

Appendix A

Jupyter Notebook part 1 (the page number is only for this Notebook)

```
[1]: import pandas as pd
import numpy as np
```

```
[2]: weather = pd.read_csv('data/2016_01_weather.CSV')
weather
```

```
[2]:
```

	time	12:51 AM	1:51 AM \
0	2016/1/1	Fair	Cloudy
1	2016/1/2	Fair	Fair
2	2016/1/3	Fair	Fair
3	2016/1/4	Partly Cloudy / Windy	Fair
4	2016/1/5	Fair	Fair / Windy
5	2016/1/6	Fair	Fair
6	2016/1/7	Fair	Fair
7	2016/1/8	Cloudy	Fair
8	2016/1/9	Cloudy	Cloudy
9	2016/1/10	Mostly Cloudy	Light Rain
10	2016/1/11	Fair	Mostly Cloudy
11	2016/1/12	Partly Cloudy / Windy	Fair
12	2016/1/13	Cloudy	Fair / Windy
13	2016/1/14	Cloudy	Mostly Cloudy
14	2016/1/15	Cloudy	Cloudy
15	2016/1/16	Mostly Cloudy	Cloudy
16	2016/1/17	Cloudy	Mostly Cloudy
17	2016/1/18	Fair	Fair
18	2016/1/19	Partly Cloudy / Windy	Fair
19	2016/1/20	Cloudy	Fair / Windy
20	2016/1/21	Fair / Windy	NaN
21	2016/1/22	Light Snow	Fair
22	2016/1/23	Light Snow	Light Snow
23	2016/1/24	Cloudy	Light Snow / Windy
24	2016/1/25	Cloudy	Partly Cloudy
25	2016/1/26	Cloudy	Cloudy
26	2016/1/27	Cloudy	Cloudy
27	2016/1/28	Cloudy	Fair
28	2016/1/29	Fair	Cloudy
29	2016/1/30	Partly Cloudy	Partly Cloudy

30	2016/1/31	Cloudy	Cloudy
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	2:51 AM	3:51 AM	4:51 AM \
0	Cloudy	Cloudy	Cloudy
1	Fair	Mostly Cloudy	Mostly Cloudy
2	Fair	Fair	Fair
3	Mostly Cloudy	Mostly Cloudy / Windy	Mostly Cloudy
4	Fair	Fair	Fair
5	Fair	Cloudy	Fair
6	Fair	Fair	Fair
7	Fair	Partly Cloudy	Fair
8	Mostly Cloudy	Mostly Cloudy	Cloudy
9	Cloudy	Cloudy	Rain
10	Mostly Cloudy / Windy	Partly Cloudy / Windy	Partly Cloudy / Windy
11	Partly Cloudy	Partly Cloudy	Mostly Cloudy
12	Partly Cloudy / Windy	Fair / Windy	Partly Cloudy
13	Cloudy	Cloudy	Cloudy
14	Partly Cloudy	Partly Cloudy	Partly Cloudy
15	Rain	Light Rain	Light Rain
16	Cloudy	Cloudy	Mostly Cloudy
17	Fair	Fair	Fair
18	Fair / Windy	Fair	Fair
19	Fair	Fair	Fair
20	Cloudy	Cloudy	Cloudy
21	Fair	Fair	Fair
22	Light Snow / Windy	Light Snow / Windy	Light Snow / Windy
23	Light Snow / Windy	Cloudy / Windy	Cloudy
24	Partly Cloudy	Fair	Fair
25	Mostly Cloudy	Cloudy	Cloudy
26	Mostly Cloudy	Cloudy	Cloudy
27	Partly Cloudy	Partly Cloudy	Fair
28	Cloudy	Cloudy	Cloudy
29	Fair	Partly Cloudy	Partly Cloudy
30	Partly Cloudy	Partly Cloudy	Cloudy

	5:51 AM	6:51 AM	7:51 AM	8:51 AM ... \
0	Cloudy	Cloudy	Mostly Cloudy	Cloudy ...
1	Partly Cloudy	Fair	Partly Cloudy	Mostly Cloudy ...
2	Fair	Fair	Fair	Fair ...
3	Mostly Cloudy	Partly Cloudy	Mostly Cloudy	Mostly Cloudy ...
4	Fair	Fair	Fair	Fair ...
5	Cloudy	Cloudy	Cloudy	Cloudy ...
6	Fair	Partly Cloudy	Partly Cloudy	Mostly Cloudy ...
7	Fair	Fair	Fair	Partly Cloudy ...
8	Cloudy	Cloudy	Cloudy	Mostly Cloudy ...
9	Heavy Rain	Rain	Rain	Heavy Rain ...
10	Fair	Fair	Fair	Fair ...

11	Mostly Cloudy	Partly Cloudy	Mostly Cloudy	Mostly Cloudy	...
12	Fair / Windy	Fair / Windy	Fair / Windy	Fair	...
13	Cloudy	Light Snow	Cloudy	Cloudy	...
14	Partly Cloudy	Cloudy	Cloudy	Cloudy	...
15	Light Rain	Cloudy	Light Rain	Light Rain	...
16	Fair	Fair	Mostly Cloudy	Cloudy	...
17	Fair / Windy	Partly Cloudy	Light Snow	Mostly Cloudy / Windy	...
18	Fair	Fair / Windy	Fair	Fair / Windy	...
19	Fair	Partly Cloudy	Fair	Partly Cloudy	...
20	Cloudy	Partly Cloudy	Fair	Fair	...
21	Fair	Fair	Fair	Mostly Cloudy	...
22	Snow / Windy	Snow	Snow / Windy	Heavy Snow / Windy	...
23	Fair / Windy	Fair	Fair	Fair	...
24	Mostly Cloudy	Cloudy	Cloudy	Cloudy	...
25	Cloudy	Cloudy	Cloudy	Cloudy	...
26	Cloudy	Cloudy	Cloudy	Cloudy	...
27	Fair	Fair	Fair	Fair	...
28	Cloudy	Mostly Cloudy	Partly Cloudy	Partly Cloudy	...
29	Fair	Fair	Fair	Fair	...
30	Cloudy	Cloudy	Mostly Cloudy	Mostly Cloudy	...

	2:51 PM	3:51 PM	4:51 PM \
0	Cloudy	Mostly Cloudy	Mostly Cloudy
1	Mostly Cloudy	Mostly Cloudy	Mostly Cloudy
2	Partly Cloudy	Partly Cloudy	Partly Cloudy
3	Fair / Windy	Fair	Fair
4	Fair	Fair	Fair
5	Fair	Fair	Fair
6	Mostly Cloudy	Mostly Cloudy	Mostly Cloudy
7	Cloudy	Mostly Cloudy	Cloudy
8	Cloudy	Cloudy	Cloudy
9	Fog	Fog	Light Rain
10	Fair	Fair	Fair / Windy
11	Cloudy	Cloudy	Cloudy / Windy
12	Fair / Windy	Fair	Partly Cloudy
13	Mostly Cloudy	Mostly Cloudy	Cloudy
14	Cloudy	Cloudy	Cloudy
15	Mostly Cloudy	Mostly Cloudy	Mostly Cloudy
16	Cloudy	Light Snow	Light Snow
17	Fair / Windy	Partly Cloudy / Windy	Mostly Cloudy / Windy
18	Fair / Windy	Fair / Windy	Partly Cloudy / Windy
19	Mostly Cloudy	Cloudy	Cloudy
20	Partly Cloudy	Partly Cloudy	Partly Cloudy / Windy
21	Cloudy	Cloudy	Cloudy
22	Heavy Snow / Windy	Heavy Snow / Windy	Heavy Snow
23	Partly Cloudy	Partly Cloudy	Partly Cloudy
24	Mostly Cloudy	Cloudy	Cloudy

25	Cloudy	Cloudy	Fair
26	Cloudy	Cloudy	Fair
27	Fair	Mostly Cloudy	Cloudy
28	Cloudy	Cloudy	Cloudy
29	Mostly Cloudy	Mostly Cloudy	Mostly Cloudy
30	Mostly Cloudy	Cloudy	Mostly Cloudy

	5:51 PM	6:51 PM	7:51 PM \
0	Partly Cloudy	Partly Cloudy	Partly Cloudy
1	Mostly Cloudy	Partly Cloudy	Fair
2	Mostly Cloudy	Partly Cloudy	Partly Cloudy
3	Fair / Windy	Fair / Windy	Fair
4	Fair	Fair	Fair
5	Fair	Fair	Fair
6	Mostly Cloudy	Mostly Cloudy	Mostly Cloudy
7	Cloudy	Cloudy	Cloudy
8	Cloudy	Cloudy	Cloudy
9	Mostly Cloudy	Partly Cloudy	Fair
10	Fair	Fair	Fair
11	Light Rain	Cloudy	Mostly Cloudy
12	Partly Cloudy	Mostly Cloudy	Partly Cloudy
13	Cloudy	Cloudy	Cloudy
14	Cloudy	Cloudy	Cloudy
15	Cloudy	Cloudy	Mostly Cloudy
16	Light Snow	Light Snow	Light Snow
17	Partly Cloudy	Partly Cloudy / Windy	Partly Cloudy / Windy
18	Partly Cloudy / Windy	Fair	Fair / Windy
19	Cloudy	Mostly Cloudy	Mostly Cloudy
20	Partly Cloudy	Mostly Cloudy	Partly Cloudy
21	Cloudy	Cloudy	Cloudy
22	Heavy Snow / Windy	Heavy Snow / Windy	Heavy Snow
23	Mostly Cloudy	Mostly Cloudy	Partly Cloudy
24	Cloudy	Cloudy	Mostly Cloudy
25	Cloudy	Cloudy	Cloudy
26	Cloudy	Cloudy	Cloudy
27	Mostly Cloudy	Partly Cloudy	Cloudy
28	Mostly Cloudy / Windy	Mostly Cloudy / Windy	Mostly Cloudy / Windy
29	Mostly Cloudy	Partly Cloudy	Partly Cloudy
30	Cloudy	Mostly Cloudy	Cloudy

	8:51 PM	9:51 PM	10:51 PM \
0	Fair	Fair	Fair
1	Fair	Fair	Fair
2	Partly Cloudy	Fair	Fair
3	Partly Cloudy / Windy	Mostly Cloudy / Windy	Mostly Cloudy / Windy
4	Fair	Fair	Fair
5	Fair	Fair	Fair

6	Fair	Fair	Fair
7	Cloudy	Cloudy	Cloudy
8	Cloudy	Light Drizzle	Cloudy
9	Mostly Cloudy	Fair / Windy	Fair / Windy
10	Fair	Fair	Fair
11	Mostly Cloudy	Cloudy / Windy	Mostly Cloudy / Windy
12	Cloudy	Cloudy	Cloudy
13	Cloudy	Partly Cloudy	Mostly Cloudy
14	Cloudy	Cloudy	Cloudy
15	Cloudy	Cloudy	Cloudy
16	Light Snow	Mostly Cloudy	Partly Cloudy
17	Fair / Windy	Fair	Fair / Windy
18	Fair	Fair	Mostly Cloudy / Windy
19	Cloudy	Cloudy	Cloudy
20	Partly Cloudy	Fair	Fair
21	Cloudy	Cloudy	Cloudy
22	Heavy Snow / Windy	Snow / Windy	Light Snow
23	Partly Cloudy	Mostly Cloudy	Mostly Cloudy
24	Fair	Fair	Fair
25	Cloudy	Cloudy	Cloudy
26	Cloudy	Cloudy	Cloudy
27	Cloudy	Cloudy	Cloudy
28	Partly Cloudy / Windy	Fair	Fair
29	Partly Cloudy	Cloudy	Mostly Cloudy
30	Cloudy	Cloudy	Cloudy

11:51 PM

0	Fair
1	Fair
2	Fair
3	Fair / Windy
4	Fair
5	Fair
6	Fair
7	Cloudy
8	Cloudy
9	Fair
10	Fair
11	Partly Cloudy
12	Cloudy
13	Cloudy
14	Cloudy
15	Mostly Cloudy
16	Partly Cloudy
17	Fair / Windy
18	Mostly Cloudy
19	Cloudy

```

20      Partly Cloudy
21      Light Snow
22 Light Snow / Windy
23      Cloudy
24      Mostly Cloudy
25      Cloudy
26      Cloudy
27      Cloudy
28      Fair
29      Mostly Cloudy
30      Cloudy

```

[31 rows x 25 columns]

```

[3]: weather.columns = ['time'] + [i for i in range(24)]
weather_list = weather.iloc[:,1:].values.tolist()
weather

```

```

[3]:
   time 0 1 \
0 2016/1/1 Fair Cloudy
1 2016/1/2 Fair Fair
2 2016/1/3 Fair Fair
3 2016/1/4 Partly Cloudy / Windy Fair
4 2016/1/5 Fair Fair / Windy
5 2016/1/6 Fair Fair
6 2016/1/7 Fair Fair
7 2016/1/8 Cloudy Fair
8 2016/1/9 Cloudy Cloudy
9 2016/1/10 Mostly Cloudy Light Rain
10 2016/1/11 Fair Mostly Cloudy
11 2016/1/12 Partly Cloudy / Windy Fair
12 2016/1/13 Cloudy Fair / Windy
13 2016/1/14 Cloudy Mostly Cloudy
14 2016/1/15 Cloudy Cloudy
15 2016/1/16 Mostly Cloudy Cloudy
16 2016/1/17 Cloudy Mostly Cloudy
17 2016/1/18 Fair Fair
18 2016/1/19 Partly Cloudy / Windy Fair
19 2016/1/20 Cloudy Fair / Windy
20 2016/1/21 Fair / Windy NaN
21 2016/1/22 Light Snow Fair
22 2016/1/23 Light Snow Light Snow
23 2016/1/24 Cloudy Light Snow / Windy
24 2016/1/25 Cloudy Partly Cloudy
25 2016/1/26 Cloudy Cloudy
26 2016/1/27 Cloudy Cloudy
27 2016/1/28 Cloudy Fair

```

28	2016/1/29	Fair	Cloudy
29	2016/1/30	Partly Cloudy	Partly Cloudy
30	2016/1/31	Cloudy	Cloudy

	2	3	4 \
0	Cloudy	Cloudy	Cloudy
1	Fair	Mostly Cloudy	Mostly Cloudy
2	Fair	Fair	Fair
3	Mostly Cloudy	Mostly Cloudy / Windy	Mostly Cloudy
4	Fair	Fair	Fair
5	Fair	Cloudy	Fair
6	Fair	Fair	Fair
7	Fair	Partly Cloudy	Fair
8	Mostly Cloudy	Mostly Cloudy	Cloudy
9	Cloudy	Cloudy	Rain
10	Mostly Cloudy / Windy	Partly Cloudy / Windy	Partly Cloudy / Windy
11	Partly Cloudy	Partly Cloudy	Mostly Cloudy
12	Partly Cloudy / Windy	Fair / Windy	Partly Cloudy
13	Cloudy	Cloudy	Cloudy
14	Partly Cloudy	Partly Cloudy	Partly Cloudy
15	Rain	Light Rain	Light Rain
16	Cloudy	Cloudy	Mostly Cloudy
17	Fair	Fair	Fair
18	Fair / Windy	Fair	Fair
19	Fair	Fair	Fair
20	Cloudy	Cloudy	Cloudy
21	Fair	Fair	Fair
22	Light Snow / Windy	Light Snow / Windy	Light Snow / Windy
23	Light Snow / Windy	Cloudy / Windy	Cloudy
24	Partly Cloudy	Fair	Fair
25	Mostly Cloudy	Cloudy	Cloudy
26	Mostly Cloudy	Cloudy	Cloudy
27	Partly Cloudy	Partly Cloudy	Fair
28	Cloudy	Cloudy	Cloudy
29	Fair	Partly Cloudy	Partly Cloudy
30	Partly Cloudy	Partly Cloudy	Cloudy

	5	6	7	8 ... \
0	Cloudy	Cloudy	Mostly Cloudy	Cloudy ...
1	Partly Cloudy	Fair	Partly Cloudy	Mostly Cloudy ...
2	Fair	Fair	Fair	Fair ...
3	Mostly Cloudy	Partly Cloudy	Mostly Cloudy	Mostly Cloudy ...
4	Fair	Fair	Fair	Fair ...
5	Cloudy	Cloudy	Cloudy	Cloudy ...
6	Fair	Partly Cloudy	Partly Cloudy	Mostly Cloudy ...
7	Fair	Fair	Fair	Partly Cloudy ...
8	Cloudy	Cloudy	Cloudy	Mostly Cloudy ...

9	Heavy Rain	Rain	Rain	Heavy Rain	...
10	Fair	Fair	Fair	Fair	...
11	Mostly Cloudy	Partly Cloudy	Mostly Cloudy	Mostly Cloudy	...
12	Fair / Windy	Fair / Windy	Fair / Windy	Fair	...
13	Cloudy	Light Snow	Cloudy	Cloudy	...
14	Partly Cloudy	Cloudy	Cloudy	Cloudy	...
15	Light Rain	Cloudy	Light Rain	Light Rain	...
16	Fair	Fair	Mostly Cloudy	Cloudy	...
17	Fair / Windy	Partly Cloudy	Light Snow	Mostly Cloudy / Windy	...
18	Fair	Fair / Windy	Fair	Fair / Windy	...
19	Fair	Partly Cloudy	Fair	Partly Cloudy	...
20	Cloudy	Partly Cloudy	Fair	Fair	...
21	Fair	Fair	Fair	Mostly Cloudy	...
22	Snow / Windy	Snow	Snow / Windy	Heavy Snow / Windy	...
23	Fair / Windy	Fair	Fair	Fair	...
24	Mostly Cloudy	Cloudy	Cloudy	Cloudy	...
25	Cloudy	Cloudy	Cloudy	Cloudy	...
26	Cloudy	Cloudy	Cloudy	Cloudy	...
27	Fair	Fair	Fair	Fair	...
28	Cloudy	Mostly Cloudy	Partly Cloudy	Partly Cloudy	...
29	Fair	Fair	Fair	Fair	...
30	Cloudy	Cloudy	Mostly Cloudy	Mostly Cloudy	...

	14	15	16 \
0	Cloudy	Mostly Cloudy	Mostly Cloudy
1	Mostly Cloudy	Mostly Cloudy	Mostly Cloudy
2	Partly Cloudy	Partly Cloudy	Partly Cloudy
3	Fair / Windy	Fair	Fair
4	Fair	Fair	Fair
5	Fair	Fair	Fair
6	Mostly Cloudy	Mostly Cloudy	Mostly Cloudy
7	Cloudy	Mostly Cloudy	Cloudy
8	Cloudy	Cloudy	Cloudy
9	Fog	Fog	Light Rain
10	Fair	Fair	Fair / Windy
11	Cloudy	Cloudy	Cloudy / Windy
12	Fair / Windy	Fair	Partly Cloudy
13	Mostly Cloudy	Mostly Cloudy	Cloudy
14	Cloudy	Cloudy	Cloudy
15	Mostly Cloudy	Mostly Cloudy	Mostly Cloudy
16	Cloudy	Light Snow	Light Snow
17	Fair / Windy	Partly Cloudy / Windy	Mostly Cloudy / Windy
18	Fair / Windy	Fair / Windy	Partly Cloudy / Windy
19	Mostly Cloudy	Cloudy	Cloudy
20	Partly Cloudy	Partly Cloudy	Partly Cloudy / Windy
21	Cloudy	Cloudy	Cloudy
22	Heavy Snow / Windy	Heavy Snow / Windy	Heavy Snow

23	Partly Cloudy	Partly Cloudy	Partly Cloudy
24	Mostly Cloudy	Cloudy	Cloudy
25	Cloudy	Cloudy	Fair
26	Cloudy	Cloudy	Fair
27	Fair	Mostly Cloudy	Cloudy
28	Cloudy	Cloudy	Cloudy
29	Mostly Cloudy	Mostly Cloudy	Mostly Cloudy
30	Mostly Cloudy	Cloudy	Mostly Cloudy

	17	18	19 \
0	Partly Cloudy	Partly Cloudy	Partly Cloudy
1	Mostly Cloudy	Partly Cloudy	Fair
2	Mostly Cloudy	Partly Cloudy	Partly Cloudy
3	Fair / Windy	Fair / Windy	Fair
4	Fair	Fair	Fair
5	Fair	Fair	Fair
6	Mostly Cloudy	Mostly Cloudy	Mostly Cloudy
7	Cloudy	Cloudy	Cloudy
8	Cloudy	Cloudy	Cloudy
9	Mostly Cloudy	Partly Cloudy	Fair
10	Fair	Fair	Fair
11	Light Rain	Cloudy	Mostly Cloudy
12	Partly Cloudy	Mostly Cloudy	Partly Cloudy
13	Cloudy	Cloudy	Cloudy
14	Cloudy	Cloudy	Cloudy
15	Cloudy	Cloudy	Mostly Cloudy
16	Light Snow	Light Snow	Light Snow
17	Partly Cloudy	Partly Cloudy / Windy	Partly Cloudy / Windy
18	Partly Cloudy / Windy	Fair	Fair / Windy
19	Cloudy	Mostly Cloudy	Mostly Cloudy
20	Partly Cloudy	Mostly Cloudy	Partly Cloudy
21	Cloudy	Cloudy	Cloudy
22	Heavy Snow / Windy	Heavy Snow / Windy	Heavy Snow
23	Mostly Cloudy	Mostly Cloudy	Partly Cloudy
24	Cloudy	Cloudy	Mostly Cloudy
25	Cloudy	Cloudy	Cloudy
26	Cloudy	Cloudy	Cloudy
27	Mostly Cloudy	Partly Cloudy	Cloudy
28	Mostly Cloudy / Windy	Mostly Cloudy / Windy	Mostly Cloudy / Windy
29	Mostly Cloudy	Partly Cloudy	Partly Cloudy
30	Cloudy	Mostly Cloudy	Cloudy

	20	21	22 \
0	Fair	Fair	Fair
1	Fair	Fair	Fair
2	Partly Cloudy	Fair	Fair
3	Partly Cloudy / Windy	Mostly Cloudy / Windy	Mostly Cloudy / Windy

4	Fair	Fair	Fair
5	Fair	Fair	Fair
6	Fair	Fair	Fair
7	Cloudy	Cloudy	Cloudy
8	Cloudy	Light Drizzle	Cloudy
9	Mostly Cloudy	Fair / Windy	Fair / Windy
10	Fair	Fair	Fair
11	Mostly Cloudy	Cloudy / Windy	Mostly Cloudy / Windy
12	Cloudy	Cloudy	Cloudy
13	Cloudy	Partly Cloudy	Mostly Cloudy
14	Cloudy	Cloudy	Cloudy
15	Cloudy	Cloudy	Cloudy
16	Light Snow	Mostly Cloudy	Partly Cloudy
17	Fair / Windy	Fair	Fair / Windy
18	Fair	Fair	Mostly Cloudy / Windy
19	Cloudy	Cloudy	Cloudy
20	Partly Cloudy	Fair	Fair
21	Cloudy	Cloudy	Cloudy
22	Heavy Snow / Windy	Snow / Windy	Light Snow
23	Partly Cloudy	Mostly Cloudy	Mostly Cloudy
24	Fair	Fair	Fair
25	Cloudy	Cloudy	Cloudy
26	Cloudy	Cloudy	Cloudy
27	Cloudy	Cloudy	Cloudy
28	Partly Cloudy / Windy	Fair	Fair
29	Partly Cloudy	Cloudy	Mostly Cloudy
30	Cloudy	Cloudy	Cloudy

	23
0	Fair
1	Fair
2	Fair
3	Fair / Windy
4	Fair
5	Fair
6	Fair
7	Cloudy
8	Cloudy
9	Fair
10	Fair
11	Partly Cloudy
12	Cloudy
13	Cloudy
14	Cloudy
15	Mostly Cloudy
16	Partly Cloudy
17	Fair / Windy

```

18      Mostly Cloudy
19      Cloudy
20      Partly Cloudy
21      Light Snow
22 Light Snow / Windy
23      Cloudy
24      Mostly Cloudy
25      Cloudy
26      Cloudy
27      Cloudy
28      Fair
29      Mostly Cloudy
30      Cloudy

```

[31 rows x 25 columns]

```

[4]: possible = []
    for i in weather_list:
        possible = possible + i

    possible = list(set(possible))
    possible
    len(possible)

```

[4]: 21

```

[5]: preci = ['Heavy Rain', 'Light Drizzle', 'Light Snow', 'Rain',
              'Light Rain / Windy', 'Heavy Snow', 'Snow', 'Light Snow / Windy',
              'Snow / Windy', 'Light Rain', 'Heavy Snow / Windy']

    remain = ['Partly Cloudy', 'Cloudy / Windy', 'Partly Cloudy / Windy',
              'Fair / Windy', 'Fair', 'Mostly Cloudy',
              'Mostly Cloudy / Windy', 'Fog', 'Cloudy']

```

[]:

```

[6]: def precipitation_or_not(condition):
    if condition in preci:
        return 'preci'
    elif condition in remain:
        return 'remain'
    else:
        return 'unknown'

```

```

[7]: for i in range(24):
    weather.loc[:,i] = weather.loc[:,i].apply(precipitation_or_not)

```

```
[8]: weather.iloc[20,2] = 'remain'
```

```
[ ]:
```

```
[9]: weather['time'] = pd.to_datetime(weather['time'], format='%Y/%m/%d')
weather
```

```
[9]:
```

	time	0	1	2	3	4	5	6	7	\
0	2016-01-01	remain	remain	remain	remain	remain	remain	remain	remain	
1	2016-01-02	remain	remain	remain	remain	remain	remain	remain	remain	
2	2016-01-03	remain	remain	remain	remain	remain	remain	remain	remain	
3	2016-01-04	remain	remain	remain	remain	remain	remain	remain	remain	
4	2016-01-05	remain	remain	remain	remain	remain	remain	remain	remain	
5	2016-01-06	remain	remain	remain	remain	remain	remain	remain	remain	
6	2016-01-07	remain	remain	remain	remain	remain	remain	remain	remain	
7	2016-01-08	remain	remain	remain	remain	remain	remain	remain	remain	
8	2016-01-09	remain	remain	remain	remain	remain	remain	remain	remain	
9	2016-01-10	remain	preci	remain	remain	preci	preci	preci	preci	
10	2016-01-11	remain	remain	remain	remain	remain	remain	remain	remain	
11	2016-01-12	remain	remain	remain	remain	remain	remain	remain	remain	
12	2016-01-13	remain	remain	remain	remain	remain	remain	remain	remain	
13	2016-01-14	remain	remain	remain	remain	remain	remain	preci	remain	
14	2016-01-15	remain	remain	remain	remain	remain	remain	remain	remain	
15	2016-01-16	remain	remain	preci	preci	preci	preci	remain	preci	
16	2016-01-17	remain	remain	remain	remain	remain	remain	remain	remain	
17	2016-01-18	remain	remain	remain	remain	remain	remain	remain	preci	
18	2016-01-19	remain	remain	remain	remain	remain	remain	remain	remain	
19	2016-01-20	remain	remain	remain	remain	remain	remain	remain	remain	
20	2016-01-21	remain	remain	remain	remain	remain	remain	remain	remain	
21	2016-01-22	preci	remain	remain	remain	remain	remain	remain	remain	
22	2016-01-23	preci	preci	preci	preci	preci	preci	preci	preci	
23	2016-01-24	remain	preci	preci	remain	remain	remain	remain	remain	
24	2016-01-25	remain	remain	remain	remain	remain	remain	remain	remain	
25	2016-01-26	remain	remain	remain	remain	remain	remain	remain	remain	
26	2016-01-27	remain	remain	remain	remain	remain	remain	remain	remain	
27	2016-01-28	remain	remain	remain	remain	remain	remain	remain	remain	
28	2016-01-29	remain	remain	remain	remain	remain	remain	remain	remain	
29	2016-01-30	remain	remain	remain	remain	remain	remain	remain	remain	
30	2016-01-31	remain	remain	remain	remain	remain	remain	remain	remain	

	8	...	14	15	16	17	18	19	20	\
0	remain	...	remain	remain	remain	remain	remain	remain	remain	
1	remain	...	remain	remain	remain	remain	remain	remain	remain	
2	remain	...	remain	remain	remain	remain	remain	remain	remain	
3	remain	...	remain	remain	remain	remain	remain	remain	remain	
4	remain	...	remain	remain	remain	remain	remain	remain	remain	
5	remain	...	remain	remain	remain	remain	remain	remain	remain	

6	remain	...	remain	remain	remain	remain	remain	remain	remain
7	remain	...	remain	remain	remain	remain	remain	remain	remain
8	remain	...	remain	remain	remain	remain	remain	remain	remain
9	preci	...	remain	remain	preci	remain	remain	remain	remain
10	remain	...	remain	remain	remain	remain	remain	remain	remain
11	remain	...	remain	remain	remain	preci	remain	remain	remain
12	remain	...	remain	remain	remain	remain	remain	remain	remain
13	remain	...	remain	remain	remain	remain	remain	remain	remain
14	remain	...	remain	remain	remain	remain	remain	remain	remain
15	preci	...	remain	remain	remain	remain	remain	remain	remain
16	remain	...	remain	preci	preci	preci	preci	preci	preci
17	remain	...	remain	remain	remain	remain	remain	remain	remain
18	remain	...	remain	remain	remain	remain	remain	remain	remain
19	remain	...	remain	remain	remain	remain	remain	remain	remain
20	remain	...	remain	remain	remain	remain	remain	remain	remain
21	remain	...	remain	remain	remain	remain	remain	remain	remain
22	preci	...	preci	preci	preci	preci	preci	preci	preci
23	remain	...	remain	remain	remain	remain	remain	remain	remain
24	remain	...	remain	remain	remain	remain	remain	remain	remain
25	remain	...	remain	remain	remain	remain	remain	remain	remain
26	remain	...	remain	remain	remain	remain	remain	remain	remain
27	remain	...	remain	remain	remain	remain	remain	remain	remain
28	remain	...	remain	remain	remain	remain	remain	remain	remain
29	remain	...	remain	remain	remain	remain	remain	remain	remain
30	remain	...	remain	remain	remain	remain	remain	remain	remain

	21	22	23
0	remain	remain	remain
1	remain	remain	remain
2	remain	remain	remain
3	remain	remain	remain
4	remain	remain	remain
5	remain	remain	remain
6	remain	remain	remain
7	remain	remain	remain
8	preci	remain	remain
9	remain	remain	remain
10	remain	remain	remain
11	remain	remain	remain
12	remain	remain	remain
13	remain	remain	remain
14	remain	remain	remain
15	remain	remain	remain
16	remain	remain	remain
17	remain	remain	remain
18	remain	remain	remain
19	remain	remain	remain

```
20  remain  remain  remain
21  remain  remain  preci
22  preci   preci   preci
23  remain  remain  remain
24  remain  remain  remain
25  remain  remain  remain
26  remain  remain  remain
27  remain  remain  remain
28  remain  remain  remain
29  remain  remain  remain
30  remain  remain  remain
```

```
[31 rows x 25 columns]
```

```
[10]: weather.to_csv('data/weather_preprocessed.csv', index=False)
```

```
[ ]:
```

Appendix B

Jupyter Notebook part 2 (the page number is only for this Notebook)

```
[1]: import pandas as pd
import numpy as np
from numpy import log, sqrt
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
```

```
[2]: df = pd.read_csv('data/yellow_tripdata_2016-01.csv', error_bad_lines=False)
df
```

```
[2]:
```

	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	\
0	2	2016-01-01 00:00:00	2016-01-01 00:00:00	
1	2	2016-01-01 00:00:00	2016-01-01 00:00:00	
2	2	2016-01-01 00:00:00	2016-01-01 00:00:00	
3	2	2016-01-01 00:00:00	2016-01-01 00:00:00	
4	2	2016-01-01 00:00:00	2016-01-01 00:00:00	
...	
10906853	2	2016-01-31 23:30:32	2016-01-31 23:38:18	
10906854	1	2016-01-05 00:15:55	2016-01-05 00:16:06	
10906855	1	2016-01-05 06:12:46	2016-03-19 20:45:50	
10906856	1	2016-01-05 06:21:44	2016-03-28 12:54:26	
10906857	1	2016-01-05 06:15:21	2016-01-05 06:15:36	

	passenger_count	trip_distance	pickup_longitude	pickup_latitude	\
0	2	1.10	-73.990372	40.734695	
1	5	4.90	-73.980782	40.729912	
2	1	10.54	-73.984550	40.679565	
3	1	4.75	-73.993469	40.718990	
4	3	1.76	-73.960625	40.781330	
...	
10906853	1	2.20	-74.003578	40.751011	
10906854	1	0.00	-73.945488	40.751530	
10906855	3	1.40	-73.994240	40.766586	
10906856	1	2.10	-73.948067	40.776531	
10906857	3	0.00	-73.960938	40.758595	

	RatecodeID	store_and_fwd_flag	dropoff_longitude	dropoff_latitude	\
--	------------	--------------------	-------------------	------------------	---

0	1	N	-73.981842	40.732407
1	1	N	-73.944473	40.716679
2	1	N	-73.950272	40.788925
3	1	N	-73.962242	40.657333
4	1	N	-73.977264	40.758514
...
10906853	1	N	-73.982651	40.767509
10906854	1	N	-73.945457	40.751530
10906855	1	N	-73.984428	40.753922
10906856	1	N	-73.978188	40.777435
10906857	2	N	-73.961006	40.758583

	payment_type	fare_amount	extra	mta_tax	tip_amount	tolls_amount	\
0	2	7.5	0.5	0.5	0.00	0.00	
1	1	18.0	0.5	0.5	0.00	0.00	
2	1	33.0	0.5	0.5	0.00	0.00	
3	2	16.5	0.0	0.5	0.00	0.00	
4	2	8.0	0.0	0.5	0.00	0.00	
...	
10906853	2	8.5	0.5	0.5	0.00	0.00	
10906854	2	2.5	0.5	0.5	0.00	0.00	
10906855	2	7.5	0.5	0.5	0.00	0.00	
10906856	1	11.5	0.0	0.5	2.45	0.00	
10906857	2	52.0	0.0	0.5	0.00	5.54	

	improvement_surcharge	total_amount
0	0.3	8.80
1	0.3	19.30
2	0.3	34.30
3	0.3	17.30
4	0.3	8.80
...
10906853	0.3	9.80
10906854	0.3	3.80
10906855	0.3	8.80
10906856	0.3	14.75
10906857	0.3	58.34

[10906858 rows x 19 columns]

```
[3]: df.columns
```

```
[3]: Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
'passenger_count', 'trip_distance', 'pickup_longitude',
'pickup_latitude', 'RatecodeID', 'store_and_fwd_flag',
'dropoff_longitude', 'dropoff_latitude', 'payment_type', 'fare_amount',
'extra', 'mta_tax', 'tip_amount', 'tolls_amount',
```



```
'improvement_surcharge', 'total_amount'],
dtype='object')
```

```
[ ]:
```

```
[4]: df.dropna(inplace=True)
df['tpep_pickup_datetime'] = pd.to_datetime(df['tpep_pickup_datetime'],
                                             format='%Y/%m/%d %H:%M', errors='coerce')
df['tpep_dropoff_datetime'] = pd.to_datetime(df['tpep_dropoff_datetime'],
                                              format='%Y/%m/%d %H:%M', errors='coerce')

df['duration'] = (df['tpep_dropoff_datetime'] -
                  df['tpep_pickup_datetime']).dt.seconds.astype(int) / 60
```

```
[5]: df['start_hour'] = df['tpep_pickup_datetime'].dt.hour
df['start_date'] = df['tpep_pickup_datetime'].dt.strftime('%Y-%m-%d')
```

```
[ ]:
```

```
[ ]:
```

```
[6]: weather = pd.read_csv('data/weather_preprocessed.csv', index_col= 'time')
weather
```

```
[6]:
```

	0	1	2	3	4	5	6	7 \
time								
2016-01-01	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-02	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-03	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-04	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-05	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-06	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-07	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-08	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-09	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-10	remain	preci	remain	remain	preci	preci	preci	preci
2016-01-11	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-12	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-13	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-14	remain	remain	remain	remain	remain	remain	preci	remain
2016-01-15	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-16	remain	remain	preci	preci	preci	preci	remain	preci
2016-01-17	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-18	remain	remain	remain	remain	remain	remain	remain	preci
2016-01-19	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-20	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-21	remain	remain	remain	remain	remain	remain	remain	remain

2016-01-22	preci	remain	remain	remain	remain	remain	remain	remain
2016-01-23	preci	preci	preci	preci	preci	preci	preci	preci
2016-01-24	remain	preci	preci	remain	remain	remain	remain	remain
2016-01-25	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-26	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-27	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-28	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-29	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-30	remain	remain	remain	remain	remain	remain	remain	remain
2016-01-31	remain	remain	remain	remain	remain	remain	remain	remain

	8	9	...	14	15	16	17	18 \
time			...					
2016-01-01	remain	remain	...	remain	remain	remain	remain	remain
2016-01-02	remain	remain	...	remain	remain	remain	remain	remain
2016-01-03	remain	remain	...	remain	remain	remain	remain	remain
2016-01-04	remain	remain	...	remain	remain	remain	remain	remain
2016-01-05	remain	remain	...	remain	remain	remain	remain	remain
2016-01-06	remain	remain	...	remain	remain	remain	remain	remain
2016-01-07	remain	remain	...	remain	remain	remain	remain	remain
2016-01-08	remain	remain	...	remain	remain	remain	remain	remain
2016-01-09	remain	remain	...	remain	remain	remain	remain	remain
2016-01-10	preci	preci	...	remain	remain	preci	remain	remain
2016-01-11	remain	remain	...	remain	remain	remain	remain	remain
2016-01-12	remain	remain	...	remain	remain	remain	preci	remain
2016-01-13	remain	remain	...	remain	remain	remain	remain	remain
2016-01-14	remain	remain	...	remain	remain	remain	remain	remain
2016-01-15	remain	remain	...	remain	remain	remain	remain	remain
2016-01-16	preci	remain	...	remain	remain	remain	remain	remain
2016-01-17	remain	remain	...	remain	preci	preci	preci	preci
2016-01-18	remain	remain	...	remain	remain	remain	remain	remain
2016-01-19	remain	remain	...	remain	remain	remain	remain	remain
2016-01-20	remain	remain	...	remain	remain	remain	remain	remain
2016-01-21	remain	remain	...	remain	remain	remain	remain	remain
2016-01-22	remain	remain	...	remain	remain	remain	remain	remain
2016-01-23	preci	preci	...	preci	preci	preci	preci	preci
2016-01-24	remain	remain	...	remain	remain	remain	remain	remain
2016-01-25	remain	remain	...	remain	remain	remain	remain	remain
2016-01-26	remain	remain	...	remain	remain	remain	remain	remain
2016-01-27	remain	remain	...	remain	remain	remain	remain	remain
2016-01-28	remain	remain	...	remain	remain	remain	remain	remain
2016-01-29	remain	remain	...	remain	remain	remain	remain	remain
2016-01-30	remain	remain	...	remain	remain	remain	remain	remain
2016-01-31	remain	remain	...	remain	remain	remain	remain	remain

	19	20	21	22	23
time					

2016-01-01	remain	remain	remain	remain	remain
2016-01-02	remain	remain	remain	remain	remain
2016-01-03	remain	remain	remain	remain	remain
2016-01-04	remain	remain	remain	remain	remain
2016-01-05	remain	remain	remain	remain	remain
2016-01-06	remain	remain	remain	remain	remain
2016-01-07	remain	remain	remain	remain	remain
2016-01-08	remain	remain	remain	remain	remain
2016-01-09	remain	remain	preci	remain	remain
2016-01-10	remain	remain	remain	remain	remain
2016-01-11	remain	remain	remain	remain	remain
2016-01-12	remain	remain	remain	remain	remain
2016-01-13	remain	remain	remain	remain	remain
2016-01-14	remain	remain	remain	remain	remain
2016-01-15	remain	remain	remain	remain	remain
2016-01-16	remain	remain	remain	remain	remain
2016-01-17	preci	preci	remain	remain	remain
2016-01-18	remain	remain	remain	remain	remain
2016-01-19	remain	remain	remain	remain	remain
2016-01-20	remain	remain	remain	remain	remain
2016-01-21	remain	remain	remain	remain	remain
2016-01-22	remain	remain	remain	remain	preci
2016-01-23	preci	preci	preci	preci	preci
2016-01-24	remain	remain	remain	remain	remain
2016-01-25	remain	remain	remain	remain	remain
2016-01-26	remain	remain	remain	remain	remain
2016-01-27	remain	remain	remain	remain	remain
2016-01-28	remain	remain	remain	remain	remain
2016-01-29	remain	remain	remain	remain	remain
2016-01-30	remain	remain	remain	remain	remain
2016-01-31	remain	remain	remain	remain	remain

[31 rows x 24 columns]

[]:

```
[7]: def fill_weather(weather, date, time):
      return weather.loc[date][time]

df['weather'] = df[['start_date', 'start_hour']].apply(
    lambda x: fill_weather(weather, x.iloc[0], x.iloc[1]), axis=1)
```

```
[8]: df.to_feather('data/yellow_tripdata_01_weather.feather')
```

```
[9]: df
```

[9]:

	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	\	
0	2	2016-01-01 00:00:00	2016-01-01 00:00:00		
1	2	2016-01-01 00:00:00	2016-01-01 00:00:00		
2	2	2016-01-01 00:00:00	2016-01-01 00:00:00		
3	2	2016-01-01 00:00:00	2016-01-01 00:00:00		
4	2	2016-01-01 00:00:00	2016-01-01 00:00:00		
...		
10906853	2	2016-01-31 23:30:32	2016-01-31 23:38:18		
10906854	1	2016-01-05 00:15:55	2016-01-05 00:16:06		
10906855	1	2016-01-05 06:12:46	2016-03-19 20:45:50		
10906856	1	2016-01-05 06:21:44	2016-03-28 12:54:26		
10906857	1	2016-01-05 06:15:21	2016-01-05 06:15:36		

	passenger_count	trip_distance	pickup_longitude	pickup_latitude	\	
0	2	1.10	-73.990372	40.734695		
1	5	4.90	-73.980782	40.729912		
2	1	10.54	-73.984550	40.679565		
3	1	4.75	-73.993469	40.718990		
4	3	1.76	-73.960625	40.781330		
...		
10906853	1	2.20	-74.003578	40.751011		
10906854	1	0.00	-73.945488	40.751530		
10906855	3	1.40	-73.994240	40.766586		
10906856	1	2.10	-73.948067	40.776531		
10906857	3	0.00	-73.960938	40.758595		

	RatecodeID	store_and_fwd_flag	dropoff_longitude	...	extra	\	
0	1	N	-73.981842	...	0.5		
1	1	N	-73.944473	...	0.5		
2	1	N	-73.950272	...	0.5		
3	1	N	-73.962242	...	0.0		
4	1	N	-73.977264	...	0.0		
...		
10906853	1	N	-73.982651	...	0.5		
10906854	1	N	-73.945457	...	0.5		
10906855	1	N	-73.984428	...	0.5		
10906856	1	N	-73.978188	...	0.0		
10906857	2	N	-73.961006	...	0.0		

	mta_tax	tip_amount	tolls_amount	improvement_surcharge	\	
0	0.5	0.00	0.00		0.3	
1	0.5	0.00	0.00		0.3	
2	0.5	0.00	0.00		0.3	
3	0.5	0.00	0.00		0.3	
4	0.5	0.00	0.00		0.3	
...		
10906853	0.5	0.00	0.00		0.3	

10906854	0.5	0.00	0.00	0.3
10906855	0.5	0.00	0.00	0.3
10906856	0.5	2.45	0.00	0.3
10906857	0.5	0.00	5.54	0.3

	total_amount	duration	start_hour	start_date	weather
0	8.80	0.000000	0	2016-01-01	remain
1	19.30	0.000000	0	2016-01-01	remain
2	34.30	0.000000	0	2016-01-01	remain
3	17.30	0.000000	0	2016-01-01	remain
4	8.80	0.000000	0	2016-01-01	remain
...
10906853	9.80	7.766667	23	2016-01-31	remain
10906854	3.80	0.183333	0	2016-01-05	remain
10906855	8.80	873.066667	6	2016-01-05	remain
10906856	14.75	392.700000	6	2016-01-05	remain
10906857	58.34	0.250000	6	2016-01-05	remain

[10906858 rows x 23 columns]

Appendix C

Jupyter Notebook part 3(the page number is only for this Notebook)

```
[1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import folium
from folium.plugins import FastMarkerCluster
from folium.plugins import HeatMap
from statsmodels.formula.api import *
import matplotlib.image as mpimg
import io
from PIL import Image
```

```
[2]: df = pd.read_feather('data/yellow_tripdata_01_weather.feather')
df["income"] = df['tip_amount'] + df['fare_amount']
df['income/duration'] = df['income'] / df['duration']
```

1 Data cleaning

```
[3]: df.describe()
```

```
[3]:
```

	VendorID	passenger_count	trip_distance	pickup_longitude \
count	1.090686e+07	1.090686e+07	1.090686e+07	1.090686e+07
mean	1.535024e+00	1.670847e+00	4.648197e+00	-7.281869e+01
std	4.987718e-01	1.324891e+00	2.981095e+03	9.168964e+00
min	1.000000e+00	0.000000e+00	0.000000e+00	-1.219343e+02
25%	1.000000e+00	1.000000e+00	1.000000e+00	-7.399151e+01
50%	2.000000e+00	1.000000e+00	1.670000e+00	-7.398138e+01
75%	2.000000e+00	2.000000e+00	3.080000e+00	-7.396610e+01
max	2.000000e+00	9.000000e+00	8.000010e+06	0.000000e+00

	pickup_latitude	RatecodeID	dropoff_longitude	dropoff_latitude \
count	1.090686e+07	1.090686e+07	1.090686e+07	1.090686e+07
mean	4.011494e+01	1.039350e+00	-7.288659e+01	4.015315e+01
std	5.051022e+00	5.186309e-01	8.900841e+00	4.903456e+00
min	0.000000e+00	1.000000e+00	-1.219335e+02	0.000000e+00
25%	4.073630e+01	1.000000e+00	-7.399107e+01	4.073481e+01

50%	4.075369e+01	1.000000e+00	-7.397942e+01	4.075413e+01
75%	4.076808e+01	1.000000e+00	-7.396196e+01	4.076962e+01
max	6.090876e+01	9.900000e+01	0.000000e+00	6.090876e+01

	payment_type	fare_amount	extra	mta_tax	tip_amount \
count	1.090686e+07	1.090686e+07	1.090686e+07	1.090686e+07	1.090686e+07
mean	1.347536e+00	1.248693e+01	3.130757e-01	4.976705e-01	1.750663e+00
std	4.910804e-01	3.556400e+01	4.156792e-01	5.046685e-02	2.623546e+00
min	1.000000e+00	-9.576000e+02	-4.261000e+01	-5.000000e-01	-2.208000e+02
25%	1.000000e+00	6.500000e+00	0.000000e+00	5.000000e-01	0.000000e+00
50%	1.000000e+00	9.000000e+00	0.000000e+00	5.000000e-01	1.260000e+00
75%	2.000000e+00	1.400000e+01	5.000000e-01	5.000000e-01	2.320000e+00
max	5.000000e+00	1.112709e+05	6.488700e+02	8.970000e+01	9.981400e+02

	tolls_amount	improvement_surcharge	total_amount	duration \
count	1.090686e+07	1.090686e+07	1.090686e+07	1.090686e+07
mean	2.933453e-01	2.997245e-01	1.564140e+01	1.520518e+01
std	1.694572e+00	1.232553e-02	3.641280e+01	5.424797e+01
min	-1.740000e+01	-3.000000e-01	-9.584000e+02	0.000000e+00
25%	0.000000e+00	3.000000e-01	8.300000e+00	6.333333e+00
50%	0.000000e+00	3.000000e-01	1.162000e+01	1.046667e+01
75%	0.000000e+00	3.000000e-01	1.716000e+01	1.688333e+01
max	9.801500e+02	3.000000e-01	1.112716e+05	1.439967e+03

	start_hour	income	income/duration
count	1.090686e+07	1.090686e+07	1.090636e+07
mean	1.354638e+01	1.423759e+01	NaN
std	6.391860e+00	3.609683e+01	NaN
min	0.000000e+00	-9.576000e+02	-inf
25%	9.000000e+00	7.350000e+00	8.976378e-01
50%	1.400000e+01	1.046000e+01	1.065217e+00
75%	1.900000e+01	1.600000e+01	1.303579e+00
max	2.300000e+01	1.112709e+05	inf

```
[4]: rid = df['RatecodeID'].value_counts()
rid
```

```
[4]: 1    10626315
     2     225019
     5     33688
     3     16822
     4      4696
     99      216
     6       102
     Name: RatecodeID, dtype: int64
```

```
[5]: df = df.loc[(df['RatecodeID'] != 99)]
```

```
[6]: # group payment type
def group_rid(x):
    if x != 1:
        return 2
    else:
        return 1
df['RatecodeID'] = df['RatecodeID'].apply(group_rid)
```

```
[7]: swf = df['store_and_fwd_flag'].value_counts()
swf
```

```
[7]: N    10843513
     Y      63129
     Name: store_and_fwd_flag, dtype: int64
```

```
[8]: pt = df['payment_type'].value_counts()
pt
```

```
[8]: 1    7181337
     2    3673602
     3     38292
     4     13410
     5         1
     Name: payment_type, dtype: int64
```

```
[9]: # group payment type
def group_payment_type(x):
    if x != 1:
        return 2
    else:
        return 1
df['payment_type'] = df['payment_type'].apply(group_payment_type)
```

```
[10]: passenger = df['passenger_count'].value_counts()
passenger
```

```
[10]: 1    7726830
     2    1561966
     5     601079
     3     436429
     6     369155
     4     210641
     0         471
     8         26
     9         23
     7         22
     Name: passenger_count, dtype: int64
```



```
[11]: df = df.loc[(df["duration"] >= 0.25) & (df["fare_amount"] > 0) & (df["extra"]_
    ↳>= 0) & (df["mta_tax"] >= 0)
        & (df["tip_amount"] >= 0) & (df["tolls_amount"] >=0) &_
    ↳(df["total_amount"]>0) & (df["income"] > 0)
        & (df["improvement_surcharge"] >= 0) & (df["trip_distance"] >= 0.
    ↳01)]
```

```
[12]: # lat, long
start_coords = ['pickup_latitude', 'pickup_longitude']
end_coords = ['dropoff_latitude', 'dropoff_longitude']
df[start_coords+ end_coords].describe()
```

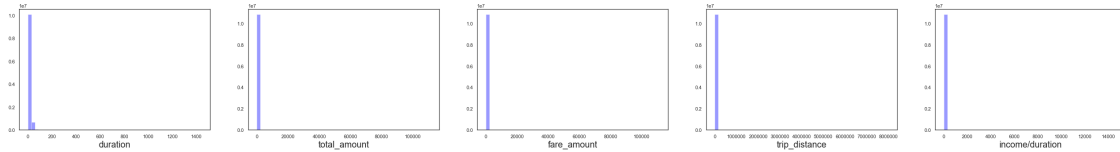
```
[12]:
```

	pickup_latitude	pickup_longitude	dropoff_latitude	dropoff_longitude
count	1.082888e+07	1.082888e+07	1.082888e+07	1.082888e+07
mean	4.016214e+01	-7.290432e+01	4.022927e+01	-7.302472e+01
std	4.863079e+00	8.827634e+00	4.585772e+00	8.323998e+00
min	0.000000e+00	-1.008229e+02	0.000000e+00	-1.008229e+02
25%	4.073648e+01	-7.399152e+01	4.073501e+01	-7.399110e+01
50%	4.075378e+01	-7.398141e+01	4.075424e+01	-7.397948e+01
75%	4.076812e+01	-7.396624e+01	4.076968e+01	-7.396216e+01
max	6.090876e+01	0.000000e+00	6.090876e+01	0.000000e+00

```
[13]: sns.set(rc={'figure.figsize':(11.7,8.27),"font.size":20,"axes.titlesize":
    ↳20,"axes.labelsize":20},style="white")
```

```
[14]: fig, ax = plt.subplots(1, 5)
sns.distplot(df['duration'], kde = False, label = "duration", color = "blue", ax_
    ↳= ax[0])
sns.distplot(df['total_amount'], kde = False, label = "total_amount", color_
    ↳="blue", ax = ax[1])
sns.distplot(df['fare_amount'], kde = False, label = 'fare_amount', color_
    ↳="blue", ax = ax[2])
sns.distplot(df['trip_distance'], kde = False, label = "duration", color_
    ↳="blue", ax = ax[3])
sns.distplot(df['income/duration'], kde = False, label = "duration", color_
    ↳="blue", ax = ax[4])

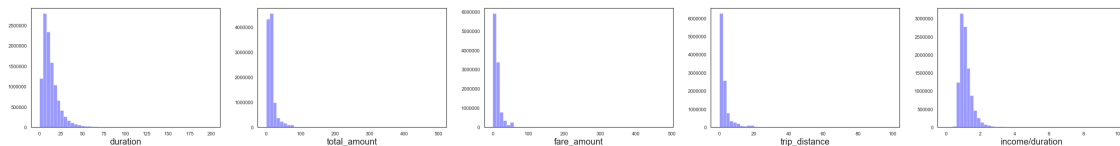
fig.set_figheight(5)
fig.set_figwidth(15)
fig.set_figwidth(25)
fig.set_figwidth(35)
fig.set_figwidth(45)
```



```
[15]: df = df.loc[(df["duration"] <= 200) & (df["total_amount"] <= 500)
               & (df['fare_amount'] <= 500) & (df['trip_distance'] <= 100) &
               ↪ (df["income/duration"] <= 10)]

fig, ax = plt.subplots(1, 5)
sns.distplot(df['duration'], kde = False, label = "duration", color = "blue", ax_
               ↪ ax[0])
sns.distplot(df['total_amount'], kde = False, label = "total_amount", color_
               ↪ "blue", ax = ax[1])
sns.distplot(df['fare_amount'], kde = False, label = 'fare_amount', color_
               ↪ "blue", ax = ax[2])
sns.distplot(df['trip_distance'], kde = False, label = "duration", color_
               ↪ "blue", ax = ax[3])
sns.distplot(df['income/duration'], kde = False, label = "duration", color_
               ↪ "blue", ax = ax[4])

fig.set_figheight(5)
fig.set_figwidth(15)
fig.set_figwidth(25)
fig.set_figwidth(35)
fig.set_figwidth(45)
```



```
[16]: df = df.loc[(df["duration"] <= 150) & (df["total_amount"] <= 100) &
               ↪ (df['fare_amount'] <= 80) & (df['trip_distance'] <= 30) & (df["income/
               ↪ duration"] <= 5)]

fig, ax = plt.subplots(1, 5)
sns.distplot(df['duration'], kde = False, color = "blue", ax = ax[0])
sns.distplot(df['total_amount'], kde = False, color = "blue", ax = ax[1])
sns.distplot(df['fare_amount'], kde = False, color = "blue", ax = ax[2])
sns.distplot(df['trip_distance'], kde = False, color = "blue", ax = ax[3])
sns.distplot(df['income/duration'], kde = False, color = "blue", ax = ax[4])
```

```

ax[0].set_title("Distribution of duration ")
ax[1].set_title("Distribution of total amount ")
ax[2].set_title("Distribution of fare amount ")
ax[3].set_title("Distribution of trip distance ")
ax[4].set_title("Distribution of income per minute")

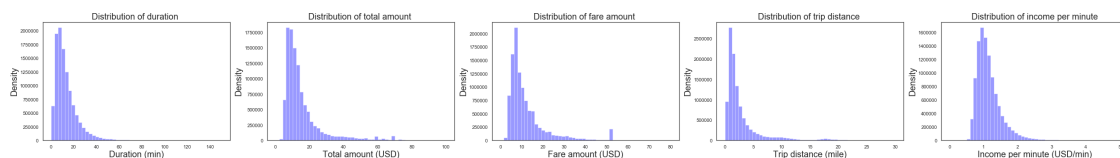
ax[0].set_xlabel("Duration (min)")
ax[1].set_xlabel("Total amount (USD)")
ax[2].set_xlabel("Fare amount (USD)")
ax[3].set_xlabel("Trip distance (mile)")
ax[4].set_xlabel("Income per minute (USD/min)")

ax[0].set_ylabel("Density")
ax[1].set_ylabel("Density")
ax[2].set_ylabel("Density")
ax[3].set_ylabel("Density")
ax[4].set_ylabel("Density")

fig.set_figheight(5)
fig.set_figwidth(15)
fig.set_figwidth(25)
fig.set_figwidth(35)
fig.set_figwidth(45)

fig.savefig('plots/distribution_narrowed_value.png')

```



```

[17]: plt.subplot(231)
sns.distplot(df['duration'], kde = False, label = "duration", color = "blue")
plt.title("Distribution\n of duration")
plt.xlabel('Duration (min)')
plt.ylabel("Density")

plt.subplot(232)
sns.distplot(df['total_amount'], kde = False, label = "total_amount", color =
    ↪ "blue")
plt.title("Distribution\n of total amount")
plt.xlabel('Total amount (USD)')
plt.ylabel("Density")

```

```

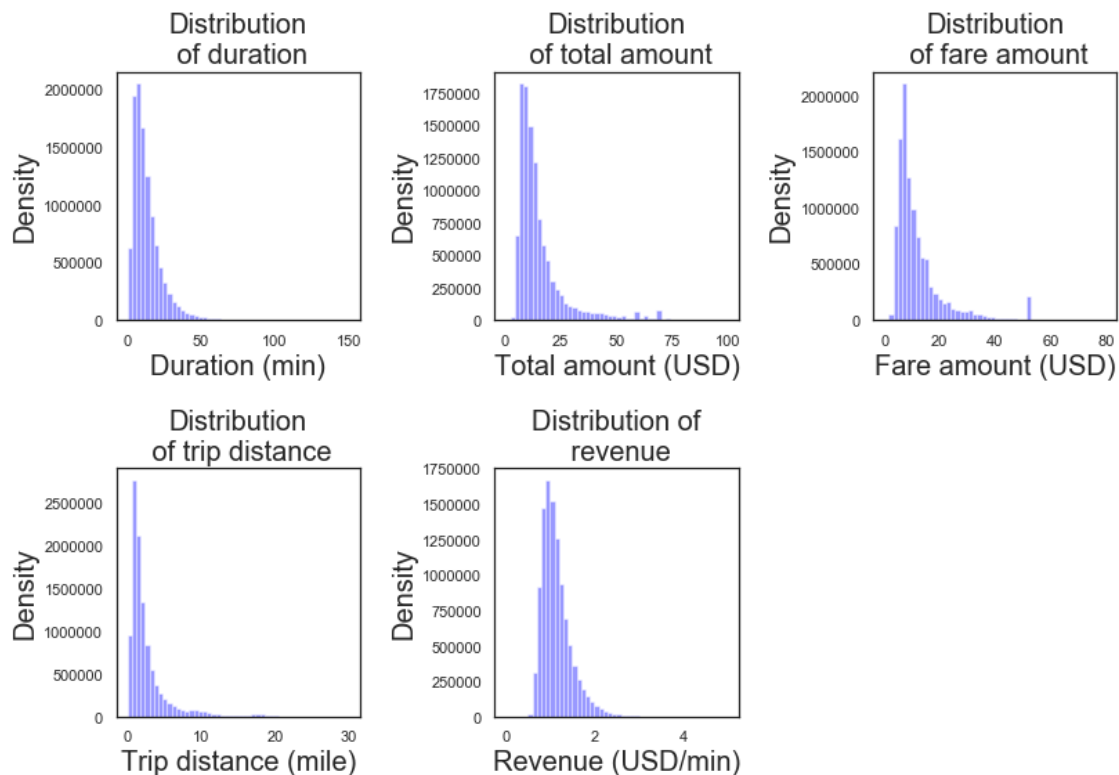
plt.subplot(233)
sns.distplot(df['fare_amount'], kde = False, label = 'fare_amount', color_
↪="blue")
plt.title("Distribution\n of fare amount")
plt.xlabel('Fare amount (USD)')
plt.ylabel("Density")

plt.subplot(234)
sns.distplot(df['trip_distance'], kde = False, label = "duration", color_
↪="blue")
plt.title("Distribution\n of trip distance")
plt.xlabel('Trip distance (mile)')
plt.ylabel("Density")

plt.subplot(235)
sns.distplot(df['income/duration'], kde = False, label = "duration", color_
↪="blue")
plt.title("Distribution of\n revenue")
plt.xlabel('Revenue (USD/min)')
plt.ylabel("Density")

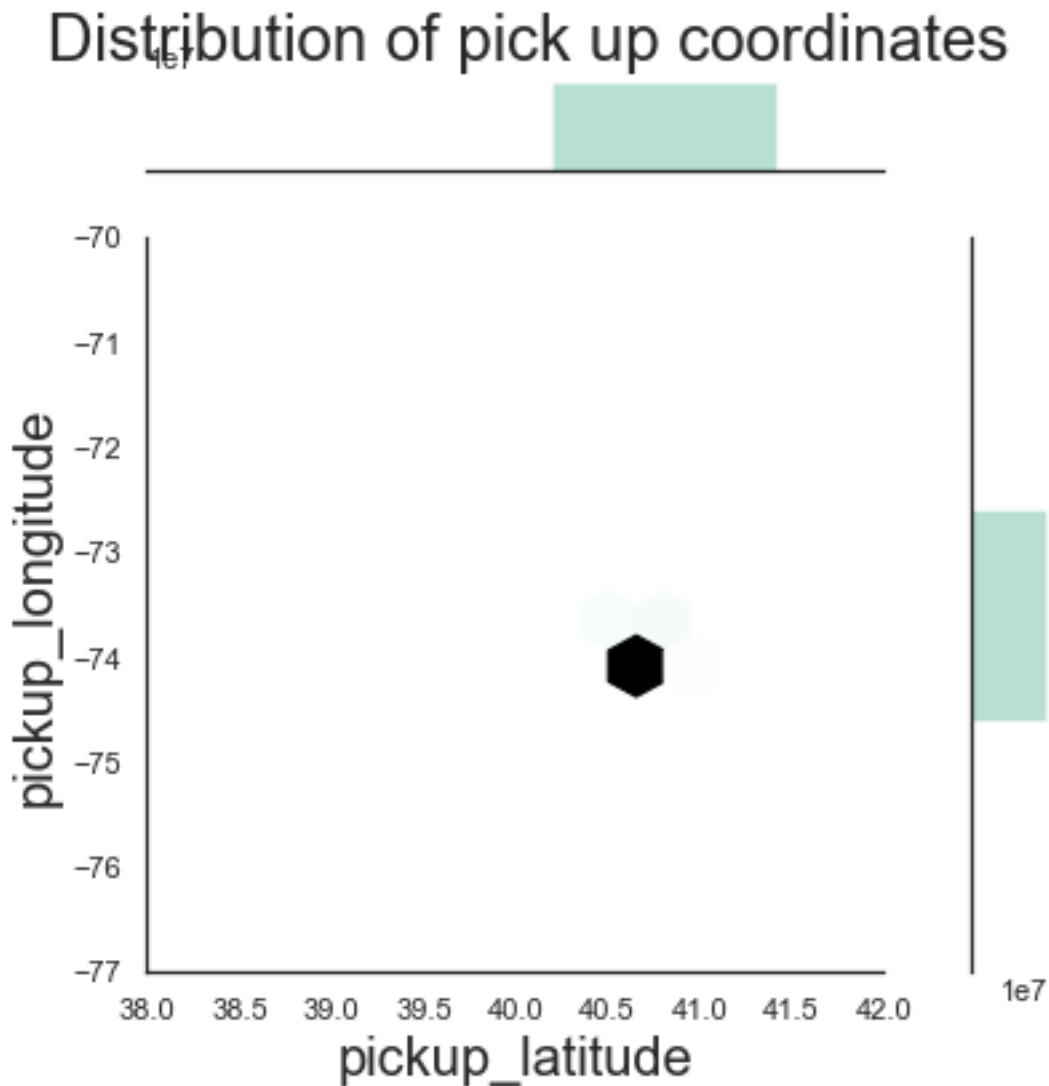
plt.tight_layout()
plt.show()

```



```
[18]: p = sns.jointplot(x='pickup_latitude',y='pickup_longitude' , data=
    ↪df,kind="hex",
        color="#4CB391", xlim=(38,42), ylim=(-77, -70), gridsize=200)

p.fig.suptitle("Distribution of pick up coordinates")
p.fig.tight_layout()
```



```
[19]: df = df.loc[(df["pickup_longitude"] < -73) & (df["pickup_longitude"] > -74.5) &
    ↪(df["pickup_latitude"] > 40.5) & (df["pickup_latitude"] < 41) &
    ↪(df["dropoff_longitude"] < -73) & (df["dropoff_longitude"] > -74.5)]
```

```
(df["dropoff_latitude"] > 40.5) & (df["dropoff_latitude"] < 41)]
```

```
[20]: df.reset_index(inplace=True, drop=True)
df
```

```
[20]:
```

	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	\
0	2	2016-01-01 00:00:00	2016-01-01 00:18:30	
1	2	2016-01-01 00:00:00	2016-01-01 00:26:45	
2	1	2016-01-01 00:00:01	2016-01-01 00:11:55	
3	1	2016-01-01 00:00:02	2016-01-01 00:11:14	
4	2	2016-01-01 00:00:02	2016-01-01 00:11:08	
...	
10624517	2	2016-01-31 21:28:59	2016-01-31 22:01:58	
10624518	2	2016-01-31 22:36:41	2016-01-31 22:45:04	
10624519	2	2016-01-31 22:53:00	2016-01-31 22:59:37	
10624520	2	2016-01-31 23:00:11	2016-01-31 23:12:08	
10624521	2	2016-01-31 23:30:32	2016-01-31 23:38:18	

	passenger_count	trip_distance	pickup_longitude	pickup_latitude	\
0	2	5.52	-73.980118	40.743050	
1	2	7.45	-73.994057	40.719990	
2	1	1.20	-73.979424	40.744614	
3	1	6.00	-73.947151	40.791046	
4	1	3.21	-73.998344	40.723896	
...	
10624517	1	7.83	-74.002953	40.750481	
10624518	1	2.50	-74.009277	40.717049	
10624519	1	1.68	-74.003578	40.750751	
10624520	1	2.65	-74.002159	40.734852	
10624521	1	2.20	-74.003578	40.751011	

	RatecodeID	store_and_fwd_flag	dropoff_longitude	...	tip_amount	\
0	1	N	-73.913490	...	0.00	
1	1	N	-73.966362	...	0.00	
2	1	N	-73.992035	...	0.00	
3	1	N	-73.920769	...	0.00	
4	1	N	-73.995850	...	0.00	
...	
10624517	1	N	-73.958153	...	5.00	
10624518	1	N	-73.994637	...	2.16	
10624519	1	N	-74.002159	...	1.00	
10624520	1	N	-73.999680	...	1.00	
10624521	1	N	-73.982651	...	0.00	

	tolls_amount	improvement_surcharge	total_amount	duration	\
0	0.0	0.3	20.30	18.500000	
1	0.0	0.3	27.30	26.750000	

2	0.0	0.3	10.30	11.900000
3	0.0	0.3	19.30	11.200000
4	0.0	0.3	12.80	11.100000
...
10624517	0.0	0.3	35.30	32.983333
10624518	0.0	0.3	12.96	8.383333
10624519	0.0	0.3	9.30	6.616667
10624520	0.0	0.3	13.30	11.950000
10624521	0.0	0.3	9.80	7.766667

	start_hour	start_date	weather	income	income/duration
0	0	2016-01-01	remain	19.00	1.027027
1	0	2016-01-01	remain	26.00	0.971963
2	0	2016-01-01	remain	9.00	0.756303
3	0	2016-01-01	remain	18.00	1.607143
4	0	2016-01-01	remain	11.50	1.036036
...
10624517	21	2016-01-31	remain	34.00	1.030824
10624518	22	2016-01-31	remain	11.66	1.390855
10624519	22	2016-01-31	remain	8.00	1.209068
10624520	23	2016-01-31	remain	12.00	1.004184
10624521	23	2016-01-31	remain	8.50	1.094421

[10624522 rows x 25 columns]

```
[21]: df.describe()
```

```
[21]:
```

	VendorID	passenger_count	trip_distance	pickup_longitude \
count	1.062452e+07	1.062452e+07	1.062452e+07	1.062452e+07
mean	1.538963e+00	1.675594e+00	2.888937e+00	-7.397336e+01
std	4.984796e-01	1.329766e+00	3.503629e+00	3.796886e-02
min	1.000000e+00	0.000000e+00	1.000000e-02	-7.443886e+01
25%	1.000000e+00	1.000000e+00	1.000000e+00	-7.399164e+01
50%	2.000000e+00	1.000000e+00	1.690000e+00	-7.398169e+01
75%	2.000000e+00	2.000000e+00	3.100000e+00	-7.396725e+01
max	2.000000e+00	9.000000e+00	3.000000e+01	-7.303445e+01

	pickup_latitude	RatecodeID	dropoff_longitude	dropoff_latitude \
count	1.062452e+07	1.062452e+07	1.062452e+07	1.062452e+07
mean	4.075104e+01	1.021407e+00	-7.397358e+01	4.075202e+01
std	2.779560e-02	1.447374e-01	3.365993e-02	3.144207e-02
min	4.050597e+01	1.000000e+00	-7.448333e+01	4.050733e+01
25%	4.073759e+01	1.000000e+00	-7.399119e+01	4.073634e+01
50%	4.075442e+01	1.000000e+00	-7.397976e+01	4.075478e+01
75%	4.076839e+01	1.000000e+00	-7.396313e+01	4.076998e+01
max	4.098892e+01	2.000000e+00	-7.306847e+01	4.099876e+01

	payment_type	fare_amount	extra	mta_tax	tip_amount \
count	1.062452e+07	1.062452e+07	1.062452e+07	1.062452e+07	1.062452e+07
mean	1.339203e+00	1.229613e+01	3.143274e-01	4.991960e-01	1.723470e+00
std	4.734389e-01	9.823765e+00	3.656012e-01	2.003404e-02	2.243046e+00
min	1.000000e+00	1.000000e-02	0.000000e+00	0.000000e+00	0.000000e+00
25%	1.000000e+00	6.500000e+00	0.000000e+00	5.000000e-01	0.000000e+00
50%	1.000000e+00	9.000000e+00	0.000000e+00	5.000000e-01	1.260000e+00
75%	2.000000e+00	1.400000e+01	5.000000e-01	5.000000e-01	2.320000e+00
max	2.000000e+00	8.000000e+01	8.500000e+00	8.900000e-01	8.800000e+01

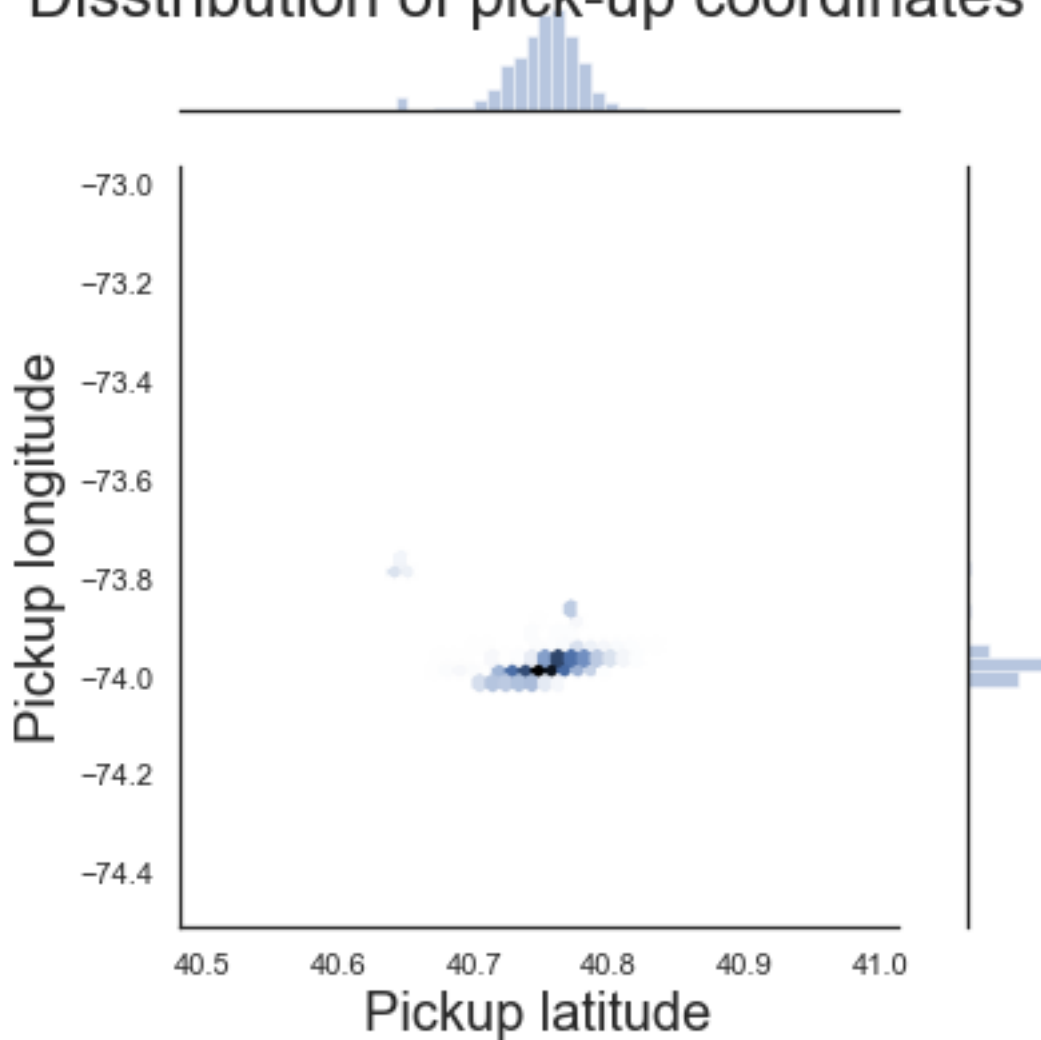
	tolls_amount	improvement_surcharge	total_amount	duration \
count	1.062452e+07	1.062452e+07	1.062452e+07	1.062452e+07
mean	2.763625e-01	2.999957e-01	1.540948e+01	1.319822e+01
std	1.280491e+00	1.138437e-03	1.213060e+01	1.011057e+01
min	0.000000e+00	0.000000e+00	3.100000e-01	2.666667e-01
25%	0.000000e+00	3.000000e-01	8.300000e+00	6.416667e+00
50%	0.000000e+00	3.000000e-01	1.162000e+01	1.051667e+01
75%	0.000000e+00	3.000000e-01	1.716000e+01	1.688333e+01
max	9.782000e+01	3.000000e-01	1.000000e+02	1.497833e+02

	start_hour	income	income/duration
count	1.062452e+07	1.062452e+07	1.062452e+07
mean	1.355524e+01	1.401960e+01	1.148759e+00
std	6.386805e+00	1.131511e+01	3.862012e-01
min	0.000000e+00	1.000000e-02	8.424600e-05
25%	9.000000e+00	7.360000e+00	8.974359e-01
50%	1.400000e+01	1.046000e+01	1.063235e+00
75%	1.900000e+01	1.595000e+01	1.295681e+00
max	2.300000e+01	9.950000e+01	5.000000e+00

```
[22]: p = sns.jointplot(x='pickup_latitude',y='pickup_longitude' , data=
      ↪df,kind="hex")
p.ax_joint.set_xlabel('Pickup latitude')
p.ax_joint.set_ylabel('Pickup longitude')
p.fig.suptitle("Disstrribution of pick-up coordinates ")
p.fig.tight_layout()

p.fig.savefig('plots/disstrribution of pick up coordinates.png')
```

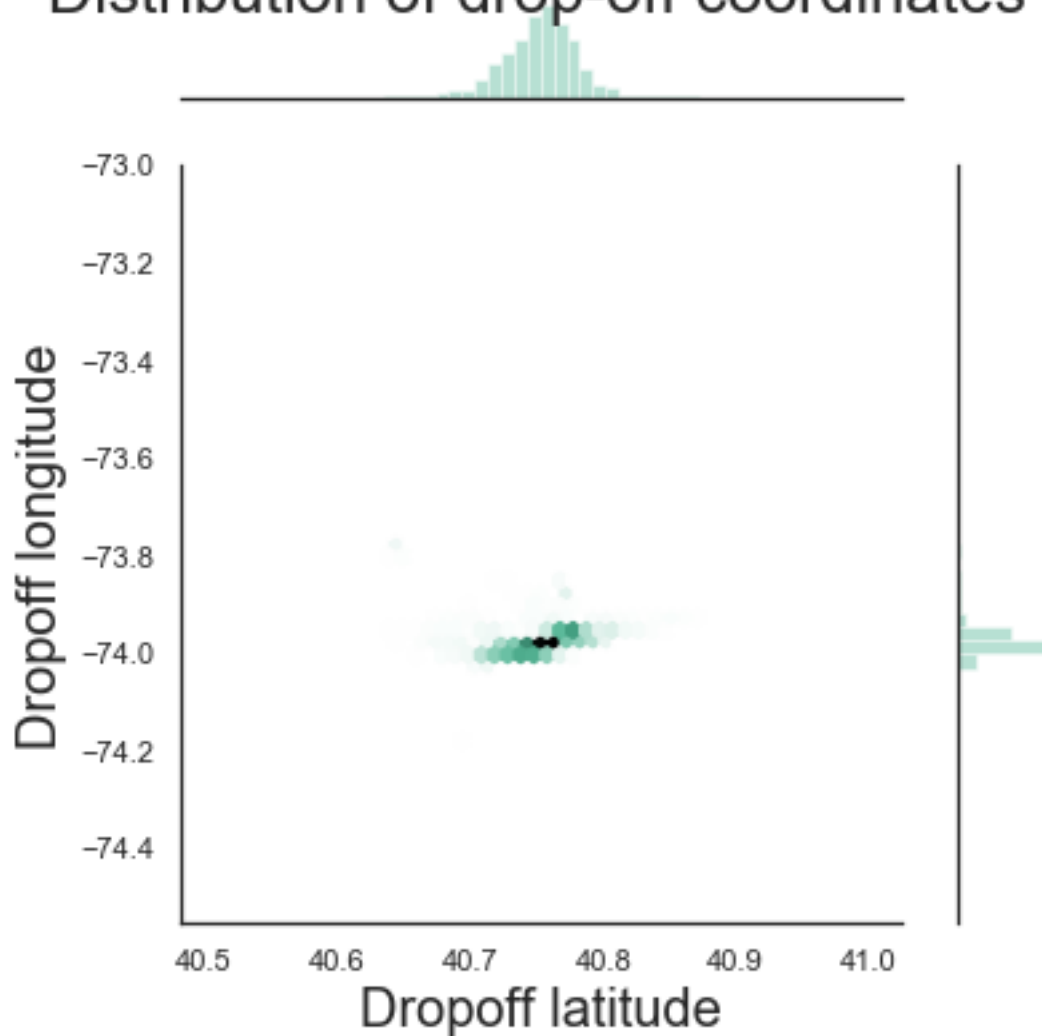

Disstribution of pick-up coordinates



```
[23]: p = sns.jointplot(x='dropoff_latitude',y='dropoff_longitude' , data=
      ↪df,kind="hex",color="#4CB391")

p.ax_joint.set_xlabel('Dropoff latitude')
p.ax_joint.set_ylabel('Dropoff longitude')
p.fig.suptitle("Distribution of drop-off coordinates")
p.fig.tight_layout()
p.fig.savefig('plots/disstribution of drop off coordinates.png')
```

Distribution of drop-off coordinates



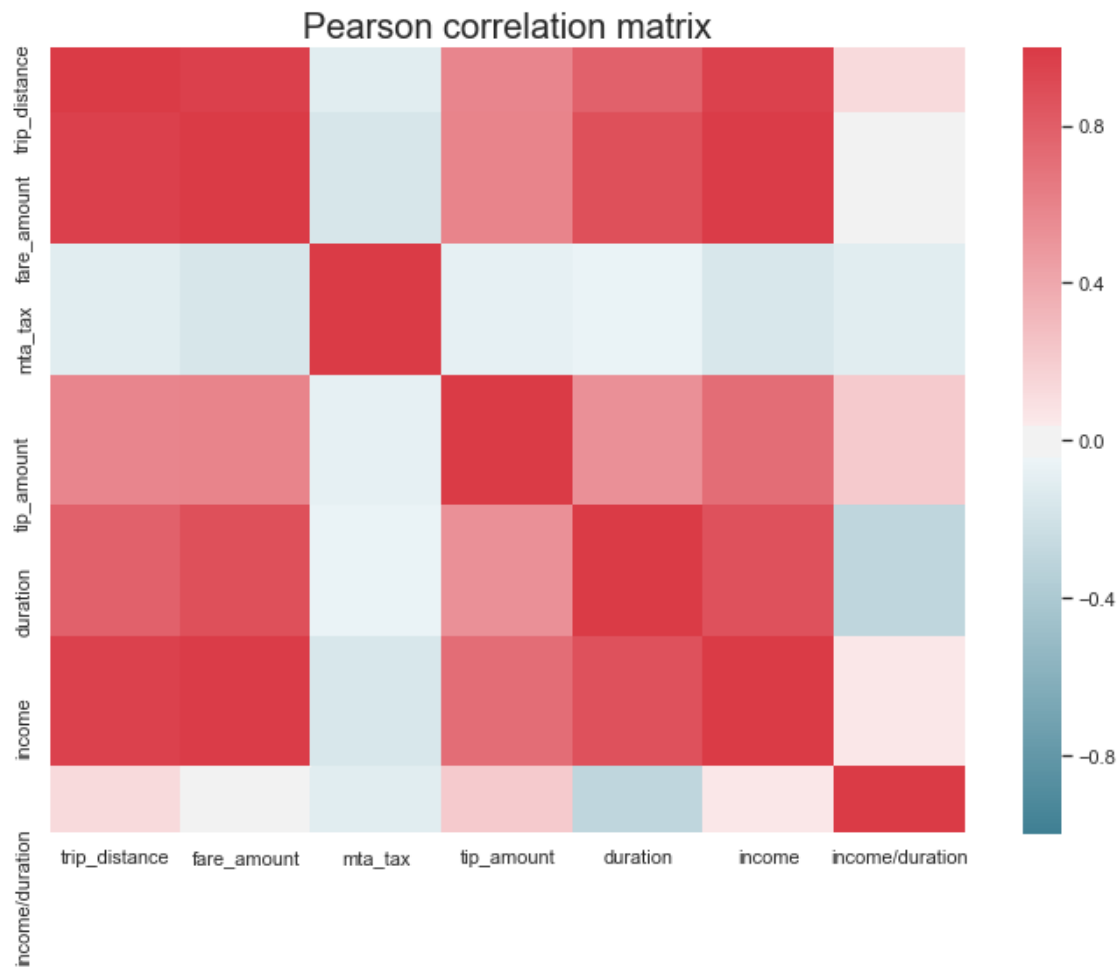
```
[24]: df.drop(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime', 'store_and_fwd_flag', 'improvement_surcharge', 'start_date'], axis=1, inplace = True)
```

```
[ ]:
```

2 Change data type

```
[25]: df['start_hour'] = df['start_hour'].astype('category')
df['payment_type'] = df['payment_type'].astype('category')
df['RatecodeID'] = df['RatecodeID'].astype('category')
df['weather'] = df['weather'].astype('category')
```

```
[26]: corr_attr=['trip_distance', 'payment_type', 'fare_amount', 'mta_tax',
               'tip_amount', 'duration', 'start_hour', 'weather', 'income', 'income/duration']
corr = df[corr_attr].corr()
sns.heatmap(corr, cmap = sns.diverging_palette(220, 10, as_cmap=True),
           square=True, center=0, vmin=-1, vmax=1)
plt.title('Pearson correlation matrix')
plt.savefig('plots/correlation.png')
plt.show()
```



```
[ ]:
```

3 Sampling

```
[27]: sub_df1 = df.sample(n=1000000, random_state=100)
sub_df2 = df.sample(n=1000000, random_state=50)
sub_df3 = df.sample(n=1000000, random_state=30)
```

```
[28]: card_df = df.loc[(df["payment_type"] == 1)]
cash_df = df.loc[(df["payment_type"] == 2)]
preci_df = df.loc[(df["weather"] != 'remain')]
remain_df = df.loc[(df["weather"] == 'remain')]
stand_df = df.loc[(df["RatecodeID"] == 1)]
other_df = df.loc[(df["RatecodeID"] == 2)]
```

```
[29]: df.columns
```

```
[29]: Index(['passenger_count', 'trip_distance', 'pickup_longitude',
'pickup_latitude', 'RatecodeID', 'dropoff_longitude',
'dropoff_latitude', 'payment_type', 'fare_amount', 'extra', 'mta_tax',
'tip_amount', 'tolls_amount', 'total_amount', 'duration', 'start_hour',
'weather', 'income', 'income/duration'],
dtype='object')
```

```
[ ]:
```

4 What is related to tip amount

```
[30]: fit = ols(formula="tip_amount ~ trip_distance + duration +payment_type +
↳start_hour + weather + duration * start_hour + duration * weather",
data=sub_df1).fit()
print(fit.summary())
```

```

                                OLS Regression Results
=====
Dep. Variable:                  tip_amount    R-squared:                  0.623
Model:                            OLS        Adj. R-squared:              0.623
Method:                 Least Squares    F-statistic:                 3.235e+04
Date:                Fri, 04 Sep 2020    Prob (F-statistic):          0.00
Time:                  20:39:32    Log-Likelihood:             -1.7400e+06
No. Observations:          1000000    AIC:                        3.480e+06
Df Residuals:              999948    BIC:                        3.481e+06
Df Model:                   51
Covariance Type:            nonrobust
=====
=====
                                coef    std err          t      P>|t|
[0.025    0.975]
```

Intercept		1.3750	0.017	82.495	0.000
1.342	1.408				
payment_type[T.2]		-2.4419	0.003	-833.912	0.000
-2.448	-2.436				
start_hour[T.1]		0.0979	0.020	4.944	0.000
0.059	0.137				
start_hour[T.2]		0.1737	0.022	8.024	0.000
0.131	0.216				
start_hour[T.3]		0.2309	0.024	9.812	0.000
0.185	0.277				
start_hour[T.4]		0.3003	0.026	11.567	0.000
0.249	0.351				
start_hour[T.5]		-0.0813	0.025	-3.211	0.001
-0.131	-0.032				
start_hour[T.6]		-0.1434	0.019	-7.705	0.000
-0.180	-0.107				
start_hour[T.7]		-0.0834	0.017	-4.960	0.000
-0.116	-0.050				
start_hour[T.8]		-0.1438	0.017	-8.617	0.000
-0.177	-0.111				
start_hour[T.9]		-0.1555	0.017	-9.215	0.000
-0.189	-0.122				
start_hour[T.10]		-0.0996	0.017	-5.913	0.000
-0.133	-0.067				
start_hour[T.11]		-0.0894	0.017	-5.317	0.000
-0.122	-0.056				
start_hour[T.12]		-0.0435	0.017	-2.619	0.009
-0.076	-0.011				
start_hour[T.13]		0.0180	0.017	1.084	0.278
-0.015	0.051				
start_hour[T.14]		0.0095	0.016	0.583	0.560
-0.022	0.041				
start_hour[T.15]		0.0570	0.016	3.569	0.000
0.026	0.088				
start_hour[T.16]		0.0489	0.016	3.024	0.002
0.017	0.081				
start_hour[T.17]		0.0359	0.016	2.263	0.024
0.005	0.067				
start_hour[T.18]		0.0183	0.016	1.155	0.248
-0.013	0.049				
start_hour[T.19]		-0.0120	0.016	-0.745	0.456
-0.044	0.020				
start_hour[T.20]		-0.0189	0.016	-1.151	0.250
-0.051	0.013				
start_hour[T.21]		-0.0351	0.017	-2.115	0.034
-0.068	-0.003				

start_hour[T.22]	-0.0265	0.017	-1.571	0.116
-0.059 0.007				
start_hour[T.23]	0.0038	0.018	0.215	0.830
-0.031 0.038				
weather[T.remain]	-0.0365	0.011	-3.179	0.001
-0.059 -0.014				
trip_distance	0.2935	0.001	439.276	0.000
0.292 0.295				
duration	0.0196	0.001	17.933	0.000
0.017 0.022				
duration:start_hour[T.1]	-0.0144	0.001	-10.871	0.000
-0.017 -0.012				
duration:start_hour[T.2]	-0.0246	0.001	-16.615	0.000
-0.027 -0.022				
duration:start_hour[T.3]	-0.0322	0.002	-20.246	0.000
-0.035 -0.029				
duration:start_hour[T.4]	-0.0321	0.002	-18.811	0.000
-0.035 -0.029				
duration:start_hour[T.5]	0.0112	0.002	6.833	0.000
0.008 0.014				
duration:start_hour[T.6]	0.0089	0.001	7.399	0.000
0.007 0.011				
duration:start_hour[T.7]	0.0026	0.001	2.455	0.014
0.001 0.005				
duration:start_hour[T.8]	0.0113	0.001	10.770	0.000
0.009 0.013				
duration:start_hour[T.9]	0.0151	0.001	14.149	0.000
0.013 0.017				
duration:start_hour[T.10]	0.0133	0.001	12.498	0.000
0.011 0.015				
duration:start_hour[T.11]	0.0141	0.001	13.256	0.000
0.012 0.016				
duration:start_hour[T.12]	0.0102	0.001	9.654	0.000
0.008 0.012				
duration:start_hour[T.13]	0.0046	0.001	4.395	0.000
0.003 0.007				
duration:start_hour[T.14]	0.0052	0.001	5.181	0.000
0.003 0.007				
duration:start_hour[T.15]	0.0013	0.001	1.301	0.193
-0.001 0.003				
duration:start_hour[T.16]	0.0055	0.001	5.575	0.000
0.004 0.007				
duration:start_hour[T.17]	0.0048	0.001	4.870	0.000
0.003 0.007				
duration:start_hour[T.18]	0.0050	0.001	4.993	0.000
0.003 0.007				
duration:start_hour[T.19]	0.0063	0.001	5.967	0.000
0.004 0.008				

duration:start_hour[T.20]	0.0043	0.001	3.992	0.000
0.002 0.006				
duration:start_hour[T.21]	0.0076	0.001	6.892	0.000
0.005 0.010				
duration:start_hour[T.22]	0.0065	0.001	5.858	0.000
0.004 0.009				
duration:start_hour[T.23]	0.0018	0.001	1.553	0.120
-0.000 0.004				
duration:weather[T.remain]	0.0045	0.001	6.221	0.000
0.003 0.006				

Omnibus:	622805.953	Durbin-Watson:	2.000
Prob(Omnibus):	0.000	Jarque-Bera (JB):	145312046.952
Skew:	1.901	Prob(JB):	0.00
Kurtosis:	61.932	Cond. No.	1.12e+03

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.12e+03. This might indicate that there are strong multicollinearity or other numerical problems.

```
[31]: fit = ols(formula="tip_amount ~ trip_distance + duration +payment_type +_
      ↪start_hour + weather + duration * start_hour + duration * weather",
      data=sub_df2).fit()
print(fit.summary())
```

OLS Regression Results

Dep. Variable:	tip_amount	R-squared:	0.626
Model:	OLS	Adj. R-squared:	0.626
Method:	Least Squares	F-statistic:	3.278e+04
Date:	Fri, 04 Sep 2020	Prob (F-statistic):	0.00
Time:	20:39:39	Log-Likelihood:	-1.7348e+06
No. Observations:	1000000	AIC:	3.470e+06
Df Residuals:	999948	BIC:	3.470e+06
Df Model:	51		
Covariance Type:	nonrobust		

	coef	std err	t	P> t
[0.025 0.975]				

Intercept	1.3755	0.017	83.172	0.000
1.343 1.408				
payment_type[T.2]	-2.4370	0.003	-836.442	0.000

-2.443	-2.431				
start_hour[T.1]		0.0572	0.020	2.905	0.004
0.019	0.096				
start_hour[T.2]		0.1291	0.021	6.033	0.000
0.087	0.171				
start_hour[T.3]		0.1337	0.024	5.682	0.000
0.088	0.180				
start_hour[T.4]		0.2179	0.026	8.423	0.000
0.167	0.269				
start_hour[T.5]		-0.0485	0.025	-1.924	0.054
-0.098	0.001				
start_hour[T.6]		-0.1698	0.019	-9.135	0.000
-0.206	-0.133				
start_hour[T.7]		-0.1338	0.017	-8.040	0.000
-0.166	-0.101				
start_hour[T.8]		-0.1768	0.017	-10.695	0.000
-0.209	-0.144				
start_hour[T.9]		-0.1775	0.017	-10.589	0.000
-0.210	-0.145				
start_hour[T.10]		-0.1067	0.017	-6.393	0.000
-0.139	-0.074				
start_hour[T.11]		-0.0648	0.017	-3.872	0.000
-0.098	-0.032				
start_hour[T.12]		-0.0270	0.017	-1.636	0.102
-0.059	0.005				
start_hour[T.13]		0.0170	0.017	1.031	0.303
-0.015	0.049				
start_hour[T.14]		0.0168	0.016	1.040	0.298
-0.015	0.049				
start_hour[T.15]		-0.0011	0.016	-0.067	0.946
-0.032	0.030				
start_hour[T.16]		0.0489	0.016	3.044	0.002
0.017	0.080				
start_hour[T.17]		0.0255	0.016	1.612	0.107
-0.005	0.056				
start_hour[T.18]		0.0106	0.016	0.676	0.499
-0.020	0.042				
start_hour[T.19]		-0.0188	0.016	-1.165	0.244
-0.050	0.013				
start_hour[T.20]		-0.0759	0.016	-4.630	0.000
-0.108	-0.044				
start_hour[T.21]		-0.0774	0.016	-4.694	0.000
-0.110	-0.045				
start_hour[T.22]		-0.0421	0.017	-2.512	0.012
-0.075	-0.009				
start_hour[T.23]		-0.0274	0.017	-1.566	0.117
-0.062	0.007				
weather[T.remain]		-0.0200	0.011	-1.757	0.079

-0.042	0.002				
trip_distance		0.2956	0.001	445.463	0.000
0.294	0.297				
duration		0.0197	0.001	18.115	0.000
0.018	0.022				
duration:start_hour[T.1]		-0.0102	0.001	-7.689	0.000
-0.013	-0.008				
duration:start_hour[T.2]		-0.0217	0.001	-14.757	0.000
-0.025	-0.019				
duration:start_hour[T.3]		-0.0255	0.002	-15.906	0.000
-0.029	-0.022				
duration:start_hour[T.4]		-0.0274	0.002	-16.282	0.000
-0.031	-0.024				
duration:start_hour[T.5]		0.0064	0.002	3.872	0.000
0.003	0.010				
duration:start_hour[T.6]		0.0119	0.001	9.932	0.000
0.010	0.014				
duration:start_hour[T.7]		0.0070	0.001	6.612	0.000
0.005	0.009				
duration:start_hour[T.8]		0.0144	0.001	13.846	0.000
0.012	0.016				
duration:start_hour[T.9]		0.0177	0.001	16.667	0.000
0.016	0.020				
duration:start_hour[T.10]		0.0150	0.001	14.281	0.000
0.013	0.017				
duration:start_hour[T.11]		0.0114	0.001	10.755	0.000
0.009	0.013				
duration:start_hour[T.12]		0.0087	0.001	8.266	0.000
0.007	0.011				
duration:start_hour[T.13]		0.0040	0.001	3.822	0.000
0.002	0.006				
duration:start_hour[T.14]		0.0045	0.001	4.487	0.000
0.003	0.006				
duration:start_hour[T.15]		0.0065	0.001	6.677	0.000
0.005	0.008				
duration:start_hour[T.16]		0.0058	0.001	5.844	0.000
0.004	0.008				
duration:start_hour[T.17]		0.0063	0.001	6.468	0.000
0.004	0.008				
duration:start_hour[T.18]		0.0058	0.001	5.729	0.000
0.004	0.008				
duration:start_hour[T.19]		0.0073	0.001	6.866	0.000
0.005	0.009				
duration:start_hour[T.20]		0.0097	0.001	8.989	0.000
0.008	0.012				
duration:start_hour[T.21]		0.0116	0.001	10.576	0.000
0.009	0.014				
duration:start_hour[T.22]		0.0073	0.001	6.651	0.000

0.005	0.009				
duration:start_hour[T.23]	0.0044	0.001	3.892	0.000	
0.002	0.007				
duration:weather[T.remain]	0.0024	0.001	3.249	0.001	
0.001	0.004				

```
=====
```

Omnibus:	530326.393	Durbin-Watson:	1.997
Prob(Omnibus):	0.000	Jarque-Bera (JB):	74084741.181
Skew:	1.544	Prob(JB):	0.00
Kurtosis:	45.054	Cond. No.	1.12e+03

```
=====
```

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.12e+03. This might indicate that there are strong multicollinearity or other numerical problems.

```
[32]: fit = ols(formula="tip_amount ~ trip_distance + duration +payment_type +_
      ↪start_hour + weather + duration * start_hour + duration * weather",
      data=sub_df3).fit()
      print(fit.summary())
```

OLS Regression Results

```
=====
```

Dep. Variable:	tip_amount	R-squared:	0.622
Model:	OLS	Adj. R-squared:	0.622
Method:	Least Squares	F-statistic:	3.225e+04
Date:	Fri, 04 Sep 2020	Prob (F-statistic):	0.00
Time:	20:39:46	Log-Likelihood:	-1.7395e+06
No. Observations:	1000000	AIC:	3.479e+06
Df Residuals:	999948	BIC:	3.480e+06
Df Model:	51		
Covariance Type:	nonrobust		

```
=====
```

```
=====
```

	coef	std err	t	P> t
--	------	---------	---	------

```
-----
```

[0.025	0.975]			
--------	--------	--	--	--

```
-----
```

Intercept	1.3999	0.017	84.202	0.000
1.367	1.432			
payment_type[T.2]	-2.4413	0.003	-833.862	0.000
-2.447	-2.436			
start_hour[T.1]	0.0751	0.020	3.775	0.000
0.036	0.114			
start_hour[T.2]	0.1229	0.022	5.697	0.000
0.081	0.165			

start_hour[T.3]	0.1560	0.024	6.576	0.000
0.110 0.202				
start_hour[T.4]	0.2289	0.026	8.871	0.000
0.178 0.279				
start_hour[T.5]	-0.0020	0.025	-0.077	0.938
-0.051 0.048				
start_hour[T.6]	-0.1406	0.019	-7.557	0.000
-0.177 -0.104				
start_hour[T.7]	-0.1495	0.017	-8.895	0.000
-0.182 -0.117				
start_hour[T.8]	-0.1527	0.017	-9.146	0.000
-0.185 -0.120				
start_hour[T.9]	-0.1564	0.017	-9.292	0.000
-0.189 -0.123				
start_hour[T.10]	-0.0727	0.017	-4.324	0.000
-0.106 -0.040				
start_hour[T.11]	-0.0774	0.017	-4.611	0.000
-0.110 -0.044				
start_hour[T.12]	-0.0186	0.017	-1.116	0.265
-0.051 0.014				
start_hour[T.13]	0.0204	0.017	1.227	0.220
-0.012 0.053				
start_hour[T.14]	0.0118	0.016	0.727	0.468
-0.020 0.044				
start_hour[T.15]	0.0310	0.016	1.935	0.053
-0.000 0.062				
start_hour[T.16]	0.0343	0.016	2.120	0.034
0.003 0.066				
start_hour[T.17]	0.0325	0.016	2.036	0.042
0.001 0.064				
start_hour[T.18]	0.0305	0.016	1.924	0.054
-0.001 0.061				
start_hour[T.19]	-0.0596	0.016	-3.690	0.000
-0.091 -0.028				
start_hour[T.20]	-0.0377	0.016	-2.292	0.022
-0.070 -0.005				
start_hour[T.21]	-0.0947	0.017	-5.680	0.000
-0.127 -0.062				
start_hour[T.22]	-0.0405	0.017	-2.405	0.016
-0.074 -0.008				
start_hour[T.23]	0.0069	0.017	0.394	0.694
-0.027 0.041				
weather[T.remain]	-0.0515	0.011	-4.507	0.000
-0.074 -0.029				
trip_distance	0.2929	0.001	438.074	0.000
0.292 0.294				
duration	0.0158	0.001	14.499	0.000
0.014 0.018				

duration:start_hour[T.1]	-0.0106	0.001	-7.872	0.000
-0.013 -0.008				
duration:start_hour[T.2]	-0.0178	0.001	-12.055	0.000
-0.021 -0.015				
duration:start_hour[T.3]	-0.0256	0.002	-15.903	0.000
-0.029 -0.022				
duration:start_hour[T.4]	-0.0255	0.002	-15.149	0.000
-0.029 -0.022				
duration:start_hour[T.5]	0.0039	0.002	2.387	0.017
0.001 0.007				
duration:start_hour[T.6]	0.0104	0.001	8.741	0.000
0.008 0.013				
duration:start_hour[T.7]	0.0105	0.001	9.789	0.000
0.008 0.013				
duration:start_hour[T.8]	0.0135	0.001	12.823	0.000
0.011 0.016				
duration:start_hour[T.9]	0.0171	0.001	15.960	0.000
0.015 0.019				
duration:start_hour[T.10]	0.0125	0.001	11.780	0.000
0.010 0.015				
duration:start_hour[T.11]	0.0132	0.001	12.381	0.000
0.011 0.015				
duration:start_hour[T.12]	0.0093	0.001	8.817	0.000
0.007 0.011				
duration:start_hour[T.13]	0.0055	0.001	5.224	0.000
0.003 0.008				
duration:start_hour[T.14]	0.0060	0.001	5.991	0.000
0.004 0.008				
duration:start_hour[T.15]	0.0043	0.001	4.330	0.000
0.002 0.006				
duration:start_hour[T.16]	0.0082	0.001	8.283	0.000
0.006 0.010				
duration:start_hour[T.17]	0.0064	0.001	6.535	0.000
0.005 0.008				
duration:start_hour[T.18]	0.0060	0.001	5.934	0.000
0.004 0.008				
duration:start_hour[T.19]	0.0121	0.001	11.424	0.000
0.010 0.014				
duration:start_hour[T.20]	0.0082	0.001	7.533	0.000
0.006 0.010				
duration:start_hour[T.21]	0.0146	0.001	13.182	0.000
0.012 0.017				
duration:start_hour[T.22]	0.0089	0.001	8.074	0.000
0.007 0.011				
duration:start_hour[T.23]	0.0022	0.001	1.909	0.056
-5.88e-05 0.004				
duration:weather[T.remain]	0.0062	0.001	8.519	0.000
0.005 0.008				

```
=====
Omnibus:                639753.491    Durbin-Watson:                2.000
Prob(Omnibus):           0.000    Jarque-Bera (JB):            156474629.192
Skew:                    1.982    Prob(JB):                     0.00
Kurtosis:                64.153    Cond. No.                     1.12e+03
=====
```

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.12e+03. This might indicate that there are strong multicollinearity or other numerical problems.

```
[33]: fit = ols(formula="tip_amount ~ trip_distance +payment_type",
               data=df).fit()
print(fit.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          tip_amount    R-squared:                0.613
Model:                  OLS          Adj. R-squared:            0.613
Method:                 Least Squares    F-statistic:              8.406e+06
Date:                  Fri, 04 Sep 2020    Prob (F-statistic):       0.00
Time:                  20:39:51          Log-Likelihood:           -1.8619e+07
No. Observations:      10624522          AIC:                     3.724e+07
Df Residuals:          10624519          BIC:                     3.724e+07
Df Model:               2
Covariance Type:       nonrobust
=====
```

```
=====
               coef      std err          t      P>|t|      [0.025
0.975]
```

```
-----
Intercept          1.5257         0.001    2367.297      0.000         1.524
1.527
payment_type[T.2]  -2.4566         0.001   -2711.455      0.000        -2.458
-2.455
trip_distance       0.3569         0.000    2915.138      0.000         0.357
0.357
=====
```

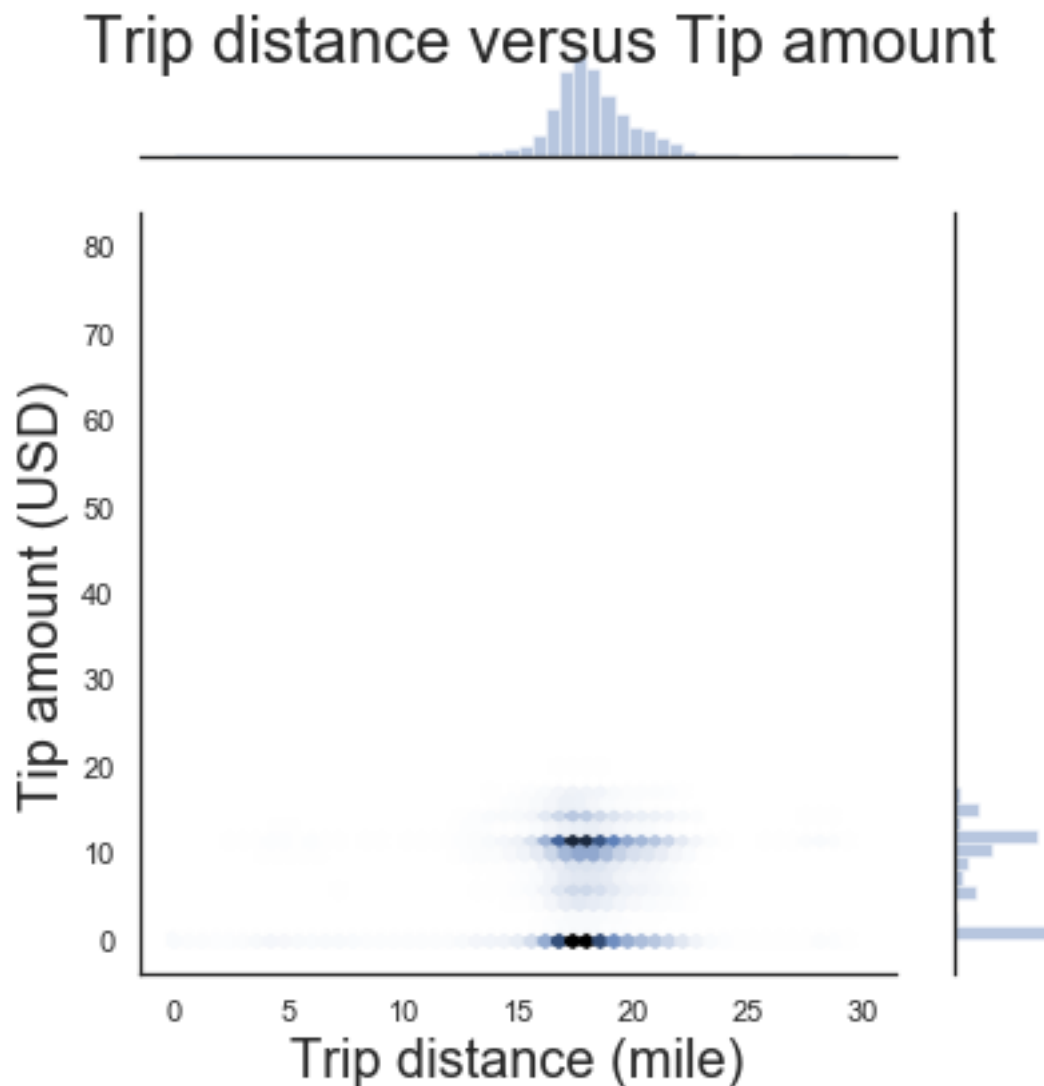
```
=====
Omnibus:                6729583.760    Durbin-Watson:                1.979
Prob(Omnibus):           0.000    Jarque-Bera (JB):            1537681233.635
Skew:                    1.965    Prob(JB):                     0.00
Kurtosis:                61.805    Cond. No.                     10.6
=====
```

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[]:

```
[34]: p = sns.jointplot(x='trip_distance',y='tip_amount',data= other_df, kind="hex",  
    ↪color="b")  
p.ax_joint.set_xlabel('Trip distance (mile)')  
p.ax_joint.set_ylabel('Tip amount (USD)')  
p.fig.suptitle("Trip distance versus Tip amount")  
p.fig.tight_layout()
```



[]:

```
[35]: tip_count = df['tip_amount'].value_counts()
tip_count
```

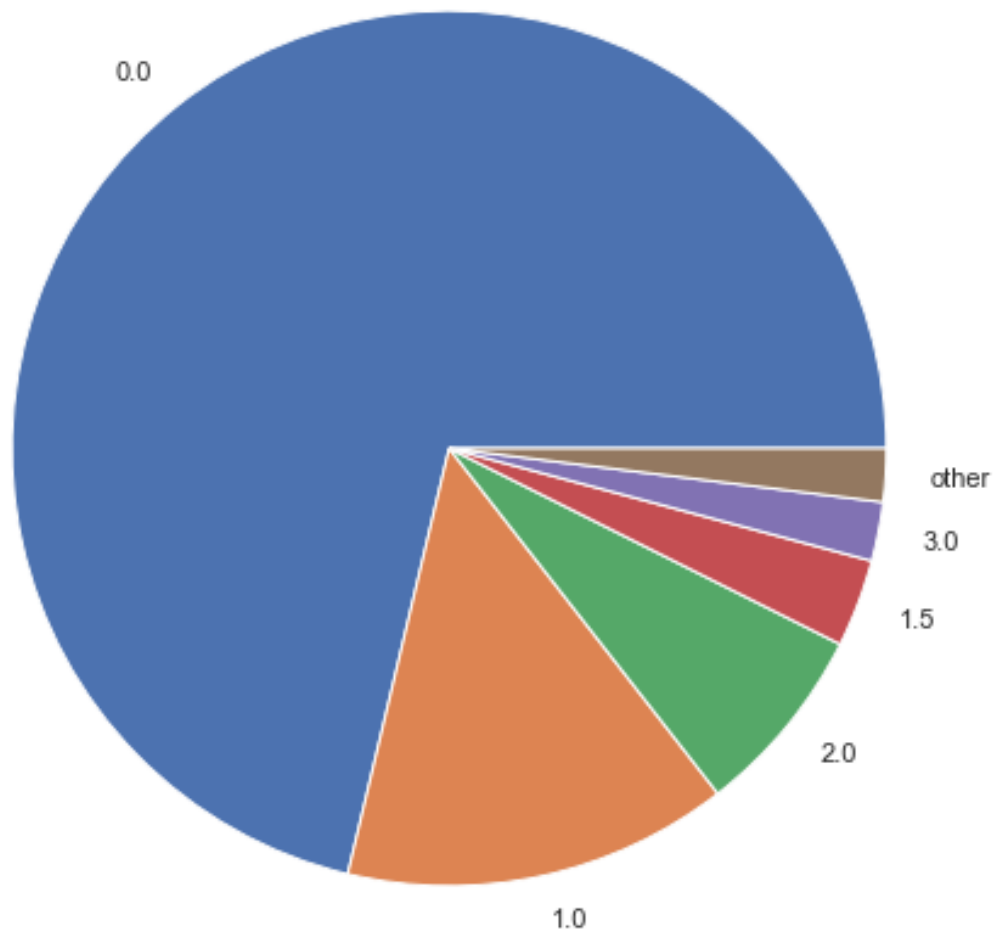
```
[35]: 0.00      3840212
      1.00      768220
      2.00      381510
      1.50      174963
      3.00      117458
      ...
      78.00         1
      77.00         1
      11.12         1
      11.13         1
      64.69         1
      Name: tip_amount, Length: 2074, dtype: int64
```

```
[36]: tip_count[5] = tip_count.iloc[5:].sum()
tip_count = tip_count.iloc[:6]
tip_count.index = tip_count.index.tolist()[:5] + ['other']
tip_count
```

```
[36]: 0.0      3840212
      1.0      768220
      2.0      381510
      1.5      174963
      3.0      117458
      other    105529
      Name: tip_amount, dtype: int64
```

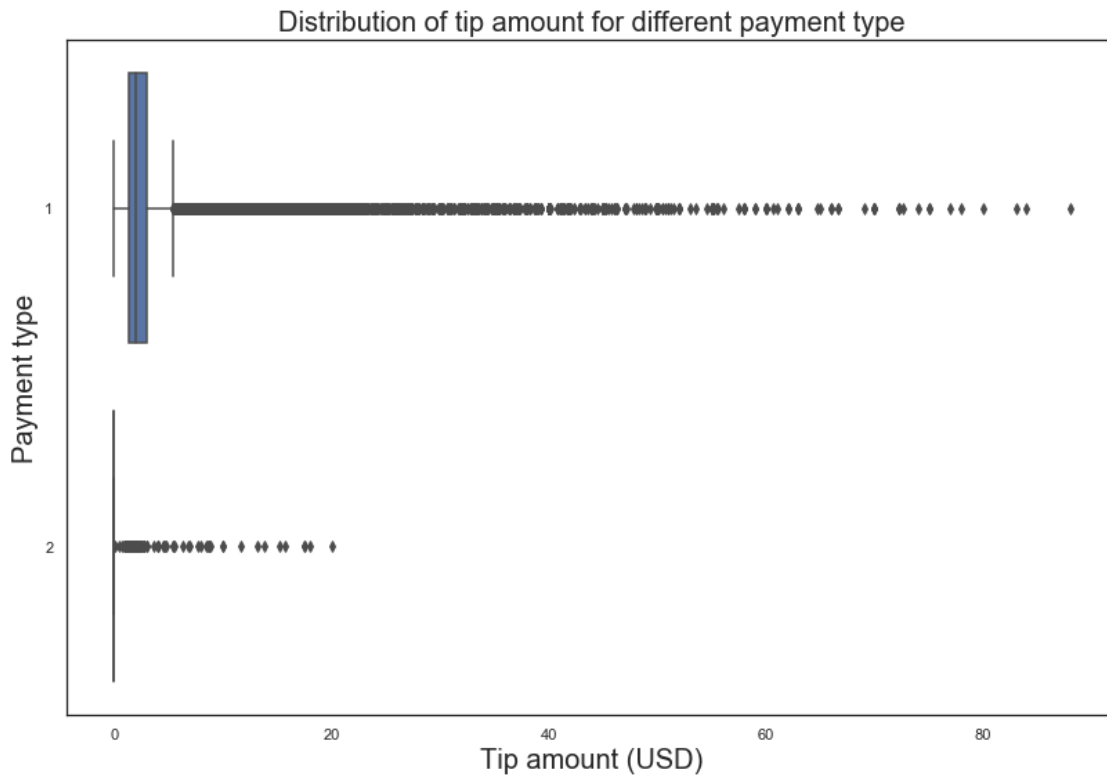
```
[37]: plt.pie(tip_count.values, labels=tip_count.index)
plt.title("Tip distribution")
plt.show()
```

Tip distribution



[]:

```
[38]: sns.boxplot(x="tip_amount", y="payment_type", data=df)
plt.title("Distribution of tip amount for different payment type")
plt.xlabel('Tip amount (USD)')
plt.ylabel("Payment type")
plt.tight_layout()
```

[]:

5 What is related to fare amount

```
[39]: fit = ols(formula="fare_amount ~ trip_distance + duration + start_hour +  
    ↳weather + duration*start_hour + duration*weather",  
    data=sub_df1).fit()  
print(fit.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          fare_amount    R-squared:                0.974
Model:                  OLS           Adj. R-squared:           0.974
Method:                 Least Squares  F-statistic:              7.451e+05
Date:                   Fri, 04 Sep 2020  Prob (F-statistic):       0.00
Time:                   20:40:04        Log-Likelihood:           -1.8819e+06
No. Observations:      1000000         AIC:                     3.764e+06
Df Residuals:          999949          BIC:                     3.765e+06
Df Model:               50
Covariance Type:       nonrobust
=====
```

[0.025 0.975]		coef	std err	t	P> t

Intercept		1.9486	0.019	101.664	0.000
1.911	1.986				
start_hour[T.1]		0.0509	0.023	2.232	0.026
0.006	0.096				
start_hour[T.2]		0.0606	0.025	2.430	0.015
0.012	0.110				
start_hour[T.3]		0.0087	0.027	0.320	0.749
-0.044	0.062				
start_hour[T.4]		-0.0441	0.030	-1.473	0.141
-0.103	0.015				
start_hour[T.5]		0.0339	0.029	1.161	0.246
-0.023	0.091				
start_hour[T.6]		0.5401	0.021	25.182	0.000
0.498	0.582				
start_hour[T.7]		0.6817	0.019	35.166	0.000
0.644	0.720				
start_hour[T.8]		0.5188	0.019	26.974	0.000
0.481	0.557				
start_hour[T.9]		0.2486	0.019	12.784	0.000
0.210	0.287				
start_hour[T.10]		0.2999	0.019	15.453	0.000
0.262	0.338				
start_hour[T.11]		0.1468	0.019	7.581	0.000
0.109	0.185				
start_hour[T.12]		0.2428	0.019	12.679	0.000
0.205	0.280				
start_hour[T.13]		0.2887	0.019	15.077	0.000
0.251	0.326				
start_hour[T.14]		0.6010	0.019	32.093	0.000
0.564	0.638				
start_hour[T.15]		0.7723	0.018	41.934	0.000
0.736	0.808				
start_hour[T.16]		0.7072	0.019	37.968	0.000
0.671	0.744				
start_hour[T.17]		0.6678	0.018	36.521	0.000
0.632	0.704				
start_hour[T.18]		0.4819	0.018	26.384	0.000
0.446	0.518				
start_hour[T.19]		0.2590	0.019	13.957	0.000
0.223	0.295				
start_hour[T.20]		0.0958	0.019	5.053	0.000
0.059	0.133				
start_hour[T.21]		0.1093	0.019	5.711	0.000
0.072	0.147				

start_hour[T.22]	0.0626	0.019	3.228	0.001
0.025 0.101				
start_hour[T.23]	-0.0171	0.020	-0.847	0.397
-0.057 0.023				
weather[T.remain]	0.0996	0.013	7.528	0.000
0.074 0.126				
trip_distance	2.0124	0.001	2613.856	0.000
2.011 2.014				
duration	0.3261	0.001	258.939	0.000
0.324 0.329				
duration:start_hour[T.1]	-0.0073	0.002	-4.754	0.000
-0.010 -0.004				
duration:start_hour[T.2]	-0.0099	0.002	-5.814	0.000
-0.013 -0.007				
duration:start_hour[T.3]	-0.0026	0.002	-1.426	0.154
-0.006 0.001				
duration:start_hour[T.4]	0.0147	0.002	7.472	0.000
0.011 0.019				
duration:start_hour[T.5]	0.0196	0.002	10.324	0.000
0.016 0.023				
duration:start_hour[T.6]	-0.0548	0.001	-39.698	0.000
-0.057 -0.052				
duration:start_hour[T.7]	-0.0573	0.001	-46.421	0.000
-0.060 -0.055				
duration:start_hour[T.8]	-0.0233	0.001	-19.245	0.000
-0.026 -0.021				
duration:start_hour[T.9]	0.0023	0.001	1.868	0.062
-0.000 0.005				
duration:start_hour[T.10]	-0.0034	0.001	-2.807	0.005
-0.006 -0.001				
duration:start_hour[T.11]	0.0090	0.001	7.313	0.000
0.007 0.011				
duration:start_hour[T.12]	0.0020	0.001	1.622	0.105
-0.000 0.004				
duration:start_hour[T.13]	-0.0040	0.001	-3.299	0.001
-0.006 -0.002				
duration:start_hour[T.14]	-0.0322	0.001	-27.775	0.000
-0.034 -0.030				
duration:start_hour[T.15]	-0.0512	0.001	-45.212	0.000
-0.053 -0.049				
duration:start_hour[T.16]	-0.0510	0.001	-44.767	0.000
-0.053 -0.049				
duration:start_hour[T.17]	-0.0488	0.001	-43.103	0.000
-0.051 -0.047				
duration:start_hour[T.18]	-0.0349	0.001	-30.004	0.000
-0.037 -0.033				
duration:start_hour[T.19]	-0.0194	0.001	-15.978	0.000
-0.022 -0.017				

```

duration:start_hour[T.20]    -0.0086    0.001    -6.836    0.000
-0.011    -0.006
duration:start_hour[T.21]    -0.0091    0.001    -7.179    0.000
-0.012    -0.007
duration:start_hour[T.22]    -0.0028    0.001    -2.205    0.027
-0.005    -0.000
duration:start_hour[T.23]     0.0033    0.001     2.515    0.012
0.001     0.006
duration:weather[T.remain]    0.0045    0.001     5.302    0.000
0.003     0.006
=====
Omnibus:                    1016425.708    Durbin-Watson:                2.000
Prob(Omnibus):              0.000    Jarque-Bera (JB):            2567932846.754
Skew:                       3.830    Prob(JB):                    0.00
Kurtosis:                   251.136    Cond. No.                    1.12e+03
=====

```

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.12e+03. This might indicate that there are strong multicollinearity or other numerical problems.

```
[40]: fit = ols(formula="fare_amount ~ trip_distance + duration + start_hour",
               data=df).fit()
print(fit.summary())
```

OLS Regression Results

```

=====
Dep. Variable:    fare_amount    R-squared:                0.973
Model:            OLS           Adj. R-squared:            0.973
Method:           Least Squares  F-statistic:             1.532e+07
Date:            Fri, 04 Sep 2020  Prob (F-statistic):          0.00
Time:            20:41:02        Log-Likelihood:           -2.0162e+07
No. Observations: 10624522      AIC:                     4.032e+07
Df Residuals:    10624496      BIC:                     4.032e+07
Df Model:        25
Covariance Type: nonrobust
=====

```

```

=====
               coef    std err          t      P>|t|      [0.025
-----
0.975]
-----
Intercept    2.3201    0.003    867.692    0.000    2.315
2.325
start_hour[T.1] -0.0492    0.004   -12.404    0.000   -0.057
-0.041

```

start_hour[T.2]	-0.0706	0.004	-16.410	0.000	-0.079
-0.062					
start_hour[T.3]	-0.0396	0.005	-8.312	0.000	-0.049
-0.030					
start_hour[T.4]	0.1059	0.005	19.868	0.000	0.095
0.116					
start_hour[T.5]	0.2606	0.006	46.680	0.000	0.250
0.272					
start_hour[T.6]	-0.0910	0.004	-21.361	0.000	-0.099
-0.083					
start_hour[T.7]	-0.0289	0.004	-7.903	0.000	-0.036
-0.022					
start_hour[T.8]	0.2317	0.004	66.160	0.000	0.225
0.239					
start_hour[T.9]	0.3171	0.004	90.572	0.000	0.310
0.324					
start_hour[T.10]	0.2916	0.004	82.908	0.000	0.285
0.299					
start_hour[T.11]	0.3046	0.003	87.433	0.000	0.298
0.311					
start_hour[T.12]	0.2999	0.003	87.276	0.000	0.293
0.307					
start_hour[T.13]	0.2674	0.003	77.717	0.000	0.261
0.274					
start_hour[T.14]	0.2011	0.003	59.117	0.000	0.194
0.208					
start_hour[T.15]	0.1137	0.003	33.389	0.000	0.107
0.120					
start_hour[T.16]	0.0058	0.003	1.662	0.097	-0.001
0.013					
start_hour[T.17]	0.0148	0.003	4.392	0.000	0.008
0.021					
start_hour[T.18]	0.0423	0.003	12.939	0.000	0.036
0.049					
start_hour[T.19]	0.0288	0.003	8.803	0.000	0.022
0.035					
start_hour[T.20]	0.0071	0.003	2.140	0.032	0.001
0.014					
start_hour[T.21]	0.0093	0.003	2.769	0.006	0.003
0.016					
start_hour[T.22]	0.0405	0.003	12.021	0.000	0.034
0.047					
start_hour[T.23]	0.0334	0.004	9.507	0.000	0.026
0.040					
trip_distance	2.0156	0.000	8559.985	0.000	2.015
2.016					
duration	0.3068	8.14e-05	3767.531	0.000	0.307
0.307					

```
=====
Omnibus:                10420296.736    Durbin-Watson:                1.978
Prob(Omnibus):           0.000    Jarque-Bera (JB):            24913210541.062
Skew:                    3.578    Prob(JB):                    0.00
Kurtosis:                240.120    Cond. No.                    451.
=====
```

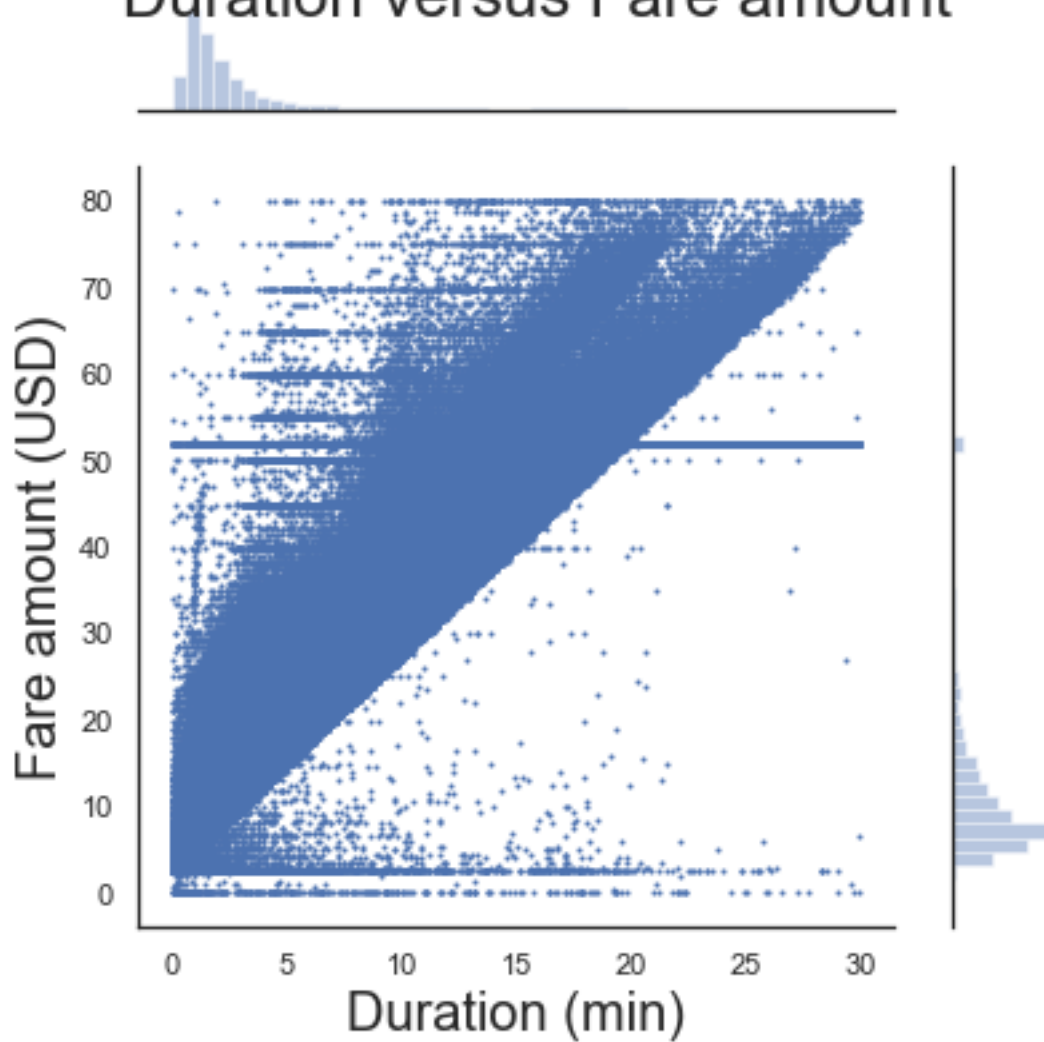
Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[]:

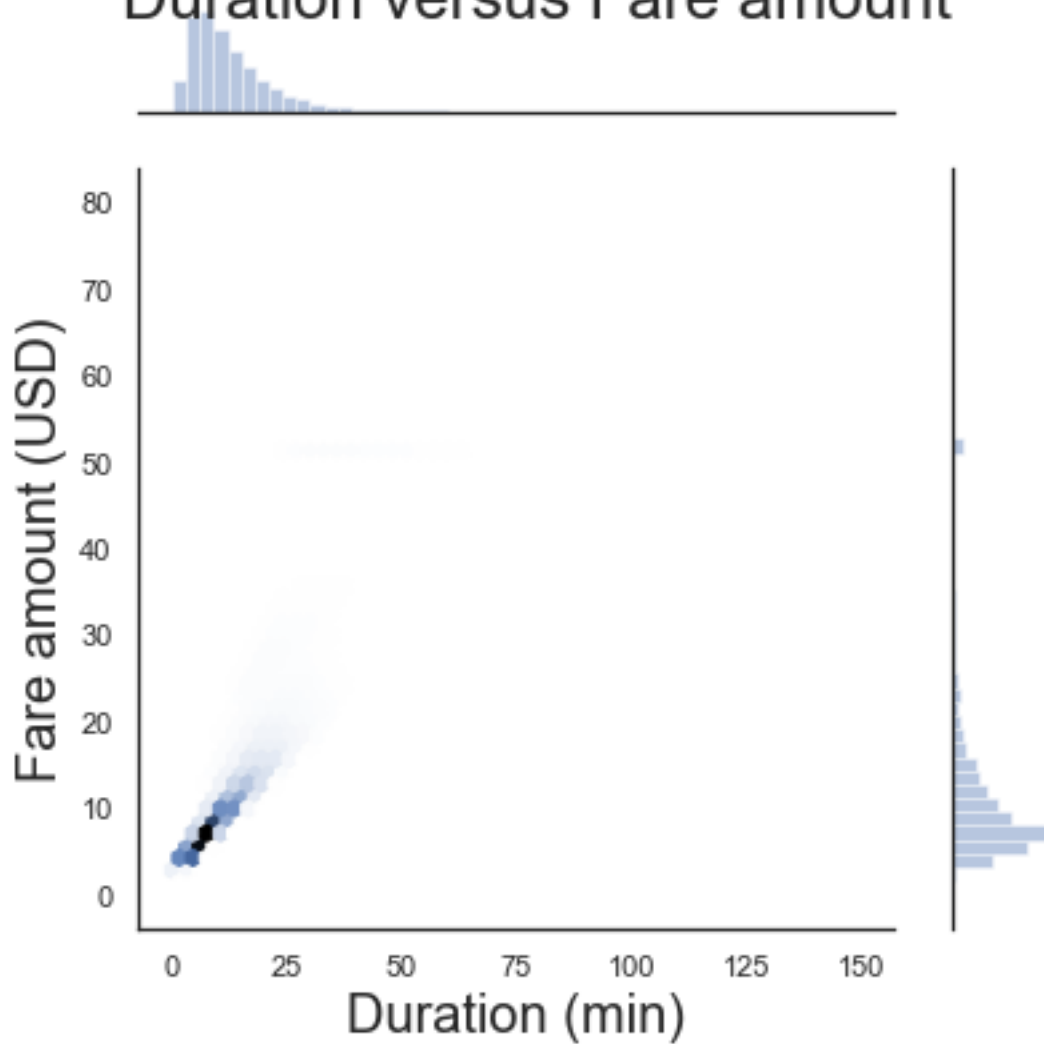
```
[41]: p = sns.jointplot(x='trip_distance',y= 'fare_amount', data= df, s=1)
      p.ax_joint.set_xlabel('Duration (min)')
      p.ax_joint.set_ylabel('Fare amount (USD)')
      p.fig.suptitle("Duration versus Fare amount")
      p.fig.tight_layout()
```

Duration versus Fare amount



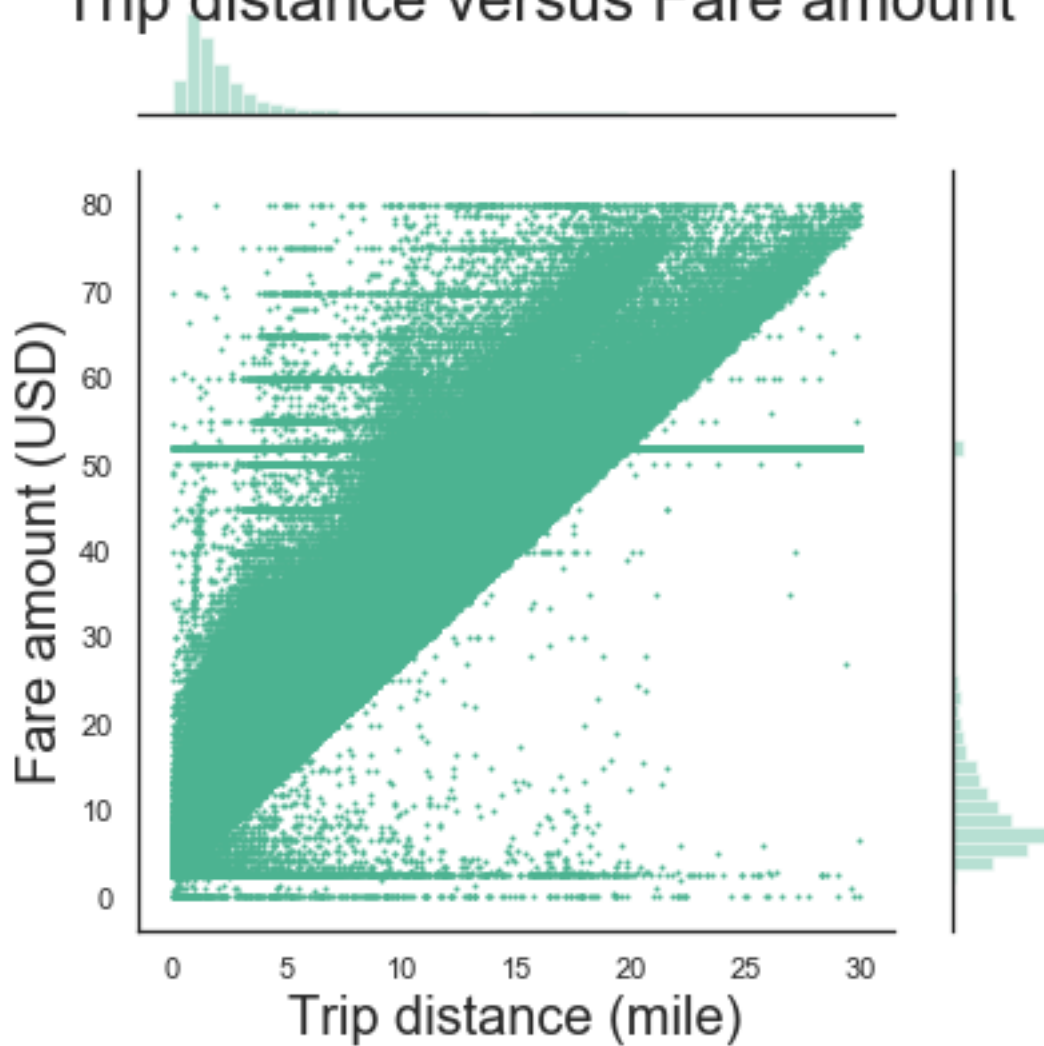
```
[42]: p = sns.jointplot(x='duration',y= 'fare_amount',data= df, kind="hex")
p.ax_joint.set_xlabel('Duration (min)')
p.ax_joint.set_ylabel('Fare amount (USD)')
p.fig.suptitle("Duration versus Fare amount")
p.fig.tight_layout()
```

Duration versus Fare amount



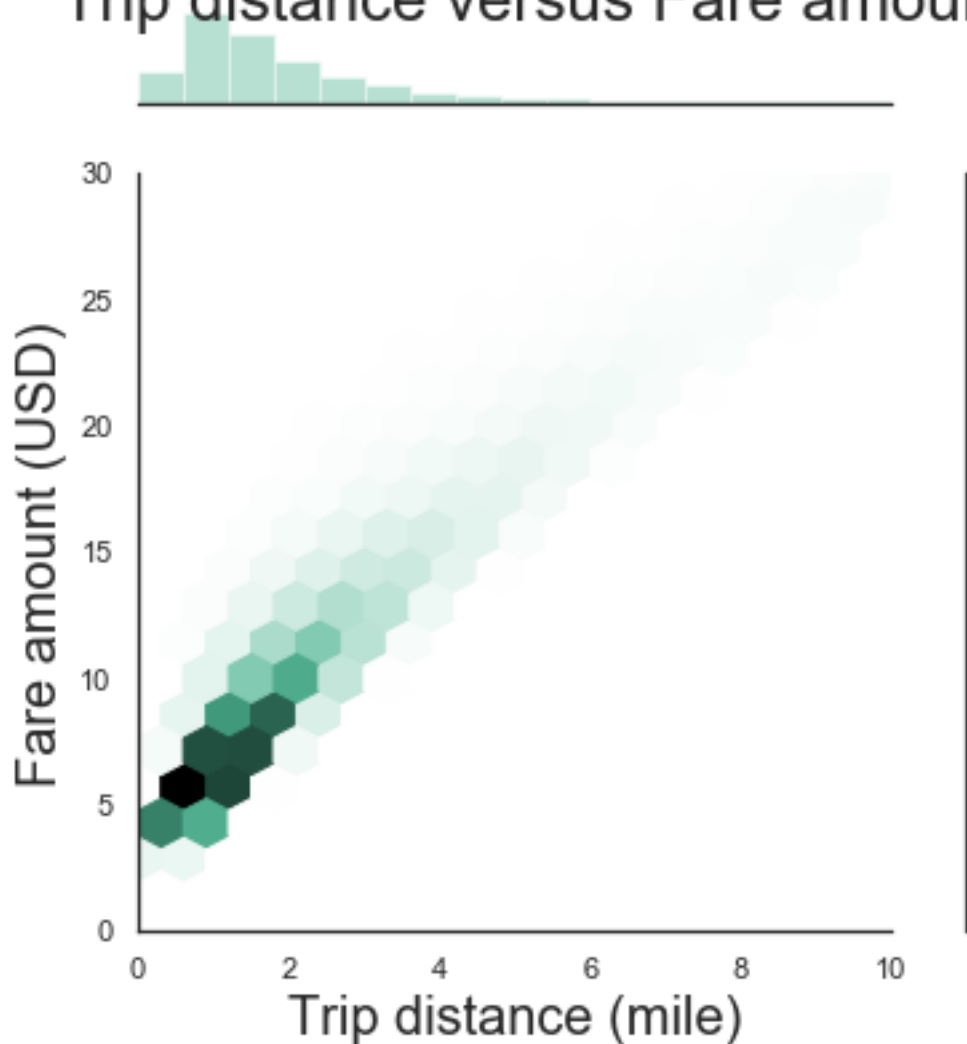
```
[43]: p = sns.jointplot(x='trip_distance',y= 'fare_amount', data= df, s=1,
    ↪color="#4CB391")
p.ax_joint.set_xlabel('Trip distance (mile)')
p.ax_joint.set_ylabel('Fare amount (USD)')
p.fig.suptitle("Trip distance versus Fare amount")
p.fig.tight_layout()
```


Trip distance versus Fare amount



```
[44]: p = sns.jointplot(x='trip_distance',y= 'fare_amount',data= df, kind="hex",  
    ↪color="#4CB391", xlim=(0,10), ylim=(0, 30))  
p.ax_joint.set_xlabel('Trip distance (mile)')  
p.ax_joint.set_ylabel('Fare amount (USD)')  
p.fig.suptitle("Trip distance versus Fare amount")  
p.fig.tight_layout()
```

Trip distance versus Fare amount



[]:

6 What is related to trip distance

```
[45]: fit = ols(formula="trip_distance ~ tip_amount + duration + start_hour + \
    ↳ payment_type + weather + RatecodeID + \
    ↳ duration* start_hour + duration* weather",
    data=sub_df1).fit()
print(fit.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          trip_distance    R-squared:                0.780
```

```

Model:                OLS      Adj. R-squared:          0.780
Method:               Least Squares    F-statistic:          6.828e+04
Date:                 Fri, 04 Sep 2020    Prob (F-statistic):      0.00
Time:                 20:44:11    Log-Likelihood:         -1.9156e+06
No. Observations:     1000000    AIC:                    3.831e+06
Df Residuals:         999947    BIC:                    3.832e+06
Df Model:              52
Covariance Type:      nonrobust

```

```

=====
=====

```

		coef	std err	t	P> t
[0.025	0.975]				

Intercept		-0.9023	0.020	-45.309	0.000
-0.941	-0.863				
start_hour[T.1]		-0.0319	0.024	-1.353	0.176
-0.078	0.014				
start_hour[T.2]		-0.0777	0.026	-3.010	0.003
-0.128	-0.027				
start_hour[T.3]		-0.0639	0.028	-2.278	0.023
-0.119	-0.009				
start_hour[T.4]		-6.041e-05	0.031	-0.002	0.998
-0.061	0.061				
start_hour[T.5]		0.3590	0.030	11.883	0.000
0.300	0.418				
start_hour[T.6]		0.6620	0.022	29.821	0.000
0.618	0.705				
start_hour[T.7]		0.4677	0.020	23.324	0.000
0.428	0.507				
start_hour[T.8]		0.2624	0.020	13.189	0.000
0.223	0.301				
start_hour[T.9]		0.2310	0.020	11.486	0.000
0.192	0.270				
start_hour[T.10]		0.3012	0.020	15.002	0.000
0.262	0.341				
start_hour[T.11]		0.2251	0.020	11.234	0.000
0.186	0.264				
start_hour[T.12]		0.1378	0.020	6.955	0.000
0.099	0.177				
start_hour[T.13]		-0.0157	0.020	-0.792	0.428
-0.055	0.023				
start_hour[T.14]		0.0112	0.019	0.580	0.562
-0.027	0.049				
start_hour[T.15]		0.0917	0.019	4.811	0.000
0.054	0.129				
start_hour[T.16]		0.1529	0.019	7.934	0.000
0.115	0.191				

start_hour[T.17]	0.1084	0.019	5.730	0.000
0.071 0.146				
start_hour[T.18]	-0.0506	0.019	-2.677	0.007
-0.088 -0.014				
start_hour[T.19]	-0.1338	0.019	-6.969	0.000
-0.171 -0.096				
start_hour[T.20]	-0.2008	0.020	-10.237	0.000
-0.239 -0.162				
start_hour[T.21]	-0.1633	0.020	-8.249	0.000
-0.202 -0.125				
start_hour[T.22]	-0.1494	0.020	-7.441	0.000
-0.189 -0.110				
start_hour[T.23]	-0.1592	0.021	-7.610	0.000
-0.200 -0.118				
payment_type[T.2]	0.9278	0.004	208.424	0.000
0.919 0.937				
weather[T.remain]	0.0412	0.014	3.008	0.003
0.014 0.068				
RatecodeID[T.2]	7.4829	0.013	567.486	0.000
7.457 7.509				
tip_amount	0.3994	0.001	355.463	0.000
0.397 0.402				
duration	0.2453	0.001	191.044	0.000
0.243 0.248				
duration:start_hour[T.1]	0.0119	0.002	7.538	0.000
0.009 0.015				
duration:start_hour[T.2]	0.0240	0.002	13.594	0.000
0.021 0.027				
duration:start_hour[T.3]	0.0373	0.002	19.655	0.000
0.034 0.041				
duration:start_hour[T.4]	0.0544	0.002	26.758	0.000
0.050 0.058				
duration:start_hour[T.5]	0.0377	0.002	19.221	0.000
0.034 0.042				
duration:start_hour[T.6]	-0.0391	0.001	-27.326	0.000
-0.042 -0.036				
duration:start_hour[T.7]	-0.0723	0.001	-56.581	0.000
-0.075 -0.070				
duration:start_hour[T.8]	-0.0911	0.001	-72.812	0.000
-0.094 -0.089				
duration:start_hour[T.9]	-0.0877	0.001	-69.046	0.000
-0.090 -0.085				
duration:start_hour[T.10]	-0.0897	0.001	-70.883	0.000
-0.092 -0.087				
duration:start_hour[T.11]	-0.0881	0.001	-69.437	0.000
-0.091 -0.086				
duration:start_hour[T.12]	-0.0807	0.001	-64.150	0.000
-0.083 -0.078				

duration:start_hour[T.13]	-0.0647	0.001	-51.737	0.000
-0.067	-0.062			
duration:start_hour[T.14]	-0.0704	0.001	-58.626	0.000
-0.073	-0.068			
duration:start_hour[T.15]	-0.0810	0.001	-69.002	0.000
-0.083	-0.079			
duration:start_hour[T.16]	-0.0846	0.001	-71.752	0.000
-0.087	-0.082			
duration:start_hour[T.17]	-0.0840	0.001	-71.667	0.000
-0.086	-0.082			
duration:start_hour[T.18]	-0.0680	0.001	-56.440	0.000
-0.070	-0.066			
duration:start_hour[T.19]	-0.0413	0.001	-32.877	0.000
-0.044	-0.039			
duration:start_hour[T.20]	-0.0141	0.001	-10.898	0.000
-0.017	-0.012			
duration:start_hour[T.21]	-0.0066	0.001	-5.063	0.000
-0.009	-0.004			
duration:start_hour[T.22]	-0.0046	0.001	-3.451	0.001
-0.007	-0.002			
duration:start_hour[T.23]	0.0104	0.001	7.594	0.000
0.008	0.013			
duration:weather[T.remain]	-0.0029	0.001	-3.306	0.001
-0.005	-0.001			

```
=====
Omnibus:                448238.632    Durbin-Watson:                2.004
Prob(Omnibus):           0.000    Jarque-Bera (JB):            14404965.415
Skew:                    1.536    Prob(JB):                     0.00
Kurtosis:                21.338    Cond. No.                     1.11e+03
=====
```

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

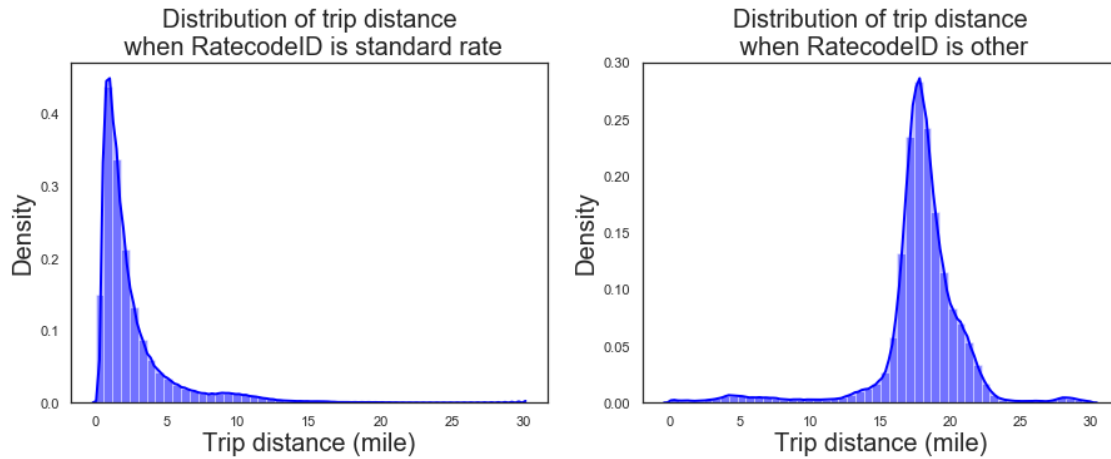
[2] The condition number is large, 1.11e+03. This might indicate that there are strong multicollinearity or other numerical problems.

[]:

```
[46]: plt.figure(figsize=(15, 5))
plt.subplot(121)
sns.distplot(stand_df ['trip_distance'], kde = True,
             kde_kws = {'shade': True, 'linewidth': 2}, color = "blue")
plt.title("Distribution of trip distance\n when RatecodeID is standard rate")
plt.xlabel('Trip distance (mile)')
plt.ylabel("Density")
```

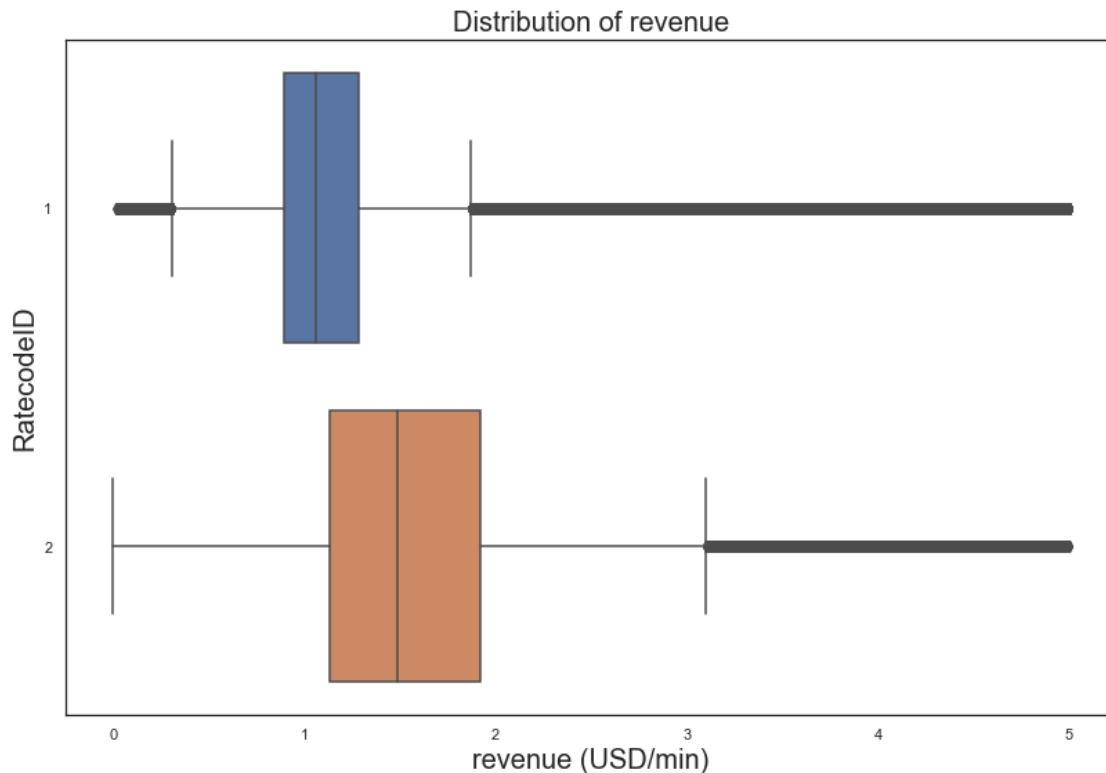
```
plt.subplot(122)
sns.distplot(other_df['trip_distance'], kde = True,
             kde_kws = {'shade': True, 'linewidth': 2}, color = "blue")
plt.title("Distribution of trip distance\n when RatecodeID is other")
plt.xlabel('Trip distance (mile)')
plt.ylabel("Density")

fig.set_figheight(5)
fig.set_figwidth(15)
```



[]:

```
[47]: sns.boxplot(x="income/duration", y="RatecodeID", data=df)
plt.title("Distribution of revenue")
plt.xlabel('revenue (USD/min)')
plt.tight_layout()
```



```
[ ]:
```

7 Delete ratecodeID = 2 from all dataset and resampling

```
[48]: df = df.loc[(df["RatecodeID"] == 1)]
```

```
[49]: df.shape
```

```
[49]: (10397081, 19)
```

```
[50]: sub_df1 = sub_df1.loc[(sub_df1["RatecodeID"] == 1)]
sub_df2 = sub_df2.loc[(sub_df2["RatecodeID"] == 1)]
sub_df3 = sub_df3.loc[(sub_df3["RatecodeID"] == 1)]
```

```
[51]: fit = ols(formula="trip_distance ~ duration + start_hour + payment_type + \
    ↳ weather + \
    duration* start_hour + duration* weather",
    data=sub_df1).fit()
print(fit.summary())
```

OLS Regression Results

=====

```

Dep. Variable:      trip_distance    R-squared:      0.616
Model:              OLS              Adj. R-squared: 0.616
Method:             Least Squares    F-statistic:    3.141e+04
Date:               Fri, 04 Sep 2020  Prob (F-statistic): 0.00
Time:               20:44:26          Log-Likelihood:  -1.8964e+06
No. Observations:   978619           AIC:            3.793e+06
Df Residuals:       978568           BIC:            3.794e+06
Df Model:           50
Covariance Type:    nonrobust

```

		coef	std err	t	P> t
[0.025 0.975]					

Intercept		-0.2641	0.021	-12.674	0.000
-0.305	-0.223				
start_hour[T.1]		-0.0232	0.024	-0.953	0.341
-0.071	0.025				
start_hour[T.2]		-0.0621	0.027	-2.337	0.019
-0.114	-0.010				
start_hour[T.3]		-0.0251	0.029	-0.868	0.385
-0.082	0.032				
start_hour[T.4]		0.0572	0.032	1.780	0.075
-0.006	0.120				
start_hour[T.5]		-0.0487	0.033	-1.495	0.135
-0.113	0.015				
start_hour[T.6]		0.0312	0.024	1.285	0.199
-0.016	0.079				
start_hour[T.7]		0.0735	0.022	3.417	0.001
0.031	0.116				
start_hour[T.8]		0.1065	0.021	5.081	0.000
0.065	0.148				
start_hour[T.9]		0.1482	0.021	7.058	0.000
0.107	0.189				
start_hour[T.10]		0.2211	0.021	10.511	0.000
0.180	0.262				
start_hour[T.11]		0.1996	0.021	9.527	0.000
0.159	0.241				
start_hour[T.12]		0.1146	0.021	5.513	0.000
0.074	0.155				
start_hour[T.13]		-0.0582	0.021	-2.785	0.005
-0.099	-0.017				
start_hour[T.14]		-0.1435	0.021	-6.975	0.000
-0.184	-0.103				
start_hour[T.15]		-0.1224	0.020	-6.038	0.000
-0.162	-0.083				
start_hour[T.16]		-0.0595	0.020	-2.909	0.004

-0.100	-0.019				
start_hour[T.17]		-0.0660	0.020	-3.293	0.001
-0.105	-0.027				
start_hour[T.18]		-0.1711	0.020	-8.590	0.000
-0.210	-0.132				
start_hour[T.19]		-0.1985	0.020	-9.862	0.000
-0.238	-0.159				
start_hour[T.20]		-0.2477	0.021	-12.068	0.000
-0.288	-0.207				
start_hour[T.21]		-0.2165	0.021	-10.494	0.000
-0.257	-0.176				
start_hour[T.22]		-0.1700	0.021	-8.145	0.000
-0.211	-0.129				
start_hour[T.23]		-0.1840	0.022	-8.476	0.000
-0.227	-0.141				
payment_type[T.2]		-0.0411	0.004	-11.409	0.000
-0.048	-0.034				
weather[T.remain]		-0.0828	0.015	-5.616	0.000
-0.112	-0.054				
duration		0.2732	0.001	195.946	0.000
0.271	0.276				
duration:start_hour[T.1]		0.0105	0.002	6.316	0.000
0.007	0.014				
duration:start_hour[T.2]		0.0224	0.002	12.172	0.000
0.019	0.026				
duration:start_hour[T.3]		0.0343	0.002	17.326	0.000
0.030	0.038				
duration:start_hour[T.4]		0.0557	0.002	25.492	0.000
0.051	0.060				
duration:start_hour[T.5]		0.0969	0.002	40.489	0.000
0.092	0.102				
duration:start_hour[T.6]		0.0321	0.002	17.880	0.000
0.029	0.036				
duration:start_hour[T.7]		-0.0421	0.001	-28.743	0.000
-0.045	-0.039				
duration:start_hour[T.8]		-0.0881	0.001	-64.460	0.000
-0.091	-0.085				
duration:start_hour[T.9]		-0.0900	0.001	-65.911	0.000
-0.093	-0.087				
duration:start_hour[T.10]		-0.0901	0.001	-65.809	0.000
-0.093	-0.087				
duration:start_hour[T.11]		-0.0933	0.001	-68.174	0.000
-0.096	-0.091				
duration:start_hour[T.12]		-0.0862	0.001	-62.963	0.000
-0.089	-0.084				
duration:start_hour[T.13]		-0.0677	0.001	-49.210	0.000
-0.070	-0.065				
duration:start_hour[T.14]		-0.0642	0.001	-48.065	0.000

-0.067	-0.062				
duration:start_hour[T.15]	-0.0696	0.001	-53.217	0.000	
-0.072	-0.067				
duration:start_hour[T.16]	-0.0708	0.001	-53.906	0.000	
-0.073	-0.068				
duration:start_hour[T.17]	-0.0746	0.001	-57.583	0.000	
-0.077	-0.072				
duration:start_hour[T.18]	-0.0634	0.001	-48.105	0.000	
-0.066	-0.061				
duration:start_hour[T.19]	-0.0398	0.001	-29.163	0.000	
-0.042	-0.037				
duration:start_hour[T.20]	-0.0128	0.001	-9.145	0.000	
-0.016	-0.010				
duration:start_hour[T.21]	-0.0024	0.001	-1.728	0.084	
-0.005	0.000				
duration:start_hour[T.22]	-0.0029	0.001	-2.047	0.041	
-0.006	-0.000				
duration:start_hour[T.23]	0.0134	0.001	9.185	0.000	
0.011	0.016				
duration:weather[T.remain]	0.0091	0.001	9.010	0.000	
0.007	0.011				

Omnibus:	479239.040	Durbin-Watson:	2.003
Prob(Omnibus):	0.000	Jarque-Bera (JB):	12934893.544
Skew:	1.801	Prob(JB):	0.00
Kurtosis:	20.443	Cond. No.	1.02e+03

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.02e+03. This might indicate that there are strong multicollinearity or other numerical problems.

[]:

```
[52]: fit = ols(formula="trip_distance ~ duration + start_hour + payment_type +
↪weather",
              data=sub_df1).fit()
print(fit.summary())
```

OLS Regression Results

Dep. Variable:	trip_distance	R-squared:	0.598
Model:	OLS	Adj. R-squared:	0.598
Method:	Least Squares	F-statistic:	5.602e+04
Date:	Fri, 04 Sep 2020	Prob (F-statistic):	0.00
Time:	20:44:28	Log-Likelihood:	-1.9188e+06

No. Observations: 978619 AIC: 3.838e+06
Df Residuals: 978592 BIC: 3.838e+06
Df Model: 26
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025
0.975]					

Intercept	0.2814	0.012	22.661	0.000	0.257
0.306					
start_hour[T.1]	0.0862	0.014	6.204	0.000	0.059
0.113					
start_hour[T.2]	0.1784	0.015	11.865	0.000	0.149
0.208					
start_hour[T.3]	0.3641	0.017	21.893	0.000	0.332
0.397					
start_hour[T.4]	0.7026	0.019	37.372	0.000	0.666
0.739					
start_hour[T.5]	0.8762	0.020	43.714	0.000	0.837
0.915					
start_hour[T.6]	0.2237	0.015	14.859	0.000	0.194
0.253					
start_hour[T.7]	-0.4487	0.013	-35.005	0.000	-0.474
-0.424					
start_hour[T.8]	-1.0021	0.012	-81.852	0.000	-1.026
-0.978					
start_hour[T.9]	-0.9907	0.012	-80.976	0.000	-1.015
-0.967					
start_hour[T.10]	-0.9136	0.012	-74.194	0.000	-0.938
-0.889					
start_hour[T.11]	-0.9772	0.012	-80.174	0.000	-1.001
-0.953					
start_hour[T.12]	-0.9621	0.012	-79.917	0.000	-0.986
-0.939					
start_hour[T.13]	-0.9005	0.012	-74.763	0.000	-0.924
-0.877					
start_hour[T.14]	-0.9453	0.012	-79.053	0.000	-0.969
-0.922					
start_hour[T.15]	-0.9996	0.012	-83.880	0.000	-1.023
-0.976					
start_hour[T.16]	-0.9531	0.012	-78.304	0.000	-0.977
-0.929					
start_hour[T.17]	-1.0099	0.012	-85.745	0.000	-1.033
-0.987					
start_hour[T.18]	-0.9570	0.011	-83.659	0.000	-0.979
-0.935					

start_hour[T.19]	-0.6886	0.011	-60.096	0.000	-0.711
-0.666					
start_hour[T.20]	-0.4191	0.012	-35.972	0.000	-0.442
-0.396					
start_hour[T.21]	-0.2589	0.012	-22.118	0.000	-0.282
-0.236					
start_hour[T.22]	-0.2031	0.012	-17.163	0.000	-0.226
-0.180					
start_hour[T.23]	-0.0070	0.012	-0.569	0.569	-0.031
0.017					
payment_type[T.2]	-0.0385	0.004	-10.447	0.000	-0.046
-0.031					
weather[T.remain]	-0.0264	0.009	-3.033	0.002	-0.044
-0.009					
duration	0.2331	0.000	1185.661	0.000	0.233
0.233					

```

=====
Omnibus:                    468487.939    Durbin-Watson:                    2.003
Prob(Omnibus):              0.000    Jarque-Bera (JB):              9516502.815
Skew:                      1.832    Prob(JB):                      0.00
Kurtosis:                  17.831    Cond. No.                      406.
=====

```

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
[53]: fit = ols(formula="trip_distance ~ duration + start_hour + payment_type",
               data=df).fit()
print(fit.summary())
```

```

                    OLS Regression Results
=====
Dep. Variable:      trip_distance    R-squared:                0.598
Model:              OLS             Adj. R-squared:           0.598
Method:             Least Squares    F-statistic:             6.189e+05
Date:               Fri, 04 Sep 2020  Prob (F-statistic):       0.00
Time:               20:45:03         Log-Likelihood:          -2.0368e+07
No. Observations:   10397081         AIC:                    4.074e+07
Df Residuals:       10397055         BIC:                    4.074e+07
Df Model:           25
Covariance Type:    nonrobust
=====
=====

```

	coef	std err	t	P> t	[0.025
0.975]					

```

-----
-----

```

Intercept	0.2651	0.003	90.971	0.000	0.259
0.271					
start_hour[T.1]	0.0749	0.004	17.670	0.000	0.067
0.083					
start_hour[T.2]	0.1835	0.005	39.971	0.000	0.175
0.193					
start_hour[T.3]	0.3630	0.005	71.304	0.000	0.353
0.373					
start_hour[T.4]	0.6985	0.006	121.783	0.000	0.687
0.710					
start_hour[T.5]	0.8469	0.006	138.262	0.000	0.835
0.859					
start_hour[T.6]	0.2392	0.005	51.817	0.000	0.230
0.248					
start_hour[T.7]	-0.4673	0.004	-118.987	0.000	-0.475
-0.460					
start_hour[T.8]	-1.0053	0.004	-268.657	0.000	-1.013
-0.998					
start_hour[T.9]	-1.0082	0.004	-269.610	0.000	-1.016
-1.001					
start_hour[T.10]	-0.9097	0.004	-241.856	0.000	-0.917
-0.902					
start_hour[T.11]	-0.9729	0.004	-261.153	0.000	-0.980
-0.966					
start_hour[T.12]	-0.9663	0.004	-262.822	0.000	-0.974
-0.959					
start_hour[T.13]	-0.9143	0.004	-247.929	0.000	-0.921
-0.907					
start_hour[T.14]	-0.9579	0.004	-262.449	0.000	-0.965
-0.951					
start_hour[T.15]	-1.0181	0.004	-279.000	0.000	-1.025
-1.011					
start_hour[T.16]	-0.9476	0.004	-254.267	0.000	-0.955
-0.940					
start_hour[T.17]	-1.0236	0.004	-283.774	0.000	-1.031
-1.016					
start_hour[T.18]	-0.9577	0.003	-274.151	0.000	-0.965
-0.951					
start_hour[T.19]	-0.7014	0.004	-200.385	0.000	-0.708
-0.695					
start_hour[T.20]	-0.4229	0.004	-118.682	0.000	-0.430
-0.416					
start_hour[T.21]	-0.2713	0.004	-75.786	0.000	-0.278
-0.264					
start_hour[T.22]	-0.2045	0.004	-56.614	0.000	-0.212
-0.197					
start_hour[T.23]	-0.0228	0.004	-6.060	0.000	-0.030
-0.015					

payment_type[T.2]	-0.0320	0.001	-28.313	0.000	-0.034
-0.030					
duration	0.2326	6.02e-05	3865.297	0.000	0.232
0.233					

```
=====
```

Omnibus:	4920433.098	Durbin-Watson:	1.839
Prob(Omnibus):	0.000	Jarque-Bera (JB):	97517120.372
Skew:	1.811	Prob(JB):	0.00
Kurtosis:	17.560	Cond. No.	404.

```
=====
```

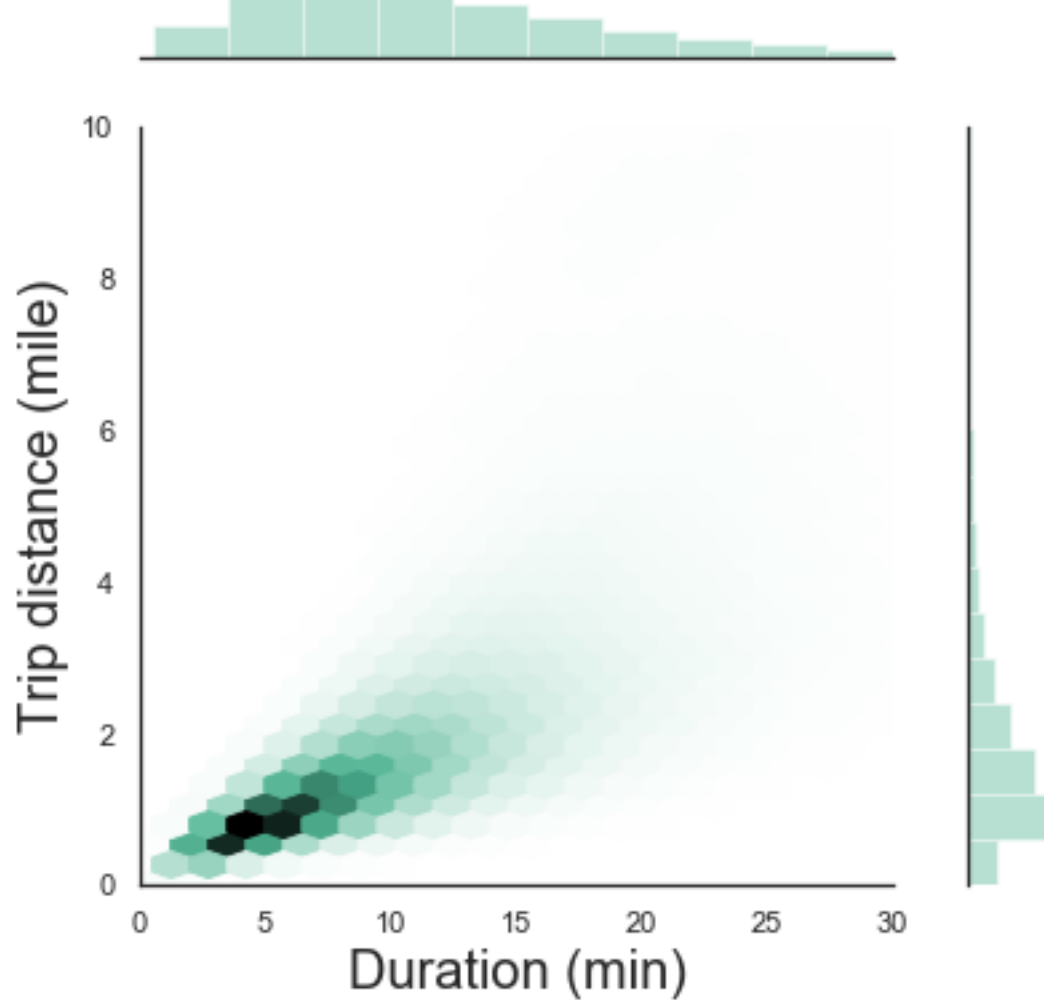
Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

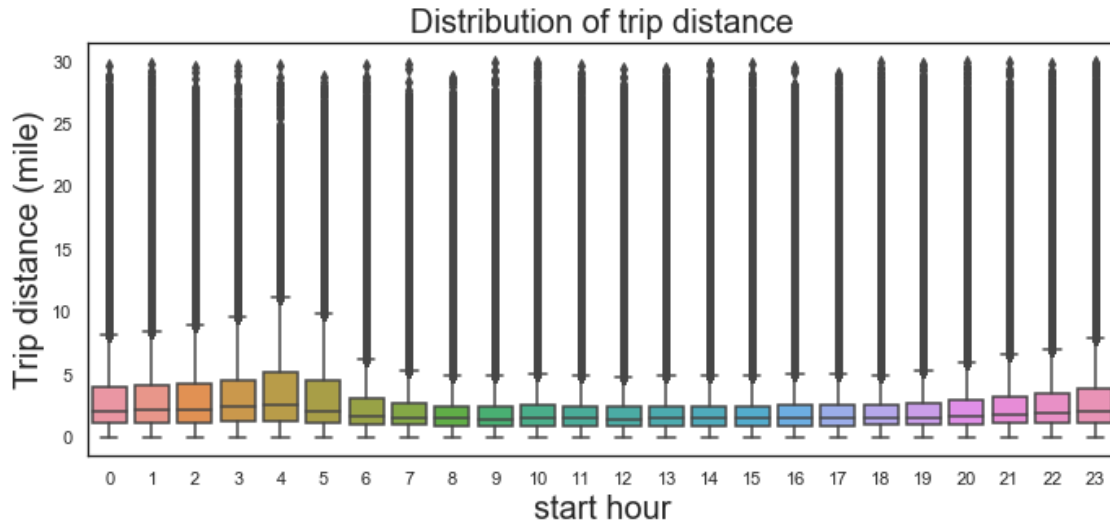
[]:

```
[54]: p = sns.jointplot(x='duration',y= 'trip_distance',data= df, kind="hex",
    ↪color="#4CB391", xlim=(0,30), ylim=(0,10), gridsize=100)
p.ax_joint.set_xlabel('Duration (min)')
p.ax_joint.set_ylabel('Trip distance (mile)')
p.fig.suptitle("Duration versus trip distance")
p.fig.tight_layout()
```

Duration versus trip distance

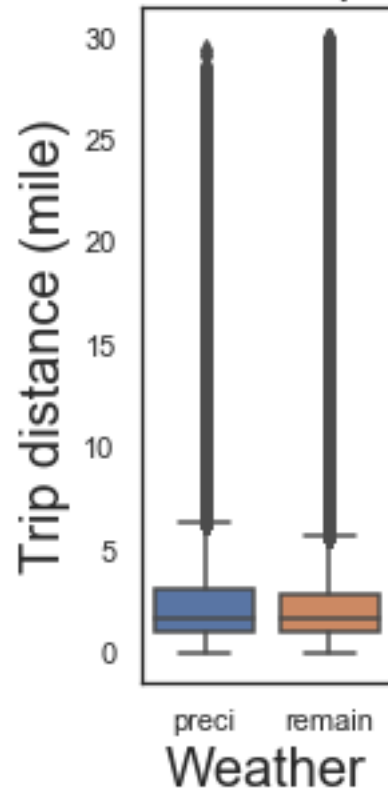


```
[55]: plt.figure(figsize=(10, 5))
sns.boxplot(x="start_hour", y="trip_distance", data=df)
plt.title("Distribution of trip distance")
plt.ylabel('Trip distance (mile)')
plt.xlabel('start hour')
plt.tight_layout()
```



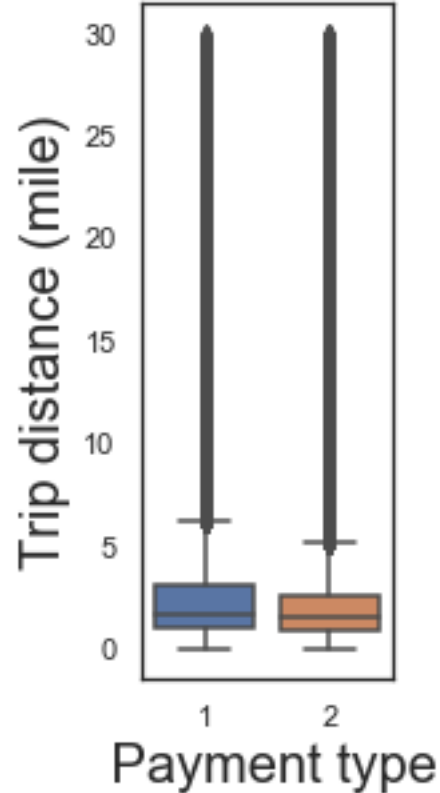
```
[56]: plt.figure(figsize=(3, 5))
sns.boxplot(x="weather", y="trip_distance", data=df)
plt.title("Distribution of trip distance")
plt.ylabel('Trip distance (mile)')
plt.xlabel('Weather')
plt.tight_layout()
```


Distribution of trip distance



```
[57]: plt.figure(figsize=(3, 5))
sns.boxplot(x="payment_type", y="trip_distance", data=df)
plt.title("Distribution of trip distance")
plt.ylabel('Trip distance (mile)')
plt.xlabel(' Payment type')
plt.tight_layout()
```

Distribution of trip distance



[]:

[]:

8 what related to income

```
[58]: fit = ols(formula="income ~ duration + payment_type +start_hour + duration * payment_type + duration * start_hour",data=sub_df1).fit()
print(fit.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          income    R-squared:                0.812
Model:                  OLS      Adj. R-squared:            0.812
Method:                 Least Squares    F-statistic:            8.606e+04
Date:                  Fri, 04 Sep 2020    Prob (F-statistic):      0.00
Time:                  20:45:42    Log-Likelihood:         -2.7340e+06
No. Observations:      978619    AIC:                    5.468e+06
Df Residuals:          978569    BIC:                    5.469e+06
=====
```

Df Model: 49
Covariance Type: nonrobust

[0.025 0.975]		coef	std err	t	P> t
Intercept		1.8370	0.038	48.529	0.000
1.763	1.911				
payment_type[T.2]		-0.2886	0.014	-19.991	0.000
-0.317	-0.260				
start_hour[T.1]		0.1167	0.057	2.034	0.042
0.004	0.229				
start_hour[T.2]		0.0243	0.063	0.389	0.697
-0.098	0.147				
start_hour[T.3]		0.0637	0.068	0.937	0.349
-0.070	0.197				
start_hour[T.4]		0.2699	0.076	3.570	0.000
0.122	0.418				
start_hour[T.5]		-0.0248	0.077	-0.323	0.747
-0.175	0.126				
start_hour[T.6]		0.0018	0.057	0.031	0.975
-0.110	0.114				
start_hour[T.7]		0.0725	0.051	1.434	0.152
-0.027	0.172				
start_hour[T.8]		0.2776	0.049	5.632	0.000
0.181	0.374				
start_hour[T.9]		0.2367	0.049	4.793	0.000
0.140	0.333				
start_hour[T.10]		0.3729	0.049	7.548	0.000
0.276	0.470				
start_hour[T.11]		0.2180	0.049	4.426	0.000
0.121	0.315				
start_hour[T.12]		0.0616	0.049	1.260	0.208
-0.034	0.157				
start_hour[T.13]		-0.3020	0.049	-6.148	0.000
-0.398	-0.206				
start_hour[T.14]		-0.3351	0.048	-6.935	0.000
-0.430	-0.240				
start_hour[T.15]		-0.1915	0.048	-4.019	0.000
-0.285	-0.098				
start_hour[T.16]		-0.0129	0.048	-0.268	0.789
-0.107	0.081				
start_hour[T.17]		-0.0552	0.047	-1.171	0.242
-0.148	0.037				
start_hour[T.18]		-0.2565	0.047	-5.480	0.000
-0.348	-0.165				

start_hour[T.19]	-0.3286	0.047	-6.944	0.000
-0.421 -0.236				
start_hour[T.20]	-0.5343	0.048	-11.075	0.000
-0.629 -0.440				
start_hour[T.21]	-0.4027	0.049	-8.301	0.000
-0.498 -0.308				
start_hour[T.22]	-0.3164	0.049	-6.455	0.000
-0.412 -0.220				
start_hour[T.23]	-0.4277	0.051	-8.377	0.000
-0.528 -0.328				
duration	1.0509	0.003	414.220	0.000
1.046 1.056				
duration:payment_type[T.2]	-0.1738	0.001	-179.995	0.000
-0.176 -0.172				
duration:start_hour[T.1]	0.0015	0.004	0.385	0.701
-0.006 0.009				
duration:start_hour[T.2]	0.0262	0.004	6.043	0.000
0.018 0.035				
duration:start_hour[T.3]	0.0552	0.005	11.853	0.000
0.046 0.064				
duration:start_hour[T.4]	0.1040	0.005	20.237	0.000
0.094 0.114				
duration:start_hour[T.5]	0.2084	0.006	36.990	0.000
0.197 0.219				
duration:start_hour[T.6]	0.0673	0.004	15.914	0.000
0.059 0.076				
duration:start_hour[T.7]	-0.0849	0.003	-24.682	0.000
-0.092 -0.078				
duration:start_hour[T.8]	-0.1818	0.003	-56.633	0.000
-0.188 -0.176				
duration:start_hour[T.9]	-0.1695	0.003	-52.874	0.000
-0.176 -0.163				
duration:start_hour[T.10]	-0.1655	0.003	-51.481	0.000
-0.172 -0.159				
duration:start_hour[T.11]	-0.1631	0.003	-50.726	0.000
-0.169 -0.157				
duration:start_hour[T.12]	-0.1487	0.003	-46.301	0.000
-0.155 -0.142				
duration:start_hour[T.13]	-0.1105	0.003	-34.218	0.000
-0.117 -0.104				
duration:start_hour[T.14]	-0.1194	0.003	-38.116	0.000
-0.126 -0.113				
duration:start_hour[T.15]	-0.1443	0.003	-46.944	0.000
-0.150 -0.138				
duration:start_hour[T.16]	-0.1509	0.003	-48.848	0.000
-0.157 -0.145				
duration:start_hour[T.17]	-0.1592	0.003	-52.251	0.000
-0.165 -0.153				

```

duration:start_hour[T.18]    -0.1377    0.003    -44.496    0.000
-0.144    -0.132
duration:start_hour[T.19]    -0.0875    0.003    -27.299    0.000
-0.094    -0.081
duration:start_hour[T.20]    -0.0243    0.003    -7.357    0.000
-0.031    -0.018
duration:start_hour[T.21]    -0.0050    0.003    -1.509    0.131
-0.011    0.001
duration:start_hour[T.22]    -0.0039    0.003    -1.166    0.243
-0.010    0.003
duration:start_hour[T.23]    0.0360    0.003    10.525    0.000
0.029    0.043
=====
Omnibus:                    472872.262    Durbin-Watson:                    2.001
Prob(Omnibus):              0.000    Jarque-Bera (JB):                55605092.808
Skew:                      1.350    Prob(JB):                        0.00
Kurtosis:                  39.829    Cond. No.                        780.
=====

```

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
[59]: fit = ols(formula="income ~ duration + payment_type +start_hour",data=df).fit()
print(fit.summary())
```

```

                                OLS Regression Results
=====
Dep. Variable:                  income    R-squared:                        0.800
Model:                          OLS      Adj. R-squared:                   0.800
Method:                        Least Squares    F-statistic:                   1.664e+06
Date:                          Fri, 04 Sep 2020    Prob (F-statistic):              0.00
Time:                          20:46:16    Log-Likelihood:                 -2.9344e+07
No. Observations:              10397081    AIC:                           5.869e+07
Df Residuals:                  10397055    BIC:                           5.869e+07
Df Model:                      25
Covariance Type:               nonrobust
=====
=====
                                coef    std err          t      P>|t|      [0.025
0.975]
-----
Intercept                3.7478      0.007    542.448    0.000      3.734
3.761
payment_type[T.2]        -2.3755      0.003   -887.310    0.000     -2.381
-2.370
start_hour[T.1]           0.0956      0.010     9.517    0.000      0.076

```

0.115					
start_hour[T.2]	0.2958	0.011	27.172	0.000	0.275
0.317					
start_hour[T.3]	0.6549	0.012	54.249	0.000	0.631
0.679					
start_hour[T.4]	1.4539	0.014	106.900	0.000	1.427
1.481					
start_hour[T.5]	1.9355	0.015	133.275	0.000	1.907
1.964					
start_hour[T.6]	0.4873	0.011	44.514	0.000	0.466
0.509					
start_hour[T.7]	-0.9951	0.009	-106.861	0.000	-1.013
-0.977					
start_hour[T.8]	-1.9803	0.009	-223.193	0.000	-1.998
-1.963					
start_hour[T.9]	-1.8977	0.009	-214.025	0.000	-1.915
-1.880					
start_hour[T.10]	-1.6679	0.009	-187.026	0.000	-1.685
-1.650					
start_hour[T.11]	-1.7957	0.009	-203.303	0.000	-1.813
-1.778					
start_hour[T.12]	-1.7816	0.009	-204.361	0.000	-1.799
-1.764					
start_hour[T.13]	-1.6951	0.009	-193.869	0.000	-1.712
-1.678					
start_hour[T.14]	-1.8381	0.009	-212.389	0.000	-1.855
-1.821					
start_hour[T.15]	-2.0287	0.009	-234.465	0.000	-2.046
-2.012					
start_hour[T.16]	-1.8938	0.009	-214.319	0.000	-1.911
-1.876					
start_hour[T.17]	-2.0793	0.009	-243.129	0.000	-2.096
-2.063					
start_hour[T.18]	-1.9590	0.008	-236.508	0.000	-1.975
-1.943					
start_hour[T.19]	-1.4165	0.008	-170.673	0.000	-1.433
-1.400					
start_hour[T.20]	-0.8467	0.008	-100.230	0.000	-0.863
-0.830					
start_hour[T.21]	-0.4974	0.008	-58.603	0.000	-0.514
-0.481					
start_hour[T.22]	-0.3422	0.009	-39.944	0.000	-0.359
-0.325					
start_hour[T.23]	0.0212	0.009	2.382	0.017	0.004
0.039					
duration	0.8976	0.000	6291.336	0.000	0.897
0.898					

=====

Omnibus:	5137951.303	Durbin-Watson:	1.883
Prob(Omnibus):	0.000	Jarque-Bera (JB):	414165231.594
Skew:	1.507	Prob(JB):	0.00
Kurtosis:	33.773	Cond. No.	404.

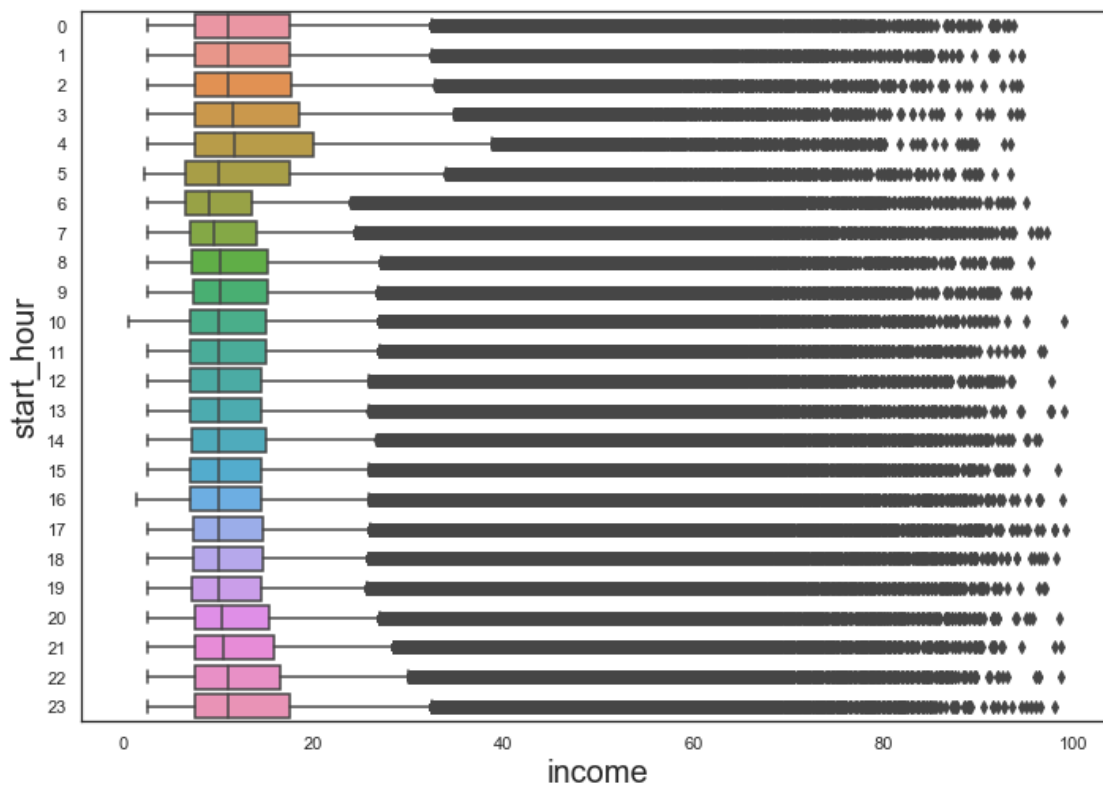
=====

Warnings:

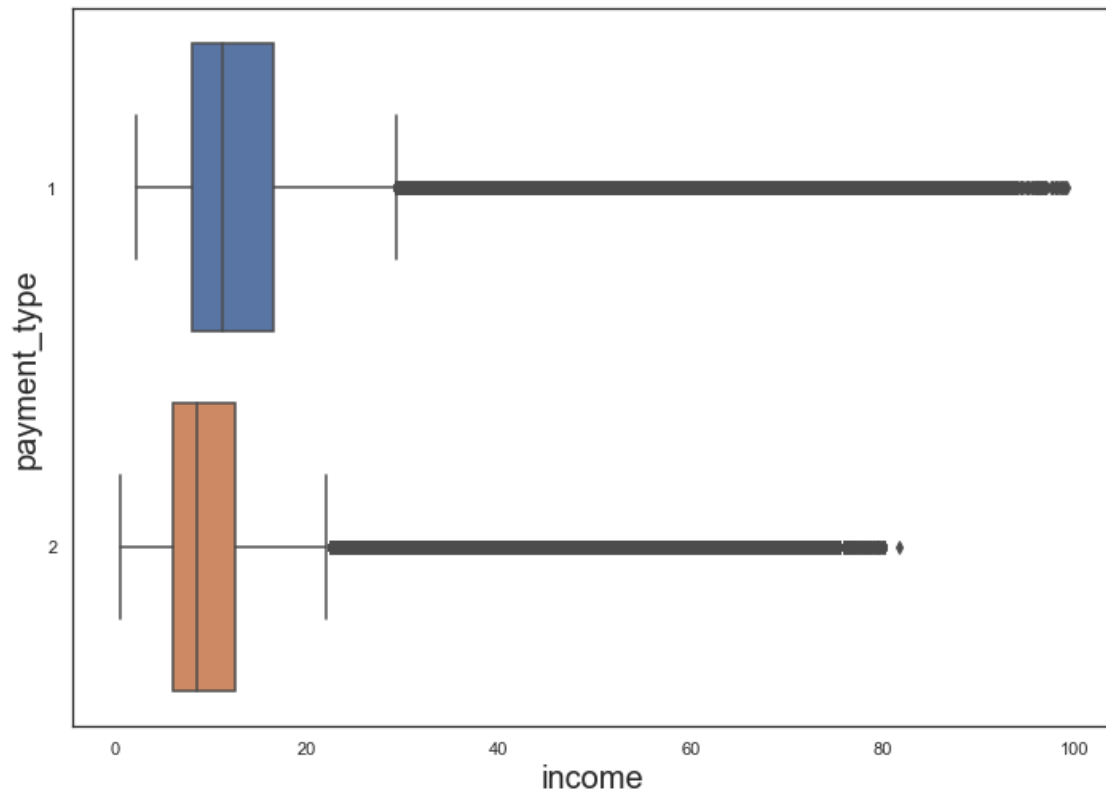
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[]:

[60]: `ax = sns.boxplot(x="income", y="start_hour", data=df)`

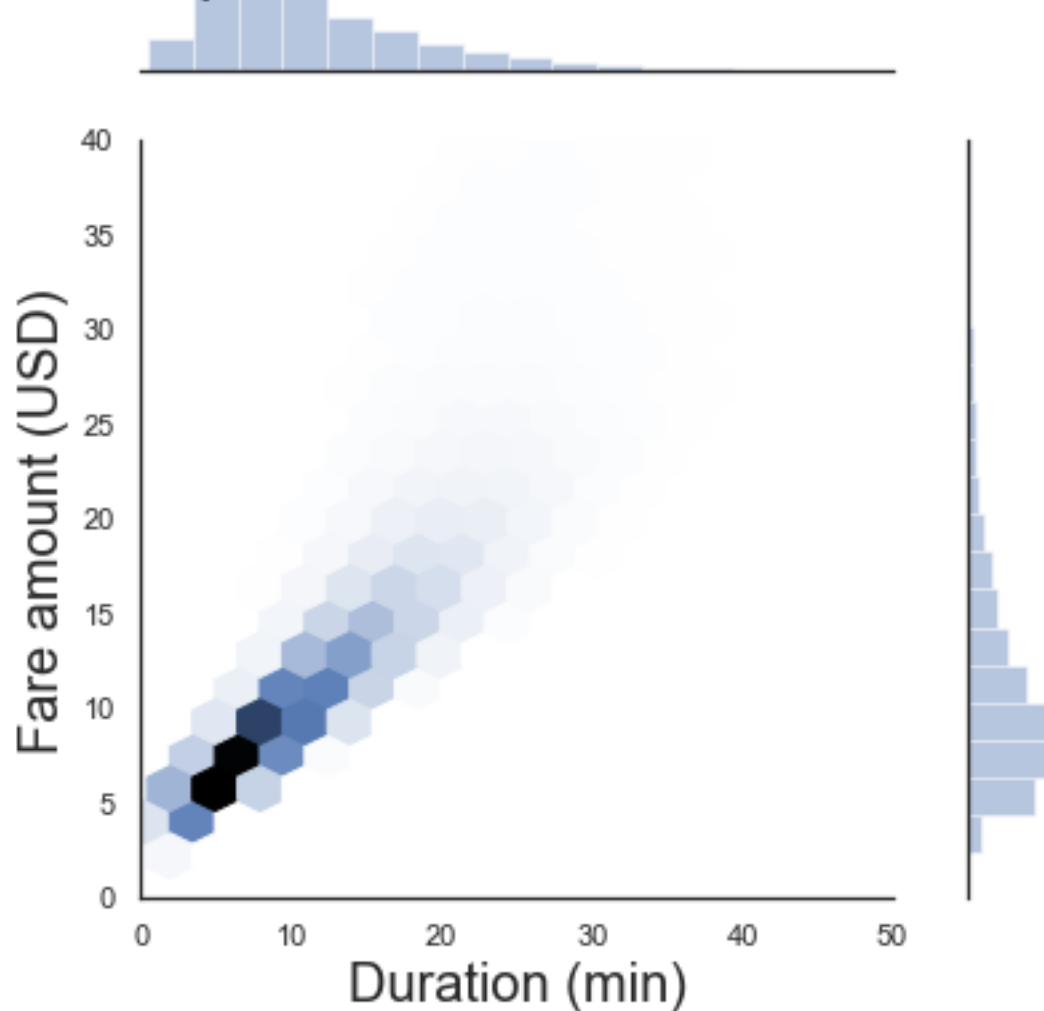


[61]: `ax = sns.boxplot(x="income", y="payment_type", data=df)`



```
[62]: p = sns.jointplot(x='duration',y= 'income',data= stand_df, kind="hex",
    ↪color="b", xlim=(0,50), ylim=(0,40))
p.ax_joint.set_xlabel('Duration (min)')
p.ax_joint.set_ylabel('Fare amount (USD)')
p.fig.suptitle("Tip amount versus Duration")
p.fig.tight_layout()
```

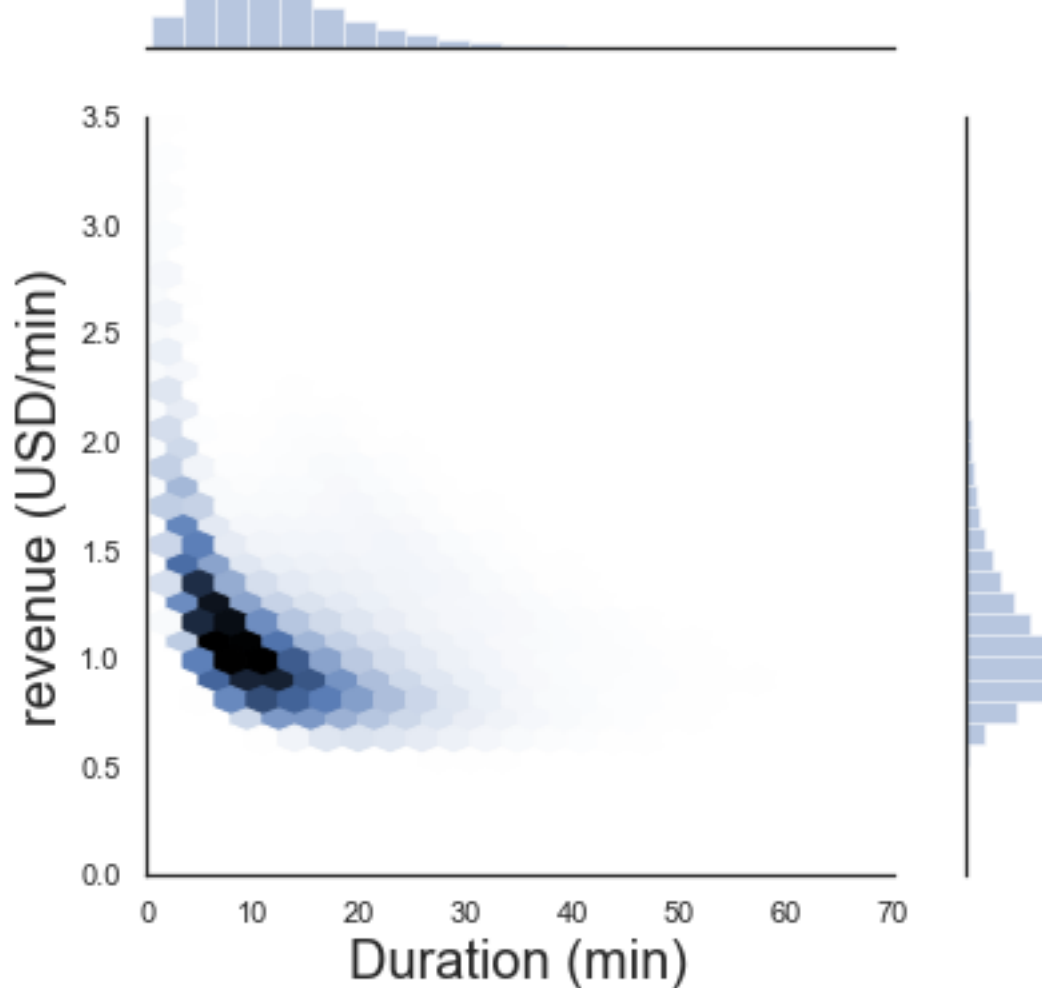

Tip amount versus Duration



[]:

```
[63]: p = sns.jointplot(x='duration',y= 'income/duration',data= stand_df, kind="hex",  
    ↪color="b", xlim=(0,70), ylim=(0,3.5))  
p.ax_joint.set_xlabel('Duration (min)')  
p.ax_joint.set_ylabel('revenue (USD/min)')  
p.fig.suptitle("Duration versus revenue")  
p.fig.tight_layout()
```

Duration versus revenue



[]:

```
[64]: for i in range(24):
    curr_data = stand_df[start_coords].loc[(df['start_hour'] == i) &
    → (df['duration'] <= 10)]
    curr = folium.Map(location=[40.75, -73.9], tiles="Stamen Terrain",
    → zoom_start=12)
    curr.add_child(HeatMap(curr_data[start_coords].values, radius=10))
    curr.save('plots/start_Heatmap_high_revenue_in' + str(i) + '.html')
```

```
[65]: for i in range(24):
```

```

curr_data = stand_df[start_coords].loc[(df['start_hour'] == i) &
↳(df['duration'] > 10)]
curr = folium.Map(location=[40.75, -73.9], tiles="Stamen Terrain",
↳zoom_start=12)
curr.add_child(HeatMap(curr_data[start_coords].values, radius=10))
curr.save('plots/start_Heatmap_low_revenue_in' + str(i) + '.html')

```

```
[ ]:
```

```

[66]: time = [0,1,2,3,4,5,6,23]
time = [str(i) for i in time]
posi = [i for i in range(1,5)] + [i for i in range(9,13)]

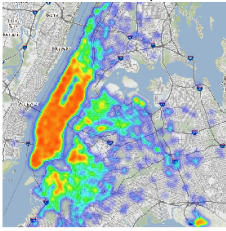
```

```

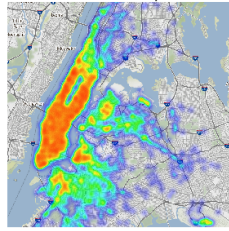
[67]: plt.figure(figsize=(20, 20))
for i in range(8):
    plt.subplot(4,4,posi[i])
    plt.title("From " + time[i-1] + ":00 to " + time[i-1] + ":59"\
        + " for \n duration shorter or equal to 5 min" )
    img = mpimg.imread("plots/heatmap/high " + time[i-1] + '.png')
    plt.imshow(img)
    plt.axis('off')
    plt.subplot(4,4, posi[i]+4)
    plt.title("From " + time[i-1] + ":00 to " + time[i-1] + ":59"\
        + " for \n duration longer than 5 min" )
    img = mpimg.imread("plots/heatmap/low " + time[i-1] + '.png')
    plt.imshow(img)
    plt.axis('off')
plt.tight_layout()
plt.show()

```

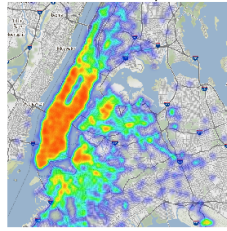
From 23:00 to 23:59 for duration shorter or equal to 5 min



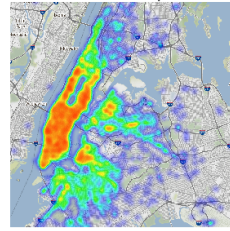
From 0:00 to 0:59 for duration shorter or equal to 5 min



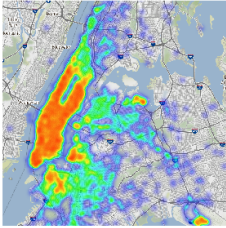
From 1:00 to 1:59 for duration shorter or equal to 5 min



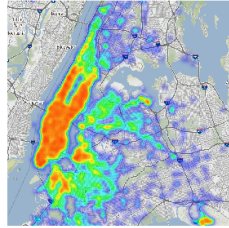
From 2:00 to 2:59 for duration shorter or equal to 5 min



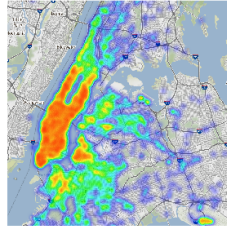
From 23:00 to 23:59 for duration longer than 5 min



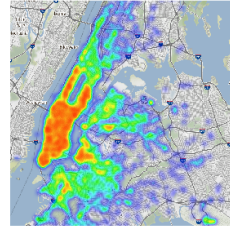
From 0:00 to 0:59 for duration longer than 5 min



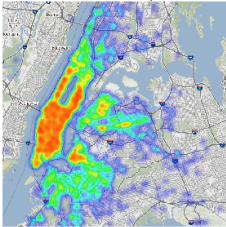
From 1:00 to 1:59 for duration longer than 5 min



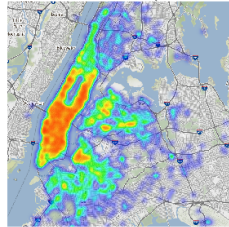
From 2:00 to 2:59 for duration longer than 5 min



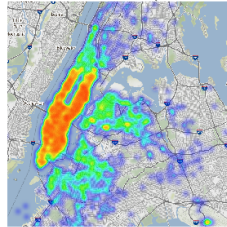
From 3:00 to 3:59 for duration shorter or equal to 5 min



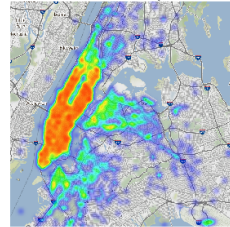
From 4:00 to 4:59 for duration shorter or equal to 5 min



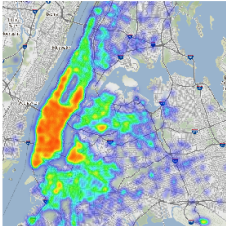
From 5:00 to 5:59 for duration shorter or equal to 5 min



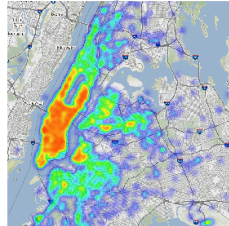
From 6:00 to 6:59 for duration shorter or equal to 5 min



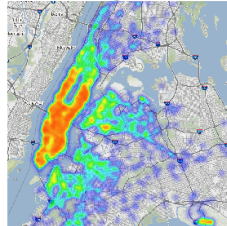
From 3:00 to 3:59 for duration longer than 5 min



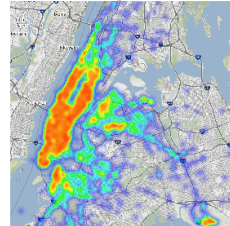
From 4:00 to 4:59 for duration longer than 5 min



From 5:00 to 5:59 for duration longer than 5 min



From 6:00 to 6:59 for duration longer than 5 min



[]:

[]: