CSE 255 Assignment II

Perfecting Passenger Pickups: An Uber Case Study

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Introduction

With rising trend of private real-time cab services like Uber and Lyft, commuters have a lot of options but drivers face a lot of competition to get passengers, making it important for them to be in the right place at the right time. Taking a metropolitan like New York City, we analyzed Uber pickups across 6 months from April to September in 2014 and report our findings and analysis. We clustered the activity across NYC to find out hot spots throughout the city on weekends, where a driver is most likely to find a passenger at a given hour in the city. We used k-means clustering for this unsupervised learning task and compared our predictions with general results from NYC. To validate our predictions, we calculated the distance between our cluster centroids and pickup points from Lyft spread across 3 months from July 2014 to September 2014. Further exploring the dataset, we analyzed the nightlife spots in NYC from Uber pickup activity from 9pm to 3am on weekends (Friday-Saturday). To validate our results on nightlife zones, we took top 25 nightlife spots in NYC from Yelp and calculated the distance for each spot to its nearest cluster centroid. We also analyzed the difference in cab frequencies and behavior of people on Holidays in that time period, namely, Easter, Independence Day, Memorial Day and Labor Day. Since Uber is the most common and popular cab service, we assumed that it could be used to model peoples' commute behavior in general. Results from tests on Lyft pickup points (our test set) proved our assumption was fairly correct.

Related Work

For our analysis, we used Uber trip data from a freedom of information request to NYC's Taxi and Limousine Commission [1]. This data has been analyzed before and used for a few FiveThirtyEight stories: Uber is Serving New York's Outer Boroughs More Than Taxis Are [2], Public Transit Should be Uber's New Best Friend [3]. There were a lot of insights gained by these articles, e.g., most of Uber rides start in Manhattan, Uber is busiest at the evening rush etc.

A systematic study of these data is necessitated by the fact that we now have huge volume of such data. There were nearly 93 million trips taken by Uber and conventional taxis over a six-month period from April to September 2014. On one hand, these studies might help cab companies understand the customer demand better and gain more revenue. On the other hand, customers benefit from these studies as they might get faster and better services. There have been many studies on similar datasets. A few of them and their findings:

1) Visualizing the paths of 10,000 taxi rides across Manhattan [4]: Using data from 10,000 taxi trips and the Google Maps API, graduate students at Columbia University created an animation of the transit arteries of New York City. The visualization recreates a 'breathing' map of Manhattan based on the migration of vehicles across the city over a period of 24 hours, displaying the periods of intensity, density and decreased activity.

2) Making a Bayesian Model to Infer Uber Rider Destinations [5]: The UberData team analyzed the riding patterns of over 3000 unique riders in San Francisco earlier in 2014. The analysis was aimed at determining which businesses Uber riders like to patronize, e.g. what kind of

food or which hotels? Uber used Bayesian statistics and drop-off points for the trips to predict where a user would be going with an accuracy of 75%.

3) The Pulse of a City: How People Move Using Uber [6]: Uber analyzed their trip activity distributed hourly across each day of the ordinary week in various cities across the world. The data was then visualized as a heatmap and various inferences were made as well as cities were compared, e.g., When is a city most alive? Which cities are more nocturnal compared to others?

Our analysis conforms to a few findings of earlier studies, like most of Uber rides start at Manhattan and Uber is busiest at evening rush. At the same time our analysis focuses on a different aspect of finding locations where an Uber driver is most likely to find a ride at a given hour and inferring nightlife hotspots of NYC.

Data & exploratory analysis on the data

Uber data for pick-ups was found at [1] and contained over 4.5 million Uber pickups in New York City from April to September 2014, and 14.3 million more Uber pickups from January to June 2015. We choose the data-set from April-September, 2014 for further analysis.

The data consisted of 4 features, date / time of the pickup, latitude and longitude of the pickup and base-id (3rd party company ID used by Uber, which is ignored for this task).
Example tuple of the form of data-set is shown below denoting 2 pickups:

4/1/2014 21:00:03, 40.7531, -74.0039, B02512
4/1/2014 21:00:05, 40.7791, -73.9623, B02512

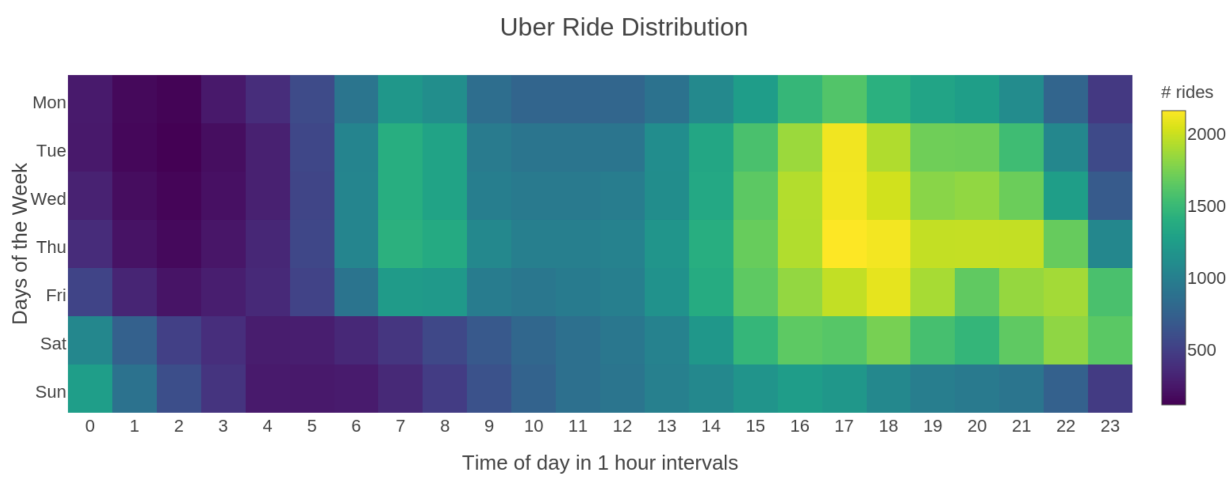


Figure 1: Heatmap showing the average Uber ride distribution day-wise for 24 hours

To explore and observe trends in data, we generated the heatmap in ***Figure 1.*** Some interesting trends observed from the data:

1) Most people leave for work on weekdays between 6:00 and 8:59.
2) Most people leave for home on weekdays between 17:00 and 18:59.
3) People stay out pretty late on Friday and Saturday nights leading to brighter than usual spots between 21:00 to 23:59 on Friday, 00:00 to 02:59 and 21:00 to 23:59 on Saturday and 00:00 to 02:59 on Sunday.
4) Most people start their weekends later than usual.

The data was henceforth pruned to retain samples for 21:00 to 23:59 on Friday, 00:00 to 02:59 and 21:00 to 23:59 on Saturday and 00:00 to 02:59 on Sunday, which is useful for our estimation of zones / points with most probable pickups at a given time and analysis of nightlife in NYC. This reduced our dataset to 404,803 points which was more suitable for a clustering task with the limited compute capacity available to us.

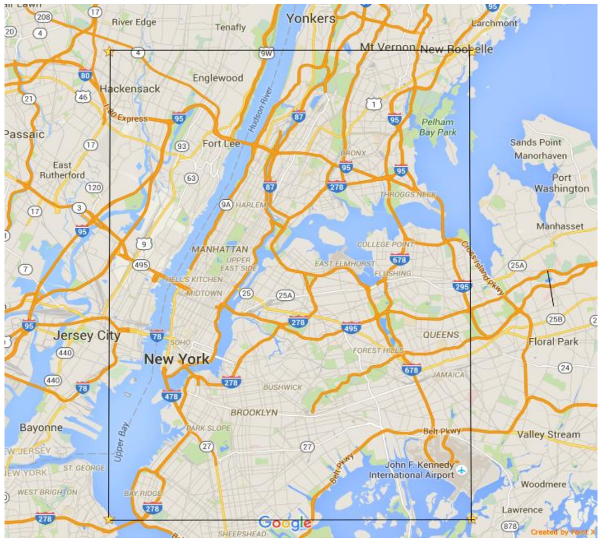


Figure 2: Area selected for analysis

Further, we chose 4 boundary points of NYC and removed points lying outside the boundary chosen as shown in ***Figure 2*** to analyze data only for NYC. This resulted in the final dataset of 396,367 data-points, which was used for the clustering task. In addition to Uber data, Lyft data for pick-ups was obtained from [1] and pruned in a similar way to use as the test dataset.

Clustering Task

Post-pruning, the data was further segregated on hourly basis into 90,115 (21:00), 95,347 (22:00), 82,687 (23:00), 59,147 (00:00), 41,389 (01:00), 27,682 (02:00) points. For clustering these pickup points, we tried three different clustering methods - k-means, DBSCAN, Mini-Batch k-Means [7]. We also looked at affinity propagation method. Affinity propagation and DBSCAN do not scale well when number of data points becomes large, especially with our compute capacity. Also, Mini-Batch k-Means was giving significantly higher MSE than the normal k-Means method, although it was a lot faster than the latter. Thus, we choose k-Means for this clustering task.

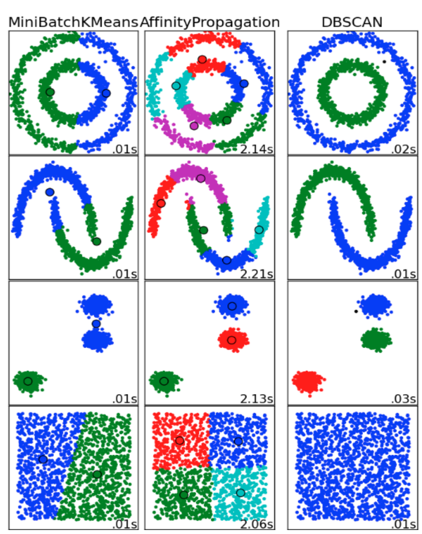


Figure 3: Comparison of different clustering methods considered (Source of Image: Scikit)

Determination of k-value for k-means clustering

We did a two-step process to determine the value of k for each hour. Firstly we found base value of k (say base k) as given in [8]. An optimal value of k was found using elbow method by plotting MSE for different values of k near the base value (base k). MSE is measured as the sum of distances of samples to their closest cluster center. From ***Figure 4***, elbow points were determined as 240 (21:00), 230 (22:00), 250 (23:00), 190 (00:00), 70 (01:00), 55 (02:00).

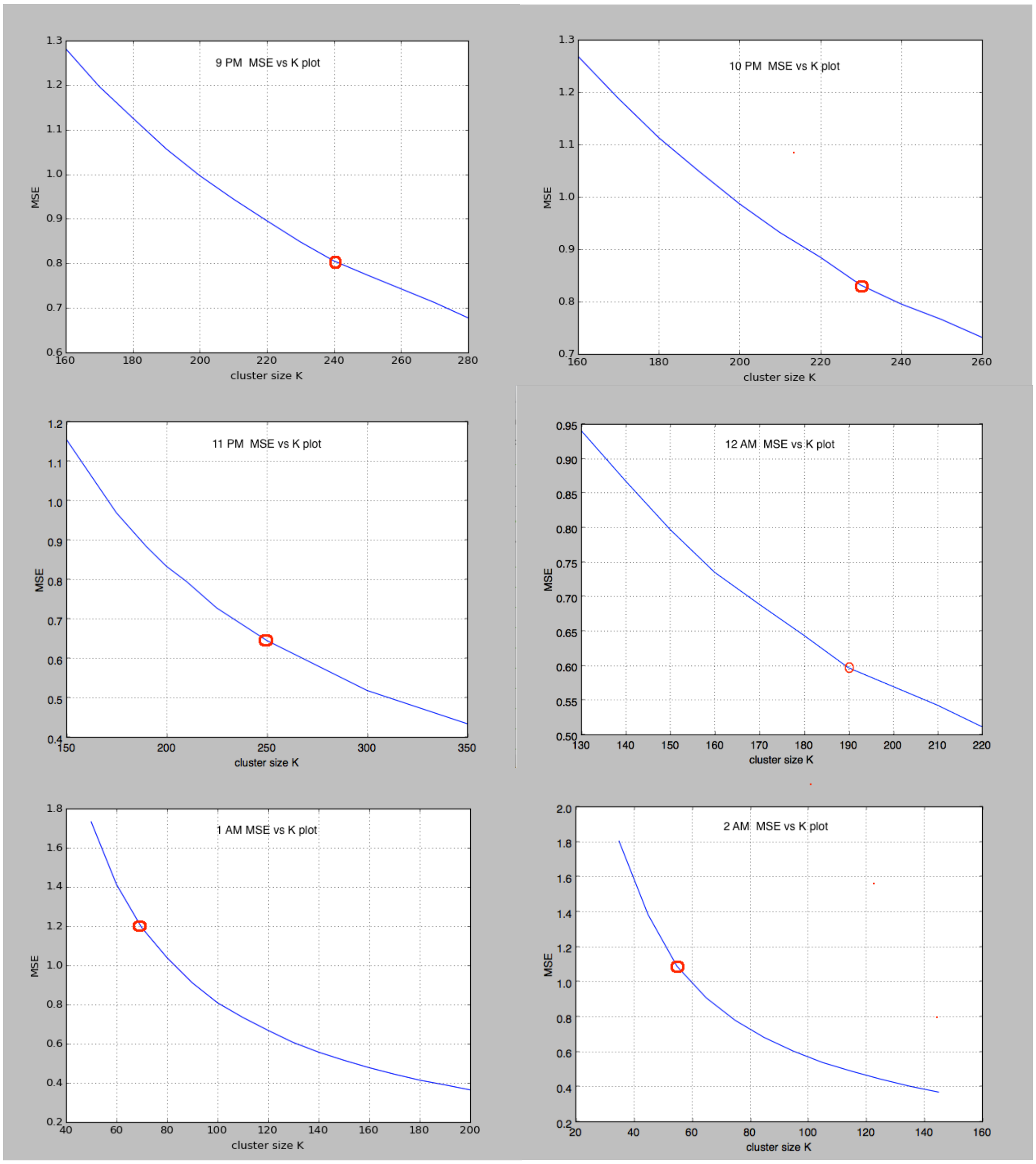


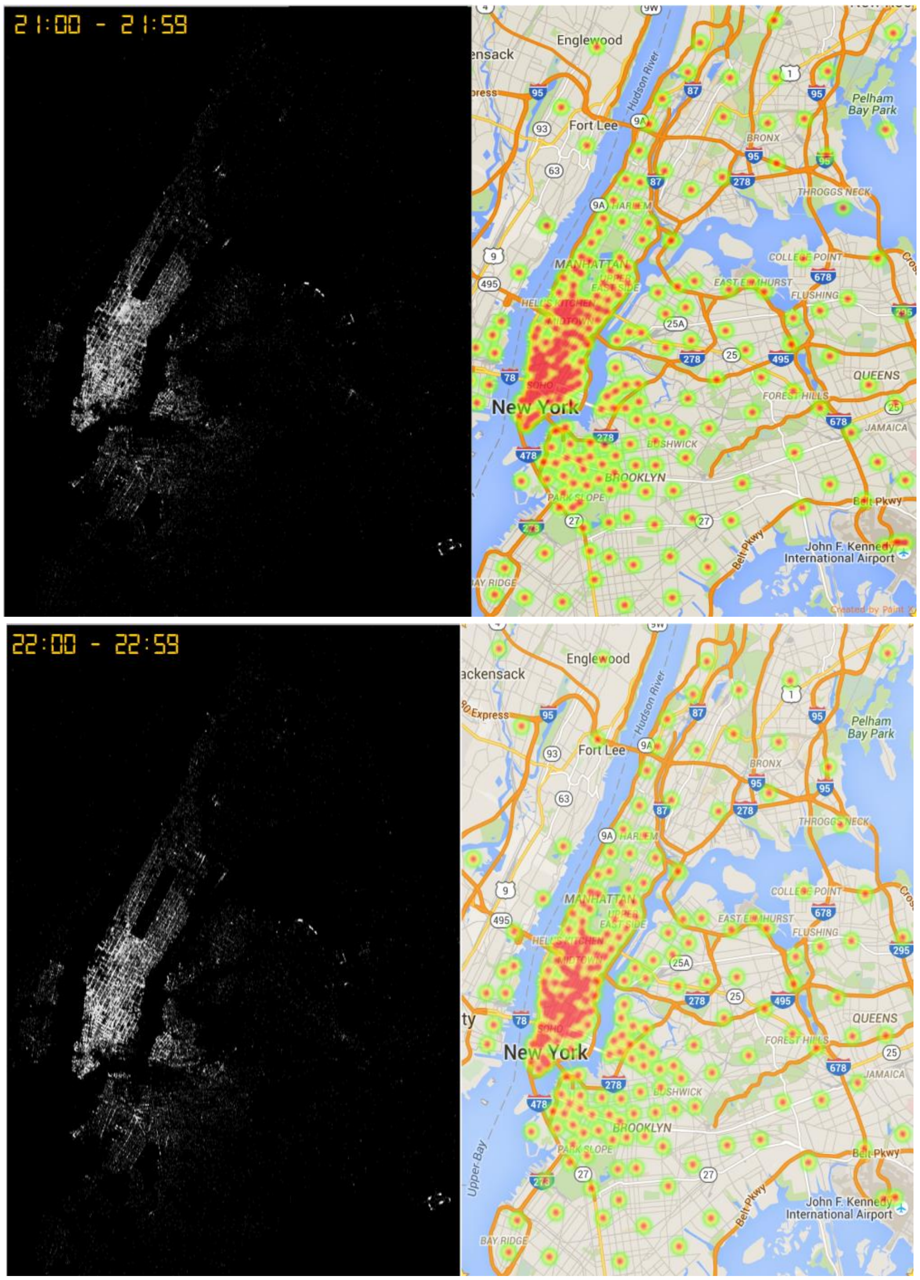
Figure 4: MSE vs Cluster Size k plot for different times

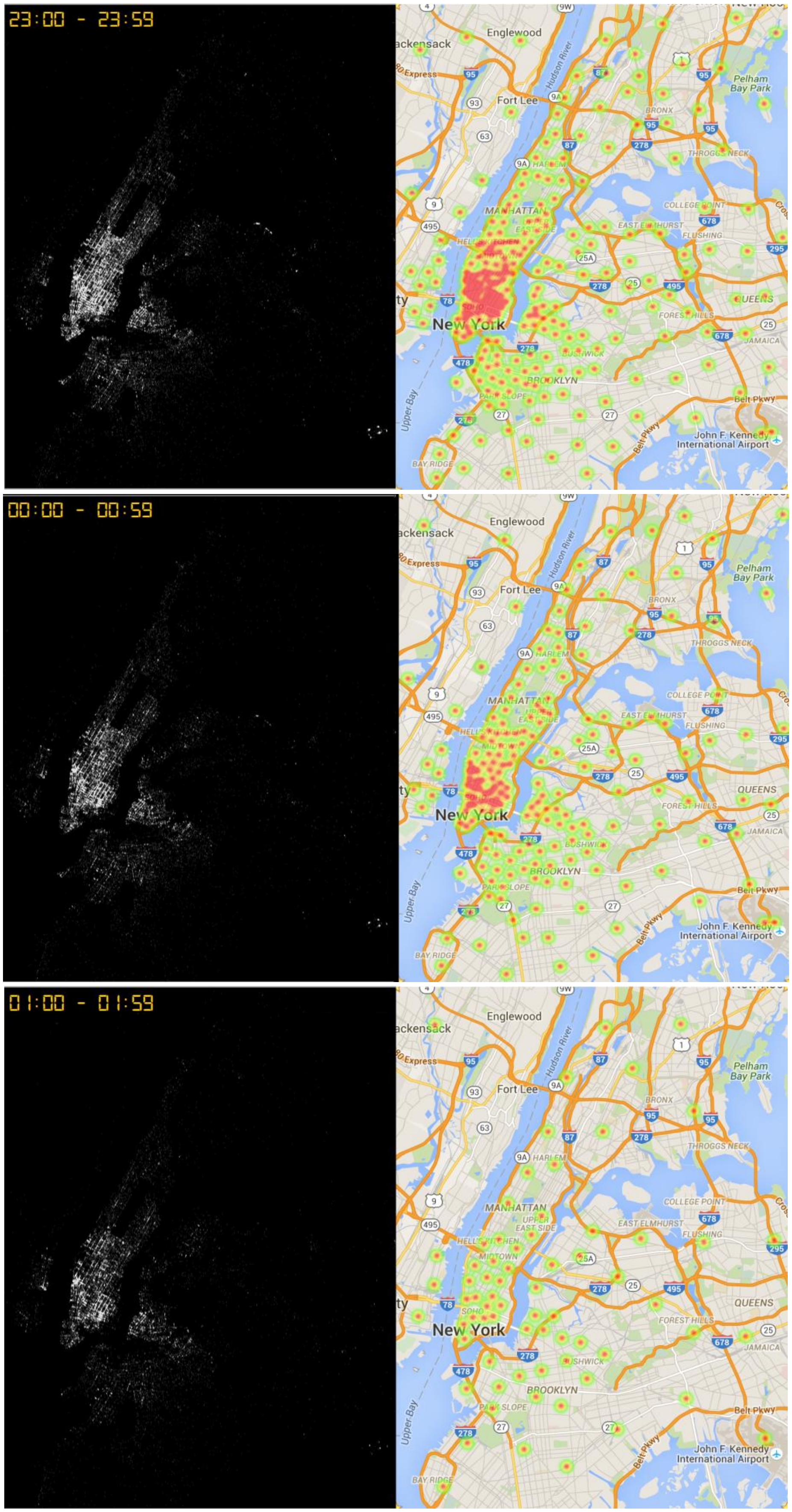
Results

After selecting the optimal k-value for each of the time interval from 9pm to 2am, we obtain the cluster centroids for each hour mentioned. These cluster centroids represent our estimates of points (latitude / longitude) where a driver could get maximum rides at different times in this interval range. The cluster centroids change with every hour, choosing the most appropriate number of clusters at every hour and localizes to the night-life centric areas at night, denoting the areas with active nightlife in NYC.

Interactive results showing cluster centroids on live NYC map for each of the different time intervals can be accessed at 21:00-21:59, 22:00-22:59, 23:00-23:59, 00:00-00:59, 01:00-01:59, 02:00-02:59.

Figure 5 shows a comparison of actual pickup points by Uber at a given hour shown in black, with white points representing each pickup made at that given hour across 6 months on the left. On the right is our estimate of points of maximum pickup probability at the given hour. We show this comparison across 9pm to 2am. The screenshots of probable pickup points can be viewed on an interactive map by accessing one of the links above.





23:00 - 23:59
00:00 - 00:59
01:00 - 01:59
Englewood
Fort Lee
Hudson River
BRONX
Pelham Bay Park
THROGGS NECK
HARLEM
MANHATTAN
COLLEGE POINT
EAST ELMHURST
FLUSHING
QUEENS
FOREST HILLS
JAMAICA
New York
BROOKLYN
PARK SLOPE
Upper Bay
BAY RIDGE
Belt Pkwy
John F. Kennedy International Airport

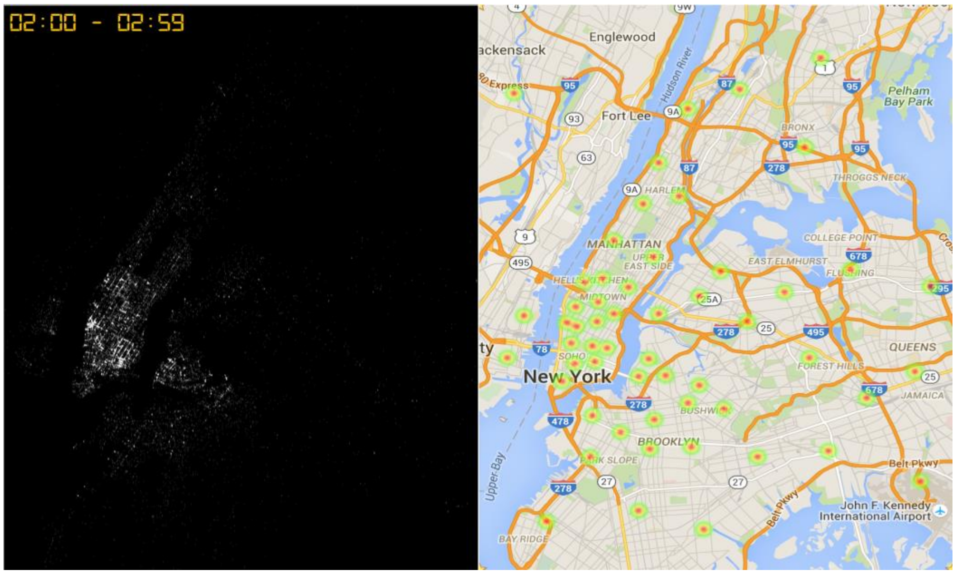


Figure 5: A comparison of actual pickup points by Uber shown in black, with white points representing pickups vs our estimate of points of maximum pickup probability at different hours

Ground Truth?

To validate our predictions for most-probable pickup hot-spots per hour, we took pickup points in NYC from Lyft data, spread across a 3 month period (from July 2014 to September 2014) and calculated the error as a measure of distance (in miles) between a Lyft pickup point and its nearest cluster centroid for that hour calculated from Uber data (Restating our main assumption here that, Uber analysis yields an accurate description of peoples' behavior). The minimum, average and maximum distances from nearest centroid for each hour are tabulated in Table 1.

Table 1: Error measures (distance in miles) for different hours on Lyft test set

Hour	Training Size	Test Size	Minimum Error (miles)	Average Error (miles)	Maximum Error (miles)
21 PM	90115	3621	0.004	0.197	1.232
22 PM	95347	4203	0.004	0.197	1.340
23 PM	82687	4747	0.004	0.186	1.051
12 AM	59147	5125	0.001	0.213	1.714
1 AM	41389	5040	0.003	0.358	2.031
2 AM	27682	5646	0.010	0.412	2.596

For the early hours of the night, the error (distance in miles) is far lesser than it is for the later hours post-midnight. This can be attributed to the training samples used for hours post-midnight. As the number of data points in training decreases the prediction error increases, which is quite obvious and expected. With a stronger compute capacity, more samples could be analyzed henceforth reducing this predictive error as well.

To quantify how accurately we predict the active night-zones in NYC, we took top 25 nightlife spots from Yelp and calculated the error (distance in miles) for each spot from the nearest cluster centroid (pickup point). Our worst prediction of nearest pickup point was off by 0.479 miles between 02:00-02:59. The other results are tabulated below in Table 2.

Table 2: Error measures for different hours for top 25 nightlife spots from Yelp

Club	21:00	22:00	23:00	0:00	1:00	2:00
Bam Cafe	0.134	0.224	0.148	0.179	0.375	0.415
Iron horse NYC	0.065	0.038	0.014	0.064	0.268	0.267
Stage karaoke lounge	0.144	0.162	0.074	0.115	0.266	0.266
Feinstein's/54 Below	0.05	0.068	0.083	0.154	0.151	0.037
Pinks NYC	0.125	0.162	0.17	0.105	0.215	0.178
Pocket Bar NYC	0.189	0.244	0.138	0.251	0.182	0.148
The Village Underground	0.138	0.016	0.018	0.14	0.02	0.117
Copper and Oak	0.097	0.117	0.084	0.135	0.1	0.058
FeatherWeight	0.22	0.031	0.069	0.108	0.302	0.479
Old Man Hustle	0.076	0.084	0.064	0.121	0.307	0.28
Ampersand	0.102	0.096	0.062	0.142	0.371	0.296
Anotheroom	0.119	0.078	0.079	0.07	0.101	0.204
RARE View Rooftop Chelsea	0.049	0.083	0.055	0.195	0.342	0.348
Set L.E.S	0.078	0.087	0.073	0.052	0.053	0.042
The Grain	0.068	0.078	0.086	0.186	0.252	0.183
Mosaic Craft Beer&Wine Bar	0.087	0.067	0.155	0.354	0.441	0.473
48 Lounge	0.088	0.112	0.167	0.212	0.236	0.376
Black Flamingo	0.168	0.175	0.205	0.235	0.227	0.464
Ceilo NYC	0.104	0.045	0.051	0.058	0.075	0.108
Le Bain at the Standard	0.121	0.089	0.09	0.083	0.093	0.132
Output NYC	0.186	0.16	0.051	0.048	0.042	0.075
Provocateur	0.072	0.05	0.05	0.011	0.062	0.069
Santo's Party House	0.145	0.137	0.191	0.175	0.198	0.142
Marquee	0.082	0.088	0.064	0.052	0.037	0.111
Mehanata	0.112	0.121	0.107	0.019	0.087	0.059

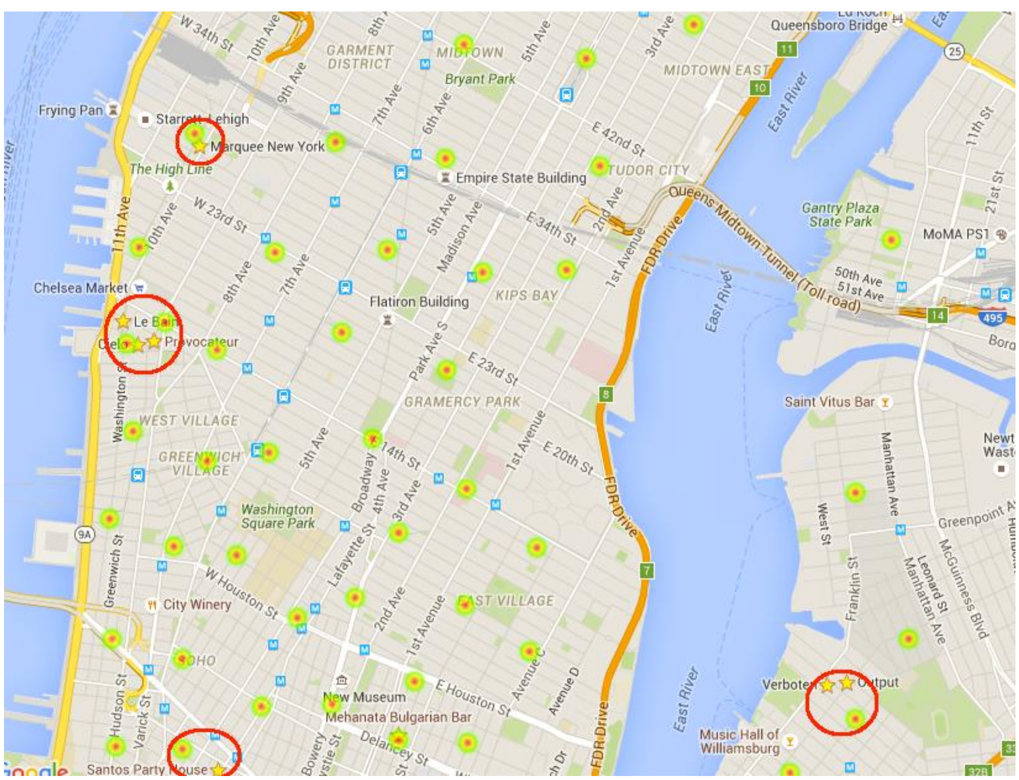


Figure 6: Map showing close proximity between our predictions and actual nightlife hotspots in NYC

Geotagging the results

We used Google's reverse geocoding API [9] for getting the street addresses corresponding to our cluster centers at different times to get human readable locations which can be used to inform drivers of current hot-spots in the neighborhood. ***Figures 7a-f*** depict these addresses weighted by cluster density at those addresses in the form of wordclouds.

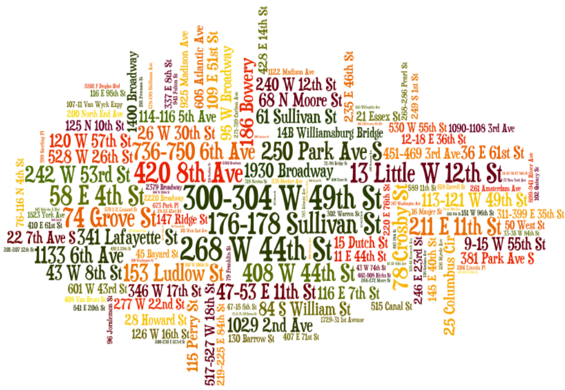


Figure 7a: Most active streets between 21:00 - 21:59

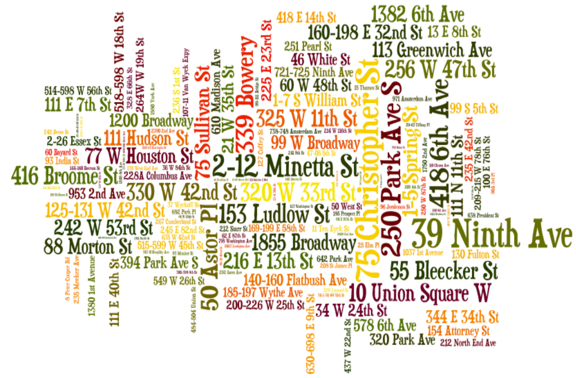


Figure 7b: Most active streets between 22:00 - 22:59

Figure 7c: Most active streets between 23:00 - 23:59

Figure 7d: Most active streets between 00:00 - 00:59

Figure 7e: Most active streets between 01:00 - 01:59

Figure 7f: Most active streets between 02:00 - 02:59

Another Interesting Insight

We decided to do another interesting analysis to find about people's behavior on holidays. Four holidays occurred between April 2014 and September 2014, Easter (Sunday), Independence Day (Friday), Memorial Day (Monday) and Labor Day (Monday). We compared each of them with the corresponding control day.

As can be seen from ***Figure 8***, people prefer staying in on holidays at almost all times except the early morning which is probably because stay out late the night before.

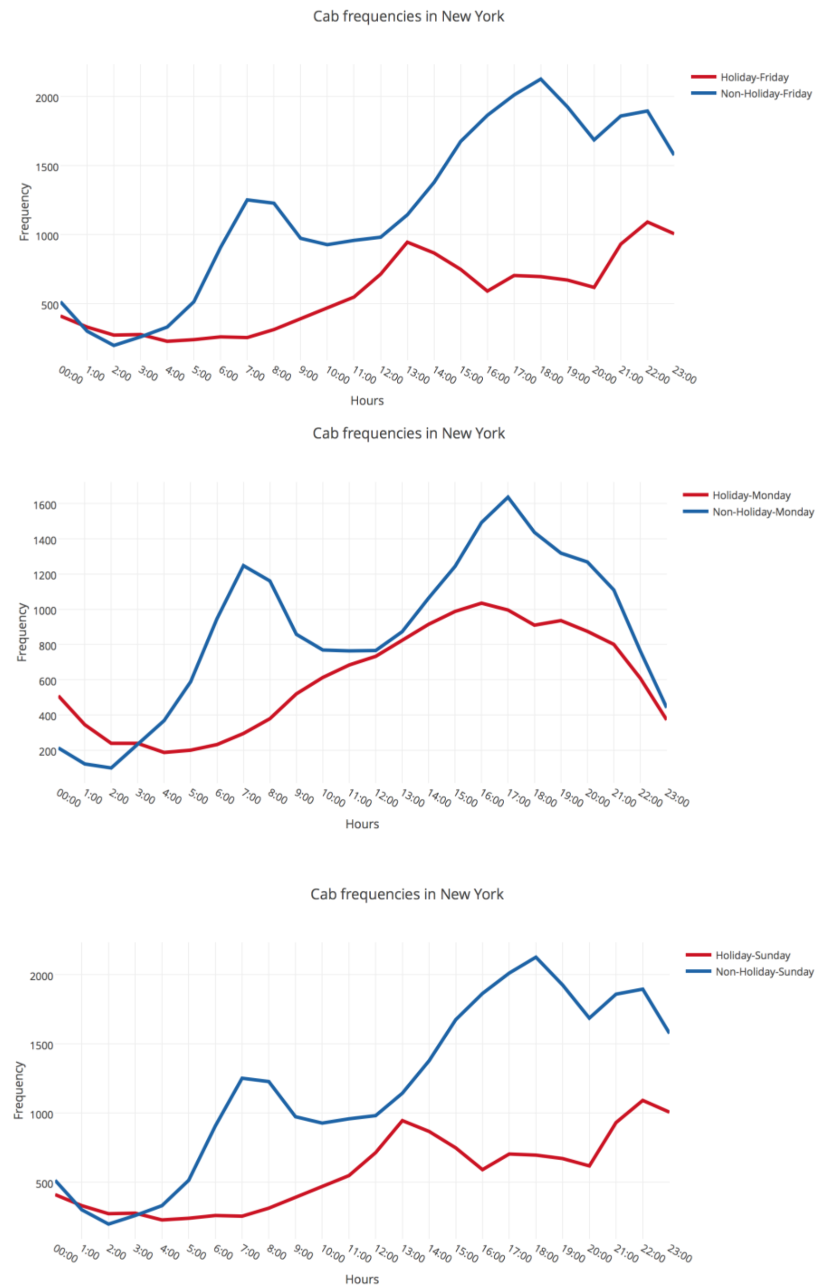


Figure 8: Ride distribution on a holiday vs a control day

Conclusion

As can be seen from the results, k-means clustering can be used to successfully and closely estimate the most likely pickup points at any given hour and also predict the top nightlife hotspots by learning trends from past Uber pickups. This has been verified using Lyft test set and is coherent with top results from Yelp.

A Day In NYC: Uber Pickups Perspective

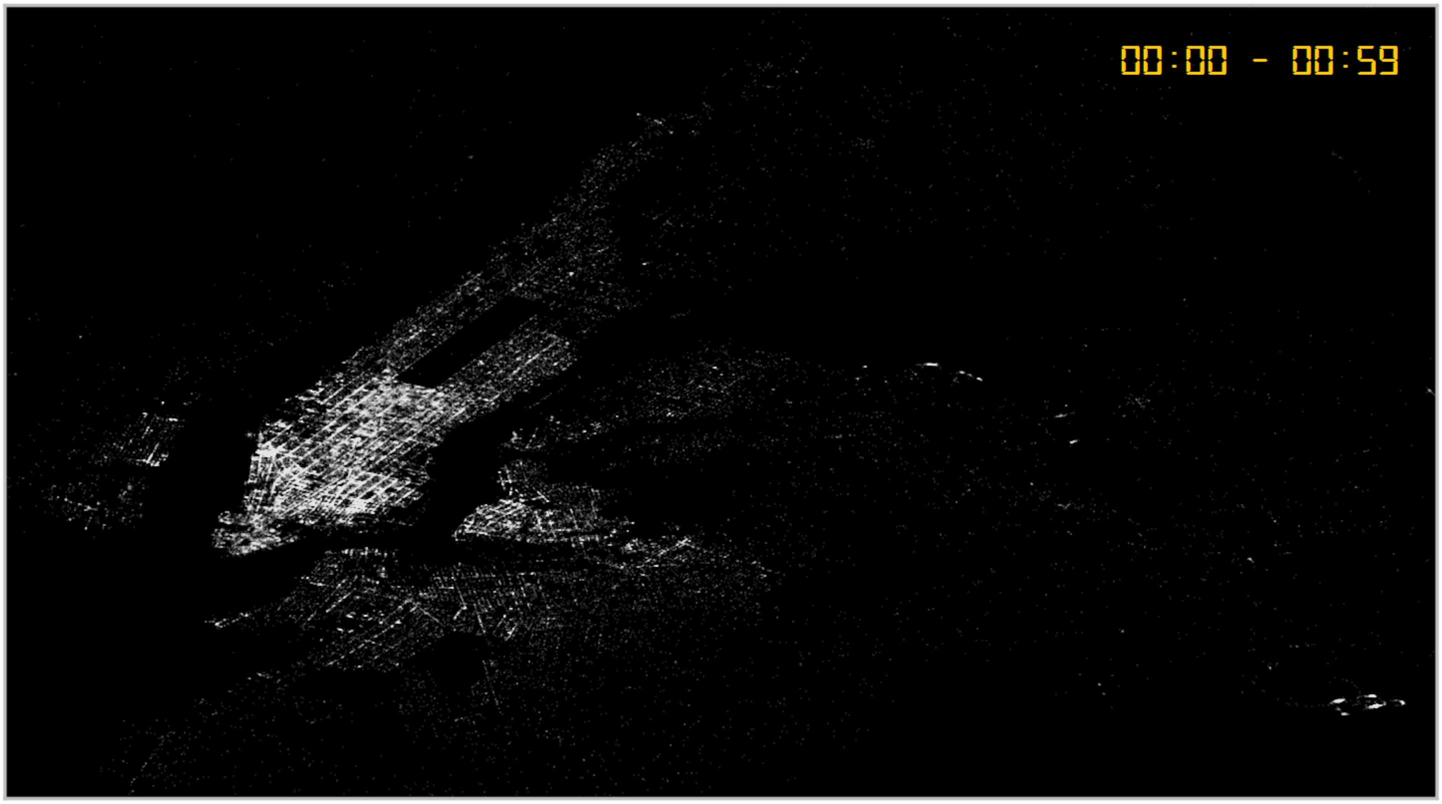


Figure 9: A visualization of actual pickup points by Uber at a given hour, with white points representing each pickup made at that given hour across 6 months

(Note: Please use adobe reader for proper animation. Otherwise please visit https://drive.google.com/file/d/0B3clgfZWa62KOVVISEVDU2dORWs/view?usp=sharing

References

[1] FiveThirtyEight Dataset http://www.texample.net/tikz/resources/

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[3] Public Transit Should be Uber's New Best Friend http://fivethirtyeight.com/features/public-transit-should-be-ubers-new-best-friend/

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[7] Scikit Clustering Methods http://scikit-learn.org/stable/modules/clustering.html#overview-of-clustering-methods

[8] Determining the number of clusters in a data set https://en.wikipedia.org/wiki/Determining_the_number_of_clusters_in_a_data_set

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[11] Plotly Technologies Inc. Collaborative data science. Montreal, QC, 2015 https://plot.ly/

[12] Yelp New York http://www.yelp.com/nyc

GitHub Code Repository Link: https://github.com/jigarsurana/uberAnalysis