Sensing and Predicting the Pulse of the City through Shared Bicycling

International Workshop on Spatio-temporal Data Mining for a Better Understanding of Human Mobility: The Bicycle Sharing System Case Study
December 5th, Paris, France

Human Computer Interaction Laboratory

@jonfroehlich
Assistant Professor Computer Science

UNIVERSITY OF MARYLAND

A quick story re: **traveling** to this workshop.

This is an operations problem
a user satisfaction problem
a perception problem

I never take Vélib'. The redistribution is completely broken.

— Girl On Train
Parisian Exchange Student from England

bikeshare research stakeholders & benefits


Transportation Research Part C 22 (2012) 88–102

Contents lists available at SciVerse ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

Measuring the impact of opening the London shared bicycle scheme to casual users

Neal Lathia *, Saniul Ahmed, Licia Capra

Dept. of Computer Science, University College London, Gower Street, London WC1E 6BT, United Kingdom

A R T I C L E I N F O

Article history:
Received 4 July 2011
Received in revised form 12 December 2011
Accepted 14 December 2011

Keywords:
Shared bicycles
Data mining
Mobility
Policy

A B S T R A C T

The increasing availability of sensor data in urban areas now offers the opportunity to perform continuous evaluations of transport systems and measure the effects of policy changes, in an empirical, large-scale, and non-invasive way. In this paper, we study one such example: the effect of changing the user-access policy in the London Barclays Cycle Hire scheme. When the scheme was launched in July 2010, users were required to apply for a key to access to the system. By December 2010, this policy was overridden in order to allow for "casual" usage, so that anyone in possession of a debit or credit card could gain access. While the transport authority measured the policy shift's success by the increased number of trips, we set out to investigate how the change affected the system's usage throughout the city. We present an extensive analysis of station data collected from the scheme's web site both pre- and post-policy change, showing how differences in both global and local behaviour can be measured, and how the policy change correlates with a variety of effects observed around the city. We find that, as expected, quicker access to the system correlates with greater week end usage; it also reinforces the week-day commuting trend. In both the pre- and post-change periods, the geographic distribution of activity at individual stations forms concentric circles around central London. However, upon policy change, a number of stations undergo a complete usage change, now exhibiting an opposite trend with respect to that which they had prior to the policy change.

1. Introduction

"Cities embody [the] political decisions made by their designers" (Zuckerman, 2011).

As the world population grows and an ever-increasing proportion of people live in cities, designing, maintaining, and promoting sustainable urban mobility modes is becoming of paramount importance. Shared bicycle schemes (Shaheen et al., 2010) are one such example: their proliferation throughout the world's metropolises clearly reflects the belief that providing easy access to healthy (and quick) modes of transport will lead cities away from the congestion and pollution problems they currently face. Shared bicycle systems operate in urban areas by providing public access to bicycles from a fixed number of stations that are distributed around the city. Travellers may pick up bicycles from any station they choose and return them to any of the station's free parking slots. No limitation is placed on the usage (in terms of origin/destination); instead, the bicycle usage is often limited by *time* (e.g., free for first *x* minutes; penalty fare imposed if the bicycle is not returned within *y* hours).

A key facet of building successful shared bicycle system, and, more broadly, any urban public transport system, is understanding how designed system characteristics, implemented as policies, affect usage. To see how design may clash with

* Corresponding author. Tel.: +44 20 7679 7214.
E-mail address: n.lathia@cs.ucl.ac.uk (N. Lathia).

0968-090X/$ - see front matter © 2011 Published by Elsevier Ltd.
doi:10.1016/j.trc.2011.12.004

1. **Operators:** benefit from more accurate models of demand for load balancing

2. **End-users:** benefit from understanding and forecasting how system will be used for trip planning

3. **Urban planners:** can use bike models to improve the bikeability of the city

4. **Social scientists & human geographers:** can study and better understand human mobility and routine

The social sciences can finally have access to masses of data that are of the same order of magnitude of their older sisters, the natural sciences

Bruno Latour, 2007
French philosopher and sociologist

data

this talk

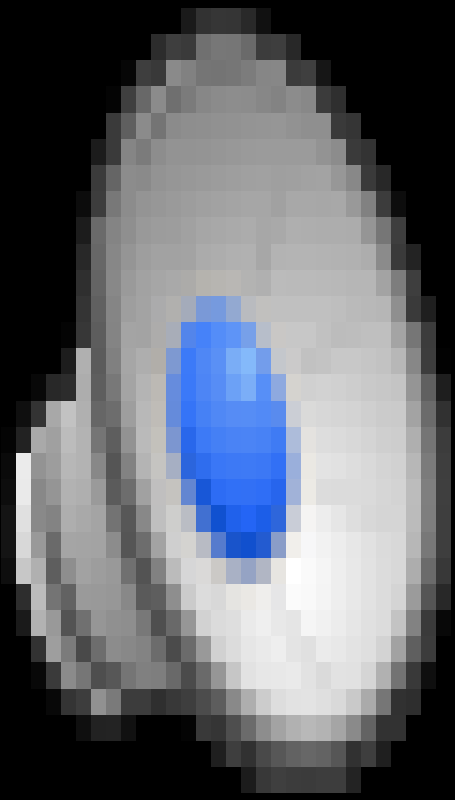
my
research

bikeshare data

granularity

Station Capacity Data

Data collection method
(1) Data dump from operator
(2) Scrape bikeshare website



bikeshare data

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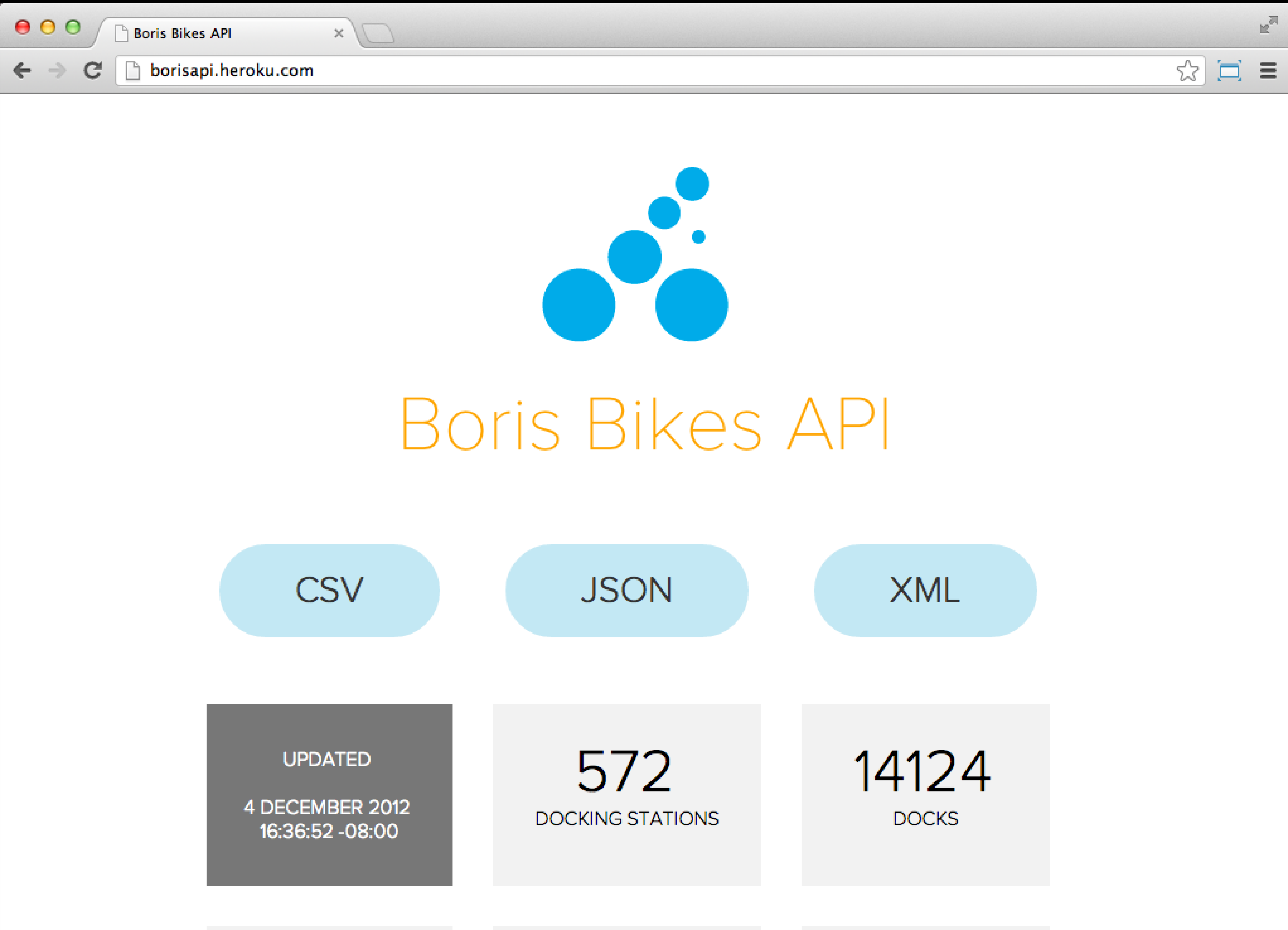

Boris Bikes API
borisapi.heroku.com
Boris Bikes API
CSV
JSON
XML
UPDATED
4 DECEMBER 2012
16:36:52 -08:00
572
DOCKING STATIONS
14124
DOCKS

bikeshare data

granularity

Station Capacity Data

O/D Bike Data

Data collection method
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(3) 3rd-party DIY APIs

Data collection method
(1) Data dump from operator
(2) ...

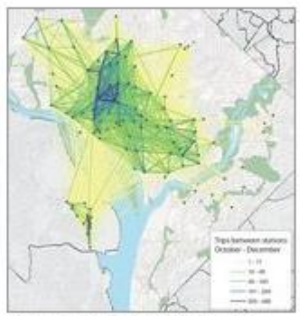
Greater Greater Washington

The Washington, DC area is great. But it could be **greater**.

Capital Bikeshare releases anonymous trip data

by David Alpert • January 11, 2012 3:32 pm

Programmers or analysts interested in studying Capital Bikeshare patterns or creating useful apps can now do a lot more. Capital Bikeshare has followed through on its promise and posted data files with individual (but anonymous) trip data.



Anyone can now make a map like this one of CaBi trip patterns. Image from CommuterPageBlog.

The files, one for each quarter going back to late 2010, list individual trips, including the time each started and ended, duration, which station it started and ended at, and an identifying number for the individual bike. It doesn't say anything about the member who used the bike, except whether they are a "registered" (annual or monthly) member or a "casual" member (daily or 3- or 5-day).

Now, people can generate tables or graphics showing the most popular station pairs, or where people most often go from an individual station, or what weather patterns make usage heavier or lighter, or where the nighttime activity is, and much more.

This data has been available for some time for London, allowing people to create animations of a day's CaBi usage and diagrams of a single bike's path over several days. The folks who built those and other tools can now even adapt their code to work for Capital Bikeshare, if they're so inclined.

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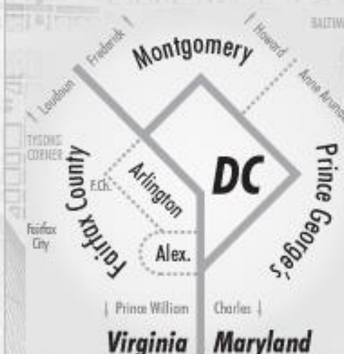
How can our region be **greater**?



Most Active **Posts**

Recent **Links**

Breakfast links: Getting around

- Metro keeping 2 Southeast bus routes
- Need to fund transit to grow
- Transit pays off
- What's going to happen to transportation?
- More DC Bikeshare delayed

Features

Animated history of Metrorail

Trip History Data | Capital B

www.capitalbikeshare.com/trip-history-data

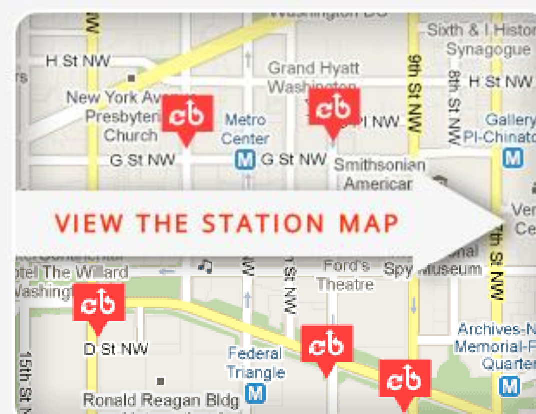
Trip History Data

Overview of the Trip History Data

When a rental occurs within the system our software collects basic data about the trip. That data can be exported from our system and used for various types of analysis or research. By making this data available we hope to stimulate that analysis or research amongst a much wider community. Please note, all private data including member names has been removed from these files.

What is included?

Each .csv file contains data for one quarter of the year. Within each file there are 7 columns.



Some Quick **Fun** Facts

Analysis Enabled by Anonymized O/D Bike Data

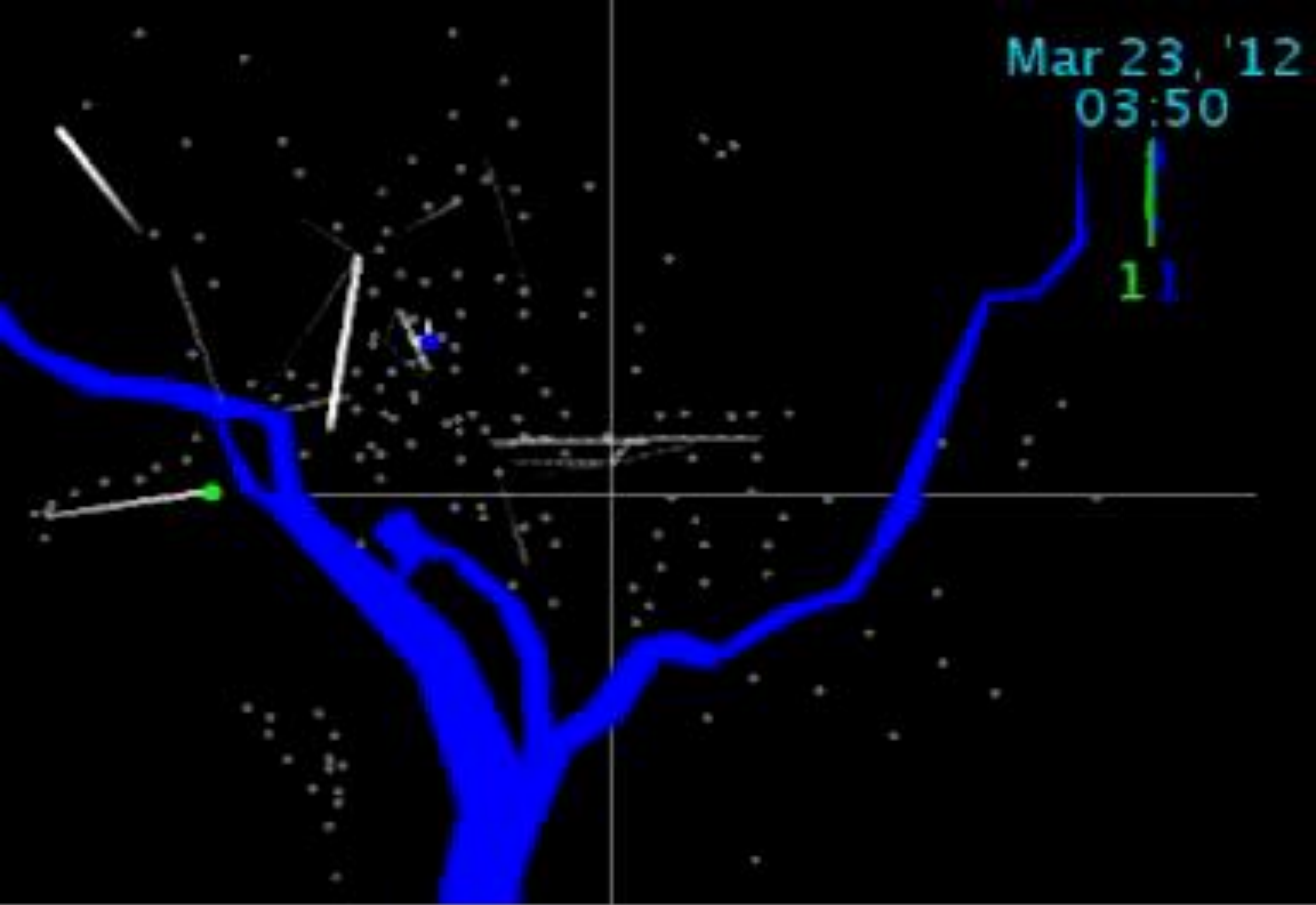
(1) "Average" trip is downhill (by -1.94 meters)

(2) Last mile usage: four most common trips are short and seem to cover areas that subway/bus do not

(3) Sixth most common trip is a return trip from Smithsonian station back to the Smithsonian station

(4) Casual vs. members usage fees: 40.7% casual riders incur fees vs. 3.3% of members incur fees

Source: *http://greatergreaterwashington.org/post/13351/capital-bikeshare-data-already-yields-interesting-facts/*



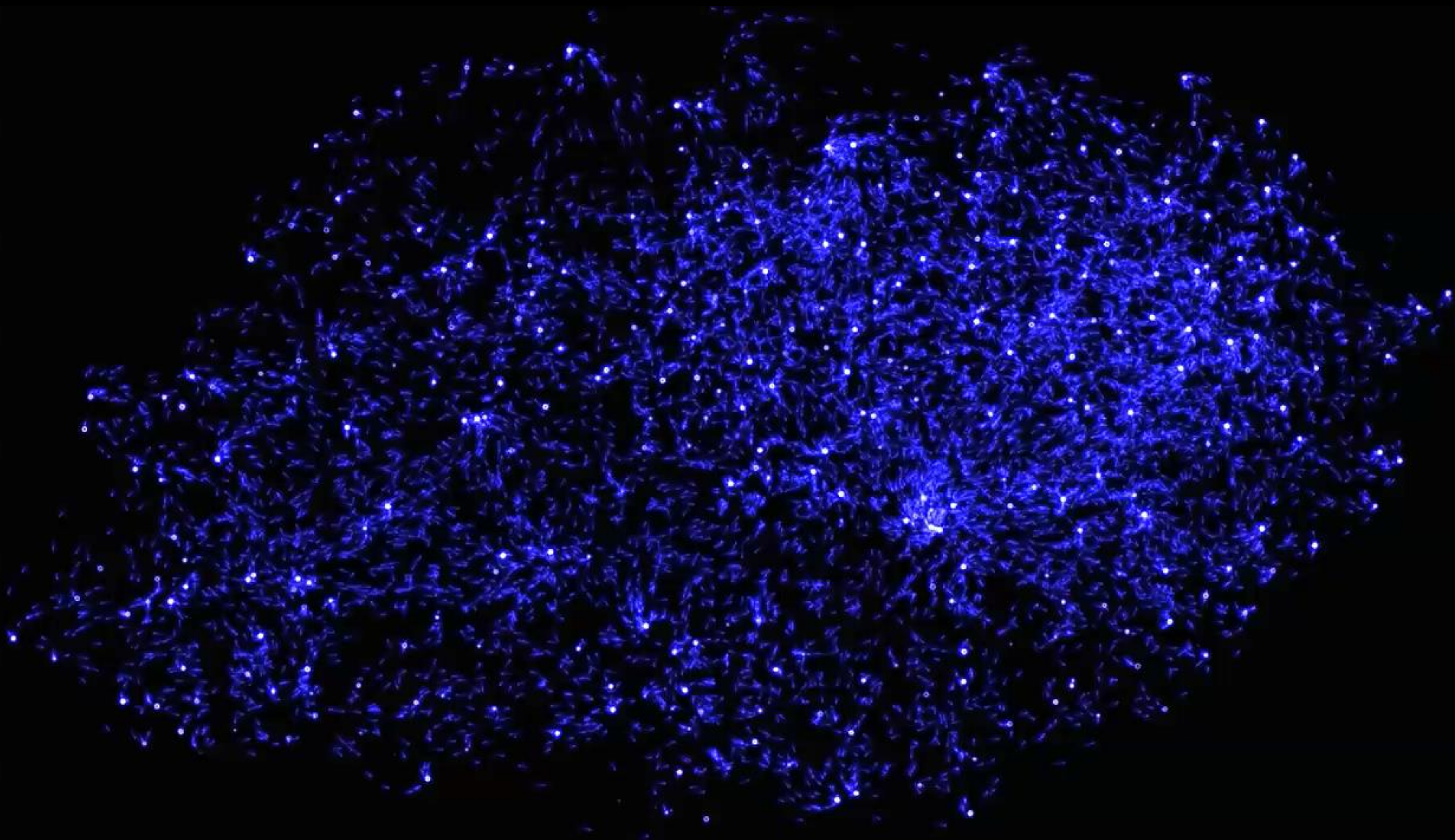
MV Jantzen, **CaBi Trips**, *http://youtu.be/-h0rV7tw1Eo*

Using **heuristics** to infer bike flow.

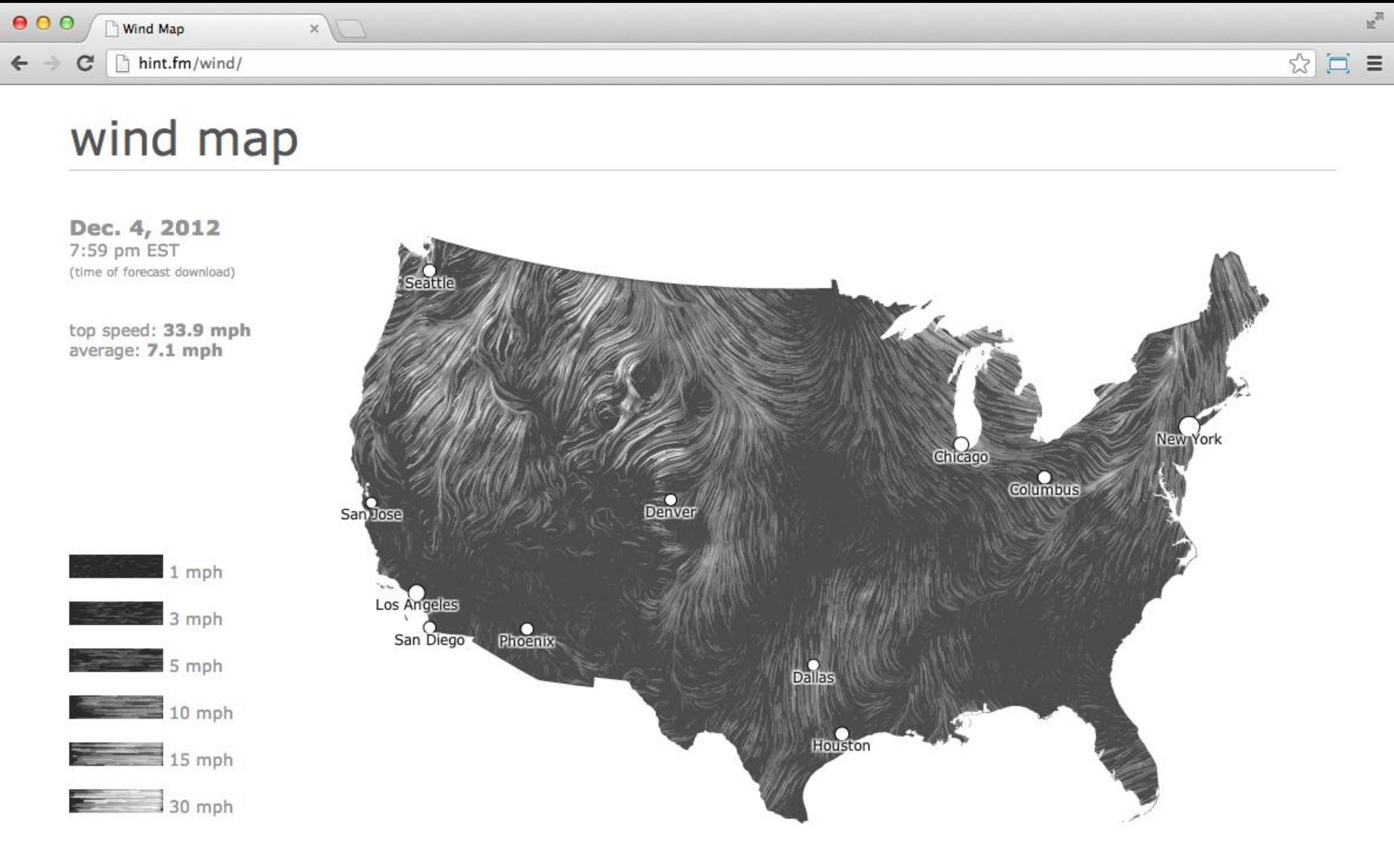
Martin Austwick & Oliver O’Brien, CASA-UCL, **Boris Bikes Redux**, *https://vimeo.com/19982736*

The routing is done using OpenStreetMap data & Routing routing scripts optimized for bike usage (*i.e.*, **constant speed** on all road types, **obeying one-way roads** and **taking advantage of marked cycleway**). I've tweaked the desirability of road types, so that the trunk and primary roads are only slightly less desirable than quieter routes.

— **Oliver O'Brien**
UCL CASL
http://oliverobrien.co.uk/2011/02/boris-bikes-flow-video-now-with-better-curves



Jo Wood, **Experiments in Bicycle Flow Animation**, *https://vimeo.com/33712288*



Fernanda Viegas & Martin Wattenberg, **Wind Map**, *http://hint.fm/wind/*

bikeshare data

granularity

Station Capacity Data

Data collection method
(1) Data dump from operator
(2) Scrape bikeshare website
(3) 3rd-party DIY APIs

O/D Bike Data

Data collection method
(1) Data dump from operator
(2) …

O/D User Data

Data collection method
(1) Data dump from operator
(2) Scrape user account logs

"Working collaboratively with Transport for London (TfL), customer records reporting a unique customer identifier, gender and postcode, have been made available. So too has a complete set of user journeys [for those customer ids]"

Identifying and Explaining Inter-Peak Cycling Behaviours within The London Cycle Hire Schem

R. Beecham[1], J. Wood[2], A. Bowerman[3]

[1]City University London, St. John's Street, London, EC1V 0HB
Email: roger.beecham.1@city.ac.uk

[2]City University London, St. John's Street, London, EC1V 0HB
Email: j.d.wood@city.ac.uk

customers using the scheme ... inter-peak usage. ... makers at TfL is to encourage this inter-peak usage.

Working with colleagues at TfL, and with access to LCHS's cus... databases, we attempt to identify and explain inter-peak trave... context, circumstances and customer characteristics that underpin... Using techniques from information visualization and geovizuali... Roberts 2004, Wood et al. 2011), we demonstrate how this ty... achieved using a visual analytics application. After outlining our... some initial findings and discuss how, in better understan... behaviours, we aim to provide insights that may directly inform... and operational decisions around the LCHS's expansion.

2. Dataset and Analysis Techniques

2.1 The LCHS Customer and Journeys Dataset

Our analysis relies on two complementary datasets: a ... complete set of journey records. For every customer regist... individual's gender and postcode are stored within a custo... customer identifier is generated. For every journey made, ... pair representing the docking station that journey started ... timestamps for these instances, are recorded within a jou...

A visual analytics approach to understanding cycling behaviour

Roger Beecham*
City University London

Jo Wood, Member, IEEE †
City University London

Audrey Bowerman‡
Transport for London

Abstract

Existing research into cycling ...

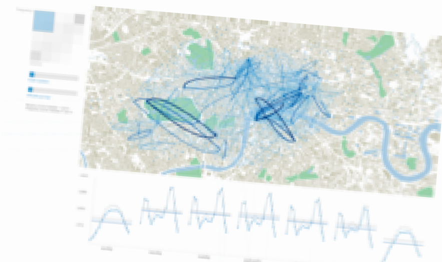


Figure 1: An early visual analytics prototype, which links customer segments (top left), with a spatial (centre) and temporal (bottom) view.

...than self-reported behaviour have generally relied on GPS logs [3] or automated traffic counts at fixed sites [6]. Due to their complexity, the former have been relatively small in scale and the latter, only reporting counts and timestamps at specific locations, too coarse to meaningfully identify behaviour.

Shared-bicycle schemes offer new research possibilities. In many recent schemes, data on usage are continually reported to central databases. Researchers working within data mining [5] [7], and information visualization [13] have queried these data to identify patterns of scheme use, as well as more nuanced space-time journey flows. This analysis has nevertheless been constrained by the level of detailed information made publicly available. Whilst a complete set of journey records, including journey origin-destination (OD) and start and end times was used by Wood *et al.* [13], these data could not be linked back to individual customers. Cyclists' journey histories, and the context framing those journeys, could not be identified. This limits the extent to which such data can be used to engage with the more complex questions around motivations and barriers to cycling [7] [13]. Working collaboratively with Transport for London (TfL), customer records reporting a unique customer identifier, gender and postcode the customer registered with, have been made available. So too has a complete set of user journeys. Linking with geodemographic and other contextual information, and querying these attribute rich data within a visual analytics application, we attempt to explore and explain cycling behaviour from an individual customer perspective.

2 Objectives and Approach

The research project aims to:

- Classify bike share customers according to the journeys they make.
- Validate, rewrite and add qualitative descriptions to these classifications paying attention to journey context; by querying the dataset at particular space-times, in response to changes internal and external to the scheme.
- Furnish social scientists, and strategists within TfL, with generalisable insights into the barriers, incentives and conditions that motivate cycling behaviour.

This approach sits comfortably within a visual analytics framework [11]. We will take a large and attribute rich dataset, query it to identify general and distinct space-time journey patterns, before creating modelled data and subsequently querying the models. Attempting to engage with difficult questions around cycling behaviours, it will be necessary to quickly consider many combinations of contextual variables and customer attributes. This might be best achieved through a highly flexible visual analytics application.

3 Early Analysis and First Visual Analytics Prototype

At the time of writing, the dataset contained 114,947 valid customer records, linked to 6,490,479 journeys. After loading data into an SQLite database, relevant derived variables were computed. Linking customers with their journeys, recency-frequency (RF) segmentation, a technique used within direct marketing [8], was performed. Matching customers' postcodes to geographic coordinates,

*e-mail: roger.beecham.1@city.ac.uk
†e-mail: j.d.wood@city.ac.uk
‡e-mail: audreybowerman@tfl.gov.uk

[1]Transport for London's cycle hire website.

Rentals | Capital Bikeshare

https://capitalbikeshare.com/member/rentals

Rentals (72)

Capital Bikeshare is currently undergoing a system update which affects your rental history statistics from being calculated accurately. During this update, your distance, calories burned and C02 lbs saved statistics will not be displayed. We are working to finalize the update and will provide correct statistics for your rental history again upon its completion. Your other rental history data has not been affected and is accurately displayed on this page. Thanks for your patience!

Start Station	Start Date	End Station	End Date	Duration	Cost
Lamont & Mt Pleasant NW	10-27-2012 10:40 am	New York Ave & 15th St NW	10-27-2012 11:22 am	42 minutes, 35 seconds	$ 1.50
Connecticut Ave & Newark St NW / Cleveland Park	10-23-2012 9:09 pm	Lamont & Mt Pleasant NW	10-23-2012 9:20 pm	10 minutes, 49 seconds	$ 0.00
Adams Mill & Columbia Rd NW	10-21-2012 10:51 am	Adams Mill & Columbia Rd NW	10-21-2012 10:51 am	9 seconds	$ 0.00
20th & Crystal Dr	10-20-2012 11:25 am	Braddock Rd Metro	10-20-2012 11:55 am	29 minutes, 30 seconds	$ 0.00
				32	

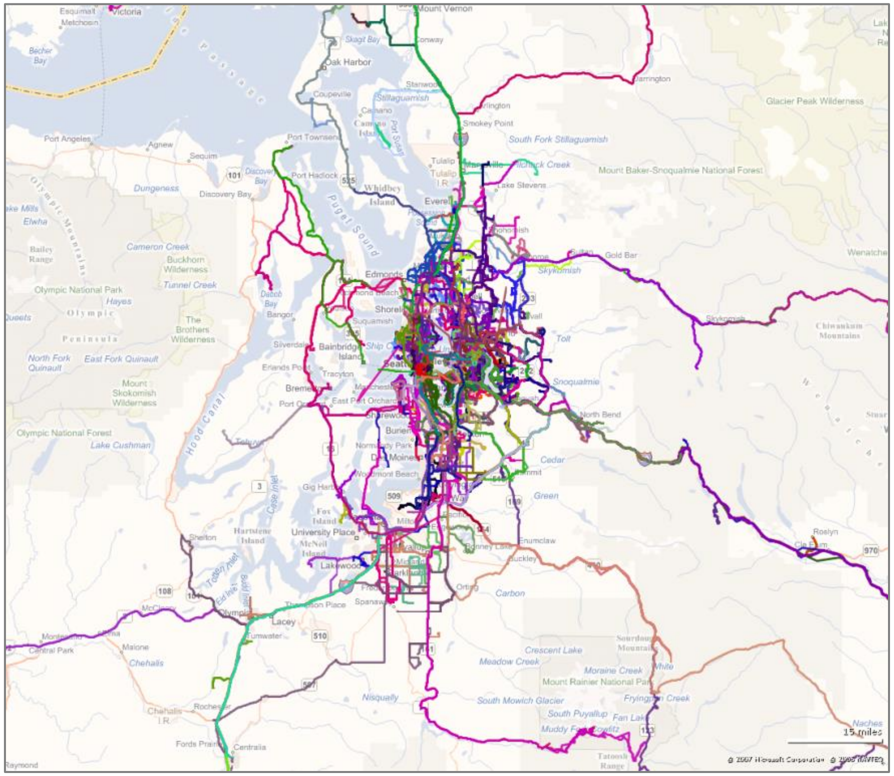
Human route repetition in **car driving**.

Route Prediction from Trip Observations

14,468 trips / 240 subjects

Description	Average	Median
trip distance (miles)	7.7	4.2
trip time (min)	16.3	11.5
num trips / day	4	3.9
num trips / subject	60.3	50
num days of data / subject	15.1	13

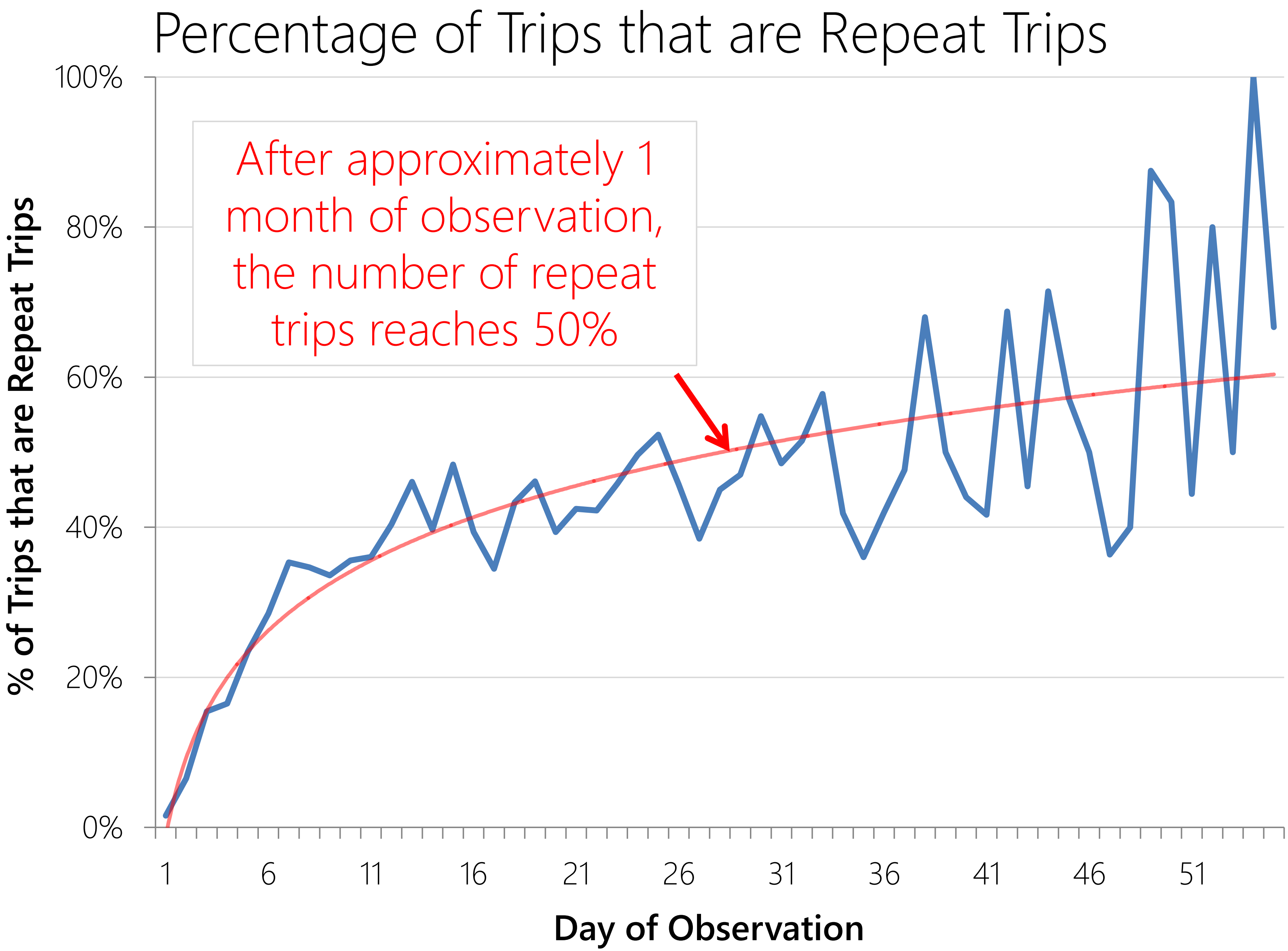
High Level Trip Stats

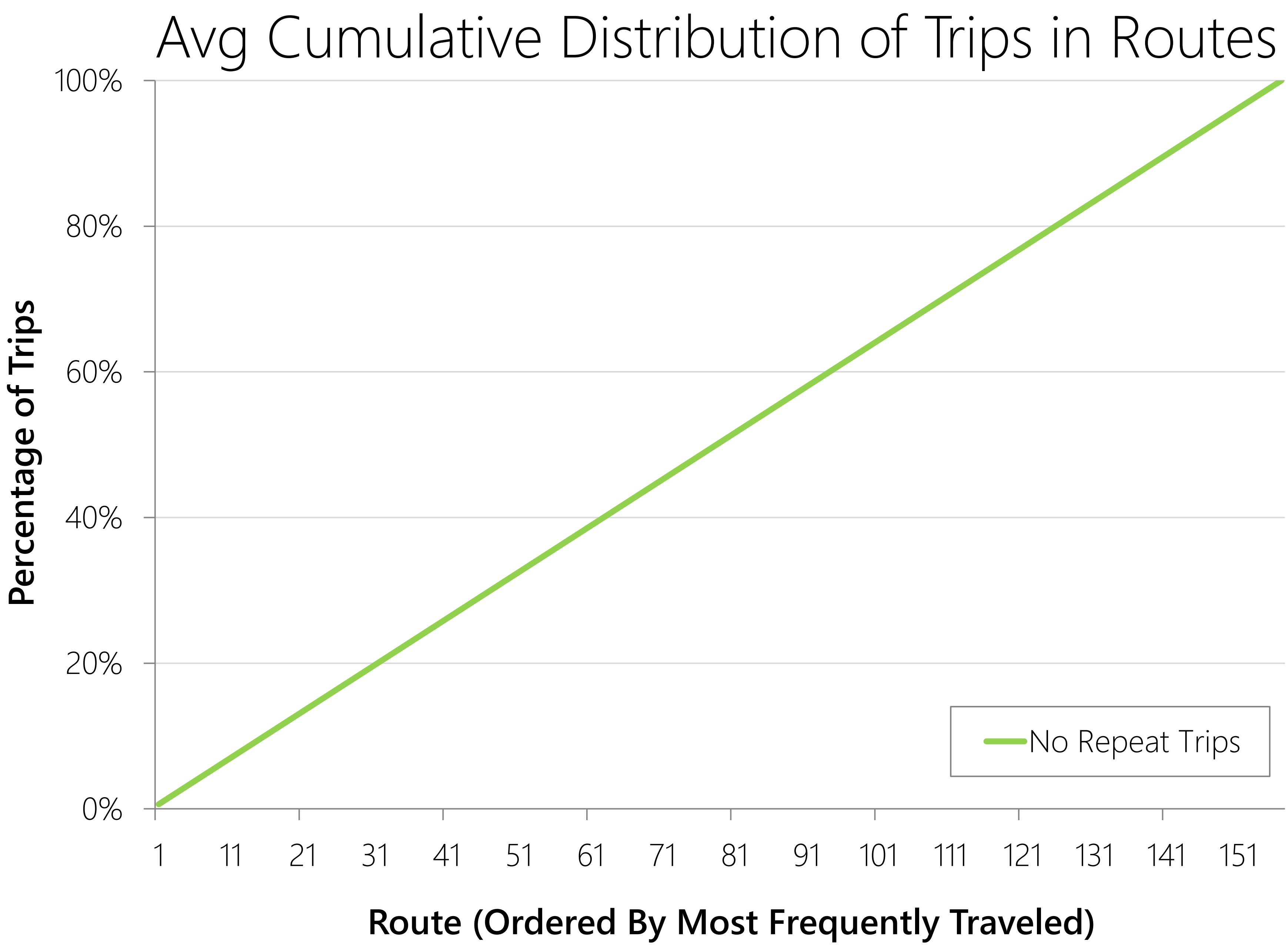


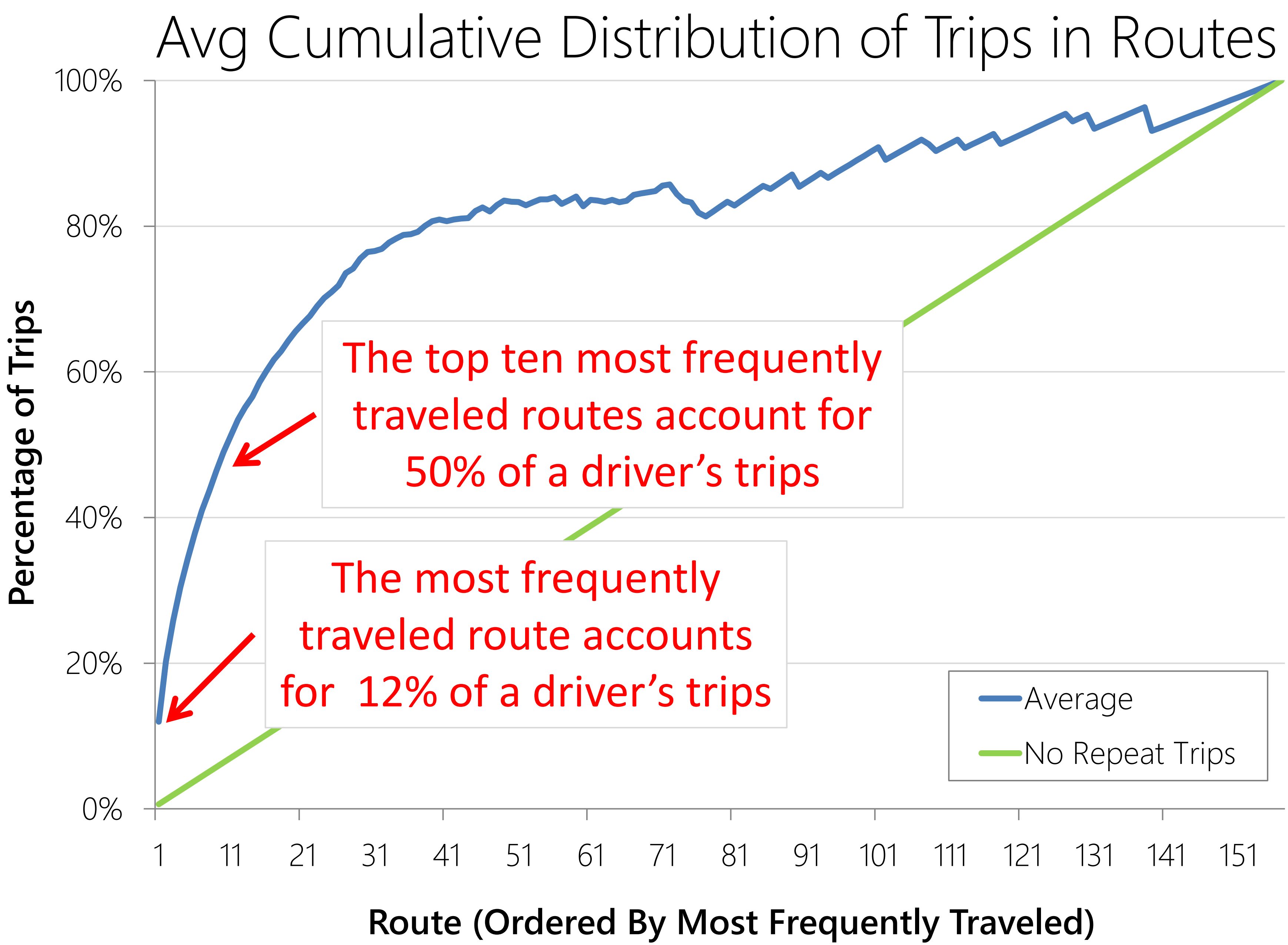
Greater Seattle Area

[Froehlich & Krumm, *Route Prediction From Trip Observations*, SAE 2008]

Percentage of Trips that are Repeat Trips


Percentage of Trips that are Repeat Trips
100%
80%
60%
40%
20%
0%
% of Trips that are Repeat Trips
After approximately 1 month of observation, the number of repeat trips reaches 50%
1
6
11
16
21
26
31
36
41
46
51
Day of Observation


Avg Cumulative Distribution of Trips in Routes
100%
80%
60%
40%
20%
0%
Percentage of Trips
1
11
21
31
41
51
61
71
81
91
101
111
121
131
141
151
Route (Ordered By Most Frequently Traveled)
No Repeat Trips



Avg Cumulative Distribution of Trips in Routes
100%
80%
60%
40%
20%
0%
Percentage of Trips
1
11
21
31
41
51
61
71
81
91
101
111
121
131
141
151
Route (Ordered By Most Frequently Traveled)
The top ten most frequently traveled routes account for 50% of a driver's trips
The most frequently traveled route accounts for 12% of a driver's trips
Average
No Repeat Trips

bikeshare data

Event Based
Station I/O with cloud when bike docked/hired

Station Capacity Data

O/D Bike Data

O/D User Data

Continuous
Use sensors to track movement

Instrumented Cities
(*e.g.*, CCTVs)

Instrumented Bicycles
(*e.g.*, GPS sensor)

Instrumented Users
(*e.g.*, mobile phones)

bikeshare data

Event Based
Station I/O with cloud
when bike docked/hired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Continuous
Use sensors to track
movement


Instrumented Cities
(*e.g.*, CCTVs)

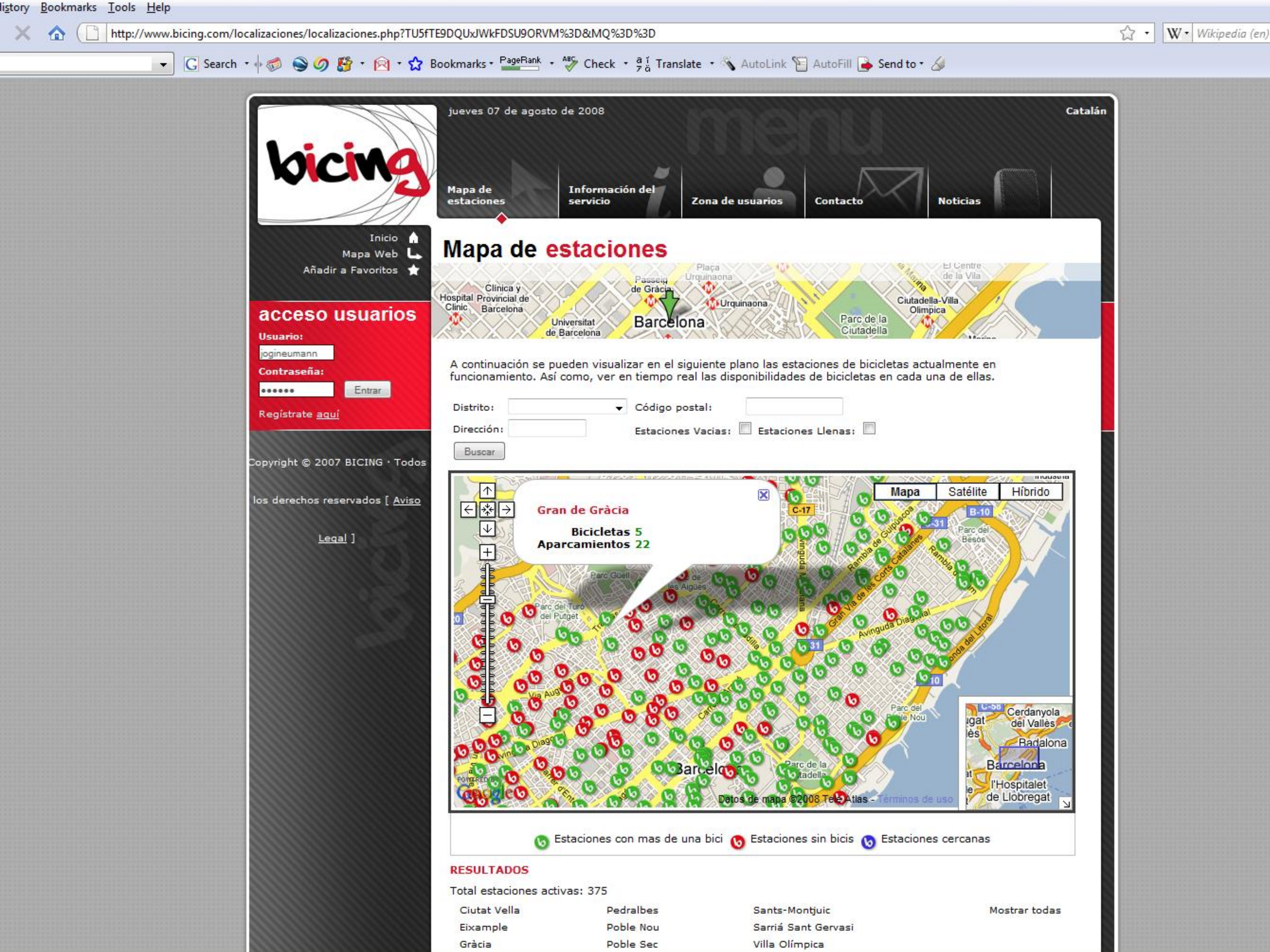

Instrumented Bicycles
(*e.g.*, GPS sensor)


Instrumented Users
(*e.g.*, mobile phones)

sensing and predicting the movement of a city via shared bicycling

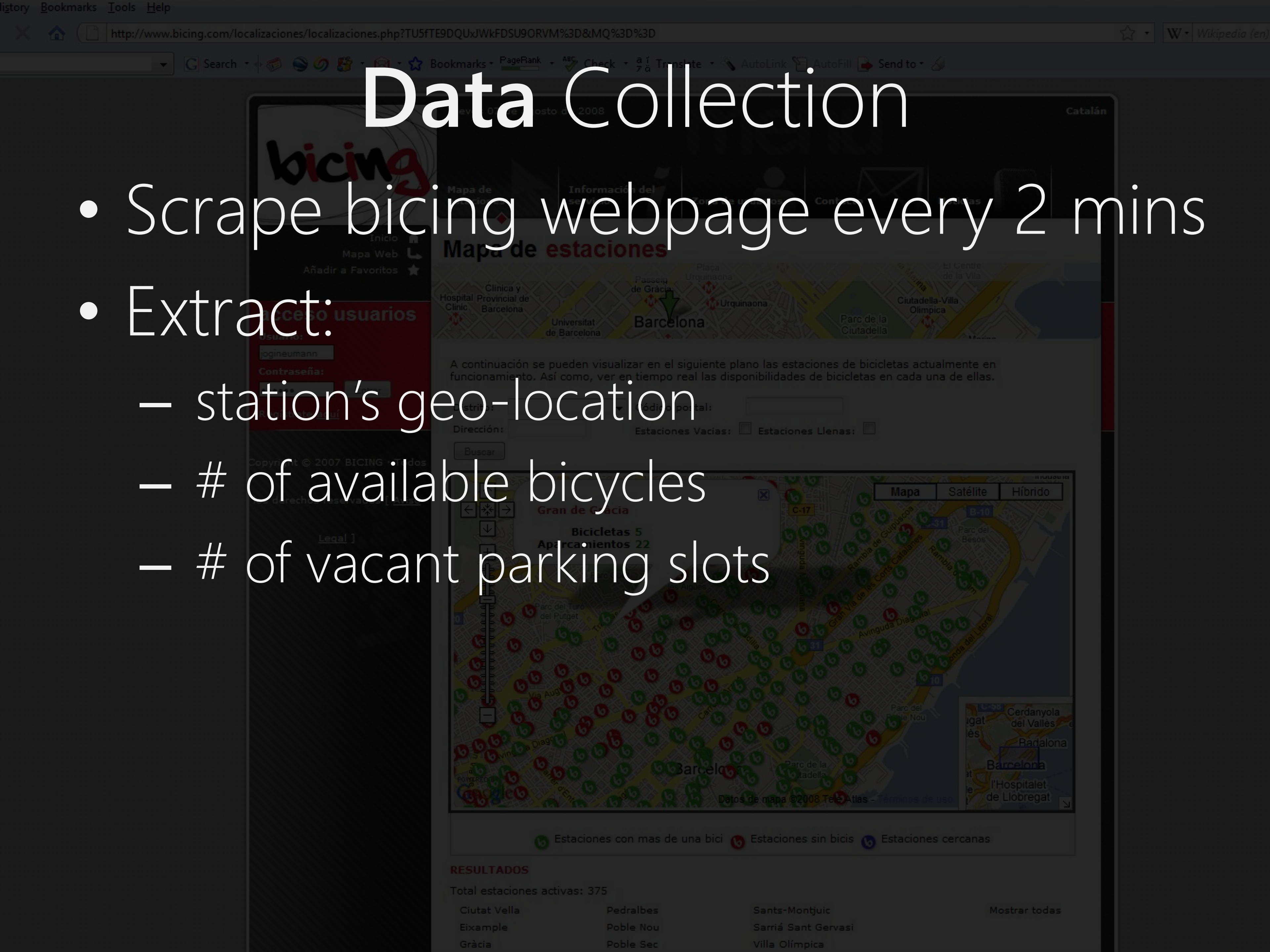
[Froehlich *et al.*, UrbanSense2008; IJCAI2009]


bicing
barcelona, spain
Summer 2008:
- 373 stations
- 6,000 bicycles
- 150,000 subscribers

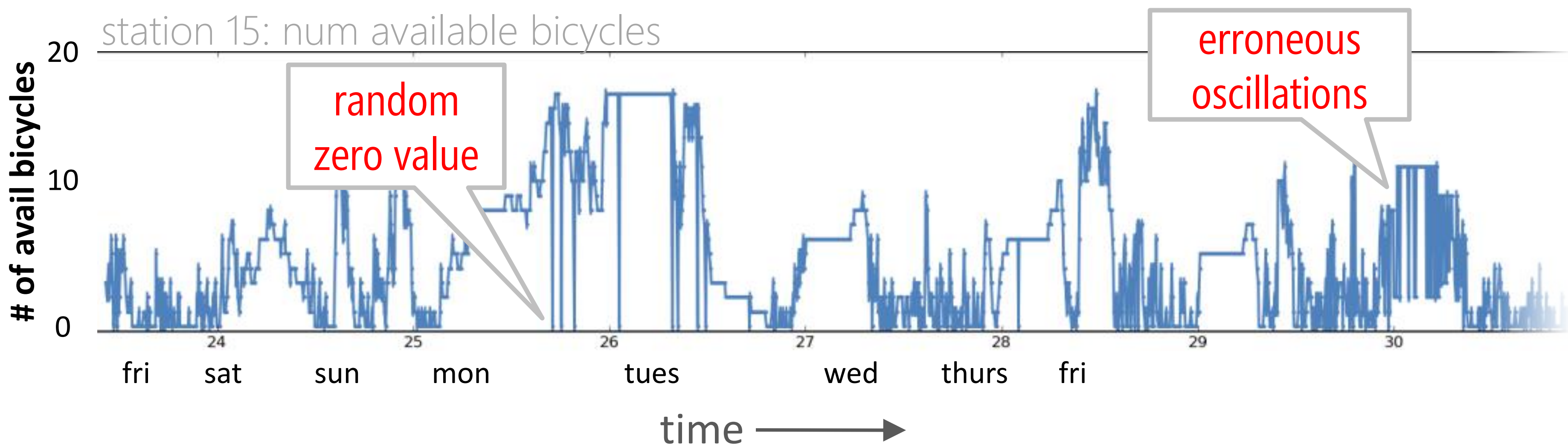

History Bookmarks Tools Help
http://www.bicing.com/localizaciones/localizaciones.php?TU5fTE9DQUxJWkFDSU9ORVM%3D&MQ%3D%3D
Search
Bookmarks
PageRank
Check
Translate
AutoLink
AutoFill
Send to
Wikipedia (en)
bicing
jueves 07 de agosto de 2008
Catalán
Mapa de estaciones
Información del servicio
Zona de usuarios
Contacto
Noticias
Inicio
Mapa Web
Añadir a Favoritos
Mapa de estaciones
acceso usuarios
Usuario:
jogineumann
Contraseña:
Entrar
Regístrate aquí
Copyright © 2007 BICING · Todos los derechos reservados [Aviso Legal]
A continuación se pueden visualizar en el siguiente plano las estaciones de bicicletas actualmente en funcionamiento. Así como, ver en tiempo real las disponibilidades de bicicletas en cada una de ellas.
Distrito:
Código postal:
Dirección:
Estaciones Vacías:
Estaciones Llenas:
Buscar
Mapa
Satélite
Híbrido
Gran de Gràcia
Bicicletas 5
Aparcamientos 22
Barcelona
Cerdanyola del Vallès
Badalona
l'Hospitalet de Llobregat
Datos de mapa ©2008 Tele Atlas - Términos de uso
Estaciones con mas de una bici
Estaciones sin bicis
Estaciones cercanas
RESULTADOS
Total estaciones activas: 375
Ciutat Vella
Pedralbes
Sants-Montjuic
Mostrar todas
Eixample
Poble Nou
Sarrià Sant Gervasi
Gràcia
Poble Sec
Villa Olímpica

Data Collection

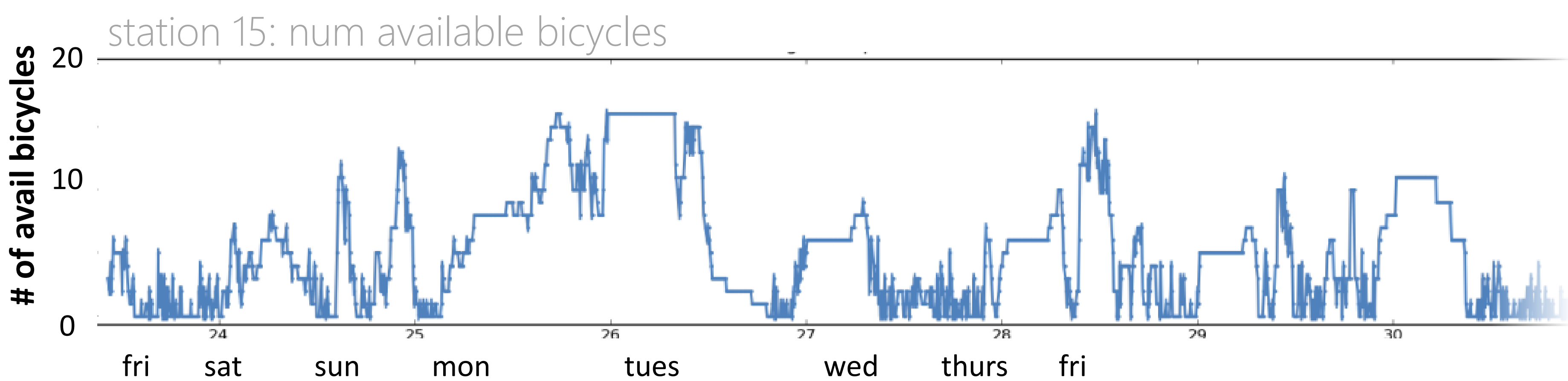
- Scrape bicing webpage every 2 mins
- Extract:
  - station's geo-location
  - # of available bicycles
  - # of vacant parking slots



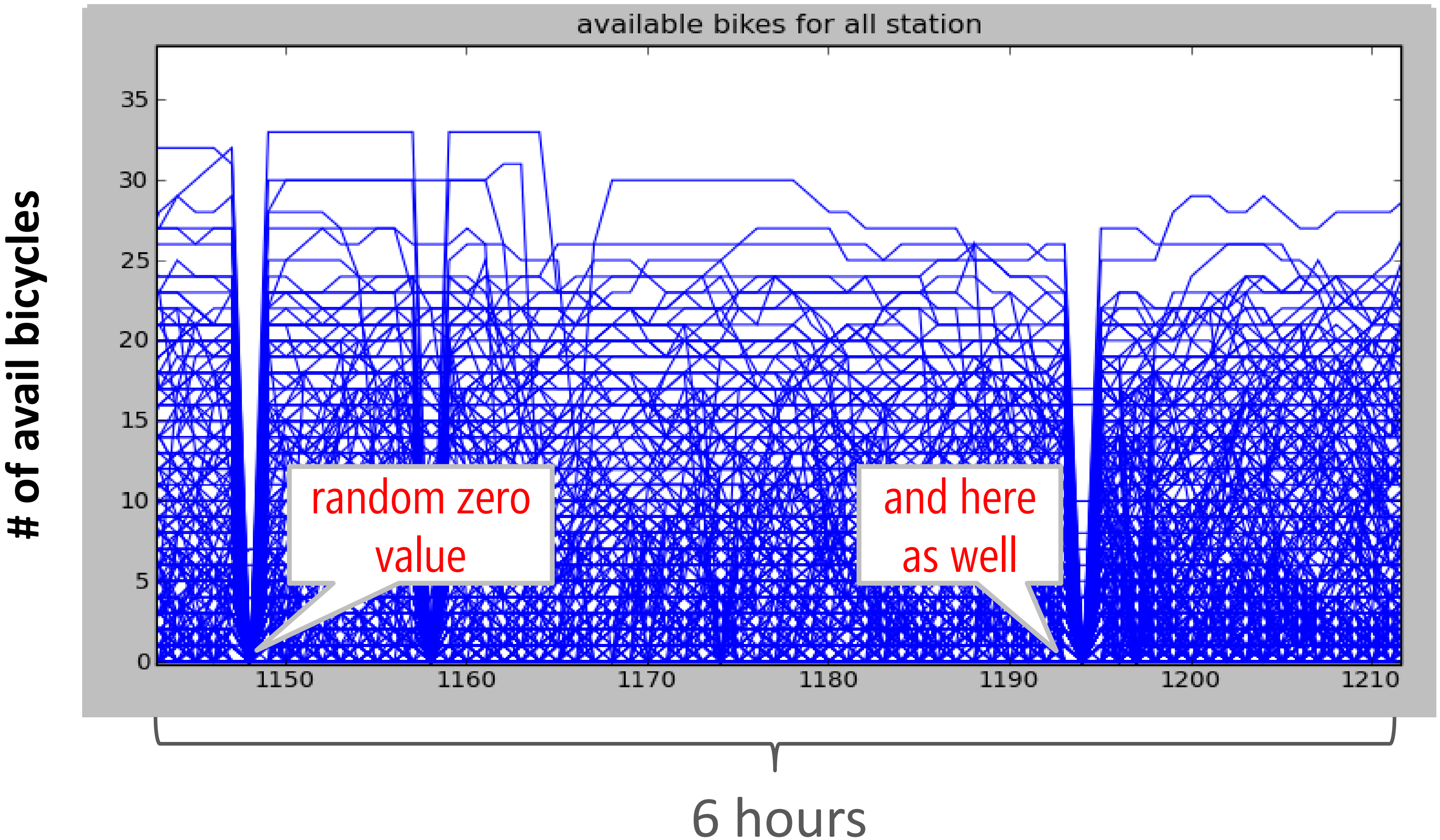
before cleansing



after cleansing



How do we know what to clean?

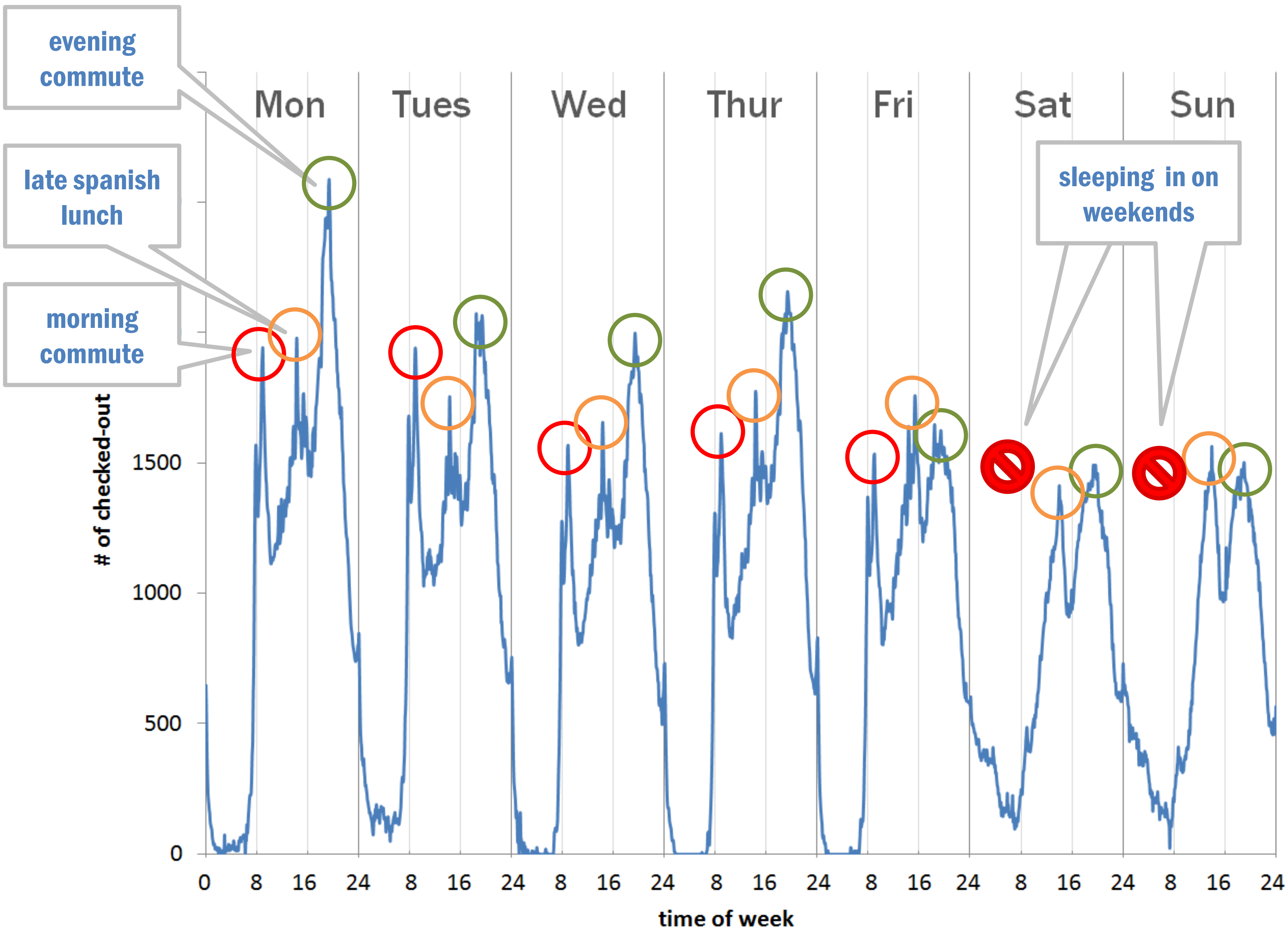


dataset

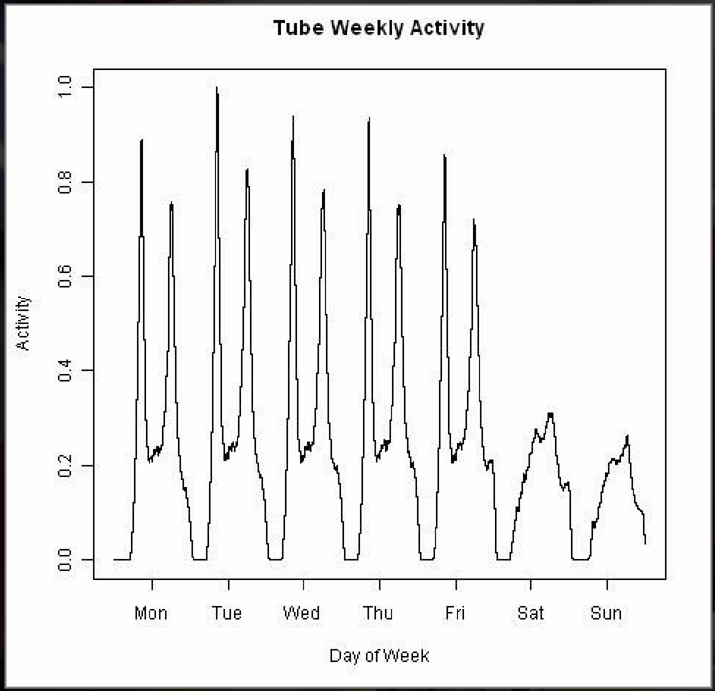
13 weeks of observations
Aug 27 – Dec 1, 2008

	raw dataset	cleaned dataset
stations	390	370
days	25K	22.7K
observations	26.1M	20.2M
parking slots	9831	9315

Num checked-out bicycles across all stations

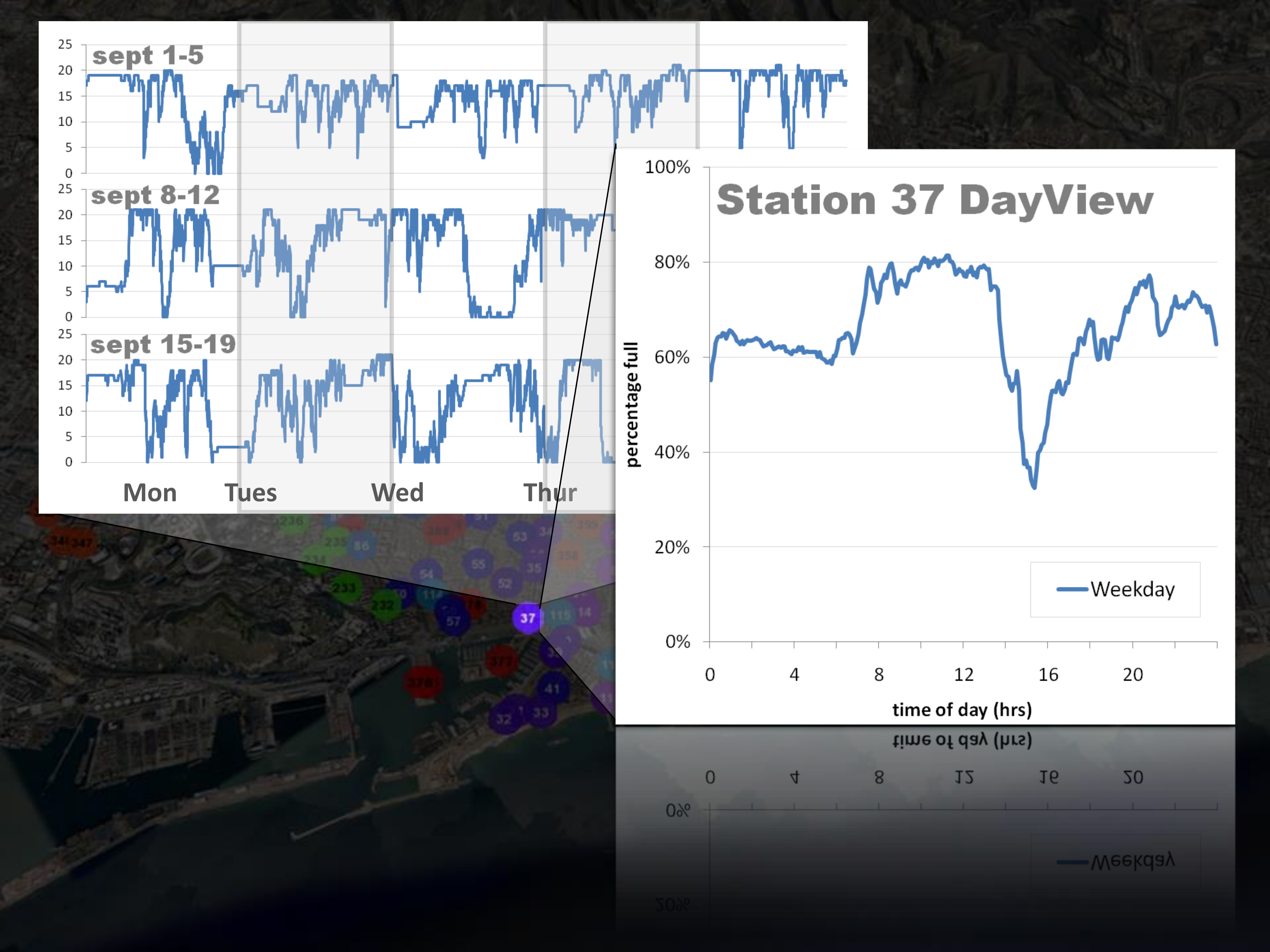


Two-spike pattern found in study of **London Underground**

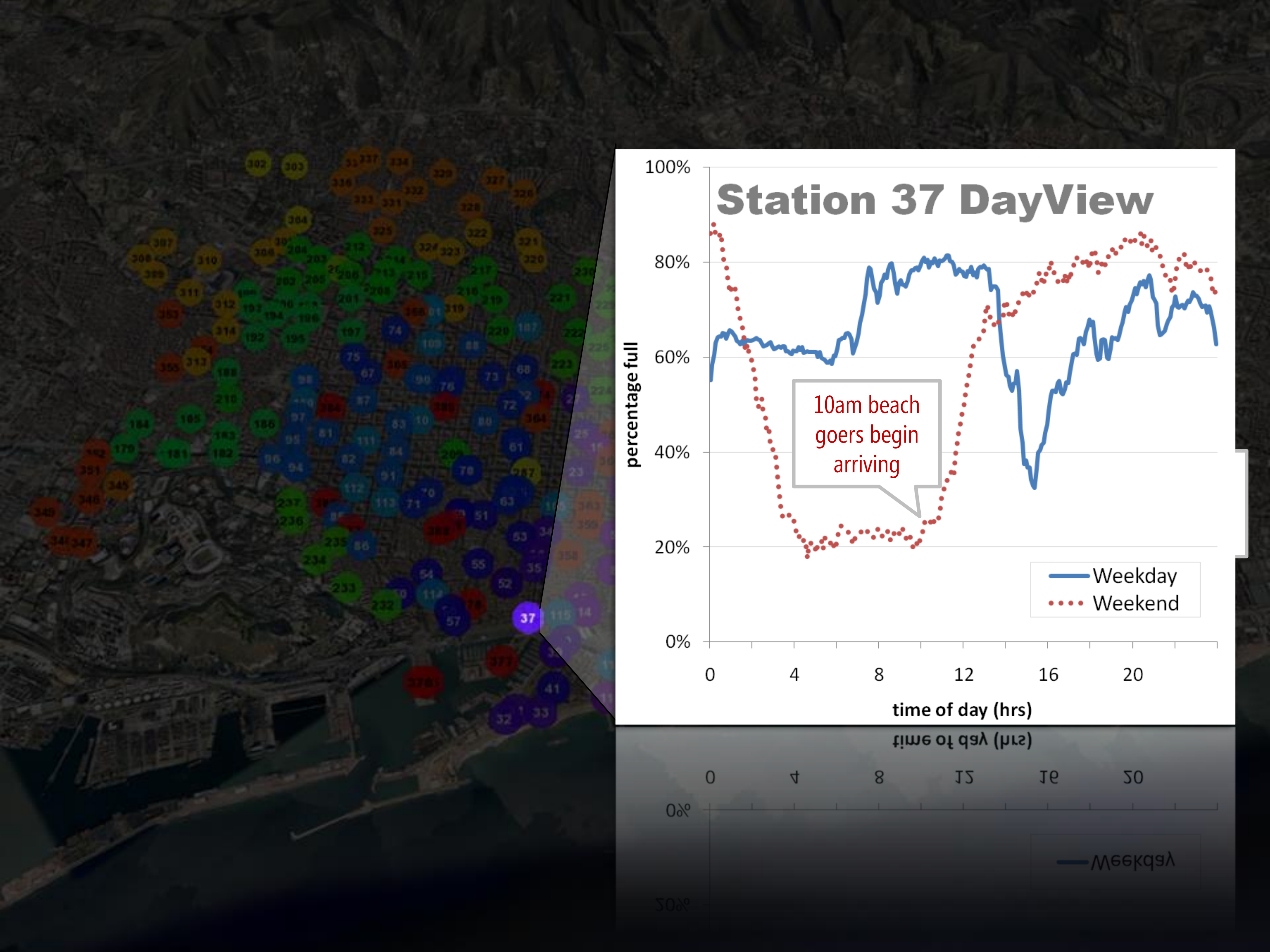


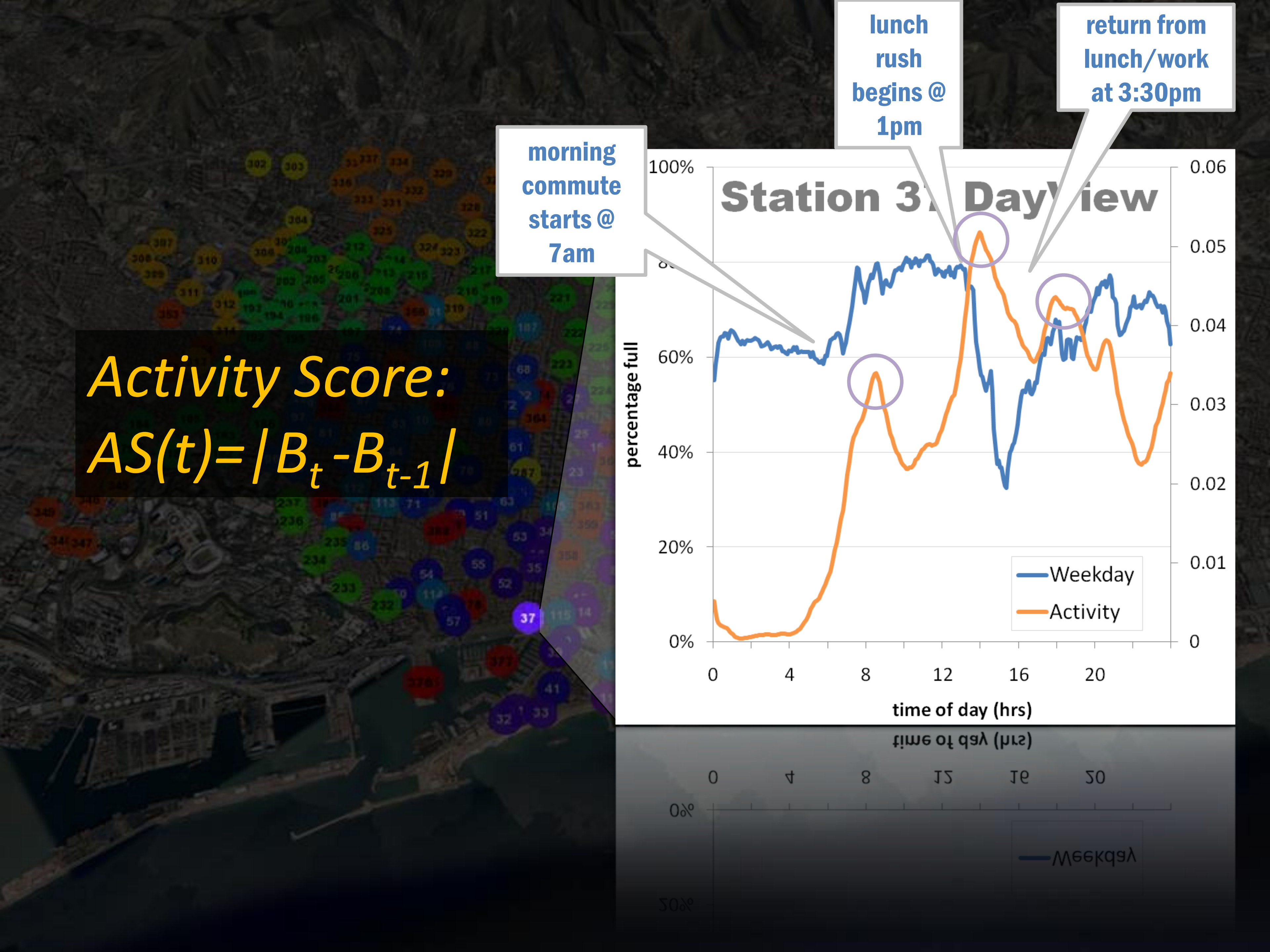
[Lathia, Froehlich & Capra, ICDM2010]

Introducing DayViews



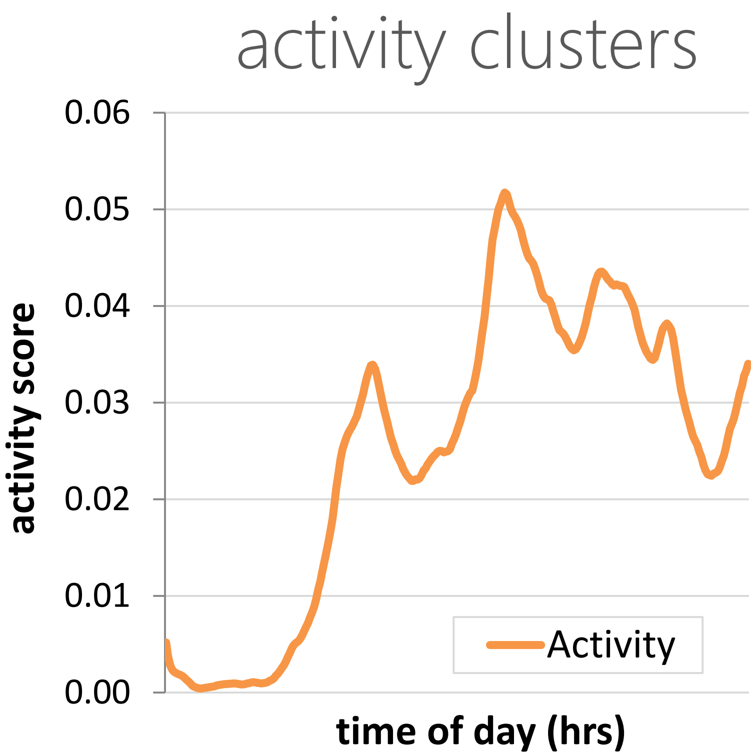
sept 1-5
sept 8-12
sept 15-19
25
20
15
10
5
0
Mon
Tues
Wed
Thur
Station 37 DayView
100%
80%
60%
40%
20%
0%
percentage full
0
4
8
12
16
20
time of day (hrs)
Weekday

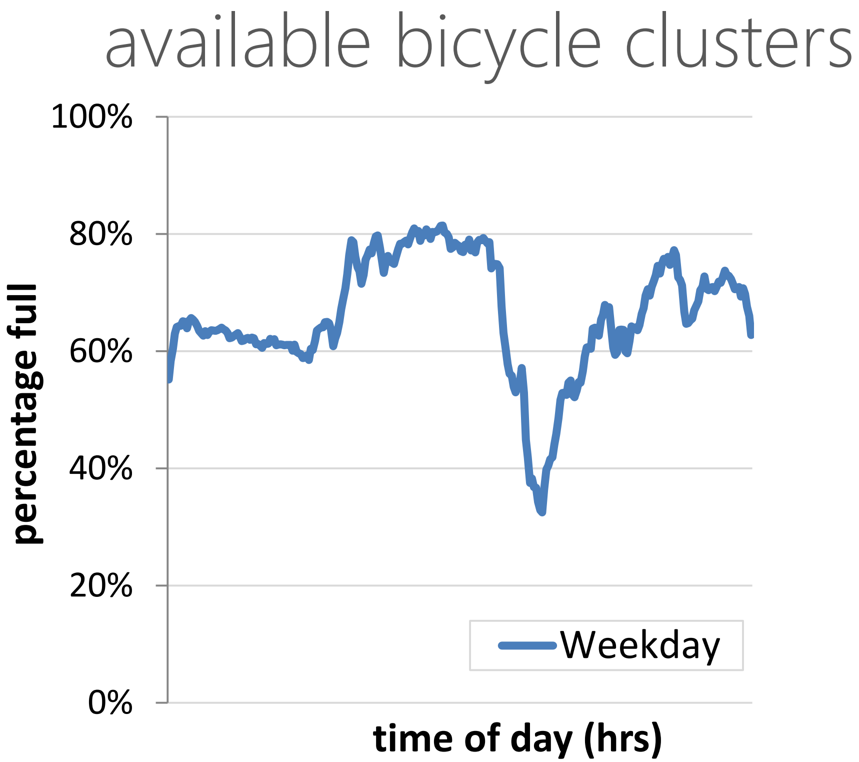

Station 37 DayView
100%
80%
60%
40%
20%
0%
percentage full
10am beach goers begin arriving
Weekday
Weekend
0
4
8
12
16
20
time of day (hrs)
37


Activity Score:
$AS(t)=|B_t - B_{t-1}|$
morning commute starts @ 7am
lunch rush begins @ 1pm
return from lunch/work at 3:30pm
Station 3
Day
iew
percentage full
100%
60%
40%
20%
0%
0.06
0.05
0.04
0.03
0.02
0.01
0
0
4
8
12
16
20
time of day (hrs)
Weekday
Activity
37

How are Bicing patterns shared across stations and distributed in the city?

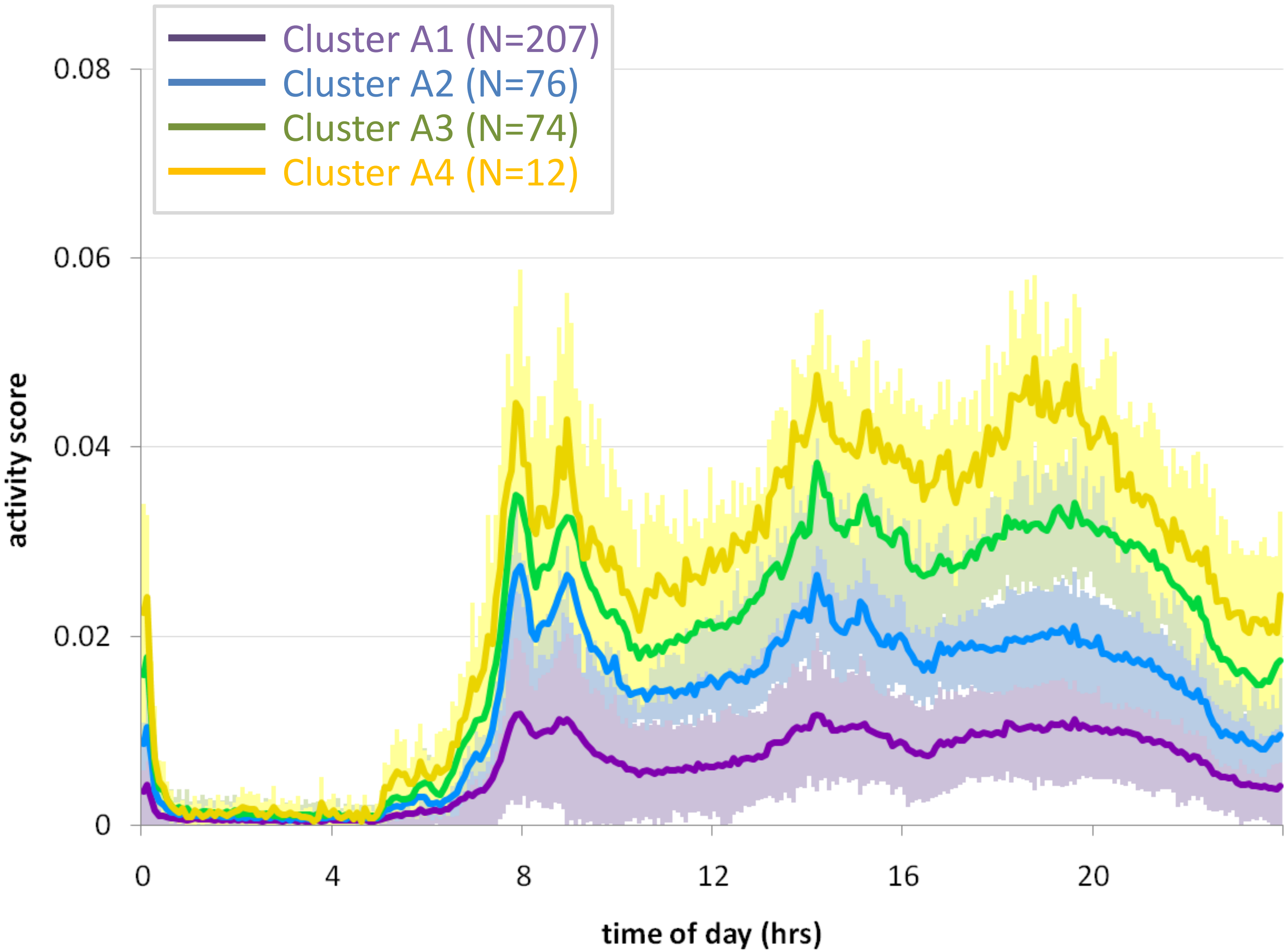
Temporal Clustering



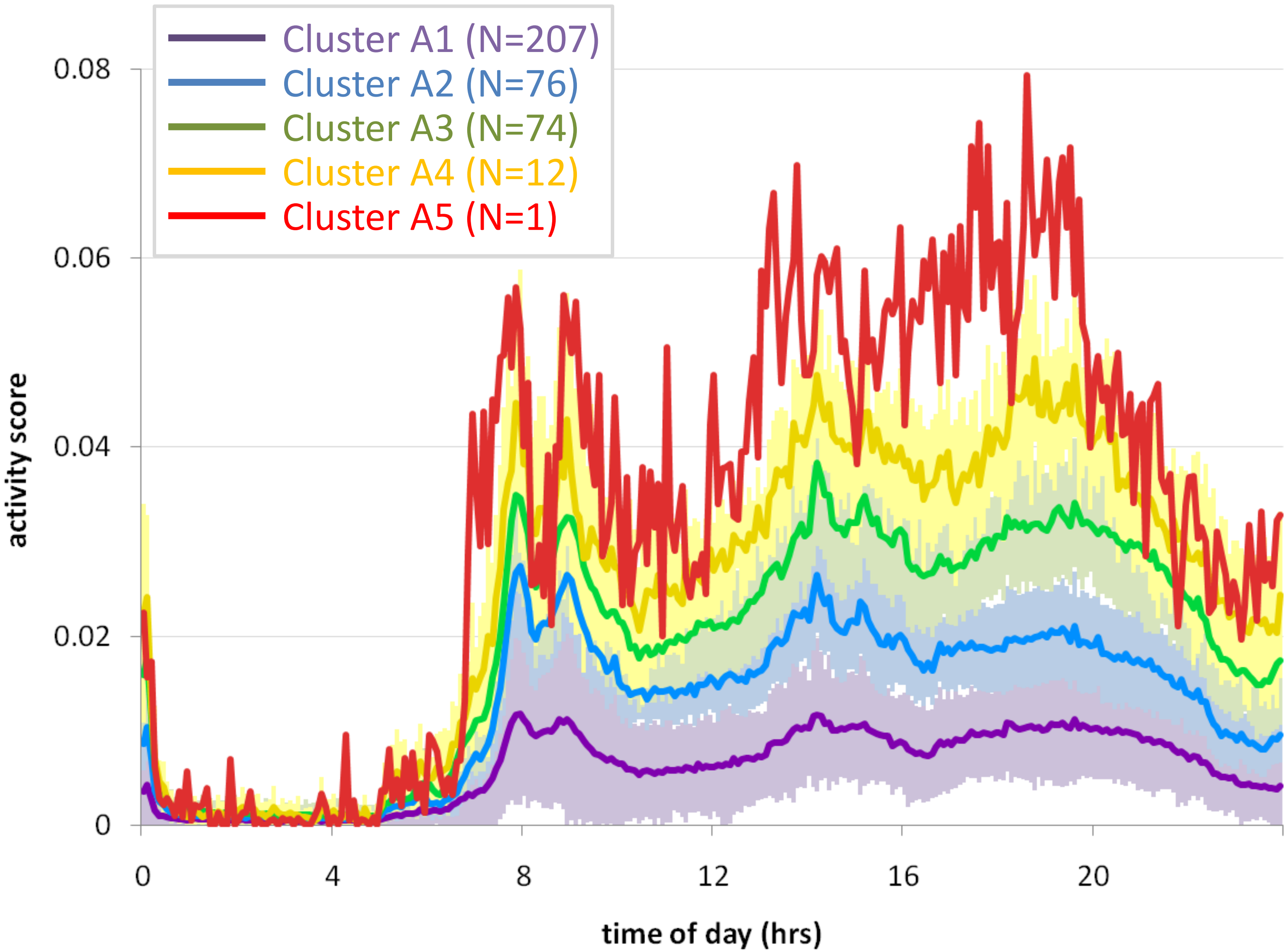


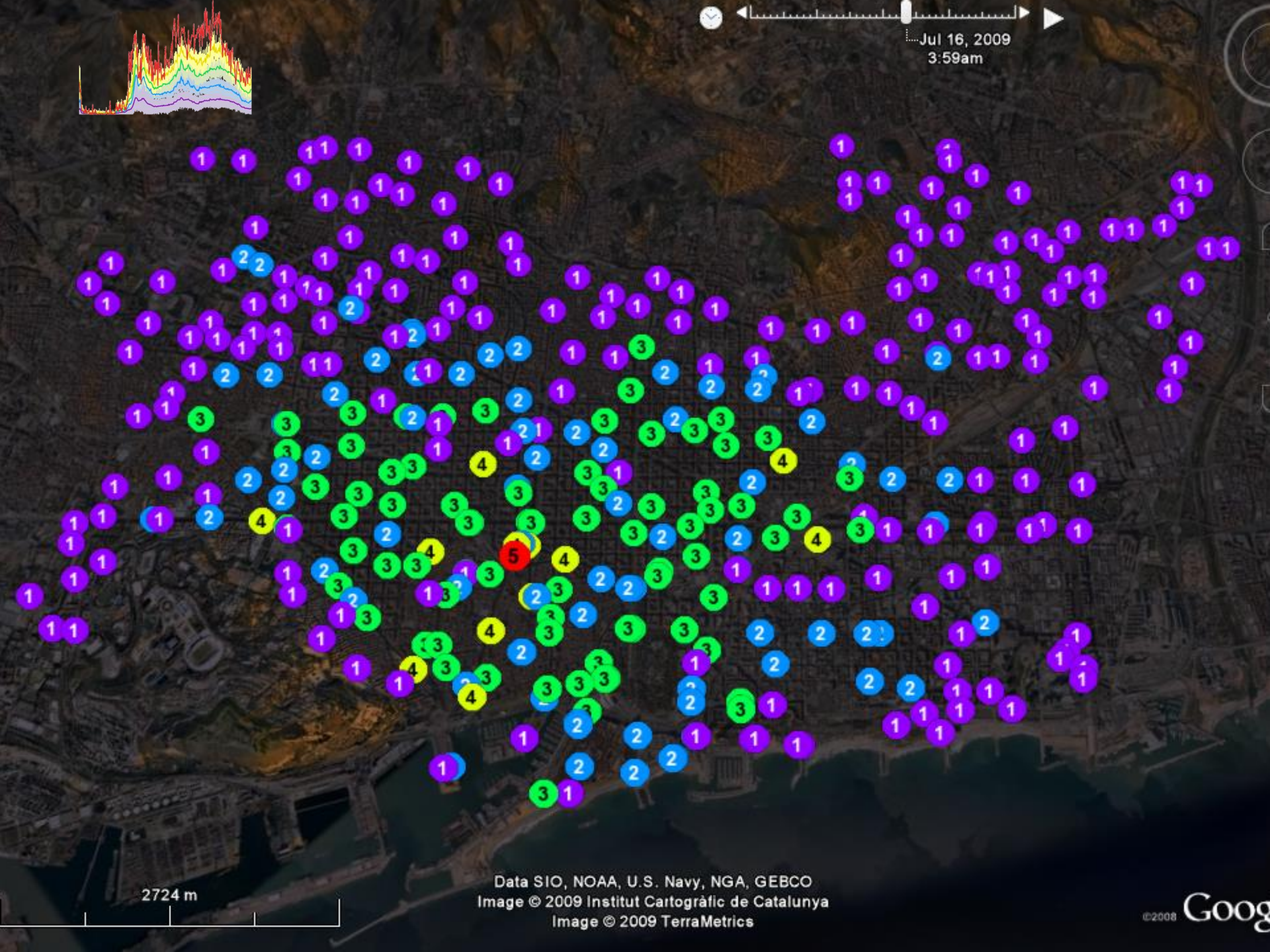
Applied dendrogram clustering with dynamic time warping as distance metric

Activity Clusters



Activity Clusters




Jul 16, 2009
3:59am
2724 m
Data SIO, NOAA, U.S. Navy, NGA, GEBCO
Image © 2009 Institut Cartogràfic de Catalunya
Image © 2009 TerraMetrics
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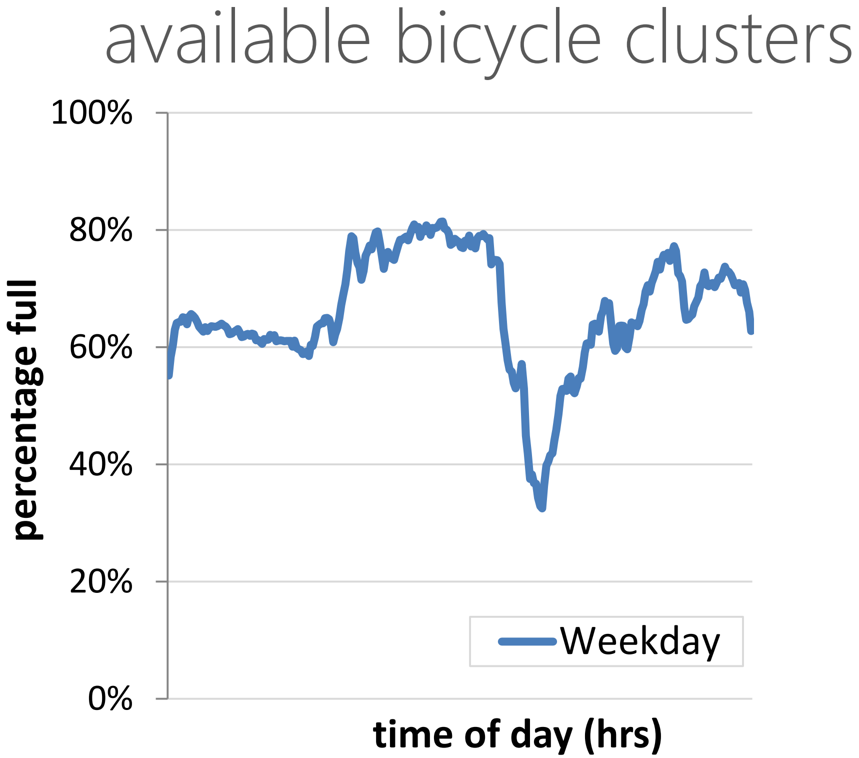
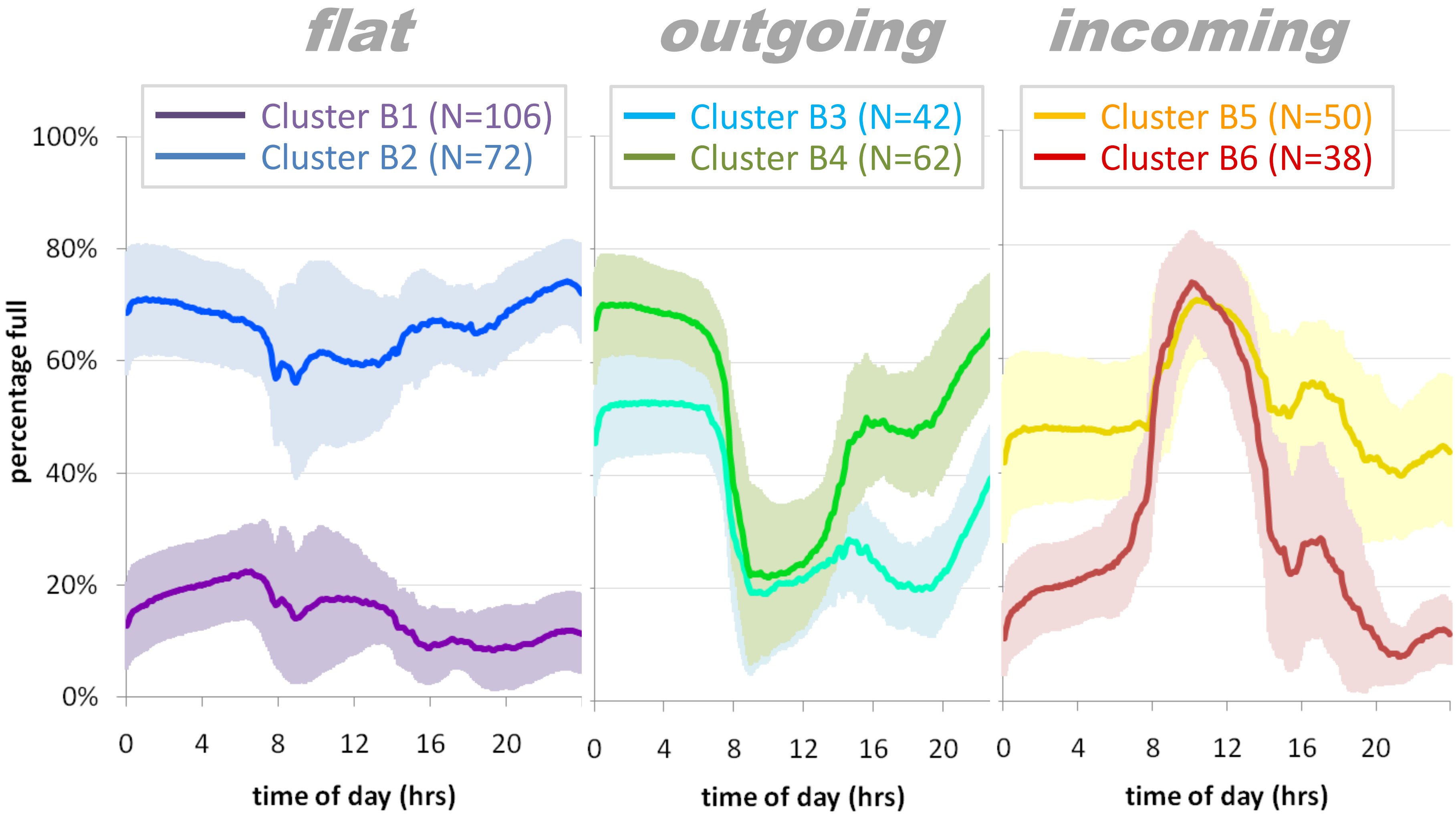
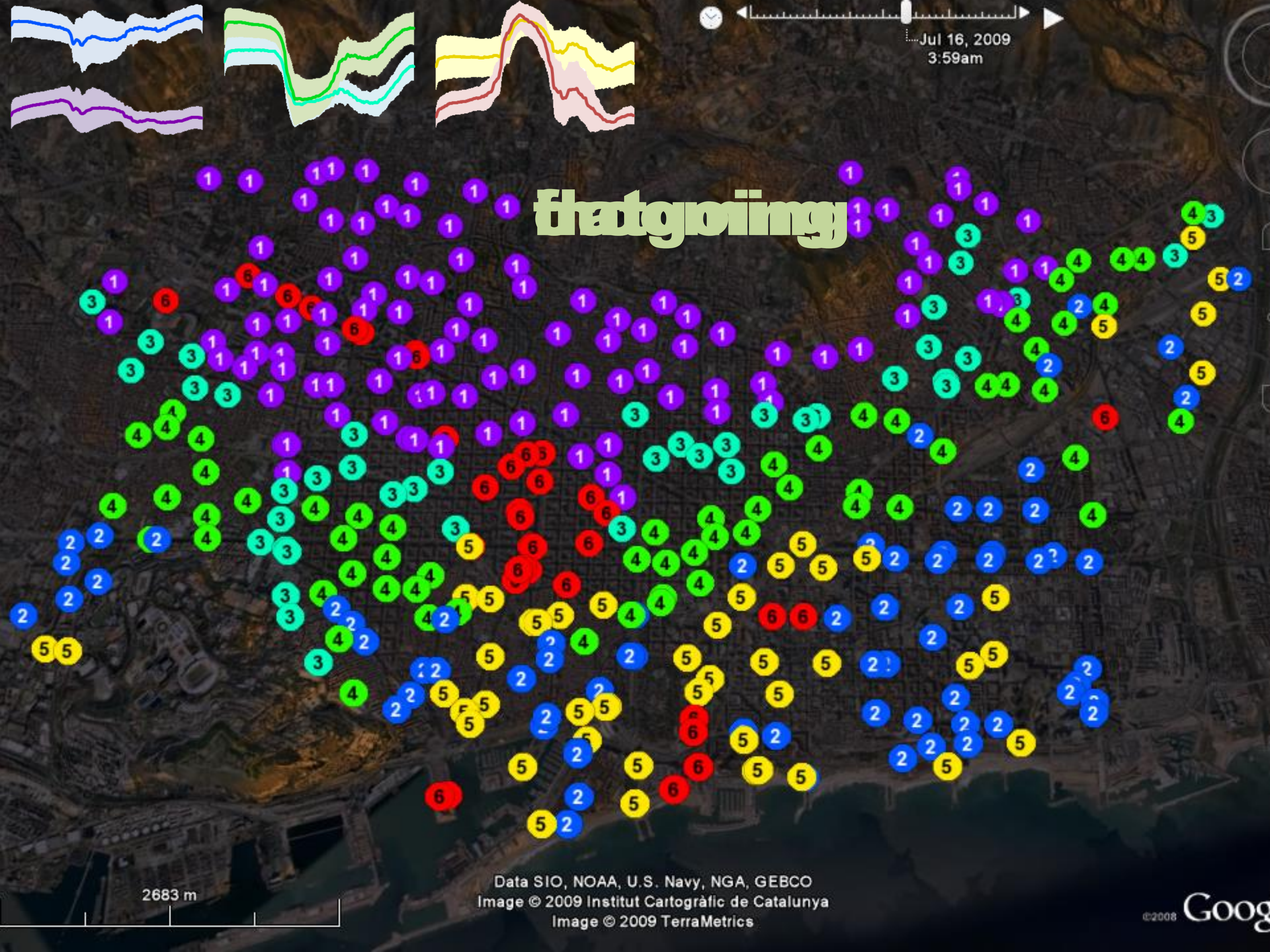
Temporal Clustering



Available Bicycle Cluster




Jul 16, 2009
3:59am
2683 m
Data SIO, NOAA, U.S. Navy, NGA, GEBCO
Image © 2009 Institut Cartogràfic de Catalunya
Image © 2009 TerraMetrics
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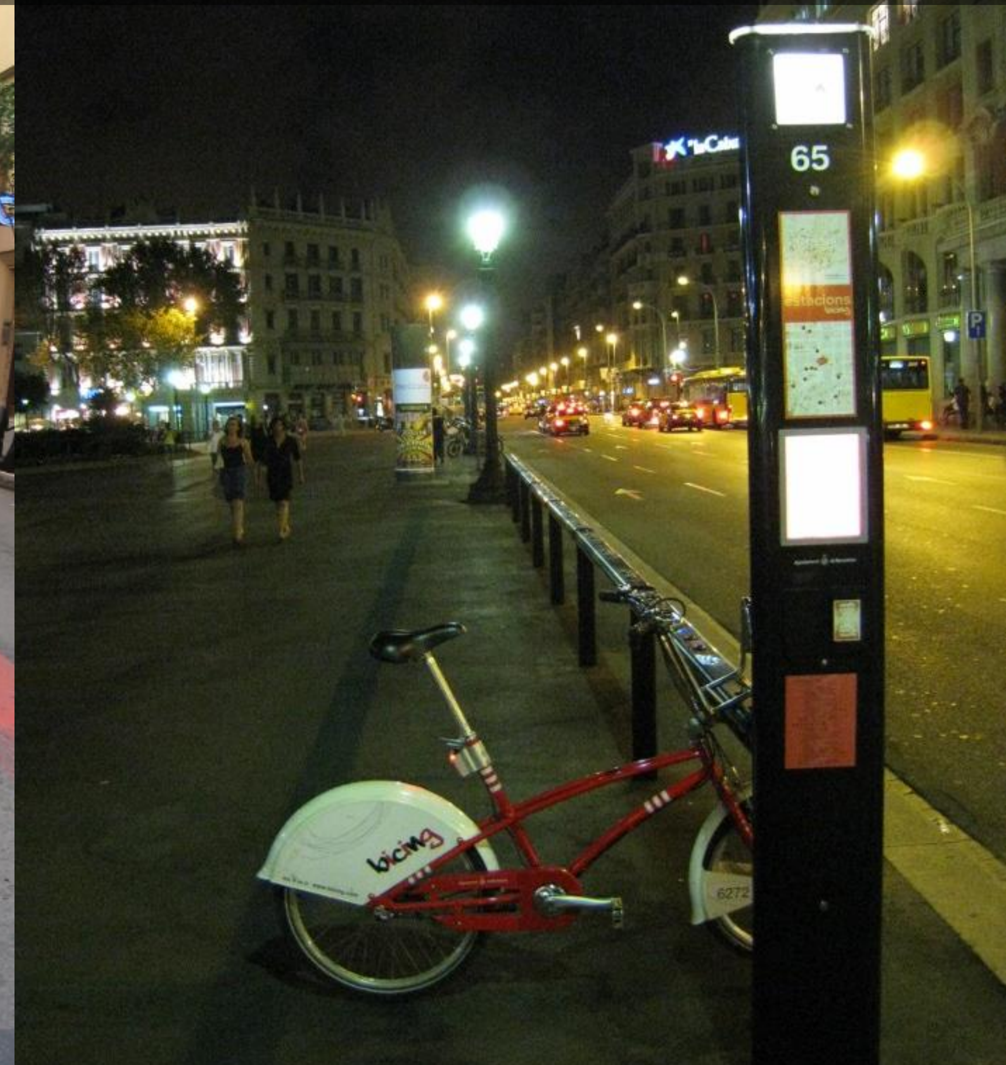
Can Bicing station usage be predicted?

Why Care?

- load balancing
- assist urban planners / city officials about expected activity
- provide new web/mobile services to bicing users

Uphill Station (midday)

Downtown Station (night)



76% of respondents had difficulty *finding a bicycle*

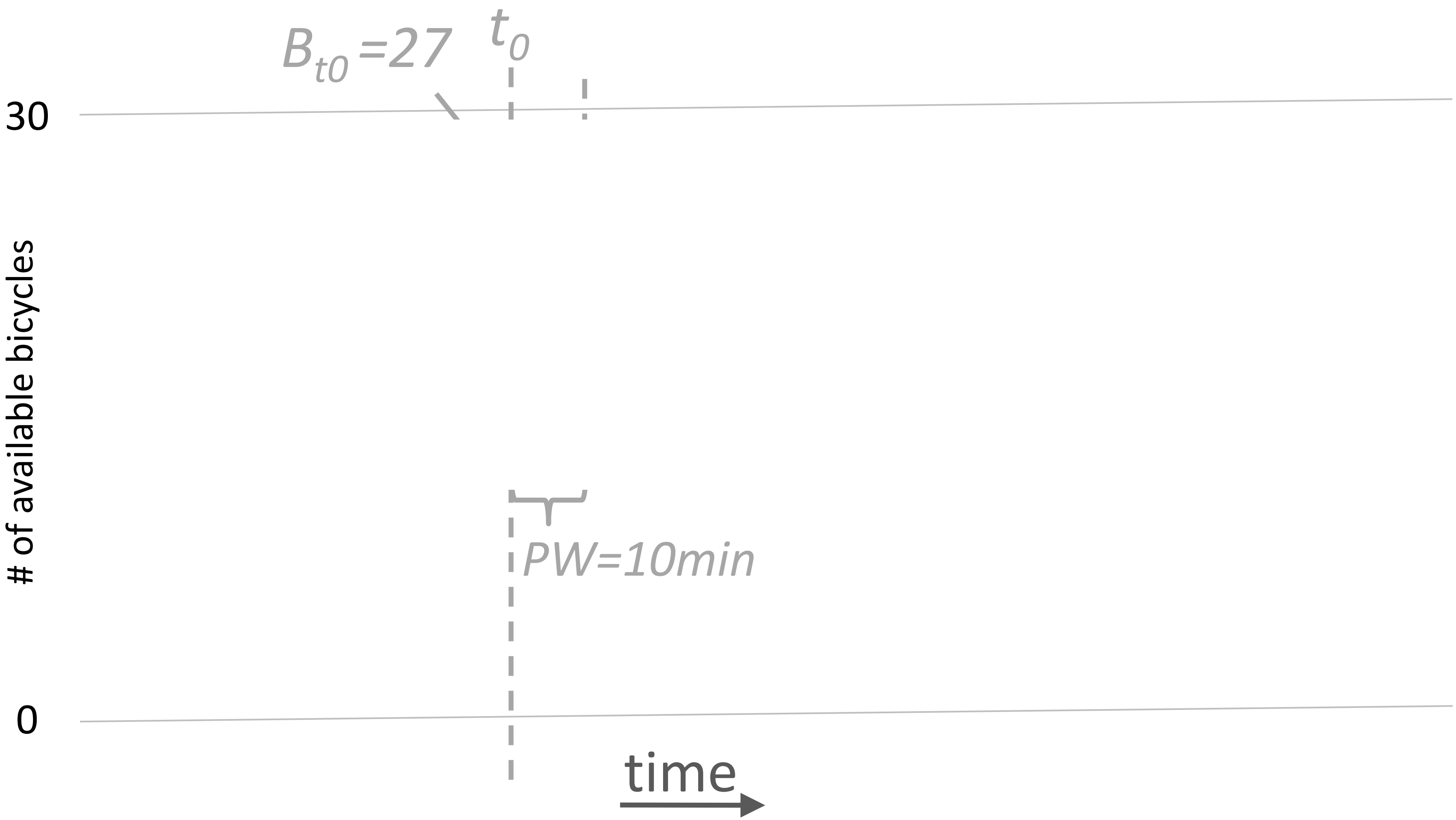
Downtown Station (morning)

66% of respondents had difficulty *finding a parking slot*

Beach Station (evening)

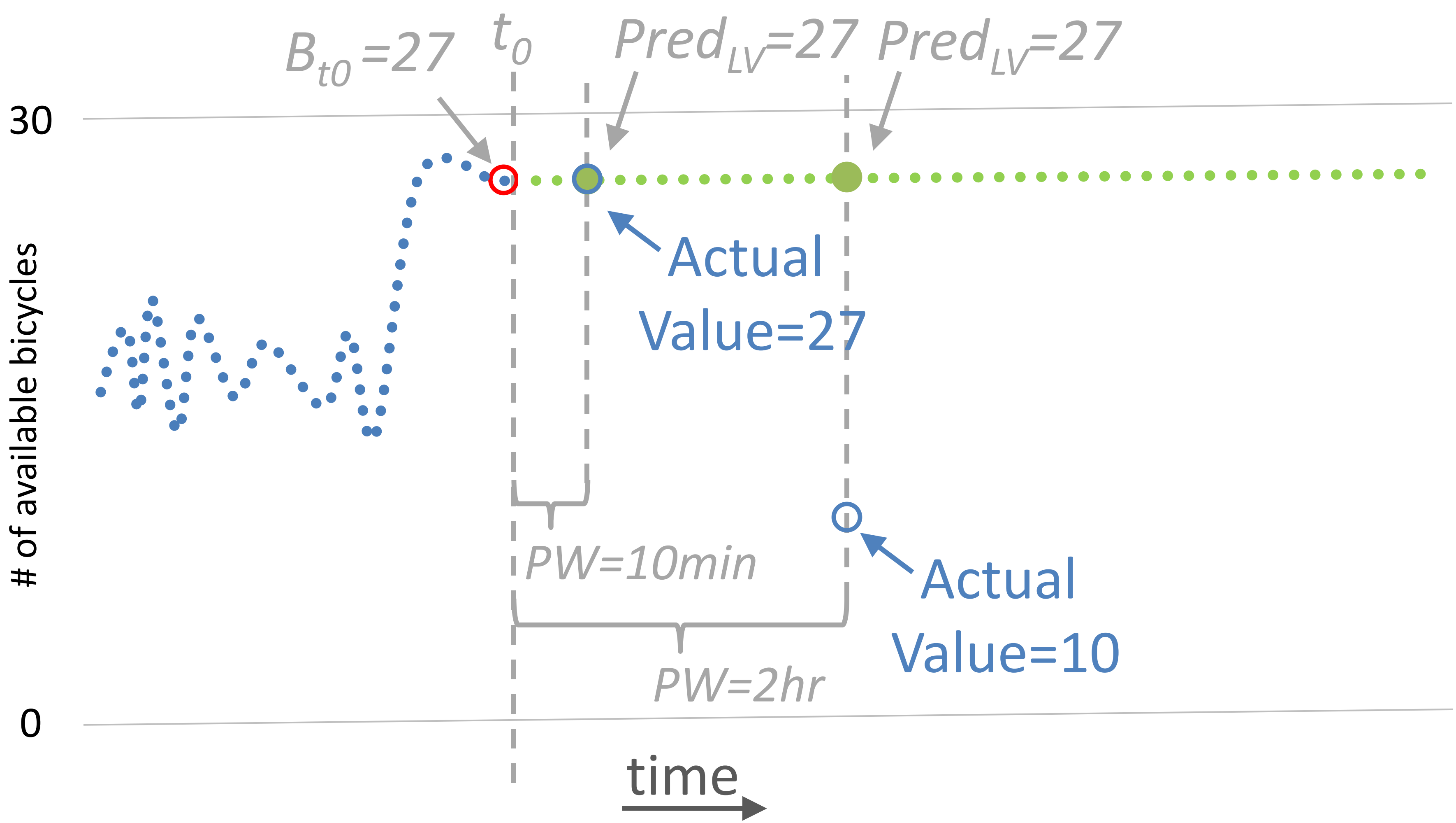
50% of respondents avoid Bicing when they are traveling to a place where they must be on time

Station Models



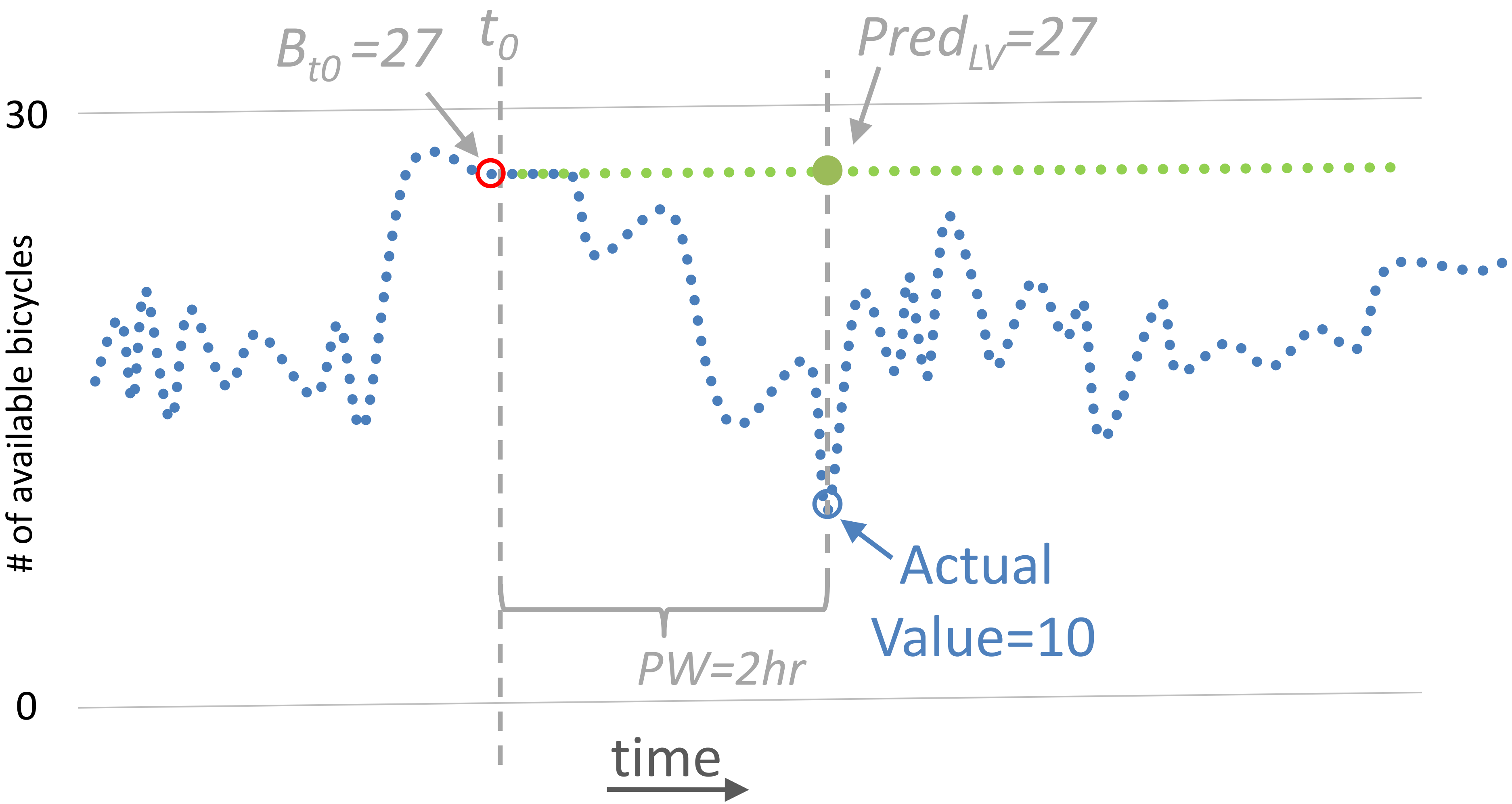
Last Value

$Pred_{LV}=(t_0, B_{t0}, PW)=B_{t0}$



$Pred_{LV}=(t_0,B_{t0},PW)=B_{t0}$

Last Value

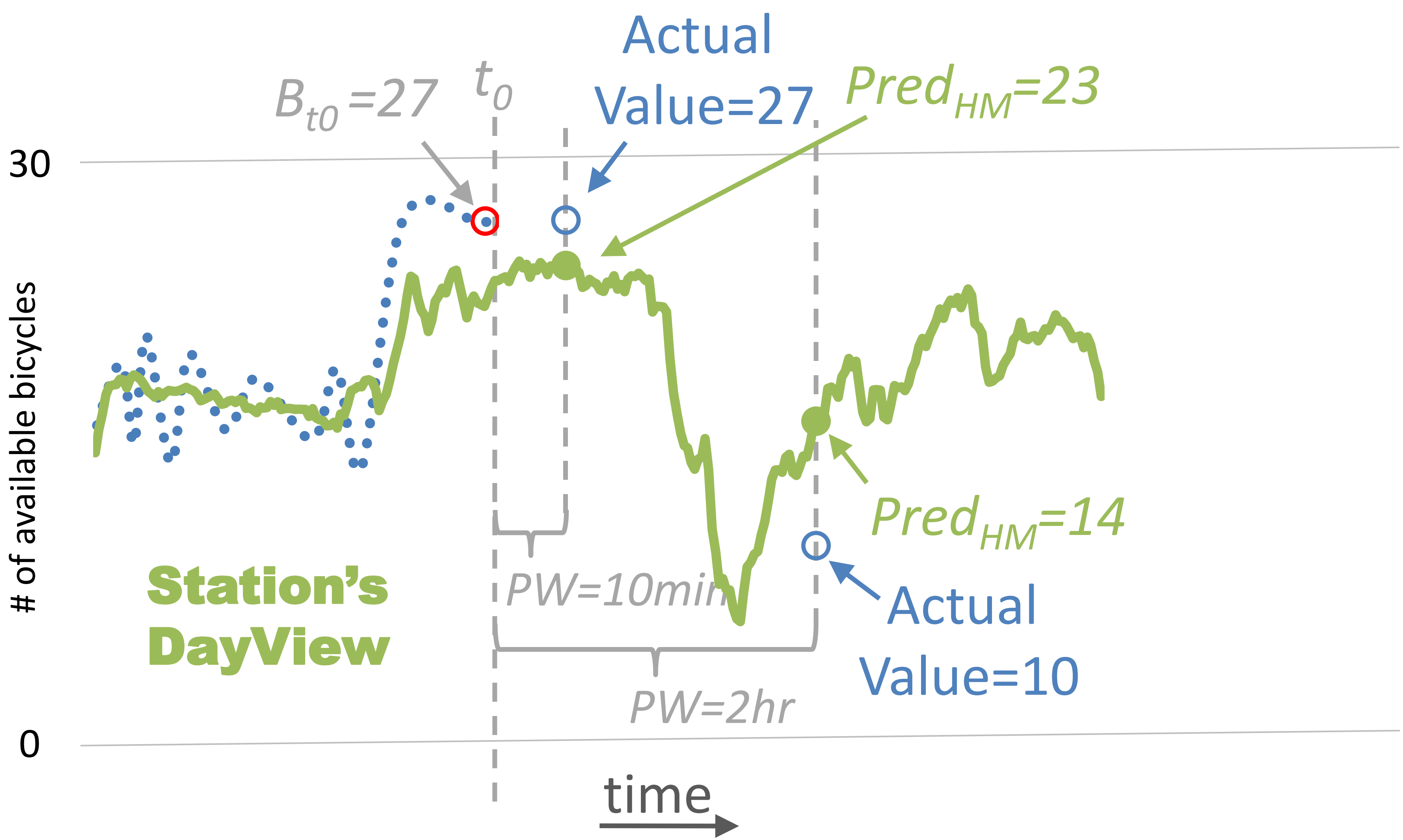


Historic Mean

$$Pred_{HM}=(t_0,B_{t0},PW)=\overline{B}_{TB_{t0+PW}}$$

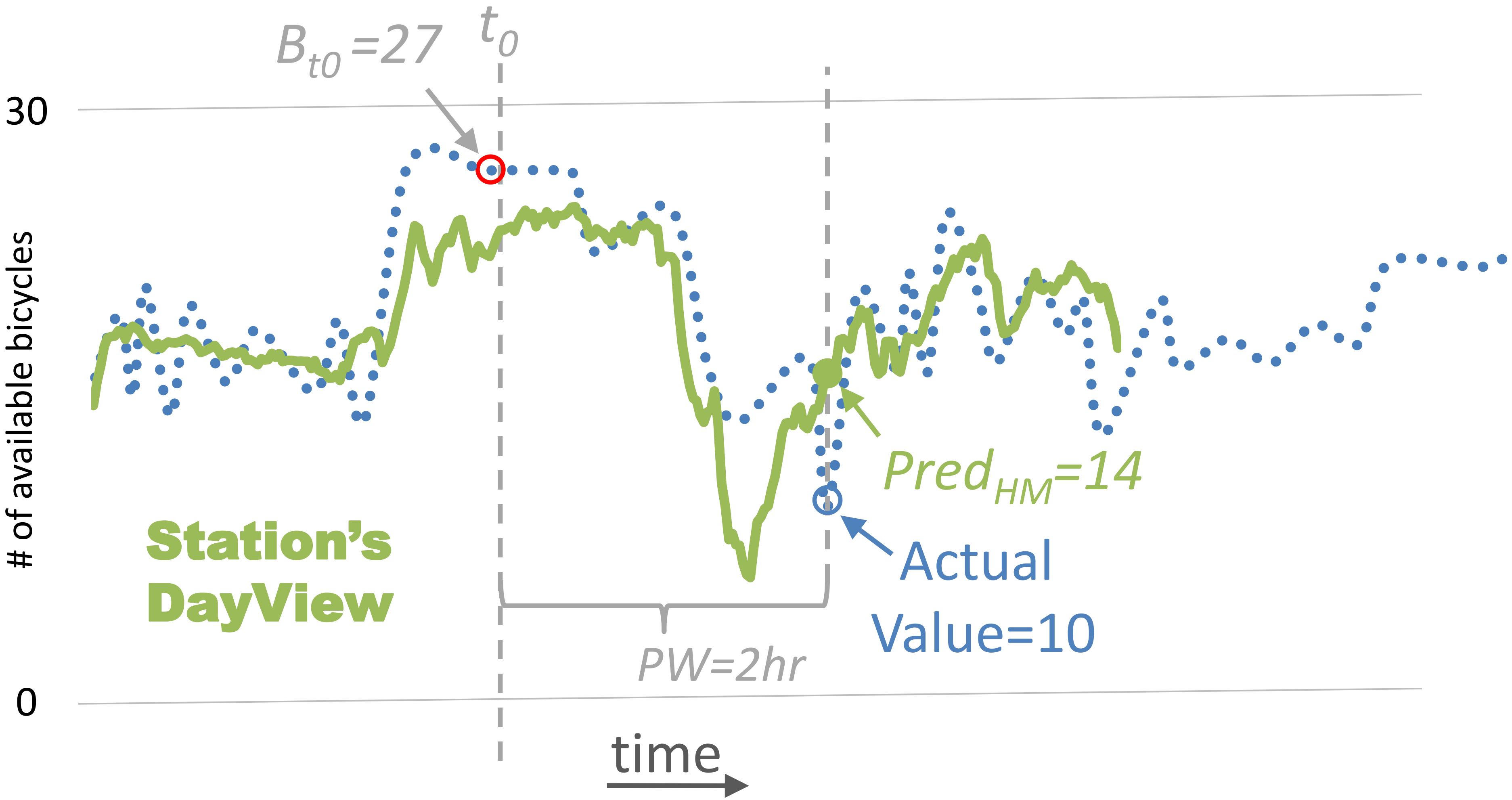
$$Pred_{HM}=(t_0, B_{t0}, PW)=\overline{B}_{TB_{t0+PW}}$$

Historic Mean



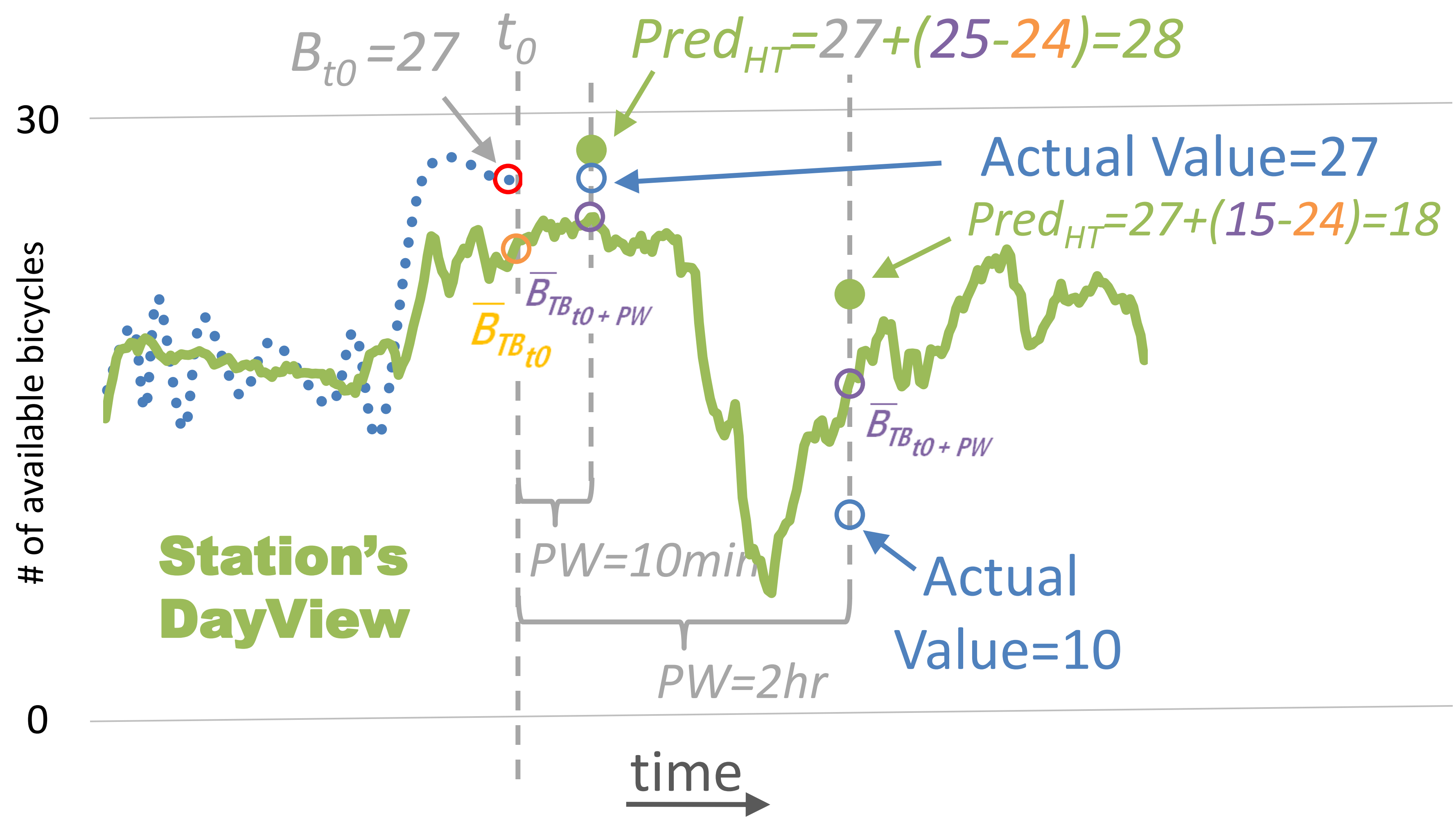
$Pred_{HM}=(t_0, B_{t0}, PW)=\overline{B}_{TB_{t0+PW}}$

Historic Mean



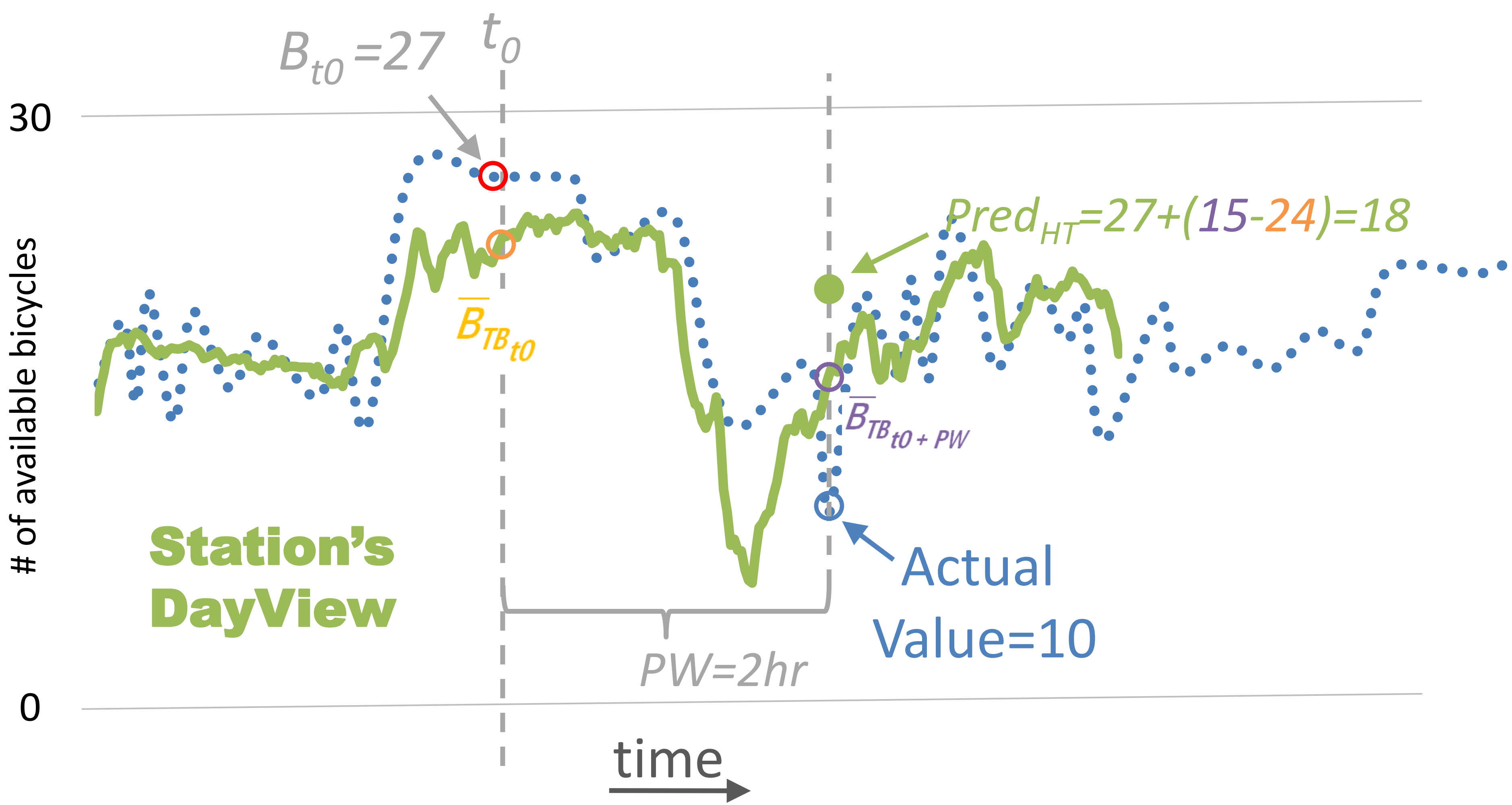
$Pred_{HT}=(t_0,B_{t0},PW)=\overline{B}_{t0}+B_{TB_{t0+PW}}-\overline{B}_{TB_{t0}}$

Historic Trend



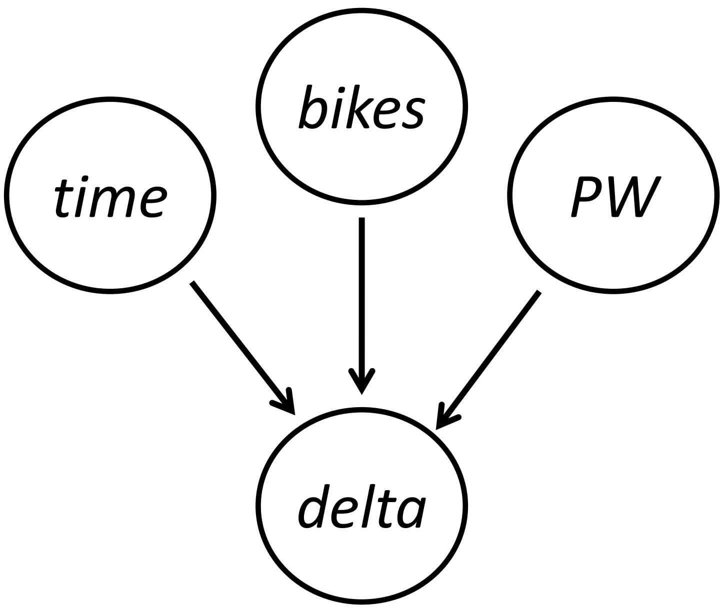
$Pred_{HT}=(t_0, B_{t0}, PW)=\overline{B}_{t0}+B_{TB_{t0+PW}}-\overline{B}_{TB_{t0}}$

Historic Trend



$$Pred_{BN}=(t_0,B_{t0},PW)=B_{t0}+delta$$

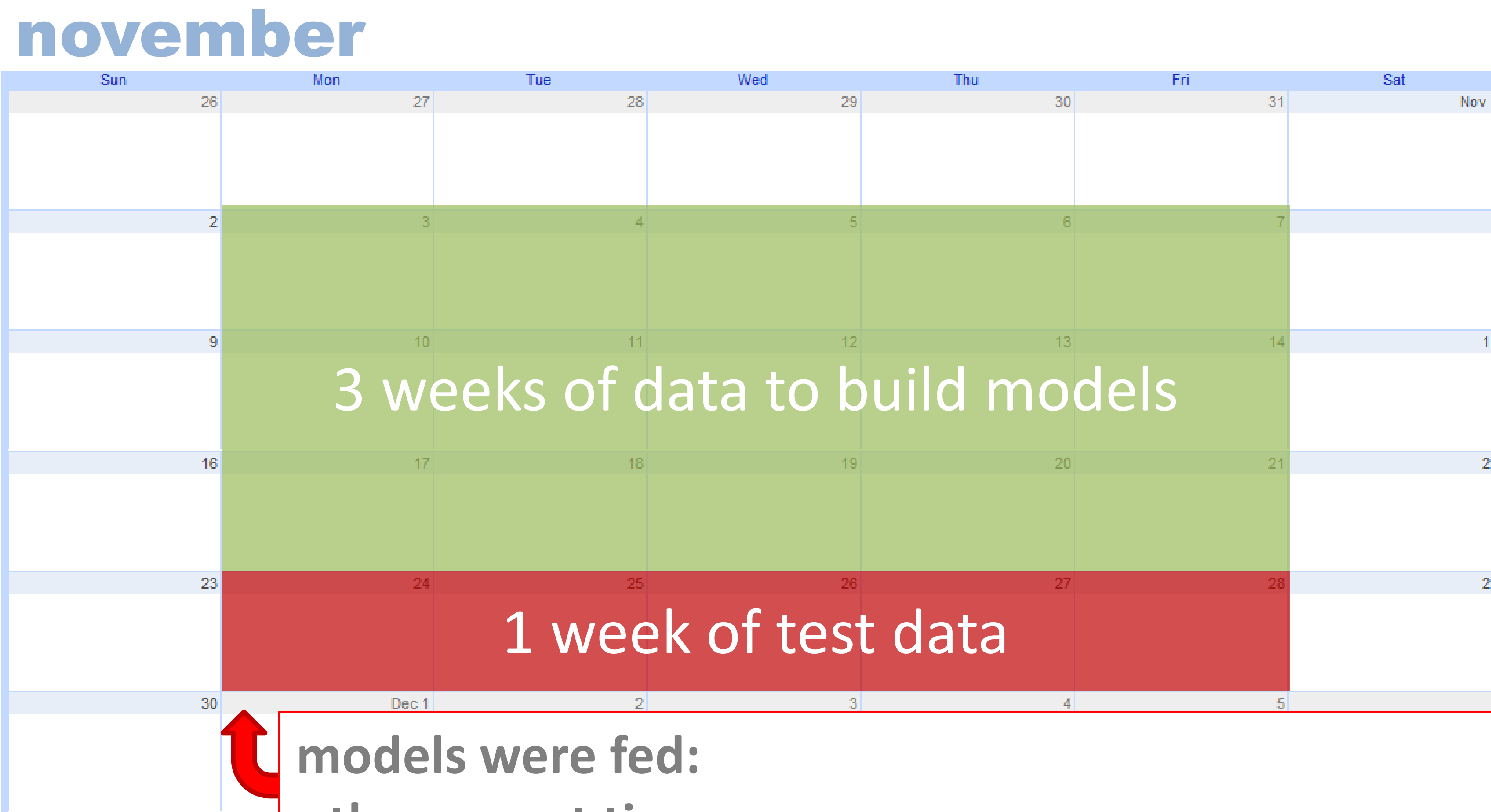
Bayesian Network



- ***time***: discrete observed node corresponding to hours in the day
- ***bikes***: the # of avail bikes at time *t*
- ***PW***: the prediction window
- ***delta***: continuous Gaussian var that represents change in number of bikes at time *t* + *PW*

Prediction made by adding the value of the *delta* node to the most recent observation

Prediction Evaluation



models were fed:
- **the current time**
- **current # of avail bicycles**
- **each of the six pw values (10,20,30,60,90,120 mins)**

Prediction Error Metric

- Absolute **difference** between the **predicted number** of bicycles & the **ground truth** observation at time t_0 + PW
- **Error** is in **number of bicycles**
  - **normalized** by the station's size

High Level Results

Model	Avg Error	Stdev of Error
Random	0.37	0.27

0.37 corresponds to roughly 9 bicycles

*error is in normalized available bicycles (nab)

High Level Results

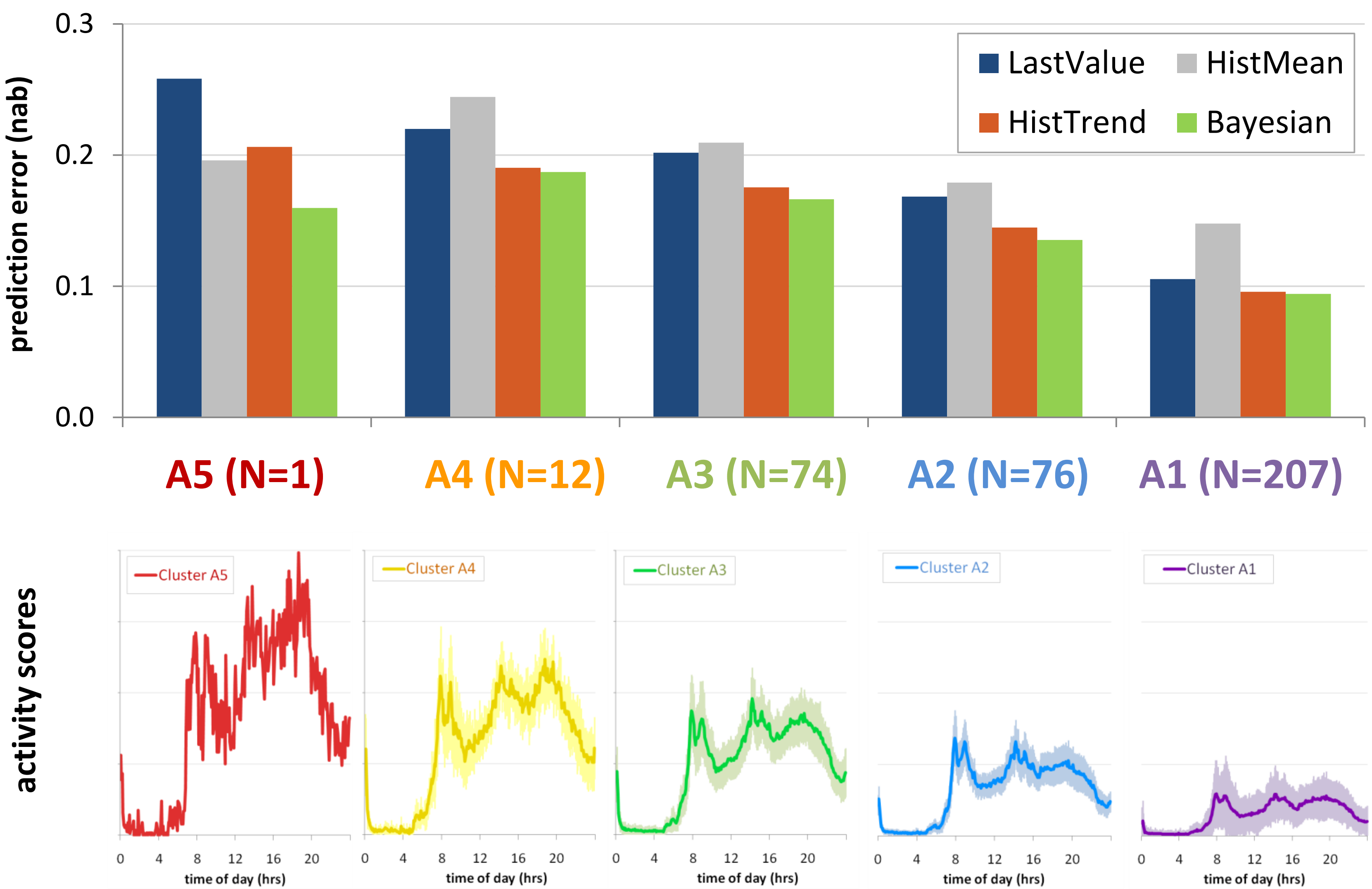
Model	Avg Error	Stdev of Error
Random	0.37	0.27
HistoricMean	0.1[illegible]	[illegible]
LastValue	0.09	0.14
HistoricTrend	0.09	0.13
Bayesian Network	**0.08**	**0.12**

0.08 corresponds to roughly 2 bicycles

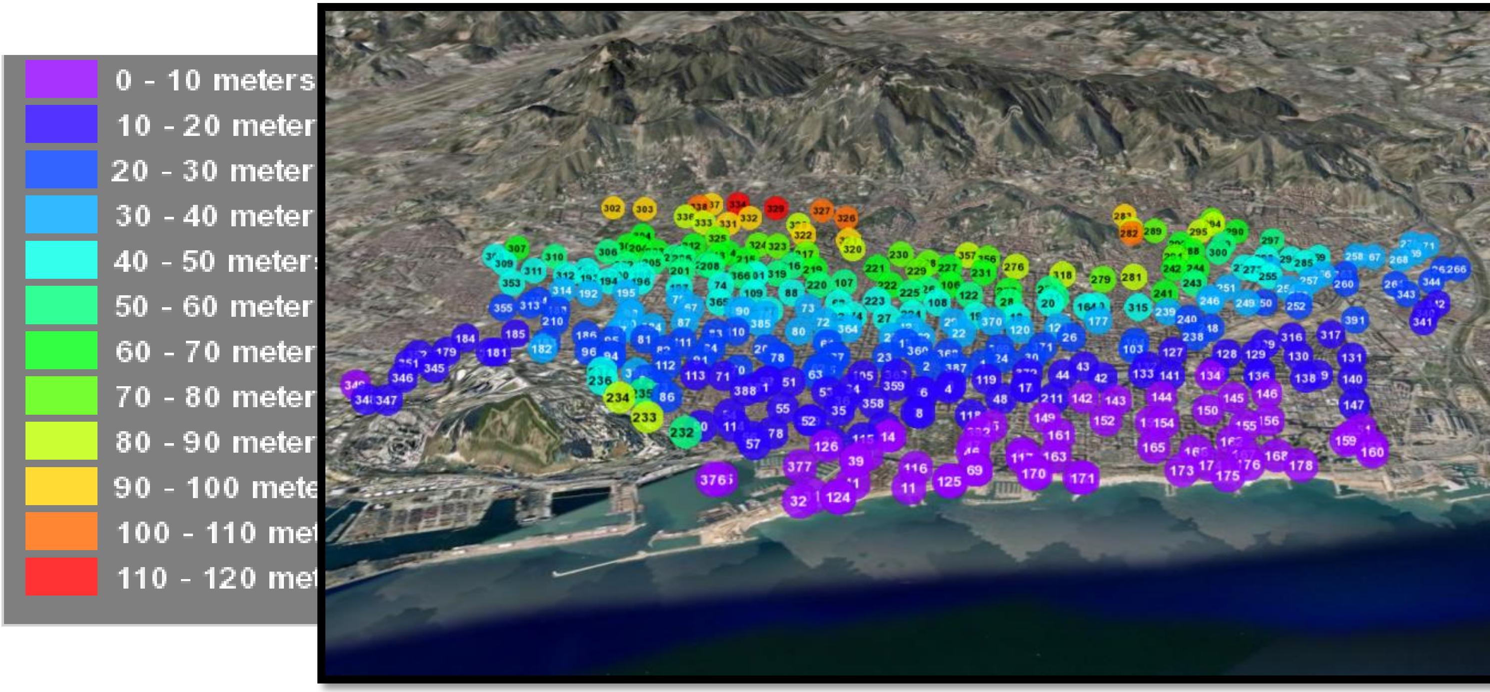
*error is in normalized available bicycles (nab)

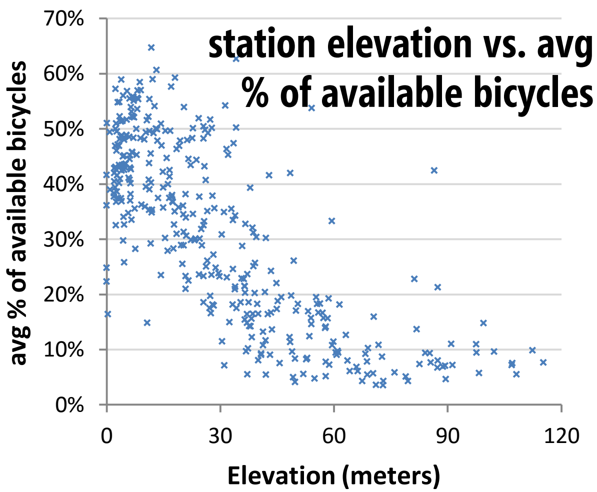
Prediction vs. Activity Cluster

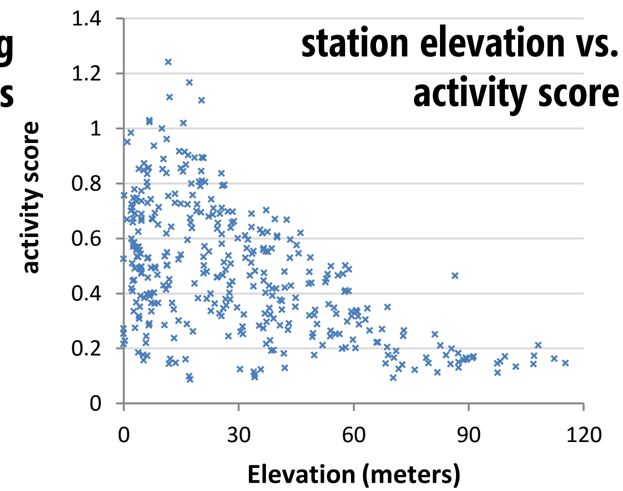
0.1 corresponds to ~2.5 bicycles at a station with 25 slots



Topographical Influences?



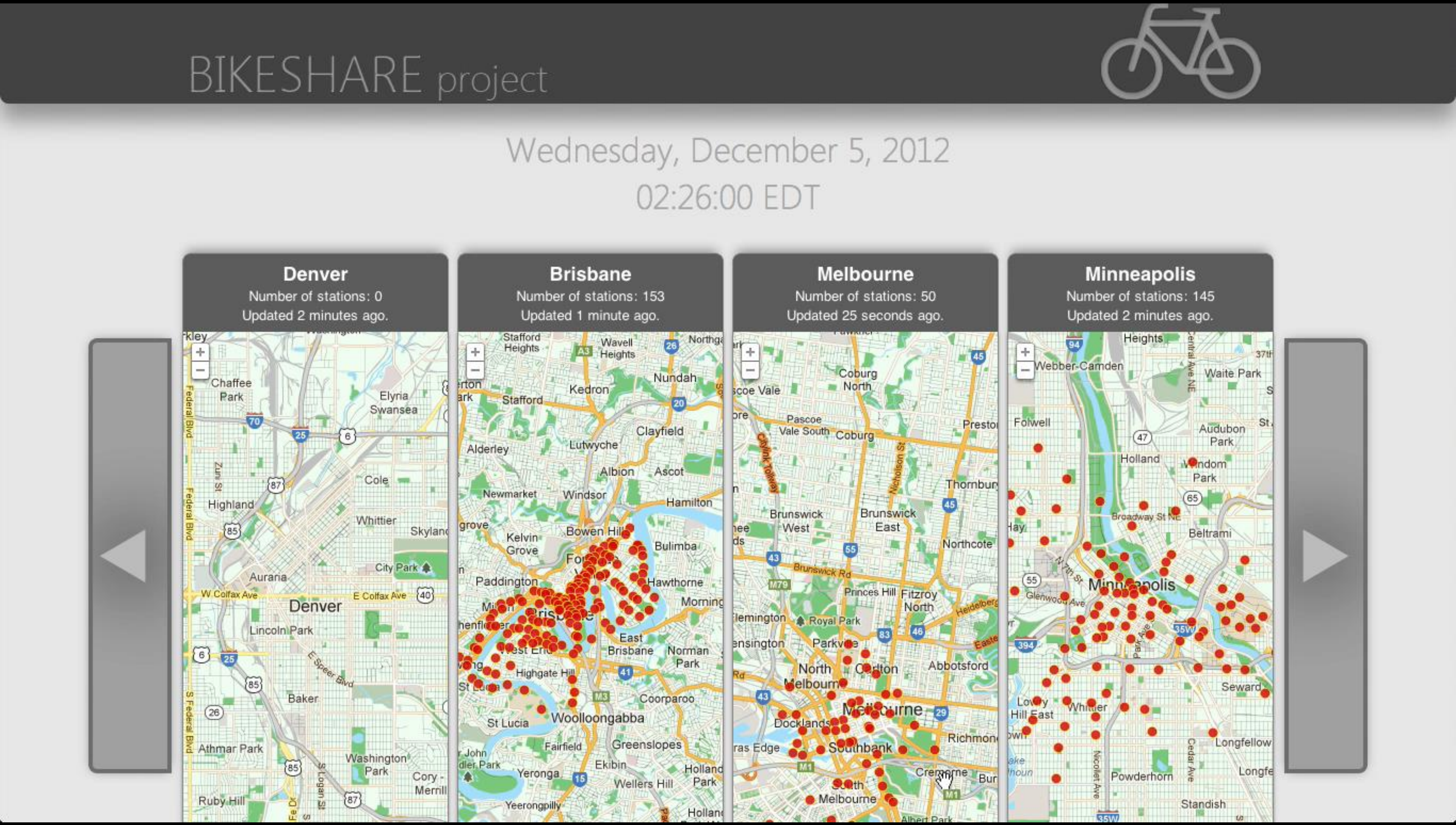





weather

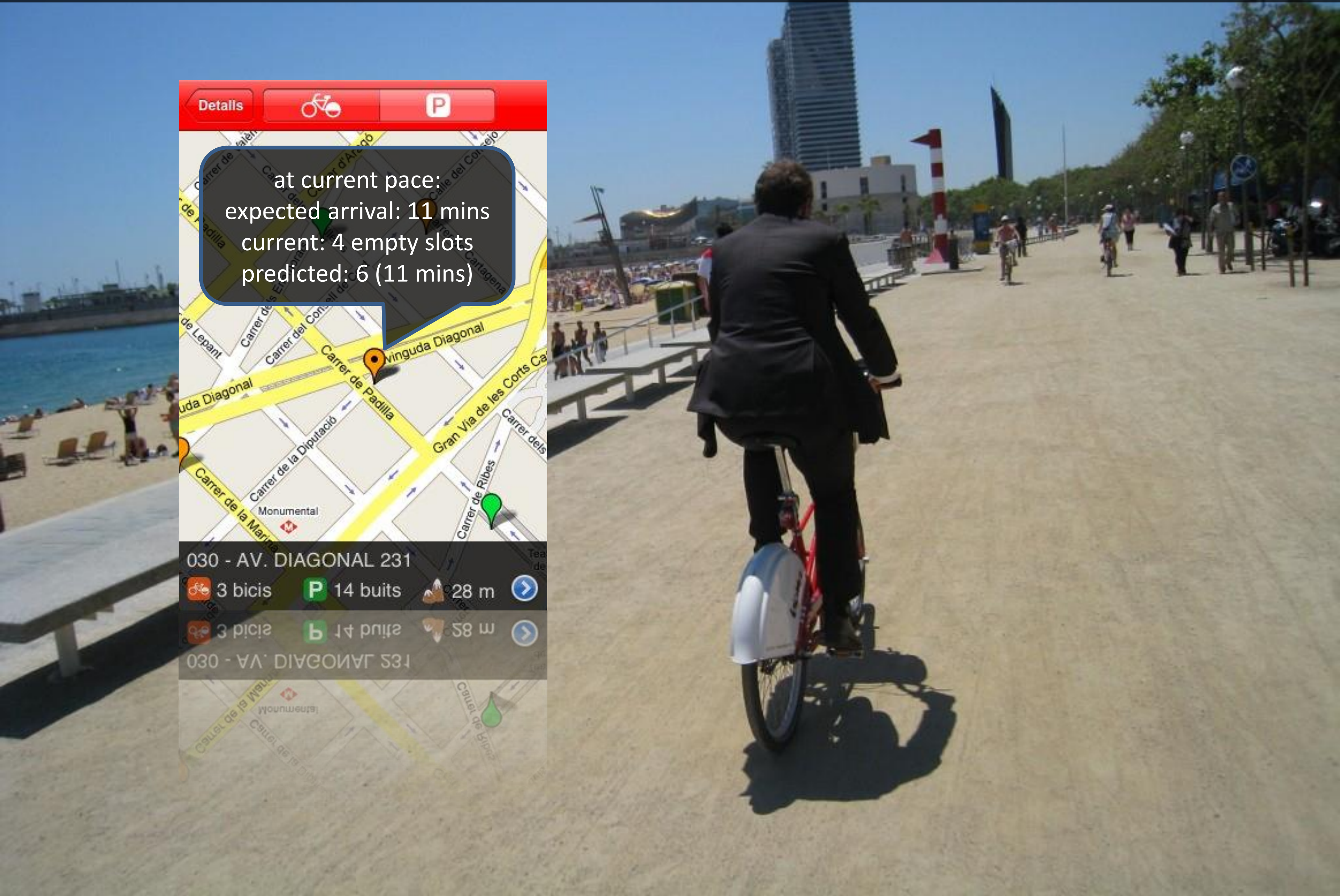
other transit sources

cross city examination



self-sustainable system

promote usage



Longitudinal Study

Related Collaborators

Related Publications

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Mining Public Transport Usage for Personalised Intelligent Transport Systems
Neal Lathia, Jon Froehlich, Licia Capra, *Proceedings of ICDM2010*

Sensing and Predicting the Pulse of the City Through Shared Bicycling
Jon Froehlich, Joachim Neumann, Nuria Oliver, *Proceedings of IJCAI2009*

Measuring the Pulse of the City Through Shared Bicycle Programs
Jon Froehlich, Joachim Neumann, Nuria Oliver, *Proceedings of UrbanSense2008*

Route Prediction From Trip Observations
Jon Froehlich, John Krumm, *Proceedings of SAE2008*

Download publications here: http://www.cs.umd.edu/~jonf/publications.html

Sensing and Predicting the Pulse of the City through Shared Bicycling

International Workshop on Spatio-temporal Data Mining for a Better Understanding of Human Mobility:
The Bicycle Sharing System Case Study
Co-organized by GERI Animatic, le Labex Futurs Urbains et l'Ecole des Ponts ParisTech
December 5th, Paris, France

HCIL Human Computer Interaction Laboratory

@jonfroehlich
Assistant Professor Computer Science

University of Maryland