Data sharing games

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Abstract

Data sharing issues pervade online social and economic environments. To foster social progress, it is important to develop models of the interaction between data producers and consumers that can promote the rise of cooperation between the involved parties. We formalize this interaction as a game, the data sharing game, based on the Iterated Prisoner’s Dilemma and deal with it through multi-agent reinforcement learning techniques. We consider several strategies for how the citizens may behave, depending on the degree of centralization sought. Simulations suggest mechanisms for cooperation to take place and, thus, achieve maximum social utility: data consumers should perform some kind of opponent modeling, or a regulator should transfer utility between both players and incentivise them.

Keywords: data sharing; iterated prisoner’s dilemma; multi-agent reinforcement learning.

1. Introduction

As recently discussed \cite{24}, data, as the intangible asset par excellence in the 21st century, is the most disputed raw material at global scale. Ours is a data-driven society and economy, with data guiding most business actions and decisions. This is becoming even more important as many business processes are articulated through a cycle of sensing-processing-acting. Indeed, Big Data is the consequence of a digitized world where people, objects and operations are fully instrumented and interconnected, producing all sorts of...

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data, both machine-readable (numbers and labels, known as structured) and human-readable (text, audio or video, known as unstructured). As data acquisition grows at sub-second speed, the capability to monetize them arises through the ability to derive new synthetic data. Thus, considered as an asset, data create markets and enhance competition. Unfortunately, it is creating bad practices as well. See [17] for an early discussion as well as the recent European directives and legislative initiatives to promote public-private B2G data partnerships, e.g. [8].

This is the main reason for analyzing data sharing games with mechanisms that could foster cooperation to guarantee and promote social progress. Data sharing problems have been the object of several contributions and studied from different perspectives. For example, [16] proposes a game theoretic approach to help users determine their optimal policy in terms of sharing data in online social networks, based on a confrontation between a user (aimed at sharing certain information and hiding the rest) and an attacker (aimed at exposing the user’s PI or concealing the information the user is willing to share). This is modelled through a zero-sum Markov game; a Markov equilibrium is computed and the corresponding Markov strategies are used to give advice to users. [12] reviews the impact of data sharing in science and society and presents guidelines to improve the efficiency of data sharing processes, quoting [22], who provide a game theoretical analysis suggesting that sharing data with the community can be the most profitable and stable strategy. Similarly, [10] consider a setting in which a group of firms must decide whether to cooperate in a project that requires the combination of data held by several of them; the authors address the question of how to compensate the firms for the data they contribute with, framing the problem as a transferable utility game and characterizing its Shapley value as a compensation mechanism.

Our approach models interactions between data owners and consumers inspired by the iterated prisoner’s dilemma (IPD) [3]. This is an elegant incarnation of the problem of how to achieve agents’ cooperation in competitive settings. Other authors have used similar models in other socio-technical problems as in politics [5], and security [18], among others. Our approach to model agent’s behavior is different and relies on multi-agent reinforcement learning (MARL) arguments [13]. Reinforcement learning (RL) has been successfully applied to games that are repeated over time, thus making it possible for agents to optimize their strategies [19]. The work of [25] also discusses the use of RL in iterated games such as Prisoner’s Dilemma, although they do not
focus on the issue of incentivizing cooperation between the players. Through RL we are able to identify relevant mechanisms to promote cooperation.

The structure of the paper is as follows. First, a qualitative description of the problem, the intervening agents and their strategies is provided. We next model it quantitatively and develop scenarios that could promote cooperation through MARL. We study those in simulated environments confirming that cooperation is both possible and the best social strategy, ending with a brief discussion.

2. Data sharing: categories, agents and strategies

Before modeling interactions between data consumers and producers, it is convenient to understand the data categories available. Even though admittedly with a blurry frontier, from a legal standpoint, there are two main ones:

- **Data that should not be bought/sold.** This refers to personal information (PI), as e.g. the data preserved in the European Union through the General Data Protection Regulation (GDPR) [11] and other citizen defense frameworks aimed at guaranteeing civic liberties. PI includes data categories such as internal information (like knowledge and beliefs, and health data); financial information (like accounts or credit data); social information (like criminal records or communication data); or, tracking information (like computer device; or location data).

- **Data that might be purchased.** Citizen’s data is a property, there being a need to guarantee a fair and transparent compensation. Accountability mitigates market frictions. For traceability and transparency reasons, blockchain-based platforms are being implemented at the moment.

A characterization of what type of data belongs to each category will depend on the context and is, most of the times, subjective.

In any case, in the last decades, modern data analytics techniques and strategies are enabling the generation of new types of data:

- **Data that might be estimated/derived.** Currently available analytics technologies have the ability of estimating efficiently citizen behavior and other characteristics by deeply analyzing Big Data. For instance,
platforms such as IBM Personality Insights [15] can estimate personality traits of a given individual using his/her tweets, thus facilitating marketing activities. As a result, the originating data becomes a new asset for a company willing to undertake its analysis.

Having mapped the available data, there is a need to understand the knowledge actually available and how is it uncovered. Within the above scenario, we consider two players in a data sharing game: the data providers (Citizen, she) and the Dominant Data Owner (DDO, he). A DDO could be a private company, e.g. GAFA (Google, Apple, Facebook, Amazon) or Telefonica, or a public institution (Government). Inspired by the classic Johari window [20], we inter-relate now what a Citizen knows or does not with what a DDO knows or does not to obtain these scenarios:

1. Citizen knows what DDO does. The citizen has created a data asset which she sells to a DDO. Sellable data create a market which could evolve in a sustainable manner if accountability and transparency are somehow guaranteed.

2. Citizen knows what DDO does not. This is the PI realm. Citizens would want legal frameworks like the GDPR or data standards preserving citizen rights, mainly ARCO-PL (access, rectification, cancellation, objection, portability and limitation) so that PI is respected.

3. Citizen does not know what DDO does. The DDO has unveiled citizen’s PI through deep analysis of Big Data. This analysis may be acceptable if data are dealt just as a target. Data protection frameworks should guarantee civil rights and liberties in such activities.

Note that we could also think of a fourth scenario in which neither the citizen knows, nor the DDO does, although this is clearly unreachable.

Once explained how knowledge is shared, we analyze how knowledge creation can be fostered to stimulate social progress, studying cooperation scenarios between Citizen and DDO. We simplify by considering two strategies for both players, respectively designated Cooperate (C) and Defect (D), leading to the four scenarios in Table 1.

Reflecting about them, the only one that ultimately fosters knowledge creation and, therefore, stimulates social progress, is mutual cooperation. It is the best scenario and produces mutual value. Cooperation begs for a FATE.

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1 As in the famous Target pregnant teenager case [14]
Table 1: Scenarios in the data sharing game.

| Citizen cooperates | DDO cooperates | DDO defects |
|--------------------|----------------|-------------|
|                     | Citizen sells data, demands data protection | Citizen taken for a ride selling data, while DDO does not pay Citizen data with services |
|                     | DDO purchases and respect Citizen data. | |
| Citizen defects     | DDO taken for a ride purchasing. Citizen selling wrong/noisy data becomes free rider. | Citizen sells wrong/noisy data does not pay for DDO services, who does not pay data with services |

(fair, accountable, transparent, ethical) technology like blockchain. In such scenario, data (Big Data), algorithms and processing technology would boost knowledge. Mutual cooperation is underpinned by decency and indulgence values such as being nice (cooperate when the other party does); provokable (punish non cooperation); forgiving (after punishing, immediately cooperate, reset credit); and clear (the other party easily understands and realises that the best next move is to cooperate).

Mutual defection is the worst scenario in societal terms: it produces a data market failure, stagnating social progress. As there is no respect from both sides, no valuable data trade will happen, and even a noisy data vs. unveiled data war will take place. Loss of freedom may arise as a result.

The scenario (Citizen cooperates, DDO defects) is the worst for the citizen, leading to data power abuses, as with the UK “ghost” plan. It would generate asymmetric information, adverse selection, and moral hazard problems, in turn producing data market failures. The DDO behaves incorrectly, there being a need to punish unethical and illegal behaviour. As an example, the GDPR sets the right to receive explanations for algorithmic decisions. There is also a need for mitigating systematic cognitive biases in algorithms. Citizens may respond by sending noisy data, rejecting data services, imposing standards over data services or setting prices according to success.

Finally, the scenario (Citizen defects, DDO cooperates) is the worst for the DDO. It leads to data market failures and shrinks knowledge. This stems from a behavior of not paying for public/private services that can be obtained anyway. In the long run, this erodes public and private services quality and creativity. This misbehavior should be punished to restore cooperation and a fair price should be demanded for services.
3. A model for the data sharing game

We model interactions between citizens and DDOs over time from the perspective of the IPD. Table 2 shows its reward bimatrix. The row player will be the Citizen, for whom cooperate means that she wishes to sell and protect her data, whereas defect means she either sells wrong data or decides not to contribute. The DDO will be the column player for whom cooperate means that he purchases and protects data, whereas defect means that he is not going to pay for the collected data or will not protect it. Payoffs satisfy the usual conditions in the IPD, that is $T > R > P > S$ and $2R > T + S$. When numerics are necessary, we adopt the choice $T = 6$, $R = 5$, $P = 1$, and $S = 0$.

It is well-known that in the one-shot version of the IPD game, the unique Nash equilibrium is $(D, D)$, leading to the social dilemma described above: the selfish rational point of view of both players leads to an inferior societal position. Similarly, if the game is played $N$ times, and this is known by the players, these have no incentive to cooperate, as we may reason by backwards induction [4]. However, in realistic scenarios, players are not sure about whether they will meet again in future and, consequently, they cannot be sure when the last interaction will be taking place [3]. Thus, it seems reasonable to assume that players will interact an indefinite number of times or that there is a positive probability of meeting again. This possibility that players might interact again is precisely what makes cooperation emerge.

The framework that we adopt to deal with the problem is MARL [7]. Each agent $a \in \{C, DDO\}$ maintains its policy $\pi_a(d_a|o_a, \theta_a)$ used to select a decision $d_a$ under some observed state of the game $o_a$ (for example, the previous pair of decisions) and parameterised by certain parameters $\theta_a$. Each agent learns how to make decisions by optimizing his policy under the expected

| Citizen | DDO |
|---------|-----|
|         |     |
| C       | $R, R$ | $S, T$ |
| D       | $T, S$ | $P, P$ |

Table 2: Payoffs in the data sharing game
sum of discounted utilities

$$\max_{\theta_a} \mathbb{E}_{\pi_a} \left[ \sum_{t=0}^{\infty} \gamma^t r_{a,t} \right],$$

where $\gamma \in (0, 1)$ is a discount factor and $r_{a,t}$ is the reward that agent $a$ attains at time $t$. The previous optimization can be performed through Q-learning or policy gradient methods [27]. The main limitation with this approach in the multi-agent setting is that if the agents are unaware of each other, they are shown to fail to cooperate [13], leading to defection every time, which is undesirable in the data sharing game.

As an alternative, in order to foster collaboration, we propose three approaches, depending on the degree of decentralization and incentivisation sought for.

- In a (totally) decentralized case, C and DDO are alone and we resort to opponent modelling strategies, as showcased in Section 4.1. However, this approach may fail under severe misspecification in the opponent’s model. Ideally, we would like to encourage collaboration without making strong assumptions about learning algorithms used by each player.

- Alternatively, a third-party could become a regulator of the data market: C and DDO use it and the regulator introduces taxes, as showcased in Section 4.2. The benefit of this approach is that the regulator only needs to observe the actions adopted by the agents, not needing to make any assumption about their models or motivations and optimizing their behaviors based on whatever social metric he considers.

- Finally, in Section 4.3 we augment the capabilities of the previous regulator to enable it to incentivize the agents, leading to further increases in the social metric considered.

To fix ideas, we focus on a social utility (SU) metric defined as the agents’ average utility

$$SU_t = \frac{r_{C,t} + r_{DDO,t}}{2}. \quad (1)$$

This requires adopting a notion of transferable utility, serving as a common medium of exchange that can be transferred between agents, see e.g. [2].
4. Three solutions via Reinforcement Learning

4.1. The decentralized case

Our first approach models the interaction between both agents as an IPD, and simulates such interactions to assess the impact of different DDO strategies over social utility. We first fix the strategy of the DDO, assume that the citizen models the DDO behaviour and simulate interactions between both agents finally assessing social utility.

We model the Citizen as a Fictitious Play Q-learner (FPQ) in the spirit of [13]. She chooses her action $d_a \in \{C, D\}$ maximizing her expected utility $\psi(d_a)$ defined through

$$\psi(d_a) = \mathbb{E}_{p_{FP}(d_b)}[Q(d_a, d_b)] = \sum_{d_b \in \{C, D\}} Q(d_a, d_b)p_{FP}(d_b),$$

where $p_{FP}(d_b)$ reflects the Citizen’s beliefs about her opponent’s actions $d_b \in \{C, D\}$ and $Q(d_a, d_b)$ is the augmented Q-function from the threatened Markov decision processes as defined in [13], an estimate of the expected utility obtained by the Citizen if both players were to commit to actions $d_a, d_b$.

We estimate the probabilities $p_{FP}(d_b)$ using the empirical frequencies of the opponent’s past plays as in Fictitious Play [6]. To further favor learning, the Citizen could place a Beta prior over $p_C \sim \mathcal{B}(\alpha, \beta)$, the probability of the DDO cooperating, with probability $p_D = 1 - p_C$ of defecting. Then, if the opponent chooses, for instance, cooperate, the citizen updates her beliefs leading to the posterior $p_C \sim \mathcal{B}(\alpha + 1, \beta)$, and so on.

We may also augment the citizen model to have memory of the previous opponent’s action. This can be straightforwardly done replacing $Q(d_a, d_b)$ with $Q(s, d_a, d_b)$ and $p_{FP}(d_b)$ with $p_{FP}(d_b|s)$ where $s \in \{C, D\} \times \{C, D\}$ is the previous pair of actions both players took. Thus, we need to keep track of four Beta distributions, one for each value of $s$. This FPQ agent with memory will be called FPM. Clearly, this approach could be expanded to account for longer memories over the action sequences. However, [21] shows that agents with a good memory-1 strategy can effectively force the iterated game to be played as memory-1, even if the opponent has a longer memory.

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2Code for all the simulations performed can be found at [https://github.com/vicgalle/data-sharing](https://github.com/vicgalle/data-sharing)
4.1.1. Experiments

We simulate the previous IPD under different strategies for the DDO and measure the impact over social utility. For each scheme, we display the social utility attained over time by the agents. For all experiments, we model the citizen as an FPM agent (with memory-1). The discount factor was set to 0.96.

**Selfish DDO.** When we assume a selfish DDO, playing always defect, our simulation confirms that this strategy will force the citizen to play defect and sell wrong data, not having incentives to abandon such strategy. Even when citizens have strong prior beliefs that the DDO will cooperate, after a few iterations they will learn that the DDO is defecting always and thus choose also to defect, as shown in Figure 1(a).

![Figure 1(a)](image)

(a) Agents’ utilities.

Figure 1(b) shows that under the defecting strategy, the social utility achieves its minimum value.

**A Tit for Tat DDO.** We next model the DDO as a player using the Tit for Tat (TfT) strategy (it will first cooperate and, then, subsequently replicate the opponent’s previous action: if the opponent was previously cooperative, the agent is cooperative; if not, it defects). This policy has been widely used in the IPD, because of its simplicity and effectiveness [3]. A recent experimental study [9] tested real-life people’s behaviour in IPD scenarios, showing that TfT was one of the most widely strategies. Figure 2 shows that under TfT, the social utility achieves its maximum value: mutual cooperation is achieved, thus leading to the optimal social utility.
It is important to mention though that if the citizen had no memory about previous actions, the policy of the DDO could not be learnt and mutual cooperation would not be achieved.

*Random behaviour among citizens.* Previously, we all citizens were assumed to act according to the FPM model. However, assuming that the whole population will behave following such complex strategies is unrealistic. A more reasonable assumption considers having a subpopulation of citizens that acts randomly. To simulate this, we modify the FP/FPM model to draw a random action with probability $0 < \epsilon < 1$ at each turn. As Figure 3 shows, where we set $\epsilon = 0.7$, this entails a huge decrease in social utility.

*A forgiving DDO.* A possible solution for this decrease in social utility consists of forcing the DDO to eventually forgive the Citizen and play cooperate regardless of her previous actions. We model this as follows: with probability $p$ the DDO will cooperate, whereas with probability $1 - p$ he will play TFT. To assess what proportion of time should the DDO forgive, we evaluated a grid of values from 0 to 100, and chose the one that produced the highest increase in social utility. The optimal value was forgiving 70% of times. As Figure 3 shows, this produces an increase of approximately half a unit in the average social utility with respect to the case of never forgiving.

Note, though, that there exists a limit value for the forgiving rate such that, if surpassed, the social utility will decrease to around 3. The reason for this is that, in this regime, when not acting randomly, the Citizen will learn that the DDO cooperates most of the time, and thus her optimal strategy
will be to defect. Thus, in most iterations the actions chosen will be \((C, D)\), leading to a social utility of around 3.

4.2. Taxation through a regulator

We discuss now an alternative solution to promote cooperation introducing a third player, a Regulator (R, it). Its objective is to nudge the behaviour of the other players through utility transfer, based on taxes. Appendix A discusses a one-shot version identifying its equilibria. As in Section 4.1, our focus is on the iterated version of this game.

At each turn, the regulator will choose a tax policy for the agents 
\[(\text{tax}_{C,t}, \text{tax}_{DDO,t}) \sim \pi_R(\cdot|o_R, \theta_R),\]
where \(o_R\) is the observed state of the game and \(\theta_R\) are relevant parameters for the regulator. Then, the other two agents will receive their corresponding adjusted utility \(\tilde{r}_{a,t}\) through
\[\tilde{r}_{a,t} = r_{a,t} - \text{tax}_{a,t} + \frac{1}{2} \sum_a \text{tax}_{a,t},\]
where the first term is the original utility (Table 2); the second one is the tax that the regulator collects from that agent; and, finally, the third one is the (evenly) redistributed collected reward. Note that
\[SU_t = \frac{r_{C,t} + r_{DDO,t}}{2} = \frac{\tilde{r}_{C,t} + \tilde{r}_{DDO,t}}{2}.\]
Thus, under this new reward regime, utility is not created nor destroyed, only transferred between players.

Let us focus now on the issue of how does the Regulator learn its tax policy. For this, we make it another RL agent that maximizes the social welfare function, thus optimizing its policy by solving

$$\max_{\theta_R} \mathbb{E}_{\pi_R} \left[ \sum_{t=0}^{\infty} \gamma^t SU_t \right].$$

Then, two nested RL problems are considered: first, the regulator selects a tax regime and, next, the other two players optimally adjust their behaviour to this regime. After a few steps, the regulator updates its policy to further encourage cooperation (higher $SU_t$), and so on. At the end of this process, we would expect that both players’ behaviours would have been nudged towards cooperation.

We thus frame learning as a bi-level RL problem with two nested loops, using policy gradient methods:

1. **(Outer loop)** The regulator has parameters $\theta_R$, imposing a certain tax policy.
   (a) **(Inner loop)** The agents learn under this tax policy for $T$ iterations:
   (b) They update their parameters:
   $$\theta_{a,t+1} = \theta_{a,t} + \eta \nabla \mathbb{E}_{\pi_a} \left[ \sum_{t=0}^{\infty} \gamma^t r_{a,t} \right].$$

2. The regulator updates its parameters:
   $$\theta_{R,t+1} = \theta_{R,t} + \eta \nabla \mathbb{E}_{\pi_R} \left[ \sum_{t=0}^{\infty} \gamma^t SU_t \right].$$

Let us highlight a few benefits of this approach. First, the Regulator makes no assumptions about the policy models of the other players (thus it does not matter whether they are just single-RL agents or are opponent-modelling). Moreover, this framework is also agnostic to the social welfare function to be optimized; for simplicity, we just use the expression (1). It is also scalable to more than two players: the regulator only needs to collect taxes for each player, and then redistributes wealth. In case that we were considering $k > 2$ agents, we would have to split the sum of taxes by $1/k$.

4.2.1. Experiments

This experiment illustrates the performance of the general framework, showing how the inclusion of a Regulator encourages the emergence of cooperative behavior.
Consider the interactions between a Citizen and a DDO. The parameter for each player is a vector $\theta_a \in \mathbb{R}^2$, with $a \in \{C, DDO\}$, representing the logits of choosing the actions, i.e. the unnormalized probabilities of choosing each decision. We consider two types of regulators.

The first one has a discrete action space defined through

$$
tax_{a,t} = \begin{cases} 
0.00 & \text{if } a_R = 0 \\
0.15 \cdot r_{a,t} & \text{if } a_R = 1 \\
0.30 \cdot r_{a,t} & \text{if } a_R = 2 \\
0.50 \cdot r_{a,t} & \text{if } a_R = 3.
\end{cases}$$

For example, when $a_R = 2$ the tax rate reaches 30%. In this case, $\theta_R \in \mathbb{R}^4$ represent the logits of a categorical random variable taking the previous values (0,1,2,3).

The second regulator adopts a Gaussian policy defined through $\pi_R(d_R|o_R, \theta_R) \sim \mathcal{N}(d_R|\theta_R, 0.05^2)$, with tax

$$
tax_{a,t} = 0.5 \cdot \text{sigmoid}(d_R) \cdot r_{a,t},$$

to allow for a continuous range in $[0, 0.5]$.

Experiments run for $T = 1000$ iterations. After each iteration, both agents perform one update of their policy parameter gradient. The regulator updates its parameters using policy gradients every 50 iterations. The decision of updating the regulator less frequently than the other agents is motivated to allow them to learn and adapt to the new tax regime and stabilise the overall learning of the system. Figure 4 displays results. For each of the three variants (no intervention, discrete, continuous) we plot 5 different runs and their corresponding means in darker color.

Clearly, under no intervention, both agents fail to learn to cooperate converging to the static Nash equilibrium $(D, D)$. We also appreciate that the discrete policy is neither effective, also converging to $(D, D)$, albeit at a much slower pace. On the other hand, the Gaussian regulator is more efficient as it allows to avoid convergence to $(D, D)$ although it does not preclude convergence to $(C, C)$. This regulator is more effective than its discrete counterpart, because it can better exploit the policy gradient information. Because of this, in the next subsection we will focus on this Gaussian regulator.

In summary, the addition of a Regulator can make a positive impact in the social utility attained in the market, preventing collapse into $(D, D)$. 

However, introducing taxes to the players is not sufficient, since in Figure 4 the social utility converged towards a value of 3, far away from the optimal value of 5.

4.3. Introducing incentives

In order to further stimulate cooperative behavior, we introduce incentives to the players via the Regulator: if both players cooperate at a given turn, they will receive an extra amount $I$ of utility, a scalar that adds to their perceived rewards. Appendix B shows that incentives complement well with the tax framework, so that mutual cooperation is possible in the one-shot version of this game. Note that, when $I > T - R$, instead of the Prisoner’s Dilemma, we have an instance of the Stag Hunt game [26], in which both $(C, C)$ and $(D, D)$ are pure Nash equilibria.

From now on, we focus the discussion in the iterated version. In this batch of experiments, players interact over $T = 1000$ iterations, and the Regulator only provides incentives during the first 500 iterations. After that, he will only collect taxes from the players and redistribute them as in Section 4.2.

Figure 5 shows results from several runs under different incentive values. A few comments are in order.

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*Achieving mutual cooperation is much simpler in this case.*
Firstly, note that as the incentive increases, also does the social utility. For an incentive of 1, the maximum reward of $(C, C)$ and $(D, C)$ is the same (6) for the Citizen, and cooperation emerges naturally. Also note that since the policies for each player are stochastic, it is virtually impossible to maintain an exact convergence towards the optimal value of 5, since a small amount of time the agents are deviating from $(C, C)$ due to the stochastic-
ity in their actions. Second, observe that even when the Regulator stops incentivizing players in the middle of the simulations, both players keep cooperating along time.

We hypothesize that the underlying tax system from Section 4.2 is necessary for players to learn to cooperate and maintain that behaviour even after the Regulator stops incentivizing them. To test this hypothesis, we repeat the experiments removing tax collection, *ceteris paribus*. Results are shown in Figure 6. Observe now that even under the presence of high incentives, both agents fail to cooperate, with social utility decaying over time. Thus, we have shown that the tax collection framework from 4.2 has a synergic effect with the incentives introduced in this Section.

5. Discussion

A defining trend in modern society is the abundance of data which opens up new opportunities, challenges and threats. In the upcoming years, social progress will be essentially conditioned by the capacity of society to gather, analyze and understand data, as this will facilitate better and more informed decisions. Thus, to guarantee social progress, efficient mechanisms for data sharing are key. Obviously, such mechanisms should not only facilitate the data sharing process, but must also guarantee the protection of the citizen’s personal information. As a consequence, the problem of data sharing not only has importance from a socioeconomic perspective, but also from the legislative point of view. This is well described in numerous recent legislative pieces from the EU, e.g. [8], as well as in the concept of flourishing in a data-enabled society [1].

We have studied the problem of data sharing from a game theoretic perspective with two agents. Within our setting, mutual cooperation emerges as the strategy leading to the best social outcome, and it must be promoted somehow. We have proposed modelling the confrontation between dominant data owners and citizens using two versions of the iterated prisoner dilemma via multi agent reinforcement learning: the decentralized case, in which both agents interact freely, and the centralized case, in which the interaction is regulated by an external agent/institution. In the first case, we have shown that there are strategies with which mutual cooperation is possible, and that a forgiving policy by the DDO can be beneficial in terms of social utility. In the centralized case, regulating the interaction between citizens and DDOs
via an external agent could foster mutual cooperation through taxes and incentives.

Besides fostering cooperation, the data sharing game may be seen as an instance of a two sided market [23]. Therefore, the creation of intermediary platforms that facilitate the connection between dominant data owners and citizens to enable data sharing would be key to guarantee social progress.

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Appendix A. One-shot game for the centralized case

We model the one-shot version of the centralized case game as a three-agent sequential game. The regulator acts first choosing a tax policy; after observing it, the agents take their actions. Introducing a regulator can foster cooperation in the one shot game.

For simplicity, consider the following policy: the regulator will retain a percentage $x$ of the reward if the agent decides to defect, and 0 if it decides to cooperate. Then, the regulator will share evenly the amount collected between both agents. With this, given the regulator’s action $x$, the payoff matrix is as in Table A.3, recalling that $T > R > P > S$.

|         | D | O |
|---------|---|---|
| **C**   | $R, R$ | $S', T'$ |
| **D**   | $T', S'$ | $P, P$ |

Table A.3: Utilities for the data sharing game

Assume that if one agent defects and the other cooperates, the first one will receive a higher payoff, that is $T' > S'$, which means that $x < 1 - \frac{S}{T}$. Depending on $x$, three scenarios arise:

1. $T' > R > P > S' \iff x < 2 \left[ \frac{P - S}{T} \right]$. This is equivalent to the prisoner’s dilemma. $(D, D)$ strictly dominates, thus being the unique Nash Equilibrium.
2. $R > T' > S' > P \iff x > 2 \left[ 1 - \frac{R}{T} \right]$. In this case, $(C, C)$ strictly dominates, becoming the unique Nash Equilibrium.
3. $T' > R > S' > P \iff x \in \left( 2 \left[ \frac{P - S}{T} \right], 2 \left[ 1 - \frac{R}{T} \right] \right)$. This is a coordination game. There are two possible Nash Equilibria with pure strategies $(C, D)$ and $(D, C)$.

Moving backwards, consider the regulator’s decision. Recall that $R$ maximizes social utility. Again, three scenarios emerge:

1. $x < 2 \left[ \frac{P - S}{T} \right]$. The social utility is $P$.
2. $x > 2 \left[ 1 - \frac{R}{T} \right]$. The social utility is $R$.
3. $x \in \left( 2 \left[ \frac{P - S}{T} \right], 2 \left[ 1 - \frac{R}{T} \right] \right)$. The social utility is $\frac{S + T}{2}$.
As \( R > P \) and \( R > \frac{T+R}{2} \) (as requested in the IPD), the regulator maximizes his payoff choosing \( x > 2 \left[ 1 - \frac{R}{T} \right] \). Therefore, \((x,C,C)\), with \( x > 2 \left[ 1 - \frac{R}{T} \right] \) is a subgame perfect equilibrium, and we can foster cooperation in the one-shot version of the game.

**Appendix B. One-shot game for the centralized case plus incentives**

Under this scenario, we consider the reward bimatrix in Table B.4, where \( I \) is the incentive introduced by the Regulator.

| Citizen | DDO       |
|---------|-----------|
|         | \( C \)   | \( D \) |
| \( C \) | \( R+I, R + I \) | \( S,T \) |
| \( D \) | \( T,S \)  | \( P,P \) |

Table B.4: Utilities for the data sharing game with incentives

Consider the case in which the agents take the \((C,D)\) pair of actions. In this case, they perceive rewards \((S,T)\). After tax collection and distribution, it leads to \((S - \frac{Sx}{2} + \frac{Tx}{2}, T - \frac{Tx}{2} + \frac{Sx}{2})\), with \( x \) being the tax rate collected by the Regulator. In order to ensure that \((C,C)\) is a Nash equilibrium, two conditions must hold:

- \( S - \frac{Sx}{2} + \frac{Tx}{2} > P \), so that agents do not switch from \((C,D)\) to \((D,D)\). This simplifies to \( x > 2\frac{(P-S)}{T-S} \).

- \( R + I > T - \frac{Tx}{2} + \frac{Sx}{2} \), so that the agents do not switch from \((C,C)\) to \((C,D)\). This simplifies to \( x > 2\frac{T-(R+I)}{T-S} \).

This shows that even if the gap between \( T \) and \( R \) is large, with the aid of incentives both agents could reach mutual cooperation, also under a tax framework, since \( I \) can grow arbitrarily to ignore the second restriction.