Public Bike Share (PBS)

IT-driven intelligence for better bikeshare

Felisa Vázquez-Abad

CUNY Institute CoSSMO. Contact: felisav@hunter.cuny.edu

Introduction

Integrating information technology for a self-regulated PBS

Felisa Vázquez-Abad, 2016

Why the hype?

A New Way to Use Bikes

Bikes are good for sustainable cities.

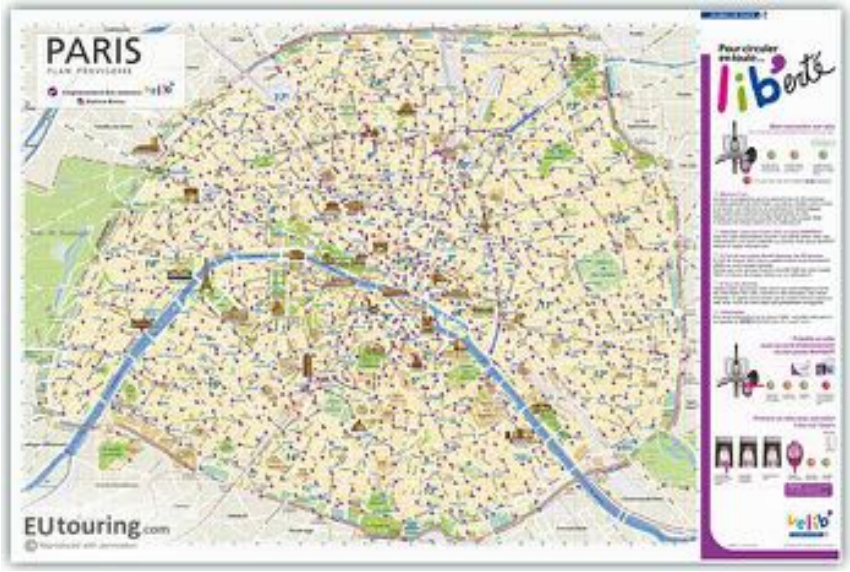
Felisa Vázquez-Abad, 2016

Brief History of Public Bike Share (PBS)

- 1st Gen (1965) Amsterdam White Bikes, many to follow.
- 2nd Gen (1995) Copenhagen "bike library": borrow with a deposit, many to follow
- 3rd Gen (1998) Rennes, Lyons: use of "smart card" technology
  - User identification
  - Information, monitoring, etc

How did Vélib achieve success?

- **Access fee:**
  - Annual memberships
  - Short term memberships
- **Usage fees:**
  - Above 30-45 minute ride
  - Geometric progression: $7, $14, etc, $441 for three hours!



Statistics: PBS is here to stay!

In early 2014, some 600 cities in 52 ries host advanced bike-sharing ith a combined fleet of more

Spain leads the world with 132 separate bike-share programs. Italy has 104, and Germany, 43.
The **world's larg bike-sharing program** is in Wuhan, China's sixth la with 9 million people and 90,000 shared hina was home to 82 bike-sharing prog combined fleet of some 380,0

The **United States** hosts 36 modern bike-sharing programs. With a number of new programs in the works and planned expansions of existing programs, the U.S. fleet is set to nearly double to over **37,000 publicly shared bicycles** by the end of 2014.

Is it working?

SECTIONS

The New York Times

SUBSCRIBE

N.Y. / REGION

Citi Bike System Successful, but Wobbly From the Start

By MATT FLEGENHEIMER MARCH 26, 2014

261 COMMENTS

Share

Tweet

Email

Save

MORE

The hard truth lurked behind the gates of the Brooklyn Navy Yard, where employees of Citi Bike were tasked with testing the program last spring after nearly a year of delays.

As workers soon realized, the system was not completely ready, plagued by fussy software and managed by an Oregon company that [illegible] its sprawling N[illegible]

A Citi Bike repair and storage station underneath the Williamsburg Bridge on Delancey Street in Manhattan. Ashley Gilbertson for The New York Times

Citi Bikes' Canadian manufacturer files for bankruptcy: report

Montreal-based PBSC Urban Solutions, a nonprofit known as Bixi, has debt of almost 50 million in Canadian dollars, the Montreal Gazette reported.

NEW YORK DAILY NEWS / Tuesday, January 21, 2014, 2:26 AM

A A A

Challenges of 3rd Gen PBS

- **Customer dissatisfaction** – lack of availability
- **Financial difficulties** – need for outside funds
- **Safety issues** -- anxiety facing route and time uncertainty may yield to reckless driving.

Customer (dis)satisfaction

Starvation: no bikes!

Dissatisfaction Index

Proportion of customers that find no bikes when and where they wish to use one.

Redistribution

Carry bikes from depot (or other nearby stations) to replenish starving stations.

Expensive to do continually. Difficult algorithmic problem.

The time limit

Unlimited number of rides, but each with a time limit,

Why do this?

- People learn: find a dock, park and get another bike
- Drivers may rush to park in time, and risk accidents
- Today 33% revenue in US PBS comes from usage fees

Significant revenue at Risk

Negative Impact on Safety

Negative Impact on Availability

Better data

Better **use** of data

Towards 4G-PBS

Felisa Vázquez-Abad, 2016

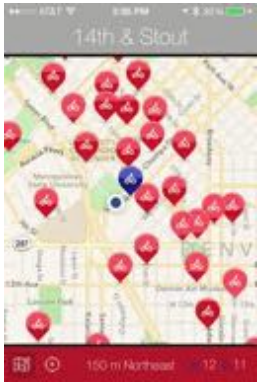
Our Vision of the Future for the 4th Gen PBS

Better data: Engage users to provide more data. Implement statistical correction of anomalies.

Better use of data: algorithms for prediction, reservations, and re-balancing. Provide users with more information.

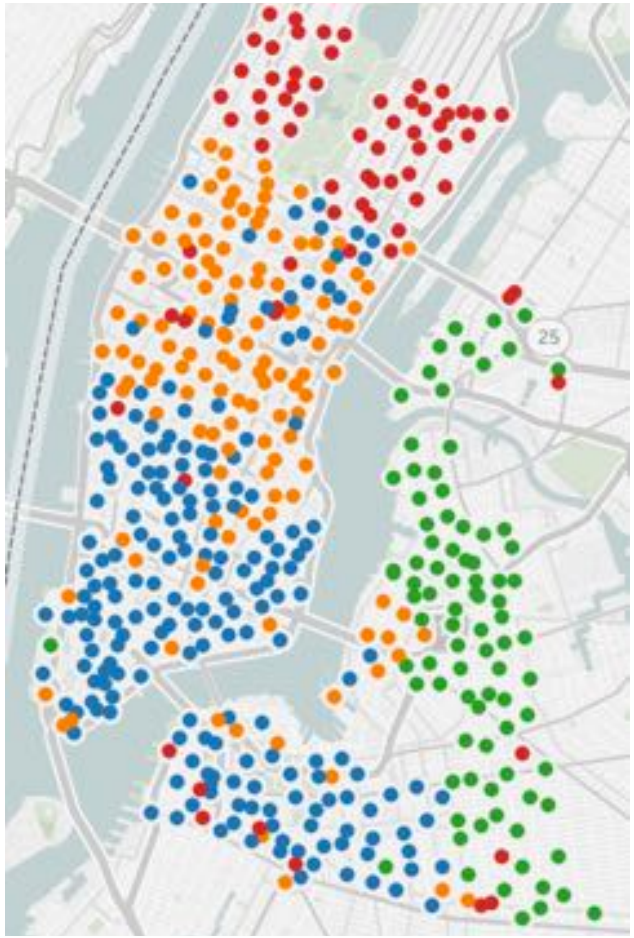
Our Vision for the 4th Gen PBS

- Integration of data analytics (GPS, customer classes, preferences, patterns)
- Humans as users but also as sensors/agents
- Incentivize redistribution by reward systems
- Allow reservations



Self-regulation: use information for

- Dock/bike dynamic reallocation
- Maintenance, expansion
- Dynamic yield management



- Classification of stations
- Redistribution
- Reservations
- Economic model
- Pricing strategies
- Simulation

Some Examples

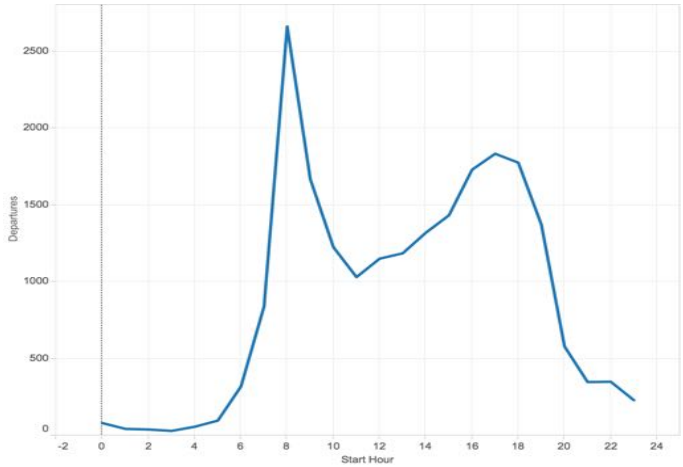
Station Classification

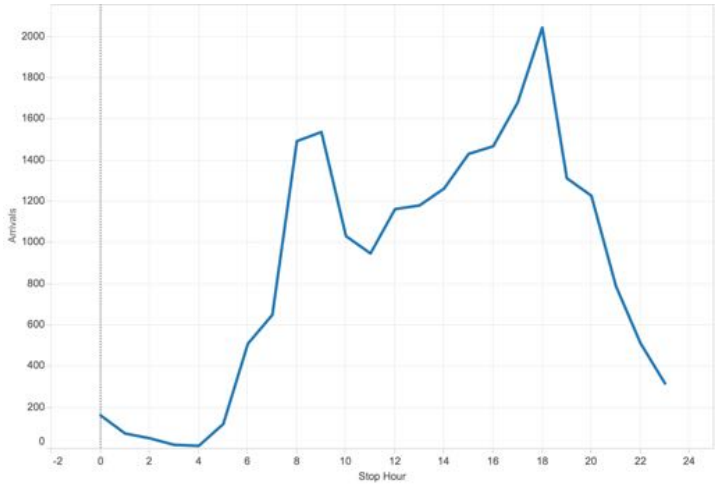
Finding patterns

Creating new knowledge

Felisa Vázquez-Abad, 2016

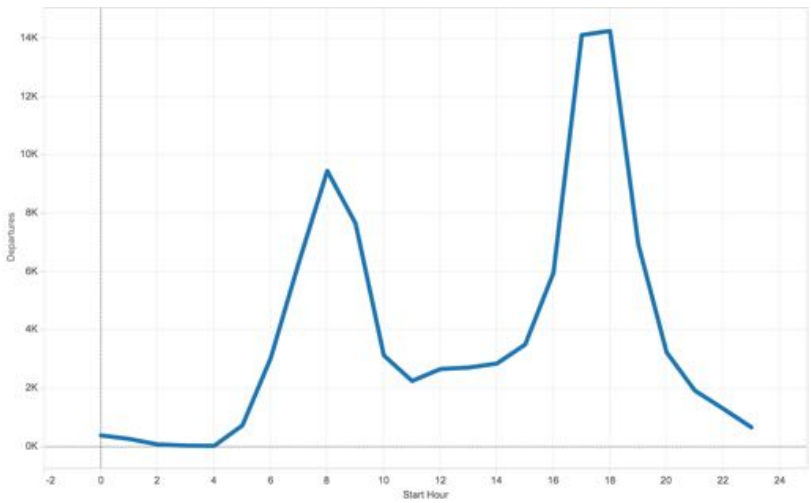
Patterns station 72

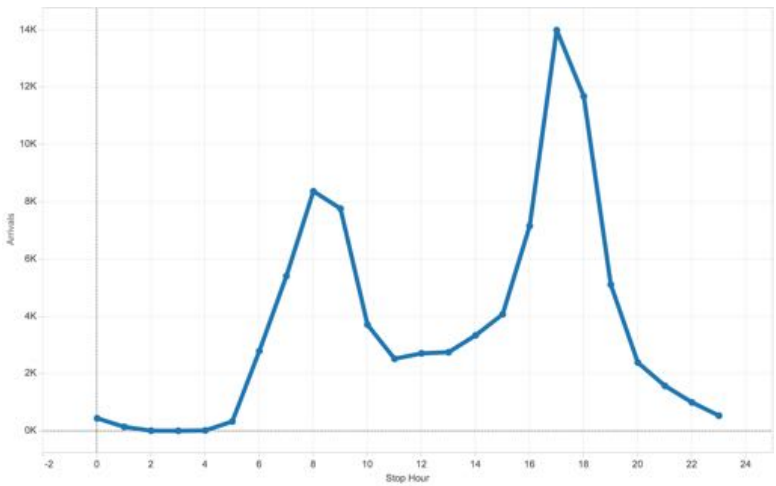




"Mirror" patterns as origin and as destination.

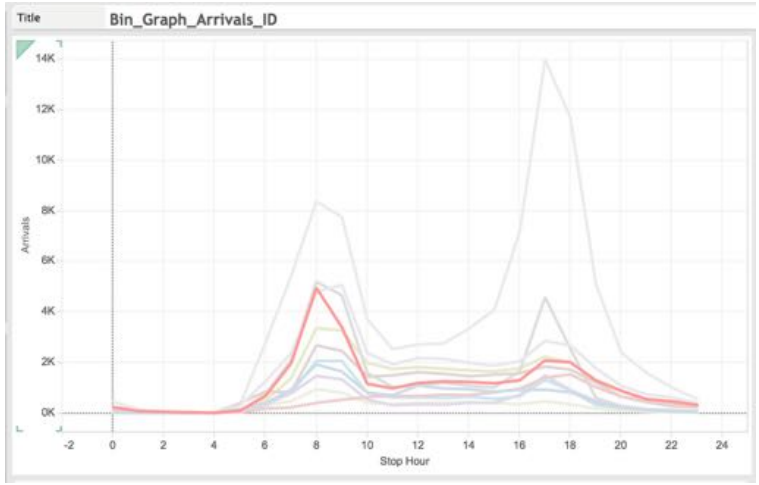
Patterns Grand Central

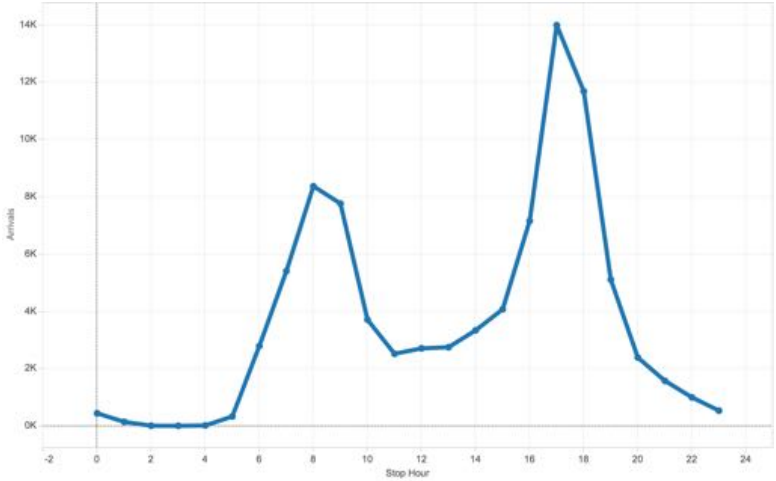




Can you guess what is going on?

Patterns Grand Central





Lack of bikes "pulls" demand on nearby stations

Unusual Patterns

Possible situations when pattern is true

- Station isolated and badly light at night
- People use subway in the morning and bike in the evening
- People use bike in the morning and other safer transport at night

Possible data anomaly

- Grand Central is known for being very popular: no bikes when origin, no docks when destination ("valet" parking)
- Historical data: trips taken
- Streaming data: actual situations and occupancy

Machine Learning ++

Training (historical data) *versus* learning (streaming data)

- Function for automatic detection of unusual patterns.
- Statistical corrections (use streaming and historical data) to assess real demand.
- Classify stations (neural nets for supervised learning, distance function for unsupervised learning).

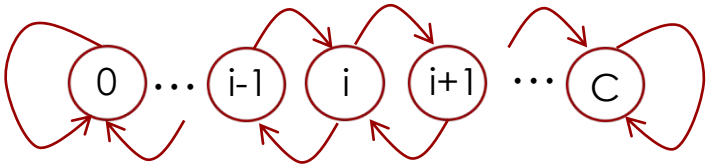
Automatic detection and classification (for any city!) and classification.

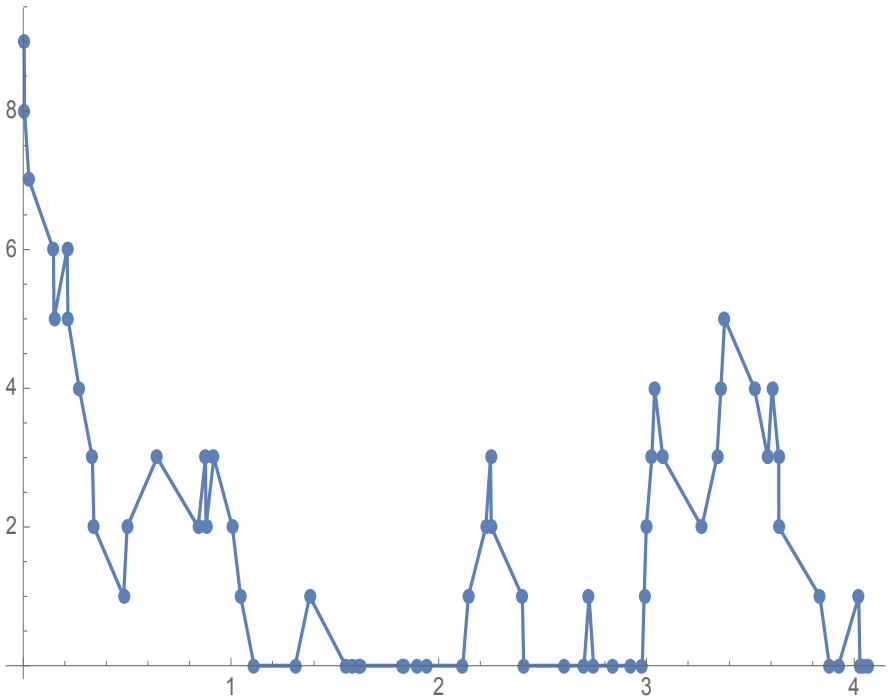
Why is this useful?

Redistribution

Birth and Death Model

- Bike comes in (birth)
- Bike goes out (death)





Model is known as the ``gambler's ruin''. Markov chain methods can be used to calculate expected time to depletion.

Using this model, we propose methods for optimizing **when** to call for redistribution to satisfy a given dissatisfaction rate α.

Day-segments: regimes and threshold controls

- **Super-starvation.** Much higher rental demand than parking. Calling the truck when empty is too late.
  - Control: call truck when there are θ bikes.
- **Starvation.** More rental demand than parking, but we can wait after station is empty.
  - Control: call truck when empty time exceeds θ minutes.
- **Neutral:** demands "balance" each other.
  - Control: None.
- **Filling.** More parking demand than rentals, but we can wait after all docks are full.
  - Control: call the truck when full time exceeds θ minutes.
- **Super Filling.** Much higher parking demand than rental. Calling the truck when station is full is too late.
  - Control: call truck when there are θ free docks.

Theoretical Results

Lemma 1. *Assume that $\lambda < \mu$ and C is total capacity. Let*

$$\tau_C(k) = \min(s\colon X(t+s) = 0 \,|\, X(t) = k)$$

denote the time until starvation of the station, and $T_C(k) = \mathbb{E}[\tau_C(k)]$, then

$$T_C(k) = A\left(\left(\frac{\mu}{\lambda}\right)^k - 1\right) + \frac{k}{\mu - \lambda},\ A = -\left(\frac{\lambda}{\mu}\right)^C \frac{\lambda}{(\mu-\lambda)^2}.$$

ρ : delay until truck arrives, from time when call is placed.
$L(\theta)$: expected length of cycle (time between two consecutive re-distributions).
$I(\theta)$: expected time empty during a cycle.

Lemma 2. *Let $R(\delta t)$ be the residual empty time during a period of time δt starting empty. Under the control policy for SS regime*

$$L(\theta) = T_{C_0-\theta}(C_0 - \theta) + \rho, \quad \text{and} \quad I(\theta) = \mathbb{E}[R(\rho - \tau_{C_0}(\theta))\mathbf{1}_{\{\tau_{C_0}(\theta)<\rho\}}].$$

Under the control policy for the S regime

$$L(\theta) = T_{C_0}(C_0) + \lambda\theta T_{C_0}(1) + \theta + \rho, \quad \text{and} \quad I(\theta) = \theta + \mathbb{E}[R(\rho)].$$

Stochastic Optimization

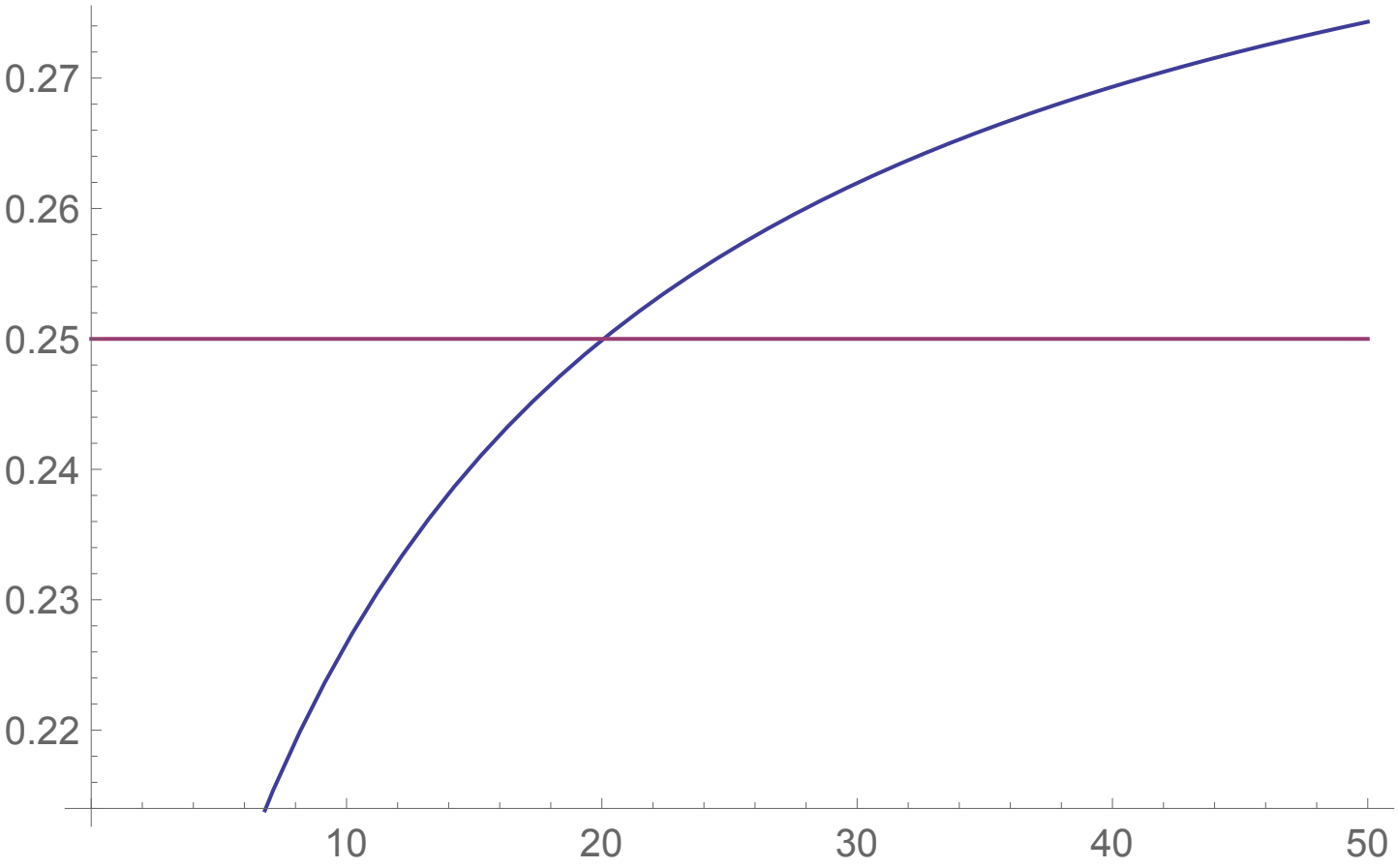
Minimize cost of redistribution subject to a constraint of the form "at least 95% of arriving clients are satisfied".

$$\min_{\theta} \left(J(\theta) \stackrel{\text{def}}{=} \frac{\kappa}{L(\theta)} \right) \qquad \text{s.t.} \quad I(\theta) \leq \alpha L(\theta)$$

- To satisfy the constraint we need to find θ^* such that $I(\theta^*)/L(\theta^*) = \alpha$ ($\alpha = 0.05$, for example).

SS or SF: stochastic binary search

S or F: target tracking with stochastic approximation.



Target Tracking

Extensions

Current work: create novel algorithms to include both stochastic models and streaming data.

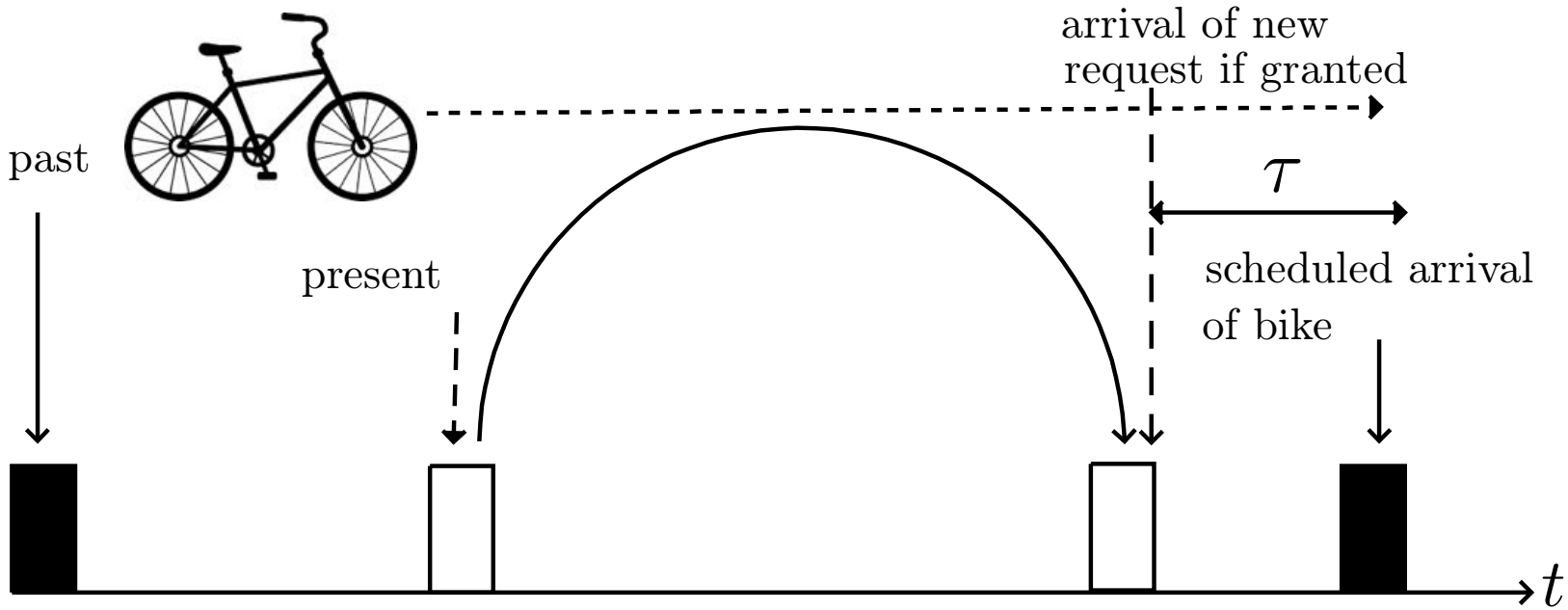
Use station classification for better predictions.

Reservations

Ranking and Selection

Applied probability models

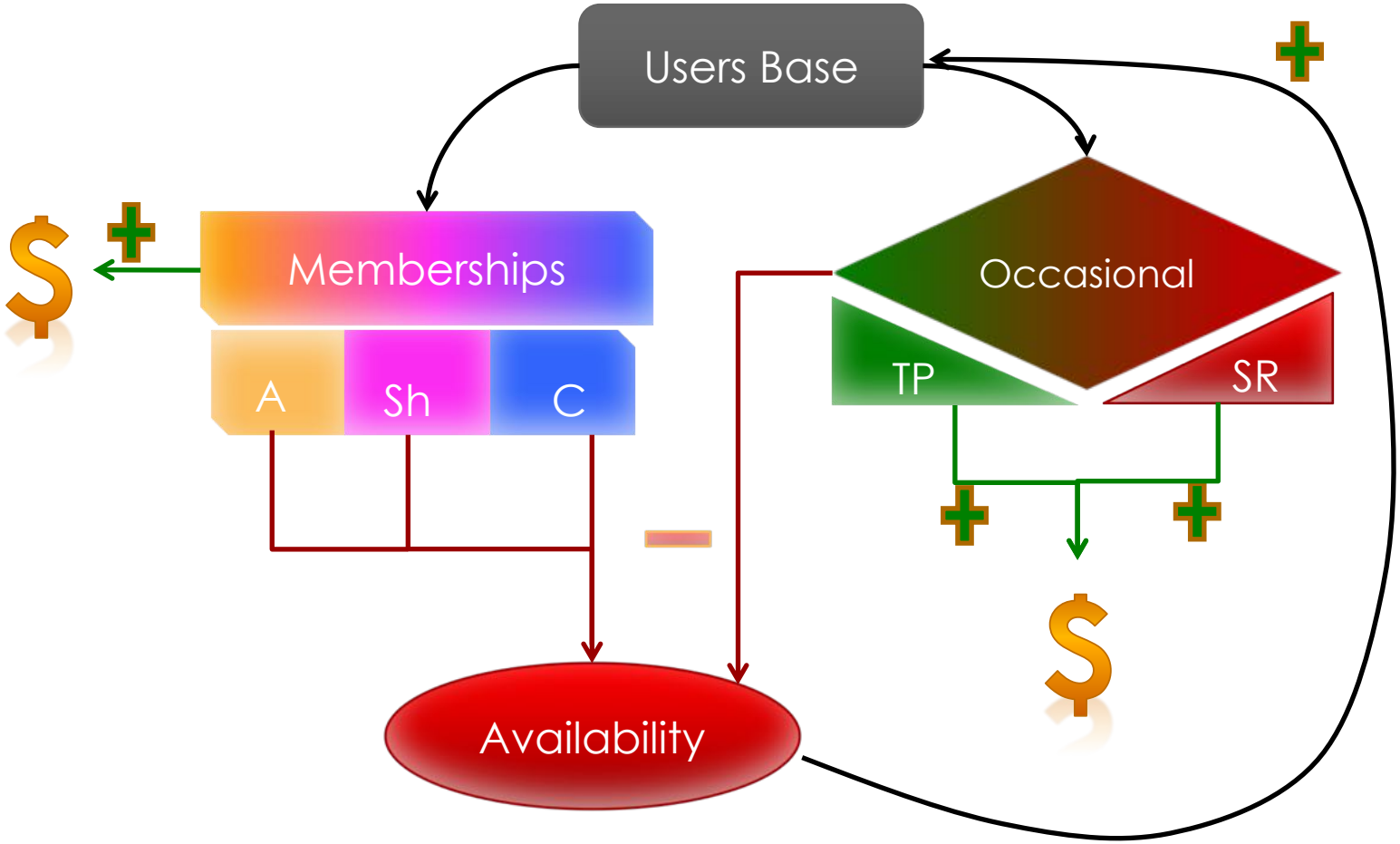
Ranking and selection



$$\mathbb{P}(X_d(t) = C_d \,|\, T_d(o) = t, S_d(t_0, t) = n) \approx \begin{cases} 0, & n \leq C_d - m_d \\ e^{-\lambda_d t} \sum_{k=0}^{m_d+n-C_d} \frac{(\lambda_d t)^k}{k!} m, & n + m_d > C_d \end{cases}$$

Economic Model

Solution 2: Economic model for pricing alternatives.



Ongoing: stochastic analysis of dynamic system with feedback for optimal balance (economic equilibrium)

Research Team

- Felisa Vázquez-Abad: stochastic optimization, probability theory, mathematical models.
- Michael Fu: optimization, applied probability.
- Ted Brown: simulations, data gathering, apps development.
- Jason Young: behavioral psychology, modeling human reactions and behavior
- Research Assistants: Silvano Bernabel, Larent Barreaud.
- Students: Cynthiaann Bryant, Paulina Toro Izasa, Greg Javens and Elias Morgenroth.

The End