Symbolic network analysis of bike sharing data

Citi Bike

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Outline

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Last version of slides (June 14, 2017, 09 : 53): bikesSDA.pdf

Kaggle

Some time ago I found on Kaggle

https://www.kaggle.com/benhamner/sf-bay-area-bike-share

a contest dealing with an analysis of data on bike sharing system in the San Francisco Bay Area. After some searching it turned out that similar data sets are available for several cities around the world (mainly in US).

Some Open data sets on Bike Sharing Systems

on my disk

Bike sharing	City	data available	# of trips
Capital	Washington, D.C.	2010/10-2016/09	14691090
Hubway	Boston	2011/07-2016/06	3930659
Divvy	Chicago	2013/01-2016/06	7867601
Citi Bike	New York	2013/07-2016/09	33319019
BABS	San Francisco	2013/08-2016/08	983648
Healthy Ride	Pittsburgh	2015/07-2016/09	118422
Indego	Philadelphia	2015/04-2016/09	673703
NiceRide	Minnesota	2010/06-2015/12	1808452
Santander C.	London	2015/01-2016/11	19212558

Data about stations

The Stations file is a snapshot of station locations and capacities during the reporting time interval:

- Station ID
- Station name
- Lat/Long coordinates
- Number of individual docking points at each station

In some cases also the data about station elevantions are available.

North American Bike Share Association's open data standard – gbfs
General Bikeshare Feed Specification; Systems using gbfs.

Most of the systems provide a feed service returning a JSON file with current status of stations.
Divvy, Indego, CitiBike stations: info, status

Reading station status in R

```
wdir <- "C:/Users/batagelj/data/bikes/philly"
setwd(wdir)
stat <- "https://gbfs.bcycle.com/bcycle_indego/station_status.json"
num <- 0
setInternet2(use = TRUE)
p1 <- proc.time()
while (num < 5){
   num <- num+1
   fsave <- paste('status_',as.character(num),'.json',sep='')
   test <- tryCatch(download.file(stat,fsave,method="auto"),
                    error=function(e) e)
   Sys.sleep(60)
   p2 <- proc.time()
   cat(p2 - p1,'\n'); flush.console()
   p1 <- p2
}
```

Data about trips

Each trip is anonymized and includes:

- Bike number
- Trip start day and time
- Trip end day and time
- Trip start station
- Trip end station
- Rider type

In some cases additional data are available: Gender, Year of birth.

Additional data sources

Weather

For cities in US we can get the weather data at NOAA, Quality Controlled Local Climatological Data

Precipitations, wind, temperature, humidity, pressure.

Maps

The ESRI shape files descriptions of maps can be found using Google.

Boston, Bay Area Cities, New York, Pittsburgh

Large temporal and spatial network data.

There were some contests for analysing of bike sharing data. Some interesting observations were presented. Also some blogs and papers were written on this topic.

In December 2016 there were 100 hits in WoS to the query `"bike sharing system*"`.

Analyses

Different overall distributions:
Pitts; Bay; Boston; NYC BSS

Impact of weather: temperature (day/night, winter), precipitations.

Cycles: year (temperature), week (working days/weekend), day (hours, parts of the day): week; days in a week

Other factors: subscriber/customer, trip duration, gendre, rider's age, speed, elevation: age

The moves of bikes among stations by the system can be recognized as those rides where the bike's next trip started at a different station from where the previous trip dropped off.
Arrivals/departures; Boston; Changes

Prediction: SF Bay Area: count prediction

Analyses

We find especially interesting a blog by

Todd W. Schneider: A Tale of Twenty-Two Million Citi Bike Rides: Analyzing the NYC Bike Share System

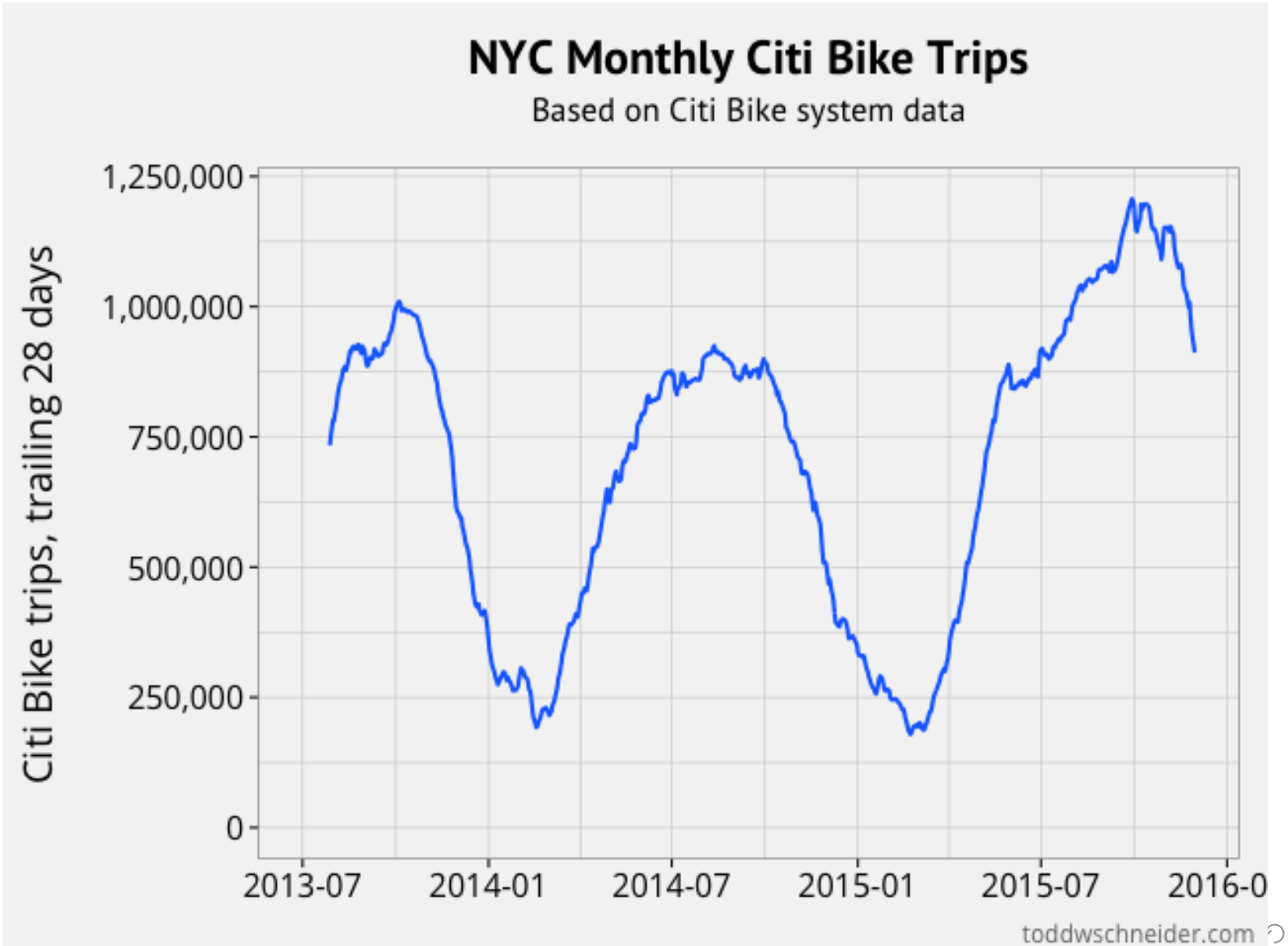
and

Jackson Whitmore: What's happening with Healthy Ride?, April 2016.

In the following slides we present some results from them.

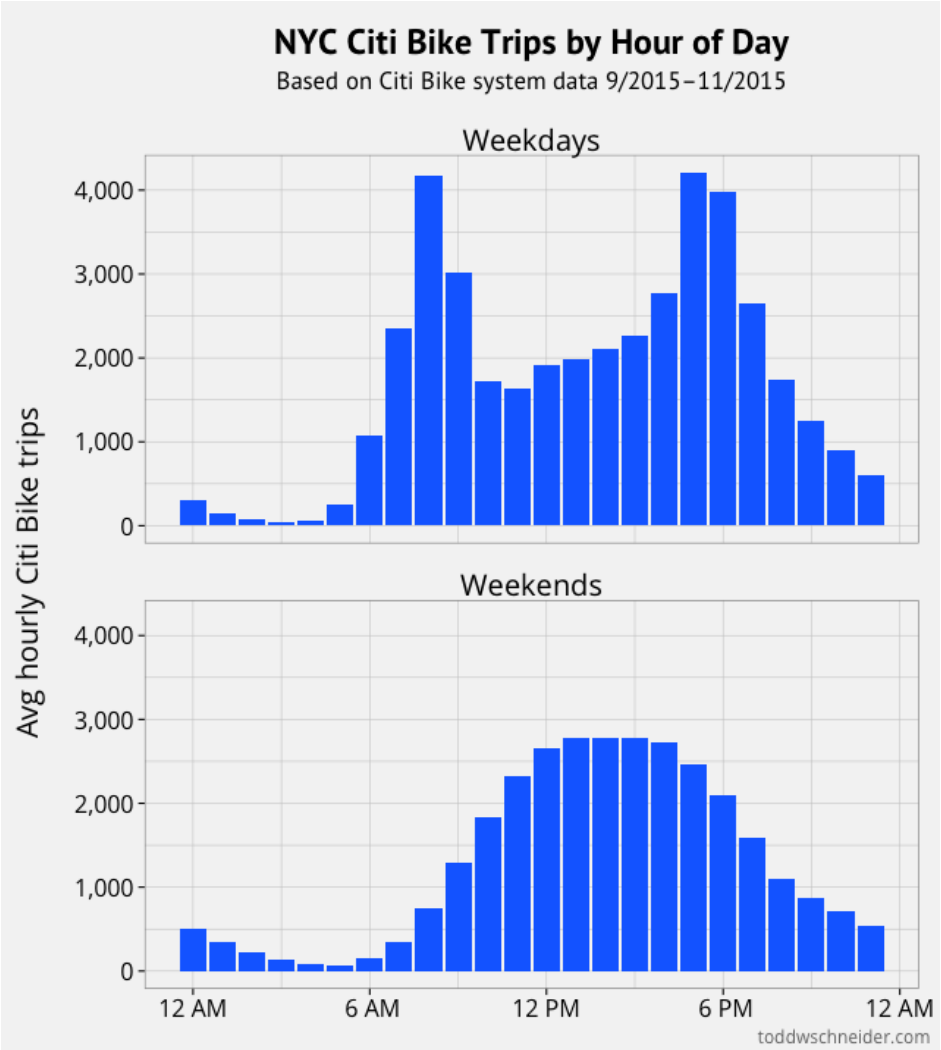
Year / Winter

by Todd W. Schneider



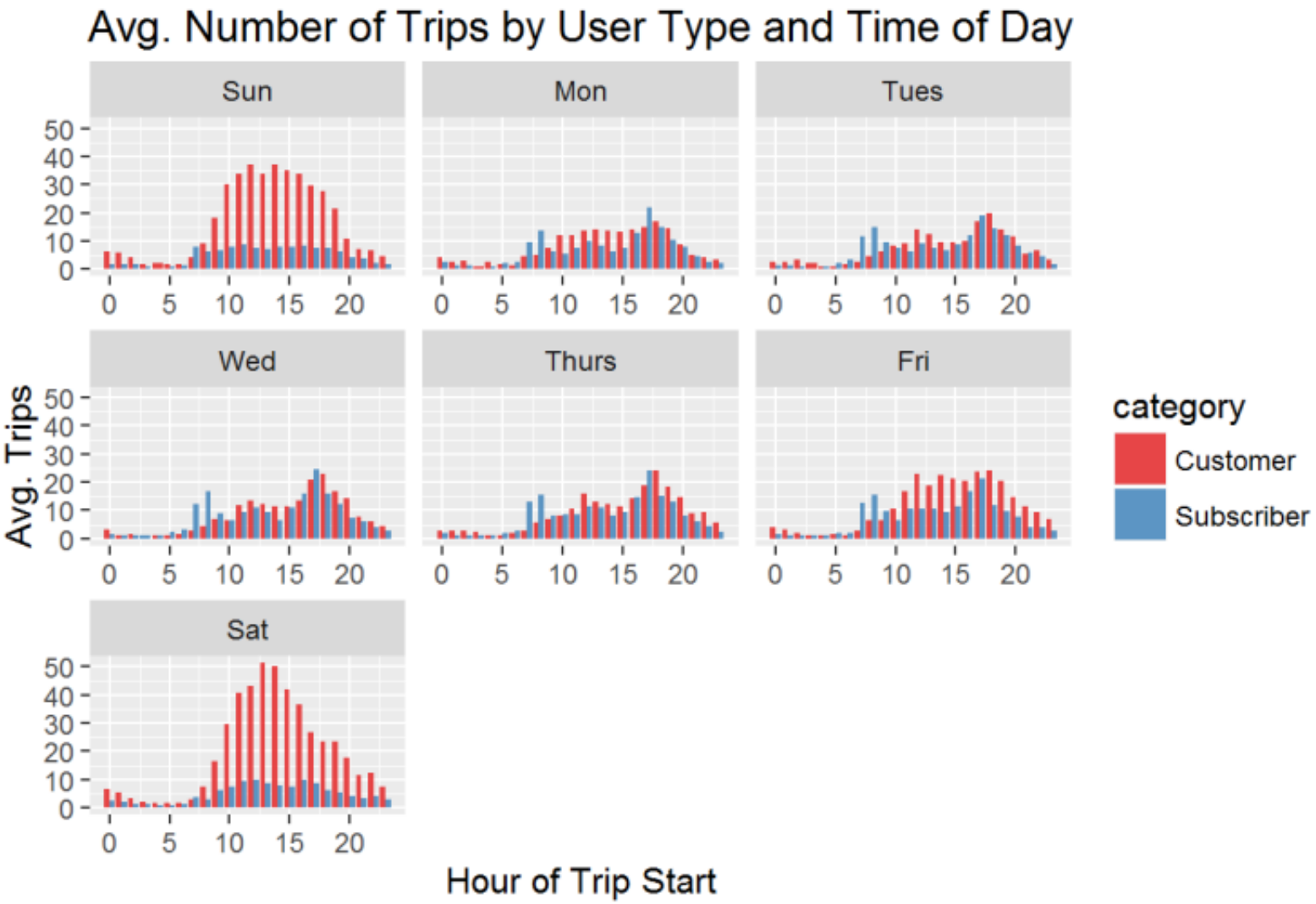
Working days / Weekend

by Todd W. Schneider



Subscribers / Custumers

by Jackson Whitmore



Bike sharing data and networks

The bike sharing data can be viewed as a spatial and temporal network:
Nodes – stations: name, location, capacity, (state)
Links – trips: from, to, start time, finish time, bike's id, rider type, gender, age

From this basic network we can construct several *derived* networks.

In most systems the data about nodes are static – fixed for longer period of time. It could be possible to collect these data using feeds.

Selecting an appropriate granulation (5 min, 15 min, 1 hour, part of a day, day, week, month, quartal, year) and some restrictions (rider type, gender, age, ...) we get the corresponding frequency distributions in nodes and on links.

Symbolic networks

Assigning distributions to nodes and links we get a *symbolic network*.

There are different distributions on links:
departures: (# of trips starting in selected time interval),
activity: (# of trips active in selected time interval),
duration: (# of trips with duration in selected time interval), etc.

and in nodes, for example:

departures: the sum of link distributions for incident links,
imbalance, etc.

Our analysis

NY Citi Bike one year data from October 2015 to September2016. 13266296 trips, 678 stations.

The Citi Bike system had an expansion in August 2015.

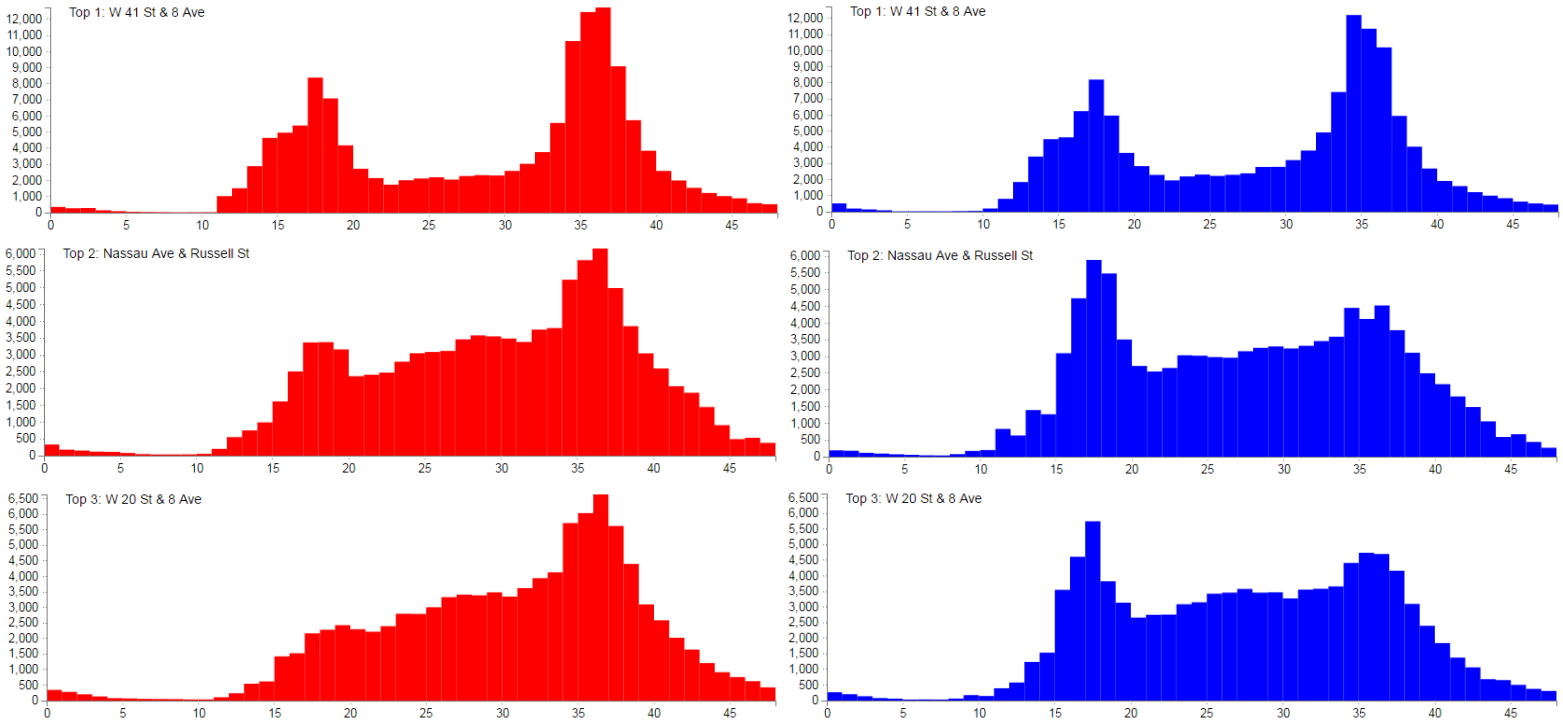
We constructed a departures network with daily distributions with half hour granulation.

First we looked for extreme elements (links or nodes).

In a selected time interval:
$flow(u, v) = \#$ of trips starting in a node u and finishing in a node v
$out(v) = \#$ of trips starting in a node v
$in(v) = \#$ of trips finishing in a node v
$flow(u, v; k) =$
$\#$ of trips starting in a node u in the$k$-th half hour and finishing in a node v
...

The most active stations / Top 3

$activity(v) = out(v) + in(v)$



n	station	trips	n	station	trips
1	W 41 St & 8 Ave	281996	6	W 45 St & 8 Ave	170593
2	Nassau Ave & Russell St	203855	7	W 38 St & 8 Ave	164378
3	W 20 St & 8 Ave	200629	8	E 14 St & Avenue B	163962
4	W 16 St & The High Line	196414	9	E 53 St & Madison Ave	162828
5	W 22 St & 8 Ave	188394	10	W 53 St & 10 Ave	161931

Imbalance

In a selected time interval:

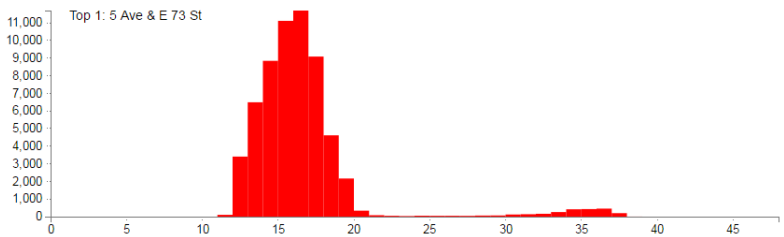
$$diff(v) = out(v) - in(v)$$

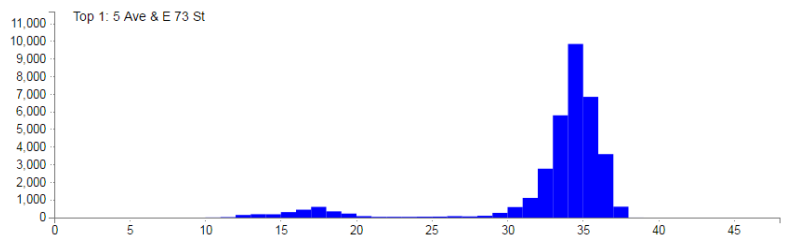
$$fDist(v) = \sum_{k=1}^{48} |out(v;k) - in(v;k)|$$

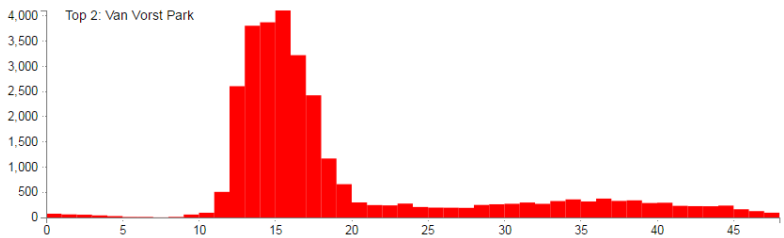
n	station	out	in	diff	station	fDist
1	5 Ave & E 73 St	60524	34559	25965	5 Ave & E 73 St	84703
2	Van Vorst Park	29962	14920	15042	Fulton St & William St	66453
3	8 Ave & W 33 St	57127	67592	-10465	E 75 St & 3 Ave	51297
4	W Broadway & Spring St	15217	23544	-8327	W 22 St & 8 Ave	50530
5	E 51 St & 1 Ave	72651	80783	-8132	E 33 St & 2 Ave	47893
6	E 75 St & 3 Ave	56302	48891	7411	Water - Whitehall Plaza	45554
7	Catherine St & Monroe St	36858	29455	7403	E 51 St & 1 Ave	34086
8	E 45 St & 3 Ave	48116	41601	6515	W 37 St & 10 Ave	33865
9	Water - Whitehall Plaza	71364	65638	5726	Cambridge Pl & Gates Ave	32562
10	6 Ave & Canal St	23473	28451	-4978	E 16 St & Irving Pl	30293

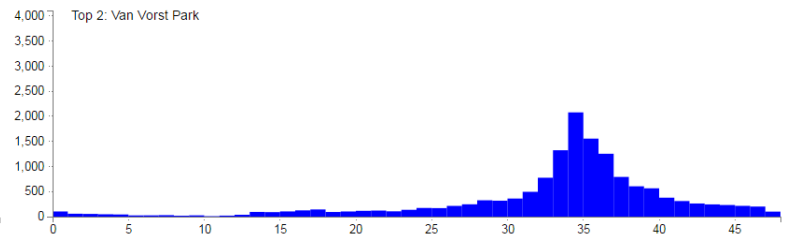
Imbalance / diff

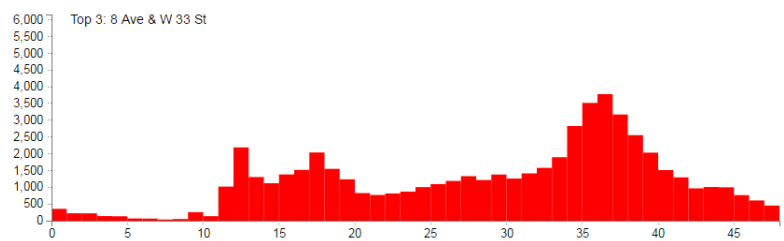
Top 4

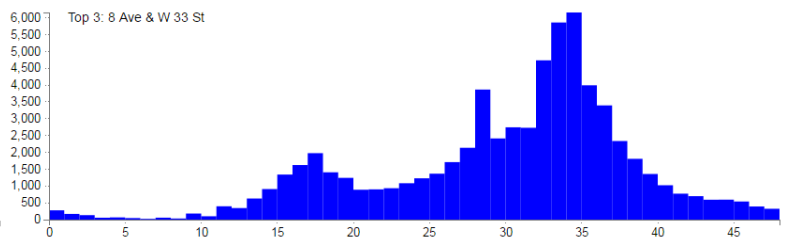


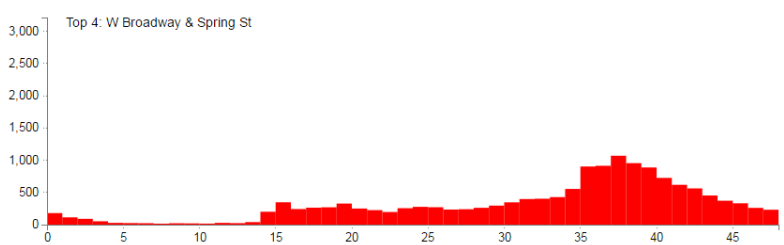


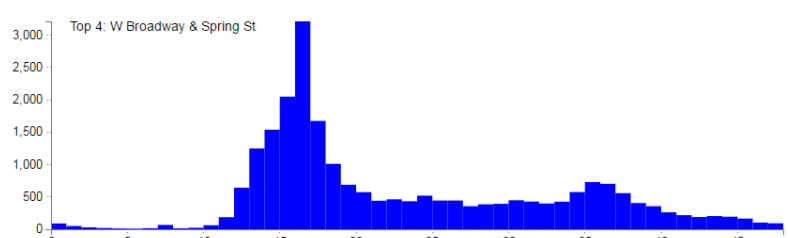






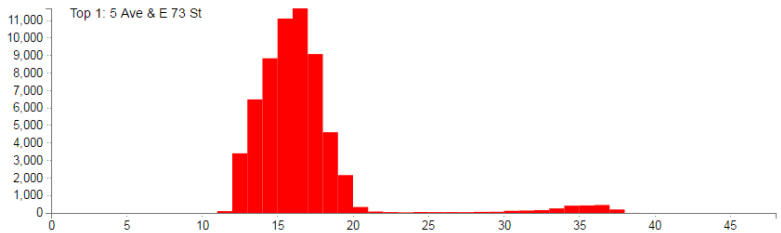


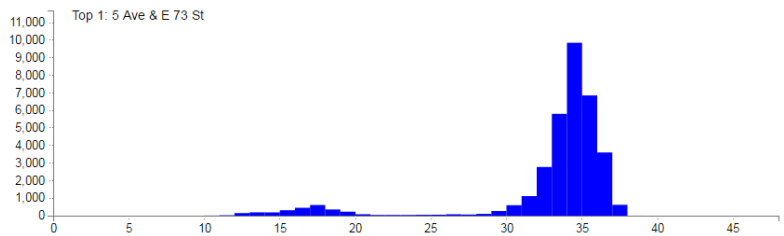


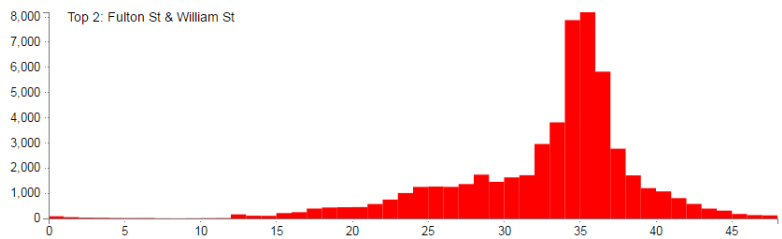


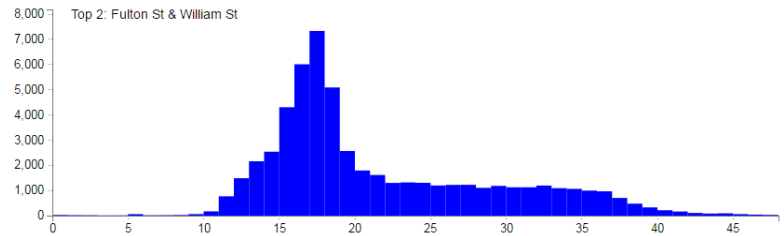
Imbalance / fDist

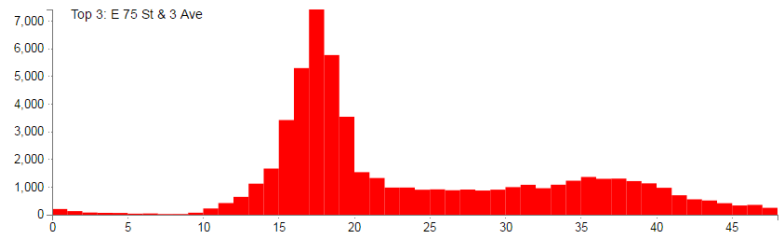
Top 4

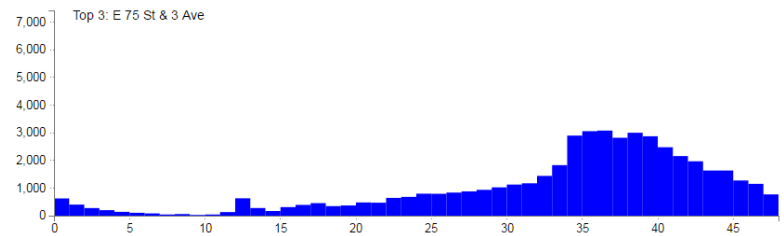


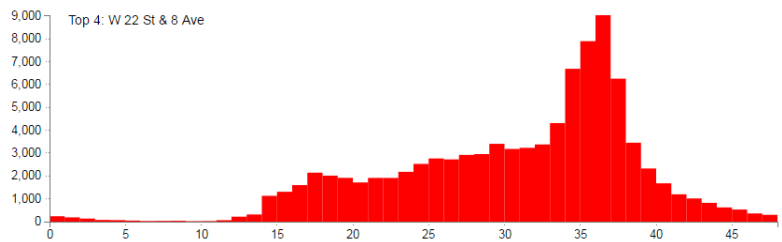


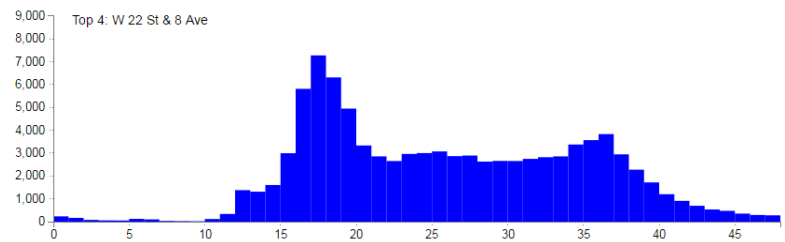




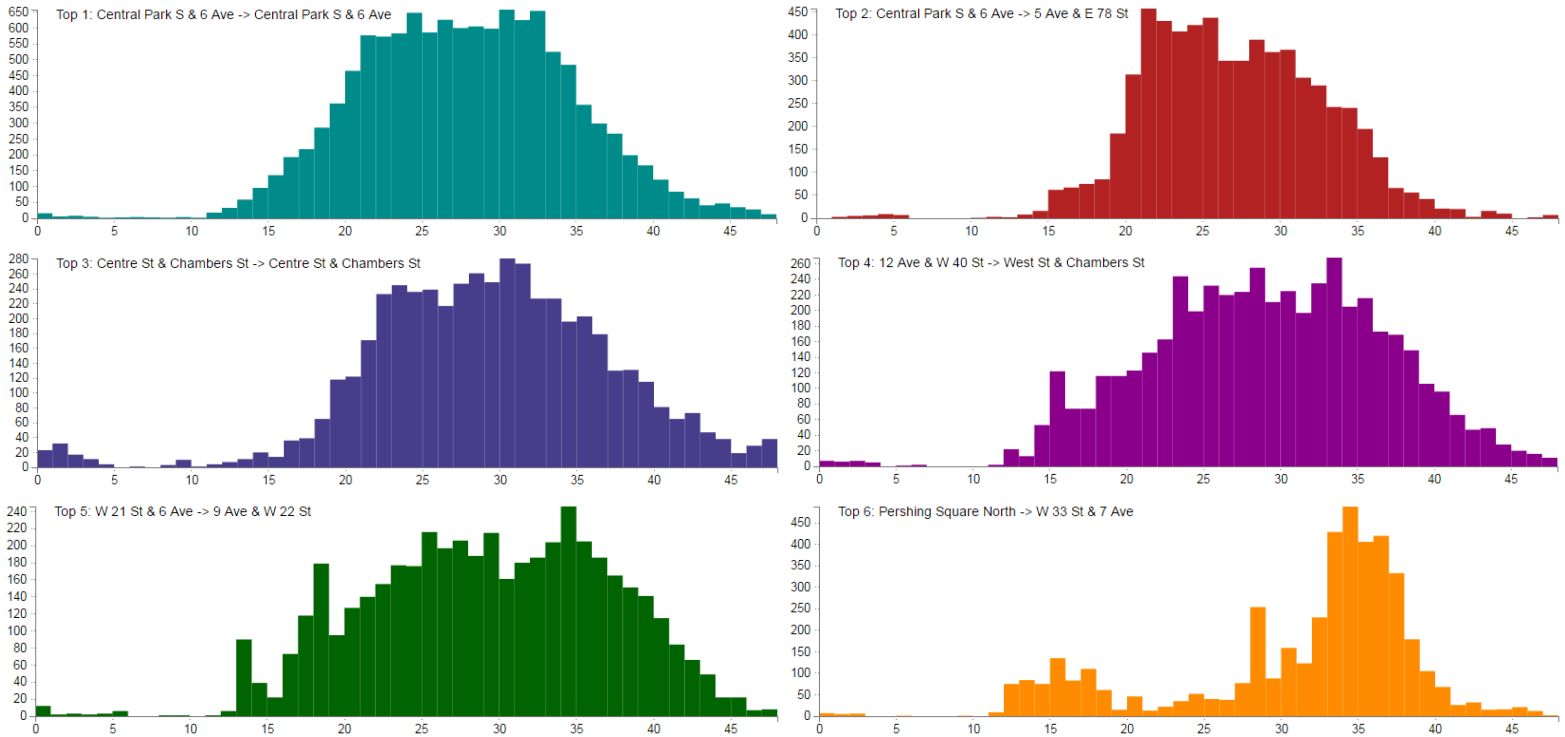








The largest flows / Top 6

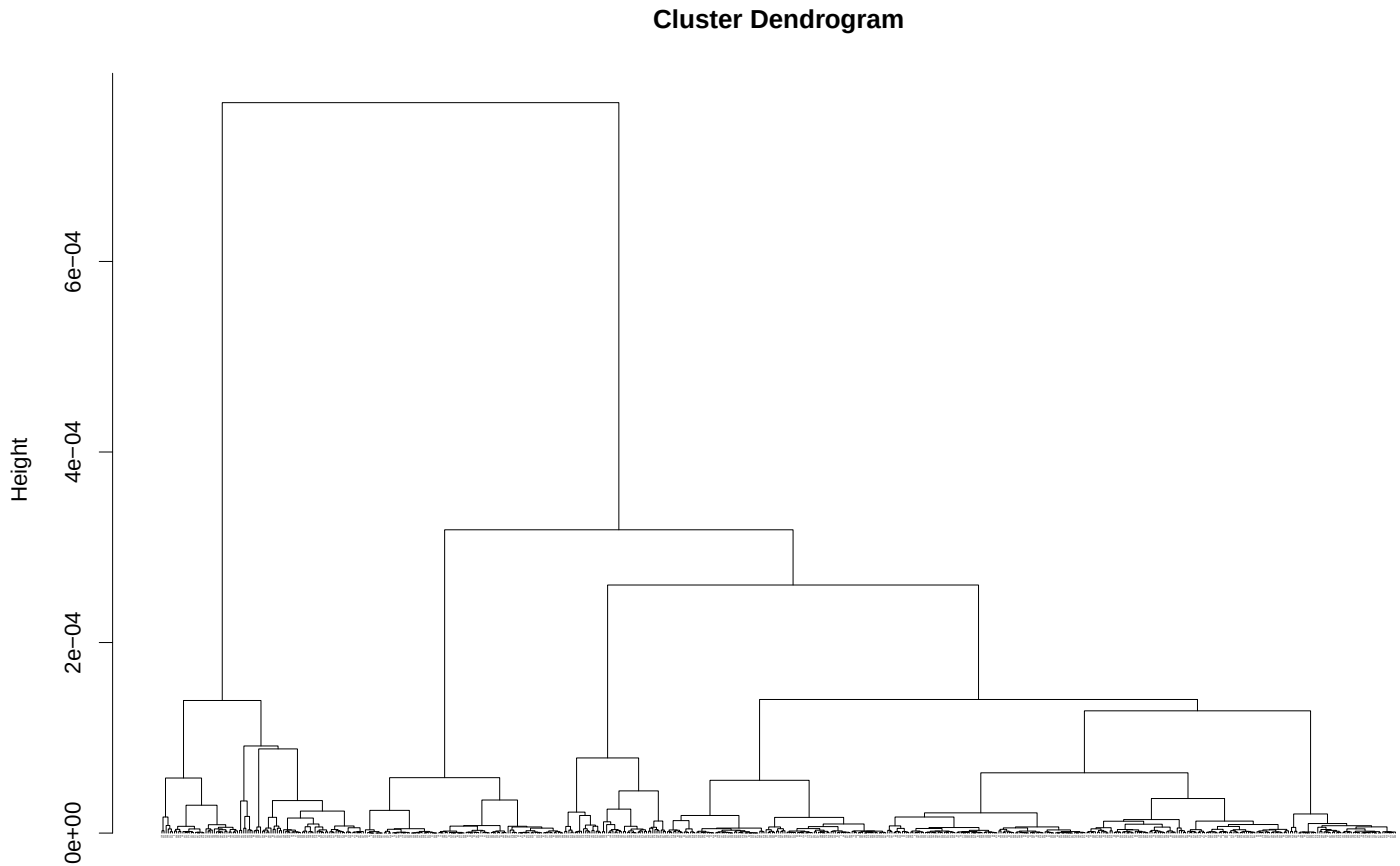


Clamix – Clustering modal valued symbolic data

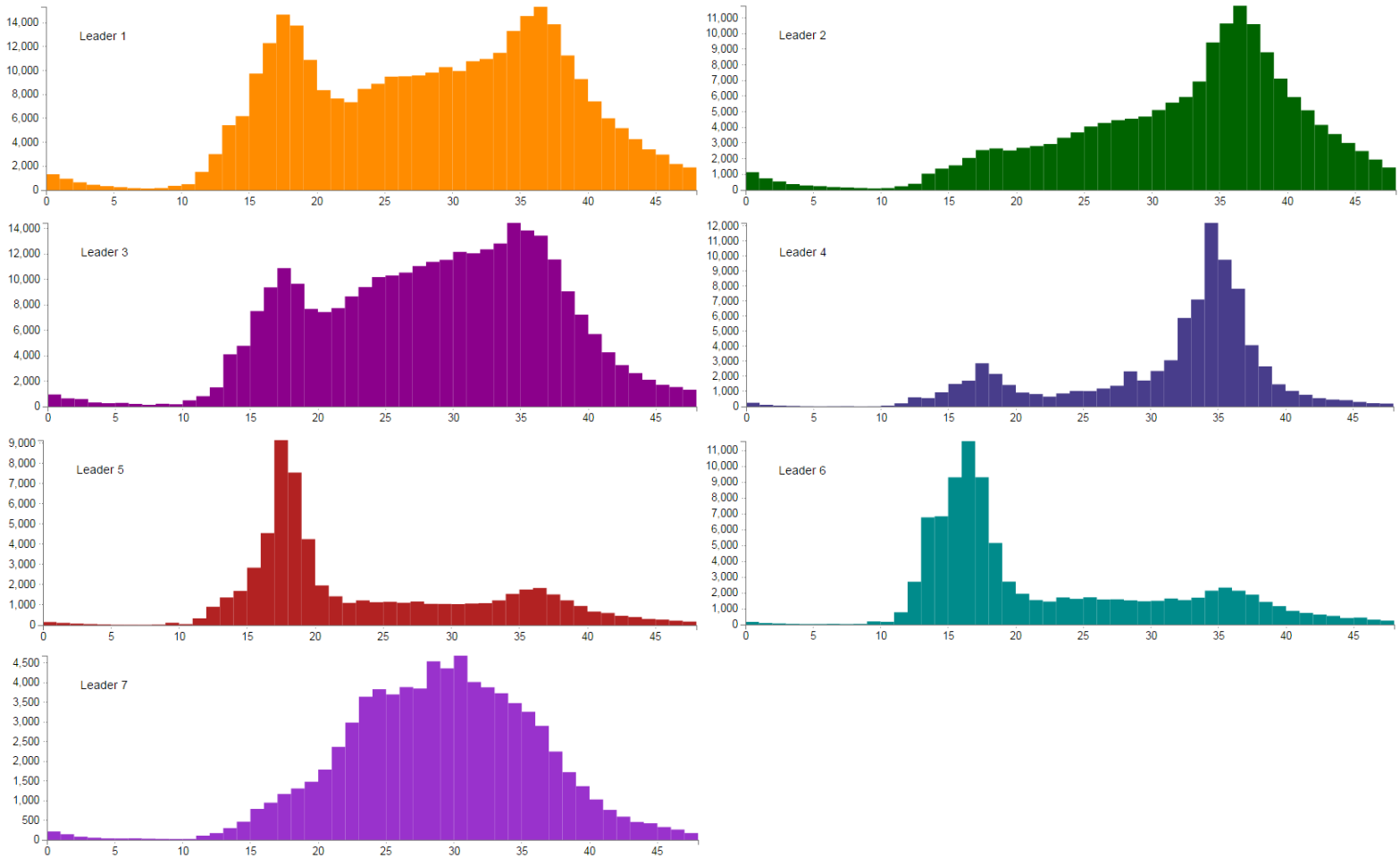
Two clustering methods for symbolic objects are implemented: the adapted leaders method and the adapted agglomerative hierarchical clustering Ward's method.
Clamix: R-forge, doc
Paper: V. Batagelj, N. Kejžar, and S. Korenjak-Černe. Clustering of Modal Valued Symbolic Data. ArXiv e-prints, 1507.06683, July 2015.

We clustered the set of 589 links with flow at least 1250. This gives as typical flow distribution shapes.

Clustering of flows



Clustering of flows / 7 clusters



Conclusions

- bike sharing data are an interesting type of data,
- prepare some extended data sets; get or collect the dynamic stations data,
- additional analyses:
  - other symbolic objects: nodes (in and out distribution), links (subscriber, custumer distribution), ...
  - stability of distribution shape through time
  - ...
- compare bike sharing systems
- Taxi (Yellow and Green) and Uber data are available for New York.

References I

1. V. Batagelj, N. Kejžar, and S. Korenjak-Černe. Clustering of Modal Valued Symbolic Data. ArXiv e-prints, 1507.06683, July 2015.
2. Lynne Billard; Edwin Diday (14 May 2012). Symbolic Data Analysis: Conceptual Statistics and Data Mining. John Wiley & Sons.
3. Bay Area Bike Share: San Francisco Bay Area - Kaggle challenge, Open data, challenge
4. Todd W. Schneider: A Tale of Twenty-Two Million Citi Bike Rides: Analyzing the NYC Bike Share System.
5. Jackson Whitmore: What's happening with Healthy Ride?, April 2016.

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