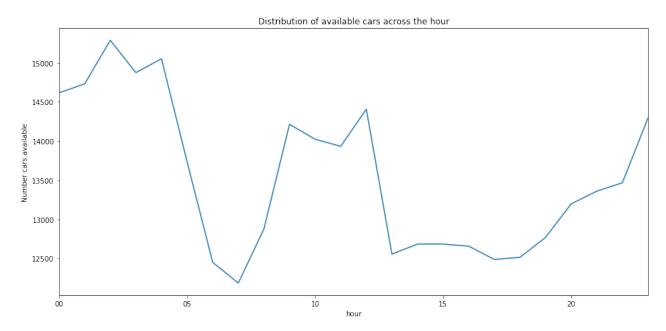
We can see from distribution above Fridays (11th january and 18th january) seems to be days where available cars are minimum and hence peak of demand comes on this day. Also we can see somewhat weekly pattern in demand here.

```
In [152]: fig, ax = plt.subplots(figsize=(15,7))
    dfl.groupby(['hour']).sum()['total_cars'].plot(ax=ax)
        ax.set_xlabel('hour')
        ax.set_ylabel('Number cars available')
        ax.set_title('Distribution of available cars across the hour')
```

Out[152]: Text(0.5, 1.0, 'Distribution of available cars across the hour')



## Learning from image 3

We can see from graph above, number of cars available dips in morning and evening commute hours. In morning, 6 AM to 8 AM and in evening 3 PM to 7 PM seems to be peak hours in terms of demand of these cars.

```
In [153]: df1_zero = df1[df1['total_cars'] == 0]
    df1_zero_grouped = df1_zero.groupby(['geohash']).count()['total_cars']

    df1_non_zero = df1[df1['total_cars'] > 0]
    df1_non_zero_grouped = df1_non_zero.groupby(['geohash']).count()['total_
```

4741\_HW1\_Q1 - Jupyter Notebook 9/18/19, 9:15 PM

```
In [154]:
           df1_zero_grouped.head(5)
Out[154]: geohash
           sv8wnz
                      304
           sv8wqb
                     1579
           sv8wqc
                     1566
           sv8wqf
                     5867
                     4785
           sv8wqq
           Name: total cars, dtype: int64
In [155]:
          df1 non zero grouped.head(5)
Out[155]: geohash
                        3
           sv8tz0
           sv8wng
                       14
           sv8wnw
                      731
           sv8wnx
                     2146
           sv8wny
                        1
           Name: total_cars, dtype: int64
           df1 geohash merged = df1 zero grouped.to frame().merge(df1 non zero grouped.to
In [156]:
In [157]:
           #df1 geohash merged.head(5)
           df1 geohash merged.rename(columns={"total cars x": "instances with 0 car
           df1 geohash merged.head(5)
Out[157]:
                   total_cars_x total_cars_y
           apohach
```

geonasn		
sv8wnz	304	2260
sv8wqb	1579	4340
sv8wqc	1566	4848
sv8wqf	5867	6759
sv8wqg	4785	5121

4741\_HW1\_Q1 - Jupyter Notebook 9/18/19, 9:15 PM

```
In [158]: df1_geohash_merged['zero cars %'] = df1_geohash_merged['total_cars_x'] /
df1_geohash_merged.head(5)
```

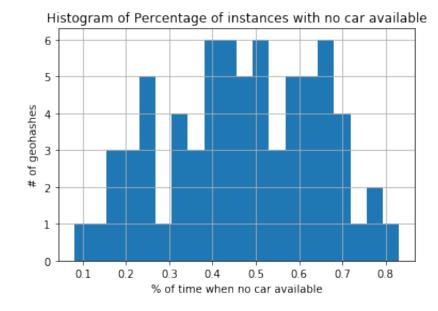
## Out[158]:

total\_cars\_x total\_cars\_y zero cars %

geohash			
sv8wnz	304	2260	0.118565
sv8wqb	1579	4340	0.266768
sv8wqc	1566	4848	0.244153
sv8wqf	5867	6759	0.464676
sv8wqg	4785	5121	0.483041

```
import pylab as pl
    dfl_geohash_merged['zero cars %'].hist(bins = 20)
    pl.title("Histogram of Percentage of instances with no car available")
    pl.xlabel("% of time when no car available")
    pl.ylabel("# of geohashes")
```

## Out[159]: Text(0, 0.5, '# of geohashes')



4741\_HW1\_Q1 - Jupyter Notebook 9/18/19, 9:15 PM

## Learning from image 4

We can see there are few geohashes which have more than 70% of times (right of the histogram above) no car being available. These are the locations where either demand is typically high and/or theses locations do not see people parking cars. There seems to be some optimizaiton scope if we can move some cars to these locations.

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