Machine Learning Model for Airbnb Yield Prediction

January 28, 2019

0.1 I. Introduction

Airbnb is a great platform that provides people online marketplace and service to arrange or offer lodging. As a travel enthusiast, Airbnb is always my first choice when I am planning a trip. Hosts need to provide details for their listed houses so that guests can use filters on the website to search for their preferred accomodations. For potential hosts, they must be very interested in how much they could earn from listing their houses on Airbnb. As far as I know, there is no such a model in public for predicting the yield of a new house on Airbnb. So, the object of this project is to apply machine learning models to help potential hosts gain some intuitions about the yield of their listed houses.

Fortunately, Inside Airbnb has already aggregated all the publicly available informations from Airbnb site for public discussion. So, the dataset obtained from this website directly should be a good starting point for my machine learning model. In particular, I will the dataset collected in New York city compiled on 06 December, 2018. When selecting features for machine learning model, besides the variables provided in the datasets, the featured photo on the listing's website and the description of listing can be crucial for attracting more guests. So, I will analyze featured photos and text mining on the descriptions and add these two new features to improve the machine learning model.

The project will be described as follows: 1. Exploratory data analysis and data preprocessing. 2. Feature engineering. 3. Machine learning model. 4. Model evaulation.

```
In [2]: # load the dataset
        import pandas as pd

        df = pd.read_csv('listings.csv')
        print ('There are {} rows and {} columns in the dataset'.format(*df.shape))
        df.head(3)
```

```
There are 49056 rows and 96 columns in the dataset
```

```
/Library/Frameworks/Python.framework/Versions/3.6/lib/python3.6/site-packages/IPython/core/inte
  interactivity=interactivity, compiler=compiler, result=result)
```

```
Out[2]:       id                        listing_url       scrape_id last_scraped  \
        0   2515   https://www.airbnb.com/rooms/2515  20181206022948   2018-12-06
        1  21456  https://www.airbnb.com/rooms/21456  20181206022948   2018-12-06
```

```
2   2539   https://www.airbnb.com/rooms/2539  20181206022948   2018-12-06

                                   name  \
0    Stay at Chez Chic budget room #1
1  Light-filled classic Central Park
2  Clean & quiet apt home by the park

                                             summary  \
0  Step into our artistic spacious apartment and ...
1  An adorable, classic, clean, light-filled one-...
2           Renovated apt home in elevator building.

                                               space  \
0  -PLEASE BOOK DIRECTLY. NO NEED TO SEND A REQUE...
1  An adorable, classic, clean, light-filled one-...
2  Spacious, renovated, and clean apt home, one b...

                                         description experiences_offered  \
0  Step into our artistic spacious apartment and ...                none
1  An adorable, classic, clean, light-filled one-...                none
2  Renovated apt home in elevator building. Spaci...                none

                                neighborhood_overview        ...           \
0                                                 NaN        ...
1  Diverse. Great coffee shops and restaurants, n...        ...
2    Close to Prospect Park and Historic Ditmas Park        ...

  requires_license license jurisdiction_names instant_bookable  \
0                f     NaN                NaN                f
1                f     NaN                NaN                f
2                f     NaN                NaN                f

  is_business_travel_ready          cancellation_policy  \
0                        f  strict_14_with_grace_period
1                        f                     moderate
2                        f                     moderate

   require_guest_profile_picture require_guest_phone_verification  \
0                              f                                f
1                              t                                t
2                              f                                f

   calculated_host_listings_count  reviews_per_month
0                               3               1.42
1                               1               0.72
2                               8               0.25

[3 rows x 96 columns]
```

In [3]: df.columns

Out[3]:
```
Index(['id', 'listing_url', 'scrape_id', 'last_scraped', 'name', 'summary',
       'space', 'description', 'experiences_offered', 'neighborhood_overview',
       'notes', 'transit', 'access', 'interaction', 'house_rules',
       'thumbnail_url', 'medium_url', 'picture_url', 'xl_picture_url',
       'host_id', 'host_url', 'host_name', 'host_since', 'host_location',
       'host_about', 'host_response_time', 'host_response_rate',
       'host_acceptance_rate', 'host_is_superhost', 'host_thumbnail_url',
       'host_picture_url', 'host_neighbourhood', 'host_listings_count',
       'host_total_listings_count', 'host_verifications',
       'host_has_profile_pic', 'host_identity_verified', 'street',
       'neighbourhood', 'neighbourhood_cleansed',
       'neighbourhood_group_cleansed', 'city', 'state', 'zipcode', 'market',
       'smart_location', 'country_code', 'country', 'latitude', 'longitude',
       'is_location_exact', 'property_type', 'room_type', 'accommodates',
       'bathrooms', 'bedrooms', 'beds', 'bed_type', 'amenities', 'square_feet',
       'price', 'weekly_price', 'monthly_price', 'security_deposit',
       'cleaning_fee', 'guests_included', 'extra_people', 'minimum_nights',
       'maximum_nights', 'calendar_updated', 'has_availability',
       'availability_30', 'availability_60', 'availability_90',
       'availability_365', 'calendar_last_scraped', 'number_of_reviews',
       'first_review', 'last_review', 'review_scores_rating',
       'review_scores_accuracy', 'review_scores_cleanliness',
       'review_scores_checkin', 'review_scores_communication',
       'review_scores_location', 'review_scores_value', 'requires_license',
       'license', 'jurisdiction_names', 'instant_bookable',
       'is_business_travel_ready', 'cancellation_policy',
       'require_guest_profile_picture', 'require_guest_phone_verification',
       'calculated_host_listings_count', 'reviews_per_month'],
      dtype='object')
```

0.2 II. Exploratory data analysis and data preprocessing

0.2.1 Data cleaning

There are 49056 observations and 96 columns in the dataset. However, not all the columns are needed for machine learning model. Especially, for a new house, there won't be any information about reviews. So columns containing informations about reviews should be dropped. These features are "review_scores_rating", "review_scores_accuracy", "review_scores_cleanliness", "review_scores_checkin", "review_scores_communication", "review_scores_location", "review_scores_value", "reviews_per_month". After carefully considering each features, these features are kept for further data analysis: > - **listing_url:** from the url, photos of the houses can be scraped. Needless to say, a comfortable featured photo of the apartment can attract more viewers and improve the yield. - **description:** description with more details about the apartment can help tourists to make the decision. - **latitude, longitude:** these two columns provide the information about the location. There are some other columns such as "transit", "zipcode", "street" are actually closely related to the location. - **property_type, room_type,**

bathrooms, bedrooms, bed_type, square_feet, amenities: these columns describe the properties of the house, such as how large is the aparment, how many bathrooms or bedrooms it has. - **guests_included, cleaning_fee, extra_people, minimum_nights, maximum_nights, availability_365, cancellation_policy:** these columns provide informations about the policy of booking a room. The house with more flexible policy may be more prefered for some tourists who are not so sure about their schedules. - **reviews_per_month:** this column is kept because it will be used later for calculating the yield. - **scrape_id:** this id is kept for later image scraping.

The data cleaning process will be performed as follows: 1. Drop all the unnecessary columns. 2. “cleaning_fee”,“extra_people”,“price” have the dollar sign before the number. Need to remove the “\$” and change the datetype from string to numerical values. 3. “property_type” has many categories, however, most of them only have few observations, so those categories can be combined into one category and name it “Other”. 4. Handle missing values. First, columns including “bathrooms”,“bedrooms”,“cleaning_fee” and “reviews_per_month” have NULL values. They can be filled in with the median. There is also a column: “square_feet” whose majority of observations is missing, so this feature can be deleted. 5. Check the distribution of variables. The distribution of “available_365” shows that some houses are only available for a few days within a year. Rooms that only available for a short time are not considered in this project.

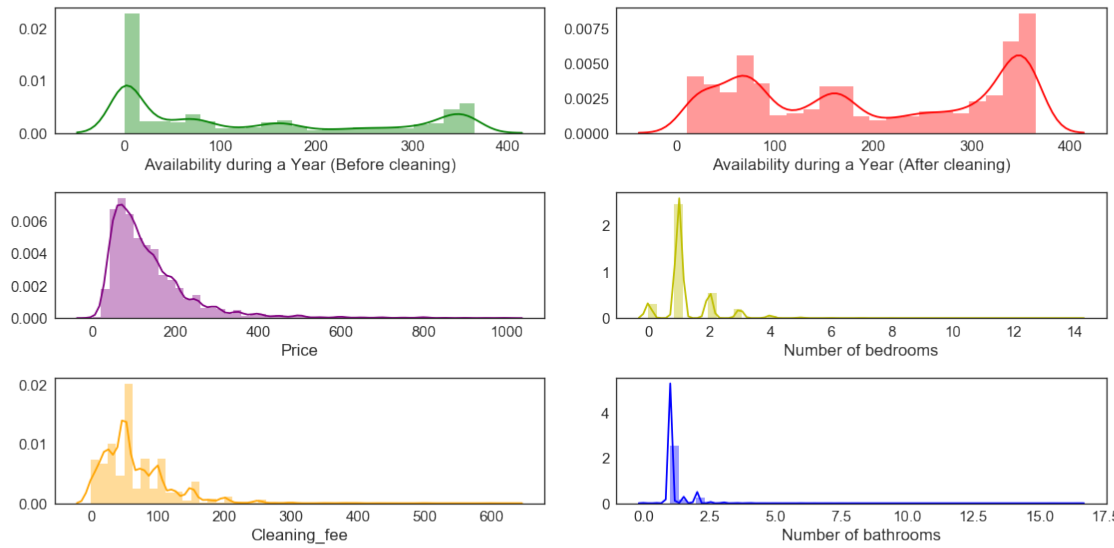
```
In [28]: import os
         import numpy as np
         import re
         import math
         import matplotlib as mpl
         import matplotlib.pyplot as plt
         import seaborn as sns

         import warnings
         warnings.filterwarnings('ignore')
```

```
In [6]: # where to save figures and results
        ROOT_DIR = os.path.dirname(os.path.realpath('__file__'))
        Image_Path = os.path.join(ROOT_DIR,'Images')

        if not os.path.exists('Images'):
            os.makedirs('Images')
        Image_path = os.path.join('Images')

        def save_fig(fig_id, tight_layout=True):
            path = os.path.join(Image_path,fig_id + ".png")
            print("Saving figure", fig_id)
            if tight_layout:
                plt.tight_layout()
            plt.savefig(path, format='png', dpi=300)
```

```
In [12]: # drop all the unnecessary columns
         feature_to_keep = ['listing_url','id','description','latitude','longitude','property_
                            'bedrooms','bed_type','price','square_feet','guests_included','clea
                            'maximum_nights','availability_365','cancellation_policy','reviews_
```

```python
new_df = df[feature_to_keep]

# remove the dollar sign before "cleaning_fee", "extra_people", "price" and change th
feature_to_remove_dollar = ['cleaning_fee','extra_people','price']
new_df[feature_to_remove_dollar] = new_df[feature_to_remove_dollar].replace('\$','',re
new_df[feature_to_remove_dollar] = new_df[feature_to_remove_dollar].apply(pd.to_numer

# merge small catergories in property_type into one category "Other"
Other = ['Bed and breakfast','Resort','Boutique hotel','Guesthouse','Hostel','Hotel',
         'Tent','Cottage','Camper/RV','Cabin','Casa particular (Cuba)','Nature lodge'
         'Island','Earth house']
new_df['property_type'].loc[new_df['property_type'].isin(Other)] = "Other"

# drop the column "square_feet"
new_df = new_df.drop('square_feet', axis = 1)

# fill NaN with median value for 'bathrooms', 'bedrooms', 'cleaning_fee', 'price'
new_df['bathrooms'] = new_df['bathrooms'].fillna(new_df['bathrooms'].median())
new_df['bedrooms'] = new_df['bedrooms'].fillna(new_df['bedrooms'].median())
new_df['cleaning_fee'] = new_df['cleaning_fee'].fillna(new_df['cleaning_fee'].median(
new_df['price'] = new_df['price'].fillna(new_df['price'].median())

# there are 523 rows missing description, drop those rows
new_df = new_df.dropna()

# EDA of other variables and drop rows with availability_365 smaller than 10
%matplotlib inline
fig,axs = plt.subplots(ncols = 2, nrows = 3, figsize = (16,8))
plt.subplots_adjust(left=0, bottom=0, right=1, top=0.9,hspace=0.5,wspace=0.3)
sns.set(style = "white",font_scale=1.5)

sns.distplot(pd.Series(new_df['availability_365'],name = "Availability during a Year
sns.distplot(pd.Series(new_df['price'], name = "Price"), color = "purple",ax = axs[1,

new_df = new_df[new_df['availability_365']>10]

sns.distplot(pd.Series(new_df['availability_365'],name = "Availability during a Year
sns.distplot(pd.Series(new_df['bedrooms'],name = "Number of bedrooms"),color = "y", a
sns.distplot(pd.Series(new_df['bathrooms'],name = "Number of bathrooms"),color = 'blu
sns.distplot(pd.Series(new_df['cleaning_fee'], name = "Cleaning_fee"), color = "orang

save_fig("Distribution_of_variables")

print ("Dataset has {} rows and {} columns.".format(*new_df.shape))
```

```
Saving figure Distribution_of_variables
Dataset has 25194 rows and 20 columns.
```



After cleaning up the data, the new dataset now has 30372 rows and 21 columns without any missing values.

0.2.2 Yield calculation

Inside Airbnb's "San Francisco Model" will be used for yield calculation. The caculation is as follows: > Yield = Average length of stay × Price × Number of reviews × 12 Months / Review_rate

Here is how the website explained the model: > Inside Airbnb's **"San Francisco Model"** uses as a modified methodology as follows: - A **review rate of 50%** is used to convert **reviews** to **estimated bookings.** - An **average length of stay** is configured for each city, and this, multiplied by the **estimated bookings** for each listings over a period gives the **occupancy rate** - Where statements have been made about the average length of stay of Airbnb guests for a city, this was used. - For example, Airbnb reported 5.5 nights as the average length of stay for guests using Airbnb in San Francisco. - Where no public statements were made about average stays, a value of **3 nights per booking** was used. - If a listing has a **higher minimum nights** value than the average length of stay, the minimum nights value was used instead. - The **occupancy rate** was **capped at 70%** - relatively high, but reasonable number for a highly occupied "hotel". - **Number of nights** booked or availble per year for the **high availability** and **frequently rented** metrics and filters were generally aligned with a city's short term rental laws designed to **protect residential housing.**

In our case, the **Average length of stay** will be 3 nights since there is no reported value. Also, if the minimum night is higher than 3 days, the average length of stay will be the value of minimum nights. 50% will be used as the review rate. The **Price** in the model should be the sum of 'price' and 'cleaning_fee' in the dataset.

```
In [13]: # calculate the Yield using San Francisco Model
         review_rate = 0.5
         new_df['average_length_of_stay'] = [3 if x < 3 else x for x in new_df['minimum_nights
         new_df['yield'] = new_df['average_length_of_stay']*(new_df['price']+new_df['cleaning_

         # reviews_per_month can be dropped now
```

```
new_df = new_df.drop('reviews_per_month',axis = 1)
new_df.head(3)

# save the current dataframe into a csv file
cleaned_listings = new_df.to_csv()
```

0.3 III. Feature engineering

0.3.1 Image analysis on featured photos

In most cases, hosts on Airbnb will upload some photos of their houses. These photos, especially the featured photo on the website, are extremely important to attract more viewers. An ideal photo should has desirable resolution and also be aesthetically attractive. Here I will use **NIMA: Neural Image Assessment** to score image quality. In NIMA, a deep convolutional neural network (CNN) is trained to predict whether the image will rated by a viewer as looking good (technically) and attractive (aesthetically).

To assess both resolution and perceptual quality, the model first initialize weights from object recognition networks, such as ImageNet, to understand general classification of objects. Then the perceptual quality assessment is achieved by fine-tuning on annotated data. This NIMA model gives a distribution of ratings for a given image on scale of 1 to 10 and also assign the probabilities. NIMA has been tested on Aesthetic Visual Analysis (AVA) datasets, and the rank given by NIMA matches closely the mean scores given by human raters.

Here, I will use the pre-trained the NIMA model Github to predict the image score for each featured photo on the website and this score will be incorporated as a new feature for machine learning model. The workflow will be as follows:

1. Use beautiful soup to scrape images from the url link of the listed houses.
2. Predict the image score use NIMA model.

In [9]:
```
import requests
from bs4 import BeautifulSoup
import urllib.request
import scipy.misc
```

In [11]:
```
# extract the url for the feature photo from 'listings_url'
listings = new_df['listing_url']
image_link = {}
for file_url in listings:
    page = requests.get(file_url)
    soup = BeautifulSoup(page.text,"html.parser")
    img_tags = soup.find_all('img')
    img_urls = [img['src'] for img in img_tags]
    for url in img_urls:
        if not url.startswith("https://a0.muscache.com/im/pictures/"):
            continue
        image_link[file_url] = url
        break
```

In [14]:
```
# add this featured photo url to the dataframe
new_df['image_link'] = new_df['listing_url'].map(image_link)
```

```
#some listings are no longer availble, so their image_link is missing.
new_df = new_df.dropna()

# set up the path for the photos output
ROOT_DIR = os.path.dirname(os.path.realpath('__file__'))
Photo_Path = os.path.join(ROOT_DIR,'Photos')

if not os.path.exists('Photos'):
    os.makedirs('Photos')
Photo_path = os.path.join('Photos')

# scraping images from the link
df_image = new_df[['id','image_link']].reset_index()

new_df = new_df.reset_index()

for i in range(len(df_image)):
   # link = df_image['image_link'][i]
    url_link = new_df['listing_url'][i]
   # print (url_link)
    link = image_link[url_link]
    photo_id = df_image['id'][i]
    image_name = os.path.join(Photo_Path,str(photo_id)+str('.jpg'))

    if not os.path.isfile(image_name):
        f = open(image_name,'wb')
        f.write(requests.get(link).content)
        f.close()
```

In [15]:
```
# take random samples
sample = df_image['image_link'][42]
photo_id = df_image['id'][42]
image_name = os.path.join(Photo_path, str(photo_id)+str('.jpg'))
img = scipy.misc.imread(image_name)
plt.imshow(img)
```

Out[15]: <matplotlib.image.AxesImage at 0x1059bd7f0>

In [30]:
```
# use NIMA model to score images
import tensorflow as tf
from keras.models import Model
from keras.layers import Dense, Dropout
from keras.applications.mobilenet import MobileNet
from keras.applications.mobilenet import preprocess_input
from keras.preprocessing.image import load_img, img_to_array
from utils import mean_score, std_score

NIMA_dic = {}
image_name = os.path.join(Photo_path, str(photo_id)+str('.jpg'))

with tf.device('/CPU:0'):
    base_model = MobileNet((None, None, 3), alpha=1, include_top=False, pooling='avg'
    x = Dropout(0.75)(base_model.output)
    x = Dense(10, activation='softmax')(x)

    model = Model(base_model.input, x)
    model.load_weights('weights/mobilenet_weights.h5')

    for i in range(len(df_image)):
        photo_id = df_image['id'][i]
        image_name = os.path.join(Photo_path, str(photo_id)+str('.jpg'))

        img = load_img(image_name)
```

```
        x = img_to_array(img)
        x = np.expand_dims(x, axis=0)
        x = preprocess_input(x)

        scores = model.predict(x, batch_size=1, verbose=0)[0]

        mean = mean_score(scores)
        std = std_score(scores)
        NIMA_dic[photo_id] = mean
        #print("NIMA Score : %0.3f +- (%0.3f)" % (mean, std))
```

In [31]:
```
# add NIMA_score to new_df
new_df['NIMA_score'] = new_df['id'].map(NIMA_dic)
```

In [33]:
```
new_df.head(5)
```

Out[33]:
```
   index                         listing_url     id  \
0      1  https://www.airbnb.com/rooms/21456  21456
1      2   https://www.airbnb.com/rooms/2539   2539
2      3   https://www.airbnb.com/rooms/2595   2595
3      4  https://www.airbnb.com/rooms/21644  21644
4      5   https://www.airbnb.com/rooms/3330   3330

                                         description   latitude  longitude  \
0  An adorable, classic, clean, light-filled one-...  40.797642 -73.961775
1  Renovated apt home in elevator building. Spaci...  40.647486 -73.972370
2  Find your romantic getaway to this beautiful, ...  40.753621 -73.983774
3  A great space in a beautiful neighborhood- min...  40.828028 -73.947308
4  This is a spacious, clean, furnished master be...  40.708558 -73.942362

  property_type        room_type  accommodates  bathrooms    ...      \
0     Apartment  Entire home/apt             2        1.0    ...
1     Apartment     Private room             4        1.0    ...
2     Apartment  Entire home/apt             2        1.0    ...
3     Apartment     Private room             1        1.0    ...
4     Apartment     Private room             2        1.0    ...

   cleaning_fee extra_people  minimum_nights  maximum_nights  \
0          40.0         28.0               5             365
1          25.0         25.0               1             730
2         100.0          0.0               1            1125
3          30.0         55.0               1              60
4         125.0         50.0               5             730

   availability_365          cancellation_policy  average_length_of_stay  \
0               248                     moderate                       5
1               365                     moderate                       3
2               350  strict_14_with_grace_period                       3
```

```
3              365   strict_14_with_grace_period                       3
4              216   strict_14_with_grace_period                       5

      yield                                          image_link  NIMA_score
0  15552.00  https://a0.muscache.com/im/pictures/111808/a94...    4.519021
1   3132.00  https://a0.muscache.com/im/pictures/3949d073-a...    5.003754
2   8658.00  https://a0.muscache.com/im/pictures/f028bdf9-e...    4.826283
3   4369.68  https://a0.muscache.com/im/pictures/43197335/5...    4.466677
4   8190.00  https://a0.muscache.com/im/pictures/41842659/5...    4.571960

[5 rows x 24 columns]
```

0.3.2 Sentiment analysis on 'description'

Description of the houses also has a great impact on guest's decision. An appropriate description can not only provide viewers with more details of the room but also leave them good impressions of the living environment using phrases such as "comfortable", "lovely bedroom", "bright and sunny room". So this part will focus on extraccting useful features from description. **Nature language processing (NLP)** and **topic modeling** will be carried out to analyze the text in 'description'.

Topic model is a widely used text-mining tools to discover the abstract "topics" hidden in a collection of documents. Here, **Latent Dirichlet Allocation (LDA)** will be used to discover topics in each description. In LDA model, a generative Bayesian inference model is used to assign each document with a probability distribution over topics, where topics are probability over words.

Before topic modeling, the number of corpus in each description needs to be reduced. Non-english words, stop words and non-alphanumeric strings will be removed. The remaining corpus will also be lemmatised so that only important and meaningful words will be kept later sentiment analysis. The corpus then needs to be converted into a **Document-term-matrix**, where each row corresponding to the documents and column corresponding to the terms.

The pipeline of topic modeling on text of description will be as follows: 1. Tokenize words, remove non-english words, stop words and non-alphanumeric strings, convert all letters to lower case, and lemmatize words. 2. Convert the remaining corpus into Document Term Matrix. 3. Apply LDA model to model topics. 4. Use pyLDAvis.gensim to visualize topics. 5. Assign each observation with the topics with highest probability.

```
In [34]: import nltk
         from nltk import word_tokenize
         from nltk.corpus import stopwords
         from nltk.stem import WordNetLemmatizer
         from nltk.tokenize import RegexpTokenizer

         from gensim.corpora.dictionary import Dictionary
         from gensim.models.tfidfmodel import TfidfModel
         from gensim.models.ldamodel import LdaModel

         import json
         import pyLDAvis.gensim
         pyLDAvis.enable_notebook()
```

In [35]:
```
def preprocess_text(corpus):
    processed_corpus = []
    english_words = set(nltk.corpus.words.words())
    english_stopwords = set(stopwords.words('english'))
    wordnet_lemmatizer = WordNetLemmatizer()
    tokenizer = RegexpTokenizer(r'[A-Za-z|!]+')
    for row in corpus:
        sentences = []
        word_tokens = tokenizer.tokenize(row)
        word_tokens_lower = [t.lower() for t in word_tokens]
        word_tokens_lower_english = [t for t in word_tokens_lower if t in english_word
        word_tokens_no_stops = [t for t in word_tokens_lower_english if not t in engli
        word_tokens_no_stops_lemmatized = [wordnet_lemmatizer.lemmatize(t) for t in wo
        for word in word_tokens_no_stops_lemmatized:
            if len(word) > 2:
                sentences.append(word)
        processed_corpus.append(sentences)
    return processed_corpus

def pipline(processed_corpus):
    dictionary = Dictionary(processed_corpus)
    doc_term_matrix = [dictionary.doc2bow(listing) for listing in processed_corpus]
    return dictionary, doc_term_matrix

def lda_topic_model(doc_term_matrix,dictionary,num_topics = 3, passes = 2):
    LDA = LdaModel
    ldamodel = LDA(doc_term_matrix,num_topics = num_topics, id2word = dictionary, pass
    return ldamodel

def topic_feature(ldamodel,doc_term_matrix,df,new_col,num_topics):
    docTopicProbMat = ldamodel[doc_term_matrix]
    docTopicProbDf = pd.DataFrame(index = df.index, columns = range(0,num_topics))
    for i,doc in enumerate(docTopicProbMat):
        for topic in doc:
            docTopicProbDf.iloc[i,topic[0]] = topic[1]
    docTopicProbDf = docTopicProbDf.fillna(0)
    docTopicProbDf[new_col] = docTopicProbDf.idxmax(axis=1)
    df_topics = docTopicProbDf[new_col]
    df_new = pd.concat([df,df_topics],axis = 1)
    return df_new
```

In [36]:
```
corpus_description = new_df['description'].astype(str)

# use nlp package to process the text in description
processed_corpus_description = preprocess_text(corpus_description)

# generate the doc_term_matrix for lda model
dictionary_description, doc_term_matrix_description = pipline(processed_corpus_descri
```

```
# lda model for topic modeling
ldamodel_description = lda_topic_model(doc_term_matrix_description,dictionary_descrip

# add the topic feature to the dataframe
final_df = topic_feature(ldamodel_description,doc_term_matrix_description,new_df,new_

# visualization of the lda model and save it as html page
p_description = pyLDAvis.gensim.prepare(ldamodel_description, doc_term_matrix_descrip
pyLDAvis.save_html(p_description,'lda_description.html')
p_description
```

Out[36]:

```
PreparedData(topic_coordinates=            Freq  cluster  topics         x         y
topic
1      34.922226        1       1 -0.008218 -0.092251
0      33.256050        1       2 -0.093856  0.051930
2      31.821728        1       3  0.102075  0.040322, topic_info=     Category
term
72     Default  10722.000000      train  10722.000000  30.0000  30.0000
44     Default  28305.000000       room  28305.000000  29.0000  29.0000
135    Default  11397.000000       away  11397.000000  28.0000  28.0000
69     Default   9902.000000       park   9902.000000  27.0000  27.0000
52     Default  11609.000000       walk  11609.000000  26.0000  26.0000
488    Default   5693.000000        min   5693.000000  25.0000  25.0000
368    Default   9669.000000     subway   9669.000000  24.0000  24.0000
53     Default   5436.000000    walking   5436.000000  23.0000  23.0000
345    Default   4595.000000     please   4595.000000  22.0000  22.0000
4      Default  14352.000000        bed  14352.000000  21.0000  21.0000
62     Default   3591.000000        bus   3591.000000  20.0000  20.0000
770    Default   4666.000000     minute   4666.000000  19.0000  19.0000
18     Default   4530.000000   distance   4530.000000  18.0000  18.0000
105    Default   7497.000000      large   7497.000000  17.0000  17.0000
41     Default   6973.000000      queen   6973.000000  16.0000  16.0000
64     Default   7409.000000      close   7409.000000  15.0000  15.0000
474    Default   4732.000000    station   4732.000000  14.0000  14.0000
103    Default   4698.000000       high   4698.000000  13.0000  13.0000
6      Default   5642.000000      block   5642.000000  12.0000  12.0000
330    Default   4458.000000        use   4458.000000  11.0000  11.0000
163    Default   3070.000000       sofa   3070.000000  10.0000  10.0000
110    Default   3958.000000     modern   3958.000000   9.0000   9.0000
47     Default   7090.000000       size   7090.000000   8.0000   8.0000
335    Default   5106.000000      fully   5106.000000   7.0000   7.0000
8      Default   5893.000000    central   5893.000000   6.0000   6.0000
253    Default   8431.000000     street   8431.000000   5.0000   5.0000
239    Default   2351.000000       loft   2351.000000   4.0000   4.0000
146    Default   4637.000000      guest   4637.000000   3.0000   3.0000
589    Default   6842.000000      place   6842.000000   2.0000   2.0000
26     Default  10792.000000       full  10792.000000   1.0000   1.0000
```

```
...       ...          ...        ...           ...      ...      ...
627    Topic3  1896.323242      brand   2602.301270   0.8285  -5.4697
539    Topic3  1022.799316       oven   1266.570190   0.9313  -6.0870
625    Topic3  1699.597168     washer   2319.497314   0.8341  -5.5792
885    Topic3  1636.939087       unit   2257.702637   0.8235  -5.6167
4      Topic3  7418.728027        bed  14352.841797   0.4851  -4.1056
47     Topic3  4026.444092       size   7090.324219   0.5792  -4.7167
61     Topic3  4871.244629   building   9060.818359   0.5244  -4.5262
26     Topic3  5570.354980       full  10792.361328   0.4836  -4.3921
5      Topic3  8544.608398    bedroom  18732.261719   0.3601  -3.9643
1      Topic3 11995.432617  apartment  30954.859375   0.1970  -3.6251
151    Topic3  5664.839844        new  12073.905273   0.3883  -4.3753
534    Topic3  2501.336182     dining   4031.940918   0.6676  -5.1928
24     Topic3  4312.537109      floor   8462.575195   0.4709  -4.6481
31     Topic3  7372.365234    kitchen  19559.476562   0.1693  -4.1118
541    Topic3  1860.073853      table   2759.417969   0.7506  -5.4890
149    Topic3  5497.965332     living  13542.403320   0.2436  -4.4052
98     Topic3  1912.665649  furnished   2916.717773   0.7231  -5.4611
71     Topic3  2766.180176   spacious   5700.879883   0.4219  -5.0921
37     Topic3  3713.686279        one  10843.396484   0.0735  -4.7976
44     Topic3  6163.111816       room  28305.009766  -0.3794  -4.2910
83     Topic3  2755.910400  beautiful   6673.035156   0.2607  -5.0958
164    Topic3  3417.180908      space  11238.115234  -0.0455  -4.8808
256    Topic3  2782.688965        two   8109.112793   0.0755  -5.0862
2      Topic3  3193.493652   bathroom  12394.978516  -0.2112  -4.9485
200    Topic3  3249.027588    private  13661.231445  -0.2912  -4.9312
79     Topic3  2565.538086       area   8562.381836  -0.0602  -5.1674
101    Topic3  2136.448486      heart   4837.126953   0.3278  -5.3504
8      Topic3  2103.172852    central   5893.778320   0.1146  -5.3661
69     Topic3  2236.740967       park   9902.964844  -0.3428  -5.3046
253    Topic3  2100.597412     street   8431.496094  -0.2447  -5.3674

[312 rows x 6 columns], token_table=      Topic      Freq           Term
term
134       1  0.463167         access
134       2  0.342569         access
134       3  0.194186         access
6028      1  0.967265    accordingly
6028      2  0.016394    accordingly
6028      3  0.016394    accordingly
216       1  0.111973         across
216       2  0.789540         across
216       3  0.097977         across
3790      1  0.954322        advised
3790      3  0.036240        advised
2539      1  0.968664        alcohol
59        1  0.500166           also
59        2  0.334117           also
```

59	3	0.165797	also
1	1	0.270878	apartment
1	2	0.341626	apartment
1	3	0.387500	apartment
6065	2	0.967424	aquarium
6065	3	0.019743	aquarium
78	1	0.009837	architectural
78	2	0.009837	architectural
78	3	0.983721	architectural
79	1	0.388910	area
79	2	0.311362	area
79	3	0.299683	area
9337	2	0.965147	arent
637	1	0.321966	around
637	2	0.623185	around
637	3	0.054624	around
...	...	...	...
330	1	0.791965	use
330	2	0.147358	use
330	3	0.060782	use
52	1	0.131786	walk
52	2	0.731540	walk
52	3	0.136695	walk
53	1	0.085719	walking
53	2	0.824632	walking
53	3	0.089766	walking
625	1	0.134943	washer
625	2	0.132356	washer
625	3	0.732917	washer
299	1	0.663803	welcome
299	2	0.208367	welcome
299	3	0.127854	welcome
57	1	0.127825	within
57	2	0.679809	within
57	3	0.192496	within
133	1	0.033859	wood
133	2	0.044743	wood
133	3	0.920251	wood
259	1	0.705241	work
259	2	0.152198	work
259	3	0.142839	work
420	1	0.793805	would
420	2	0.147738	would
420	3	0.058177	would
1302	1	0.030929	zoo
1302	2	0.951938	zoo
1302	3	0.017183	zoo

```
[670 rows x 3 columns], R=30, lambda_step=0.01, plot_opts={'xlab': 'PC1', 'ylab': 'PC
```

pyLDAvis package is a great package to visualize the LDA model. The area of the circles means the prevalence of each topic. Here I chose the cluster the corpus into three topics. The red bar represents the estimated term frequency within selected topic and the blue bar represents the overall term frequency. In topic 1, the prevalent term is about layout of the room, for example, there are words "kitchen", "bathroom", "bedroom". Topic 2 is about the living environment because it has words "new","private","space","large". Topic 3 is correlated with location or transit with words "subway", "walk","away". There are some overlaps among these three topics, which can be improved to better serve the machine learninng model. At this moment, I will go ahead with the current model.

0.4 IV. Machine learning model

In this part, 3 regression algorithms: **linear regression, decision tree** and **random forest** will be trained to predict the yield. Linear regression is the simplest algorithm and will be used as the baseline model. Decision tree model can capture the nonlinear relationships in the dataset while random forest is a more complex model and able to provide higher accuracy.

To measure the accuracy of the model, MSE (mean squared error) is used as evaluation metrics. The target for prediction is "yield". "price" and "reviews_per_month", "average_length_of_stay" have strong correlation with "yield" because they are used for yield calculation. Catergorical features also need to be converted to numerical features so that they can be fed into machine learning algorithms. To split the whole dataset into a training set and a testing set, the dataset will be randomly shuffled first and 25% will be used as the splitting ratio.

Once the 3 algorithms have been applied and trained, they will be compared based on MSE value. The smaller MSE, the better accuracy. The best algorithm will be chosen and the model will be further fine-tuned using GridSearchCV function in scikit-learn. The to-do list in this part is:

1. Clean-up the dataset: separate the "yield" from the dataset and save it as the target, drop "price", "average_length_of_stay" and "reviews_per_month", convert catergorical variables into numerical features. Other columns including "level_0", "id", "listing_url", "description","image_link" can be dropped as well since they are not needed any more.
2. Randomly shuffle the dataset to remove inherent order and split the dataset into a training set and a test set using 75:25 ratio.
3. Use linear regression, decision tree, and random forest separately to train the model and calculate the MSE value.
4. Select the model with lowest MSE value for further refinement.

In [38]:
```
# drop unnecessary columns
cols_to_drop = ['price','average_length_of_stay','minimum_nights','cleaning_fee','inde
final_df = final_df.drop(cols_to_drop, axis = 1)

# convert strings to numerical features
categorical_feats = ['property_type', 'room_type', 'bed_type', 'cancellation_policy',
final_df = pd.get_dummies(final_df, columns = categorical_feats, drop_first = False)

# separate the target variable "yield" from the dataset
target = final_df['yield']
final_df = final_df.drop(['yield'], axis = 1)
```

```python
print ("Final dataset has {} rows, {} columns.".format(*final_df.shape))
```

```
Final dataset has 21770 rows, 35 columns.
```

In [23]:
```python
final_df.head(5)
```

Out[23]:
```
   index                          listing_url     id  \
0      1  https://www.airbnb.com/rooms/21456  21456
1      2   https://www.airbnb.com/rooms/2539   2539
2      3   https://www.airbnb.com/rooms/2595   2595
3      4  https://www.airbnb.com/rooms/21644  21644
4      5   https://www.airbnb.com/rooms/3330   3330

                                         description   latitude  longitude  \
0  An adorable, classic, clean, light-filled one-...  40.797642 -73.961775
1  Renovated apt home in elevator building. Spaci...  40.647486 -73.972370
2  Find your romantic getaway to this beautiful, ...  40.753621 -73.983774
3  A great space in a beautiful neighborhood- min...  40.828028 -73.947308
4  This is a spacious, clean, furnished master be...  40.708558 -73.942362

  property_type        room_type  accommodates  bathrooms        ...          \
0     Apartment  Entire home/apt             2        1.0        ...
1     Apartment     Private room             4        1.0        ...
2     Apartment  Entire home/apt             2        1.0        ...
3     Apartment     Private room             1        1.0        ...
4     Apartment     Private room             2        1.0        ...

   extra_people minimum_nights  maximum_nights  availability_365  \
0          28.0              5             365               248
1          25.0              1             730               365
2           0.0              1            1125               350
3          55.0              1              60               365
4          50.0              5             730               216

          cancellation_policy  average_length_of_stay     yield  \
0                    moderate                       5  15552.00
1                    moderate                       3   3132.00
2  strict_14_with_grace_period                      3   8658.00
3  strict_14_with_grace_period                      3   4369.68
4  strict_14_with_grace_period                      5   8190.00

                                          image_link  NIMA_score  \
0  https://a0.muscache.com/im/pictures/111808/a94...         NaN
1  https://a0.muscache.com/im/pictures/3949d073-a...         NaN
2  https://a0.muscache.com/im/pictures/f028bdf9-e...         NaN
3  https://a0.muscache.com/im/pictures/43197335/5...         NaN
```

```
4  https://a0.muscache.com/im/pictures/41842659/5...         NaN

  description_topic
0                 2
1                 0
2                 2
3                 1
4                 1

[5 rows x 25 columns]
```

```
In [39]: # split the training set and testing set
         from sklearn.model_selection import train_test_split
         from sklearn.metrics import mean_squared_error,r2_score
         seed = 42
         X_train,X_test,y_train,y_test = train_test_split(final_df,target,random_state=seed)
```

```
In [40]: final_df.to_csv('final_df.csv')
```

0.4.1 Linear regression

```
In [41]: from sklearn.linear_model import LinearRegression

         linreg = LinearRegression().fit(X_train, y_train)
         y_pred_linreg = linreg.predict(X_test)

         print("Mean squared error: %.3f" %mean_squared_error(y_test,y_pred_linreg))
         print("Variance score: %.3f" %r2_score(y_test,y_pred_linreg))
```

```
Mean squared error: 4781289307.734
Variance score: 0.104
```

0.4.2 Decision trees

```
In [42]: from sklearn.tree import DecisionTreeRegressor
         for K in [1,3,5,7,10,15,20,30]:
             dt_reg = DecisionTreeRegressor(random_state = seed, max_depth = K).fit(X_train,y_
             y_dt_pred = dt_reg.predict(X_test)
             print ("max_depth = " + str(K))
             print ("Mean squared error: %.3f" %mean_squared_error(y_test,y_dt_pred))
             print ("Variance score: %.3f" %r2_score(y_test,y_dt_pred))
```

```
max_depth = 1
Mean squared error: 5024803151.882
Variance score: 0.059
max_depth = 3
Mean squared error: 4789684788.300
Variance score: 0.103
```

```
max_depth = 5
Mean squared error: 4588601834.546
Variance score: 0.140
max_depth = 7
Mean squared error: 4941400033.278
Variance score: 0.074
max_depth = 10
Mean squared error: 7397470407.079
Variance score: -0.386
max_depth = 15
Mean squared error: 8291334303.409
Variance score: -0.553
max_depth = 20
Mean squared error: 8903546780.280
Variance score: -0.668
max_depth = 30
Mean squared error: 9127202991.476
Variance score: -0.710
```

0.4.3 Random forest

```
In [43]: from sklearn.ensemble import RandomForestRegressor

         for K in [1,3,5,7,10,15,20]:
             rf_reg = RandomForestRegressor(random_state = seed, bootstrap = True, criterion =
                                            max_features = 'auto', min_samples_split = 5, n_es
             y_rf_pred = rf_reg.predict(X_test)

             print ("Max_depth = " + str(K))
             print("Mean squared error: %.3f" %mean_squared_error(y_test,y_rf_pred))
             print("Variance score: %.3f" %r2_score(y_test,y_rf_pred))
```

```
Max_depth = 1
Mean squared error: 4933940765.512
Variance score: 0.076
Max_depth = 3
Mean squared error: 4792797066.583
Variance score: 0.102
Max_depth = 5
Mean squared error: 4714308643.520
Variance score: 0.117
Max_depth = 7
Mean squared error: 4708215874.375
Variance score: 0.118
Max_depth = 10
Mean squared error: 4678417980.839
Variance score: 0.124
```

```
Max_depth = 15
Mean squared error: 4653522451.420
Variance score: 0.128
Max_depth = 20
Mean squared error: 4671374608.185
Variance score: 0.125
```

0.5 V. Fine tuning and model evaluation

As expected, random forest gave the lowest MSE and highest variance score. So this part will focusing on fine tuning the model and test how robust the model is. It will be structured into three parts:

1. Using GridSearchCV to fine tuning the model using random forest regressor.
2. Check the importance of each feature in the dataset, especially the two features from image analysis and text mining.
3. Test the robustness of the model by using a different seed.

In [44]:
```
from sklearn.model_selection import GridSearchCV

param_grid = {"n_estimators" :[150,175,200,225,250,300],
              "criterion": ['mse'],
              "max_features": ['auto'],
              "max_depth": [3,5,7,9,11,15,20],
              "min_samples_split":[4,6,8,10,12],
              "bootstrap":[True]}

rf_fine = RandomForestRegressor(random_state = seed)
rf_cv = GridSearchCV(rf_fine,param_grid,cv=5).fit(X_train,y_train)
y_rf_cv_pred = rf_cv.predict(X_test)
print("Mean squared error: %.3f" % mean_squared_error(y_test, y_rf_cv_pred))
print('Variance score: %.3f' % r2_score(y_test, y_rf_cv_pred))
print("Best Parameters: {}".format(rf_cv.best_params_))
```

```
Mean squared error: 4637113425.384
Variance score: 0.131
Best Parameters: {'bootstrap': True, 'criterion': 'mse', 'max_depth': 15, 'max_features': 'auto
```

In [45]:
```
rf_final = rf_cv.best_estimator_
feature_import = rf_final.feature_importances_*100
feature_import = pd.DataFrame(list(zip(feature_import,X_train.columns.values)))
feature_import = feature_import.sort_values(by=0,axis=0,ascending=False)
feature_import.columns = ['importance %','feature']
print(feature_import[:20])
```

```
    importance %                                                     feature
1      18.040199                                                   longitude
```

```
0       17.378363                                          latitude
2       12.976208                                     accommodates
8       10.915914                                 availability_365
9        8.753188                                       NIMA_score
18       6.882709                        room_type_Entire home/apt
7        5.939127                                   maximum_nights
4        4.540373                                         bedrooms
5        3.179635                                  guests_included
6        3.088270                                     extra_people
3        2.322952                                        bathrooms
13       1.532435                              property_type_House
34       0.658664                              description_topic_2
14       0.462011                               property_type_Loft
11       0.456593                        property_type_Condominium
29       0.406894  cancellation_policy_strict_14_with_grace_period
26       0.400477                     cancellation_policy_flexible
32       0.353673                              description_topic_0
19       0.343429                           room_type_Private room
17       0.230167                          property_type_Townhouse
```

Location has a combined importance of 36% - 18.4% from longitude and 17.5% from latitude, which make sense to me. A convenient location can be very attractive for viewers. Other features such as "accommodates" and "availability_365" also occupied 13.5% and 11.1% importance. Interestingly, the **NIMA score** engineered from photos on the website have **9.3%** of importance. The other feature **"description_topic"** also has combined **>1%** of importance (sum of "description_topic_2" and "description_topic_0"). This information shows that there are valuable information in the photo and description text.

To test the robustness of the model, random_state for shuffling dataset will be changed, the ratio of training set and test set will also be changed to 0.3.

```
In [46]: random_state = 35
         X_train,X_test,y_train,y_test = train_test_split(final_df,target,test_size = 0.3,rand
```

```
In [47]: # Fit and make prediction
         rf_final.fit(X_train, y_train)
         rf_y_pred = rf_final.predict(X_test)

         # The mean squared error
         print("Mean squared error: %.2f" % mean_squared_error(y_test, rf_y_pred))
         # Explained variance score: 1 is perfect prediction
         print('Variance score: %.2f' % r2_score(y_test, rf_y_pred))
```

```
Mean squared error: 4209814319.47
Variance score: 0.14
```

There is no significant difference after adjusting the random state and proportions of training set and test set, which demonstrate that the final model is robust.

0.6 VI. Conclusion and reflection

The original goal of this project is to apply machine learning algorithms to give potential hosts some insights on how much they can earn from listing their beloved houses on Airbnb. The information from Inside Airbnb is definitely very helpful. Combined my own experience of browsing accommodations in Airbnb, I added two additional features: image score and topic modeling from web photos and descriptions. It turned out that these two features actually contain valuable informations. Of couse, my solution is not perfect, here are two points I would like to spend more time on further improving my model.

1. There are some overlaps among the three topics, so potential improvement would be implement the topic modeling methods. It would be worthwhile comparing LDA with other algorithms, such as Non-negative matrix factorization.
2. Should I consider time effect? If a host gets very positive reviews from first few guests, it's possible that new viewers will also consider choosing their houses. How should I predict time series?

Having spent lots of time on data in chemistry as a chemistry PhD candidate, I always want to know the data in real world and what we can learn from it. I had a great time when doing this project. From designing the workflow, analyzing images to text mining, I learnt a lot and am very pleased to see that my model has suggested some informations from images and text on the website. In the end, I would also like to learn how to design a web application where hosts can actually upload their photos and informations about their houses and get an estimation of their yield using the model.