Decision-Making for Uncoordinated User Access to Limited (Distributed) Resources
Or
Resource Competition in a Highly Networked World of Humans and Things

Decision-Making for <u>Uncoordinated</u> User Access to <u>Limited</u> (Distributed) Resources

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Decision-Making for **Uncoordinated** User Access to (Distributed) **Limited Resources**

***** A classical and very old problem! *****

Accessing a Single (common) Acoustical Channel by uncoordinated Users

(… an old problem for humans, e.g., at a cocktail party …)

… to TALK or NOT to TALK?

(shared air, acoustical)

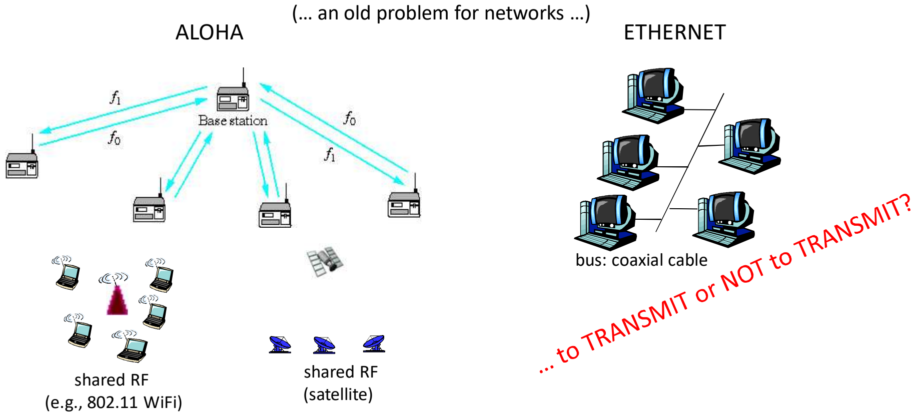
- **Competition** for common acoustical channel
- **Competition cost** , if attempting to talk when others also talk

Humans adopt behaviors to mitigate competition costs (conflict avoidance / resolution)

- Some info about the level of competition (sense, inference or knowledge)

Accessing a single (common) RF Channel by uncoordinated Users

(… an old problem for networks …)



- **Competition** for common RF channel
- **Competition cost** , if attempting to transmit when others also transmit

Design mechanisms to mitigate competition cost (contention avoidance/resolution protocols)
- Some info about the level of competition (inference or knowledge via channel feedback)

Uncoordinated access
of a common resource by distributed users
can bring benefits
(simplicity, efficiency, feasibility, privacy,…)

…. but it costs
(collisions / their resolution and avoidance)

"price of Anarchy" (PoA)

* E. Koutsoupias, C. H. Papadimitriou, "Worst-case equilibria", Computer Science Review, 2009.

PoA= { Cost of the **uncoordinated** approach } / { Cost under optimal (**coordinated**) approach }

= {max benefit (**coordinated**)} / { max benefit of the (**uncoordinated**) **approach**}

<u>For ALOHA</u>

max throughput of ALOHA = 0.36 (or 0.18 without even time coordination)

max throughput (**coordinated**) = 1.00

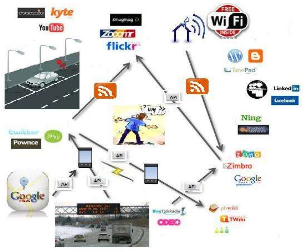
PoA = { 1} / { 0.36 } = **2.77** or { 1} / { 0.16 } = **5.55** without even time coordination

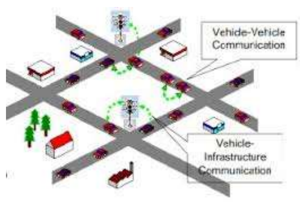
Accessing a Common/Limited Resource by uncoordinated Users

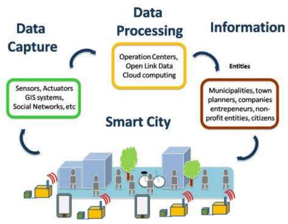
***An increasingly relevant problem appearing in today's smart and connected world! ***

Increasing need for accessing Distributed Resources in Smart and Connected Environments

(… a current and growing problem in a highly networked world…)







(A) **The state of resources easily detected (city-wide and beyond) by proliferating networked sensors / IoT** (e.g. available vs non-available resource)

(B) **Resource state diffused widely by highly networked world / social networking / smartphone proliferation /exploding IoT**

- A potentially large number of interested users may become aware of resource availability

  ➔ high competition for limited, inexpensive resources.

competition emerges

Is wide resource state diffusion always good?

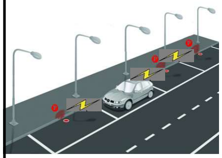
(more) information ➔ easier/better decisions ?

Some earlier work on benefits of wide information diffusion

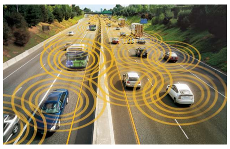
Enhance NAPS (Non-Assisted Parking Search) exploiting ICT-enabled information diffusion

- OAPS: opportunistically-assisted parking search

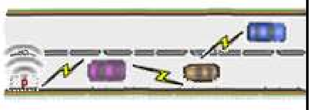
Parking spots equipped with sensors



Vehicles with wireless interfaces / storage / processing capability



Inter-vehicle & vehicle-parking spot communication



E. Kokolaki, M. Karaliopoulos, I. Stavrakakis, "Opportunistically-assisted parking service discovery: now it helps, now it does not", Pervasive and Mobile Computing (PMC), Elsevier, 2012.

Observation

under **concentrated destinations** within a particular (hotspot) road:

- information dissemination → synchronizes movement patterns
  → intensifies competition / increases # of competitors
  - OAPS worse than NAPS

(More) Information may yield worse performance!
(" more is less")

Increased Competition is to blame!

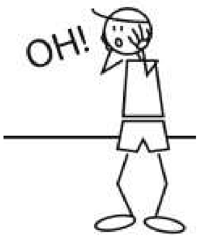
(more) information → easier/better decisions ?

A free resource over there !!!

Go for it!

Opps!

!?!

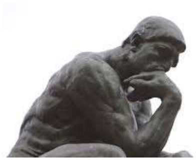


Better if I were not told anything!!!

?

(more) information ➔ easier/better decisions ?

A free resource over there !!!



???

Think wiser !

The broad environment and problem formulation

Some info about the state (availability) of a desirable low-cost resource provided to potential users.

- If a user attempts to use such a resource (**COMPETE**):
  - if it is successful (i.e. not taken by others), it will incur a **low cost.**
  - If it fails, it will incur a **failure cost**. Then, the user will have to resort to an always available (unlimited) alternative resource and pay **also** **the high cost** of that resource.
- If a user ignores the low-cost resource availability info (**NOT COMPETE**) and goes for the high-cost (unlimited) resource, it will pay the **high cost.**

The challenge:
Users need to decide how to access the limited resources effectively –
Humans are frequently driving such decisions

Major Question posed

TO COMPETE OR NOT TO COMPETE?

that is the question

to compete for a limited and inexpensive resource or not
and go for the unlimited, expensive alternative?
*(cost of failing in the competition: use of the expensive resource PLUS pay a **failing penalty**)*

Uncoordinated Access to Limited Resources

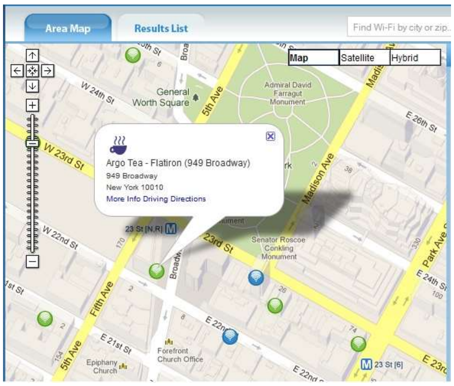
Competing for congestible goods

Resource Selection problem

Example: Access point association

Cheap but best-effort (public) WLAN

vs. More reliable, high-speed fee-based wireless access point



Competition reduces quality of service

Example: Route selection

Slower (public) toll-free road

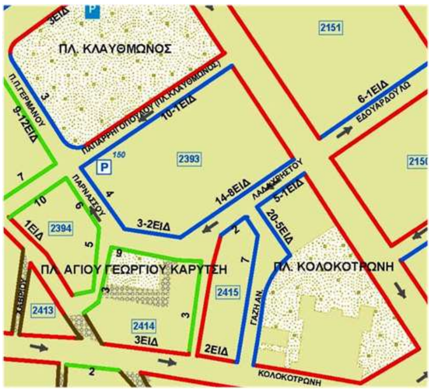
Vs Faster toll road

Competition reduces quality of service

Example: Parking spot selection

Cheap but scarce (public) on-street parking

vs. Expensive but abundant parking lots



Competition reduces quality of service

Problem Formulation

Uncoordinated Access to Limited Resources -Competing for congestible goods - Resource Selection problem

(parking spot resource example)

- ***K*** distributed non-communicating users (competitors)
  - **aware** of the availability of ***R*** resources

- **Ternary** cost model for the users
  - ***Low Cost of Competing with success :*** $c_{osp,s}$
  - ***Medium Cost for not Competing :*** $c_{pl} = \beta \, c_{osp,s}$ ($\beta>1$)
  - ***High Cost of Competing and failing :*** $c_{osp,f} = \gamma \, c_{osp,s}$ ($\gamma>\beta$)

$\delta = \gamma - \beta > 0$ (penalty factor of anarchy)

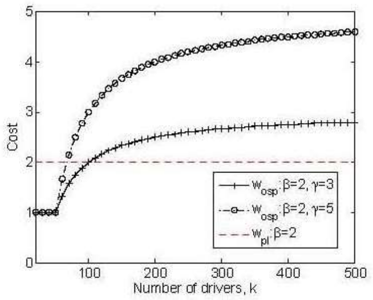
Congestion curve/dynamics: cost of a user when K compete

- Cost of a non-competing (pl) user is fixed (independent of k): $w_{pl}(k) = c_{pl}$
- Cost of a competing (osp) user when ***K>R*** :

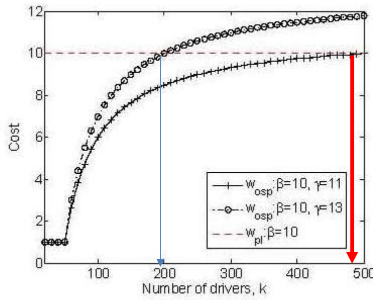
$$w_{osp}(k) = \min(1, R/k) c_{osp,s} + \left(1 - \min(1, R/k)\right) \gamma c_{osp,s}$$

- non-decreasing function of demand K

Up to 480 (δ=1) or 200 (δ=3) users is beneficiary to compete for 50 resources



Small non-competing cost (2)



Large non-competing cost (10)

R=50 resources – competing with success cost, $c_{osp,s} = 1$

How are decisions to compete or not to compete taken?

The full rationality vs. bounded rationality assumptions

Assumptions affecting how selections / decisions are made:

- Perfect *vs.* imperfect **information/knowledge** on number of competitors
- Full or limited **computational capacity** of decision-maker to assess the impact of choices
- Cognitive **biases** of decision-maker

Uncoordinated Resource Selection problem formulation:

- ❑ **Full Rationality: perfect knowledge, unlimited computational capacity**
- ❑ **Bounded Rationality: Limited / imperfect information / computational limits**
- ❑ **Bounded Rationality: (human-related) computational limits - cognitive biases**
  - **inputs from behavioral economics, cognitive psychology, etc**
  - **models for (human-driven) bounded rationality**

CASE A

- ❑ **Full Rationality: perfect knowledge, unlimited computational capacity**
- ❑ **Bounded Rationality: Limited / imperfect information / computational limits**

Study based on (classical) Expected Utility Maximization Framework

E. Kokolaki, M. Karaliopoulos, I. Stavrakakis, "Leveraging information in parking assistance systems", IEEE Transactions on Vehicular Technology, 2013.

Uncoordinated Resource Selection Problem

- Amount of finite resources ***R*** and prices/costs are known (e.g.,via ICT technology)

- **unbounded / bounded rationality wrt resource demand (# of competitors)**

Complete knowledge (of parking demand)	**Strategic game (A)**
Probabilistic knowledge	**Bayesian game** (B)
Strictly incomplete knowledge	**Pre Bayesian game** (pB)

Methodology
- ➢ **Equilibrium states**
- ➢ **Optimal outcomes**
- ➢ **Comparison via Price of Anarchy**

Uncoordinated Resource Selection Problem

- Amount of finite resources ***R*** and prices/costs are known (e.g.,via ICT technology)

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Knowledge	Game
Complete knowledge (of parking demand)	**Strategic game (A)**
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Methodology
- **Equilibrium states**
- **Optimal outcomes**
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The (strategic) parking spot selection game Γ(N)

- N drivers / players
- ***R*** on-street-parking – ***osp*** (public) + Infinite parking lot – ***pl*** (private) spots

- Action set: {***osp*** (public) , ***pl*** (private) }
- Action of player i : α_i
- Actions of all players except player i: α_{-i}
- Action profile $\alpha=(\alpha_i , \alpha_{-i})$ ➔ 2**N of them

- Action meta-profile α(m): any profile with m players competing
  ➔ N+1 meta-profiles

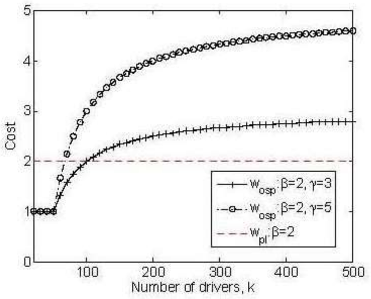
RECALL: Cost for choosing action PL or OSP

- ❑ Cost of a non-competing (pl) user is fixed (independent of k): $w_{pl}(k) = c_{pl}$
- ❑ Cost of a competing (osp) user when ***k>R*** :

$$w_{osp}(k) = \min(1, R/k)c_{osp,s} + \left(1 - \min(1, R/k)\right)\gamma c_{osp,s}$$

  - ➢ non-decreasing function of demand k

Up to 480 (δ=1) or 200 (δ=3) users is beneficiary to compete for 50 resources



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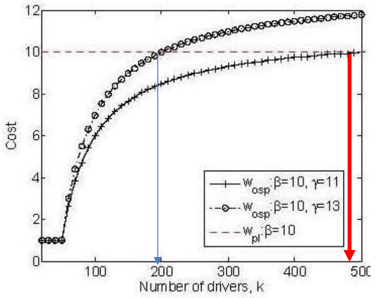


Large non-competing cost (10)

R=50 resources – competing with success cost, $c_{osp,s}$ =1

The (strategic) parking spot selection game

Expected **cost for player *i*** under action profile α=($α_i$, $α_{-i}$)

$$c_i^N(a_i, a_{-i}) = \begin{cases} w_{osp}(N_{osp}(a)), & \text{for } a_i = osp \\ w_{pl}(N - N_{osp}(a)), & \text{for } a_i = pl \end{cases} \quad (= c_{pl} \text{ , fixed })$$

- ***Nash Equilibrium state:***

  a situation in which no player can decrease its cost (increase its utility) by changing his strategy unilaterally

  Every symmetric game with two strategies has an equilibrium in pure strategies

  - Cheng, S.G. et al.: Notes on the equilibria in symmetric games, Proc. 6th Workshop On Game Theoretic And Decision Theoretic Agents (collocated with IEEE AAMAS). New York, USA (2004)

Derivation of pure equilibrium states/strategies

- The action profile α=($α_i$, $α_{-i}$) is a pure Nash equilibrium if for all *i*∈*N*

$$a_i \in \arg\min_{a_i' \in A_i} (c_i^N(a_i', a_{-i}))$$

- How to find EQ:

  Identify the conditions on the number of competing agents that break the equilibrium definition and reverse them.

  A driver is motivated to change his action in the following circumstances

$$when\ a_i = pl \text{ and } w_{osp}(N_{osp}(a)+1) < c_{pl} \qquad \textbf{(*)}$$

$$when\ a_i = osp \text{ and } w_{osp}(N_{osp}(a)) > c_{pl} \qquad \textbf{(**)}$$

Derivation of pure equilibrium states/strategies

Lemma: a player is motivated to change his action $α_i$ as follows

- $a_i = \text{pl}$ and (a) $N_{\text{osp}}(a) < R \leq N$ or

  (b) $R \leq N_{\text{osp}}(a) < N_0 - 1 \leq N$ or

  (c) $N_{\text{osp}}(a) < N \leq R$
- $a_i = \text{osp}$ and $R < N_0 < N_{\text{osp}}(a) \leq N$

where $N_0 = R(\gamma - 1)/\delta \in \mathbb{R}$.

Hint: for (b), require that (*) holds and for the second bullet require that (**) holds and get the condition on $N_{osp}(α)$

Pure equilibrium strategies

The strategic parking spot selection game has the following EQ profiles

a) for $N \leq N_0$, a unique NE profile a^* with $N_{\text{osp}}(a^*) = N_{\text{osp}}^{\text{NE},1} = N$;

b.1) for $N > N_0$ and $N_0 \in (R, N) \setminus \mathbb{N}^*$, $\binom{N}{\lfloor N_0 \rfloor}$ NE profiles a' with $N_{\text{osp}}(a') = N_{\text{osp}}^{\text{NE},2} = \lfloor N_0 \rfloor$;

b.2) for $N > N_0$ and $N_0 \in [R+1, N] \cap \mathbb{N}^*$, $\binom{N}{N_0}$ NE profiles a' with $N_{\text{osp}}(a') = N_{\text{osp}}^{\text{NE},2} = N_0$ and $\binom{N}{N_0-1}$ NE profiles $a^\star$ with $N_{\text{osp}}(a^\star) = N_{\text{osp}}^{\text{NE},3} = N_0 - 1$.

Pure Nash EQ strategies

The strategic resource selection game has the following EQ profiles

# drivers, N	#competing drivers for OSP (public) parking under NE
$\leq \frac{R(\gamma-1)}{\delta}$	N
$> \frac{R(\gamma-1)}{\delta}$	$\frac{R(\gamma-1)}{\delta}$

Efficiency of pure equilibrium states/strategies

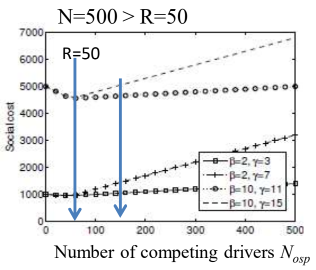
Efficiency Metric**: **The Price of Anarchy (PoA ≥ 1)**

= [social cost under EQ state] / [optimal social cost]

<u>Social cost under action profile α</u>:

$$C(N_{osp}(a)) = \sum_{i=1}^{N} c_i^N(a) = \begin{cases} c_{osp,s}(N\beta - N_{osp}(a)(\beta - 1)), & \text{if } N_{osp}(a) \le R \\ c_{osp,s}(N_{osp}(a)\delta - R(\gamma - 1) + \beta N), & \text{if } R < N_{osp}(a) \le N \end{cases}$$

Use under a* : if N ≤ N_0 use $N_{osp}(\alpha^*)$ = N ; if N ≥ N_0 use $N_{osp}(\alpha^*) = N_{\text{osp}}^{\text{NE},2} = \lfloor N_0 \rfloor$

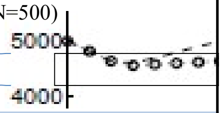


cost minimized at $N_{osp} = R =$ ***<u>50</u>***

Social cost increases as N_{osp} moves away from *R* (lack of coordination penalty)

Cost at EQ: $N_{osp} = N_{\text{osp}}^{\text{NE},2} = \lfloor N_0 \rfloor = \lfloor R(\gamma-1)/\delta \rfloor$
$= R*(15-1)/(15-10) = R*2.8=$***<u>140</u>*** (<N=500)

lack of coordination penalty of 500



** E. Koutsoupias, C. H. Papadimitriou, "Worst-case equilibria", Computer Science Review, 2009.

Efficiency of pure equilibrium states/strategies

<u>Optimal social cost</u>: (exactly min{R,N} players compete – no fail and all osp spots used)

$$C_{opt} = \sum_{i=1}^{N} c_i^N(a_{opt}) = c_{osp,s}[min(N,R) + \beta \cdot max(0, N-R)]$$

<u>Price of Anarchy</u>

$$\text{PoA} = \begin{cases} \frac{\gamma N - (\gamma-1)\min(N,R)}{\min(N,R) + \beta \max(0, N-R)}, & if\ N_0 \ge N \\ \frac{\lfloor N_0 \rfloor \delta - R(\gamma-1) + \beta N}{R + \beta(N-R)}, & if\ N_0 < N \end{cases}$$

= 5000 / 4500 = 1.11

PoA ≤ 1 / [1-R/N] , for N>R

Efficiency of pure equilibrium states/strategies

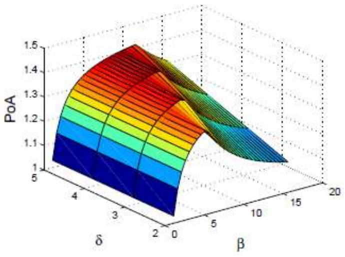
Optimal social cost, Copt
$c_{osp,s}[\min(N,R)+\beta\max(0,N-R)]$

↑ R competing drivers

# drivers, N	Social cost in EQ, Ceq	
$\leq \frac{R(\gamma-1)}{\delta}$	$c_{osp,s}[N\gamma-\min(N,R)(\gamma-1)]$	N compete
$> \frac{R(\gamma-1)}{\delta}$	$c_{osp,s}\beta N$	R(γ-1)/δ compete

PoA>1 : due to competition and paying the (lack-of-coordination) cruising cost

Pricing (β) and failure cost/ overhead (δ) shaping guidelines



N=500,R=160,$c_{osp,s}$=1€

β	δ	PoA→ 1
$\geq \frac{\delta(N-R)+R}{R}$	>0	↑β
$< \frac{\delta(N-R)+R}{R}$	>0	↓β
>1	$\leq \frac{R(\beta-1)}{N-R}$	↓δ

The (strategic) mixed-action selection game

Practical strategies for real systems / a mixed action $p = (p_{osp}, p_{pl})$

Expected cost for player choosing *osp* or *pl*, respectively, when all N-1 play according to the mixed-action p

$$c_i^N(osp,p) = \sum_{N_{osp}=0}^{N-1} w_{osp}(N_{osp}+1)B(N_{osp};N-1,p_{osp})$$

$$c_i^N(pl,p) = c_{pl}$$

Expected cost for symmetric profile (all play according to the mixed-action p)

$$c_i^N(p,p) = p_{osp}\cdot c_i^N(osp,p) + p_{pl}\cdot c_i^N(pl,p)$$

The (strategic) mixed-action selection game

- ***Existence of Mixed-action Nash Equilibrium:***

  Every symmetric game with more than two players and increasing cost functions (of the number of players) has a unique mixed-action equilibrium

  - Ashlagi, I., Monderer, D., Tennenholtz, M.: Resource selection games with unknown number of players. In: Proc. AAMAS '06. Hakodate, Japan (2006)

- ***The Mixed-action Nash Equilibrium state:***

  The strategic parking spot selection game has a unique mixed-action NE

$$p^{\mathrm{NE}} = (p_{\mathrm{osp}}^{\mathrm{NE}}, p_{\mathrm{pl}}^{\mathrm{NE}}), \quad \text{where } p_{\mathrm{osp}}^{\mathrm{NE}} = 1 \text{ if } N \leq N_0 \text{ and } p_{\mathrm{osp}}^{\mathrm{NE}} = N_0/N \text{ if } N > N_0, \text{ with } p_{\mathrm{osp}}^{\mathrm{NE}} + p_{\mathrm{pl}}^{\mathrm{NE}} = 1 \text{ and } N_0 \in \mathbb{R}.$$

  Sketch of proof: Set the requirement to be fulfilled by the profiles at EQ:

$$c_i^N(osp, p^{NE}) = c_i^N(pl, p^{NE})$$

Equilibrium states/strategies (pure / mixed-action strategie

- Pure NE

# drivers, N	#competing drivers for public parking space
$\leq \frac{R(\gamma-1)}{\delta}$	N
$> \frac{R(\gamma-1)}{\delta}$	$\frac{R(\gamma-1)}{\delta}$

- Symmetric mixed-action NE

# drivers, N	Probability of competing for public parking space
$\leq \frac{R(\gamma-1)}{\delta}$	1
$> \frac{R(\gamma-1)}{\delta}$	$\frac{R(\gamma-1)}{\delta N}$

Uncoordinated Resource Selection Problem

Drivers = strategic players

- Amount of finite resources ***R*** and prices/costs are known (e.g.,via ICT technology)
- **unbounded / bounded rationality wrt resource demand (# of competitors)**

Complete knowledge (of parking demand) — **Strategic game (A)**

Probabilistic knowledge — **Bayesian game** (B)

Strictly incomplete knowledge — **Pre Bayesian game** (pB)

Methodology
- **Equilibrium states**
- **Optimal outcomes**
- **Comparison via Price of Anarchy**

Decision-making under demand knowledge constraints (a type of bounded rationality)

- The **Bayesian model: probabilistic (demand) information**
  - Players know
    a) probability for a player to be active (interested in parking)
    b) total number of players
- The **pre Bayesian model: strictly incomplete (demand) information**
  - Players know their total number (***upper bound on competitors***)

A Bayesian parking spot selection game

- $A_i = \{osp, pl, \emptyset\}$ *is the set of potential actions for each driver* $i \in \mathcal{N}$;
- $\Theta_i = \{0, 1\}$ *is the set of types for each driver* $i \in \mathcal{N}$, *where* 1 (0) *stands for active (inactive) drivers;*
- $S_i : \Theta_i \to A_i$ *is the set of possible strategies for each driver* $i \in \mathcal{N}$;
- $c_i^{N_B}(s(\vartheta), \vartheta)$ *is the cost functions for each driver* $i \in \mathcal{N}$, *for every type profile* $\vartheta \in \times_{k=1}^{N} \Theta_k$ *and strategy profile* $s(\vartheta) \in \times_{k=1}^{N} S_k$, *that are functions of* $w_{osp}(\cdot)$ *and* $w_{pl}(\cdot)$, *as defined for* $\Gamma(N)$, *and also written as* $c_i^{N_B}(s(\vartheta), \vartheta) = c_i^{N_B}(s_i(\vartheta_i), s_{-i}(\vartheta_{-i}), \vartheta_i, \vartheta_{-i})$;
- p_{act} *is the probability for a driver to be active.*

A Bayesian parking spot selection game

Equilibria:

For the game $\Gamma_B(N)$, the strategy profile $s' \in \times_{k=1}^{N} S_k(\vartheta_k = 1)$ is a Bayesian NE if, for all $i \in \mathcal{N}$ with $\vartheta_i = 1$

$$s_i(\vartheta_i) \in \arg\min_{s_i' \in S_i} (c_i^{N_B}(s_i(\vartheta_i), s_{-i}(\vartheta_{-i}), \vartheta_i, \vartheta_{-i})) \quad \text{or,}$$

$$s_i(\vartheta_i) \in \arg\min_{s_i' \in S_i} \sum_{\vartheta_{-i}} f_\Theta(\vartheta_{-i}/\vartheta_i) c_i^{\sum_k \vartheta_k}(s_i', s_{-i}(\vartheta_{-i}), \vartheta_i, \vartheta_{-i})$$

Derivation approach

$$c_i^{N_B}(pl, p) = c_{pl} \qquad c_i^{N_B}(osp, p) = \sum_{n_{act}=0}^{N-1} c_i^{n_{act}+1}(osp, p) B(n_{act}; N-1, p_{act})$$

Equilibria:

The Bayesian parking spot selection game $\Gamma_B(N)$ has unique symmetric equilibrium profiles $p^{NE_B} = (p_{osp}^{NE_B}, p_{pl}^{NE_B})$, with $p_{osp}^{NE_B} + p_{pl}^{NE_B} = 1$. More specifically:

- a unique pure (Bayesian Nash) equilibrium with $p_{osp}^{NE_B} = 1$, if $p_{act} < \frac{N_0}{N}$,
- a unique symmetric mixed-action Bayesian Nash equilibrium with $p_{osp}^{NE_B} = \frac{N_0}{N p_{act}}$, if $p_{act} \geq \min(\frac{N_0}{N}, 1)$,

where $N_0 \in \mathbb{R}$.

Equilibrium states under probabilistic knowledge (Bayesian Game)

- Symmetric mixed-action Bayesian Nash equilibria

Activation probability, p_{act}	(symmetric) Probability of competing
$< \frac{R(\gamma-1)}{\delta N}$	1
$\geq \min\left(\frac{R(\gamma-1)}{\delta N}, 1\right)$	$\frac{R(\gamma-1)}{\delta N p_{act}}$

Equilibrium states under strict uncertainty (pre-Bayesian model)

Knowledge of an upper bound on demand, N

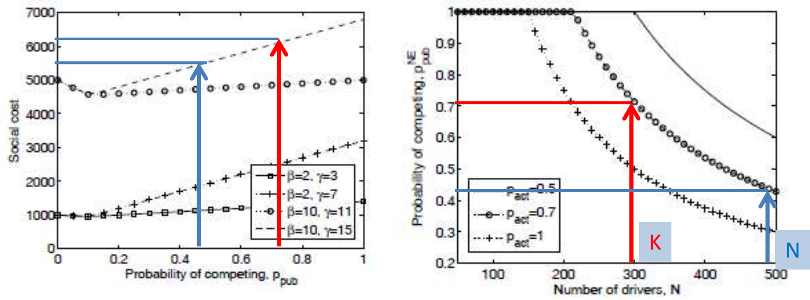
For **the pre-Bayesian resource selection game** it holds that

Symmetric mixed-action *safety-level equilibrium* (playing to min worst cost)

↕

Symmetric mixed-action equilibrium of the strategic game Γ(N) with N players

Less-is-more phenomena under strictly incomplete knowledge of resource demand



- Social cost increases with the probability of competing
- Probability of competing (in EQ states), decreases with N
- If N is maximum number of players and K(<N) is real number of active players (interested in the resource) , then in the safety-level equilibrium,

$$p_{pub,N} < p_{pub,K} \rightarrow \text{social\_cost}_N < \text{social\_cost}_K$$

(provided the average number of competing players is still over R)

EQ strategies for Strategic, Bayesian and pre-Bayesian Resource Selection Game

TABLE I
EQUILIBRIUM STRATEGIES FOR THE STRATEGIC, BAYESIAN AND PRE-BAYESIAN PARKING SPOT SELECTION GAME

strategic Parking Spot Selection Game, $\Gamma(N)$		
Condition	Equilibrium type	Equilibrium expression
$N \leq N_0,\ N_0 \in \mathbb{R}$	pure Nash Eq	$N_{osp}^{NE} = N$
$N > N_0,\ N_0 \in (R, N)\setminus\mathbb{N}^*$	pure Nash Eq	$N_{osp}^{NE} = \lfloor N_0 \rfloor$
$N > N_0,\ N_0 \in [R+1, N] \cap \mathbb{N}^*$	pure Nash Eq	$N_{osp}^{NE} = N_0,\ N_{osp}^{NE} = N_0 - 1$
$N > N_0,\ N_0 \in \mathbb{R}$	mixed-action Nash Eq	$p_{osp}^{NE} = \frac{N_0}{N}$
Bayesian Parking Spot Selection Game, $\Gamma_B(N)$		
Condition	Equilibrium type	Equilibrium expression
$p_{act} < \frac{N_0}{N},\ N_0 \in \mathbb{R}$	pure Bayesian Nash Eq	$p_{osp}^{NE_B} = 1$
$p_{act} \geq \min(\frac{N_0}{N}, 1),\ N_0 \in \mathbb{R}$	mixed-action Bayesian Nash Eq	$p_{osp}^{NE_B} = \frac{N_0}{N p_{act}}$
pre-Bayesian Parking Spot Selection Game, $\Gamma_{pB}(N)$		
Condition	Equilibrium type	Equilibrium expression
$N \leq N_0,\ N_0 \in \mathbb{R}$	pure safety-level Eq	$p_{osp}^{NE_{pB}} = 1$
$N > N_0,\ N_0 \in \mathbb{R}$	mixed-action safety-level Eq	$p_{osp}^{NE_{pB}} = \frac{N_0}{N}$

CASE B :

- **Bounded Rationality: (human-related) computational limits - cognitive biases**
  - **inputs from behavioral economics, cognitive psychology, etc**
  - **models for bounded rationality and assessment of its impact**

Classical Expected Utility Maximization Framework not adequate

E. Kokolaki, M. Karaliopoulos, I Stavrakakis, "On the human-driven decision-making process in competitive environments", Internet Science Conference, 2013

RECALL: Decisions under Full Rationality

Expected Utility Theory framework

- **Strategic agents** with perfect information, without behavioral biases, aiming at maximizing own welfare
  - –quantified by the expected gain/cost of their actions through EUT framework
- **Expected Utility Theory (EUT) framework**
  - –Expected utility of a lottery equals the sum of the utilities of the lottery outcomes, $U(x_i)$, times their probabilities of the outcomes, $p(x_i)$

$$EU = \sum_{x_i} p(x_i)U(x_i), \quad x_i : \text{choice / alternative.}$$

- **Nash equilibrium**
  - –captures best response in terms of expected utility maximization

Deviations from Full Rationality

- **(Cumulative) Prospect Theory**
  - maintains most of the concepts/assumptions of EUT
  - manipulates both utility measures and prob. to account for biases against risk
- **Alternative decision-making models & Equilibrium (EQ) concepts (Quantal Response, Rosenthal)**
  - Use probabilistic choice models to capture any unobserved and omitted elements, estimation/computational errors, individual's mood, perceptual variations or cognitive biases
  - In line with the fact that individuals are more likely to make better choices than worse choices, but do not necessarily make the very best choice

Prospect Theory motivation (1)

In several choice problems, individuals' preferences systematically violate EUT !!!

Allais' paradox (indication that people assess utilities and probabilities of outcomes differently from what full rationality/ EUT predicts => contradictions under EUT formulation)

PROBLEM 1: Choose between

A:	2,500 with probability	.33,	B:	2,400 with certainty
	2,400 with probability	.66,		
	0 with probability	.01;		
$N = 72$	[18]			[82]*

Percentage of responses

$EUT_{prospectB} > EUT_{prospectA} \Leftrightarrow$ u(2400)>.33u(2500)+.66u(2400)$\Leftrightarrow$ **.34u(2400) > .33u(2500)**

PROBLEM 2: Choose between

C:	2,500 with probability	.33,	D:	2,400 with probability	.34,
	0 with probability	.67;		0 with probability	.66.
$N = 72$	[83]*			[17]	

$EUT_{prospectC} > EUT_{prospectD} \Leftrightarrow$ **.33u(2500) > .34u(2400)**

Prospect Theory motivation (2)

Four-fold pattern of risk attitude: (again, violation of ETU framework)

- High probabilities: risk aversion for gains & risk seeking for losses
- Low probabilities: risk seeking for gains & risk aversion for losses

TABLE I

PREFERENCES BETWEEN POSITIVE AND NEGATIVE PROSPECTS

Positive prospects				Negative prospects			
Problem 3: $N = 95$	(4,000, .80) [20]	<	(3,000). [80]*	Problem 3': $N = 95$	(−4,000, .80) [92]*	>	(−3,000). [8]
Problem 4: $N = 95$	(4,000, .20) [65]*	>	(3,000, .25). [35]	Problem 4': $N = 95$	(−4,000, .20) [42]	<	(−3,000, .25). [58]
Problem 7: $N = 66$	(3,000, .90) [86]*	>	(6,000, .45). [14]	Problem 7': $N = 66$	(−3,000, .90) [8]	<	(−6,000, .45). [92]*
Problem 8: $N = 66$	(3,000, .002) [27]	<	(6,000, .001). [73]*	Problem 8': $N = 66$	(−3,000, .002) [70]*	>	(−6,000, .001). [30]

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Prospect Theory formulation (Kahneman & Tversky, 1979)*

Defines prospects

$$\text{Prospect}: (x_1, p_1; x_2, p_2; \ldots; x_n, p_n)$$

Desirability of a prospect is quantified through generalization of the utility functions and their weighting through *weighting functions* $\pi(p_i)$

$$U = \sum_{i=1}^{n} \pi(p_i) v(x_i)$$

- Decision maker is still a utility maximizer

* Daniel Kahneman and Amos Tversky, "Prospect Theory: An Analysis of Decision under Risk", *Econometrica*, *47(2)*, pp. 263-291, March 1979

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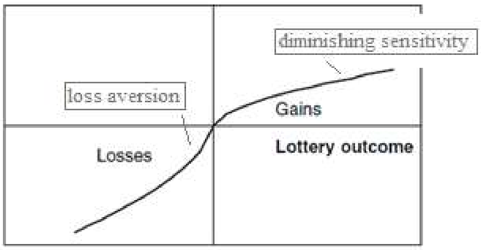
The Prospect Theory (PT) model

Diminishing sensitivity:

- Impact of a chance diminishes with distance from Reference Point
  (a gain from reference 50 to 100 is less valuable than from 0 to 50)
  (people are more sensitive to extreme outcomes and less to intermediate ones)

Loss aversion:

- Curve is steeper for losses than for gains
  (a high loss hurts more than a high pleasure)



A Hypothetical Value Function

The Cumulative PT (CPT) model (Tversky & Kahneman, 1992)

$$\text{Prospect} : (x_1, p_1; x_2, p_2; ...; x_n, p_n)$$

CPT fixes some (experimentally observed) inconsistencies of PT

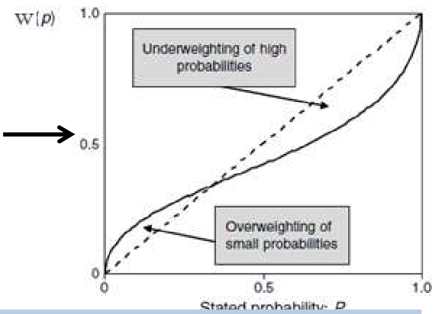
Modifies the probability weighting functions

- PT : transforms probabilities of separate outcomes
- CPT: transforms probabilities of {an outcome or anything better (or worse) than that}

Desirability of a prospect quantified through generalizing:

A. **Outcome probabilities $\{p_i\}$ via decision weights $\{w(p_i)\}$**
   (diminishing sensitivity: more sensitive around 0 and 1, and less in the middle)

B. Outcome values $\{x_i\}$ via utility functions $\{U(x_i)\}$



A. Tversky and D. Kahneman, "Advances in prospect theory: cumulative representation of uncertainty", Journal of Risk and Uncertainty, 5, 1992.

The Cumulative PT (CPT) model (Tversky & Kahneman, 1992)

Desirability of a prospect quantified through generalizing:

A. Outcome probabilities $\{p_i\}$ via decision weights $\{w(p_i)\}$

B. Outcome values $\{x_i\}$ via utility functions $\{U(x_i)\}$

CPT value of the prospect $(x_1, p_1; \ldots; x_n, p_n)$:

$$U = \sum_{i=1}^{k} \pi_i^- v(x_i) + \sum_{i=k+1}^{n} \pi_i^+ v(x_i), \qquad x_1 \leqslant \ldots \leqslant x_k \leqslant 0 \leqslant x_{k+1} \leqslant \ldots \leqslant x_n.$$

where the decision weights (i.e. the numbers π_i^-, π_i^+) are defined by:

$$\pi_1^- = w^-(p_1), \qquad \pi_i^- = w^-(p_1 + \cdots + p_i) - w^-(p_1 + \cdots + p_{i-1}) \qquad 2 \leqslant i \leqslant k$$

$$\pi_n^+ = w^+(p_n), \qquad \pi_i^+ = w^+(p_i + \cdots + p_n) - w^+(p_{i+1} + \cdots + p_n) \qquad k+1 \leqslant i \leqslant n-1$$

$$v(x) = \begin{cases} x^\alpha & \text{if } x \geq 0 \\ -\lambda(-x)^\beta & \text{if } x < 0. \end{cases} \qquad \begin{matrix} w^+(p) = p^\gamma/[p^\gamma + (1-p)^\gamma]^{1/\gamma} \\ w^-(p) = p^\delta/[p^\delta + (1-p)^\delta]^{1/\delta}. \end{matrix} \qquad \begin{matrix} w^+(0) = w^-(0) = 0 \\ w^+(1) = w^-(1) = 1. \end{matrix}$$

The values that best fit the experimental results of Kahneman & Tversky are: $\left\{ \begin{matrix} \alpha = \beta = 0.88; \ \lambda = 2.25; \\ \gamma = 0.61; \ \delta = 0.69 \end{matrix} \right.$

Equilibrium concepts over Cumulative Prospect Thy

- **Nash Equilibrium state**: no player can increase his/her utility (*expected utility value*) by changing his/her strategy unilaterally
  - Mixed-action profiles:
    - *EU value of strategy 1 = EU value of strategy 2*
- **CPT Equilibrium state**: no player can increase his/her utility (*cumulative prospect value*) by changing his/her strategy unilaterally
  - Mixed-action profiles:
    - *CPT value of prospect 1 = CPT value of prospect 2*

Applying CPT to Resource Selection Problem

Two alternatives/prospects: ***l*** (limited resource, osp) and ***u*** (unlimited resource, pl)

CPT value for prospects ***l*** and, ***u*** respectively:

$$CPT_l = \sum_{n=1}^{N} \pi_n^- u(g_l(n)) \qquad CPT_u = u(c_u)$$

With the cost of selecting prospect l when k others do the same given by

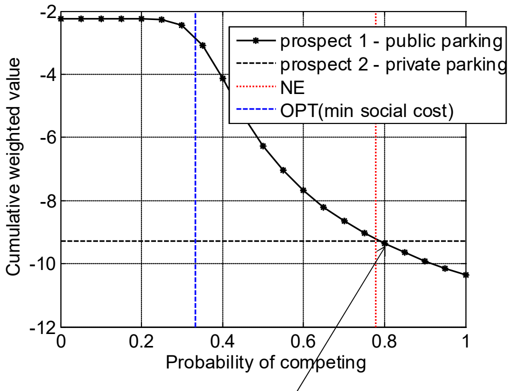
$$g_l(k) = min(1, R/k)c_{l,s} + (1 - min(1, R/k))c_{l,f}$$

and the probabilities p_k for this are Binomial (N, p_l^{CPT})

Both prospects consist of negative outcomes / costs

Applying CPT to Resource Selection Problem

- N= 150 , R=50
- $c_{osp,s}$ =1
- β = 5 (c_{pl} = 5)
- γ=8
- δ = 3



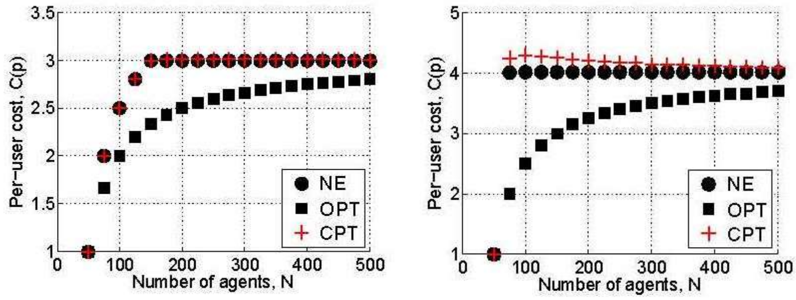
CPT eq: 0.79 NE: 0.78 OPT: 0.33

CPT equilibrium condition :

CPT value of prospect 1 = CPT value of prospect 2

Some results

R=50 (δ=1, low risk) (δ=16, high risk)



(a) $\beta = 3, \gamma = 4$ (c) $\beta = 4, \gamma = 20$

- Small deviation from the full rationality framework
- More risk-prone behavior under high penalty cost (δ)
  - Competing probabilities: NE: 0.59 , CPT: 0.61
- Both full rational (NE) and biased (CPT) practices are more costly than OPT

Deviations from Full Rationality

- **Alternative decision-making models & Equilibrium (EQ) concepts (Quantal Response, Rosenthal)**
  - Use probabilistic choice models to capture any unobserved and omitted elements, estimation/computational errors, individual’s mood, perceptual variations or cognitive biases
  - In line with the fact that individuals are more likely to make better choices than worse choices, but do not necessarily make the very best choice
    - Due to noise/disturbances in their anticipation of exact choices’ payoffs

Quantal response equilibrium (McKelvey & Palfrey, 1995)

Introduce some **randomness in the decision-making process** to capture people's inability to play always the strategy that maximizes the expected utility

- "Choices are made with probabilities that are monotone in their expected payoffs"
- Logit QRE => disturbances/errors follow extreme value distribution (smaller mistakes are more likely to occur that more serious ones)

$$p(r_1) = \frac{e^{-\lambda EU(r_1)}}{e^{-\lambda EU(r_1)} + e^{-\lambda EU(r_2)}}$$

$$p(r_1) = 1 - p(r_2)$$

λ∈[0, ∞] : rationality control parameter
λ→ 0 : random decision
λ→ ∞ : full rationality (Nash EQ)
[cost differences (i.e., *EU*(.)) are emphasized more through a more responsive distribution to cost changes, in line with the more emphasis in differences expected by a more rational decision-maker.]

R. McKelvey and T. Palfrey, "Quantal response equilibria for normal form games", Games and Economic Behavior, 1995.

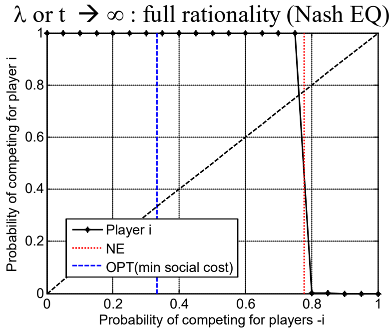
Quantal response equilibrium for Resource Selection Problen

$$p_l^{QRE} = \frac{e^{-tc(l,p^{QRE})}}{e^{-tc(l,p^{QRE})} + e^{-tc(u,p^{QRE})}} \qquad c(l,p) = \sum_{n=0}^{N-1} g_l(n+1)B(n;N-1,p_l)$$

$$p^{QRE} = (p_l^{QRE}, p_u^{QRE}),\ p_u^{QRE} = 1 - p_l^{QRE} \qquad c(u,p) = c_u$$

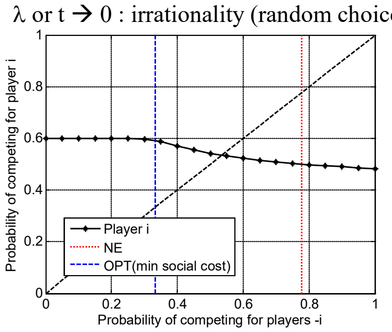
At EQ, prob of competing of player i equals the belief for the way (i.e. prob) the others play which is used in calculating c(l,p)

λ or t → ∞ : full rationality (Nash EQ)



QRE: 0.77 NE: 0.78 OPT: 0.33

λ or t → 0 : irrationality (random choice)



QRE: 0.55 NE: 0.78 OPT: 0.33

Rosenthal equilibrium (Rosenthal, 1989)

"The difference in probabilities with which two actions are played equals a parameter *t* multiplied by the difference of the corresponding expected costs"

$$p(r_1) - p(r_2) = t\left(EU(r_1) - EU(r_2)\right)$$

$$p(r_1) = 1 - p(r_2)$$

t $\in [0,\infty]$: rationality control parameter
t → ∞ : full rationality

R. Rosenthal, "A bounded-rationality approach to the study of noncooperative games", Int. J. Game Theory, 1989.

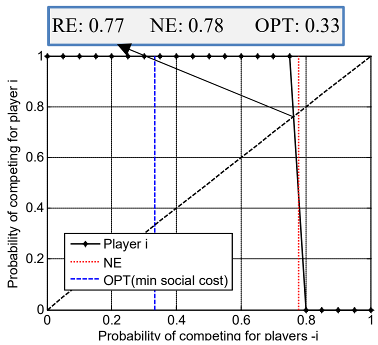
Rosenthal equilibrium for Resource Selection Problem

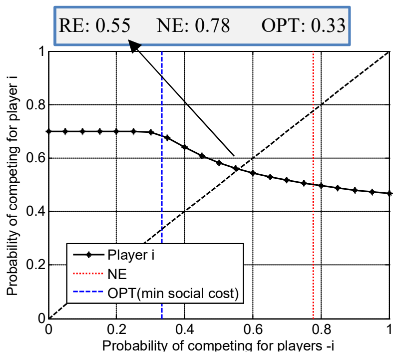
$$p_l^{RE} - p_u^{RE} = -t(c(l, p^{RE}) - c(u, p^{RE}))$$

$$p^{RE} = (p_l^{RE}, p_u^{RE}),\ p_u^{RE} = 1 - p_l^{RE}$$

t → ∞ : full rationality (NE)

t → 0 : no rationality (random choice)

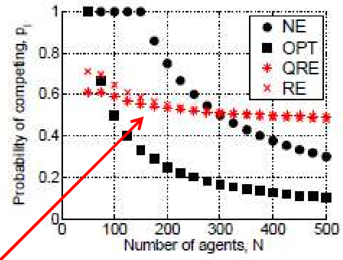


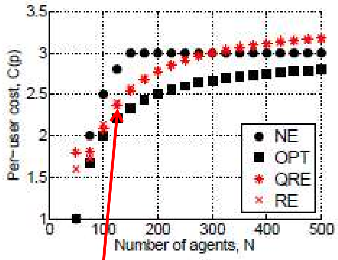


Some results

Very low rationality level (t = λ= 0.2)

- R=50
- $c_{osp,s}$ =1
- β = 3 (c_{pl} = 3)
- γ=4
- δ = 1
- t = λ= 0.2





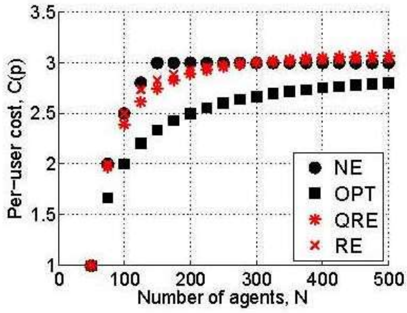
Competing prob close to .5 (random choice)
Rationality parameter close to 0

under low/medium demand (N<300)
the inaccuracies in computing the best action as modeled in these equilibrium concepts decrease the competing probability and hence,
the per-user cost in these cases is drawn to near-optimal levels.

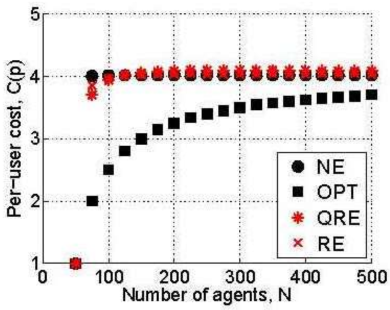
Some results

Med-high rationality level (t = λ= 3)

R=50 , $c_{osp,s}$ =1 , t = λ= 3



β = 3 (c_{pl} = 3), γ=4

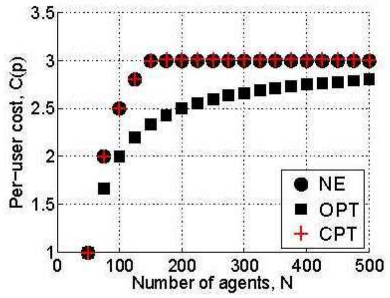


β = 4 (c_{pl} = 4), γ = 20

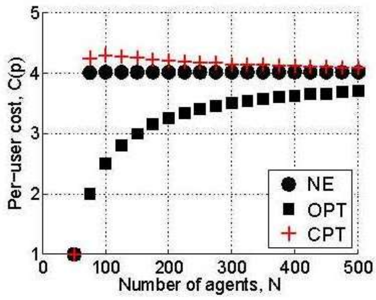
- ❑ RE and QRE costs closer to NE
- ❑ The higher the difference of - expected - costs of the two options, the less RE and QRE differ from NE, since the identification of the best action becomes easier.

Some results

R=50 (δ=1, low risk) (δ=16, high risk)



(a) $\beta = 3, \gamma = 4$



(c) $\beta = 4, \gamma = 20$

- Small deviation from the full rationality framework
- More risk-prone behavior under high penalty cost (δ)
  - Competing probabilities: NE: 0.59 , CPT: 0.61
- Both full rational (NE) and biased (CPT) practices are more costly than OPT

Deviations from Full Rationality

- ❑ (Cumulative) Prospect Theory
  - maintains most of the concepts/assumptions of EUT
  - manipulates both utility measures and prob. to account for biases against risk
- ❑ Alternative decision-making models & Equilibrium (EQ) concepts (Quantal Response, Rosenthal)
  - Use probabilistic choice models to capture any unobserved and omitted elements, estimation/computational errors, individual's mood, perceptual variations or cognitive biases
  - In line with the fact that individuals are more likely to make better choices than worse choices, but do not necessarily make the very best choice
- ❑ **Heuristics**
  - ❑ Fast and frugal reasoning solutions / decisions
  - ❑ Emphasis on cognitive processes underlying decisions
  - ❑ Satisfying instead of maximization of expected utilities (Simon 1955)

Heuristic strategy for the resource selection problem

Satisficing: instead of computing/comparing expected costs, it estimates the probability to hit an empty public spot and plays according to this.

***Confidence* heuristic rule**: "risk competing for resource r_1 according to the probability of winning one of the R resources"

- Under the belief that other players think the same way

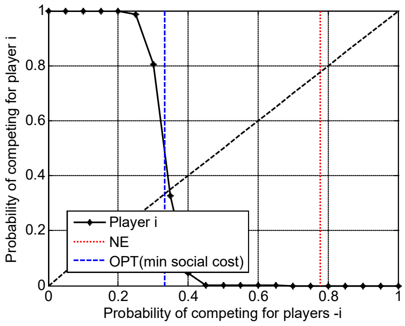
- Fixed-point equation

$$p(r_1) = \Pr(\#competitors < R) = \sum_{j=0}^{R-1} Bin(j, N-1; p(r_1))$$

Heuristic strategy for the resource selection problem

- *Confidence* heuristic: "risk for public parking space according to the probability of winning public parking space"

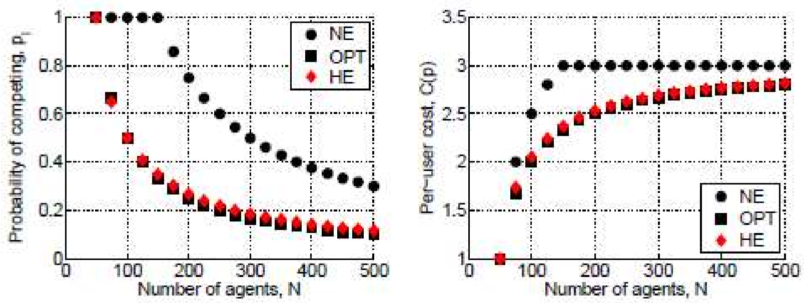
$$p_{osp} = \Pr(\#competitors < R) = \sum_{j=0}^{R-1} Bin(j; N-1, p_{osp})$$



$$HE = 0.34,\ NE = 0.78,\ \text{OPT} = 0.33$$

Some results

Confidence heuristic



- Yields near-optimal results
- Implicitly seeks to avoid tragedy of commons effects

Conclusions for the models of bounded rationality

Formulation of the parking spot selection application drawing on models from behavioral economics and cognitive psychology

- **(Cumulative) Prospect Theory** :
  - The decision maker is still a utility maximizer
  - The desirability of outcomes is expressed through the transformed probabilities of them
  - Small deviation from the full rationality framework
- **Alternative equilibrium concepts (Quantal Response Equilibrium, Rosenthal equilibrium)**
  - The decision maker is a satisfizer
  - Symmetric mixed-action equilibria as fixed-point solutions
  - A degree of freedom quantifies the rationality in the model (convergence to the Nash equilibrium as the free parameter goes to infinity)
- **Heuristics**
  - The decision maker is a satisfizer
  - Confidence heuristic: fast and frugal reasoning solution that is shown to yield near-optimal results within the particular application concept

Real Players
vs
Nash EQ vs Rosenthal EQ
vs
Random vs Optimal

An experimental comparative study

María Pereda, Juan Ozaita, Ioannis Stavrakakis, and Angel Sanchez, "**Competing for congestible goods: experimental evidence on parking choice**", Scientific Reports (a Nature Research journal), 2020.

Nash EQ vs Rosenthal EQ vs optimal

An experimental study

N=20 players with N known to all.

Choices: a yellow lot with only S {5, 10} slots, or a blue lot with unlimited capacity.

At the end of each round, participants had an associated payoff, resulting from subtracting their decision costs from their initial endowed 100 points.

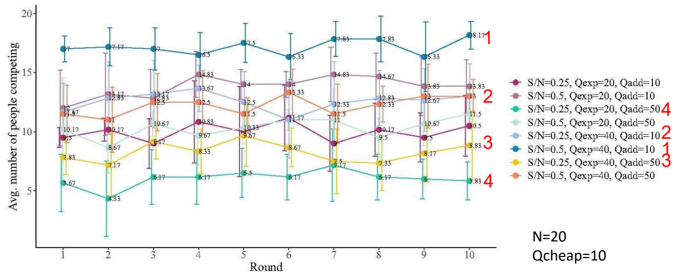
After each round, participants were reminded of:

- their previous decision
- the type of slot they ended up using,
- their payoff for that round,
- the number of yellow slots occupied.

Results from the experimental study

(how players actually decide)

.nature.com/scientificreports/



N=20
Qcheap=10

Figure 1. Average number of people competing as a function of round number in the eight treatments of our experiment. Error bars represent ± one standard deviation of the mean.

For different S/N ratios: competition is higher when S/N is higher (more spaces available for N fixed). (**1** vs **2**)

For the same S/N ratio, competition is lower for higher Qadd. (**2** vs **3**)

For the same S/N ratio and Qadd, competition is higher for higher Qexp (**3** vs **4**)

Nash EQ vs EXP

(experimental study)

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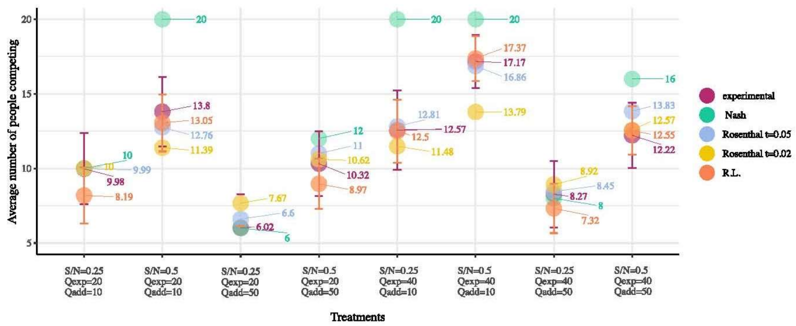

Figure 2. Average number of people competing per treatment versus Nash and Rosenthal equilibria. Magenta: experimental results; turquoise: Nash; blue: Rosenthal, $t = 0.05$; yellow: Rosenthal, $t = 0.02$; orange: Reinforcement learning (R.L.) model. Error bars represent ± one standard deviation of the mean. Points overlap for all sets on the first treatment, except for R.L. simulation results.

Nash EQ predicting not high competition is close to Exp

(experimental study)

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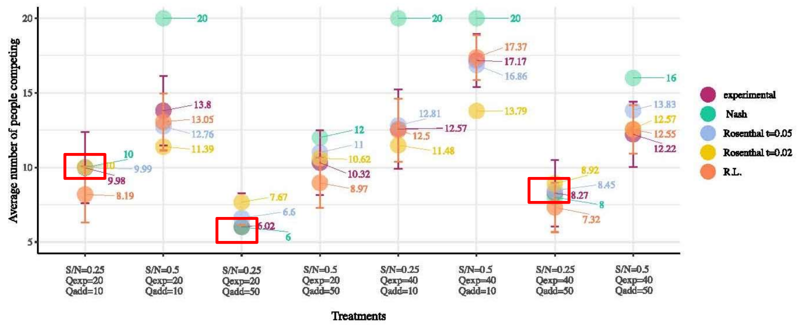

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Nash EQ close to exp in 3 out of 8 experiments

- Occurs when Nash EQ suggests that half or less participants should compete

Nash EQ predicting high competition is away from Exp

(experimental study)

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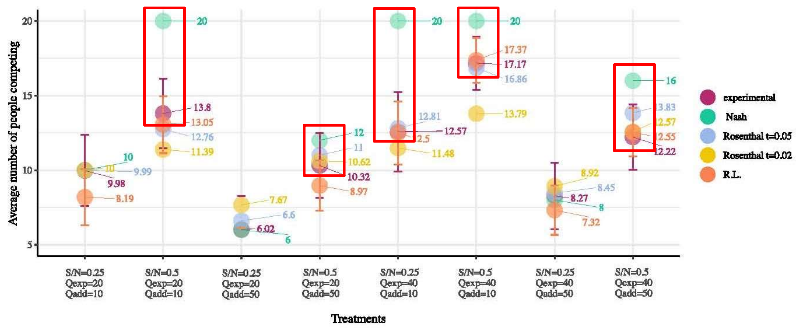

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Nash EQ away from exp in 5 out of 8 experiments

- Occurs when Nash EQ suggests that more than half participants should compete
- For such parameters, people have difficulties in estimating what would be a rational response

Rosenthal EQ (0.05) vs EXP vs Nash EQ

(experimental study)

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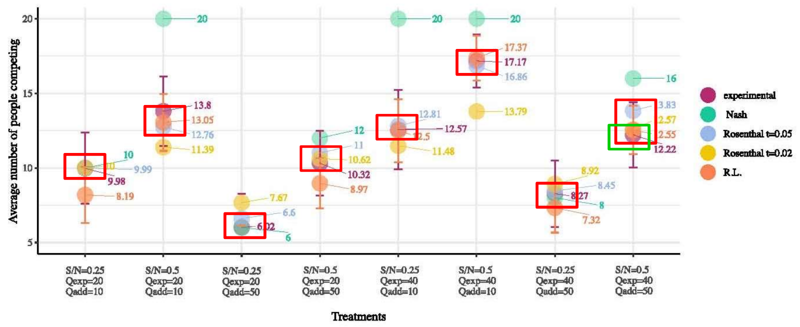

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RE(0.05) clearly closer than NE (mean distance from exp 4.6 vs 22.2)

RE(0.02) closer than RE(0.05) and NE, when harder to decide (think less rational)

Nash EQ / Rosenthal EQ / EXP / vs RANDOM / OPTIMAL

An experimental study

- ❑ RANDOM decision (0.5*N compete):
  - ➢ EXP away from random choice (mean distance 21.5)
- ✓ Real users do not decide RANDOM
- ❑ OPTIMAL (coordinated): min {N, S} = S
  - ➢ EXP and RE(0.05) are about equally close to the OPTIMAL
  - ➢ Nash EQ furthest away from OPTIMAL
- ✓ Real users decide more effectively than the fully rational approach
- ✓ The bounded rationality of real users can be captured well by the Rosenthal model

Decision-Making for Uncoordinated User Access to (Distributed) Limited Resources

* A classical, old but ever modern and challenging problem *

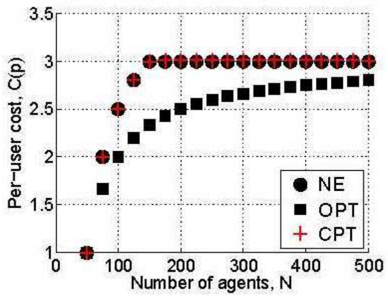
Presented and discussed various decision models under full rationality and bounded rationality (human-driven)

Tried to shed some light into the relevance and effectiveness of alternative decision models and equilibrium concepts, that could be considered when humans drive the decisions.

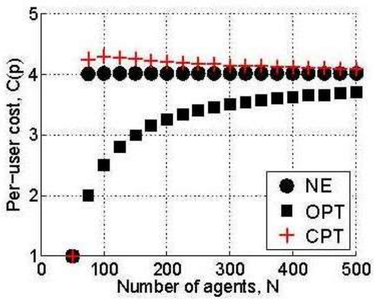
Extra slides start

CPT framework: Cost - Performance

R=50 (δ=1, low risk) (δ=16, high risk)



(a) $\beta = 3, \gamma = 4$



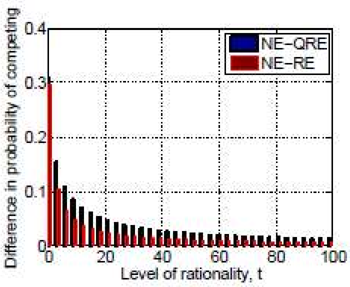
(c) $\beta = 4, \gamma = 20$

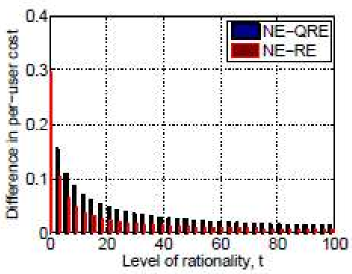
- Small deviation from the full rationality framework
- More risk-prone behavior under high penalty cost (δ)
- Both full rational (NE) and biased (CPT) practices are more costly than OPT

Some results

Impact of rationality on difference of competing probabilities / costs (QRE-NE and RE-NE)

R=50 , $c_{osp,s}$=1, β = 3 (c_{pl} = 3), γ=4, N=180, **t = λ in [0.1,100]**





Congestion-cost-cutting Approaches In Resource-limited Competitive Environments

Coordinated Resource Allocation through Social Applications

Resolve competition through ICT and IoT

*E. Kokolaki, M. Karaliopoulos, I. Stavrakakis, **"Parking assisting applications: effectiveness and side-issues in managing public goods"**, 3rd AWARE workshop on Challenges for Achieving Self-Awareness in Autonomic Systems of the Self-Adaptive and Self-Organizing systems conference (SASO 2013), Sept. 9-13, 2013, Philadelphia*

Decentralized Resource Allocation through Social Applications

User would subscribe to be able to more effectively use public resources in a competitive environment

Social apps for parking resources:

(Sfpark, **Parking Defenders**, Parkomotivo)

Some important questions

Are these apps effective and "fair" to their users?

- Do they require high user subscription to be effective?
- Do they treat equally similar users?
- **Do they create a wealth (through coordination and congestion cost cutting) that rightfully distribute to their users?**
  - **Or simply benefit by eliminating competition by non-users (exclusion)?**

What is the *impact on non-users?*

- Are non-users of these apps suffering substantially
  - (or almost excluded from) accessing **public goods**?

3 Driver profiles

- **Traditional** user/driver (non-users of the application)
- App user/driver:
  - **Defender** (sharer, fully cooperative)
    - Announces upcoming freed-up spot
    - Waits for selected app user to come
    - Rates other defender upon parking
    - Earns credit and improves its ranking
  - **Seeker** (free rider – not fully cooperative)
    - Rates defender upon parking

Effectiveness of the social parking application: low to moderate parking demand (45% , 75%)

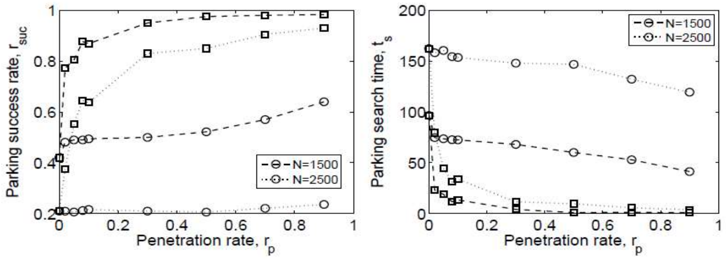
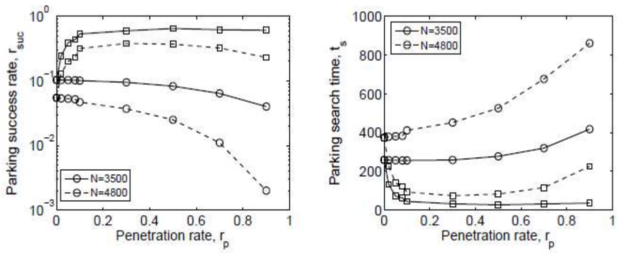


Fig. 3. Performance indices for Non-users (circles) and Sharers (squares) at low to moderate parking demand: $n_{FR} = 0\%$.

- Application users ***experience better performance*** than traditional driver
- The advantage for Defenders emerges ***even at low penetration rates***
- **Win – win situations**: Non-users also improve their performance!

(the effective competition that non-users experience is mitigated)

Effectiveness of the social parking application: Very high parking demand (105%, 145%)



a. Parking success rates

b. Parking search times

Performance indices for Non-users (circles) and Sharers (squares) at high parking demand:

At high penetration rates:

- Non-user exclusion trends
- Sharer performance deterioration due to own competition

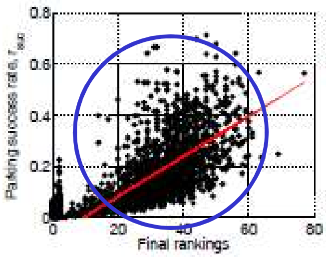
Effectiveness of the incentive mechanism and some concerns on its fairness

It is ***effective***…

- higher success rates are coupled with higher rankings

But ***not fair***…

- it discriminates against identical users (=users with similar interests, needs and attitude towards cooperation)
- It induces **rich-get-richer phenomena**: winners in the initial competition round earn credits that offer them a competitive edge in the following rounds

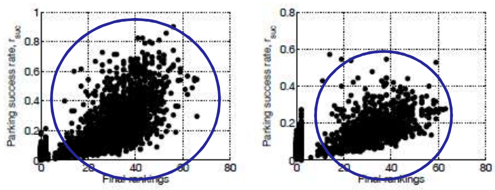


Impact of Seekers on the incentive mechanism's fairness

Seekers tend to ***restore fairness***

↑ Seekers' portion → ↓ parking spot handovers →

↓ opportunities for credit-building/emergence of high rankings



a. $r_s = 30\%$ b. $r_s = 70\%$

Conclusions

Investigated effectiveness / appropriateness of distributed, social public resource (parking) management apps

- **Effective and mostly non-exclusive to non-users**
  - Users' improved performance is mostly due to the **increased efficiency they generate in the parking process, rather than excluding** traditional users from competing for the resources.
  - **Non-Users also benefit from the reduced anarchy** and coordination that the App brings

- Incentive mechanism is effective
  - But it induces rich-club phenomena and difficulties to newcomers

- Seekers (free-riders) seem to alleviate those problems

SUMMARY of Resource Competition in a Highly Networked World of Humans and Things

Motivation (environment – early study)

Decision-making in uncoordinated competitive environment - formulation

- **rational case – Price of Anarchy**
- **limited info case**
- **human driven case**
  - **Prospect Thy**
  - **alternative models**
  - **heuristics**

Alternative, partially coordinated approaches

- **ICT-supported distributed apps**