

Getting the Agent to Wait

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Engagement as Objective

- Several environments:
 - Expert advice: legal and consulting services
 - Social Media: main source of revenue is advertising
 - Recommender Systems: TikTok, YouTube, Google News

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- Incentives of the platform/expert (Principal) and the user (Agent) are *misaligned*:
 - Principal: maximize engagement (time on platform / billable)
 - Agent: acquire accurate information *as quickly as possible*
- **Central question:** how does the principal optimally release information over time, and what does that imply for what users end up believing?

This Paper

- A dynamic information-design framework where the principal chooses *when* and *what* to reveal, allowing:
 - **Belief disagreement** (agree-to-disagree, à la Aumann 1976)
 - **Private agent beliefs** – non-personalized vs. personalized communication
- Two design questions:
 1. How should an expert release information to a user whose prior differs from his own?
 2. Does personalization (one feed per user) improve welfare relative to mass communication (one feed for everyone)?
- **Why we should care:** personalized news feeds are routinely blamed for **polarization** and *filter bubbles*.

Preview of Results

- **Catering to the bias** (disagreeing priors):
 - Principal first reveals the state the agent **prefers**
 - Principal first reveals the state the agent already thinks is **likely**
 - Engagement converges to a *steady-state belief frontier*

Preview of Results

- **Catering to the bias** (disagreeing priors):
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 - Engagement converges to a *steady-state belief frontier*
- **Speed vs. quality** (private beliefs):
- If types differ too much:
 - Non-personalized: information arrives *faster* but agents exit *less informed*
 - Personalized: slower exit, but beliefs are closer to the truth

THE MODEL

The Model

- Time is continuous
- Agent trying to take the most accurate action $a \in A$ as soon as possible

$$u_A(\omega, a, T) = \delta_A e^{-\delta_A T} \hat{u}(\omega, a)$$

- Underlying state: $\omega \in \Omega = \{0, \dots, N\}$
 - In most of the presentation: $N = 2$
- Time spent acquiring information: T
- Principal's payoff :

-

$$\int_0^T e^{-\delta_P t} dt = \frac{1 - e^{-\delta_P T}}{\delta_P}$$

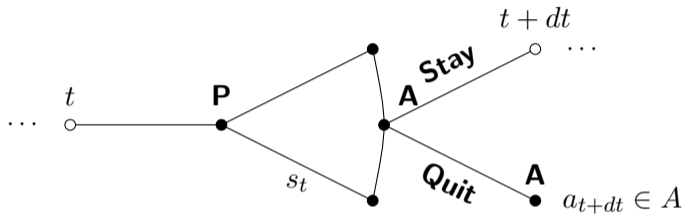
Possibility of (belief) Disagreement ---

- Priors

$$\mu_A = \mathbb{P}_A(\omega = 1), \mu_P = \mathbb{P}_P(\omega = 1) \in (0, 1)$$

- Learning is Bayesian
- Start from $\mu_{A,0}$ and $\mu_{P,0}$ being public information:
 - Later allow for $\mu_{A,0}$ being private.

The Model: Timing



- P: commitment type
- A: no commitment

The Model

- P chooses an information structure.
- A mapping from the space of history realizations to probability distributions over signals at t .

$$\left(S_\infty \times \Omega, \mathcal{F}, \mathbb{P}_P, \left\{ \mathcal{F}_{t,P} \right\}_{t \in \mathbb{R}_+} \right)$$

- S_∞ : the set of history of signal realizations,
- Each member is of the form s^∞ , \mathcal{F} is a σ -algebra over $S_\infty \times \Omega$,
- \mathbb{P}_P : probability measure from the principal's perspective
- $\mathcal{F}_{P,t} \subset \mathcal{F}_{P,t'} \subset \mathcal{F}, \forall t < t'$ is a filtration.
- A's information is similar:

$$\mathbb{P}_A(S) = \sum_{j \in \Omega} \mu_{A,j} \cdot \mathbb{P}_P(S \times \Omega | \omega = j)$$

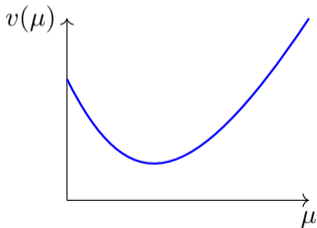
The Model

- We define the payoff function of the agent upon exiting:

$$v(\mu) = \max_{a \in A} \mathbb{E}_{\mu} [\hat{u}(a, \omega)]$$

Assumption. The Payoff function is strictly convex and differentiable.

- allows us to take derivatives



Leave with Perfect Info

Lemma. If A exits after history s^t , then $\mu_A(s^t) = \mathbb{E}_A [\omega = 1 | s^t] \in \{0, 1\}$ a.e.

- Idea of proof: If not, then split the signal into 2 fully revealing signals each with probability $\mu_A(s^t)$.
- Mean preserving spread: Increases the value of staying at all histories.
- Allows P to reduce the probability of exit and increase his payoff.
- Crucial Assumption: common knowledge about priors

Recommendation Mechanism ---

- By Carathéodory's theorem: 3 signals suffice per period
 - Combined with the Lemma (leave with perfect info): signals are $\Omega \cup \{\text{No News}\}$
 - Each period: agent either exits with **full information** about ω , or stays and updates beliefs from the absence of revelation

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 - Each period: agent either exits with **full information** about ω , or stays and updates beliefs from the absence of revelation
- Recommendation mechanism: Myerson ('82, '86)
 - P recommends exit accompanied by simultaneous revelation of ω
 - **Conditional** D.D.F's (decumulative distribution functions):

$$G_\omega(t) = \Pr(\text{exit} \geq t \mid \omega), \quad \forall \omega \in \Omega, \quad G_\omega(0) = 1$$

- $G_\omega(t)$: non-increasing; same for both P and A conditional on ω

Beliefs and Likelihood Ratio

- Principal's unconditional survival and posterior:

$$G_P(t) = \mu_{P,0}G_1(t) + (1 - \mu_{P,0})G_0(t), \quad \mu_P(t) = \frac{\mu_{P,0}G_1(t)}{G_P(t)}$$

- Agent's unconditional survival:

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- Relative likelihood ratio (constant over time):

$$\ell = \frac{\mu_{A,0}}{1 - \mu_{A,0}} \frac{1 - \mu_{P,0}}{\mu_{P,0}}, \quad \mu_A(t) = \frac{\ell\mu_P(t)}{\ell\mu_P(t) + 1 - \mu_P(t)}$$

Optimal Information Provision

$$\max_{G_0, G_1} \int_0^\infty \frac{e^{-\delta_P t} - 1}{\delta_P} dG_P(t)$$

subject to

$$-\int_t^\infty e^{-\delta_A(s-t)} [\mu_{A,0} v(1) dG_1(s) + (1 - \mu_{A,0}) v(0) dG_0(s)] \\ \geq G_A(t) v(\mu_A(t)), \quad \forall t$$

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- Everything in red is written under the *agent's* prior
- Constant likelihood ratio $\ell \Rightarrow$ a change of variable absorbs the disagreement

Reformulation: Disagreement \rightarrow Planner's Prior _____

- Define the *disagreement-adjusted* agent payoff:

$$\tilde{v}(\mu_P) \equiv [\ell\mu_P + 1 - \mu_P] v\left(\frac{\ell\mu_P}{\ell\mu_P + 1 - \mu_P}\right), \quad \tilde{v}(1) = \ell v(1), \quad \tilde{v}(0) = v(0)$$

$$\max_{G_0, G_1} \int_0^\infty \frac{e^{-\delta_P t} - 1}{\delta_P} dG_P(t)$$

subject to

$$\begin{aligned} - \int_t^\infty e^{-\delta_A(s-t)} [\mu_{P,0} \tilde{v}(1) dG_1(s) + (1 - \mu_{P,0}) \tilde{v}(0) dG_0(s)] \\ \geq G_P(t) \tilde{v}(\mu_P(t)), \quad \forall t \end{aligned}$$

- Same structure as the common-prior problem – but with \tilde{v} in place of v
- Disagreement is absorbed into the curvature of \tilde{v} via ℓ

PROPERTIES OF OPTIMAL COMMUNICATION

More Patient Principal

Assumption. The principal is more patient than the agent, i.e., $0 \leq \delta_P < \delta_A$.

- Key implication: information is revealed at a slow rate via a state-dependent jump process
 - Exit is rare: $\Pr(\text{exit in } (t, t + dt)) \rightarrow 0$ as $dt \rightarrow 0$
 - A is kept always **indifferent** between staying and exiting

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 - A is kept always **indifferent** between staying and exiting
- Why? Agent's payoff $e^{-\delta_A T}$ as a function of exit time T is **more convex** than the principal's $\frac{1 - e^{-\delta_P T}}{\delta_P}$

Revelation Rates and Belief Dynamics

- Belief upon staying, $\mu(t)$, evolves differentially over time
- Let $\frac{G'_\omega(t)}{G_\omega(t)} = -g_\omega(t) \leq 0$ be the rate at which state ω is revealed. Then:

$$\mu'(t) = (g_0(t) - g_1(t)) \mu(t) (1 - \mu(t))$$

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- **No news is news:** the *absence* of revelation is itself informative
 - If $g_0 > g_1$: state 0 is revealed faster
 - \Rightarrow surviving without news \Rightarrow more confident state is 1 $\Rightarrow \mu$ drifts up

Binding IC: Flow Equation

- Since A is kept indifferent at all times, staying and exiting yield the same payoff
- Differentiating the IC \Rightarrow the **flow value** of staying must equal the flow value of the exit option:

$$\begin{aligned} \delta_A v(\mu(t)) = & \underbrace{\mu(t) g_1(t) [v(1) - v(\mu(t))] + (1 - \mu(t)) g_0(t) [v(0) - v(\mu(t))]}_{\text{change in payoff when state is revealed}} \\ & + \underbrace{\mu(t) (1 - \mu(t)) (g_0(t) - g_1(t)) v'(\mu(t))}_{\text{change from smooth belief drift (no news)}} \end{aligned}$$

- Interpretation:
 - LHS: flow cost of staying = value of exit $v(\mu(t))$
 - RHS: expected change in continuation value from revelation + drift
 - Jump terms: state revealed \Rightarrow payoff jumps from $v(\mu)$ to $v(1)$ or $v(0)$
 - Drift term: no news \Rightarrow beliefs shift smoothly \Rightarrow exit option changes by $v'(\mu) \mu'$

HJB Equation



$$\underbrace{\delta_P V(\mu)}_{\text{required return}} = \max_{g_0, g_1 \geq 0} \underbrace{1}_{\text{flow}} - \underbrace{[\mu g_1 + (1 - \mu) g_0] V(\mu)}_{\text{loss from exit}} + \underbrace{\mu(1 - \mu)(g_0 - g_1) V'(\mu)}_{\text{belief drift effect}}$$

subject to the agent's binding IC.

- Three forces acting on V :
 - Flow income: earns 1 per unit time while A stays
 - Termination risk: if state revealed, A exits, $V \rightarrow 0$
 - Belief drift: no news shifts μ smoothly, changes V

One State at a Time

- HJB is **linear** in $(g_0, g_1) \Rightarrow$ optimum is at a **corner**
 - Either reveal only $\omega = 1$, or only $\omega = 0$ (not both at once)

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- P compares the **cost-per-unit-of-IC-benefit** of each state:
 - Reveal whichever state is **cheaper** to reveal
- “**Cater to the bias**”: cheaper state is typically the one A is already leaning toward
 - A’s exit option $v(\mu)$ is already close to $v(\mathbf{1}_\omega)$
 - Confirming what A already believes costs less continuation value

Steady State

- Belief $\mu(t)$ converges to a **steady state** μ^* :
 - At μ^* , both states revealed at the **same rate** \Rightarrow belief drift vanishes
 - P switches between revealing $\omega = 0$ and $\omega = 1$ exactly at μ^*

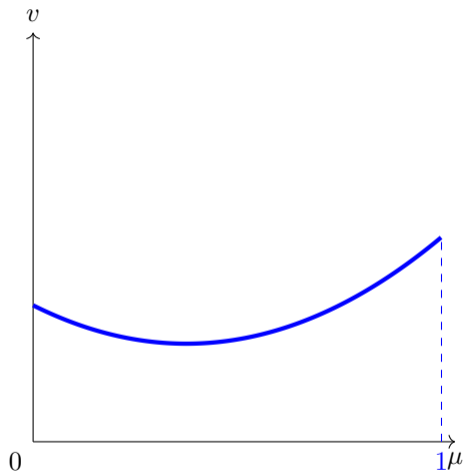
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- Envelope theorem applied to HJB gives the **geometric** condition:

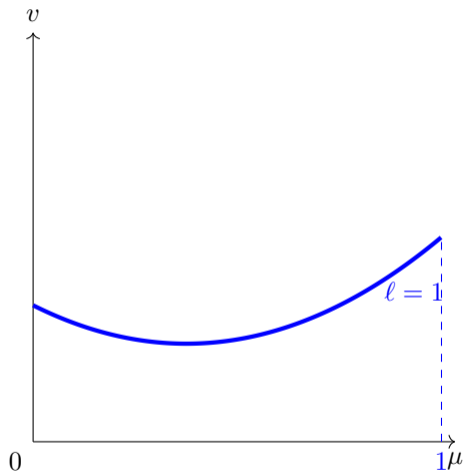
$$v'(\mu^*) = -\frac{\delta_P [v(1) - v(0)]}{\delta_A - \delta_P}$$

- Tangent to agent's value at μ^* has slope equal to this critical value

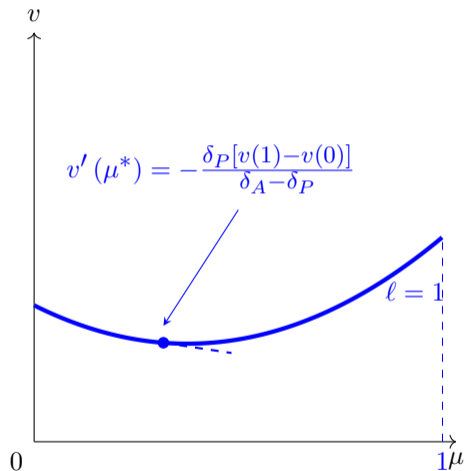
Steady State: Catering to the Bias



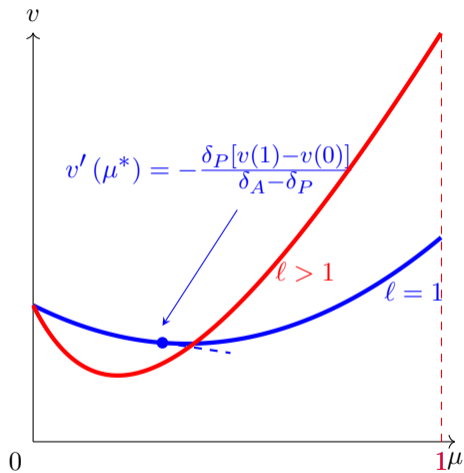
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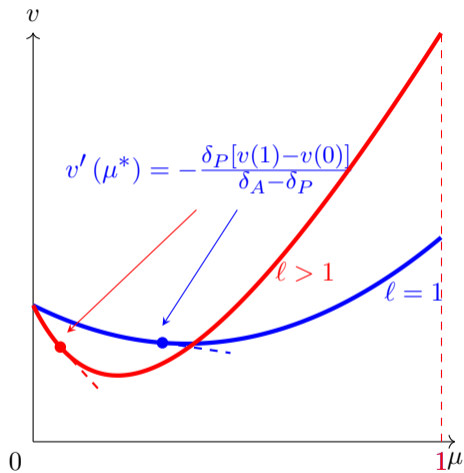
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Steady State: Catering to the Bias



MORE THAN TWO STATES

Finite Number of States

- Finite number of states: $\Omega = \{0, 1, \dots, N - 1\}$
- HJB:

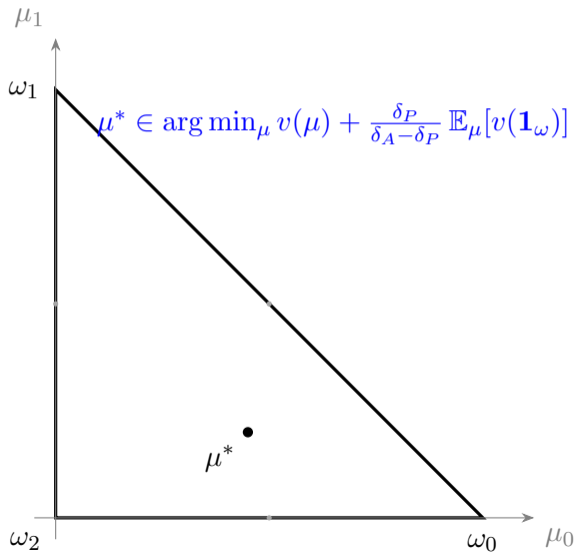
$$\delta_P V(\mu) = \max_{g_j \geq 0} 1 - \sum_j g_j \mu_j \left[V(\mu) + \frac{\partial V}{\partial \mu_j} - \nabla V \cdot \mu \right]$$

subject to

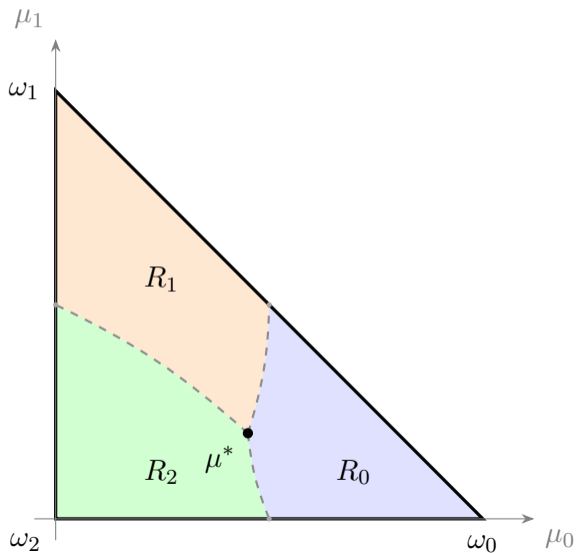
$$\delta_A v(\mu) = \sum_j \mu_j g_j \left[v(\mathbf{1}_j) - v(\mu) - \frac{\partial v}{\partial \mu_j} + \mu \cdot \nabla v \right]$$

- Implications:
 - Local linearity: almost always one state is revealed
 - Hierarchical revelation: See example with $|\Omega| = 3$.

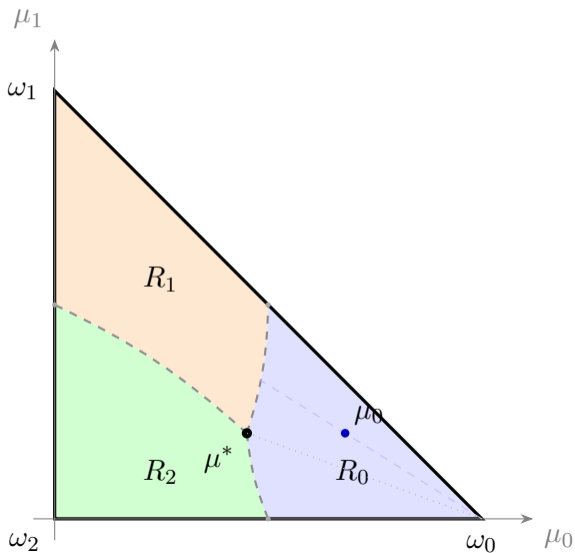
Example with 3 states



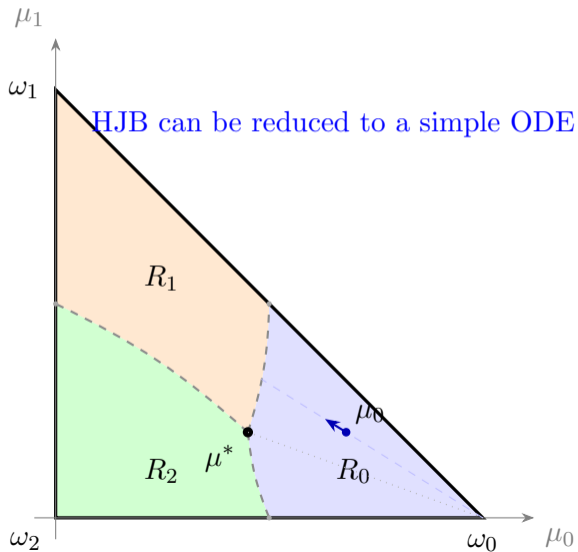
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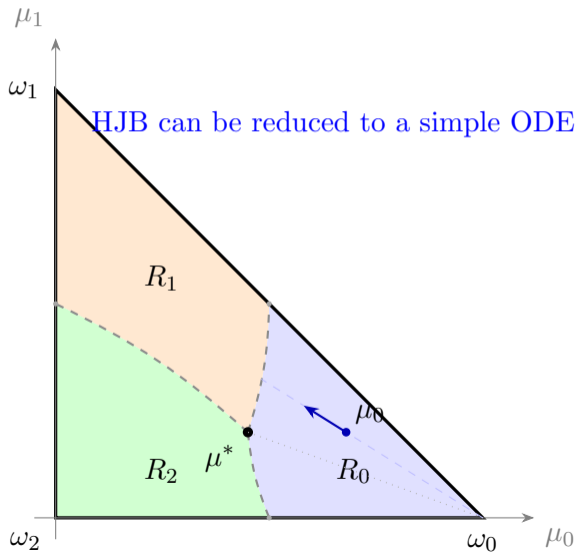
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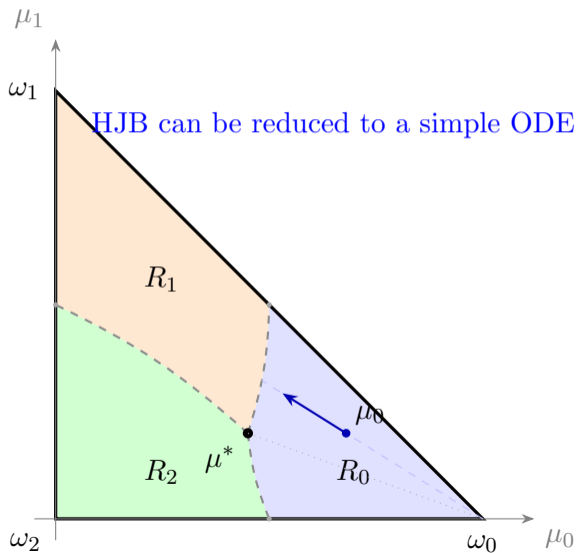
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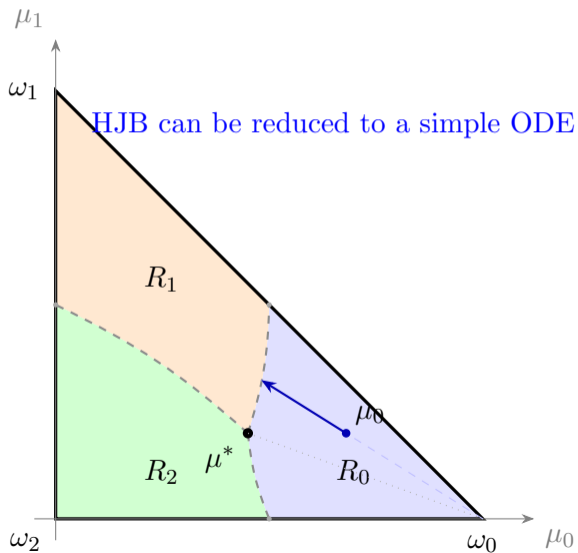
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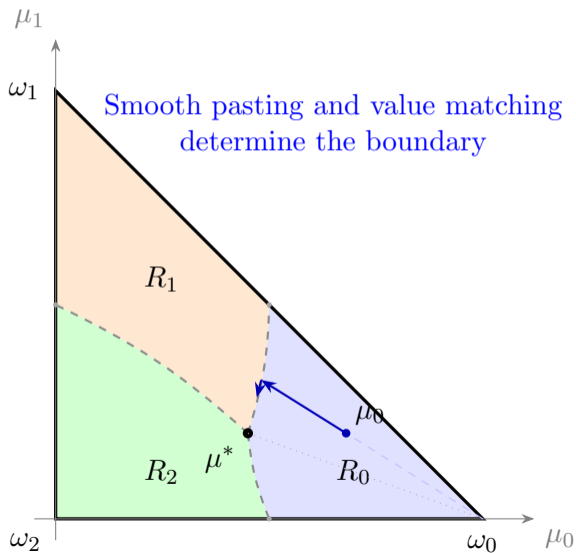
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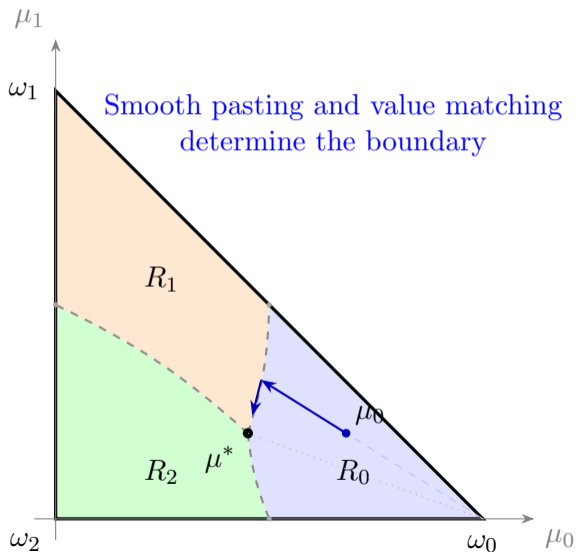
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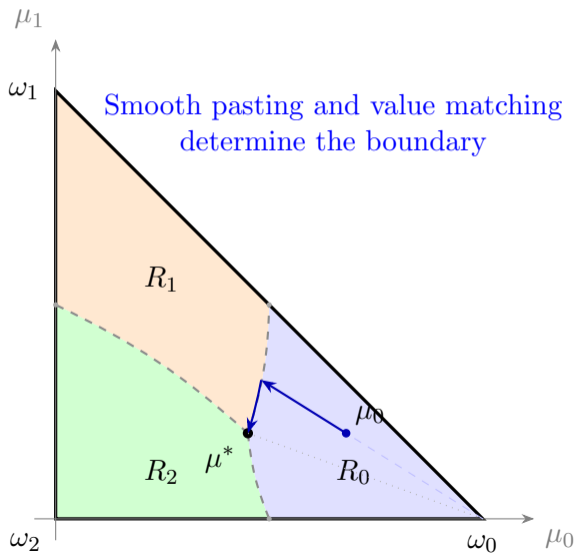
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Example with 3 states



Example with 3 states



NON-PERSONALIZED COMMUNICATION

Non-Personalized Communication

- How does communication change when μ_A is not observed?
- A's belief is either $\mu_{A,0}^L$ or $\mu_{A,0}^H$, with $\mu_{A,0}^L < \mu_{A,0}^H$, while the principal's belief is $\mu_{P,0}$, $\alpha_\theta = \Pr(\mu_{A,0}^\theta)$.
- P chooses $\left(S_\infty, \mathcal{F}, \mathbb{P}_P, \left\{ \mathcal{F}_{t,P} \right\}_{t \geq 0} \right)$ but cannot control who listens and who exits

Non-Personalized Communication

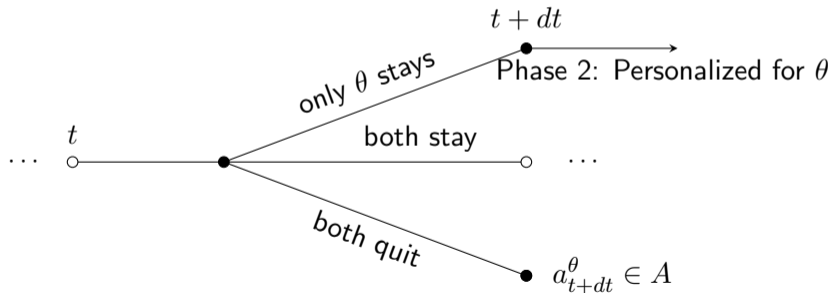
Lemma. The best equilibrium of the game from the principal's perspective can be described by a communication policy together with a recommendation strategy for each type such that:

1. If type θ is recommended to quit following signal history s^t , the value of staying engaged for θ is not higher than $v(\mu_A^\theta(s^t))$,
2. If type θ is recommended to stay following signal history s^t , the value of staying engaged for θ is not lower than $v(\mu_A^\theta(s^t))$,

where $\mu_A^\theta(s^t)$ is the agent of type θ 's belief induced by the communication policy.

Two Phases of Communication

1. *Full Engagement Phase* (Phase 1): Both types are engaged until a transition signal arrives.
2. *Partial Engagement Phase* (Phase 2): Transition to phase 2 happens when it is recommended that only one type stays. With one type engaged, we revert to the personalized case.



Resulting HJB

HJB

$$\delta_P V(\mu) = \max_{g_\omega, w_\theta, \mu_E} 1 + \mathbb{E}_\mu g_\omega \times (W - V(\mu)) \\ + (g_0 - g_1) \mu (1 - \mu) V'(\mu)$$

subject to

$$\mu_E = \frac{\mu g_1}{\mu g_1 + (1 - \mu) g_0}, \text{IC}$$

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subject to

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Exit Problem

$$W(w_H, w_L, \mu_E) = \max_{\tau \in \Delta \Delta \Omega} \sum_{\theta=H,L} \tau_\theta \alpha^\theta V_\theta(\mu_\theta)$$

subject to

$$\sum_{\theta=H,L} \tau_\theta \mu_\theta + \tau_1 \times 1 + \tau_0 \times 0 = \mu_E$$

$$\mathbb{E}_\tau v_\theta(\mu) = w_\theta$$

No Catering to the Bias

Proposition. If $\mu_{A,0}^L < \mu_{P,0} < \mu_{A,0}^H$, then there exists $\underline{\Delta} > 0$ such that if $\mu_{A,0}^H - \mu_{A,0}^L < \underline{\Delta}$, then at the stationary μ_P^* , $\tau_1^* + \tau_0^* = 1$. Revelation rate λ^* is higher than the personalized revelation rates:

$$\lambda^* > \lambda_H^*, \lambda_L^*.$$

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- No personalization stage
- Personalization leads to less uncertainty when uninformed.
- Faster learning: personalization leads to higher belief polarization

Quality–Speed Trade-off

Proposition. If $\mu_{A,0}^L < \mu_{P,0} < \mu_{A,0}^H$, then there exists $\bar{\Delta} > 0$ such that if $\mu_{A,0}^H - \mu_{A,0}^L > \bar{\Delta}$, then at the stationary μ_P^* , $\tau_1^* + \tau_0^* = 0$.

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- Quality–Speed trade-off:
 - Personalization leads to higher speed of delivery of information
 - But information is not fully revealing in the first stage

Related Literature

- Information economics and Bayesian Persuasion:
 - Rayo and Segal (2010), Kamenica and Gentzkow (2011) and many many many more!

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- Models of Dynamic Communication
 - Ely and Szydlowski (2020), Orlov, Skrzypacz, Zryumov (2020), Che, Kim and Meierendorf (2022), Hebert and Zhong (2022): difference in payoffs and information revelation policies
 - Koh and Sanguanmoo (2024), Koh, Sanguanmoo and Zhong (2024)

Conclusion

- Developed a dynamic model of information provision when the principal wants to maximize engagement
- Principal caters to the bias
 - State that the agent likes
 - State that the agent thinks is more likely
- More than two types, two phases
 - Keep both types
 - Cater to one type
- A lot more to be done:
 - Time Inconsistency: digital addiction
 - Competition
 - Optimal regulation without violating first amendment (in the U.S.)

THANK YOU FOR STAYING
ENGAGED!