Finding new parking lots

According to out of car report

Maitree Hirunteeyakul

Abstract

In order to reduce the number of owned cars, the city of Tel Aviv launched a shared-car project, called AutoTel.

The concept is so simple just pick the phone find the nearby car in the nearby parking lot then grab it.

The big problem of project and huge obstacle for user is sometimes in the vitrified parking lot there is no car available, so the customer need to walk to the other car parking lot which is more far from them.

Motivation

The question is “where is the best place to set up a new parking lot”

What mean “best” for this project?

- The location need to be set at the high car running out problems area.
- The number of location need to be appropriate and worth to invent.
    - That mean if number of the new car location too high the company would not be able to invent.
    - And sometimes when we add more location it might not have a significant change in performance

Dataset

Shared Cars Locations

Location history of shared cars in every minute.

Columns

1. timestamp
2. latitude
3. longitude
4. total_cars
5. carsList

Total raw data row : 6.68 milion

Data Preparation and Cleaning

Since Kaggle data preview show there is no Missing data and Mismatched data all we need to do is get the right data.

As you can see the raw data also contain the cell that got no problems with car availability, so we need to filter them off.

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
rawdata = pd.read_csv('../input/sample_table.csv')
rawdata=rawdata[rawdata['total_cars']==0]
#rawdata=rawdata[:100]
rawdata.head()
```

Out[1]:

	timestamp	latitude	longitude	total_cars	carsList
12	2019-01-10 11:45:55.070781 UTC	32.083175	34.776552	0	[]
13	2019-01-10 11:45:55.070781 UTC	32.088379	34.775111	0	[]
14	2019-01-10 11:45:55.070781 UTC	32.074877	34.773515	0	[]
15	2019-01-10 11:45:55.070781 UTC	32.098603	34.778565	0	[]
16	2019-01-10 11:45:55.070781 UTC	32.094780	34.797280	0	[]

Research Question

Where should be best for setting a new parking lot for services?

Methods

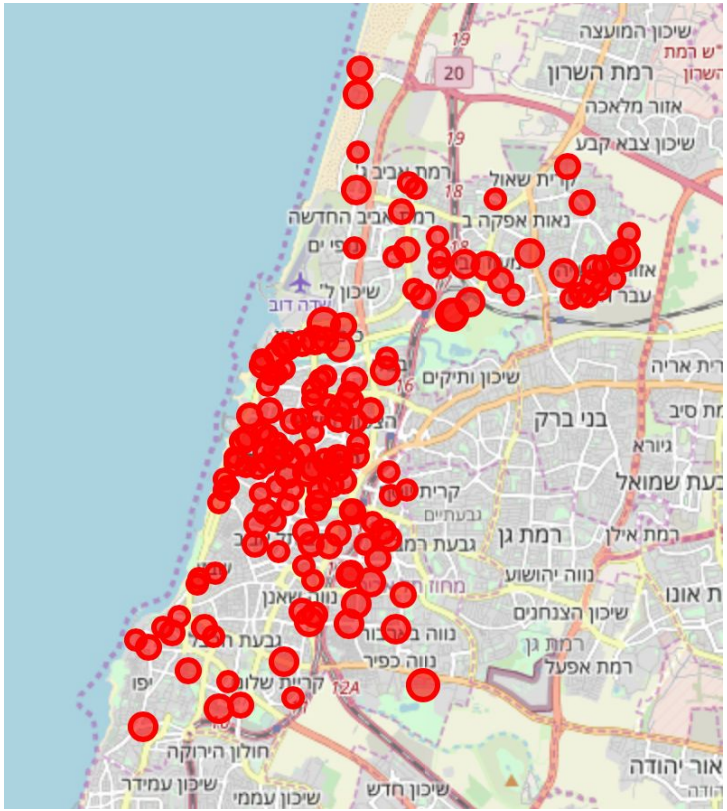
- Get the location which is non-duplicated
- Count frequency of each location
- Filter only high report frequency
- Using k-mean to clustering the best place to handle the whole area
  - Try k-mean with differences k
  - Finding the best k from Elbow method
  - Apply the k to k-mean
- Weight all the new parking lots by their nearby frequency
- Sort the new locations by their weigh
- Plot the new parking lots

Findings

This figure show the spot of high car not available record and also how frequency of each spot by their size.

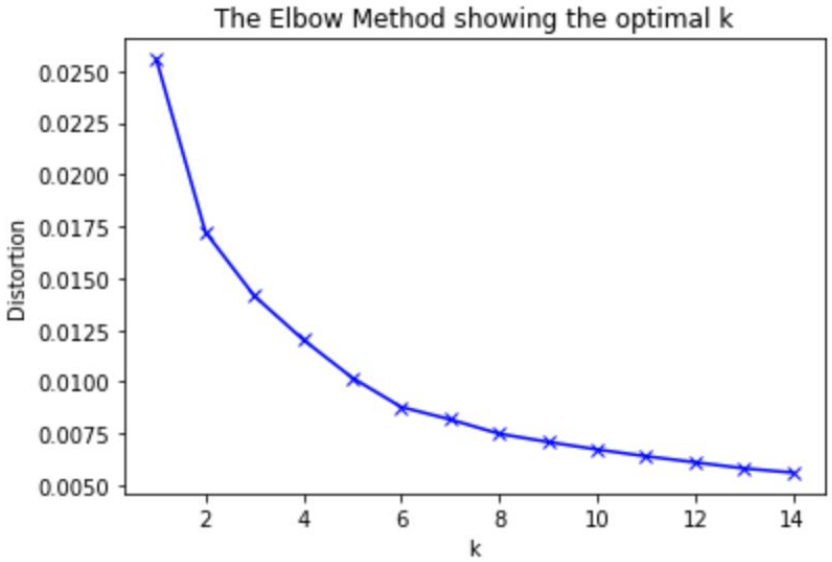
As you can see the high record (more than 12,000 records) likely to be on the urban area.

But we still need to use k-mean to find best for clustering.



Findings

This graph show the RSQR of each k value. As you can see after k=6 the line is going non-significant drop, so the best number of spot should be 6 because it most worth to invent and get covered the most of area.



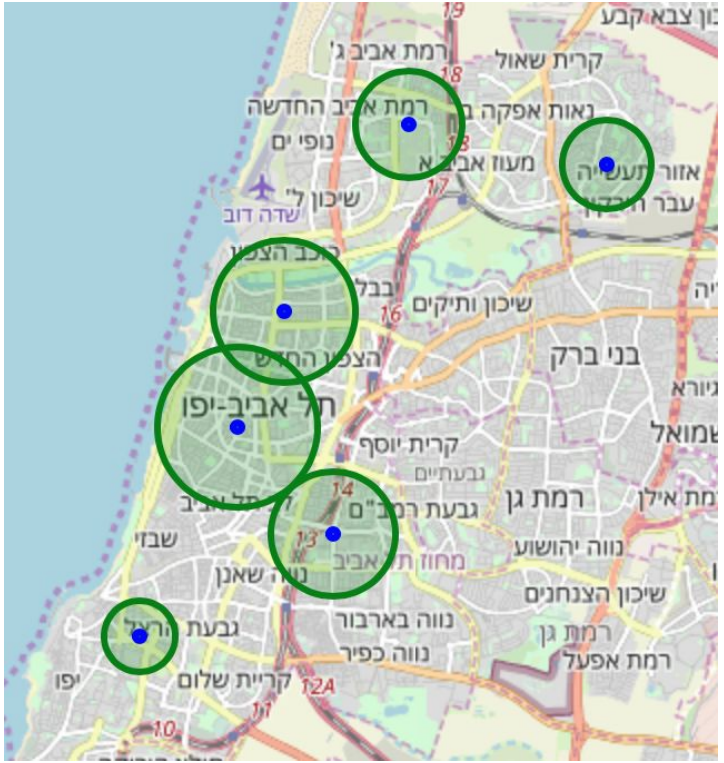
Findings

From clustering and weigh form important how high demand here now we know where is the best spot to set a new parking lot location.

In [15]:

```
sortedcenter=[]
print("Sorted centers weight by high amough of nearby report")
for i in range(len(sortedstation)-1,-1,-1):
    sortedcenter.append(list(centers[sortedstation[i]]))
    print(sortedcenter[len(sortedcenter)-1])
#print(sortedcenter)
```

```
Sorted centers weight by high amough of nearby report
[32.077680666666666, 34.77707469047619]
[32.09270566666667, 34.784460333333335]
[32.063701615384616, 34.7919135]
[32.1172959047619, 34.80350871428571]
[32.11202070588235, 34.834323]
[32.050175352941174, 34.76225070588235]
```



Limitations

This result might not appropriate to use with the same likely service

for example

This location might not mean people who need a ride are going to pin this location for online car taxi sharing (Lyft,Uber,Grab), cause this services is looking for difference target (who want a drive not want a ride) from them and the system is completely not the same.

Conclusions

Where is the best place to set a new parking lot :

(32.077680666666666, 34.77707469047619)

From the 6 location that should be a new parking lot (from Finding slide) this one have most nearby reports.

If the company looking for a new place this should be first to bult.

References

Your personal public transportation. One Way Car-Share. (n.d.). Retrieved from

https://www.autotel.co.il/en/

Using the elbow method to determine the optimal number of clusters for k-means clustering. (n.d.). Retrieved from

https://bl.ocks.org/rpgove/0060ff3b656618e9136b

Project Notebook

https://www.kaggle.com/mattjunk/find-new-park

Some Data virtualization could not be able to show well in pdf format, Such as : folim Map.

Please feel free to take a look at real kernal on my kaggle

Finding a new parking location according to out of car report

Get the data and masking for only no car avalable record

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
rawdata = pd.read_csv('../input/sample_table.csv')
rawdata=rawdata[rawdata['total_cars']==0]
#rawdata=rawdata[:100]
rawdata.head()
```

Out[1]:

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16	2019-01-10 11:45:55.070781 UTC	32.094780	34.797280	0	[]

In [2]:
```
rawdata=rawdata.reset_index(drop=True)
print("Amount of running out of car report : ",len(rawdata))
print("Amount of unique time : ",len(rawdata['timestamp'].uni
```

```
que()))
```

```
Amount of running out of car report :  3099723
Amount of unique time :  18998
```

In [3]:
```
rawdata.head()
```

Out[3]:

	timestamp	latitude	longitude	total_cars	carsList
0	2019-01-10 11:45:55.070781 UTC	32.083175	34.776552	0	[]
1	2019-01-10 11:45:55.070781 UTC	32.088379	34.775111	0	[]
2	2019-01-10 11:45:55.070781 UTC	32.074877	34.773515	0	[]
3	2019-01-10 11:45:55.070781 UTC	32.098603	34.778565	0	[]
4	2019-01-10 11:45:55.070781 UTC	32.094780	34.797280	0	[]

Get the location of all report

some of them happend in the same location, so we need to find how many places there are.

In [4]:
```
locationset=set()
for i in range(len(rawdata)):
    locationset.add((rawdata.latitude[i],rawdata.longitude[i]
))
print("Amount of places : ",len(locationset))
```

```
Amount of places :  238
```

In [5]:
```
locationset=list(locationset)
```

and also we need a frquency of happening in each places to find where is the best answer for new location.

In [6]:
```
countfolocation=np.zeros(len(locationset))
for i in range(len(rawdata)):
    countfolocation[locationset.index((rawdata.latitude[i],ra
wdata.longitude[i]))]+=1
print("First five of frequency count of each location")
countfolocation=list(countfolocation)
print(countfolocation[:5])
```

```
First five of frequency count of each location
[18798.0, 16201.0, 14616.0, 14318.0, 10633.0]
```

Filter under 12.000 record out

After I saw the data without filtered it seem used to be record almost every spot of exsited.

So I need to filter it out to focus on most exact high report place.

In [7]:
```
for i in range(len(countfolocation)-1,-1,-1):
    if countfolocation[i]<12000:
        del countfolocation[i]
        del locationset[i]
```

Plot all the location

In [8]:
```
x=list((locationset[i][0]) for i in range(len(locationset)))
y=list((locationset[i][1]) for i in range(len(locationset)))
import folium      #  folium libraries
from   folium.plugins import MarkerCluster
from statistics import mean
map_world = folium.Map(location=[mean(x), mean(y)], tiles = '
OpenStreetMap', zoom_start = 12)

#  add Locations to map
for i in range(len(x)):
    folium.CircleMarker(
        [x[i], y[i]],
        radius=4*(countfolocation[i]/10000),
        popup=countfolocation[i],
        fill=True,
        color='Red',
        fill_color='Red',
        fill_opacity=0.6
        ).add_to(map_world)

#  display interactive map
map_world
```

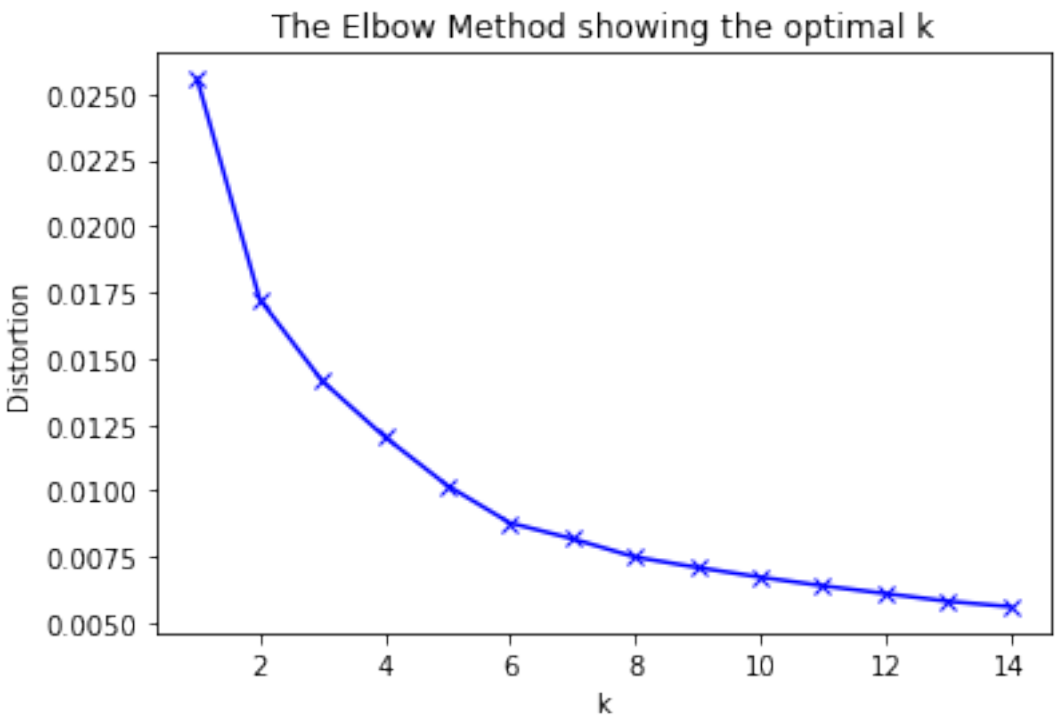
Out[8]:

Finding the best k for k-mean

In [9]:
```
from sklearn.cluster import KMeans
from sklearn import metrics
from scipy.spatial.distance import cdist
X = np.array(list(zip(x, y))).reshape(len(x), 2)
distortions = []
K = range(1,15)
for k in K:
    kmeanModel = KMeans(n_clusters=k).fit(X)
    kmeanModel.fit(X)
    distortions.append(sum(np.min(cdist(X, kmeanModel.cluster
_centers_, 'euclidean'), axis=1)) / X.shape[0])
#distortions
```

Useing Elbow graph

In [10]:
```
plt.plot(K, distortions, 'bx-')
plt.xlabel('k')
plt.ylabel('Distortion')
plt.title('The Elbow Method showing the optimal k')
plt.show()
```



from graph in point k=6 is appropriate because after that point doesn't have a significant changed.

Apply k-mean model

so now we groupping them to 6 group

In [11]:
```
kmeanModel = KMeans(n_clusters=6).fit(X)
centers = kmeanModel.cluster_centers_
y_kmeans = kmeanModel.predict(X)
print("The nearest new praking lot location for first five lo
cation : ",y_kmeans[:5])
```

```
The nearest new praking lot location for first five location
:  [1 5 3 3 2]
```

Get new parking location

from center of each group

In [12]:
```
#print(len(y_kmeans),len(x),len(X))
print("Location of each new parking lot in order index")
print(centers)
```

```
Location of each new parking lot in order index
[[32.11202071 34.834323  ]
```

```
 [32.09270567 34.78446033]
 [32.05017535 34.76225071]
 [32.07768067 34.77707469]
 [32.1172959  34.80350871]
 [32.06370162 34.7919135 ]]
```

Count how many report each spot supported

In [13]:
```
newstation=np.zeros(6)
for i in range(len(y_kmeans)):
    newstation[y_kmeans[i]]+=countfolocation[i]
print("Counting for the number of the report rely on each new
location")
print(newstation)
```

```
Counting for the number of the report rely on each new locati
on
[244443. 513000. 237433. 580791. 312707. 389749.]
```

Sort the location by their important

The important is measured by how many times this nearby places has been reported

In [14]:
```
import numpy
sortedstation=(numpy.argsort(newstation))
print("Sorted index by frequency of report near by each locat
ion")
print(sortedstation)
```

```
Sorted index by frequency of report near by each location
[2 0 4 5 1 3]
```

The location that comes firt that mean the most worth to invent

In [15]:
```
sortedcenter=[]
print("Sorted centers weight by high amough of nearby report"
)
for i in range(len(sortedstation)-1,-1,-1):
    sortedcenter.append(list(centers[sortedstation[i]]))
    print(sortedcenter[len(sortedcenter)-1])
#print(sortedcenter)
```

```
Sorted centers weight by high amough of nearby report
[32.077680666666666, 34.77707469047619]
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[32.11202070588235, 34.834323]
[32.050175352941174, 34.76225070588235]
```

Plot for new location to park

for plotting the larger spot is the more need to built

In [16]:
```
map_world = folium.Map(location=[mean(x), mean(y)], tiles = '
OpenStreetMap', zoom_start = 12)

for i in range(len(centers)):
    folium.CircleMarker(
        [sortedcenter[i][0], sortedcenter[i][1]],
        radius=4*(9-i),
        popup=i+1,
        fill=True,
        color='Green',
        fill_color='Green',
        fill_opacity=0.2
        ).add_to(map_world)

for i in range(len(centers)):
    folium.CircleMarker(
        [sortedcenter[i][0], sortedcenter[i][1]],
        radius=2,
        popup=i+1,
        fill=True,
        color='Blue',
        fill_color='Blue',
        fill_opacity=0.6
        ).add_to(map_world)

map_world
```

Out[16]: