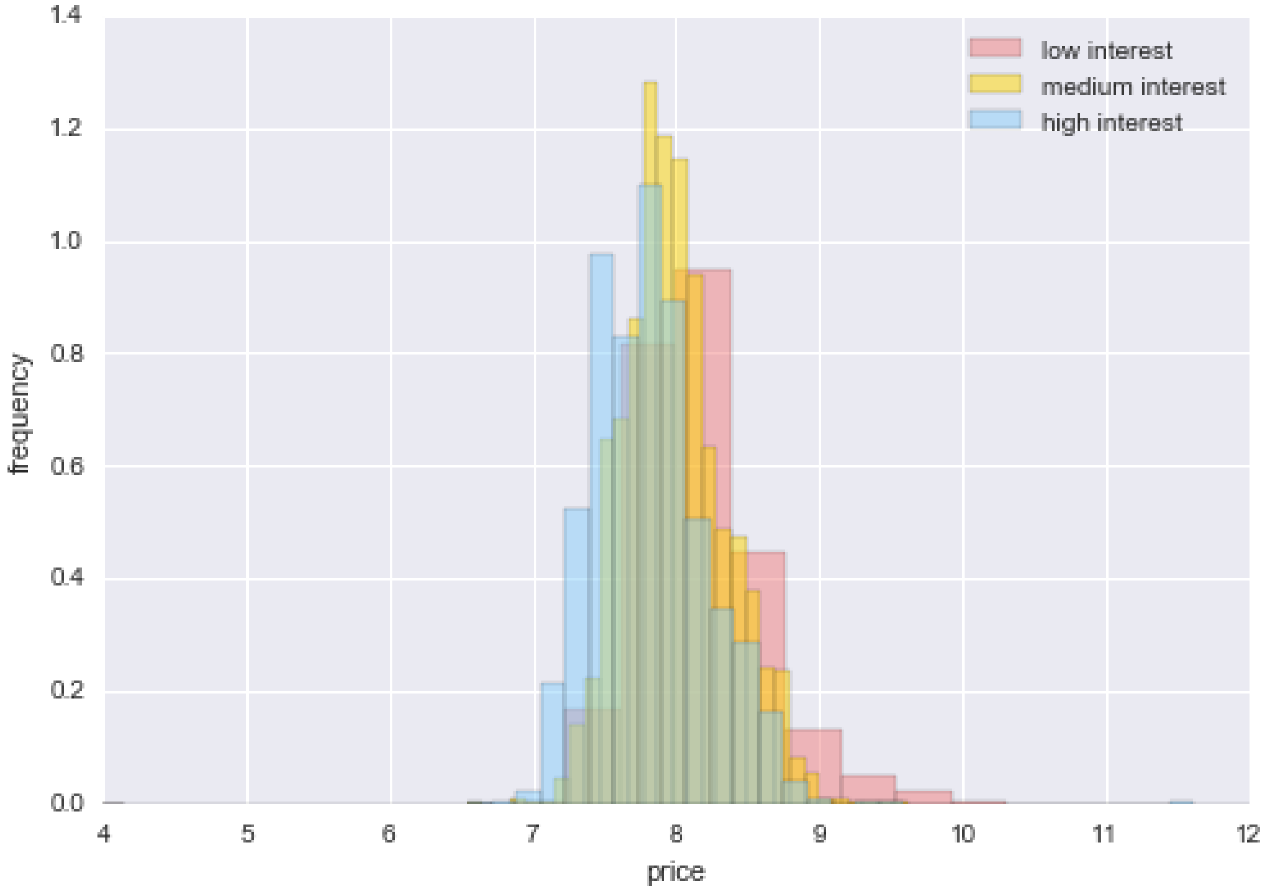
6. Identify Key Features



The first six most important features are
hcc_manager_id_pred_1 hcc_manager_id_pred_2
hcc_building_id_pred_1 hcc_building_id_pred_2
price
pricePerRoom.

→ Key features determine the interest level are: manager id, building id, price, price per room.

6. Identify Key Features



From the ML modeling, price is a key factor in determining the interest level of apartment rental listings. This agrees with our statistical analysis that the price of apartments with low interest level and high interest level are statistically significant. By fitting our data using machine learning models, we can conclude the cause-and-effect relationship between price and interest level.

7. Take-home message

1, Naïve Bayes and SVM performs really bad. Maybe because naïve assumption doesn't hold while SVM is good for "linear" separation which may not be the case here.

2, Tree based models like random forests, xgboost and lightGBM are not sensitive to features scales, so feature scaling is not needed. Feature scaling in logistic regression doesn't decrease the Log Loss either.

3, Changing price to normal distribution doesn't improve the prediction result from logistic regression and tree-based methods.

4, LightGBM performs better and faster than xgboost in all investigated cases.

5, Among all tried ML algorithms, only XGBoost and lightGBM can handle NAN value.

6, Given that this is a classification problem and our goal is to achieve the lowest Log Loss score, collinearity between features doesn't need to be considered.

7, Preliminary statistical analysis shows correlation between features and interest levels while machine learning model identifies key features with causation to interest levels.

8, The first six most important features are hcc_manager_id_pred_1, hcc_manager_id_pred_2, hcc_building_id_pred_1, hcc_building_id_pred_2, price, pricePerRoom.