Data Bootcamp Final Project: AirBnB and the Starbucks Effect in NYC

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We know that property values can be positively influenced or predicted by the presence of Starbucks (https://qz.com/334269/what-starbucks-has-done-to-american-home-values/), but what about short term accomodation prices? The purpose of this project is to see whether Starbucks is affecting more dynamic, short term rental prices. To do that, we will explore the relationship between Starbucks and AirBnb in the context of New York City. Specifically, we would like to examine the correlation between Starbucks proximity and AirBnb prices, as well as the effect over time of Starbucks locations on AirBnb availability.

Contents:

Data Report

Datasets:

1. Starbucks: The 'All Starbucks Locations in the World' dataset on Socrata (https://opendata.socrata.com/Business/All-Starbucks-Locations-in-the-World/xy4y-c4mk)
2. AirBnb: AirBnb 'Get The Data' listing data on New York City (http://insideairbnb.com/get-the-data.html)

Both datasets used in this project are accessible to the public.

The Starbucks dataset was compiled by Chris Meller on Socrata, though the API that allowed the database to be scraped was discontinued in July, 2017 and the most recent store added is dated December, 2016. It was first scraped in December, 2013 so only stores opened after that date include a usable time element. The dataset also includes contact and location information. Because this dataset is hosted on Socrata, it is possible to query the SODA API for New York specifically. Note that there are some stores that are different brands owned by Starbucks.

AirBnb released troves of NYC data two years ago (https://www.nytimes.com/2015/12/02/technology/airbnb-releases-trove-of-new-york-city-home-sharing-data.html?_r=0) as part of their Inside AirBnb initiative. They also list information on other localities all around the world. This dataset includes over 60 datapoints including location, availability, pricing, reviews, and more. Unfortunately no one has begun a hosted database of this information over time, so the only data that could be used as a timeseries is availability, which is noted in days out of the last 30, 60, 90, and 365. Unfortunately, at this writing, that does not overlap with timeseries data from Starbucks, and the averaging required to look at these periods dilutes the data significantly. Note that this database is only available for download and is extremely large.

Packages

- `Requests` used to query SODA API
- `Pandas` used to generate dataframes, analyze
- `Basemap` used to map
- `Matplotlib` used to plot
- `Numpy` used for logs
- `Geopy` used to determine distances
- `Datetime` used for timeseries
- `Statsmodels` used for regression line
- `Seaborn` used for easy best fit line

In [1070]:
```
import requests #importing requests module for api
import pandas as pd #importing pandas module for DataFrames
from mpl_toolkits.basemap import Basemap #importing basemap for maps
import matplotlib.pyplot as plt #importing matplotlib for graphs and plots
import numpy as np #importing numpy for analysis
from geopy.distance import great_circle #importing geopy for distance calculations
from datetime import date #importing datetime for timeseries
import statsmodels.api as sm #importing statsmodels for regression line
import statsmodels.formula.api as smf #importing statsmodels for regression line
import seaborn as sns #importing seaborn for easy regression lines

%matplotlib inline
#renders matplotlib plots in Jupyter Notebook
```

Importing Data

Starbucks from Socrata API

In [1071]:
```
#socrata api url queried for New York
r = requests.get('https://opendata.socrata.com/resource/xy4y-c4mk.json?country_subdivision=NY'
)
x = r.json()
stardf = pd.DataFrame(x)
stardf.columns
```

Out[1071]:
```
Index(['brand', 'city', 'coordinates', 'country', 'country_subdivision',
       'current_timezone_offset', 'first_seen', 'latitude', 'longitude',
       'name', 'olson_timezone', 'ownership_type', 'phone_number',
       'postal_code', 'store_id', 'store_number', 'street_1', 'street_2',
       'street_3', 'street_combined', 'timezone'],
      dtype='object')
```

In [1072]:
```
stardf.shape
```

Out[1072]:
```
(640, 21)
```

Scrubbing Starbucks Data

There are 640 Starbucks locations in New York State. The city location data is thrown off by the use of boroughs, so we have to use state level selection querying the API. One observation for someone interested in following up is that every starbucks has a store number and a store id. We'll use store id for the purpose of this project.

To clean this data we'll need to do two things:

1. Reduce the number columns: we really only need an identifier, location, and creation timestamp
2. Change the types for calculations: coordinates to floats and timeseries information to datetime

```
In [1073]: #choosing useful columns
           stardf = stardf[['store_id',                 #identifier
                            'longitude','latitude',      #location data
                            'first_seen',                #timeseries data
                            'country_subdivision']].copy() #data for easy merge

           #changing type of timeseries data
           stardf['first_seen'] = pd.to_datetime(stardf['first_seen']) #pandas making timeseries data int
           o datetime format
           stardf['first_seen'] = [time.date() for time in stardf['first_seen']] #really only need date,
            not hours and mins

           #changing type of location data
           stardf.longitude = stardf.longitude.astype(float).copy()  #to float
           stardf.latitude = stardf.latitude.astype(float).copy()  #to float

           stardf.head()
```

Out[1073]:

	store_id	longitude	latitude	first_seen	country_subdivision
0	6348	-73.831879	40.714371	2013-12-08	NY
1	6491	-73.288651	40.806366	2013-12-08	NY
2	6535	-76.236130	43.046398	2013-12-08	NY
3	6551	-73.947243	40.631264	2013-12-08	NY
4	6590	-73.975327	40.789288	2013-12-08	NY

AirBnb from downloaded CSV

In [1074]:
```
#local csv file
airlist = '/Users/marketem/Data_Bootcamp/listings.csv'
# create dataframe
airdf = pd.read_csv(airlist)
airdf.columns
```

```
/Users/marketem/anaconda/lib/python3.6/site-packages/IPython/core/interactiveshell.py:2717: D
typeWarning: Columns (43,88) have mixed types. Specify dtype option on import or set low_memo
ry=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

Out[1074]:
```
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')
```

Scrubbing AirBnb Data
Wow, over 44,000 AirBnb's in New York City. As we can see there is also a huge number of columns, most of which we won't use for this analysis. It is worth it to note that there is potential in exploring the comprehensive review data here, although it wasn't used in this project. To clean this up:

1. For size: Get rid of the columns we don't need
2. For calculations: Remove unnecessary figures '$' and ',' from pricing

Again the city data is complicated by boroughs, so the state will be used for merging purposes later (the dataset is specifically New York City, though).

Previously, I tried cleaning up the dataset by removing inactive AirBnbs, but AirBnb has done a good job of purging accomodations that aren't current. We'll leave the full set here for the first map, but afterwards this project will use a representative sample.

In [1075]:
```
#Selecting useful columns
airdf = airdf[['id',          #identifier
               'price',       #price
               'latitude', 'longitude', #location
               'state']].copy() #state for merge

#Cleaning price column
airdf.price = airdf.price.str.replace("$","") #removing '$'
airdf.price = airdf.price.str.replace(",","") #removing ','
airdf.price = airdf.price.astype(float) #change type to float
airdf.head()
```

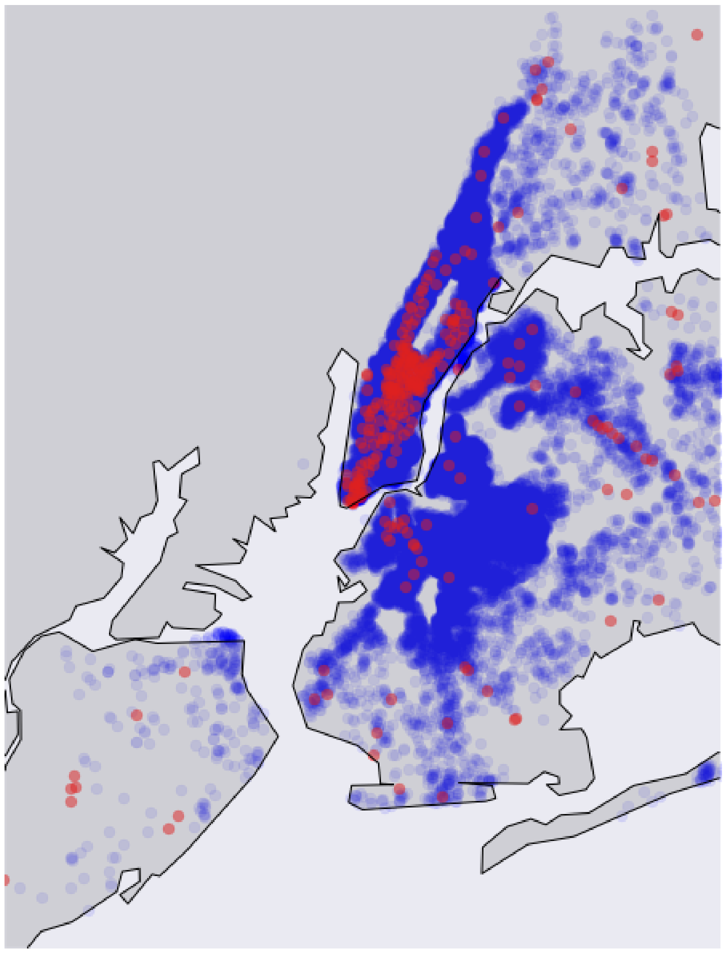
Out[1075]:

	id	price	latitude	longitude	state
0	18461891	110.0	40.774142	-73.916246	NY
1	20702398	50.0	40.849191	-73.786509	NY
2	6627449	125.0	40.849775	-73.786609	NY
3	19949243	100.0	40.848838	-73.782276	NY
4	1886820	300.0	40.841144	-73.783052	NY

Heat Map

First, let's get a general idea of how Starbucks and AirBnb's map onto eachother geographically in New York City.

In [1076]:
```
#Make a map of New York City

plt.figure(figsize=(8,12)) #basic figure which can be read into Basemap

nyc_map = Basemap(projection='merc', # mercantile projection
                  resolution = 'h', # high res for local map
                  llcrnrlon=-74.206, llcrnrlat=40.513, # setting the corner coordinates of the
 map
                  urcrnrlon=-73.806, urcrnrlat=40.913) # centered on New York City: 40.7128° N,
 74.0060° W

nyc_map.drawcoastlines() #adding coastlines to the map

nyc_map.fillcontinents(color='grey', alpha = 0.25, lake_color='aqua') #filling the map with a
 color

##############################################################################################
###########

#Add Starbucks and AirBnb locations as points on the map

#plotting airbnb data - placed on bottom to accommodate density

x,y = nyc_map(airdf.longitude.tolist(),airdf.latitude.tolist()) # pulling longitude and latitu
de for points
nyc_map.scatter(x,y, latlon = False, alpha = 0.1, color = "blue") # using scatter to plot in B
LUE

#plotting starbucks data

x,y = nyc_map(stardf.longitude.tolist(),stardf.latitude.tolist()) # pulling longitude and lati
tude for points
nyc_map.scatter(x,y, latlon = False, alpha = .5, color = "red") # using scatter to plot in RED

plt.show()
```



This heat map gives us a general overview of the New York City area and the presence of Starbucks (in red) and AirBnb's (in blue). There does seem to be heavy correlation between the two, but that does not appear to be true at the fringes. It is possible that Starbucks may be currently leading future development of AirBnbs, but we also must consider other possibilites as well, such as certain areas being demarcated as industrial or commercial.

Proximity and Price

To replicate the 'Starbucks Effect' among AirBnb rentals we will look for correlation between the closeness of Starbucks and the price level of AirBnbs. Specifically, we'll look at Starbucks within a radius of 1 mile from each AirBnb (what would reasonably be considered walking distance) and calculate the distance to the closest starbucks within that radius. That proximity will be plotted against price.

To examine proximity and price, we will:

- Take a sample of the AirBnb data
- Merge Starbucks data and AirBnb sample
- Compute the distance between each AirBnb from our sample and all Starbucks (long computation)
- Make some calculations based on that distance
- Merge them back into final usable dataframe
- Plot distance calculations against price

In [1077]:
```
#Here we're taking 5% of the overall AirBnb dataset

airdf_sample = airdf.sample(n=2215) #sample method to select randomly
airdf_sample.shape
```

Out[1077]:
```
(2215, 5)
```

In [1078]:
```
#merge every airbnb with all starbucks locations
air_star = pd.merge(airdf_sample, stardf, left_on='state', right_on= 'country_subdivision')
air_star.head()
```

Out[1078]:

	id	price	latitude_x	longitude_x	state	store_id	longitude_y	latitude_y	first_seen	country_subdivision
0	20439257	145.0	40.7003	-73.940138	NY	6348	-73.831879	40.714371	2013-12-08	NY
1	20439257	145.0	40.7003	-73.940138	NY	6491	-73.288651	40.806366	2013-12-08	NY
2	20439257	145.0	40.7003	-73.940138	NY	6535	-76.236130	43.046398	2013-12-08	NY
3	20439257	145.0	40.7003	-73.940138	NY	6551	-73.947243	40.631264	2013-12-08	NY
4	20439257	145.0	40.7003	-73.940138	NY	6590	-73.975327	40.789288	2013-12-08	NY

Distance calculation

In [1079]:
```
t = datetime.datetime.now()
```

In [1080]:
```
#determine distance between each AirBnb and all Starbucks with geopy great circle function

air_star['distance'] = air_star.apply(               # distance information in new column 'di
stance'
    lambda x: great_circle((x['latitude_x'], x['longitude_x']), # function set geopy great cir
cle
                           (x['latitude_y'], x['longitude_y'])).miles, axis = 1) #uses lon/lat
 info to calculate
                                                                                  #returns mile
s
air_star.head()
```

Out[1080]:

	id	price	latitude_x	longitude_x	state	store_id	longitude_y	latitude_y	first_seen	country_subdivision	
0	20439257	145.0	40.7003	-73.940138	NY	6348	-73.831879	40.714371	2013-12-08	NY	5
1	20439257	145.0	40.7003	-73.940138	NY	6491	-73.288651	40.806366	2013-12-08	NY	3
2	20439257	145.0	40.7003	-73.940138	NY	6535	-76.236130	43.046398	2013-12-08	NY	2
3	20439257	145.0	40.7003	-73.940138	NY	6551	-73.947243	40.631264	2013-12-08	NY	4
4	20439257	145.0	40.7003	-73.940138	NY	6590	-73.975327	40.789288	2013-12-08	NY	6

In [1081]:
```
t1 = datetime.datetime.now()
print('That took:',t1 - t)
```

```
That took: 0:02:02.545410
```

Done! Hopefully that didn't take more than 5 minutes.

Worth it to note here that before limiting max distance some distances are very long (because they are from NYC AirBnb's to Starbucks locations all over the state). By reducing the maximum distance to walking distance (1 mile) we eliminate this problem.

In [1082]:
```
#1 mile buffer to remove state-wide distances and to make walking calculations later

air_star = air_star[air_star['distance'] < 1].copy() #boolean operation returning only rows di
stance
                                                                               #of 1 mile or less

################################################################################################
#########

#Basic distance computations

#Closest starbucks (amin), furthest starbucks(amax) and mean distance to all starbucks(mean) w
ithin 1 mile

air_star_calcs = air_star.groupby('id')['distance'].agg([pd.np.min, pd.np.max, pd.np.mean]) #g
roupby airbnb id
                                                                      #agg function for numpy distance c
alculations

air_star_calcs.reset_index(inplace=True) #resetting index to avoid 'id' column issues later

air_star_calcs.head()
```

Out[1082]:

	id	amin	amax	mean
0	2595	0.078272	0.993374	0.548531
1	3647	0.187328	0.993532	0.635104
2	7241	0.068063	0.987421	0.686800
3	7816	0.234224	0.986925	0.699353
4	8025	0.217324	0.995442	0.664362

In [1083]:
```
#merging calculations into dataframe for plotting
a = air_star[['id','price']] #pulling price
b = air_star_calcs[['id','amin']] #pulling closest distance to starbucks (amin)

price_and_proximity = pd.merge(a, b, how='inner', right_on='id', left_on='id') #merged by 'id'


price_and_proximity.head()
```

Out[1083]:

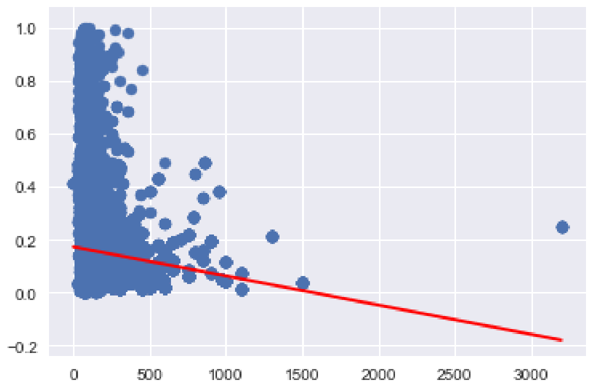
	id	price	amin
0	13731019	92.0	0.11489
1	13731019	92.0	0.11489
2	13731019	92.0	0.11489
3	13731019	92.0	0.11489
4	13731019	92.0	0.11489

Plotting proximity and price

Using the closest distance to a Starbucks we'll see if any correlations exist with price.

```
In [1084]: #Regression model for trend line

           results = smf.ols("amin ~ price",      #trend relationship
                             data=price_and_proximity).fit() #datafame to pull from

           pred = results.predict(exog = price_and_proximity["price"].sort_values()) #setting x-variable
            for stats model predict

           fig, ax = plt.subplots()

           ax.scatter(price_and_proximity['price'], price_and_proximity['amin']) #scatter with price and
            distance
           ax.plot(price_and_proximity["price"].sort_values(), pred , color = 'r', linewidth = 2.0)  #plo
           tting trend line
```

```
Out[1084]: [<matplotlib.lines.Line2D at 0x14540fe80>]
```



We can get a sense for the correlation, but we'll use quantiles, below, show the relationship more clearly.

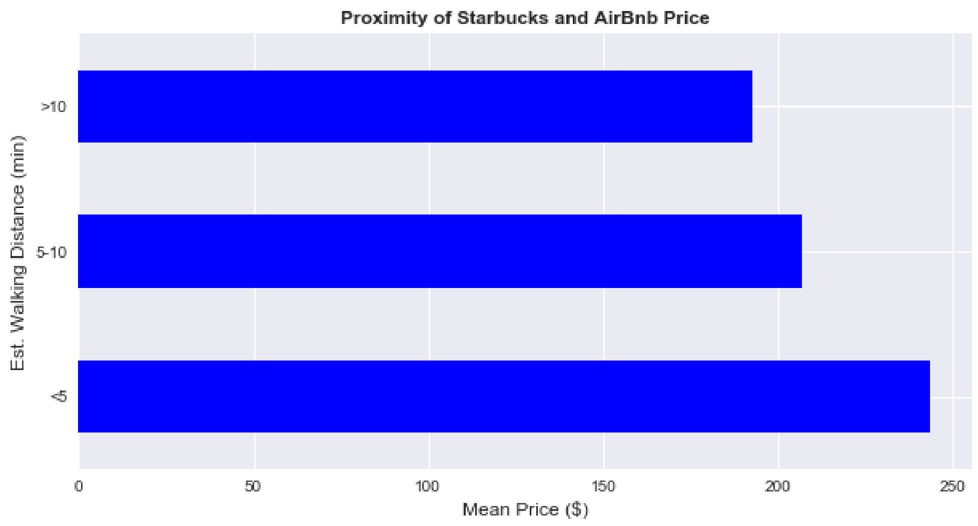
An average person walks at 4mph, completing one mile in 15 minutes. The following quantiles are broken into estimated walking times, which is especially illustrative in New York City where walking is very prevelant.

```
In [1085]: #looking at price quantiles and distance averages

           quantiles = 3 #number quantiles
           labels = ["<5","5-10",">10"] #labels

           q = pd.qcut(price_and_proximity["amin"], # quantiles by minimum distance
                           quantiles,            # number quantiles
                           labels = labels)       # labels

           g = price_and_proximity.groupby(q)    # groupby quantiles

           price_amin_quantiles = g['price'].mean() # apply to mean price for each quantile

           price_amin_quantiles.to_frame()
```

Out[1085]:

	price
amin	
<5	243.432163
5-10	206.829652
>10	192.483294

```
In [1108]: #now let's put that in a graph

           fig, ax = plt.subplots(figsize=(10,5))

           price_amin_quantiles.plot(kind='barh', ax=ax, color = 'b') #plotting bar graph

           plt.xlabel('Mean Price ($)', fontsize='large')  #label x axis for price
           plt.ylabel('Est. Walking Distance (min)',fontsize='large')   #label y axis for walking time
           plt.title('Proximity of Starbucks and AirBnb Price', fontsize='large', fontweight='bold') #add
            title

           plt.show()
```



Breaking this down into quantiles shows us a clear correlation between the distance to the nearest starbucks and the price of that AirBnb. Previously, I did map this into more quantiles and found that the result was linear.

Recency and Price

Now that we have seen there is a definite positive correlation between proximity and price, let's try to identify that on a timeline. Specifically, we'd like to see if the presence of a Starbucks predicts increasing prices. This roughly translates to a hypothesis: the longer an AirBnb has had a Starbucks very close, the higher their price will be. Since we have seen that a Starbucks within .33 miles of an AirBnb is correlated to increased price, we will limit the maximum distance to this level.

To test this, we will:

- Isolate Starbucks with timeseries information and maximum distance
- Determine how long (recency) each Airbnb has had a new starbucks nearby
- Merge recency data with pricing data
- Plot AirBnb prices by the length of time they have had a starbucks nearby

```
In [1087]: #Here we're only looking at Starbucks that were not in the original scrape from December, 2013

           new_stars = stardf.loc[stardf['first_seen'] != date(2013,12,8)].copy() #using precise original
            scrape time
           new_stars.shape

Out[1087]: (131, 5)
```

Ok, now we have only 131 Starbucks from our earlier 640, all added to the Starbucks website after December 2013. It is necessary to note that because we excluded the Starbucks without useful timeseries data, there may have been additional Starbucks within this range that will not be counted in the following graphs.

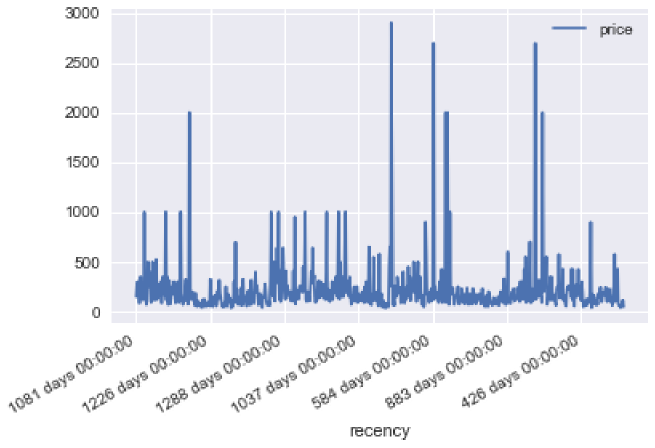
Now we'll determine how many days the starbucks have been around, and then use the store id to link that to distance information.

```
In [1088]: #creating recency data by subtracting the first seen date from December 1, 2017

           new_stars['recency'] = datetime.date(2017,12,1) - new_stars['first_seen']  #new recency column

           new_stars = new_stars[['store_id','recency']].copy()  #just the columns we need
```

```
In [1089]: #merging recency and pricing information

           #bringing in distance data from earlier allows us to limit maximums
           stars_recency = pd.merge(air_star_dist[['id','price','distance','store_id']], new_stars, #pric
           ing, recency, DISTANCE
                                    left_on='store_id', right_on= 'store_id') #matched by store id

           stars_recency = stars_recency[stars_recency['distance'] < 0.3].copy() #limiting distance maxim
           ums
```

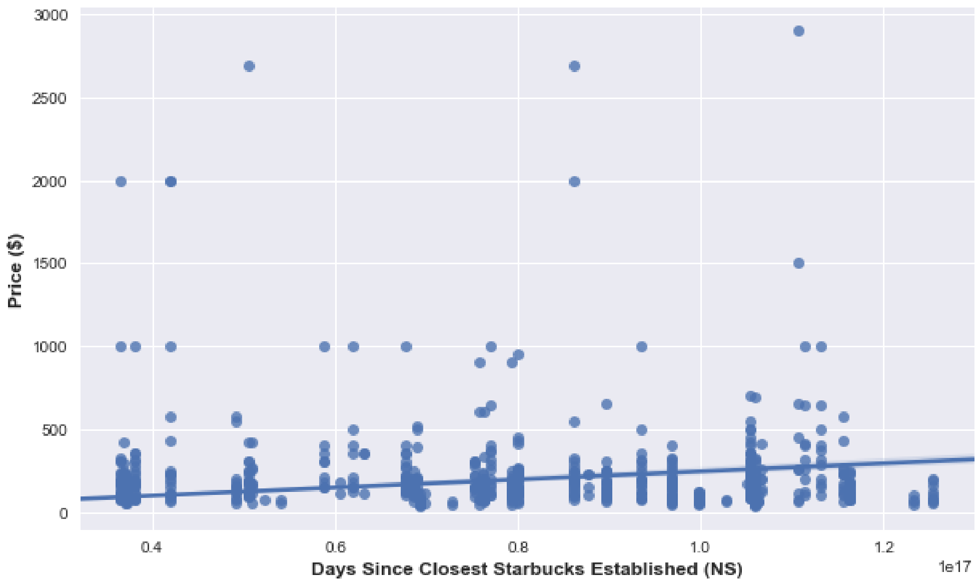
```
In [1101]: #create dataframe with only necessary columns for plotting
           stars_recency_plot = stars_recency[['price','recency']]

           #quick plot of recency and price
           stars_recency_plot.plot('recency')
```

```
Out[1101]: <matplotlib.axes._subplots.AxesSubplot at 0x135004be0>
```



Ok, this shows us roughly how prices look across the days since the closest starbucks was established, but let's look at a scatterplot to establish a trend.

```
In [1107]: #data to plot
           x = np.array(stars_recency_plot.recency.astype(int)) #setting axis data as arrays
           y = np.array(stars_recency_plot['price']) #setting axis data as arrays

           ax, fig = plt.subplots(figsize=(10,6))

           ax = sns.regplot(x,y,data=stars_recency_plot) #log of y for visual spread, and linear regressi
           on line

           ax.set_xlabel('Days Since Closest Starbucks Established (NS)', fontsize='large', fontweight='b
           old') #x-axis label
           ax.set_ylabel('Price ($)', fontsize='large', fontweight='bold') #y-axis label

Out[1107]: <matplotlib.text.Text at 0x164d6d1d0>
```



With a linear regression model on the scatterplot we can clearly see a correlation between length of time a starbucks has been within a 5 minute walk, and the price of the AirBnb. However, using both graphs above, we can also see that the real difference in price (in dollars) is relatively small.

Conclusion

In conclusion, there is a positive correlation between both:

- the proximity of Starbucks and AirBnb prices
- the amount of time a Starbucks has been close and AirBnb prices

We saw first that there does appear to be a correlation, generally, in geographic terms through the use of a heat map. We also noted that there are some exceptions at the edges of areas with AirBnb's that could be further explored. Next, we looked at the distance to the closest starbucks within walking distance (1 mile, or 15 minutes), and how that compared to prices. Using quantiles broken into three groups, it was very apparent that there is a correlation between proximity and Price. Finally, we explored the amount of time that a Starbucks has existed nearby (very close, 0.33 miles or 5 minutes walking) and the relationship of that to pricing. Again, we saw a possitive correlation here.

However, there are many factors that might have affected the outcome of these correlations, and the real difference in price is actually very small. Further research could be conducted through the collection of AirBnb data, specifically prices over time, in tandem with freshly collected Starbucks data. Using a timeseries could show more conclusive evidence for Starbucks predicting an increase in prices, as opposed to happening simultaneously.

Final Tip: if you're thinking of buying an apartment to rent out on AirBnb, maybe look at the closest Starbucks, and how long it's been there!