

Sizing, Incentives and Redistribution in Bike-sharing Systems

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G-scop seminar, dec 2011, Grenoble

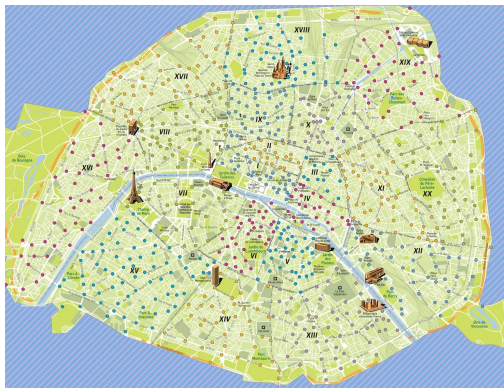
1. joint work with Christine Fricker (Inria)

Outline

- 1 Introduction and model
- 2 Detailed study of the homogeneous case
- 3 Adding some Heterogeneity
- 4 Conclusion and future work

A new transportation system.

- Bike sharing systems started in the 60s.
- Increasing popularity since Velib' in Paris (2007).
- > 400 cities. Ex : Lausanne, Barcelona, Montreal, Washington.
- Various size : from 200 to more than 50000 bikes.



Map of Velib' stations in Paris (France).

Example of Velib' :

- 20000 bikes
- 2000 stations.

Usage :

- Take a bike from any station.
- Use it.
- Return it to a station of your choice.

Public but different from public transportation

Business model (in most of the cities)

- publicity in exchange of guarantee of service.

Many advantages :

- Good for the town (pollution, traffic jams, health, image) ;
- Good for the citizen (cheap, quick, no bike to buy, no risk of theft).

However : **congestions problems.**

Empty station



:(

Full station



:(

Good stations



:)

problematic stations

- Goal of city : minimize the number of **problematic stations.**
- Goal of operator : minimize the running cost.

How to manage them ?

Identify bottlenecks :

- time dependent arrival rate : daily period
- heterogeneity : popular or non popular stations (housing and working areas, uphill and downhill stations,...)
- random choices of users.

Strategic decisions

- Planning : number of stations, location, size.
- Long term operation decisions : static pricing, number of bikes.
- Short term operating decisions : dynamic pricing, repositioning.

Research challenges :

- Quantify what can be asked by the city.
- Modelling : temporal and spacial dependencies.

Our approach

Congestion due to **flows** and **random choices**

In this talk : study the impact of random choices

- 1 Qualitative behavior and quantitative impact of different factors.
- 2 Strategies : redistribution (trucks) and incentives (pricing).

Related work :

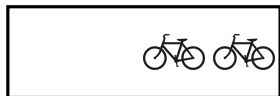
- Traces analysis, clustering (Borgnat et al. 10, Vogel et al. 11, Nair et al. 11]
- Redistribution based of forecast [Raviv et al. 11, Chemla et al. 09]
- Few stochastic models. In a similar context : limiting regime with infinite capacity [Malyshev Yakovlev 96, Georges Xia 10]

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The simplest case : homogeneous

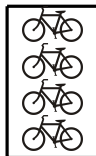
$$C = 4$$



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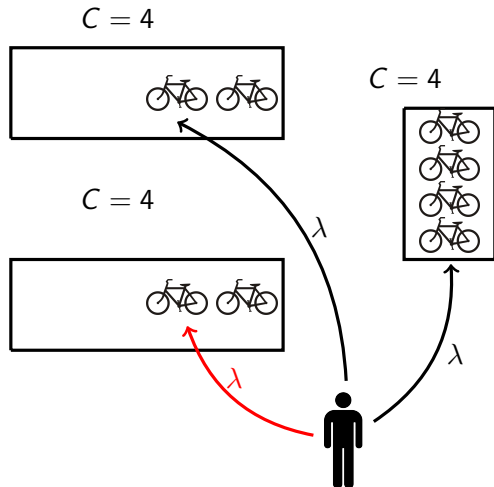
For all N stations :

- Fixed capacity C

Will be extended to non-homogeneous :

- arrival rate, routing probability

The simplest case : homogeneous



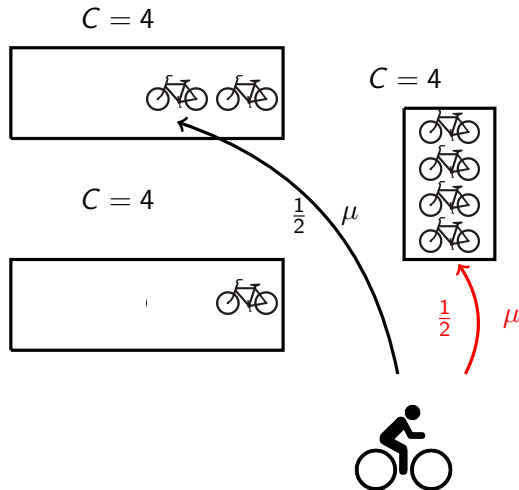
For all N stations :

- Fixed capacity C
- Arrival rate λ .

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The simplest case : homogeneous



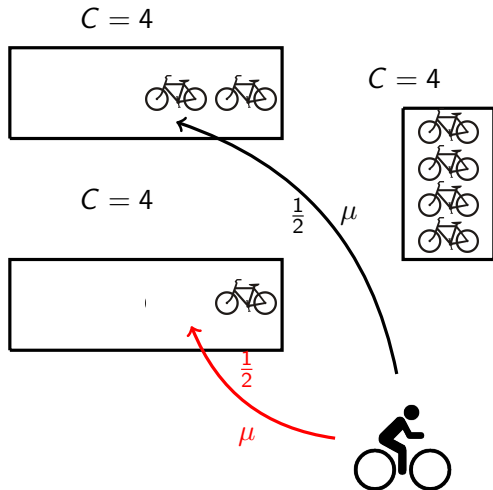
For all N stations :

- Fixed capacity C
- Arrival rate λ .
- Routing matrix : homogeneous.
- Travel time : exponential of mean $1/\mu$.

Will be extended to non-homogeneous :

- arrival rate, routing probability

The simplest case : homogeneous



For all N stations :

- Fixed capacity C
- Arrival rate λ .
- Routing matrix : homogeneous.
- Travel time : exponential of mean $1/\mu$.
- Other destination chosen if full (\approx local search).

Will be extended to non-homogeneous :

- arrival rate, routing probability

A first result : steady state distribution of stations

- Compute the fraction of station with i bikes.

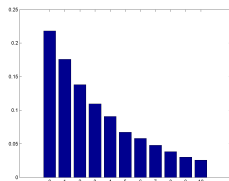
Theorem

There exists ρ , such that *in steady state*, as N goes to infinity :

$$x_i = \frac{1}{N} \# \{ \text{stations with } i \text{ bikes} \} \propto \rho^i.$$

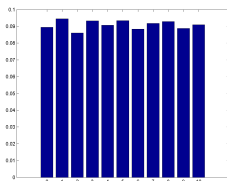
We have $\rho \leq 1$ iff $s \leq \frac{C}{2} + \frac{\lambda}{\mu}$ where s be the average number of bikes per stations.

$$s < \frac{C}{2} + \frac{\lambda}{\mu}$$



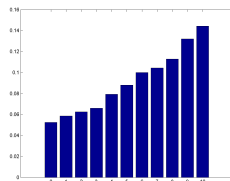
$$\rho < 1$$

$$s = \frac{C}{2} + \frac{\lambda}{\mu}$$



$$\rho = 1$$

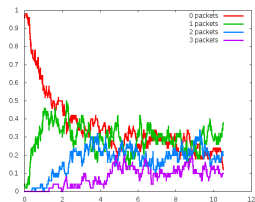
$$s > \frac{C}{2} + \frac{\lambda}{\mu}$$



$$\rho < 1$$

Proof based on mean field approximation

$$x_i = \frac{1}{N} \#\{\text{stations with } i \text{ bikes}\}$$

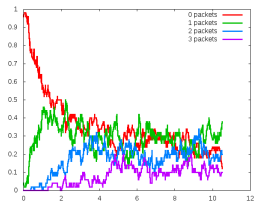


For fixed N , X_i is a complicated stochastic process

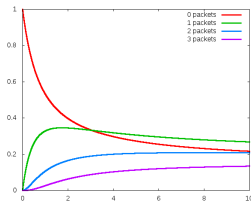
- Reversible process but steady state not explicit.

Proof based on mean field approximation

$$x_i = \frac{1}{N} \#\{\text{stations with } i \text{ bikes}\} \propto \rho^i$$



$N \rightarrow \infty$
➔



For fixed N , X_i is a complicated stochastic process

- Reversible process but steady state not explicit.

System described by an ODE

- The ODE has a unique fixed point.
- Closed-form formula.

Use **mean field** approximation [Kurtz 79]

- Study the system when the number of stations N goes to infinity.

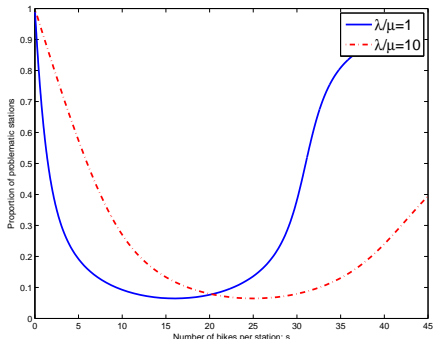
Consequences : optimal performance for $s \approx C/2$

Fraction of **problematic stations** (=empty+full) x_0+x_C is minimal for

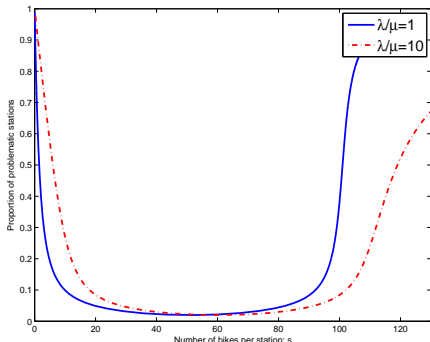
$$\rho = 1 \quad \text{i.e.} \quad s = s_c \stackrel{\text{def}}{=} \lambda/\mu + C/2$$

- Prop. of problematic stations is at least $2/(C+1)$ and “flat” at s_c .

Ex : for $C = 30$: at least 6.5% of problematic stations.



(a) $C = 30$.



(b) $C = 100$.

y-axis : Prop. of problematic stations. x-axis : number of bikes/station s .

Improvement by dynamic pricing : “two choices” rule

- Users can observe the occupation of stations.
- Users choose the **least loaded** among 2 stations close to destination to return the bike (ex : force by pricing)

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Paradigm known as “*the power of two choices*” :

- Comes from balls and bills [Azar et al. 94]
- Drastic improvement of service time in server farm [Vvedenskaya 96, Mitzenmacher 96]

Question : what is the effect on bike-sharing systems ?

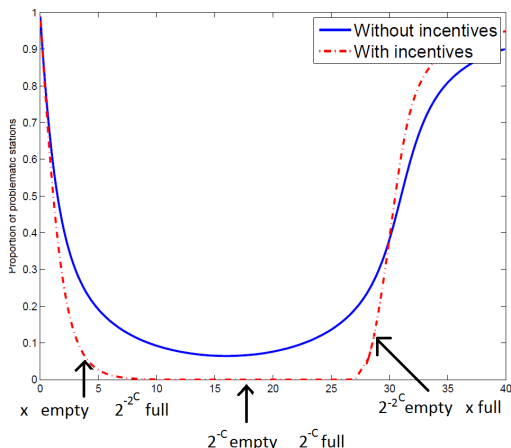
Characteristics :

- 1 **Finite capacity** of stations.
- 2 Strong **geometry** : choice among **neighbors**.

Two choices – finite capacity but **no geometry**

With no geometry, we can solve in **close-form**.

- Proof uses similar **mean field** argument.

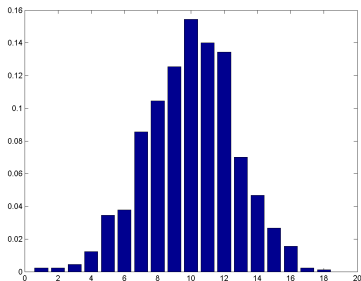


Choosing two stations **at random**, improves perf. from $1/C$ to 2^{-C}

Two choices – taking geometry into account

Problem hard to solve : mean field do not apply (geometry) :(.

- Existing results for balls and bins (see [Kenthapadi et al. 06])
- Only numerical results exists for server farms (ex : [Mitzenmacher 96])



We rely on simulation

Occupancy of stations

x-axis = occupation of station.

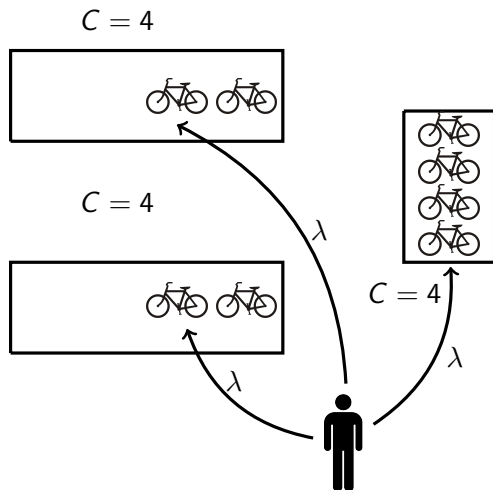
y-axis : proportion of stations.

Recall : with no incentives, the distribution would be uniform.

Empirically :

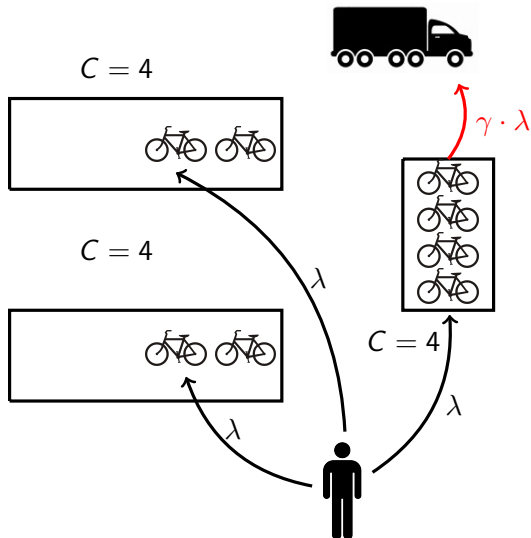
- with geometry 2D : proportion of problematic stations is $\approx 2^{-C/2}$.
(recall : with no-geometry : 2^{-C} , with no incentive : $1/C$).

Improvement by redistribution



Same model as before
with a truck

Improvement by redistribution



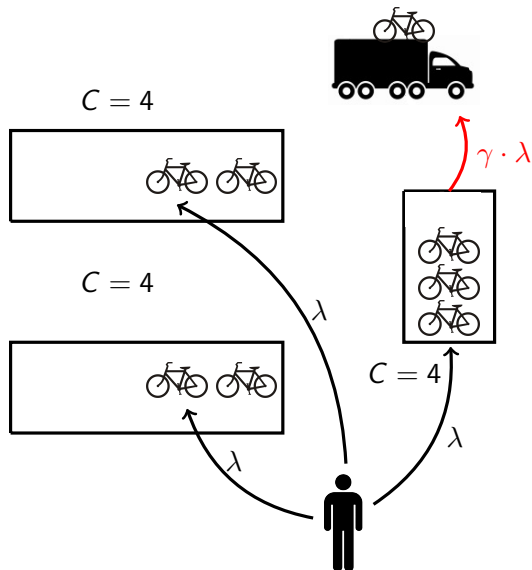
Same model as before
with a truck

With rate $\gamma \cdot \lambda$:

- Take a bike from the most loaded.
- Put it in the least loaded.

Question : what should γ be? 10%, 20%, more?

Improvement by redistribution



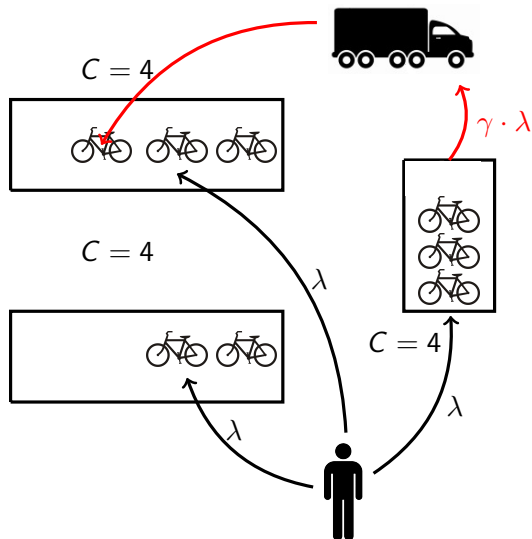
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Question : what should γ be? 10%, 20%, more?

Optimal rate of regulation is $1/(C - 1)$

Recall C is the capacity, s the fleet size and N the number of stations.

Theorem

As N goes to infinity, we have :

- The number of problematic stations decreases as γ increases.
- If $\gamma > \frac{1}{2[C - (s - \lambda/\mu)] - 1}$, then there is no problematic stations.

For example : if $s = \frac{C}{2} + \frac{\lambda}{\mu}$, a **regulation rate of $1/(C - 1)$** suffices.

Proof. Again mean field approximation but with *discontinuous dynamics*

- The dynamical system is described by a **differential inclusion**

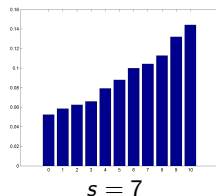
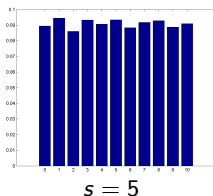
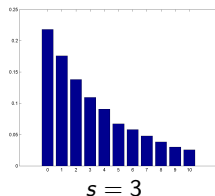
$$\dot{x} \in F(x).$$

- The DI has a unique solution. We can solve in close-form.
See [Gast Gaujal 2010].

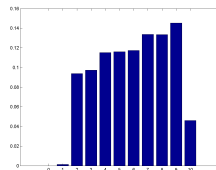
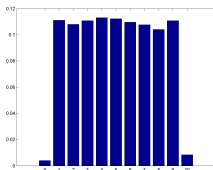
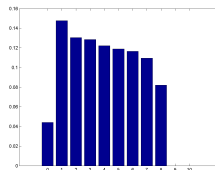
Optimal rate of regulation, illustration

Example : capacity is $C = 10$. Fleet size is 3,5 or 7 bikes/stations.

1 No regulation, $\gamma = 0$



2 Regulation ($\gamma = 10\%$).



x-axis = occupancy of stations, from 0 to 10.

y-axis = proportion of stations.

Conclusion on the homogeneous model

		prop. of problematic stations	ex : $N = 30$
Original model		$1/C$	6.5%
Two choices	(random)	2^{-C}	$10^{-9} \approx 0$
	(geom)	$2^{-C/2}$	$10^{-4.5}$
Regulation	$\gamma > \frac{1}{C-1}$	0	$\gamma = .032$

However : as mentioned before, there are some important factor :

- time dependent arrival rate : daily period
- heterogeneity : popular or non popular stations
(housing and working areas, uphill and downhill stations,...)

Outline

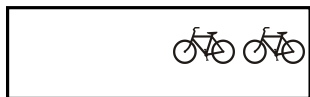
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Heterogeneous model

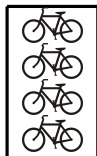
$$C_2 = 3$$



$$C_1 = 5$$



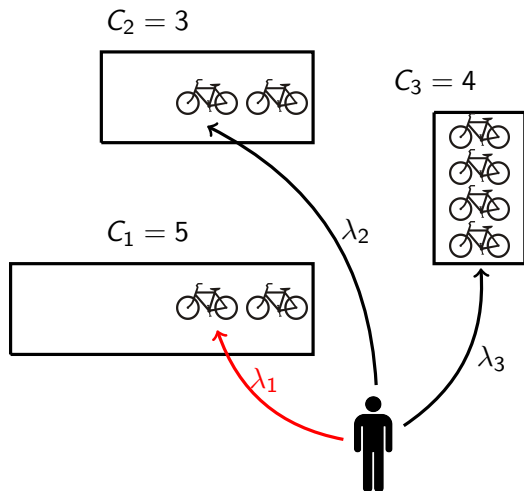
$$C_3 = 4$$



For each station i :

- Fixed capacity C_i

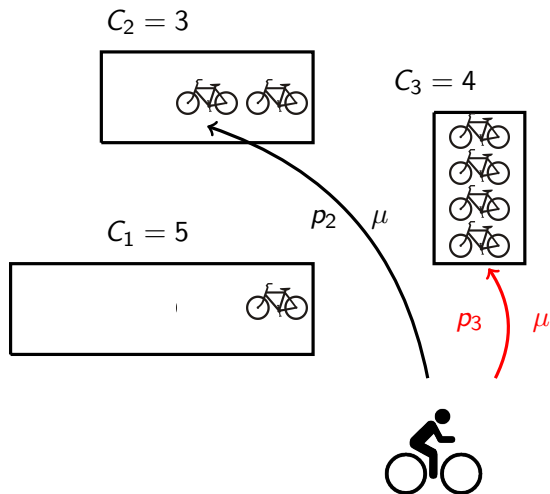
Heterogeneous model



For each station i :

- Fixed capacity C_i
- Arrival rate λ_i .

Heterogeneous model



For each station i :

- Fixed capacity C_i
- Arrival rate λ_i .
- Popularity of station p_i .
- Travel time : exponential of mean $1/\mu$.
- Local search if full.

Steady state performance

There are N stations. Assume that as N goes to infinity, the popularity of the parameters $p_i = (\lambda_i, \rho_i)$ goes to some distribution.

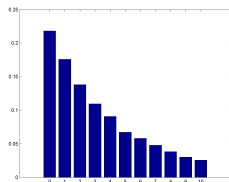
Theorem (Propagation of chaos-like result)

There exists a function $\rho(p)$ such that for all k , if stations $1, \dots, k$ have parameter p_1, \dots, p_k , then, as N goes to infinity :

$$P(\#\{\text{bikes in stations } j\} = i_j \text{ for } j = 1..k) \propto \prod_{j=1}^k \rho(p_j)^{i_j}$$

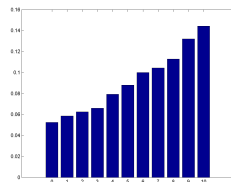
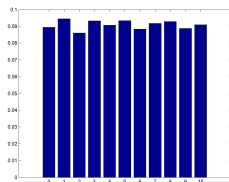
Depending on popularity, stations have different behaviors :

Popular start



→

Popular destination



Steady-state performance : numerical example

- In general, ρ is the solution of a fixed-point equation.
- Can be plotted in closed form for particular cases.

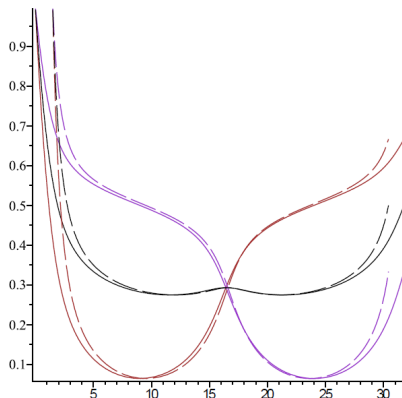


Figure: Two types of stations : popular and non-popular for arrivals : $\lambda_1/\lambda_2 = 2$.

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Current and future work

Good understanding of the **symmetric model**

- **Performance poor** : $1/C$ problematic stations (even for symmetric!).
- Simple incentives helps a lot : $2^{-C/2}$.
- **Optimal regulation** rate is function of capacity : $1/C$.

Current and future work

- Building a **realistic model** of Paris (using traces).
- Analyze **transient and steady-state** behavior.
- Difference effect of **flows vs random perturbations**.
- Develop models to **approximate the influence of geometry**.