



Bikes

V. Batagelj,
A. Ferligoj

Kaggle

Data sets

Analyses

Conclusions

References

Symbolic network analysis of bike sharing data

Citi Bike

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CMStatistics 2016

Sevilla, 9-11. December 2016

Bikes

V. Batagelj,
A. Ferligoj

Kaggle

Data sets

Analyses

Conclusions

References

- 1 Kaggle
- 2 Data sets
- 3 Analyses
- 4 Conclusions
- 5 References



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Last version of slides (12. december 2016, 14:39):
[bikes.pdf](#)



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Kaggle

Data sets

Analyses

Conclusions

References

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

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Kaggle

Data sets

Analyses

Conclusions

References

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



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Data sets

Analyses

Conclusions

References

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 elevations 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

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Kaggle

Data sets

Analyses

Conclusions

References

```
wdir <- "C:/Users/batagelj/data/bikes/philly"  
setwd(wdir)  
stat <- "https://gbfs.bicycle.com/bicycle_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

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Data sets

Analyses

Conclusions

References

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

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Analyses

Conclusions

References

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*".



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A. Ferligoj

Kaggle

Data sets

Analyses

Conclusions

References

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



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Bikes

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A. Ferligoj

Kaggle

Data sets

Analyses

Conclusions

References

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

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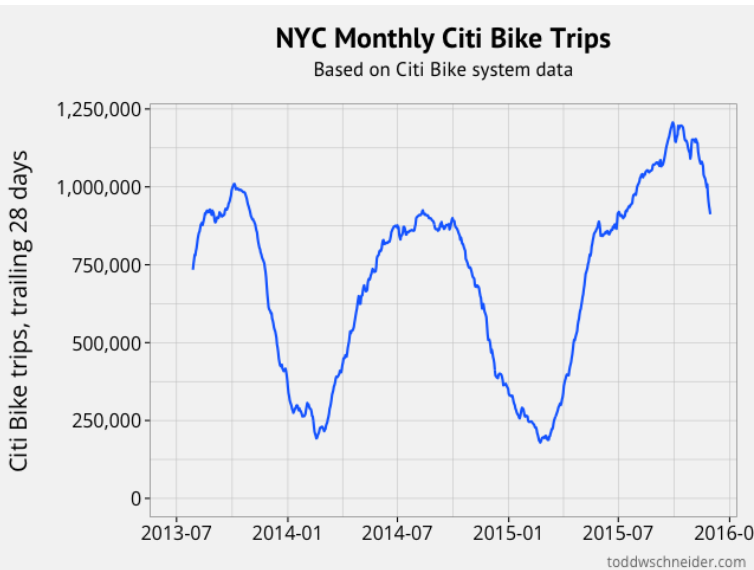
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Data sets

Analyses

Conclusions

References



toddwschneider.com

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Working days / Weekend

by Todd W. Schneider

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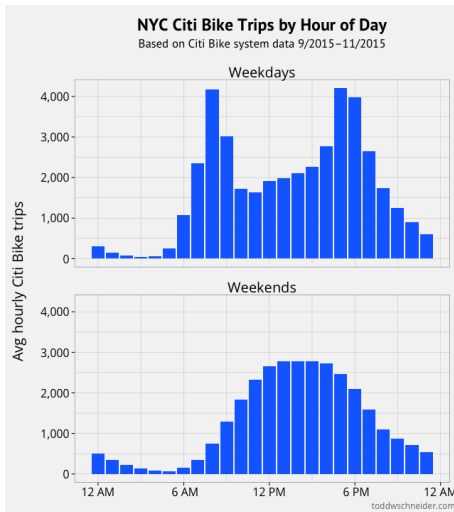
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Data sets

Analyses

Conclusions

References





Subscribers / Customers

by Jackson Whitmore

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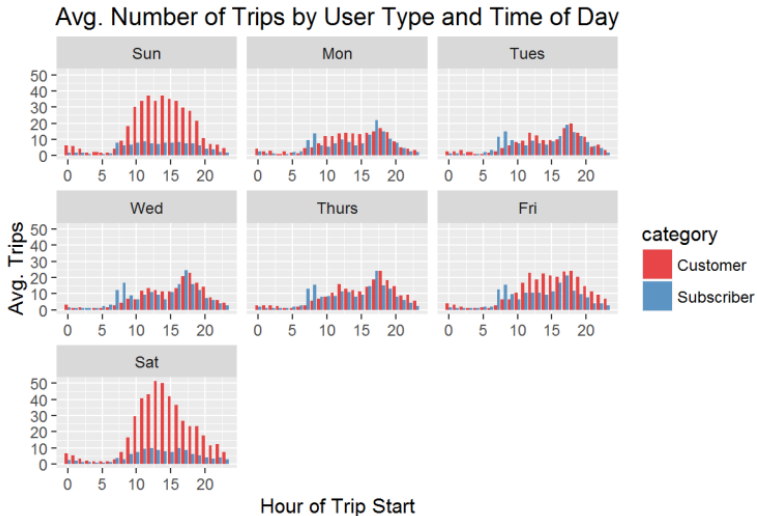
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Data sets

Analyses

Conclusions

References





Bike sharing data and networks

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Data sets

Analyses

Conclusions

References

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.

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Kaggle

Data sets

Analyses

Conclusions

References

Symbolic data analysis (SDA) is an extension of standard data analysis where symbolic data tables are used as input and symbolic objects are outputted as a result. The data units are called symbolic since they are more complex than standard ones, as they not only contain values or categories, but also include internal variation and structure. SDA was proposed by Edwin Diday in 1980's (see [book](#)). 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

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Data sets

Analyses

Conclusions

References

NY Citi Bike one year data from October 2015 to September 2016.
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

$$\text{activity}(v) = \text{out}(v) + \text{in}(v)$$

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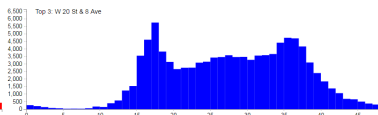
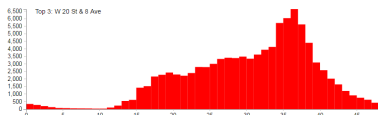
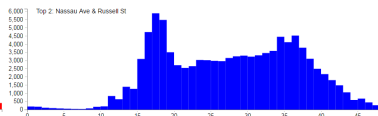
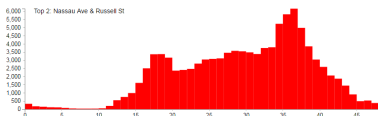
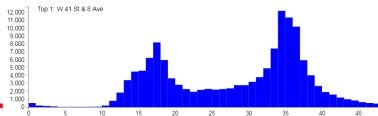
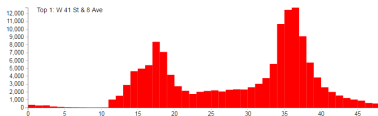
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Data sets

Analyses

Conclusions

References



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

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In a selected time interval:

$$\text{diff}(v) = \text{out}(v) - \text{in}(v)$$

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

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

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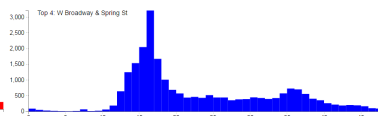
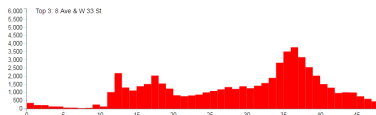
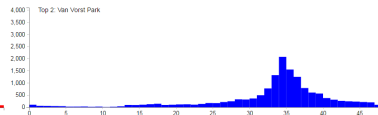
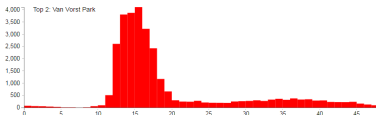
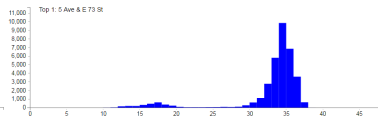
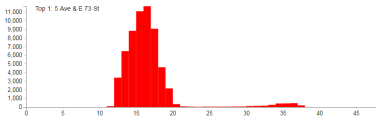
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Data sets

Analyses

Conclusions

References





Imbalance / fDist

Top 4

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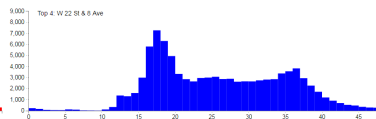
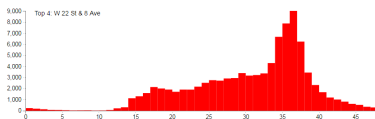
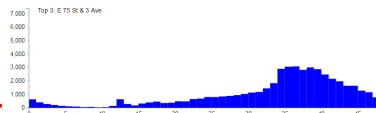
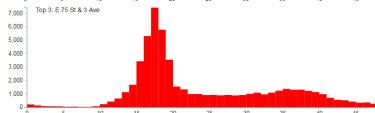
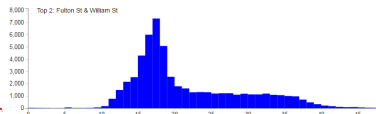
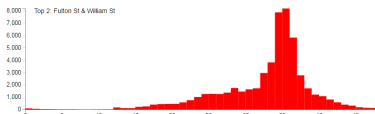
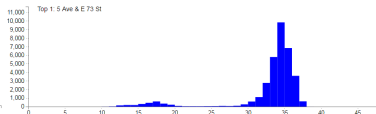
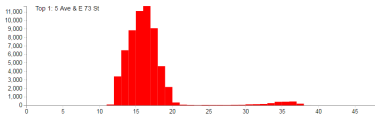
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Data sets

Analyses

Conclusions

References





The largest flows / Top 6

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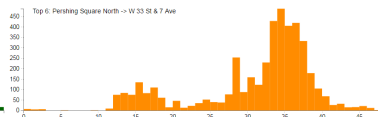
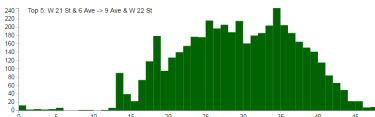
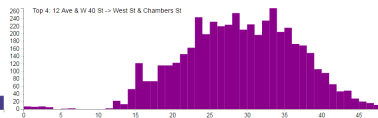
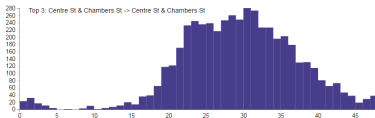
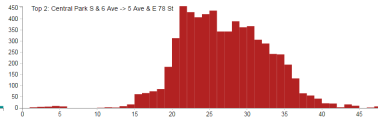
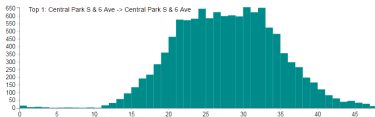
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Data sets

Analyses

Conclusions

References





Clamix – Clustering modal valued symbolic data

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Data sets

Analyses

Conclusions

References

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

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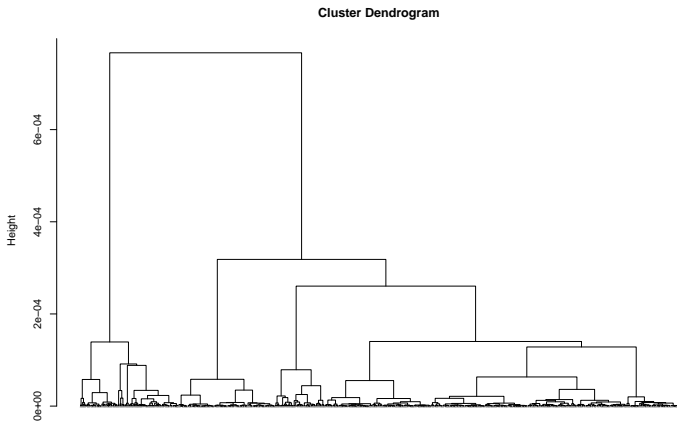
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Data sets

Analyses

Conclusions

References





Clustering of flows / 7 clusters

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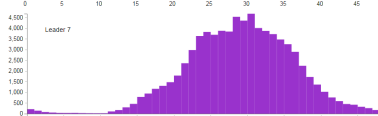
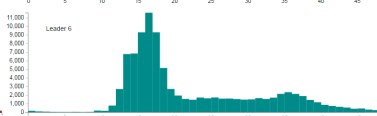
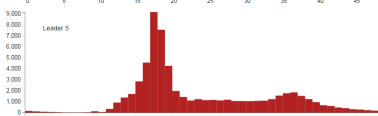
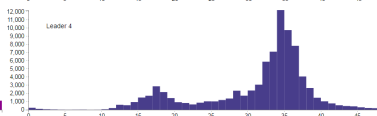
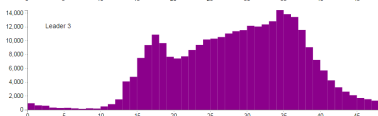
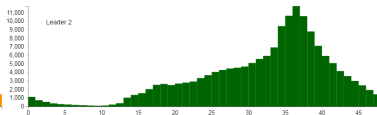
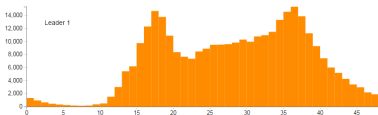
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Data sets

Analyses

Conclusions

References



Bikes

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A. Ferligoj

Kaggle

Data sets

Analyses

Conclusions

References

- 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, customer distribution), ...
 - stability of distribution shape through time
 - ...
- compare bike sharing systems
- Taxi (Yellow and Green) and Uber data are available for New York.

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Kaggle

Data sets

Analyses

Conclusions

References

- 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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Bikes

V. Batagelj,
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Kaggle

Data sets

Analyses

Conclusions

References

This work was supported in part by the Slovenian Research Agency (research programs P1-0294 and research projects J5-5537 and J1-5433).

The first author's attendance on the conference was partially supported by the COST Action IC1408 – CRoNoS.