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Thursday, April 6, 2023

1. Introduction



Chat with Digital Privacy.pdf

summarize the paper in four bullet points

Certainly! Here are four key points from the paper:

- 1. Digital businesses collect vast amounts of personal data from users, which can be used to improve their services and generate revenue.
- 2. However, there is a misalignment of incentives between digital businesses and users when it comes to data privacy. Businesses may prioritize collecting and using data over protecting user privacy, while users may want more control over their personal information.
- 3. The authors propose a framework for analyzing the trade-offs between data collection and protection, based on the business revenue model and the value that users place on their data.
- 4. Recent regulations in the EU, California, and China have focused on increasing user awareness and control over their personal data, but there is still much work to be done to ensure digital privacy for all users.

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1. Introduction

Questions

- ► (Users) What are the trade-offs that people face when using online services? What are the determinants of harmful use of users' data?
- ► (Platform) What are the incentives of digital businesses to collect and protect users' data?
- ► (Government) What actions should be taken by regulatory authorities in order to protect consumer privacy and maximize social welfare?

2. Model

Model: Timeline

- 1. Platform chooses **data strategy** (ξ , C) ("terms and agreements")
 - ▶ **data collection** $\xi \in [0, 1]$, proportion of user' activity to record and store
 - ▶ data protection $C \in [0, \infty)$, a costly investment
- 2. Users $I \ni i \in [0, 1]$ and $M \to \infty$ adversaries $J \ni j$ simultaneously decide
 - User *i* chooses **activity** a_i , and $\bar{a} = \int a_i di$ is aggregate activity.
 - ▶ Adversary *j* with characteristic $\gamma_j \sim U[0, M]$ chooses to **attack** or not.

2. Model

Model: Payoffs

1. Platform chooses (ξ, C) :

$$\Pi(\boldsymbol{\xi}, \boldsymbol{C}) = (1 - P) \cdot \overline{\boldsymbol{a}} + P \cdot \boldsymbol{\xi} \overline{\boldsymbol{a}} - \psi \boldsymbol{C}$$

- ightharpoonup P = 1: Purely usage-driven
- ightharpoonup P = 0: Purely data-driven
- $ightharpoonup P \in [0,1]$: e.g., ad-driven Google Facebook, user activity + data-based ad
- 2. User *i* chooses a_i :

$$U(\underline{a_i}, \overline{a}) = \underbrace{\underline{a_i} - \underline{a_i}^2/2}_{\text{usage payoff}} + \underbrace{\underline{\beta a_i \overline{a}}}_{\text{network effect}} + \underbrace{(\rho - \omega)\underline{a_i \xi}}_{\text{positive and negative info externalities}}$$

where ω is the expected number of attacking adversaries.

3. Adversary *j* with characteristic $\gamma_j \sim U[0, M]$ attacks:

$$\pi(\gamma_j) = \xi \overline{a} - \gamma_j C$$

Equilibrium interactions of users and adversaries

Proposition 1

Fix Platform's data strategy (ξ, C) . The ensuing subgame has a unique equilibrium in which users' and adversaries' activities are

$$\overline{a}^*(\xi,C) = \frac{C \cdot (1 + \rho \xi)}{C \cdot (1 - \beta) + \xi^2}$$
, and

$$\omega^*(\xi, C) = \frac{\xi}{C} \overline{a}^*(\xi, C) = \frac{\xi + \rho \cdot \xi^2}{C \cdot (1 - \beta) + \xi^2}.$$

Proof Sketch

adversaries:
$$\pi(\gamma_j) = \xi \overline{a} - C \ge 0 \Rightarrow \gamma_j \ge \frac{\xi}{C} \overline{a} \Rightarrow \omega^* = \frac{\xi}{C} \overline{a}$$

users: $1 - a_i + \beta \overline{a} + (\rho - \frac{\xi}{C} \overline{a}) \xi = 0$.

Comparative statics of ξ and C

Users' activity $\overline{a}^*(\xi, C)$ and data collected $\xi \overline{a}^*(\xi, C)$ both

- ▶ increase in data protection *C* and
- first increase and then decrease in data collection ξ

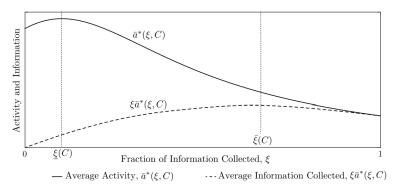


Figure 1: Users' activity $\bar{a}^*(\xi, C)$ and data collected $\xi \bar{a}^*(\xi, C)$ as a function of data collection ξ .

Explanation

- ▶ When $\xi \sim 0$ increases, positive externalities $\rho \cdot \xi$ increase from e.g., tailored services to users. An increased demand for platform service.
- When ξ continues to increases, negative externalities become relevant, as more data are available and more adversaries are incentivized to attack. At some point, the cost outweighs the benefit.
- ► Three regions:
 - ▶ Small $\xi < \xi(C)$: users' activity and data collected both increase
 - ▶ Intermediate $\xi \in (\underline{\xi}(C), \overline{\xi}(C))$: users' activity decreases but data collected increases
 - ▶ Large $\xi > \overline{\xi}(C)$: users' activity and data collected both decrease
- Consumer surplus

$$CS(\xi, C) = \frac{1}{2}\overline{a}^*(\xi, C)^2$$

Platform's optimal collection and protection

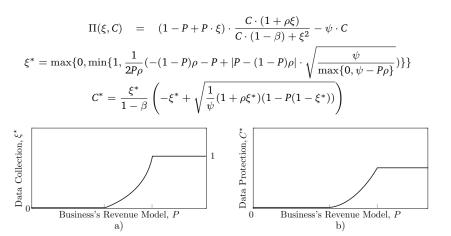
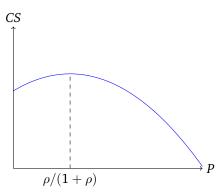


Figure 2: Equilibrium data collection and data protection strategies as a function of the business's revenue model, P (higher P implies a more data-driven business model).

Consumer surplus

Proposition 2

If $P < \rho/(1+\rho)$ [equivalently, $\rho > P/(1-P)$], then a more data-driven (higher P) platform generates weakly higher CS. Otherwise, CS weakly decreases with P.



Explanation

As *P* increases, two conflicting effects arise

- 1. Increase in data collection decreases users' activity. [stronger when ρ is smaller]
- 2. Increase in data protection increases users' activity. [stronger when ρ is larger]

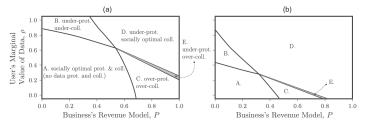
Government: no intervention comparison

Welfare-maximizing government:

$$(\xi^W, C^W) \in \operatorname{argmax}_{\xi, C} \alpha \cdot \operatorname{CS}(\xi, C) + (1 - \alpha) \cdot \Pi(\xi, C).$$

- ▶ never undercollection $\xi^* \ge \xi^W$ and overprotection $C^* \ge C^W$.
- ▶ Usage-driven business P = 0: undercollection $\xi^* \leq \xi^W$ and underproctection $C^* \leq C^W$.

Figure 3. Regions of Inefficiencies in the Business's Data Strategy Relative to the Socially Optimal Strategy as a Function of the Business's Revenue Model, P, and Users' Marginal Value of Data, ρ



Note. The numerical example is generated with the following parameters: $\alpha = 0.5$, $\beta = 0$, and (a) $\psi = 0.35$ or (b) $\psi = 0.1$.

Government: optimal interventions

Proposition 4

The following two-pronged policy induces an efficient equilibrium.

- ightharpoonup a required minimum data protection level $C_{\min} = C^{W}$.
 - ▶ (Proposition 3: only imposing this requirement, e.g., FTC may reduce CS)
- ► a liability fine or a data collection tax
 - ▶ a liability fine proportional to the expected damage from adversaries

$$\ell^* = \frac{\alpha}{1 - \alpha} \frac{C^W}{2r(\xi^W, C^W)(\xi^W)^2}$$

a data collection tax rate

$$t^* = \frac{\alpha}{1 - \alpha} \frac{\overline{a}^*(\xi^W, C^W)}{r(\xi^W, C^W)\xi^W}$$

Discussions

- ► Possibility of joint data collection (Appendix C.7)
 - ▶ Joint data collection and revenue decision may hurt consumers.
 - Merging dataset but keeping data collection decision (and revenue decision) separate does not affect consumers
- ▶ Pay for data (Appendix C.8)
 - Suppose users are paid. There may exist a regime in which users' incentives for activity are so strong that the platform can gain from an imposed payment by increasing data collection.

Contribution

- ▶ Different components of a business' data strategy.
- ► Compare data-driven and usage-driven revenue models.
- ▶ Positive and normative implications of data policy design.

Related literature

- "An active interdisciplinary area of research that studies the consequences for market outcomes of the ability of digital institutions to amass large data sets..."
- Related work
 - ► How user info is disclosed, traded, or inferred (Ali+, Bergemann+, Bonatti+, Fudenberg+, Ichihashi+): user action=user info.
 - Mechanisms to extract info: Fainmesser, Galeotti, Jullien, Ali Benabou, Elliott, Smolin, Bonatti
 - ► More recent work investigates the impact of privacy regulation on platforms and users: Argenziano Bonatti (2021), Bimpikis Ozdaglar Yildiz (2021 OR), Markovich Yehezkel (2021), Chen (2022)
 - Glaeser Scheinkman (2000), Non-market interactions. (users-adversaries game)

