NYC Yellow Taxi Data

- EDA and visualization only with data from Jaunary in 2015
- · Used data in BigQuery open data scource

```
In [2]: import chart_studio.plotly as py
import cufflinks as cf
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")

plt.style.use('ggplot')
print(cf.__version__)

%config InlineBackend.figure_format = 'retina'
cf.go_offline()
```

0.17.3

1. Preprocessing

```
In [57]: df.tail(10)
Out[57]:
```

```
        pickup_hour
        cnt

        734
        2015-01-31 14:00:00
        25059

        735
        2015-01-31 15:00:00
        25886

        736
        2015-01-31 16:00:00
        23822

        737
        2015-01-31 17:00:00
        25794

        738
        2015-01-31 18:00:00
        30804

        739
        2015-01-31 19:00:00
        32436

        740
        2015-01-31 20:00:00
        27555

        741
        2015-01-31 21:00:00
        27477

        742
        2015-01-31 22:00:00
        29862

        743
        2015-01-31 23:00:00
        29856
```

```
In [58]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 744 entries, 0 to 743
Data columns (total 2 columns):
# Column Non-Null Count Dtype
--- 0 pickup_hour 744 non-null datetime64[ns]
1 cnt 744 non-null int64
dtypes: datetime64[ns](1), int64(1)
memory usage: 11.8 KB
```

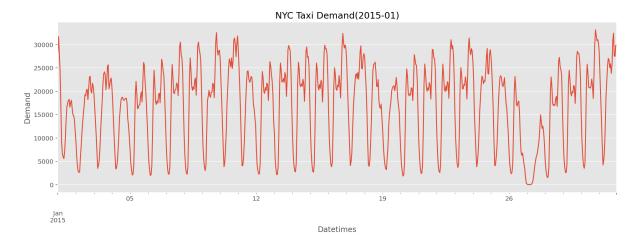
· There is no outliers

2. Pattern

```
In [59]: df = df.set_index('pickup_hour')
```

```
In [60]: df.plot(title='NYC Taxi Demand(2015-01)', figsize=(16,5), legend=False)
    plt.xlabel('Datetimes')
    plt.ylabel('Demand')
```

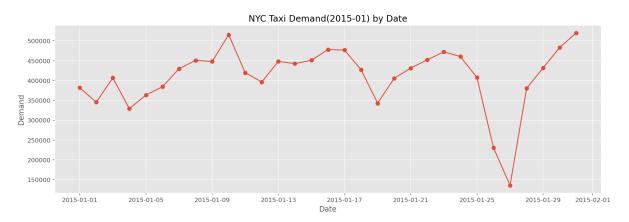
Out[60]: Text(0, 0.5, 'Demand')



- Lowest demand on Jan 27, 2015 03:00
 - due to January 2015 blizzard

Demand by 'Date'

Out[67]: Text(0, 0.5, 'Demand')



Demand by 'date' and by 'hour'

```
In [63]: df['weekday'] = df.index.weekday
    df['hour'] = df.index.hour
    df['weeknum'] = df.index.week
```

In [64]: | df.head(2)

Out[64]:

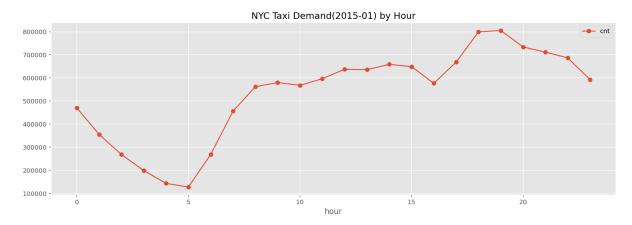
cnt	Date	weekday	hour	weeknum
-----	------	---------	------	---------

pickup_hour

2015-01-01 00:00:00	28312	2015-01-01	3	0	1
2015-01-01 01:00:00	31707	2015-01-01	3	1	1

```
In [65]: df.groupby('hour')[['cnt']].sum().plot(title='NYC Taxi Demand(2015-01) b
    y Hour', style='-o', figsize=(16,5))
```

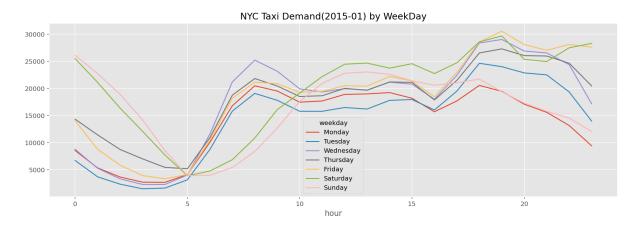
Out[65]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8b3e747d00>



• Peak Hour: 18:00 - 19:00

• Off-peak: 05:00

Out[79]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8b43362d30>

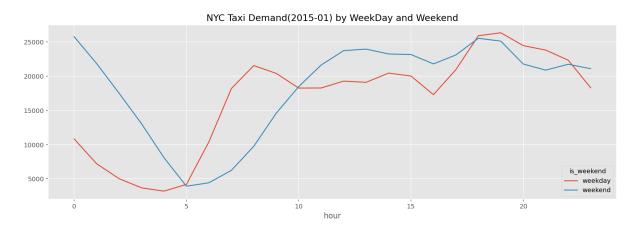


· There are two different trend lines between weekday and weekend

Demand 'Weekday' and 'Weekend'

```
In [80]: df['is_weekend'] = ((pd.DatetimeIndex(df.index).dayofweek) // 5 == 1).as
type(int)
```

Out[82]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8b38e17490>



- In weekday, The demands were rapidly increased during 05:00 8:00
- In weekend, the demands were gradually increased during 07:00 12:00
 - Highest demand on midnight

Heatmap by 'day' and 'hour'

								_
0 -	8552.75	6719.25	8787	14326.4	14054.2	25487.2	26099	- 30000
Н -	5360.5	3707	5283.25	11440.4	8785.6	21118.6	22754.8	
2 -	3675.25	2361.75	3337.75	8753.6	5856.8	16382	18918	
m -	2730	1504	2307	7030.2	3948.6	12112	14226.5	
4 -	2691.25	1633.75	2297.25	5444.8	3341.8	7730.4	8549.25	- 25000
٦ -	4134.25	3159	4057.75	5198.2	4150	3911.8	3933.25	
9 -	10065.2	8757.25	11587	10925	10476	4775.6	3983.5	
	16805.8	15820.5	21199.2	18754	18194.6	6866.8	5437	
∞ -	20491.5	19087.2	25219	21822	21141.8	10864.2	8367.75	- 20000
ი -	19523.8	17816.5	23168.5	20452.4	20887.2	16092.6	12709.5	
10	17472	15789.2	19927.2	18513	19261.4	19139.8	17623.2	
	17686.5	15787.2	19353.5	18655.8	19461.6	22176.2	20931.8	
hour 12 11	18895.5	16485.5	19966.5	20012.2	20504.8	24463.2	22797	- 15000
m -	18992	16207.5	19705.8	19665.6	20420.8	24672	23043.5	13000
1 4	19236.2	17799	21159.2	21190.2	22205.4	23745.2	22601.2	
- 5	18196	17957.2	20797.5	21120.2	21371.6	24556.4	21411	
16 1	15692.5	16034	18004.8	17873	18450.8	22746	20581	
	17700.2	19508.8	22432.2	21493.8	22978.8	24729.8	21053.2	- 10000
8 -	20559	24636.8	28379.2	26537	28569	28580.8	21713.2	
1 6	19470.8	24012	29024.8	27292.6	30551.4	29679.6	19395.5	
20 1	17094	22860.2	26898.5	26051.6	28076	25360	17275.8	
21 2	15598.5	22501.8	26550.8	25974.4	27044.2	24953.2	15779	- 5000
22 2	13167.2	19352	24384.2	24652.2	28099	27495.2	14528.2	
23 2	9427	13983	17168.8	20464	27606	28303	12062.2	
7	0	i	2	3	4	5	6	
		_	_	weekday		-		

• Demand increased at Fiday night and Saturday night

3. Geographical EDA

```
In [90]: %%time
         query = """
         WITH base_data AS (
           SELECT
           FROM `bigquery-public-data.new york taxi trips.tlc yellow trips 2015`
           WHERE EXTRACT(MONTH from pickup datetime) = 1
         ), temp AS (
           SELECT nyc_taxi.*, gis.*
           FROM (
             SELECT *
             FROM base data
             WHERE pickup latitude <= 90 and pickup latitude >= -90
             ) as nyc taxi
           JOIN (
             SELECT zip code, state code, state name, city, county, zip code geom
             FROM `bigguery-public-data.geo us boundaries.zip codes`
             WHERE state code='NY'
             ) as gis
           ON st contains(zip code geom, st geogpoint(pickup longitude, pickup la
         titude))
         )
         SELECT
           zip_code,
           city,
           ST ASTEXT(zip code geom) as zip code geom,
           DATETIME TRUNC(pickup datetime, hour) as pickup hour,
           count(*) as cnt
         FROM temp
         GROUP BY zip code, city, zip code geom, pickup hour
         ORDER BY pickup hour
         0.00
         df = pd.read gbq(query=query, dialect='standard', project id='mobility-3
         20516')
```

```
Downloading: 100% | 87020/87020 [04:52<00:00, 297.23rows/s]

CPU times: user 7.19 s, sys: 987 ms, total: 8.18 s

Wall time: 5min 22s
```

```
In [91]: df.head()
```

Out[91]:

	zip_code		zip_code_geom	pickup_hour	cnt
0	11218	New York city	POLYGON((-73.991929 40.642205, -73.991734 40.6	2015-01-01	14
1	11225	New York city	POLYGON((-73.964786 40.662054, -73.965025 40.6	2015-01-01	10
2	10024	New York city	POLYGON((-73.98814 40.781409, -73.987414 40.78	2015-01-01	869
3	11514	Carle Place CDP	POLYGON((-73.624059 40.755152, -73.623723 40.7	2015-01-01	1
4	10010	New York city	POLYGON((-73.993739 40.741617, -73.994028 40.7	2015-01-01	1045

```
In [92]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 87020 entries, 0 to 87019
```

Data columns (total 5 columns):

#	Column	Non-Nu	ull Count	Dtype
0	zip_code	87020	non-null	object
1	city	87020	non-null	object
2	zip_code_geom	87020	non-null	object
3	pickup_hour	87020	non-null	datetime64[ns]
4	cnt	87020	non-null	int64
.11		1/11		-1-41 (2)

dtypes: datetime64[ns](1), int64(1), object(3)
memory usage: 3.3+ MB

Highest demand by 'zip code'

```
In [93]: zip_code_agg_df = df.groupby(['zip_code', 'zip_code_geom'])[['cnt']].sum
   ().reset_index()
```

```
In [94]: zip_code_agg_df.head()
```

Out[94]:

	zip_code	zip_code_geom	cnt
0	10001	POLYGON((-74.00828 40.750272, -74.008255 40.75	627563
1	10002	POLYGON((-73.997504 40.714069, -73.9973 40.713	234527
2	10003	POLYGON((-73.999366 40.731323, -73.999604 40.7	704598
3	10004	MULTIPOLYGON(((-74.018008 40.705935, -74.01801	59700
4	10005	POLYGON((-74.012508 40.70676774.0124 40.706	52454

In [96]: zip_code_agg_df.tail()

Out[96]:

		zip_code	zip_code_geom	cnt	percent
٠	369	13656	POLYGON((-76.067267 44.140696, -76.067236 44.1	1	0.0
	370	13691	POLYGON((-75.88536 44.23349, -75.88501 44.2310	1	0.0
	371	14072	MULTIPOLYGON(((-78.935536 42.965442, -78.93553	1	0.0
	372	14527	MULTIPOLYGON(((-77.121905 42.624718, -77.12188	1	0.0
	373	14801	POLYGON((-77.442016 42.140918, -77.44193 42.14	1	0.0

```
In [97]: filter_agg_df = zip_code_agg_df[zip_code_agg_df['percent'] > 0.000]
```

• Omit 0 percent (unnecessary)

```
In [98]: filter_agg_df.sort_values(by='cnt', ascending=False)
```

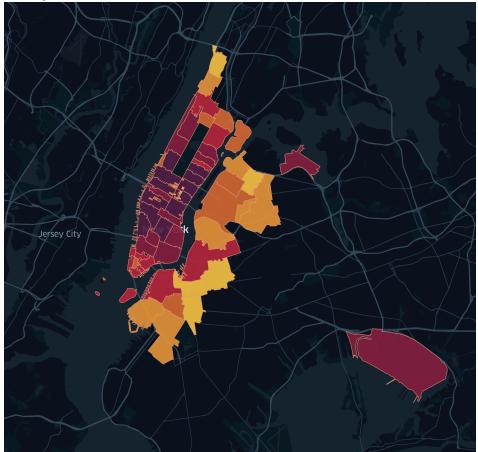
Out[98]:

	zip_code	zip_code_geom	cnt	percent
16	10019	POLYGON((-74.003568 40.763799, -74.003767 40.7	817267	0.066
2	10003	POLYGON((-73.999366 40.731323, -73.999604 40.7	704598	0.057
19	10022	POLYGON((-73.977201 40.758538, -73.977655 40.7	679831	0.055
13	10016	POLYGON((-73.987298 40.744682, -73.987746 40.7	663540	0.054
9	10011	POLYGON((-74.012285 40.74387, -74.012359 40.74	647831	0.053
194	11205	POLYGON((-73.980649 40.701561, -73.980729 40.7	8437	0.001
54	10167	POLYGON((-73.975352 40.755303, -73.975807 40.7	8186	0.001
45	10112	POLYGON((-73.980426 40.759899, -73.980886 40.7	8135	0.001
60	10173	POLYGON((-73.979937 40.754783, -73.980395 40.7	7966	0.001
44	10111	POLYGON((-73.97845 40.759065, -73.978039 40.75	6898	0.001

72 rows × 4 columns

```
In [99]: filter_zip_code = filter_agg_df['zip_code'].to_list()
In [100]: filter_agg_df.to_csv("zip_code_ratio.csv", index=False)
```

- Visualization using Kepler.gl
- Darker color means higher demand

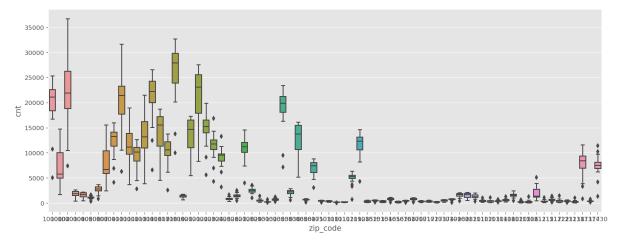


4. Finding pattern

boxplot for demand by 'zip code'

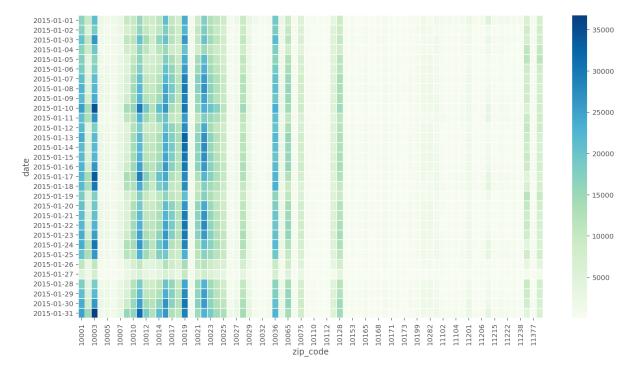
```
In [101]: zip_df = df[['zip_code', 'zip_code_geom', 'pickup_hour', 'cnt']]
In [102]: zip_df['date'] = zip_df['pickup_hour'].dt.date
In [103]: filter_zip_df = zip_df[zip_df['zip_code'].isin(filter_zip_code)]
In [104]: filter_zip_daily_df = filter_zip_df.groupby(['zip_code','date'])[['cnt']].sum().reset_index()
```

```
In [110]: plt.figure(figsize=(16, 6));
    sns.boxplot(x='zip_code', y='cnt', data=filter_zip_daily_df);
```



Heatmap by 'date' and 'zip code'

Out[94]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc6ee38a610>



- Highest demand: 10019
- Next zip code: 10001, 10003, 10011, 10015, 10022
- There are pattern in 2015-01-10, 01-17, 01-24, 01-31

Trips per zip code by hours

```
filter_zip_df['hour'] = filter_zip_df['pickup_hour'].dt.hour
          plt.figure(figsize=(15,8))
In [97]:
          sns.heatmap(filter_zip_df.pivot_table('cnt', index='hour', columns='zip_
          code', aggfunc='mean'),
                      lw=.5, cmap='GnBu')
Out[97]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc6ee4d54f0>
                                                                                      1750
                                                                                      1500
                                                                                     1250
                                                                                      1000
            13
                                                                                      750
            16
            17
            18
            19
            20
                                                                                      - 250
            21
            22
```

10110

zip_code

10112

10171 10173 10199

11102

11201

• Higher demand between 18:00 - 22:00

10014

• Higher demand by 'zip code': 10001, 10003, 10011, 10015, 10019, 10022, 10036