An analysis of 2015 NYC Green Taxi Trip Data

Analyzing large datasets with Python



24th February 2017

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A look at the dataset

- 19 233 766 (> 19 millions) observations
- ~3Gb
- Features:

```
vendorid
                              Trip_distance
                         10
pickup_datetime
                              Fare amount
                         11
dropoff_datetime
                         12
                              Extra
Store_and_fwd_flag
                         13
                              MTA tax
rate_code
                         14
                              Tip_amount
Pickup_longitude
                         15
                              Tolls_amount
Pickup_latitude
                         16
                              Ehail fee
Dropoff_longitude
                              Improvement_surcharge
                         17
Dropoff_latitude
                         18
                              Total_amount
Passenger_count
                         19
                              Payment_type
Trip_distance
                         20
                               Trip_type
```

• To make the problem tractable with my modest resources, I reduced the number of observations via random sampling (~5%)

Some stats

	vendorid	rate_code	Pickup_longitud	e Pickup_latitude
mean	1.782501	1.099008	-73.826362	40.689645
std	0.412545	0.637620	2.836832	1.563842
min	1.000000	1.000000	-115.174675	0.000000
25%	2.000000	1.000000	-73.959190	40.699361
50%	2.000000	1.000000	-73.945099	40.746895
75%	2.000000	1.000000	-73.916901	40.803665
max	2.000000	99.000000	0.00000	41.292233

Dropoff_longitude Dropoff_latitude Passenger_count Trip_distance

mean	-73.828218	40.689380	1.371483	2.882150
std	2.797645	1.542149	1.044929	2.947592
min	-115.174850	0.000000	0.000000	0.000000
25%	-73.966963	40.700444	1.000000	1.070000
50%	-73.944321	40.748108	1.000000	1.900000
75%	-73.909386	40.792949	1.000000	3.640000
max	0.00000	41.637573	8.000000	105.740000

Some stats

	Fare_amount	Extro	а МТ <i>А</i> _	tax	Tip_amount
mean std min 25% 50% 75% max	12.331019 10.256481 -200.000000 6.500000 9.500000 15.000000 499.000000	0.353044 0.365783 -1.000000 0.000000 0.500000 0.500000 1.000000	0.486347 0.086079 -0.500000 0.500000 0.500000 0.500000	0.000 0.000 2.000	988 . <mark>000000</mark> 9000

	Tolls_amount	Ehail_fee	Improvement_s	urcharge	Total_amount
mean	0.112948	NaN	0.290724	14.79553	0
std	1.033035	NaN	0.053963	12.065141	
min	0.000000	NaN	-0.300000	-200.0000	000
25%	0.00000	NaN	0.300000	7.80000	0
50%	0.000000	NaN	0.300000	11.30000	0
75%	0.00000	NaN	0.300000	17.80000	00
max	235.000000	NaN	0.300000	499.300	0000

Cleaning data

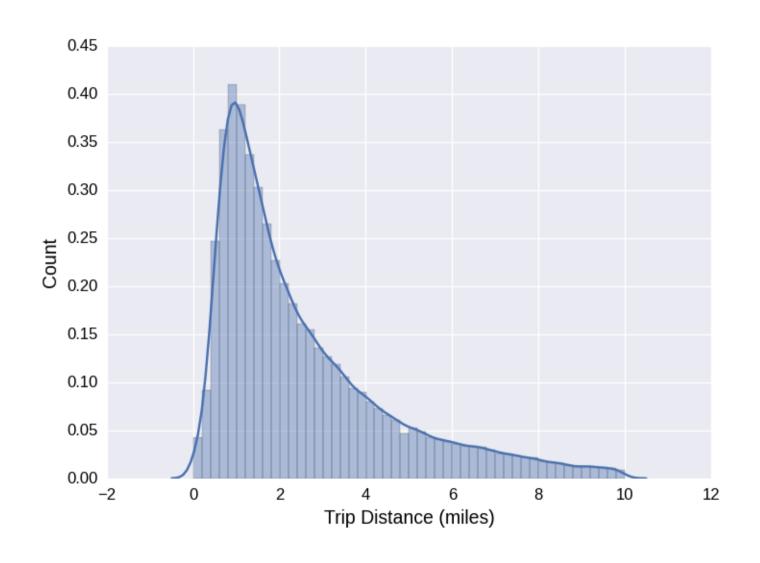
• I parsed the data and applied **filters** to some features

```
• e. g.  |x - x_{AVG}| < 3 \sigma \qquad x = latitude,  fare, ...  x > 0 \qquad x = num.  Passengers (...)
```

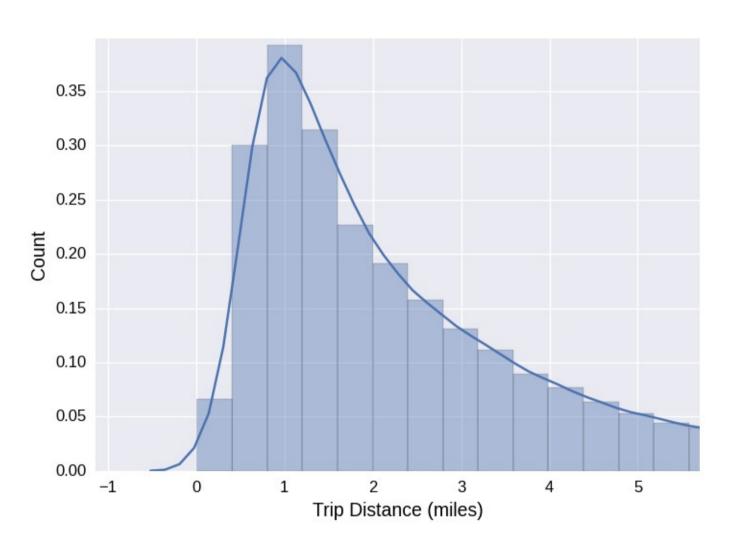
Created derived variables:

```
Week_day
Month_day
Hour 1-to-24
Shift type Morning/afternoon/night
Speed
Tip_percentage
With_tip
Origin (Manhattan or not)
```

Trip Distance

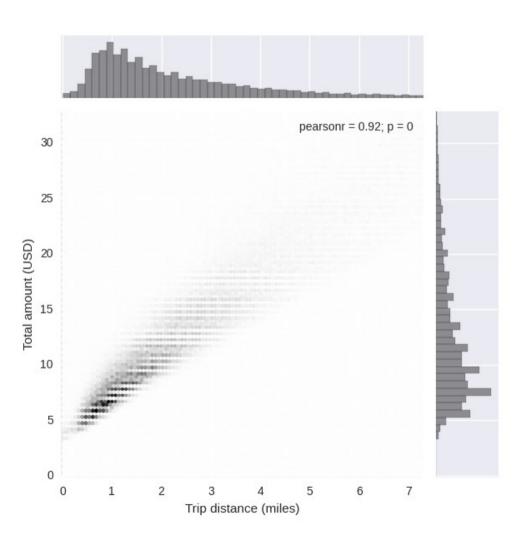


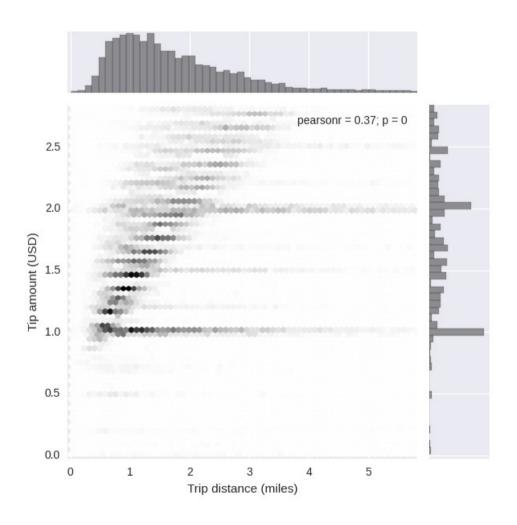
Trip Distance



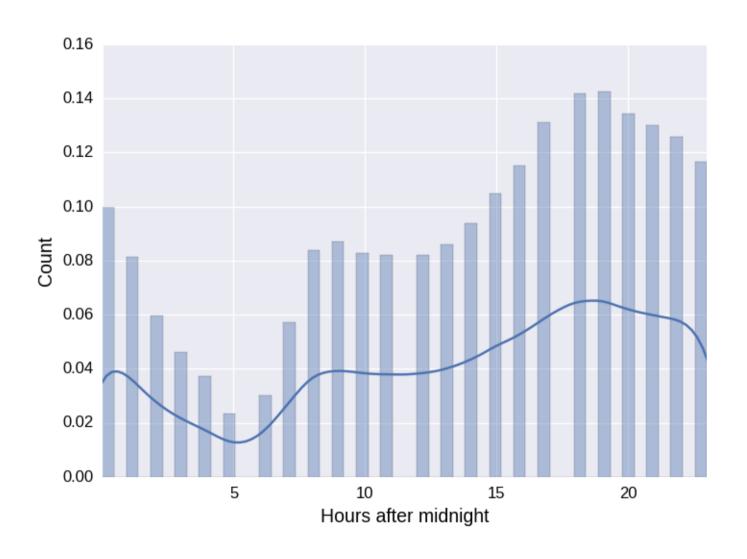
Right-skewed distribution due to lower bound (0)

Correlations

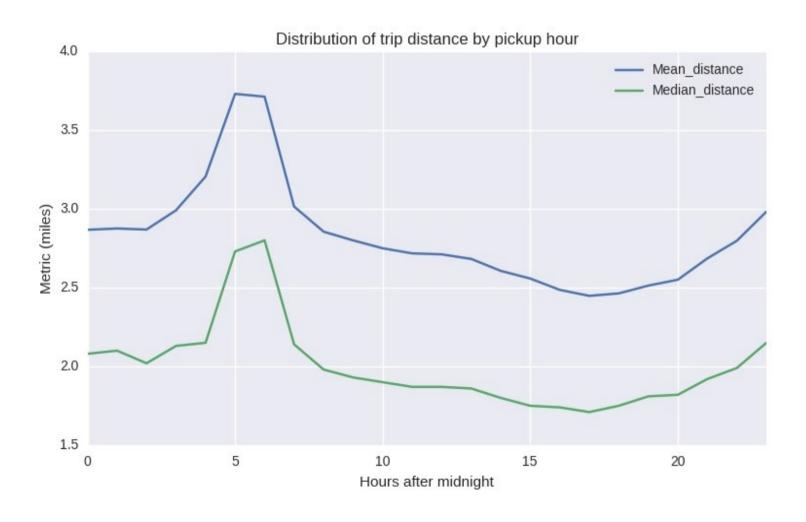




Pickup hour

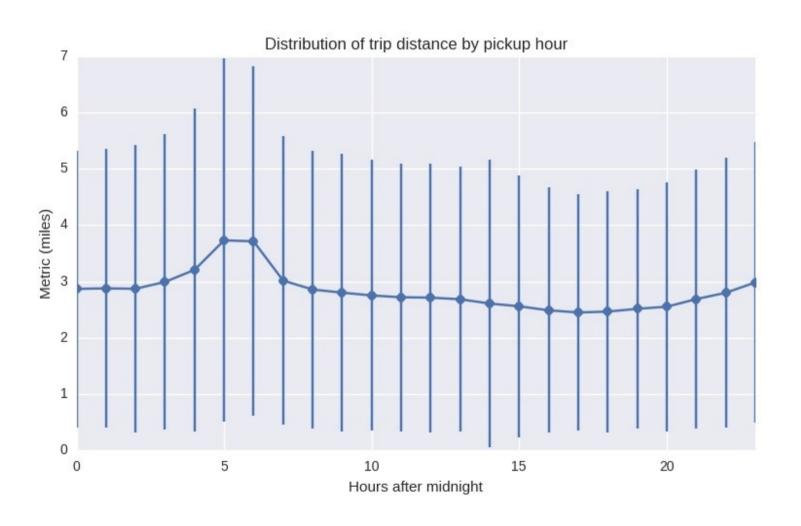


Trip Distance by hour

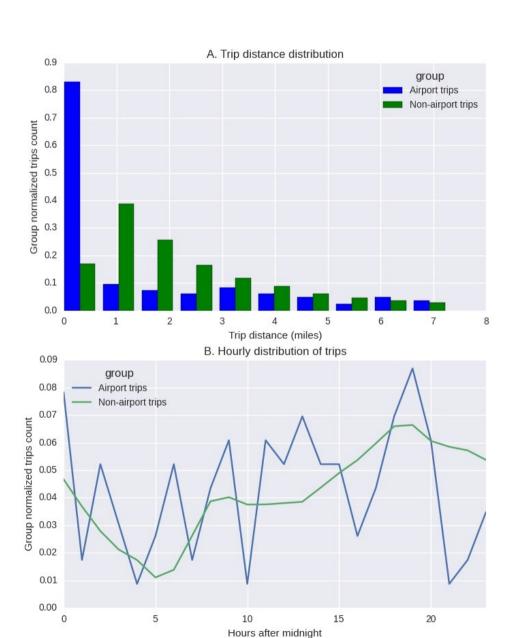


Longer travels in the morning 5am-7am

Trip Distance by hour

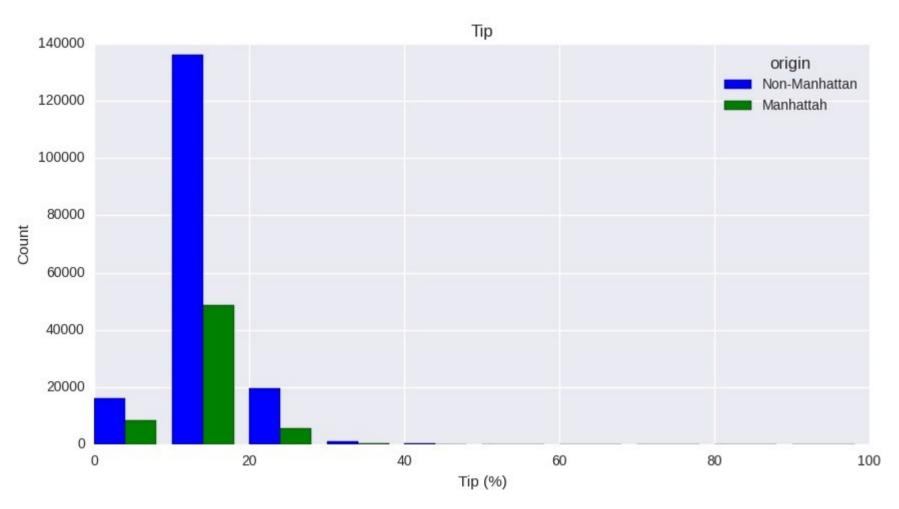


Trip Distance by hour



- Number of trips to/from NYC airports:
 115
- Average total charged amount (before tip) of trips to/from NYC airports:
 \$ 23.9934782609 per trip

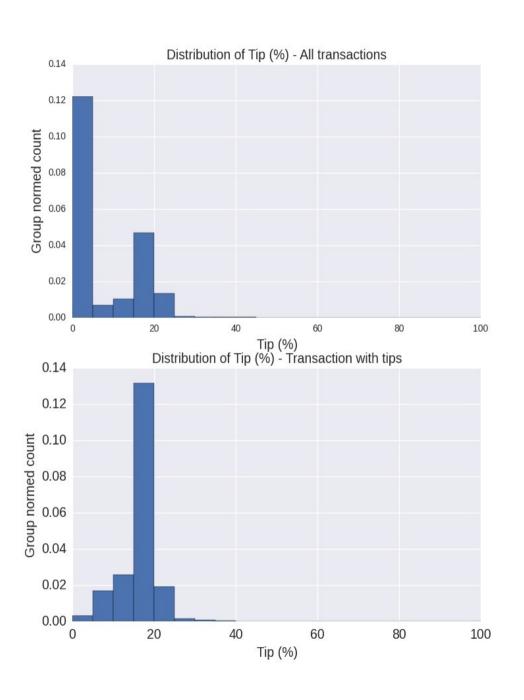
Tip and Trip origin

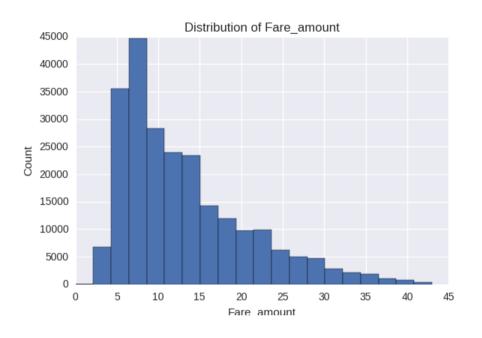


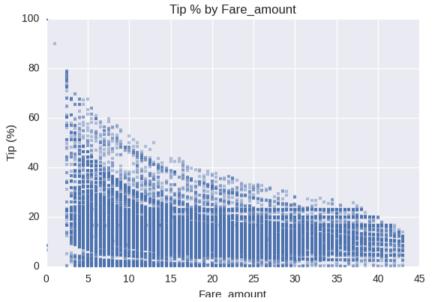
t-test results:

statistics = 37.11635088218631, p-value = 1.0641940231098476e-299

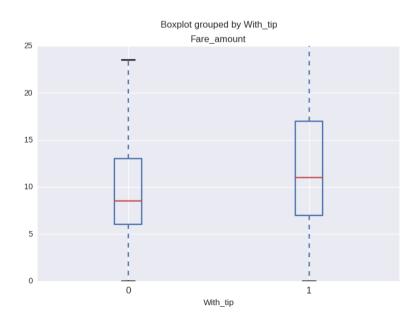
 \rightarrow the two distributions are different at 95% level of confidnce

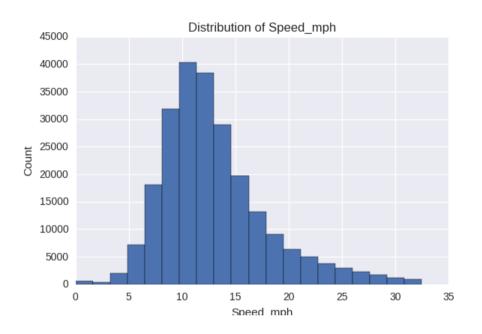


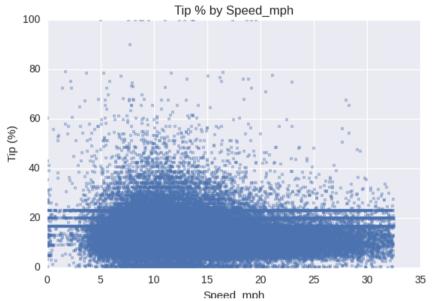




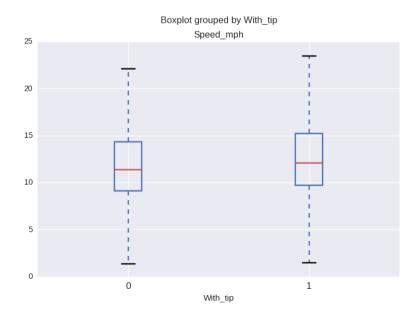
t-test results: (-65.553446118735991, 0.0)

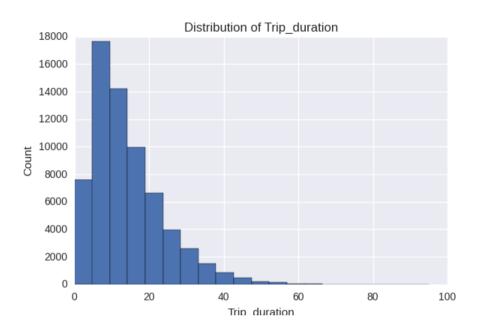


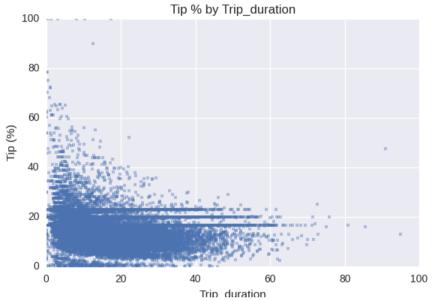




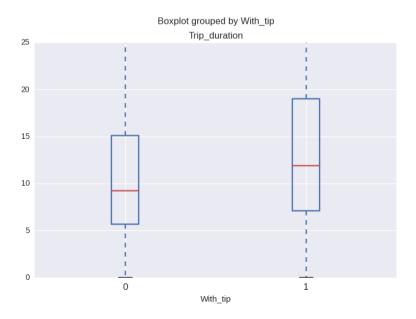
t-test results: (-23.83456220, 2.47366441e-125)



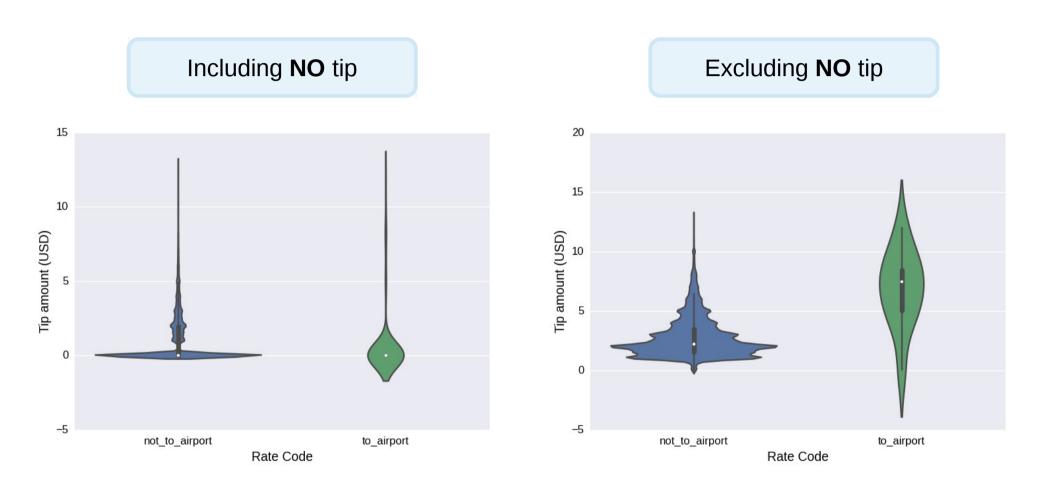




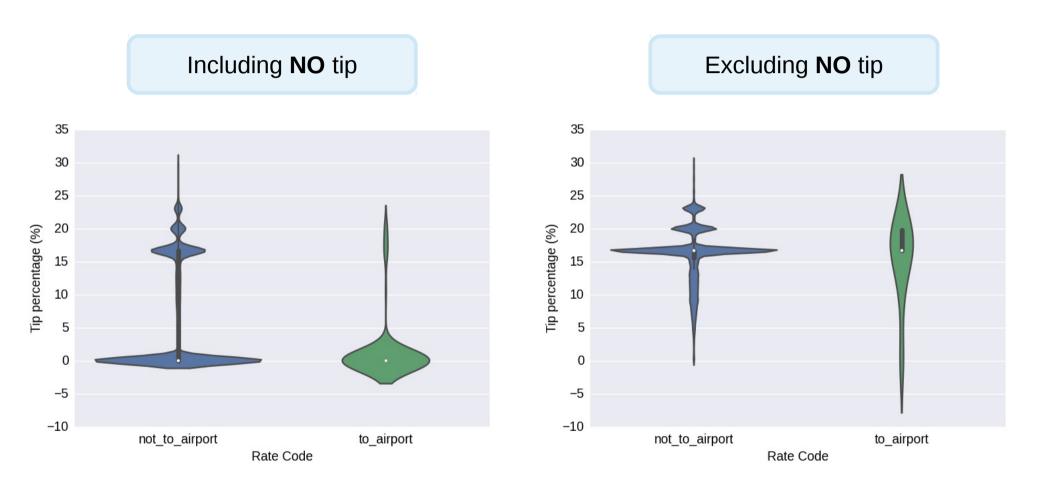
t-test results: (-2.1104725, 0.03481)



Tip and Trip type



Tip % and Trip type



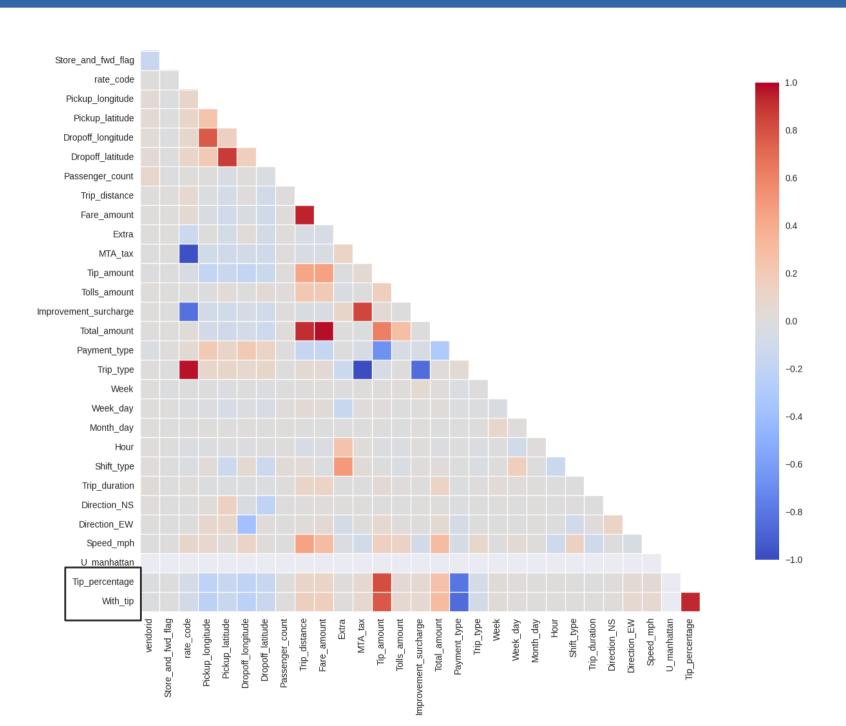
Tip % and payment method



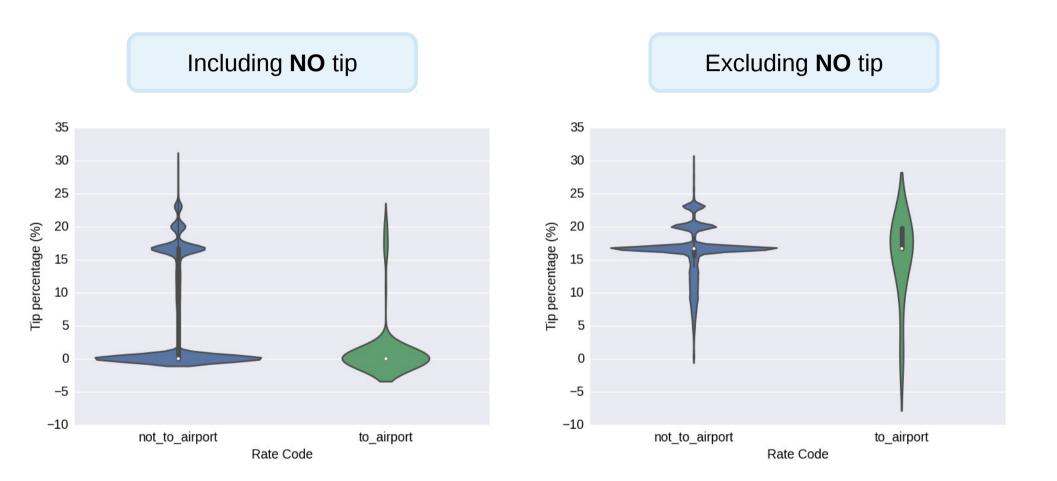
Credit Card Cash

- >>> len(df3[(df3.Payment_type == 2) & (df3.Tip_amount>0)]) → 0
- CURIOUS: no transaction with cash has a tip
- Checking back on the full dataset: only 19 cash transactions have a tip >0, i.e. $\sim 0.0001\%$

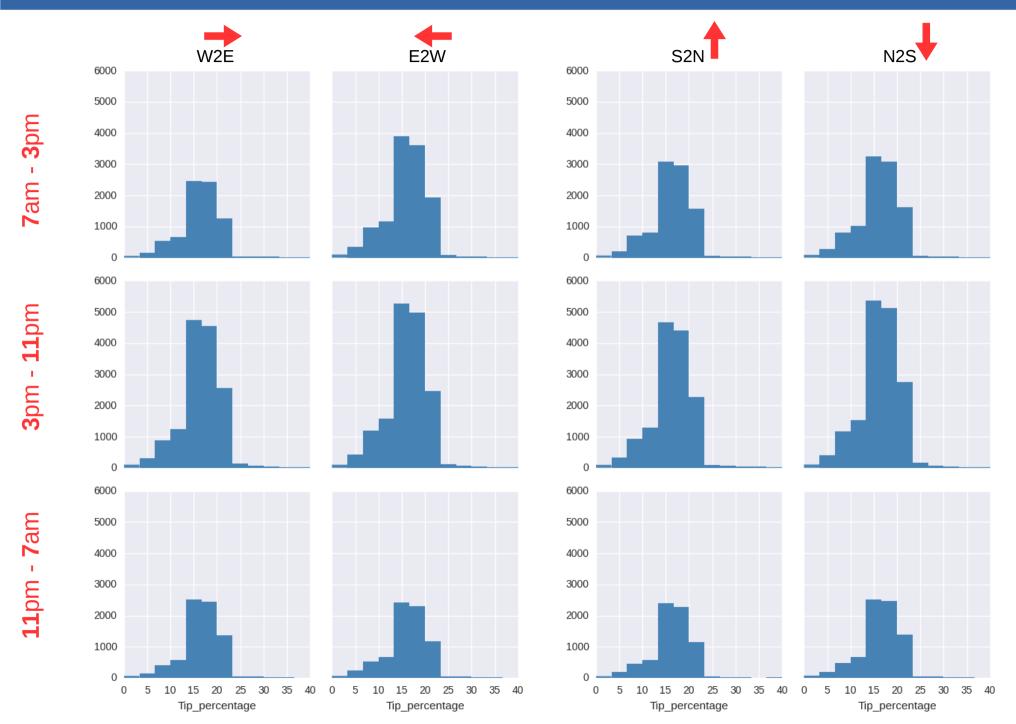
Correlation plot



Tip and Trip type



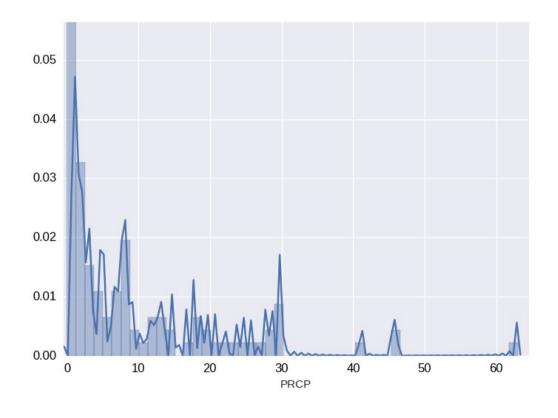
Tip and Shift type



Precipitations

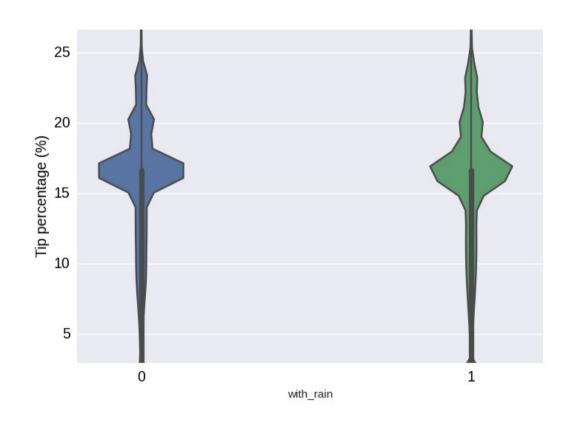
• Climate data obtained from:





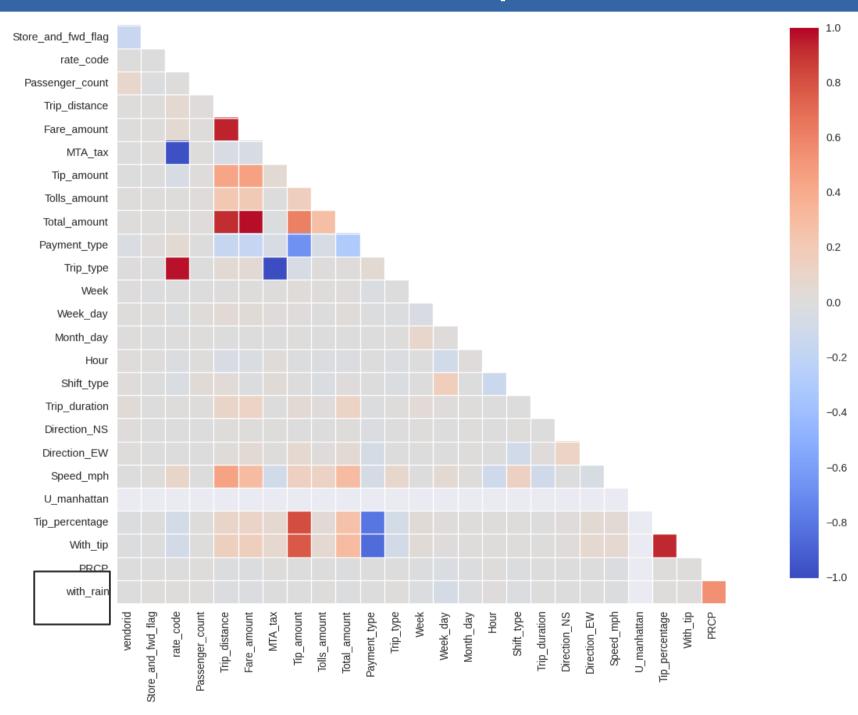
Rain on 30% of days in a year

Precipitations

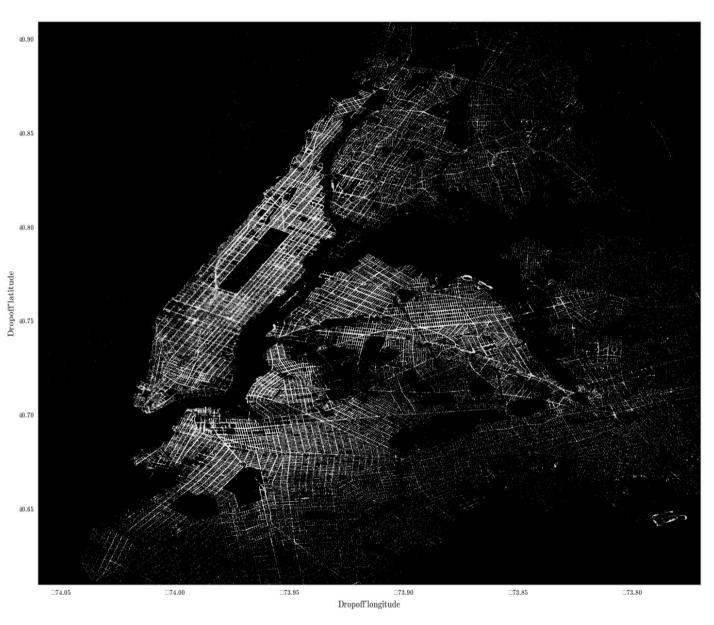


• Rain has no effect on tip

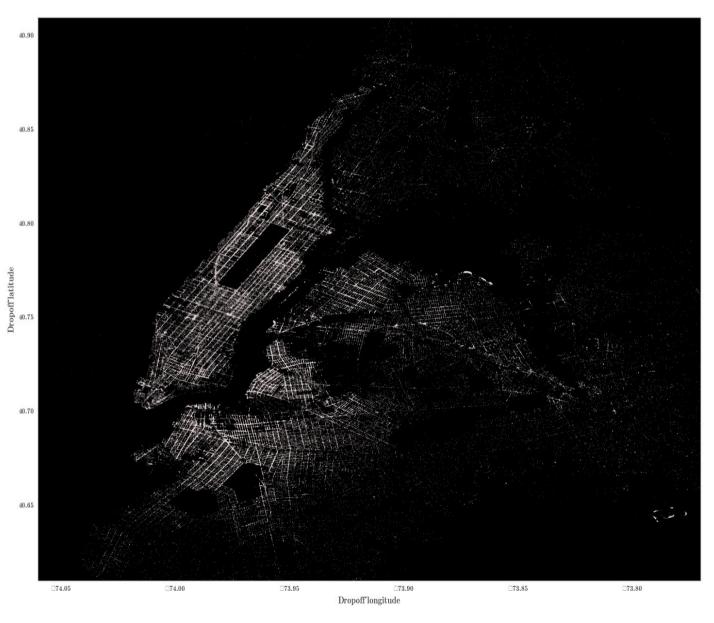
Correlation plot



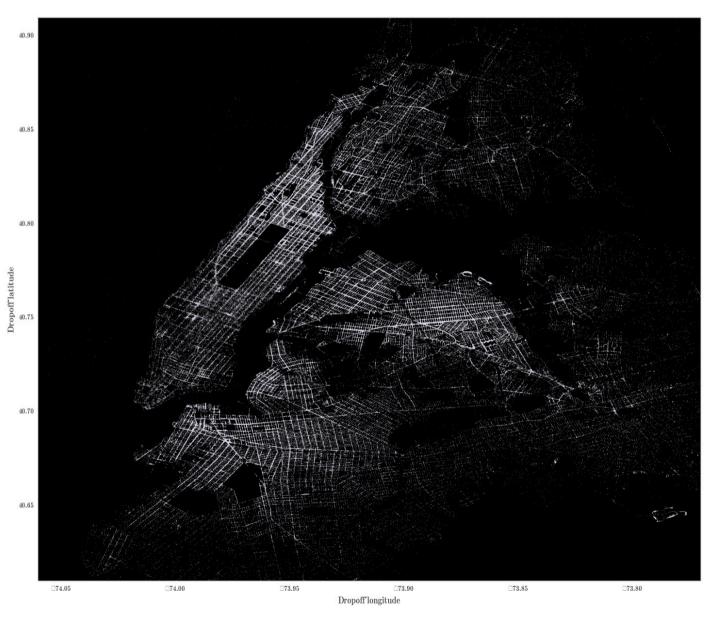
Mapping the data



Mapping the data: tip>mean

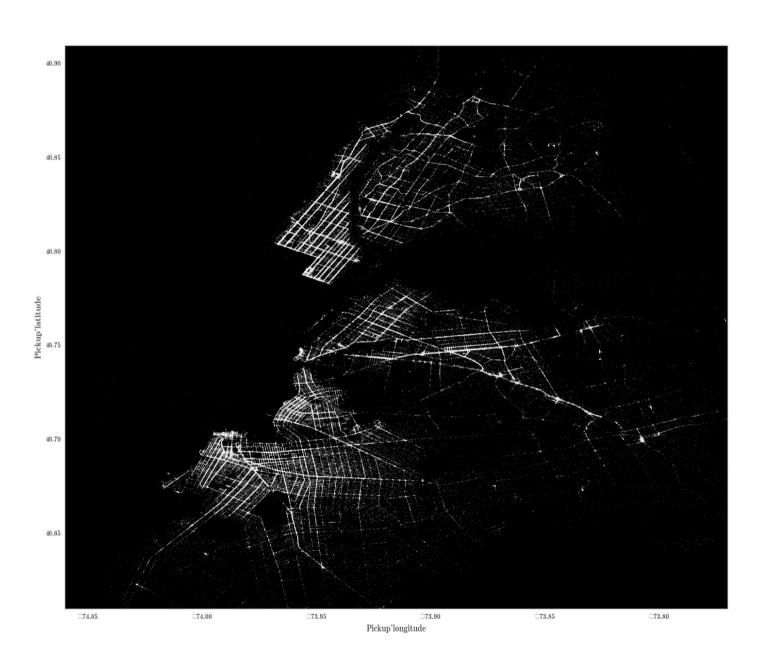


Mapping the data: tip<mean



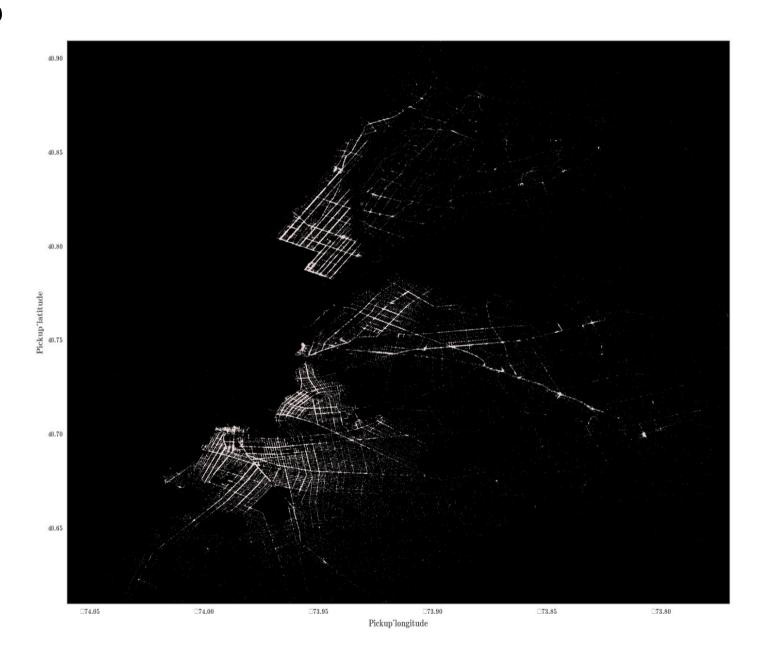
Mapping the data

Pickup



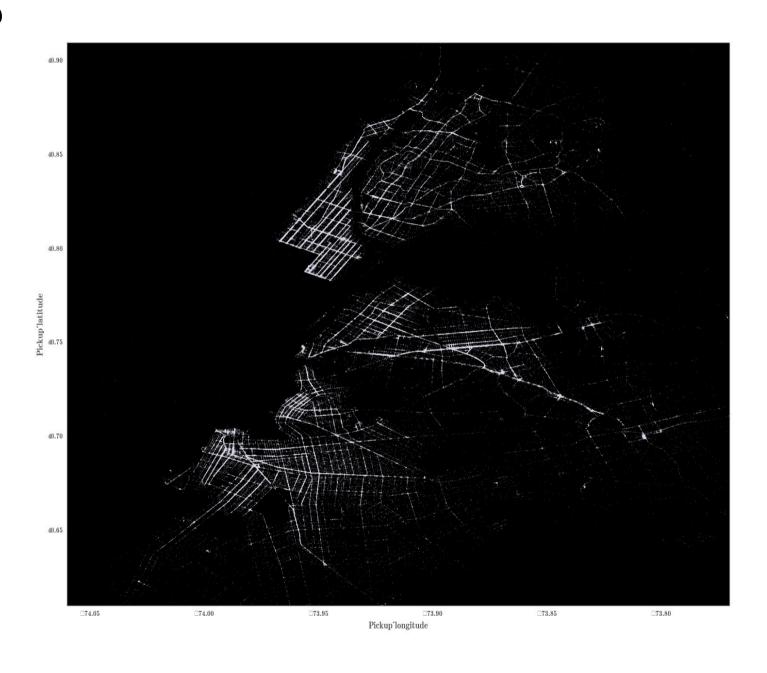
Mapping the data: tip>mean

Pickup



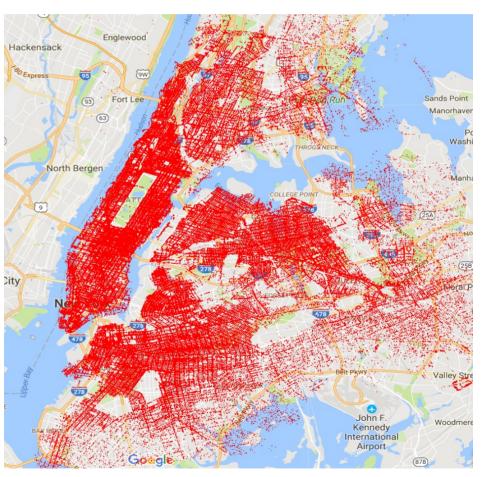
Mapping the data: tip<mean

Pickup



Mapping the data





Classification model

- Classify a transaction with and without tip
- Target = with tip
- Predictors = Payment_type, Total_amount, Trip_duration, Speed,
 MTA_tax, Extra, Hour, Direction_NS, Direction_EW, with_rain
- Training sample size: 10000
- 5-fold cross validation
- Optimized number of trees: 150

•

Classification model

Model report:

Accuracy: 0.9937

AUC Score (Train): 0.999914898879

CV Score - Mean: 0.9959447 | Std: 0.001198673 | Min: 0.9941585 | Max: 0.997252

