



# NYC Apartments: Analyzing Rental Listings

Prashant Tatineni

# Problem Statement

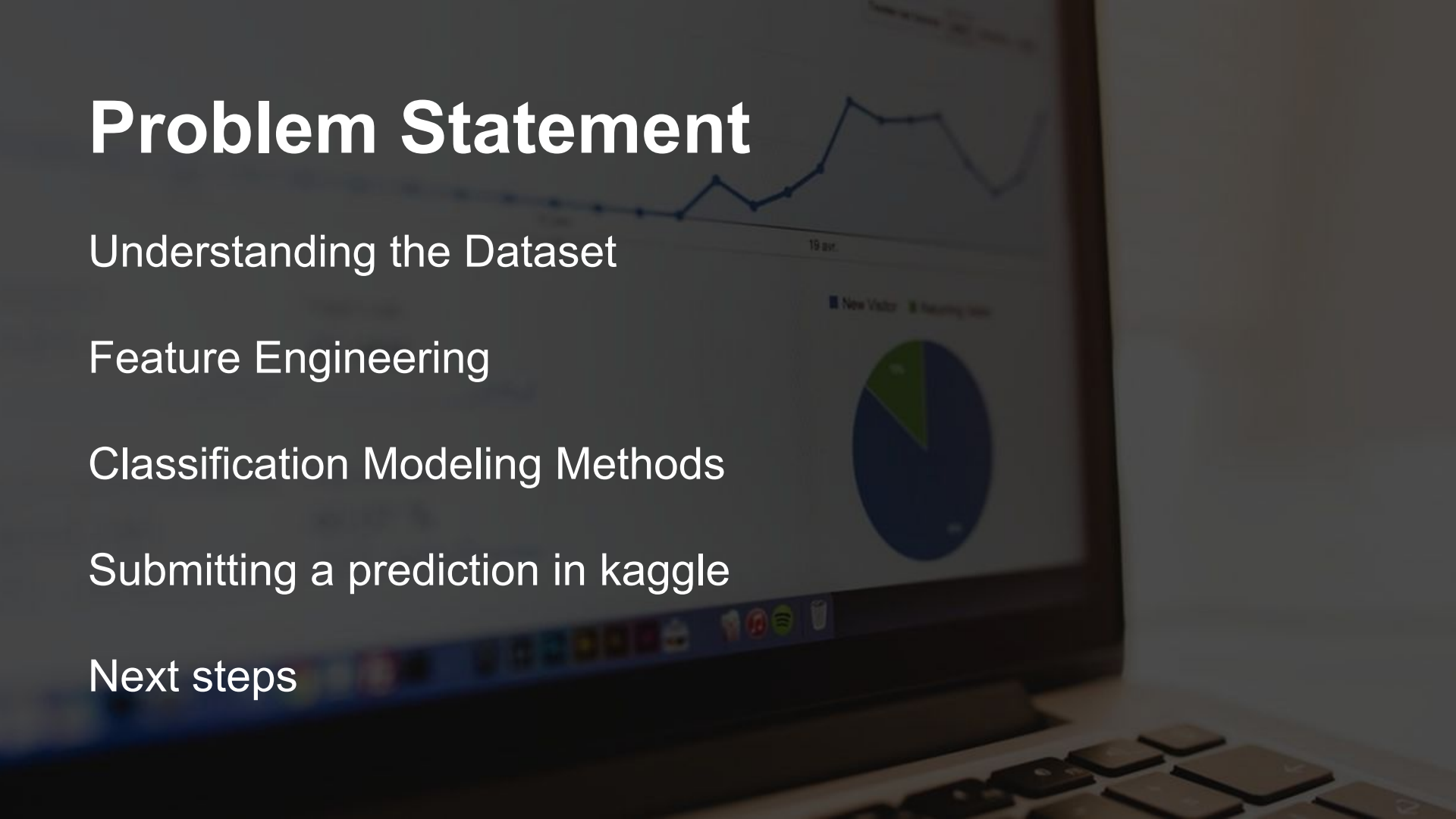
Understanding the Dataset

Feature Engineering

Classification Modeling Methods

Submitting a prediction in kaggle

Next steps



# Can we predict the popularity of a rental listing?

- **Motivation and Assumptions**

- Rental listings should receive more inquiries to be more profitable for rental owners.
- More inquiries means that the listings are of higher quality.
- Higher quality listings benefit the rental market as a whole.

- **Dataset from current Kaggle competition**

- *“How much interest will a new rental listing on Renthop receive?”*
- Actual listing data from April through June 2016
- Interest level = High, Medium, or Low



renthop



TWO SIGMA

Problem Statement

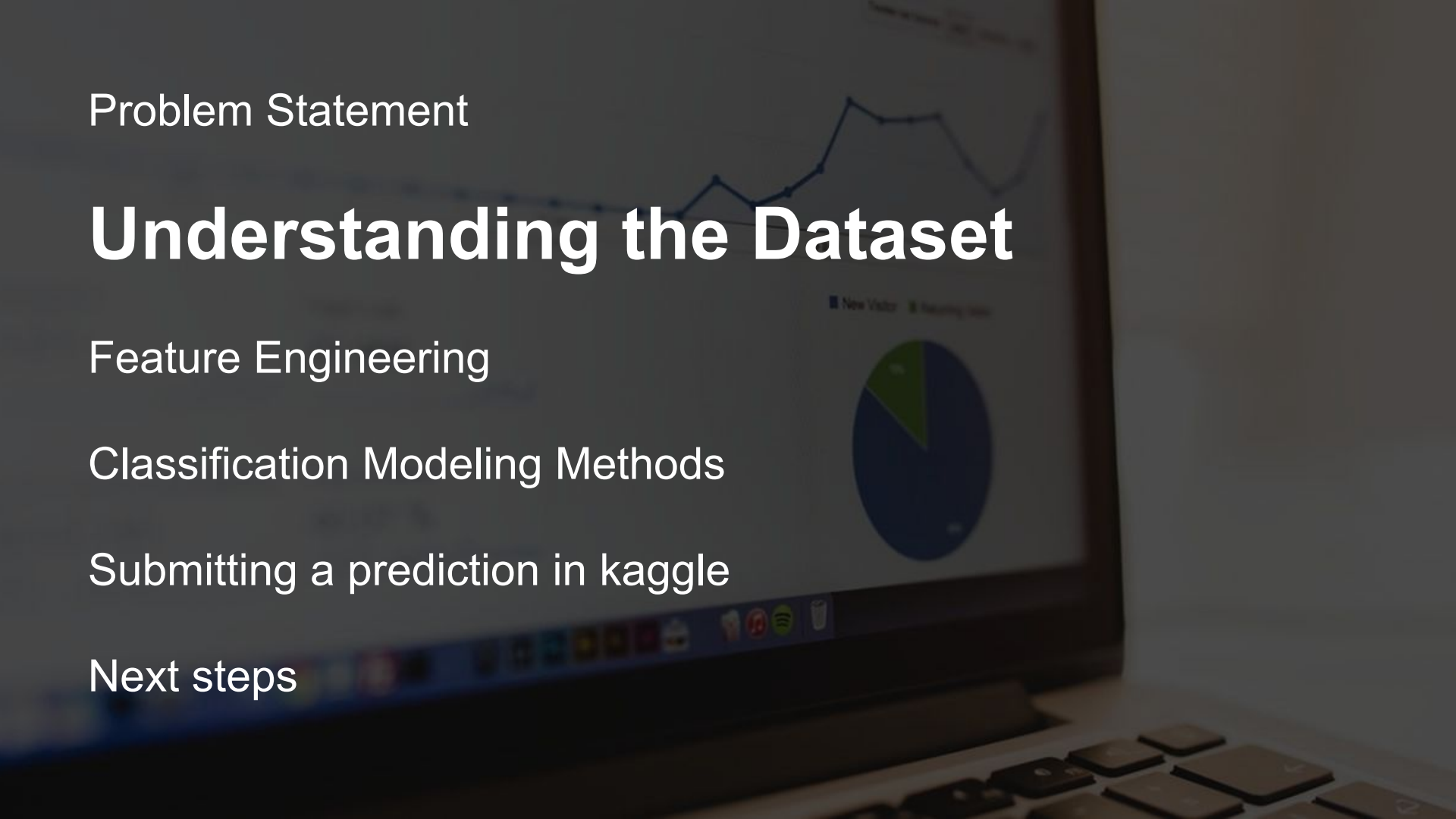
# Understanding the Dataset

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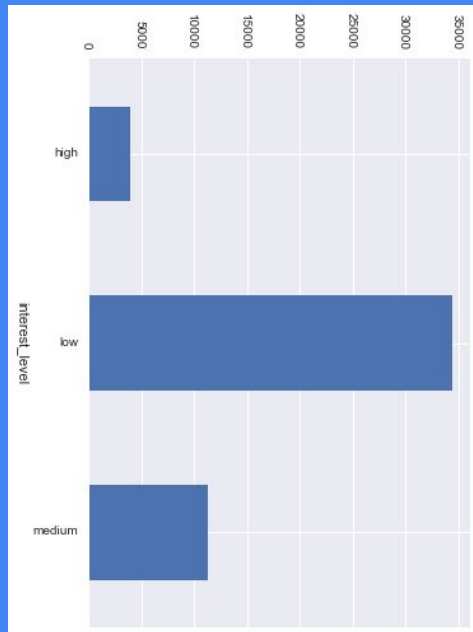
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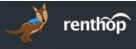


# Understanding the dataset

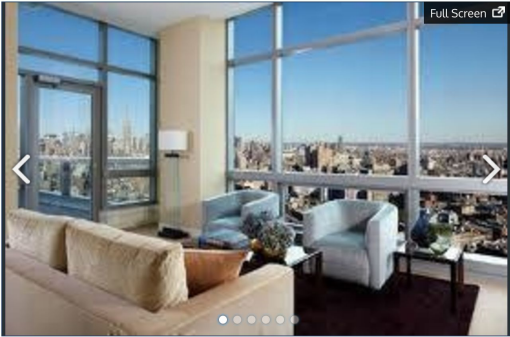
- **One target variable:**
  - *interest\_level = High, Medium, Low*
- **ID columns:**
  - *listing\_id*
  - *manager\_id*
  - *building\_id*
- **Text/Photos:**
  - *description*
  - *[features]*
  - *[photos]*
- **Numerical:**
  - *price*
  - *bathrooms*
  - *bedrooms*
  - *created\_date*
- **Location:**
  - *latitude*
  - *longitude*
  - *display\_address*
  - *street\_address*



# Renthop Listings - Example

 Search Buildings Resources Need a Roommate?


[« Back to Search](#) [New to NYC? Check out our NYC Renter's Guide](#)



### Studio at W 42 St.





Hell's Kitchen, Midtown Manhattan, Manhattan

**Studio** | 1 Bath | **Immediate** Move-In  
Listing Posted 6 hours ago

 **shai gil**  
caliber associated

\$2,570  
Per Month

85.1  
HopScore

## Description

The building located in prime midtown west location. The amenities include: Weekday Shuttle Service in the Mornings & Evenings to & from Second Avenue. 24-hour white glove service. Concierge services. On-site parking garage. Hertz Connect for car rental. Off-street private driveway. Quarter-acre park, 7s playground, Dog run. Health club. swimming pool.

brand new studio features the following: Floor to ceiling windows, City Skyline & the Hudson River. High ceilings 9'-11". Window shades, Bosch Washer/Dryer. Streamlined open kitchens. Cabinets of Zebrano/Wenge wood grain laminate. Stainless steel appliances. Wine coolers. shower stalls in addition to bath tubs, double sinks. Porcelain tile floors and walls. Carrera marble countertop. Kohler bath fixtures.

Don't miss it!!!! \*\*NO FEE & 2 MONTH FREE\*\* Net effective price \*AVAILABLE 24/7!!

I SPECIALIZE IN THE RENTAL MARKET FOR THE PAST FEW YEARS, FEEL FREE TO CONTACT ME FOR FURTHER ASSISTANT. SHAI GIL 9543484066 [sgil@calibernyc.com](mailto:sgil@calibernyc.com) I'LL BE MORE THEN HAPPY TO ASSIST YOU WITH YOUR SEARCH AND MAKE SURE TO SAVE YOUR SEARCH AS STRESS FREE!! All photos, amenities, and descriptions are a direct feed from the brokerage.

When calling refer to RentHop MX ID 928822

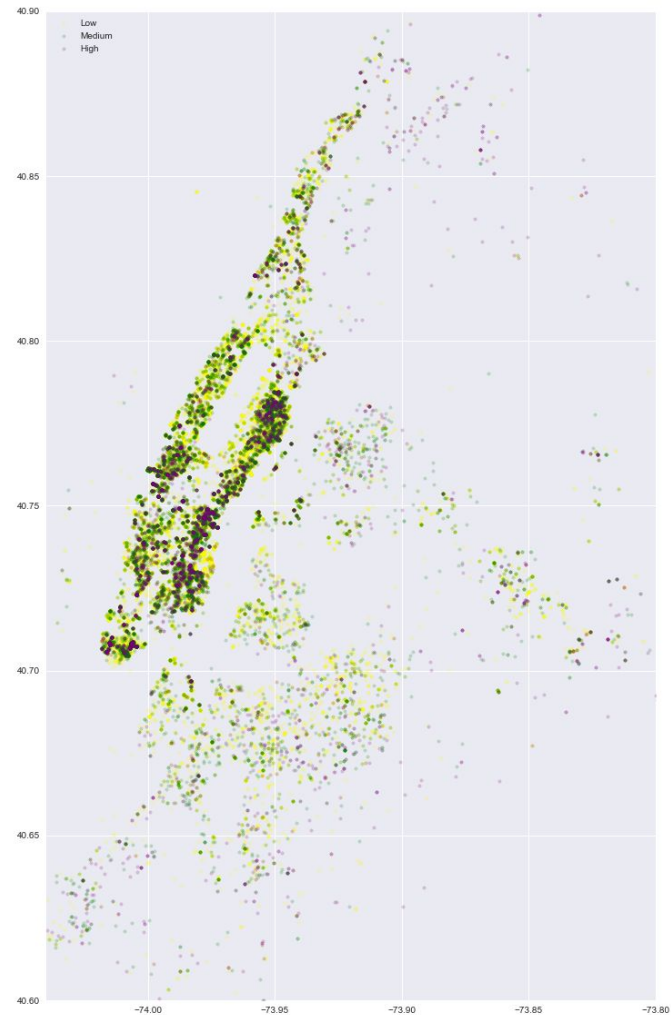
## Features & Amenities

- |                       |                       |                   |
|-----------------------|-----------------------|-------------------|
| ✓ No Fee              | ✓ Swimming Pool       | ✓ Roof Deck       |
| ✓ Dining Room         | ✓ Doorman             | ✓ Elevator        |
| ✓ Fitness Center      | ✓ Laundry in Building | ✓ Laundry in Unit |
| ✓ High Speed Internet | ✓ Dishwasher          | ✓ Hardwood Floors |
| ✓ Outdoor Space       | ✓ New Construction    | ✓ Dogs Allowed    |
| ✓ Cats Allowed        |                       |                   |

## On the Map

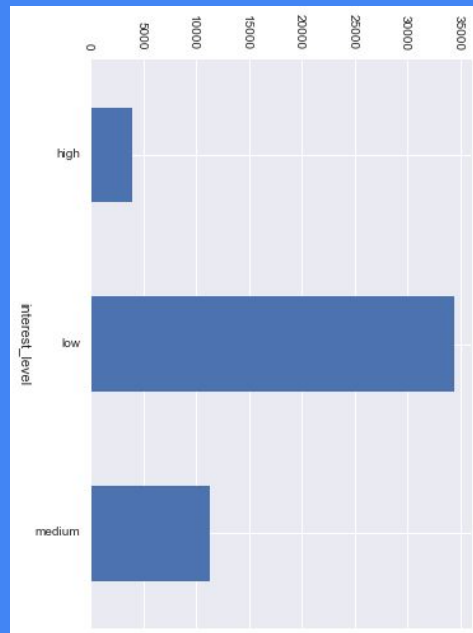


# Listing Data plotted (Lat/Long)



# Understanding the dataset

- **One target variable:**
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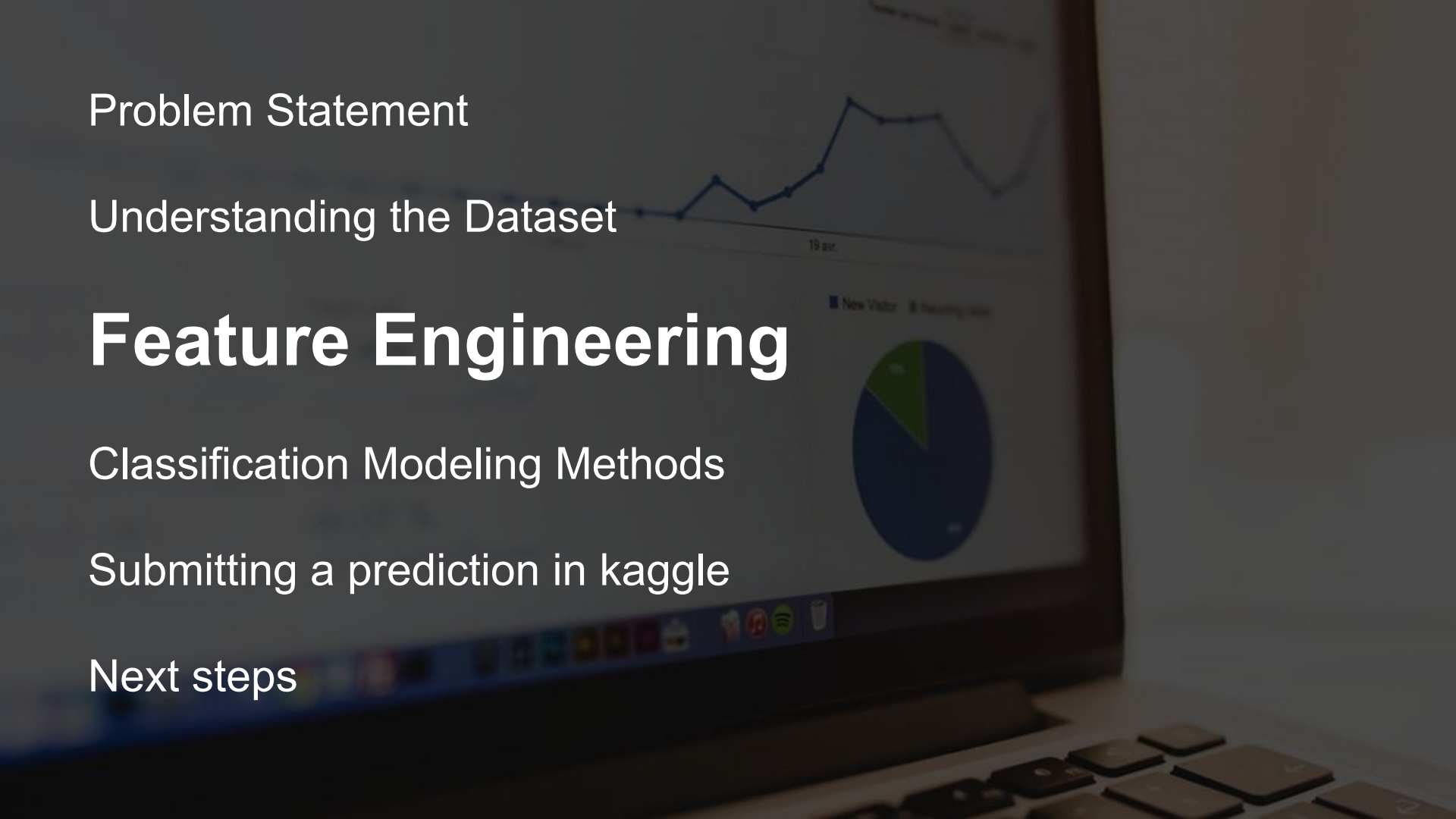
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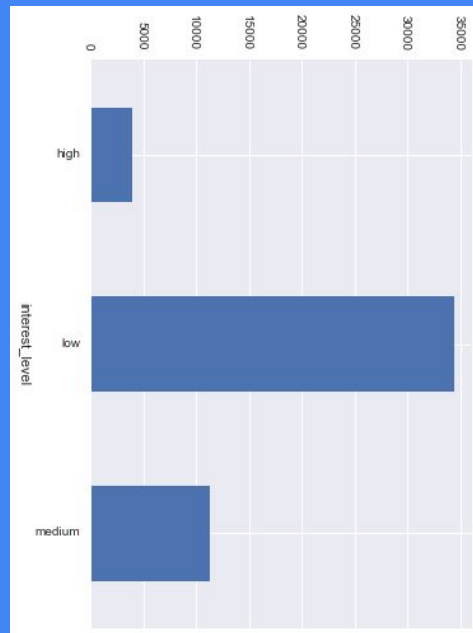
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# Understanding the dataset

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# Using “manager performance” as a feature

- Some managers have many listings
- We can group by manager and assign weights:
  - High = 1
  - Medium = 0
  - Low = -1
- Use training set only to calculate manager performance

```
df_train.shape
```

```
(49352, 15)
```

```
df_train.groupby('manager_id')['listing_id'].count().shape
```

```
(3481,)
```

manager_count	manager_skill
34	-0.117647
29	0.413793
29	0.413793
10	-0.700000
78	-0.320513

# Reducing the number of feature categories in the listings

## Features & Amenities

- ✓ No Fee
- ✓ Dining Room
- ✓ Fitness Center
- ✓ High Speed Internet
- ✓ Outdoor Space
- ✓ Cats Allowed
- ✓ Swimming Pool
- ✓ Doorman
- ✓ Laundry in Building
- ✓ Dishwasher
- ✓ New Construction
- ✓ Roof Deck
- ✓ Elevator
- ✓ Laundry in Unit
- ✓ Hardwood Floors
- ✓ Dogs Allowed

```
(pd.DataFrame({'category' : cats.keys(),  
              'count' : cats.values()})).sort_values('count',  
                                                    ascending=False).head(10)
```

	category	count
505	elevator	26273
121	hardwood floors	23558
1293	cats allowed	23540
1232	dogs allowed	22035
902	doorman	20967
215	dishwasher	20806
82	laundry in building	18944
1031	no fee	18079
338	fitness center	13257
833	laundry in unit	9435

```
(pd.DataFrame({'category' : cats.keys(),  
              'count' : cats.values()})).shape
```

```
(1294, 2)
```

## features

[Doorman,  
Elevator,  
Fitness  
Center, Cats  
Allow...

[Hardwood  
Floors, No  
Fee]

## Reducing the number of feature categories in the listings

## Features & Amenities

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```
pd.get_dummies(df_train['categories']  
               .apply(pd.Series).stack()).sum(level=0)
```



# Reducing the number of feature categories in the listings

Top Categories: High



Top Categories: Medium



Top Categories: Low



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# Classification Methods: Comparison

Initial Feature Set: 'Bathrooms','bedrooms','price','latitude','longitude', 'days_old','num_words','num_features','num_photos'	Logistic Loss <b>sklearn.metrics.log_loss()</b>
Logistic Regression (binomial)	0.71776
Logistic Regression (multinomial/newton-cg)	0.71441
KNN (n_neighbors=100)	0.75956
Bernoulli NaiveBayes	0.76274
MLP (hidden_layer_sizes=(100,50,10))	0.65063
Random Forest(n_estimators=1000)	0.62541



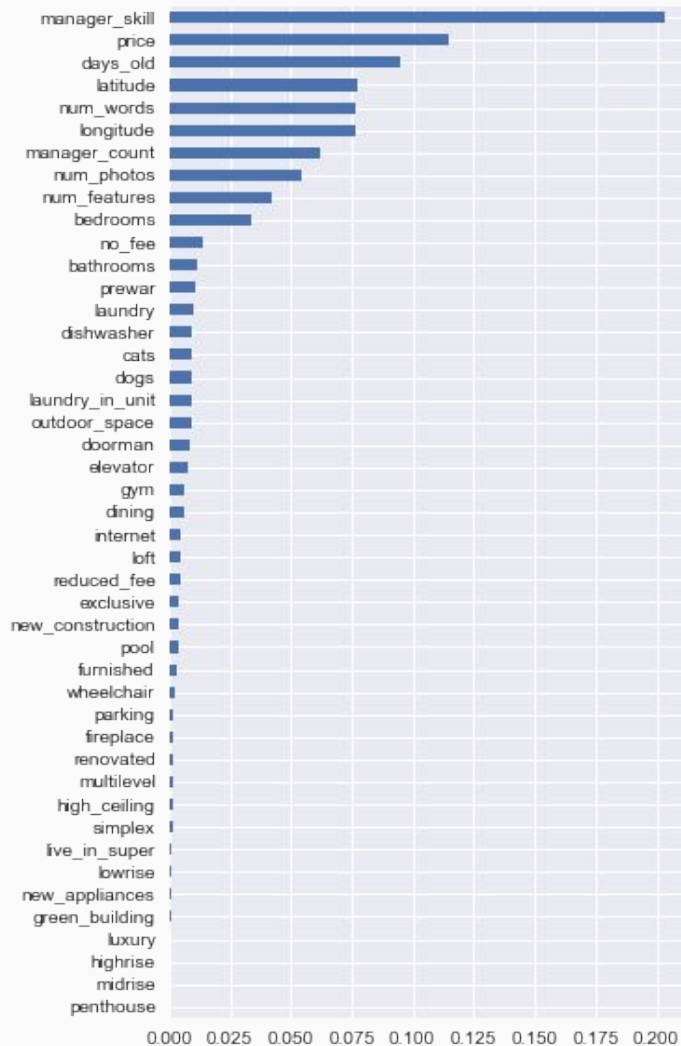
# Classification Methods:

## Random Forest

Input Variable Set sklearn.RandomForestClassifier(n_estimators=1000)	Logistic Loss sklearn.metrics.log_loss()		
'Bathrooms','bedrooms','price','latitude','longitude', 'days_old','num_words','num_features','num_photos'	0.63817		
+ Feature categories	0.62023		
+ Manager count and manager skill	0.59985 / with 73.5% accuracy	Precision	Recall
	Class = High	50.2%	30.4%
	Class = Medium	48.6%	35.3%
	Class = Low	80.2%	91.0%

# Classification Methods: Random Forest

- Feature Importances



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**Submitting a prediction in kaggle**

Next steps

# Submitting prediction in kaggle



## Two Sigma Connect: Rental Listing Inquiries

How much interest will a new rental listing on RentHop receive?

591 teams · 2 months to go

[Overview](#) [Data](#) [Kernels](#) [Discussion](#) [Leaderboard](#) [More](#) [My Submissions](#) [Submit Predictions](#)

### File descriptions

- **train.json** - the training set
- **test.json** - the test set
- **sample\_submission.csv** - a sample submission file in the correct format
- **images\_sample.zip** - listing images organized by listing\_id (a sample of 100 listings)
- **Kaggle-renthop.7z** - (optional) listing images organized by listing\_id. Total size: 78.5GB compressed. I

Submissions are evaluated using the [multi-class logarithmic loss](#). Each listing has one true class. For each listing, you must submit a set of predicted probabilities (one for every listing). The formula is then,

$$\text{logloss} = -\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^M y_{ij} \log(p_{ij}),$$

### Submission File

You must submit a csv file with the listing\_id, and a probability for each class.


The order of the rows does not matter. The file must have a header and should look like the following:

```
listing_id,high,medium,low
7065104,0.07743170693194379,0.2300252644876046,0.6925430285804516
7089035,0.0, 1.0, 0.0
...
```

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

# Submitting prediction in kaggle

Two Sigma  
CONNECT



Two Sigma Connect: Rental Listing Inquiries

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OverviewDataKernelsDiscussionLeaderboardMore

My SubmissionsSubmit Predictions

Public LeaderboardPrivate Leaderboard

This leaderboard is calculated with approximately 40% of the test data.  
The final results will be based on the other 60%, so the final standings may be different.

Refresh

#	Δ1w	Team Name 	Kernel	Team Members	Score 	Entries	Last
1	—	 Silogram		 ★★★★★	0.51399	20	19h
2	—	Michael Jahrer		 ★★★★★	0.52067	27	4d
3	▲1	NxGTR		 ★★★★	0.52810	55	4h
353	▼70	Pau Bellot Pujalte		 ★	0.60639	9	5d
354	▲110	Prashant		 ★★	0.60653	8	4h
355	▼71	Matthijs Brouns		 ★★	0.60668	11	3d

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# Next steps

- **Opportunities remaining in the dataset:**
  - Incorporate image data
  - Further refine treatment of *manager\_id*
- **Classification modeling:**
  - Apply text classification on the *description* feature
  - Incorporate cross-validation
  - Improve understanding of the effect of features



# Questions?

An aerial view of the New York City skyline at dusk. The Empire State Building is prominently featured in the center, illuminated with its characteristic red, white, and blue lights. The city is densely packed with skyscrapers, and the lights from the buildings and streets are visible against the darkening sky. The Hudson River and the New York Harbor are visible in the background.

Prashant Tatineni