On the human-driven decision-making process in competitive environments

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ABSTRACT

The emergence of intelligent sensing and communication technologies fosters the generation and dissemination of huge amounts of information that collectively enriches people's awareness about their environment and its resources. With this information at hand, users then decide how to access these resources to best serve their interests. However, situations repeatedly emerge where the users' welfare is better satisfied by the same finite set of resources and the uncoordinated access to them gives rise to tragedy of commons effects and serious congestion problems.

In this paper, we study generic scenarios, where some non-excludable finite resource is of interest to a population of distributed users with variable perceptions about the resource supply and demand for it. The high-level question we address is how efficiently the competition about the resources is resolved under different assumptions about the way the users make their decisions. The users are first viewed as strategic perfectly informed software agents that make fully rational decisions attempting to minimize the cost of accessing the acquired resource. We then exploit insights from experimental economics and cognitive psychology to model agents of bounded rationality who either do not possess perfect information or cannot exploit all the available information due to time restrictions and computational limitations. We derive the operational states in which the competing influences are balanced (*i.e.*, equilibria) and compare them against the Nash equilibria that emerge under full rationality and the optimum resource assignment that could be determined by a centralized entity. Our results provide useful insights to the dynamics emerging from the agents' behavior as well as theoretical support for the practical management of limited-capacity resources.

1. INTRODUCTION

The advances in the broader information and communication technologies (ICT) sector have dramatically changed the role of end users and resulted in unprecedented rates of information generation and diffusion. The integration of sensing devices of various sizes, scope and capabilities with mobile communication devices, on the one hand, and the wide proliferation of online social applications, on the other, leverage the heterogeneity of users in terms of interests, preferences, and mobility, and enable the collection of huge amounts of information with very different spatial and temporal context. When shared, this information can enrich people's awareness about and foster more efficient management of a broad range of resources, ranging from natural goods such as water and electricity, to human artefacts such as urban space and transportation networks.

Besides generating information, the end users may be actively involved in its dissemination, and even make use of it for their own good and benefit. In this paper, we study generic scenarios, where some *non-excludable finite resource* is of interest to a population of distributed users and the information that is generated and may be shared concerns the *resource demand* and *supply*. When the amount of resource is large and the interested user population is small, users can readily opt for using it. When, however, the resource's supply cannot satisfy the demand for it, an inherent competition for the resource emerges that should be factored by users in their decision to opt for accessing this resource or not. The underlying assumption here is that the decision to opt for the finite resource under high competition bears the risk of an excess cost in case of a failure (*i.e.*, go for the limited resource but find it unavailable). This cost captures the impact of congestion phenomena that appear in various ICT sectors when distributed and uncoordinated high volume demand appears for some limited service. Examples include congestion phenomena that emerge on a toll-free road that is advertised as the best alternative to a blocked main road due to an accident (*e.g.*, Google Maps with Traffic Layer); long car cruising when searching for cheap on-street parking spots in busy urban environment (*e.g.*, [1], [2]); or high access delays when users associate with low-cost wireless access points in hotspot areas (*e.g.*, [14]).

In such settings, various critical decisions need to be taken by the entities that are involved in the production, dissemination and consumption of information. Hence, the decision to acquire and distribute the information or not, may account for own-interest priorities, such as preserving own resources or hiding information from potential competitors. In this paper, we focus on the way the entities make use of the accumulated knowledge. Essentially, the main dilemma faced by the end user possessing resource information is *whether to compete or not* for using these resources.

Internet Science Conference'13, April 10-11, 2013, Brussels.
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This very fundamental question is investigated in this paper by factoring cognitive heuristics/biases in the human-driven decision-making process. Overall, the high-level question that we address is how efficiently the competition about the resources is resolved under different assumptions about the way the agents make their decisions. In essence, we are more concerned with the comparison of the decision-making under *full* and *bounded rationality* conditions. The key assumption is that human activity takes place within a fairly autonomic networking environment, where each agent runs a service resource selection task and seeks to maximize her benefit, driven by self-oriented interests and biases. As the full rationality reference, we frame the case where the agents (typically software engines) avail all the information they need to reach decisions and, most importantly, are capable of exploiting all information they have at hand; whereas users of bounded rationality either possess partial information about the resources or they are totally aware of them but it might be too complex in time and computational resources to exploit all the available information. Typically, decision-makers respond to these complexity constraints by acting heuristically. At the same time, their behavior is prone to case-sensitive biases that may lead to perceptual variations or distortions and inaccurate/not rational judgments that shape their competitiveness.

We introduce key concepts and present the assumptions for the environment under consideration in Section 2. The prescriptions of the full rational decision-making are defined in 3. In Section 4, we outline and implement four different models of bounded rationality within the particular environment, drawing on the Cumulative Prospect Theory, the Rosenthal and Quantal Response Equilibria concepts as well as the heuristic reasoning. Numerical results that are obtained employing these models are then presented in Section 5. The conclusions of the study are outlined in Section 6.

2. THE RESOURCE SELECTION TASK

We apply the general concept introduced in Section 1 to scenarios whereby the agents make their decision independently within a particular time window over which they start the resource selection task. In essence, we consider settings where N agents are called to decide between two alternative sets of resources. The first set consists of R low-cost resources while the second one is unlimited but with more expensive items. Those who manage to use the low-cost resources pay $c_{l,s}$ cost units, whereas those heading directly for the safer, but more expensive option pay $c_u = \beta \cdot c_{l,s}, \beta > 1$, cost units. However, agents that first decide to compete for the low-cost resources but fail to acquire one suffering the results of congestion, pay $c_{l,f} = \gamma \cdot c_{l,s}, \gamma > \beta$ cost units. The excess penalty cost $\delta \cdot c_{l,s}$, with $\delta = \gamma - \beta > 0$, reflects the "virtual" cost of wasted time till eventually being served by the more expensive option.

In the following sections, we describe (qualitatively) the scenario of the ideal full rational and strategic cost-minimizing engines against four scenarios, consisting in imperfect information availability and behavioral biases, whereby the agents' decisions are made under bounded rationality conditions. We present how these four bounded rationality expressions can be modelled in a way that enables their analysis and the quantitative assessment of their impact on the efficiency of the resource selection task.

3. FULL RATIONAL DECISION-MAKING

In the ideal reference model of the perfectly or fully rational decision-making, the main assumption is that the decision-maker is a software engine that in the absence of central coordination, acts as rational strategic agent that explicitly considers the presence of identical counter-actors to make rational, yet selfish decisions aiming at minimizing what *it* will pay for a single resource. The intuitive tendency to head for the low-cost resources, combined with their scarcity in the considered environments, give rise to *tragedy of commons* effects [13] and highlight the game-theoretic dynamics behind the resource selection task.

Indeed, the collective full-rational decision-making can be formulated as an instance of *resource selection games*, whereby N players compete against each other for a finite number R of common resources [3]. In [16] we have analyzed the strategic resource selection game in the context of parking search application whereby drivers are faced with a decision as to whether to compete for the low-cost but scarce on-street parking space or directly head for the typically over-dimensioned but more expensive parking lots. An assistance service announces information of perfect accuracy about the demand (number of users interested in the resources/parking spots), supply (number of low-cost resources/on-street parking spots) and pricing policy, that eventually, manages to steer drivers' decisions. We derive the equilibrium behaviors of the drivers and compare the costs paid at the equilibrium against those induced by the ideal centralized system that optimally assigns the low-cost resources and minimizes the social cost. We quantify the efficiency of the service using the Price of Anarchy (PoA) metric, computed as the ratio of the two costs (*i.e.*, worst-case equilibrium cost over optimal cost).

In general, we show that PoA deviates from one, implying that, at equilibrium, the number of user nodes choosing to compete for the low-cost resources exceeds their supply. The PoA can be reduced by properly manipulating the price differentials between the two types of resources. Notably, our results are inline with earlier findings about *congestion pricing* (*i.e.*, imposition of a usage fee on a limited-capacity resource set during times of high demand), in a work with different scope and modelling approach [18]. The results of this study will serve as a benchmark for assessing the impact of different rationality levels and cognitive biases on the efficiency of the resource selection process.

4. DEVIATIONS FROM FULL RATIONALITY

In this section we study the decision-making process under four levels of agents' rationality which result in difference degrees of responsiveness to specific price differentials between low-cost and expensive resources. In all cases, we derive the agents' choices in the stable operational conditions in which all competing influences are balanced.

4.1 Motivation

The maximization of user benefit under perfect and real-time information about the dynamic characteristics of the environments described in Sections 1, 2, is a clearly unrealistic assumption for individuals' decision-making. In this section, we iterate on several expressions of *bounded rationality* in decision-making. This is an umbrella term for different deviations from the fully rational paradigm: incomplete information about environment and other people's behavior, time, computational and processing constraints, and cognitive biases in assessing/comparing alternatives. Experimental work shows that, practically, people exhibit such bounded rationality symptoms and rely on simple rules of thumb (heuristic cues) to reach their decisions in various occasions and tasks. Overall, we have identified the following instances of bounded rationality as worth exploring and assessing in the context of the resource selection task:

Incomplete information about the demand - The most apparent deviation from the perfect information norm relates to the amount of information agents have at their disposal. As two distinct variations hereby, we consider probabilistic (stochastic) information and full uncertainty.

The four-fold pattern of risk aversion - Particular experimental data show that human decisions exhibit biases of different kinds, in comparing alternatives. For instance, a huge volume of experimental evidence confirms the fourfold pattern of risk attitudes, namely, people's tendency to be risk-averse for alternatives that bring gains and risk-prone for alternatives that cost losses, when these alternatives occur with high probability; and the opposite risk attitudes for alternatives of low probability [25].

Own-payoff effects - This is another type of bias that was spotted in the context of experimentation with even simple two-person games, such as the generalized matching pennies game. Theoretically, in these matching pennies games, a change in a player's own payoff that comes with a particular strategy/choice, must not affect that player's choice probability. However, people's interest for a particular strategy/choice is shown to increase as the corresponding payoff gets higher values. This behavior makes choice probabilities range continuously within 0 and 1 and not jump from 0 to 1 as soon as the corresponding choice gives the highest payoff. This bias gives further credit to Simon's early arguments ([22], [23]) that humans are satisficers rather than maximizers, *i.e.*, that they are more likely to select better choices than worse choices, in terms of the utility that comes with them, but do not necessarily succeed in selecting the very best choice.

Cognitive heuristics - Cognitive science suggests that people draw inferences (*i.e.*, predict probabilities of an uncertain event, assess the relevance or value of incoming information *etc.*), exploiting heuristic principles. The cognitive heuristics could be defined as fast, frugal, adaptive strategies that allow humans (organisms, in general) to reduce complex decision tasks of predicting, assessing, computing to simpler reasoning processes. In the salient of heuristic-based decision theory, notions such as recognition, priority, availability, fluency, familiarity, accessibility, representativeness and adjustment - and - anchoring stand out. One of the simplest and well - studied heuristic is the recognition heuristic [9]. It is applied as follows: "If there are N alternatives, then rank all n recognized alternatives higher on the criterion under consideration than the $N - n$ unrecognized ones". The order at which different reasons are examined to make a final decision is defined by the priority heuristic [6]. The availability heuristic is stated as "a graded distinction among items in memory, measured by the order or speed with which they come to mind or the number of instances of categories one can generate". Cognitive researchers have conceptualized a distinct version of availability heuristic, named as fluency heuristic. In particular, the authors in [21] give the definition: "a strategy that artfully probes memory for encapsulated frequency information that can veridically reflect statistical regularities in the world". What is more, "the degree of knowledge a person has of a task or object" is termed as familiarity [12]. The accessibility heuristic [17] argues that "feeling - of - knowing judgments are based on the amount and intensity of partial information that rememberers retrieve when they cannot recall a target answer". Following the representativeness heuristic, people answer probabilistic questions by evaluating the degree to which a given event/object resembles/is highly representative of another one. When people adjust a given initial value to yield a numerical prediction, they devise the adjustment - and - anchoring heuristic. Tversky and Kahneman in [26] discuss biases to which some of the abovementioned heuristics could lead, digging people's responses that are in favor of or against a specific set of alternative choices.

In the following sections, all these effects are incorporated in distinct decision-making analytical models. We account for symmetric scenarios whereby the entire population exhibits the same instance of bounded rationality and the knowledge of this deviation from full rationality is common among individuals. In a more advanced modelling effort [7], the "cognitive hierarchy" approach assumes a distribution of cognitive steps of iterated reasoning, where the zero-step agents just randomize over their strategy space while higher-step agents take account of the intelligence and complexity of others' reasoning.

4.2 Bayesian and pre-Bayesian models

Practically, within a dynamic and complex environment, perfectly accurate information about the resource demand is hard to obtain. For instance, the resource operator may, depending on the network and information sensing infrastructure at her disposal, provide the competing agents with different amounts of information about the demand for resources; for example, historical statistical data about the utilization of the low-cost resources. Thus, in this case, the information is impaired in accuracy since it contains only some estimates on the parameters of the environment.

In the same vein, in [15], we assume a more realistic realization of the parking assistance service where drivers have only knowledge constraints, while they satisfy all other criteria of full rationality, *i.e.*, they are selfish agents who are capable of defining their actions in order to minimize the cost of occupying a parking spot. That is, no computational or time constraints deteriorate the quality of their decisions. However, they either share common probabilistic information about the overall parking demand or are totally uncertain about it[1]. From a modelling point of view, we extend the game formulation for the full rationality case (ref. Section 3) to accommodate the two expressions of uncertainty. In particular, we formulate this type of bounded rationality drawing on Bayesian and pre-Bayesian models and prescriptions of the classical Game Theory.

In the Bayesian model of the game, the agents determine their actions on the basis of private information, their types.

[1]Since the supply of parking space is static information that can be broadcast to the drivers or be known through offline media (website, news), the assumption is that drivers have knowledge of the parking capacity.

The type in this game is a binary variable indicating whether an agent is in search of resources (active player). Every agent knows her own type, yet she ignores the real state at a particular moment in time, as expressed by the types of the other players, and, hence, she cannot deterministically reason out the actions being played. Instead, she draws on common prior probabilistic information about the activity of agents to derive estimates about the expected cost of her actions. Thus, now, the agents try to minimize the expected cost, instead of the pure cost that comes with a strategy, and play/act accordingly. Similarly to the full rationality case, we derive our conclusions drawing on the equilibrium states. In particular, we end up with the Bayesian Nash equilibrium, whereby no agent can further lower her expected cost by unilaterally changing her strategy.

In the worst-case scenario (strictly incomplete information/full uncertainty), the agents may avail some knowledge about the upper limit of the potential competitors for the resources (*i.e.*, drivers in search of on-street parking space or spots in parking lots), yet their actual number is not known, not even probabilistically. This time, we see the resulting agents' interactions as an instance of pre-Bayesian games and build the discussion in terms of safety-level equilibria; namely, operational states whereby every player minimizes over her strategy set the worst-case (maximum) expected cost she may suffer over all possible types and actions of her competitors. Interestingly enough, we show less-is-more phenomena under uncertainty, whereby more information does not necessarily improve the efficiency of service delivery but, even worse, may hamstring users' efforts to minimize the cost incurred by them.

For years, the main approaches to collective decision-making, whereby the decisions of one agent affect the gain/cost experienced by others, draw on Expected Utility Theory (EUT). Agents are considered as strategic and fully rational, namely, they can compute the expected utility of all possible action profiles exploiting all available information about their own and the others' utilities (*i.e.*, the expected utility of one's action equals the sum of her utilities for all possible opponents' actions times the probabilities of their occurrence). In such setting, the classical solution concept of the game is embodied by the Nash Equilibrium (NE), the action profile that no agent would like to unilaterally deviate from. Essentially, the NE captures the agents' best responses in terms of expected utility maximization.

However, experimental data suggest that human decisions reflect certain limitations, that is, they exhibit biases of different kinds in comparing alternatives and maximizing their welfare in terms of the expected utility that comes with an alternative (ref. Section 4.1). To accommodate the empirical findings, researchers from economics, sociology and cognitive psychology, have tried either to expand/adapt the Expected Utility framework or completely depart from it and devise alternative theories as to how decision alternatives are assessed and decisions are eventually taken.

In the following sections we first give the general analytical framework of the decision-making model and then its application to the resource selection task as outlined in Section 2.

4.3 Cumulative Prospect Theory

Tversky and Kahneman in [25] proposed the Cumulative Prospect Theory (CPT) framework to explain, among others, why people buy lottery tickets and insurance policies at the same time or the fourfold pattern of risk attitude (ref. Section 4.1). According to EUT, if X denotes the set of possible outcomes of a lottery, its expected utility equals the sum of the outcomes' utilities, $U(x), x \in X$, times the probabilities of their occurrence, $pr(x)$, that is, $EU = \sum_{x \in X} pr(x)U(x)$. In CPT, the desirability of the alternatives-lotteries (now termed prospects) is still given by a weighted sum of prospect utilities, only now both components of the EUT (*i.e.*, outcomes and probabilities) are modified. However, agents are still maximizers, *i.e.*, they try to maximize the expected utilities of their prospects.

The CPT value for prospect X is given by

$$CPT_X = \sum_{i=1}^{k} \pi_i^- u(x_i) + \sum_{i=k+1}^{n} \pi_i^+ u(x_i) \tag{1}$$

where $x_1 \leq ... \leq x_k$ are negative outcomes/losses and $x_{k+1} \leq ... \leq x_n$ positive outcomes/gains.

In particular, the decision weights π_i^-, π_i^+ are functions of the cumulative probabilities of obtaining an outcome x or anything better (for positive outcomes) or worse (negative outcomes) than x. They are defined as follows:

$$\begin{aligned} \pi_1^- &= w^-(pr_1) \\ \pi_i^- &= w^-(pr_1 + ... + pr_i) - w^-(pr_1 + ... + pr_{i-1}), \\ &\qquad 2 \leq i \leq k \end{aligned} \tag{2}$$

$$\begin{aligned} \pi_n^+ &= w^+(pr_n) \\ \pi_i^+ &= w^+(pr_i + ... + pr_n) - w^+(pr_{i+1} + ... + pr_n), \\ &\qquad k+1 \leq i \leq n-1 \end{aligned} \tag{3}$$

In [25], the authors propose concrete functions for both weighting and utility functions,

$$u(x_i) = \begin{cases} x_i^a, \text{ if } x_i \geq 0 \\ -\lambda(-x_i)^b, \text{ if } x_i < 0 \end{cases} \tag{4}$$

$$w^+(p) = p^c / [p^c + (1-p)^c]^{1/c} \tag{5}$$

$$w^-(p) = p^d / \left[p^d + (1-p)^d\right]^{1/d} \tag{6}$$

$$w^+(0) = w^-(0) = 0 \tag{7}$$

$$w^+(1) = w^-(1) = 1 \tag{8}$$

Both functions are consistent with experimental evidence on risk preferences. Indeed, empirical measurements reveal a particular pattern of behavior, termed as loss aversion and diminishing sensitivity. Loss aversion refers to the fact that people tend to be more sensitive to decreases than to increases in their wealth (*i.e.*, a loss of 80 is felt more that a gain of 80); whereas diminishing sensitivity (appeared in both the value and the weighting function) argues that people are more sensitive to extreme outcomes and less in intermediate ones.

The parameter $\lambda \geq 1$ measures the degree of loss aversion, while the parameters $a, b \leq 1$ the degree of diminishing sensitivity. The curvature of the weighting function as well as the point where it crosses the 45° line are modulated by the parameters c and d. Tversky and Kahneman estimated the parametric values that best fit their experimental data at $\lambda = 2.25, a = b = 0.88, c = 0.61, d = 0.69$.

4.3.1 Applying Cumulative Prospect Theory to the resource selection task

In the uncoordinated resource selection problem, the decisions are made on two alternatives/prospects: the low-cost, limited-capacity resource set, on one side and the more expensive but unlimited resource set, on the other side. In addition, both prospects consist only of negative outcomes/costs.

The CPT value for the low-cost prospect is given by

$$CPT_l = \sum_{n=1}^{N} \pi_n^- u(g_l(n)) \quad (9)$$

where $g_l(k)$, with $g_l(1) \leq ... \leq g_l(N)$, is the expected cost for an agent that plays the action "low-cost/limited-capacity resource set". It is a function of the number of agents k taking this action, and is given by

$$g_l(k) = min(1, R/k)c_{l,s} + (1 - min(1, R/k))c_{l,f} \quad (10)$$

The decision weights and utility functions are defined by (2)-(8). The possible $n \leq N$ outcomes, for the number n of agents choosing the low-cost resources, occur with probability $pr(n)$ that follows the Binomial probability distribution $B(n; N, p_l^{CPT})$, with parameters the total number of agents, N, and the probability to compete for the low-cost resources, p_l^{CPT}.

The CPT value for the certain prospect "expensive/unlimited resource set" is given by (4) and equals

$$CPT_u = u(c_u) \quad (11)$$

It is possible to extend the equilibrium concept inline with the principles of CPT. Namely, under an equilibrium state, no agent has the incentive to deviate from this unilaterally because by changing her decision, she will only find herself with more expected cost. Thus, the symmetric mixed-action equilibrium strategy $p^{CPT} = (p_l^{CPT}, p_u^{CPT})$, $p_u^{CPT} = 1 - p_l^{CPT}$, is derived when equalizing the CPT values of the two prospects, $CPT_l = CPT_u$.

4.4 Rosenthal and Quantal Response Equilibria and their application to the resource selection task

Both casual empiricism as well as experimental work suggested systematic deviations from the prescriptions of EUT and hence, classical Game Theory (Nash Equilibrium predictions). In Section 4.1 we briefly present the own-payoff effects that constitute the most common pattern of deviations from Nash predictions in matching pennies games. Triggered by this kind of observations, Rosenthal in [20] and, later, McKelvey and Palfrey in [19], propose alternative solution concepts to the Nash equilibrium. The underlying idea in both proposals is that "individuals are more likely to select better choices than worse choices, but do not necessarily succeed in selecting the very best choice". Rosenthal argued that "the difference in probabilities with which two actions x and y are played is proportional to the difference of the corresponding expected gains (costs)". For the actions "low-cost/limited-capacity resource set" and "expensive/unlimited resource set", the Rosenthal equilibrium strategy $p^{RE} = (p_l^{RE}, p_u^{RE})$, $p_u^{RE} = 1 - p_l^{RE}$ is given as a fixed-point solution of the equation

$$p_l^{RE} - p_u^{RE} = -t(c(l, p^{RE}) - c(u, p^{RE})) \quad (12)$$

where $c(l,p)$ and $c(u,p)$ are the expected costs for choosing "low-cost/limited-capacity resource set" and "expensive/unlimited resource set", when all other agents play the mixed-action $p = (p_l, p_u)$, namely,

$$c(l,p) = \sum_{n=0}^{N-1} g_l(n+1)B(n; N-1, p_l) \quad (13)$$

and

$$c(u,p) = c_u \quad (14)$$

The degree of freedom $t \in [0, \infty]$[2] quantifies the rationality of agents, here seen as a synonym of the knowledge they possess and, primarily, their capacity to assess the difference in the utilities between two outcomes. Thus, the model's solution converges to the Nash equilibrium as parameter t goes to infinity.

In a similar view of people's rationality, McKelvey and Palfrey have shown that these "own-payoff effects", *i.e.*, people's inability to play always the strategy that maximizes (minimizes) the expected utility (cost), can be explained by introducing some randomness into the decision-making process. Actually, one can think this kind of randomness and, ultimately, these inaccurate/not rational judgments with respect to cost minimization, as reflecting the effects of estimation/computational errors, individual's mood, perceptual variations or cognitive biases. McKelvey and Palfrey implement these effects into a new equilibrium concept, the Quantal Response equilibrium. For instance, if the randomness follows an exponential distribution (*i.e.*, *logistic errors*, iid mistakes with an extreme value distribution, smaller mistakes are more likely to occur than more serious ones), the response function/probability to play the action "low-cost/limited-capacity resource set" in this equilibrium state $p^{QRE} = (p_l^{QRE}, p_u^{QRE})$, $p_u^{QRE} = 1 - p_l^{QRE}$ is given using (13) and (14) by,

$$p_l^{QRE} = \frac{e^{-tc(l,p^{QRE})}}{e^{-tc(l,p^{QRE})} + e^{-tc(u,p^{QRE})}} \quad (15)$$

Likewise, the free parameter t plays the same role, abstracting the rationality level.

Addressing human behavior in real-life choice problems by using alternative equilibrium solutions emerges as a typical approach for analytical investigations. In a similar study in [8], a capacity-constrained supplier divides the limited supply among prospective retailers. The latter are assigned quantities proportional to their orders, so they have an incentive to inflate their orders to secure more favorable allocated quantities (when facing capacity constraints). They choose their orders strategically but not always perfectly rationally; the optimization of individual payoffs is prone to errors inline with the quantal response model. Other studies, take explicitly into account similar deviations from perfect rationality in attackers' behavior to improve security systems. In [27], the defender has a limited number of resources to protect a set of targets (*i.e.*, flights) and selects

[2] In the Rosenthal equilibrium the rationality parameter t is subject to the constraint that the resulting probabilities range in [0,1].

the optimal mixed strategy, which describes the probability that each target will be protected by a resource. The attacker chooses a target to attack after observing this mixed strategy. This context can be encountered in selective checking applications where the (human) adversaries monitor and exploit the checking patterns to launch an attack on a single target.

4.5 Heuristic decision-making and its application to the resource selection task

A criticism against analytic models of bounded rationality, such as the CPT or the alternative equilibria concepts, is that they do not describe the processes (cognitive, neural, or hormonal) underlying a decision but just predict it. Furthermore, they give no insight as to how should the corresponding models be parameterized each time. On the other hand, models that rely on cognitive heuristics constitute more radical approaches to the decision-making task that originate from the cognitive psychology domain and specify the underlying cognitive processes while they make quantitative predictions. Indeed, heuristic decision-making reflects better Simon's early arguments in [22], [23] that humans are satisficers rather than maximizers.

Todd *et al.* in [24] list and discuss a number of simple heuristic approaches for a particular instance of the resource selection task, namely, the parking search in the simple context of a long dead-end street, with two one-directional lanes leading to (approach lane) and away from (return lane) a destination and a parking strip between the two lanes. One of the simplest example is the "fixed-distance" heuristic that ignores all spaces in the approach lane until the car reaches D places from the destination and then takes the first vacancy (in the approach or the return lane). If none leaves his/her parking place before the last arrival and the first vacancy is not detected during the trip in the approach lane, the driver pays an extra cost that penalizes the travel along the return lane. Overall, all these heuristics rely on related rules for search that have been suggested from other domains (*i.e.*, psychology, economics) and criteria that have been identified as important for drivers such as the parking fee, parking time limits, distance from drivers' travel destination, accessibility and security level [11], [10].

In an effort to get the satisficing notion in our resource selection setting, we came up with a simple kind of heuristic rule in competitive resource selection tasks, arguing that instead of computing/comparing the expected costs of choices, individuals estimate the probability to get one of the "popular" resources and play according to this. In essence, as common sense suggests, agents appear overconfident under low demand for the scarce low-cost resources and underconfident otherwise. Similar to equilibrium solutions in Section 4.4, we define the equilibrium heuristic strategy $p^{HE} = (p_l^{HE}, p_u^{HE})$, $p_u^{HE} = 1 - p_l^{HE}$, by the fixed-point equation

$$p_l^{HE} = \sum_{n=0}^{R-1} B(n; N-1, p_l^{HE}) \qquad (16)$$

where $B(n; N-1, p_l^{HE})$ is the Binomial probability distribution with parameters $N-1$ and p_l^{HE}, for n agents competing for the low-cost resources.

5. NUMERICAL RESULTS

Table 1: Sensitivity analysis of the CPT parameter b**:** $N = 100, R = 50, \beta = 4, \gamma = 8$

b **value**	0.616 (−30%)	0.704 (−20%)	0.792 (−10%)	0.88 (0%)	0.968 (+10%)
p_l^{CPT}	0.8837	0.8836	0.8835	0.8834	0.8834

Table 2: Sensitivity analysis of the CPT parameter d**:** $N = 100, R = 50, \beta = 4, \gamma = 8$

d **value**	0.552 (−20%)	0.621 (−10%)	0.69 (0%)	0.7590 (+10%)	0.828 (+20%)
p_l^{CPT}	0.8934	0.8876	0.8834	0.8805	0.8786

In Sections 3 and 4, we iterate on decision-making models for full rational agents and individuals that exhibit systematically deviations from the full rational behavior and show how the agents resolve in distributed manner the problem of coordinating, that is, which partition of agents will gain the low-cost resources and which will pay the service more expensively. In this section, we consider the resource selection task described in Section 2 and plot the derived agents' choices along with the associated per-user costs incurred in the equilibrium states of the system, under different charging schemes for the two resource sets. The average per-user cost in the symmetric case where every agent performs the mixed-action $p = (p_l, p_u)$ is given by (13) and (14), as follows

$$C(p) = p_l c(l, p) + p_u c(u, p) \qquad (17)$$

Ultimately, we compare the Cumulative Prospect Theory decision-making model, the Rosenthal and Quantal Response equilibria as well as the heuristic reasoning against what the full rational decision-making yields ([16], Theorem 2). Interested readers are referred to [15] for a similar discussion on the Bayesian and pre-Bayesian models in the context of the parking search application.

In addition, we plot the different types of equilibria against the optimal/ideal centralized resource allocation, where the full information processing and decision-making tasks lie with a central entity. Agents issue their requests to a central server, which monitors the limited-capacity resource set, possesses precise information about its availability, and assigns it so that the overall cost paid by agents is minimized. Thus, in an environment with R low-cost resources, whereby such an ideal centralized system serves the requests of $N(\geq R)$ agents, exactly R $(N - R)$ agents would be directed to the low-cost (resp. more expensive) option and no one would pay the excess penalty cost.

For the numerical results, usage of the limited resources costs $c_{l,s} = 1$ unit whereas the cost of the more expensive resources β and the excess penalty cost parameter δ range in $[3, 12]$ and $[1, 16]$ units, respectively.

5.1 Cumulative Prospect Theory

Although the CPT model was originally suggested to rationalize empirical findings in financial lottery experiments, it has been successfully exploited to accommodate data sets for different decision-making models. In [5], the authors review empirical estimates of prospect theory under different (parametric) assumptions, incentives, tasks and samples. In a transportation paradigm more similar to our

Table 3: Sensitivity analysis of the CPT parameter λ: $N = 100, R = 50, \beta = 4, \gamma = 8$

λ **value**	1.8 (-20%)	2.025 (-10%)	2.25 (0%)	2.475 ($+10\%$)	2.7 ($+20\%$)
p_l^{CPT}	0.8834	0.8834	0.8834	0.8834	0.8834

setting, Avineri *et al.* in [4] first conduct a route-choice stated-preference experiment and then explain the results parametrizing their route choice model with values similar to the ones that Tversky and Kahneman found for their archetypal model in [25]. In the absence of proper experiment measurements on the particular resource selection paradigm that could validate this theory, it is not suggested that the parameter set $b = 0.88, d = 0.69, \lambda = 2.25$, as was introduced in Section 4.3, reflects the actual agents' choices. Thus, we use the default parametric values to explore the existence (or not) of the same risk attitudes towards losses in the particular environment (ref. Section 2) and conduct a sensitivity analysis on the parameters b, d, λ in the end of the section to address these concerns.

Motivated by the simple experiments on preferences about positive and negative prospects that, eventually, reveal the four-fold pattern of risk attitude [25], we iterate on the most interesting case studies for the cost differentials between the certain prospect (*i.e.*, c_u for the expensive/unlimited resource set) and the best or worst outcome of the risky one (*i.e.*, $c_{l,s}$ or $c_{l,f}$ for the low-cost/limited-capacity resource set). As Figures 1a, 1b suggest, when the agents have the opportunity to experience a marginally or significantly lower charging cost at low or high risk, respectively, their biased risk-seeking behavior turns to be full rational, and thus, minimizes the expected cost over others' preferences. On the contrary, in the face of a highly risky option reflected in significant extra penalty cost (Fig. 1c), the risk attitude under the two types of rationality starts to differ, yet both suggest being more conservative. For instance, when $N = 100$ agents compete for $R = 50$ low-cost resources, the expected utility maximization framework results in the Nash equilibrium $p_l^{NE} = \frac{R(\gamma-1)}{\delta N} = 0.59$, with expected cost values $c(l, p^{NE}) = c(u, p^{NE}) = c_u$ whereas the CPT suggests playing with $p_l^{CPT} = 0.61$ that equalizes the relevant values $CPT_l = CPT_u = -7.62$. Under the prescriptions of CPT, at the mixed-action $p^{NE} = (0.59, 0.41)$, the cumulative prospect values become $CPT_l = -6.74$ and $CPT_u = -7.62$ which leads to a risk-prone behavior, inline with the theory for losses: an agent may decrease the prospect cost by switching her decision from the certain more expensive resource set to the risky low-cost one. On the other hand, at the mixed-action p^{CPT} the expected costs for the two options differ, namely, $c(l, p^{CPT}) = 4.49$ and $c(u, p^{CPT}) = c_u = 4$.

Overall and as Figure 2 implies, both the full rational and the biased practice are more risk-seeking than they should be, increasing the actual per-user cost (or equivalently, the social cost) over the optimal levels. As a result, being prone to biased behaviors cannot score better than acting full rationally[3].

The sensitivity of these results to the particular CPT parametric values $b = 0.88, d = 0.69, \lambda = 2.25$, can be drawn from Tables 1, 2 and 3, respectively. The CPT model evolves to the expected utility maximization one that gives $p_l^{NE} = 0.875$, as the parameters go to one. In general, although we admit that the ultimate validation of our analytical results would come out of real, yet costly and difficult experimentation with in-field measurements, the effect of the parameters is shown to be limited.

5.2 Rosenthal and Quantal Response Equilibria

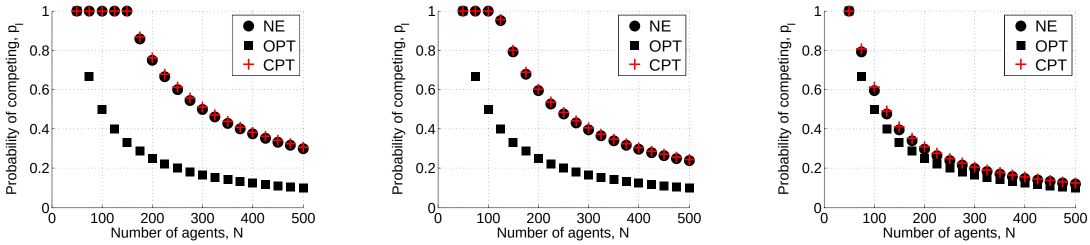
Within the typical game-theoretic setting, the agents' expected costs from different strategies are determined by their beliefs about others' preferences. Eventually, these beliefs may generate choice probabilities according to a particular response function that is not necessarily *best*, inline with the expected utility maximization norms. Yet under this kind of response functions, such as those in the form of (12) or (15), the resulting - Rosenthal and Quantal Response - equilibria impose the requirement that the beliefs match the equilibrium choice probabilities, as in the Nash equilibrium solutions.

Figure 3 plots these two alternative types of equilibrium strategies and the resulting per-user costs when individuals cannot always choose the actions that best satisfy their preferences, that is when the rationality parameter t is 3. First, the implementation of bounded rationality increases randomness into agents' choices and hence, draws choice probabilities towards 0.5. As a result, when competition exceeds the capacity of the low-cost resources, computational limitations lead to more conservative actions comparing to the Nash equilibrium competing probabilities when $N < \frac{2R(\gamma-1)}{\delta}$ and less, otherwise. Second, the more different the - expected - costs of the two options are, the less the Rosenthal and Quantal Response equilibrium differ from the Nash one, since the identification of the best action becomes easier. Thus, we notice almost no or limited difference when the risk to compete for a very small benefit is high due to the significant extra penalty cost δ (Fig. 3c) or the high demand for the resources (Fig. 3a, $N > 300$). The same reason underlies the differences between the Rosenthal and the Quantal Response equilibrium. Essentially, the three types of equilibrium form a three-level hierarchy with respect to their capacity to identify the less costly resource option, with the Quantal Response equilibrium at the bottom level and the Nash one at the top level.

Since the per-user cost is minimized at lower competing probabilities, the inaccurate but frugal computation of the best action saves not only time and computational resources but also, usage cost when $N < \frac{2R(\gamma-1)}{\delta}$ (Fig. 3b).

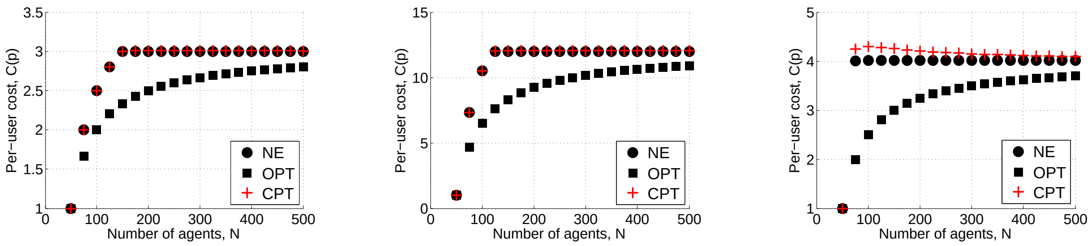
The impact of computational limitations becomes more sharp at even lower values of the rationality parameter. In Figure 4, we plot the probability of competing for the low-cost resources and the resulting per-user cost, when $t = 0.2$. Again higher differences in behavior are observed in settings where it is not clear which of the two resource options costs less. This is the case of Figure 4a, where the choices are decided almost randomly. On the other hand, when the risk is high when choosing the limited resources, as in Figure 4c,

[3]In [16], we investigate the game-theoretic equilibrium strategies and the resulting Price of Anarchy metric, which compares the induced social cost at equilibrium states against the optimal one, to quantify the inefficiency of equilibria for a wide range of charging schemes.



a. $\beta = 3, \gamma = 4$ b. $\beta = 12, \gamma = 20$ c. $\beta = 4, \gamma = 20$

Figure 1: Probability of competing in CPT equilibrium, for $R = 50$, under different charging schemes.



a. $\beta = 3, \gamma = 4$ b. $\beta = 12, \gamma = 20$ c. $\beta = 4, \gamma = 20$

Figure 2: Per-user cost in CPT equilibrium, for $R = 50$, under different charging schemes.

even that low rationality level generates decisions similar to the full rational ones.

Interestingly, when $\beta = 3$, $\gamma = 4$ and $N < \frac{2R(\gamma-1)}{\delta}$, the decrease in competing probability that comes with imperfect rationality, draws the per-user cost to near-optimal levels (Fig. 4b). However, when the penalty cost is high, any - limited - increase in competitiveness due to inaccurate cost discrimination causes significant overhead (Fig. 4d).

As a last note, Figure 5 illustrates the impact of the rationality parameter t on the equilibrium choice probabilities. Starting with a difference $\delta_{prob,t\sim 0} = p_l^{QRE,RE} - p_l^{NE} = 1/2 - \frac{R(\gamma-1)}{\delta N}$ under a pure stochastic decision-making model, the bounded rational reasoning approximates the full rational practice, as t goes to infinity. When $N \sim (N-1)$, as in our setting, this difference in competing probability can be translated in gains (less cost) or losses (more cost) in the ultimate per-user cost, by (17), as follows:

$$\begin{aligned}\delta_{cost,t} &= C(p^{QRE,RE}) - C(p^{NE}) \\ &\approx \delta_{prob,t} \cdot \delta c_{l,s}, \quad \text{if } R/((N-1)(p_l^{NE} + \delta_{prob,t})) < 1 \\ &\approx c_{l,s}(p_l^{NE} + \delta_{prob,t} - R/(N-1)) - \\ &\quad c_{l,f}(p_l^{NE} - R/(N-1)) - \delta_{prob,t} c_{pl}, \quad \text{o/w}\end{aligned}$$

5.3 Heuristic decision-making

Typically, under time and processing limitations, the fast and frugal reasoning approaches emerge as the only solution. In fact, the cognitive heuristics operate as adaptive strategies that allow agents to turn complex decision tasks of predicting others' preferences, assessing corresponding utilities or costs, determining best or better actions, to simpler decision-making tasks. Within a highly competitive environment and in the face of a penalty cost ($\delta c_{l,s}$), the heuristic reasoning just estimates the competition levels (*i.e.*, according to (16)) and plays according to this. At equilibrium,

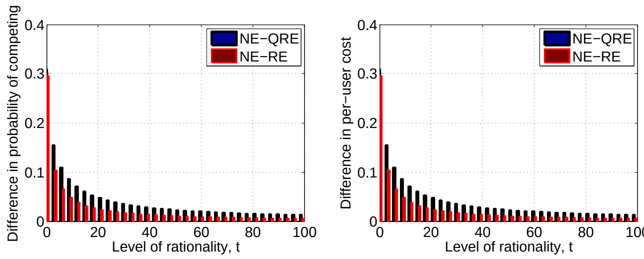


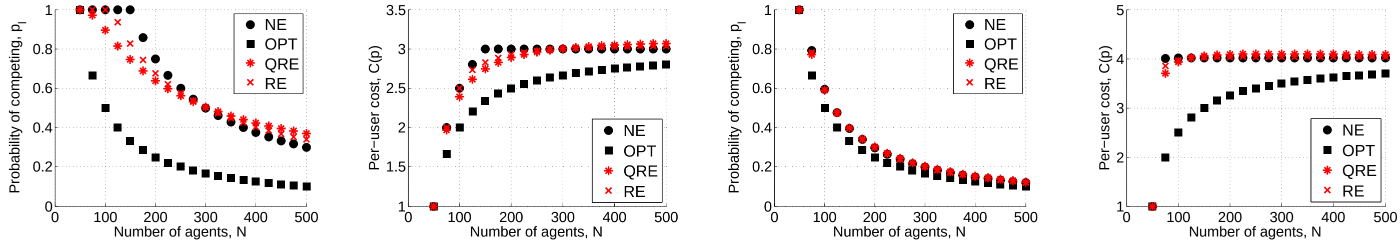
Figure 5: Difference between the probability of competing in the Quantal Response, Rosenthal equilibria and that in Nash equilibrium (left) and the resulting per-user cost difference (right), for $R = 50, N = 180$, under fixed charging scheme $\beta = 3, \gamma = 4$ and $t = [0.1, 100]$ (from imperfect to perfect rationality).

the beliefs that formulate the competition level match the actual choice probabilities, as in Section 5.2.

Interestingly, this trivial modelling approach leads to near-optimal results. Unlike CPT or the alternative equilibrium solutions, it does not take into account the charging costs. Yet, this reasoning mode expresses a pessimistic attitude that takes for granted the failure in a possible competition with competitors that outnumber the resources. As a result, it implicitly seeks to avoid the tragedy of common effects and hence, eventually, yields a socially beneficial solution.

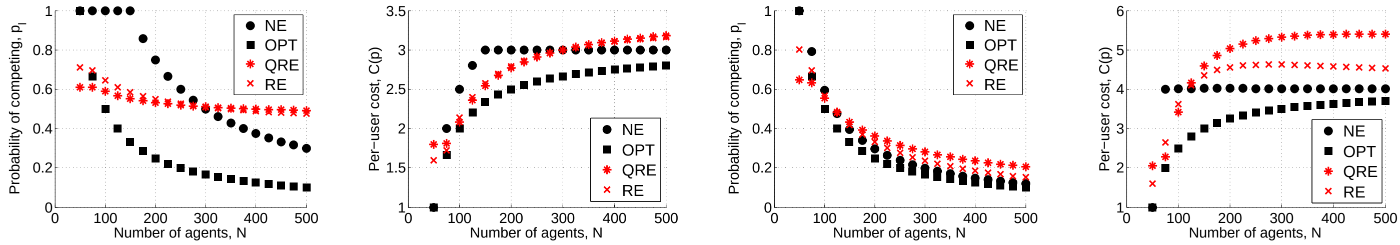
6. CONCLUSIONS

In this study, we consider environments where the tragedy of commons effects emerge on a limited-capacity set of inexpensive resources. Agents choose independently to either compete for these resources running the risk of failing the competition and having to take an unlimited, yet more ex-



a. $\beta = 3, \gamma = 4$ b. $\beta = 3, \gamma = 4$ c. $\beta = 4, \gamma = 20$ d. $\beta = 4, \gamma = 20$

Figure 3: Probability of competing in the Quantal Response and Rosenthal equilibria and the resulting per-user cost, for $R = 50$, $t = 3$.



a. $\beta = 3, \gamma = 4$ b. $\beta = 3, \gamma = 4$ c. $\beta = 4, \gamma = 20$ d. $\beta = 4, \gamma = 20$

Figure 4: Probability of competing in the Quantal Response and Rosenthal equilibria and the resulting per-user cost, for $R = 50$, $t = 0.2$.

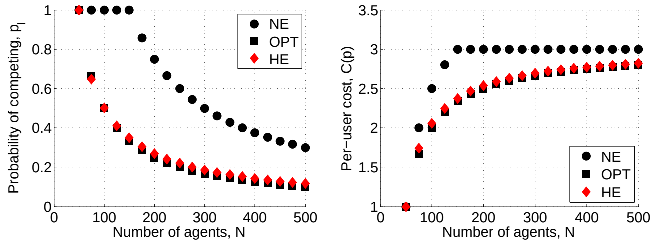


Figure 6: Probability of competing in heuristic equilibrium (left) and the resulting per-user cost (right), for $R = 50$, under fixed charging scheme $\beta = 3, \gamma = 4$.

pensive option after paying a penalty cost, or prefer from the beginning the more secure but expensive option. In their decisions, they consult (or not) information about the competition level (*i.e.*, demand), the supply (*i.e.*, capacity) and the employed pricing policy on the resources. This content might be available through ad-hoc/opportunistic interaction or broadcast from the resource operators, through information assistance systems.

Drawing insights from cognitive science, we assess how cognitive heuristics/biases affect the efficiency of real-life resource selection applications, yet without assessing the exact relevance of the heuristics/biases in particular application paradigms. Bayesian and pre-Bayesian variants of the strategic resource selection game are investigated to express incompleteness in agents' knowledge, while people's biased behavior within the particular competitive environment is captured via the Cumulative Prospect Theory framework. We view the two resource alternatives, in particular, as prospects and verify numerically the agents' risk-prone attitude under particular charging schemes on the resources. Alternative equilibria solutions (Rosenthal and Quantal Response) model the impact of people's time-processing limitations on their decisions, inline with Simon's argument that humans are satisficers rather than maximizers. We tune the rationality parameter in the Rosenthal and Quantal Response equilibria, to model agents of different rationality levels and thus, different degrees of responsiveness to various cost differentials between the two resource options, ranging from pure guessing to perfectly rational reasoning (Nash equilibrium). We identify environments where the impaired reasoning, as expressed by the two alterative equilibrium concepts, leads to less costly choices compared to the Nash solutions. In the more radical approach, the agents decide heuristically based on the estimated probability to win the competition for the low-cost resources. Interestingly and unlike the other models, the heuristic decision-making results in near-optimal per-user/social cost, albeit far from what the perfect rationality yields. Starting from these results, our intention is to explore scenarios with a richer mix of agent behaviors, catering for various expressions of rationality that interact with each other. This takes us to more advanced models such as the "cognitive hierarchy" in [7] with different distributions for the complexity level of agents' reasoning.

7. ACKNOWLEDGEMENTS

This work has been supported in part by the European Commission IST-FET project RECOGNITION (FP7-IST-257756) and the European Commission under the Network of Excellence in Internet Science project EINS (FP7-ICT-288021).

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