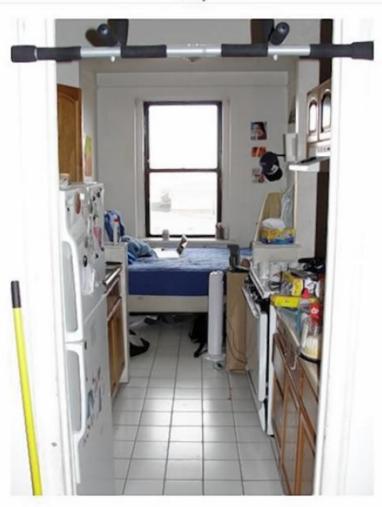
Predicting popularity of a NYC apartment listing using renthop data



THE WORST ROOM

A BLOG ABOUT TRYING TO FIND AFFORDABLE HOUSING IN NEW YORK CITY

8 May



Only \$300!

Source: TheWorstRoom.com

Washington Heights, Manhattan. \$300/month

(The Breakfast Nook)

Outline

- Renthop action statement: "Apartment hunting can be overwhelming, but we realized that finding a new home isn't about looking at every apartment listing, it's about looking at the best ones. Quality, not quantity."
- Quality is measured on a 'HopScore'
- Each listing includes features, descriptions, bathrooms, bedrooms, pictures, location etc.

Project Summary

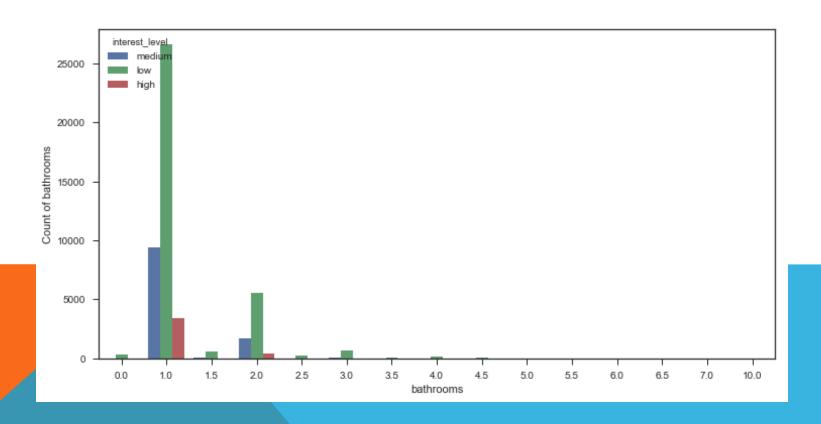
- Given features can we predict interest level?
- Interest level prediction of an apartment in NYC being either High, Medium or Low
- Using Log Loss formula to evaluate the difference between predicted and actual results
- Data comes from the renthop website's actual listings which are anonymized by building id

Summary continued

- Plan: Using Language Processing algorithms on the features & descriptions to transform categorical variables to continuous to feed into the models
- Use regression and classifier models to predict interest level

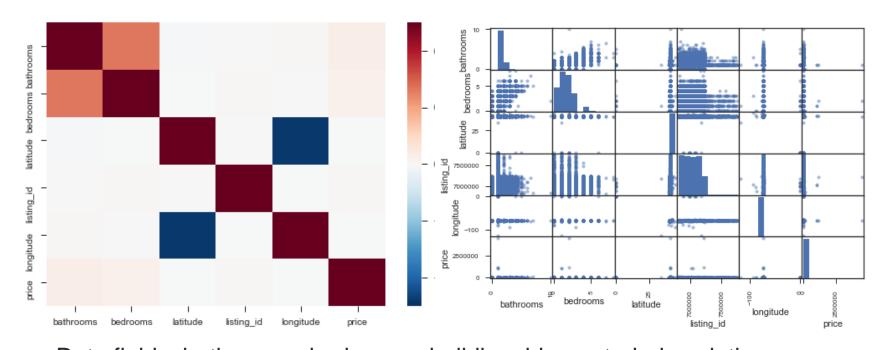
MODELING INSIGHTS

There were 313 listings(out of 49352) with no bathrooms and people were still interested:



Modeling insights continued

Scatter plots and correlation map of variables;



Data fields: bathrooms, bedrooms, building_id, created, description, display_address, features, latitude, longitude, manager_id, photos(links), price, street_address, interest_level

Modeling

 Best model for the baseline log loss seems to be RandomForrestClassifier;

```
model = RandomForestClassifier(n_estimators=1000)
model.fit(X_train, y_train)
y_val_pred = model.predict_proba(X_val)
log_loss(y_val, y_val_pred)

0.64024243797863556

model = GradientBoostingClassifier()
model.fit(X_train, y_train)
y_val_pred = model.predict_proba(X_val)
log_loss(y_val, y_val_pred)

0.71865436526725646

0.71865436526725646

0.71865436526725646
```

Insights on Features variable

Wordcloud of the features;
 Wordcloud for features

```
Laundry_in_Building DishwasherBardwood_Floors
                                                          No_Fee Dogs_Allowed
                            Center Laundry Laundry Laundry
  Dining Room Doorman
 Outdoor_Space Dogs_Allowed
  Hardwood Floors Doorman
                   Llowed Cats Allowed
        Laundry_in_Building Laundry_in_UnitHigh_Speed_Internet Dishwasher
```

Feature Engineering

Helper function to reduce the amount of unique words in the features columns

```
def clean(a):
   a = str(a)
                                                            Map words into a matrix
   a = a.replace('-', ' ')#etc.etc.
   a = a.replace('_', ' ')
   a = a.replace('&', 'and')
                                                           from sklearn pandas import DataFrameMapper
   a = a.replace('24/7', '24')
                                                           mapper = DataFrameMapper([
   a = a.replace('24hr', '24')
                                                                ('featured', CountVectorizer(binary=True, ngram_range=(1, 2)))
   a = a.replace('24hour', '24')
   a = a.replace('24 hour', '24')
   a = a.replace('a/c', 'aircon')
   a = a.replace('air conditioner', 'aircon')
                                                           features sparse=mapper.fit transform(df)
   a = a.replace('bicycle', 'bike')
   a = a.replace('concierge', 'doorman')
   a = a.replace('concierge service', 'doorman')
                                                           X = sparse.hstack([df[new cols to keep], features sparse]).tocsr()
   a = a.replace('counter tops', 'counters')
   a = a.replace('countertops', 'counters')
                                                           v = df['interest level']
   a = a.replace('granite kitchen', 'granite counters')
                                                           X train, X val, y train, y val = train test split(X,y, test size=0.33)
    a = a.replace('dish washer', 'dishwasher')
    a = a.replace('full tie', 'ft')
   a = a.replace('indoor swimming pool', 'indoor pool')
   a = a.replace('laundry on every floor', 'laundry on floor')
   a = a.replace('media screening room', 'media room')
    a = a.replace('one month free rent', 'one month free')
   a = a.replace('prewar', 'pre war')
    a = a.replace('roofdeck', 'roof deck')
   a = a.replace('ss appliance', 'stainless')
   a = a.replace('storage facilities', 'storage')
    a = a.replace('twenty four hour', '24')
   a = a.replace('washer and dryer', 'washer/dryer')
    a = a.replace('wi fi', 'wifi')
    return a
```

Results

Did my Feature Engineering improve results;

```
model = GradientBoostingClassifier()
model.fit(X_train, y_train)
y_val_pred = model.predict_proba(X_val.toarray())
log_loss(y_val, y_val_pred)
0.62762756094982386
```

• By .02!

Conclusion

- A Log Loss of ~.64 ranks about 1,800 of the 2,488 submissions(72nd percentile!)
- .49194 was the best
- Approaches for future work; more feature engineering on text features(word2vec etc.), image processing, neighborhood classification with lat/longitude, xgboost if I can ever get it to work on my laptop

The end!

Data from: https://www.kaggle.com/c/two-

sigma-connect-rental-listing-inquiries

Always looking for work/and or project collaborations!

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