# Non-Bayesian Information Design:

## Learning and LLM-Based Approaches

Tao Lin

Microsoft Research (2025) → CUHK-Shenzhen (2026)

# Information Design

An economic model about ***information asymmetry***: *one player ("sender") strategically reveals information to influence the decision of another player ("receiver").*


Examples:

- Advertising
  - Seller reveals product information to buyers
- School designs letter grading scheme
- Professor writing recommendation letter
- ...

# **Information Design** is a form of "Persuasion"

One Quarter of GDP Is Persuasion

*By* DONALD MCCLOSKEY AND ARJO KLAMER*

— The American Economic Review Vol. 85, No. 2, 1995.

Home › Publications › Economic Roundup Issue 1, 2013 › Persuasion is now 30 per cent of US GDP

Persuasion is now 30 per cent of US GDP

Gerry Antioch[1]

**Date:** 06 June 2013

# Classical Information Design Models

- Many classical models for information design:
  - "Information Disclosure Games" (Grossman, 1981; Milgrom 1981)
  - "Cheap Talk" (Crawford & Sobel, 1982)
  - "Bayesian Persuasion" (Kamenica & Gentzkow, 2011)
  - …
- **Common modeling approach:**
  - **Abstract signal space:** The information transmitted from sender to receiver is modeled by a random variable $s$ correlated with the state of the world $\omega$
  - **Bayesian receiver:** The receiver does Bayes update after receiving $s$
- Importantly, *how the signal $s$ is communicated (e.g., wording)* doesn't matter.
- Our work: *non-Bayesian* information design, via "learning + LLM" approaches.

# Outline

- Background on a Classical Information Design Model: "Bayesian Persuasion" [Kamenica & Gentzkow, 2011]
- Information Design with a Learning Receiver
- Information Design with Large Language Models

# Example of **Bayesian Persuasion**: Recommendation Letter

Sender

Prior $\mu$

State of the world $\omega$

Signal $s$

Receiver


$p = 0.2$ → *suitable* → "*suitable*" / "*not suitable*"

$0.8$ → *not suitable* → "*suitable*" / "*not suitable*"

?

Utility:

$u(\text{hire}, \omega) = 1$

$u(\text{not hire}, \omega) = 0$

**Q:** What's the professor's optimal recommendation strategy?

Utility:

$v(\text{hire}, \mathit{suitable}) = 1$

$v(\text{hire}, \mathit{not\ suitable}) = -1$

$v(\text{not hire}, \omega) = 0$

***Bayesian reasoning:***

Hire if $\Pr(\mathit{suitable} \mid s) \geq 0.5$

# Example of **Bayesian Persuasion**: Recommendation Letter

Sender

Prior $\mu$

State of the world $\omega$

Signal $s$

Receiver


$p = 0.2$ → *suitable* → *"suitable"*

$0.8$ → *not suitable* → *"suitable"*

*"not suitable"*

Utility:

$u(\text{hire}, \omega) = 1$

$u(\text{not hire}, \omega) = 0$

**Q:** What's the professor's optimal recommendation strategy?

- **Always say "suitable"**: recruiter does not hire; professor gets 0

Utility:

$v(\text{hire}, \mathit{suitable}) = 1$

$v(\text{hire}, \mathit{not\ suitable}) = -1$

$v(\text{not hire}, \omega) = 0$

***Bayesian reasoning:***

Hire if $\Pr(\mathit{suitable} \mid s) \geq 0.5$

# Example of **Bayesian Persuasion**: Recommendation Letter

Sender

Prior $\mu$

State of the world $\omega$

Signal $s$

Receiver


$p = 0.2$ *suitable* $\xrightarrow{0.2}$ *"suitable"*

$0.8$ *not suitable* $\xrightarrow{0.8}$ *"not suitable"*

Utility:

$u(\text{hire}, \omega) = 1$

$u(\text{not hire}, \omega) = 0$

**Q:** What's the professor's optimal recommendation strategy?

- **Always say "suitable"**: recruiter does not hire; professor gets 0

- **Hoest Recommendation:** professor gets 0.2

Utility:

$v(\text{hire}, \mathit{suitable}) = 1$

$v(\text{hire}, \mathit{not\ suitable}) = -1$

$v(\text{not hire}, \omega) = 0$

***Bayesian reasoning:***

Hire if $\Pr(\mathit{suitable} \mid s) \geq 0.5$

# Example of **Bayesian Persuasion**: Recommendation Letter

Sender

Receiver


Prior $\mu$

State of the world $\omega$

Signal $s$

$p = 0.2$ → *suitable* $\xrightarrow{0.2}$ *"suitable"*

$0.8$ → *not suitable* $\xrightarrow{0.2}$ *"suitable"*

*not suitable* $\xrightarrow{0.6}$ *"not suitable"*

Utility:

$u(\text{hire}, \omega) = 1$

$u(\text{not hire}, \omega) = 0$

**Q:** What's the professor's optimal recommendation strategy?

- **The optimal strategy** (partial info revelation):
  - *if suitable, say "suitable";*
  - *if not, say "suitable" w.p.* $25\%$

Professor gets $0.4$

Utility:

$v(\text{hire}, suitable) = 1$

$v(\text{hire}, not\ suitable) = -1$

$v(\text{not hire}, \omega) = 0$

***Bayesian reasoning:***

Hire if $\Pr(suitable \mid s) \geq 0.5$

# **Key Assumptions** in Classical BP Theory

*Learning*

- **Commitment:**
  - Sender can commit to a randomized mapping ("signaling scheme") $\pi: \Omega \to \Delta(S)$ before state realization.
- **Bayesian receiver:**
  - The receiver knows the prior $\mu$ and the sender's signaling scheme $\pi$, and does Bayes update after receiving signal $s$ (and best responds)

- **Abstract signal space:**
  - Language doesn't matter – only the correlation between signal and state matters.

*LLM*

# Outline

- Background on a Classical Information Design Model: "Bayesian Persuasion" [Kamenica & Gentzkow, 2011]
- Information Design with a Learning Receiver
- Information Design with Large Language Models

# Generalized Principal-Agent Problem with a Learning Agent



Tao Lin


Yiling Chen

Harvard University



ICLR (International Conference on Learning Representations), 2025

Quantitative Economics, 2026

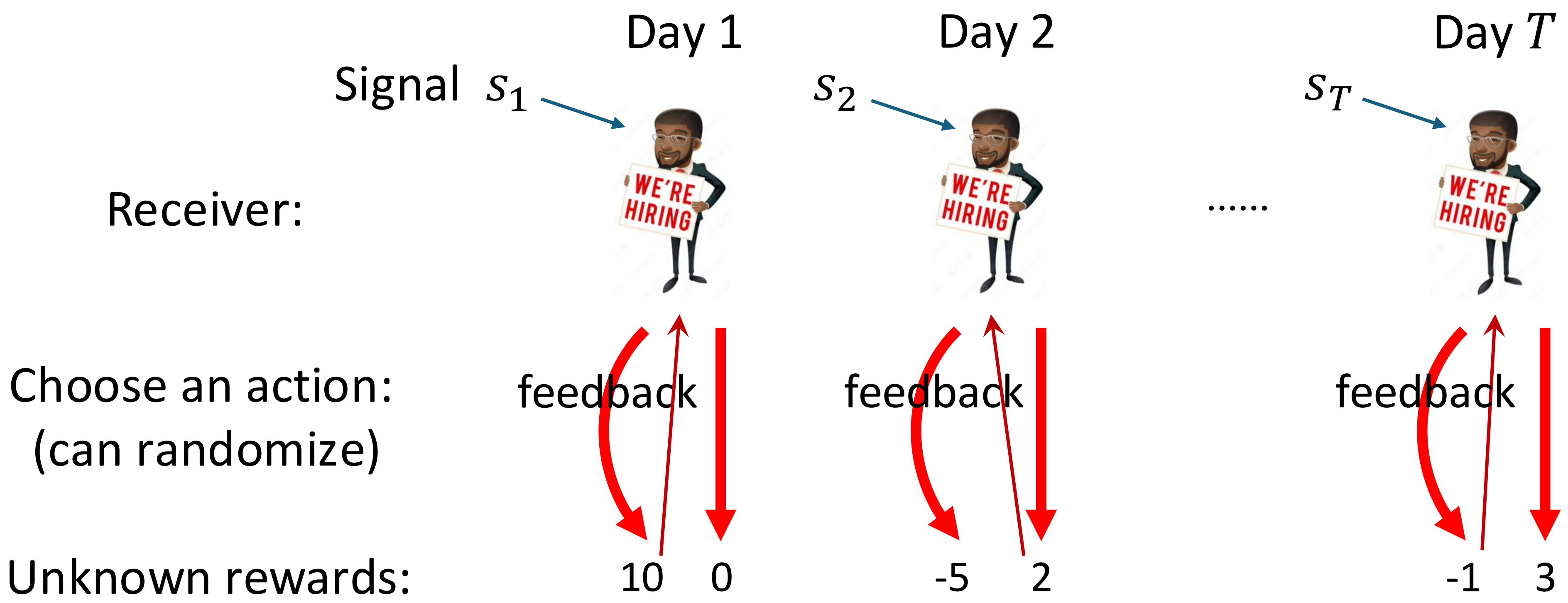
# Learning in games has a long history

- Adaptive Dynamics & Fictitious Play: Brown (1951), Robinson (1951), Shapley (1953)
- The Theory of Learning in Games: Fudenberg & Levine (1991)
- No-regret learning and correlated equilibrium:
  - Hart & Mas-Colell (2000); Blum & Mansour (2007)
- Prediction, Learning, and Games: Cesa-Bianchi & Lugosi (2006)
- ……

*Our work:*

- *Replaces the Bayesian receiver with a learning receiver in information design problems*
- *Studies whether the learning outcome matches the classical outcome.*

# Receiver's Learning Problem: *Contextual Multi-Armed Bandit*



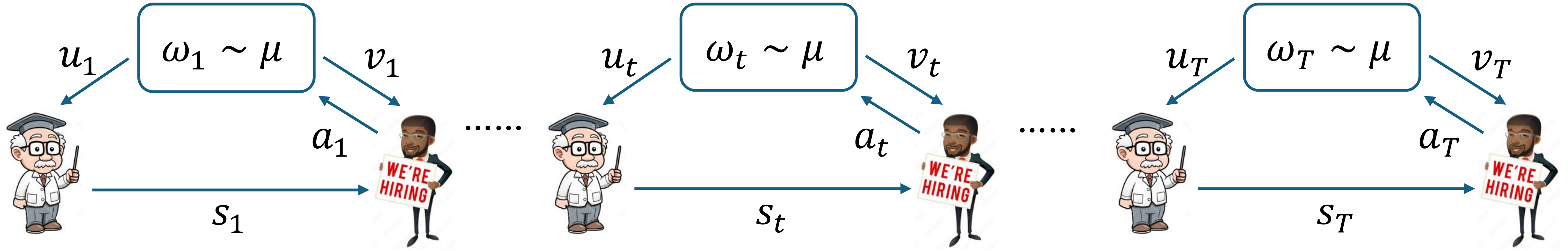

**(Contextual) No-Regret Property**

For any sequence of unknown rewards, after $T$ rounds,

$$\mathbb{E}[\textbf{Total reward obtained}] \geq \textbf{Total reward of the best signal-to-action mapping} - O(\sqrt{T})$$

No-regret learning algorithms exist; most are based on "smoothed best response to history".

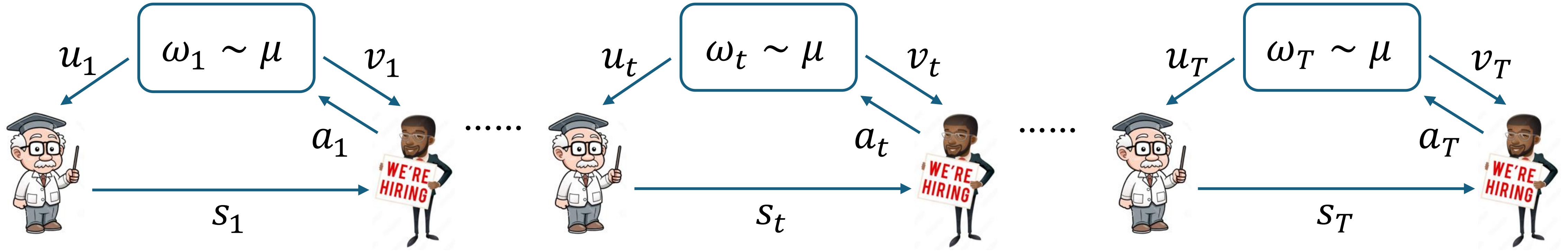
# Information Design with a Learning Receiver




- Two players: sender and receiver
- Sender knows the state distribution $\mu \in \Delta(\Omega)$, *which the receiver doesn't need to know*
- At each round $t$:
  - The receiver uses a **Contextual MAB** algorithm to decide, for each possible signal, what action to choose: $\rho_t: S \to \Delta(A)$ *(based on history)*
  - State $\omega_t \sim \mu$ is realized
  - Sender sends signal $s_t \sim \pi_t(\cdot|\omega_t)$
  - Receiver takes action $a_t \sim \rho_t(\cdot|s_t)$
  - The two players obtain utilities $u(a_t, \omega_t)$, $v(a_t, \omega_t)$

No commitment: "Bayesian Persuasion" = "Cheap Talk" (Crawford & Sobel, 1982)

# Information Design with a Learning Receiver




**Our Questions:**

With a learning receiver,

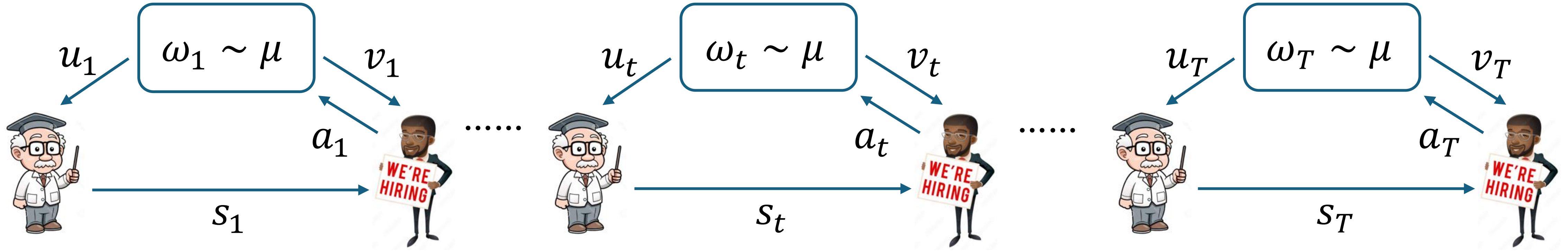
- Can the sender still achieve the classical outcome (with commitment and Bayesian receiver)?

$$U_{\text{sender}}(\text{learning receiver}) \geq U^*_{\text{sender}}(\text{Bayesian receiver})$$

- Can the sender ***do better than*** the classical outcome?

$$U_{\text{sender}}(\text{learning receiver}) > U^*_{\text{sender}}(\text{Bayesian receiver})$$

# Main Contributions

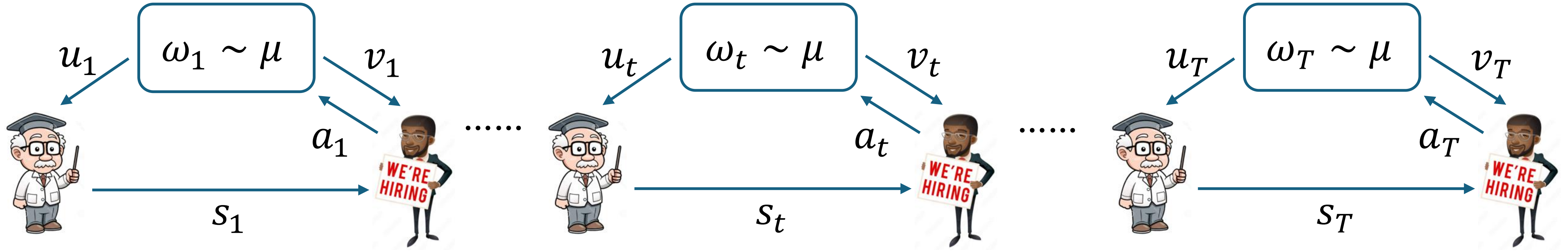



**Result 1:**

With a learning receiver,

- The sender can achieve the classical outcome:
  - $U_{\text{sender}}(\text{learning receiver}) \geq U^*_{\text{sender}}(\text{Bayesian receiver}) - O\left(\sqrt{\text{Reg}(T)}\right)$
  - **How?** Just use the optimal signaling scheme $\pi^*$ in the classical setting. The receiver will learn to best respond as $T \to \infty$
  - **Why** $O\left(\sqrt{\text{Reg}(T)}\right)$ **?** The receiver may take $\sqrt{\text{Reg}(T)}$-sub-optimal action in $\sqrt{\text{Reg}(T)}$ fraction of time, causing a total loss of $\sqrt{\text{Reg}(T)}$ to the sender.

# Main Contributions




**Result 2:**

With a learning receiver,

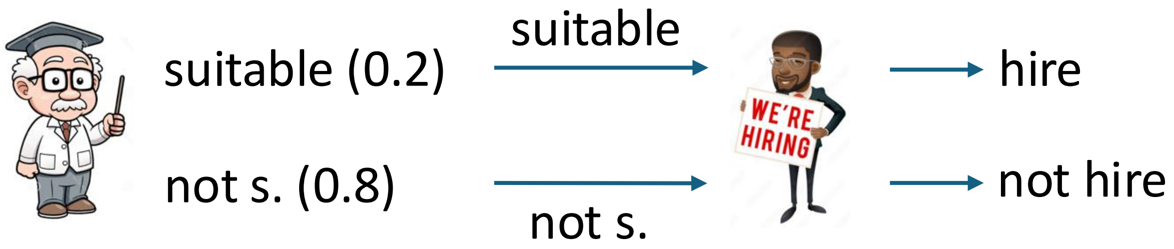
- The sender can achieve the classical outcome.
- Can the sender ***do better than*** the classical outcome?
  - **Yes**, for all "smoothly-best-responding" no-regret learning receivers: ∃ instance,

$$U_{\text{sender}}(\text{learning receiver}) > U^*_{\text{sender}}(\text{Bayesian receiver}) + \text{Const}$$

  - **No**, for all "no-swap-regret" learning receivers.

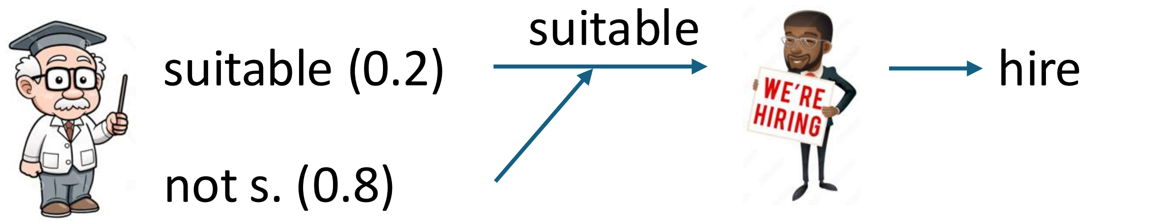
# Intuition for why ***doing better*** is possible: Dynamic Strategy

First,
honest recommendation:



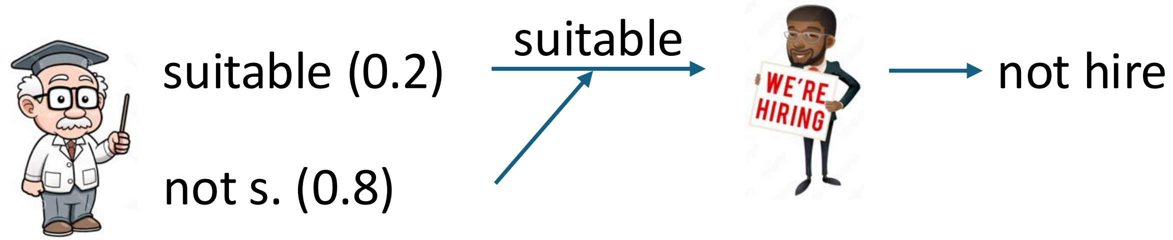

*gets 0.2*

Then, always
say “suitable”:




*gets 1*

After some time, the
receiver will realize that
the signal is not truthful:




*gets 0*

*Average utility > 0.4 ?*

# No-Swap-Regret Learning Algorithms

**No-Regret**

For any sequence of reward functions, after $T$ rounds,

$$\mathbb{E}\left[\sum_{t=1}^{T} v_t(a_t)\right] \geq \max_{a \in A} \mathbb{E}\left[\sum_{t=1}^{T} v_t(a)\right] - O(\sqrt{T}).$$

Many no-regret MAB algorithms do "smoothed best response to history".

**No-Swap-Regret**

For any sequence of reward functions, after $T$ rounds,

$$\mathbb{E}\left[\sum_{t=1}^{T} v_t(a_t)\right] \geq \max_{\phi: A \to A} \mathbb{E}\left[\sum_{t=1}^{T} v_t(\phi(a_t))\right] - O(\sqrt{T}).$$

No-swap-regret MAB algorithms exist: [Hart & Mas-Colell, 2000] [Blum & Mansour, 2007]

*Why can't the sender exploit a no-swap-regret learning receiver?*

- Consider the signal-action pair $(s_t, a_t)$ as a *joint signal* from some signaling scheme $\tilde{\pi}$.
- No-swap-regret guarantees approximate best response to $\tilde{\pi}$.

# Our & Previous Work on Learning in Principal-Agent Games

- "Smoothly-best-responding" no-regret learning agents are exploitable in many games [1] [2]
- If the agent does **no-swap-regret** learning, then the principal
  - *cannot exploit* the agent in the games in [1] [2]: $U(\text{learning}) < U^*(\text{rational}) + o(1)$
  - *can exploit* the agent in some other games [3]: $U(\text{learning}) > U^*(\text{rational}) + const$

No-Swap-Regret is Not Exploitable

Games with
**complete information**

[1] *Bimatrix Stackelberg Games*
[2] *Contract Design*
……

?

No-Swap-Regret is Exploitable

Games where
the **agent** has
**private information**

[3] *Auctions*
……

[1] Deng, Schneider, Sivan (2019). Strategizing against No-regret Learners.
[2] Guruganesh, Kolumbus, Schneider, Talgam-Cohen, Vlatakis-Gkaragkounis, Wang, Weinberg (2024). Contracting with a Learning Agent.
[3] Braverman, Mao, Schneider, Weinberg (2018). Selling to a No-Regret Buyer.

# Our & Previous Work on Learning in Principal-Agent Games

- "Smoothly-best-responding" no-regret learning agents are exploitable in many games [1] [2]
- If the agent does **no-swap-regret** learning, then the principal
  - *cannot exploit* the agent in the games in [1] [2]: $U(\text{learning}) < U^*(\text{rational}) + o(1)$
  - *can exploit* the agent in some other games [3]: $U(\text{learning}) > U^*(\text{rational}) + const$

No-Swap-Regret is Not Exploitable

Games with **complete information**

[1] *Bimatrix Stackelberg Games*
[2] *Contract Design*
……

**[Our work]**

Games where the **principal** has **private information**, while the agent does not:

*e.g., Information Design*

No-Swap-Regret is Exploitable

Games where the **agent** has **private information**

[3] *Auctions*
……

[1] Deng, Schneider, Sivan (2019). Strategizing against No-regret Learners.
[2] Guruganesh, Kolumbus, Schneider, Talgam-Cohen, Vlatakis-Gkaragkounis, Wang, Weinberg (2024). Contracting with a Learning Agent.
[3] Braverman, Mao, Schneider, Weinberg (2018). Selling to a No-Regret Buyer.

# Outline

- Background on a Classical Information Design Model:
  "Bayesian Persuasion" [Kamenica & Gentzkow, 2011]
- Information Design with a Learning Receiver
- Information Design with Large Language Models

# Information Design with Large Language Models


Paul Dütting
Google Research

Safwan Hossain[†]
Harvard University

Tao Lin
Harvard University

Renato Paes Leme
Google Research

Sai Srivatsa Ravindranath
Harvard University

Haifeng Xu
University of Chicago

Song Zuo
Google Research


Working paper (arXiv 2025)

# **Key Assumptions** in Classical BP Theory

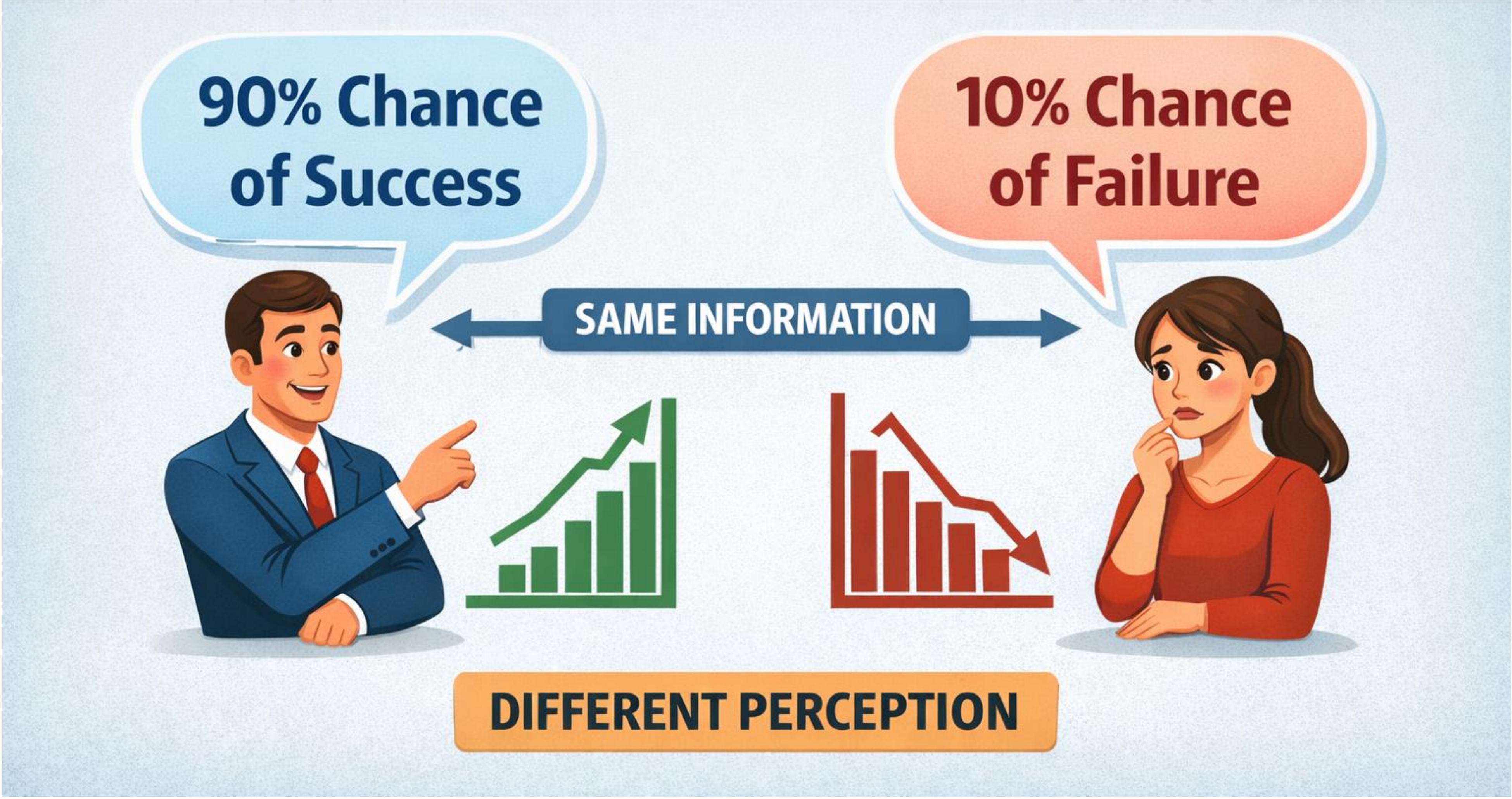
*Learning*

- **Commitment**:
  - Sender can commit to a randomized mapping ("signaling scheme") $\pi: \Omega \to \Delta(S)$ before state realization.
- **Bayesian receiver:**
  - Knowing the prior $\mu$ and signaling scheme $\pi$, the receiver does Bayes update after receiving signal $s$ (and then best responds)

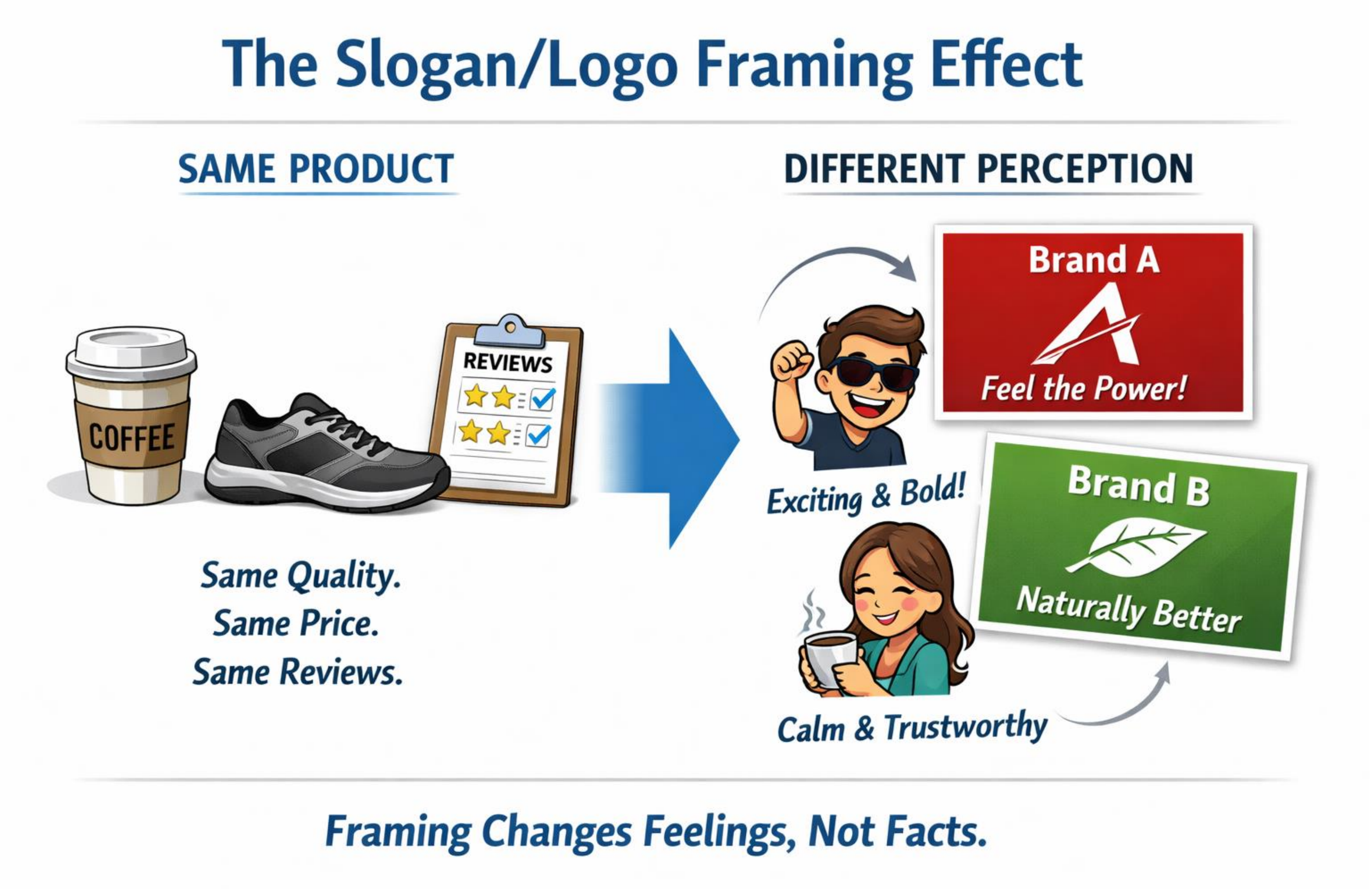
- **Abstract signal space:**
  - Language doesn't matter – only the correlation between signal and state matters.

*We aim to capture the linguistic aspect of persuasion*

# **Example 1:** Framing Effect (Tversky & Kahneman, 1981)



# **Example 2:** Slogan/Logo of a Brand



# Our Contributions

1) We propose a **theoretical model** for “Information Design with Framing Effect”.

2) We use **Large Language Models** to
   - simulate real-world framing effect, and
   - optimize framing.

# A **Theoretical Model** for "Persuasion with Framing Effect"

- Two players: sender  receiver 

- Sender chooses a framing $c$ from a set of framings $C$
  - Sender has prior belief $\mu_0 \in \Delta(\Omega)$ for the state
  - The framing $c$ shapes the receiver's *prior belief* to be $\mu_c = \ell(c)$
  - $\ell: C \to \Delta(\Omega)$ is a "*belief oracle*"
- With the receiver's prior belief being $\mu_c$, Bayesian Persuasion game happens:
  - Sender designs a signaling scheme $\pi: \Omega \to \Delta(S)$, and sends signal $s \sim \pi(\cdot|\omega)$
  - After receiving $s$, the receiver obtains posterior belief $\mu_c(\cdot \mid s, \pi)$ by Bayes-updating from $\mu_c$, and chooses an optimal action $a^*_{s,\pi}(\mu_c) \in \operatorname{argmax}_{a \in A} \sum_{\omega \in \Omega} \mu_c(\omega|s,\pi) v(a,\omega)$
  - Sender obtains utility $u\left(a^*_{s,\pi}(\mu_c), \omega\right)$

Framing $c$ can be though of a "context":

- does not depend on the state $\omega$, but still affects the receiver's prior belief

(non-Bayesian effect)

# We study two sub-problems

- Two players: sender  receiver 

- Sender chooses a framing $c$ from a set of framings $C$
  - Sender has prior belief $\mu_0 \in \Delta(\Omega)$ for the state
  - The framing $c$ shapes the receiver's *prior belief* to be $\mu_c = \ell(c)$
  - $\ell: C \to \Delta(\Omega)$ is a "*belief oracle*"
- With the receiver's prior belief being $\mu_c$, Bayesian Persuasion game happens:
  - Sender designs a signaling scheme $\pi: \Omega \to \Delta(S)$, and sends signal $s \sim \pi(\cdot\,|\omega)$
  - After receiving $s$, the receiver obtains posterior belief $\mu_c(\cdot \mid s, \pi)$ by Bayes-updating from $\mu_c$, and chooses an optimal action $a^*_{s,\pi}(\mu_c) \in \mathrm{argmax}_{a\in A} \sum_{\omega\in\Omega} \mu_c(\omega|s,\pi) v(a,\omega)$

**Problem 1: Framing-Only Optimization:**

Fix $\pi$, find $\max_{c\in C} \mathbb{E}_{\omega\sim\mu_0,\, s\sim\pi(\cdot|\omega)}\left[\, u\left(a^*_{s,\pi}(\mu_c), \omega\right)\,\right]$

**Problem 2: Joint Optimization:**

$$\max_{c\in C,\, \pi:\Omega\to\Delta(S)} \mathbb{E}_{\omega\sim\mu_0,\, s\sim\pi(\cdot|\omega)}\left[\, u\left(a^*_{s,\pi}(\mu_c), \omega\right)\,\right]$$

# Main Theoretical Finding:
# **Joint Optimization** *is easier than* **Framing-Only Optimization**

**Theorem 1:**

Computing the optimal framing $c^*$ is NP-hard

**Theorem 2:**

There exists a $\mathrm{poly}\left( |\Omega|^{\frac{\log |A|}{\varepsilon^2}} \right)$ time algorithm to compute an $\varepsilon$-optimal $(c^*, \pi^*)$ pair (under some oracle assumptions)

**Problem 1: Framing-Only Optimization:**

Fix $\pi$, find $\max_{c \in C} \mathbb{E}_{\omega \sim \mu_0,\, s \sim \pi(\cdot|\omega)} \left[ u\left(a^*_{s,\pi}(\mu_c), \omega\right) \right]$

**Problem 2: Joint Optimization:**

$$\max_{c \in C,\, \pi: \Omega \to \Delta(S)} \mathbb{E}_{\omega \sim \mu_0,\, s \sim \pi(\cdot|\omega)} \left[ u\left(a^*_{s,\pi}(\mu_c), \omega\right) \right]$$

# Main Theoretical Finding:
# **Joint Optimization** *is easier than* **Framing-Only Optimization**

**Intuitions:**

- Optimizing framing $c$ is equivalent to optimizing prior belief $\mu_c \in B = \{\ell(c): c \in C\}$
- Write the sender's objective as a function of $\mu_c$ and $\pi$:

$$U(\mu_c, \pi) = \mathbb{E}_{\omega\sim\mu_0,\, s\sim\pi(\cdot|\omega)}\left[\, u\left(a^*_{s,\pi}(\mu_c), \omega\right)\right]$$

- **Observation 1:** *Fixing $\pi$, $U(\mu_c, \pi)$ is a* ***discontinuous*** *function of $\mu_c$*
  - Small change in $c$ (small change in $\mu_c$) $\rightarrow$ Small change in posterior belief $\rightarrow$ Sudden change in receiver's action $\rightarrow$ Large change in sender's utility
- **Observation 2:** $U^*(\mu_c) = \max\limits_{\pi:\Omega\to\Delta(S)} U(\mu_c, \pi)$ *is a* ***continuous*** *function of $\mu_c$*

**Problem 1: Framing-Only Optimization:**

Fix $\pi$, find $\max\limits_{c\in C} \mathbb{E}_{\omega\sim\mu_0,\, s\sim\pi(\cdot|\omega)}\left[\, u\left(a^*_{s,\pi}(\mu_c), \omega\right)\right]$

**Problem 2: Joint Optimization:**

$$\max_{c\in C,\, \pi:\Omega\to\Delta(S)} \mathbb{E}_{\omega\sim\mu_0,\, s\sim\pi(\cdot|\omega)}\left[\, u\left(a^*_{s,\pi}(\mu_c), \omega\right)\right]$$

# Our Contributions

1) We propose a **theoretical model** for “Information Design with Framing Effect.

2) We use **Large Language Models** to
   - simulate real-world framing effect, and
   - optimize framing.

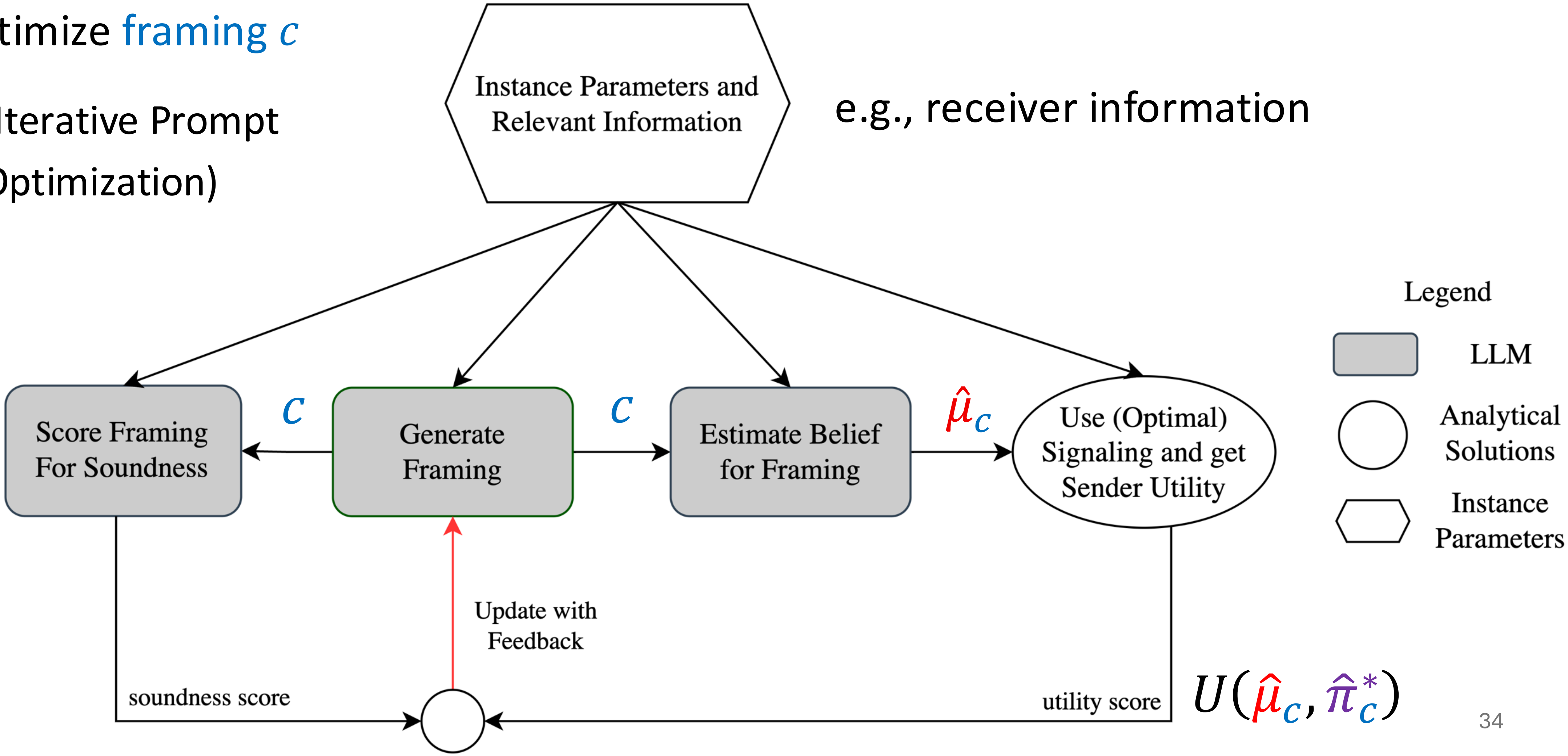
# Framing-Signaling Joint Optimization using LLM

We use LLM to do two things:

- Simulate the framing-to-belief oracle $\ell: c \mapsto \mu_c$
- Optimize framing $c$

(Iterative Prompt Optimization)

e.g., receiver information




$U(\hat{\mu}_c, \hat{\pi}_c^*)$

# Case Study: House Buying

**Sender:** a realtor
(house-selling agent)

**State:** quality of a house

**Framing** $c$**:** description of the realtor:

*"Meet **Jeremy Hammond**, a dedicated realtor with over 8 years of experience, specializing in finding the perfect homes for outdoor enthusiasts like you.... Trust Jeremy to help you discover a home that complements your active lifestyle while staying within your budget."*

*State-independent!*

**Signal (recommendation)** $s$**:** "buy" or "not buy"

**Receiver:** a potential house-buyer

**Henry** lives in Boston and is an avid outdoor person who enjoys hiking and being in nature. For him, a "good" house has low maintenance, affords easy access to trails, biking, running etc, and far from the main city. He is single and doesn't like a family-oriented house. He is looking for houses less than $500,000.

# Experiment 1: Use LLM to simulate the belief oracle $\ell: c \mapsto \mu_c$

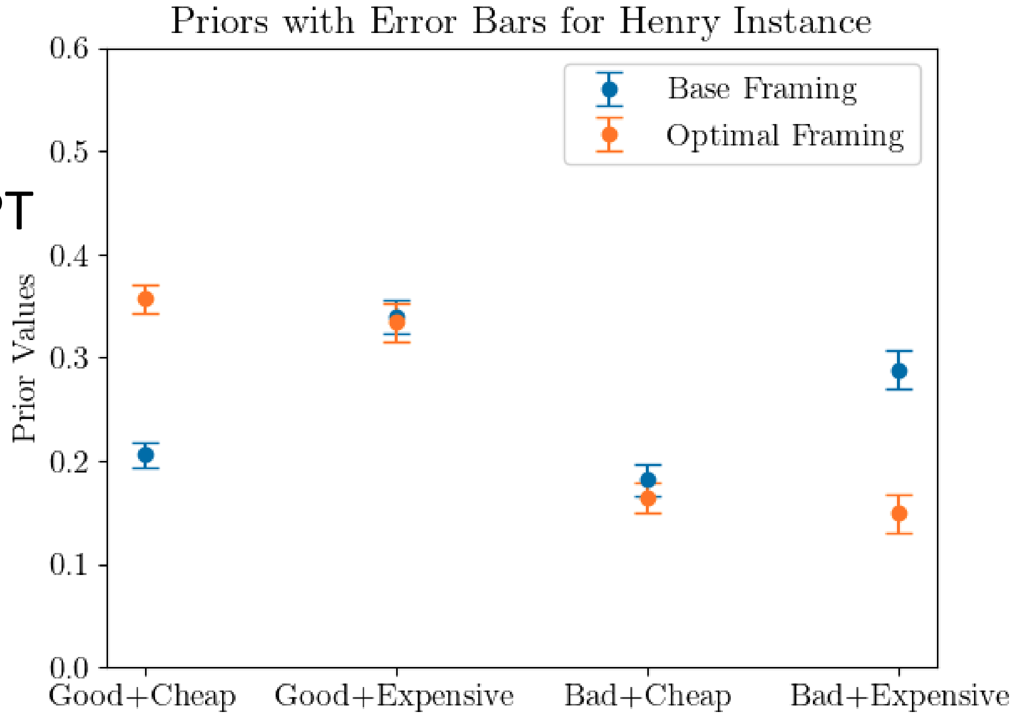
Why?

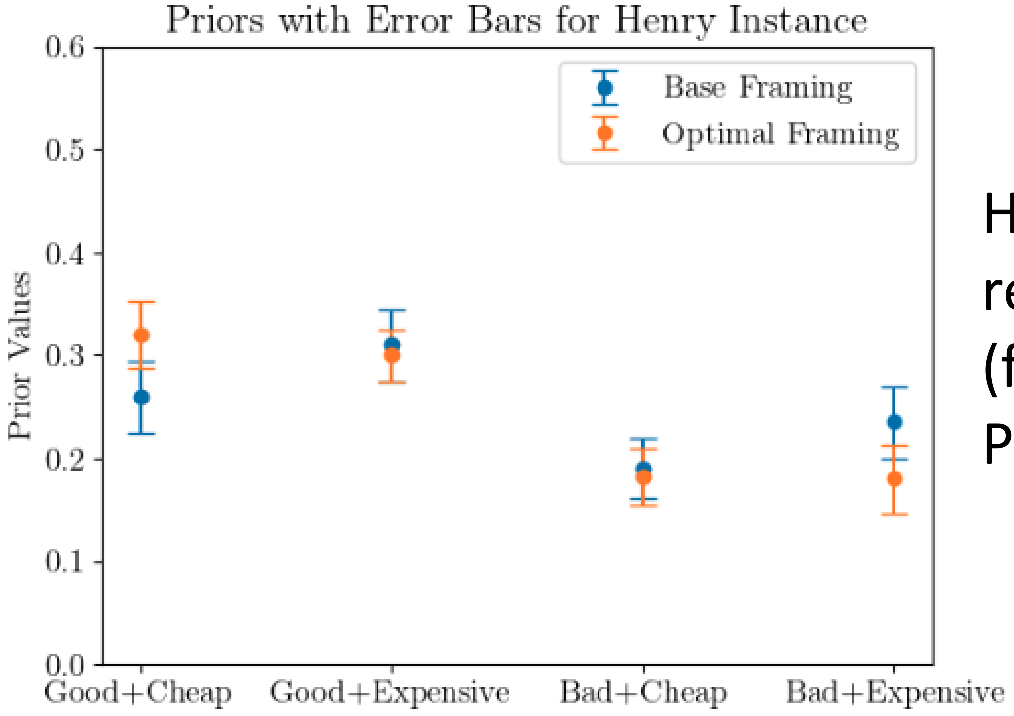
- Previous works showed that prompted LLM can simulate specific group of people.
- When people delegate decisions to AI agents, we will persuade AI agents.

How?

- Provide the realtor description $c$ to LLM (without recommendation $s$)
- Ask LLM to output the buyer's prior belief about the state of the house.

Chat-GPT 4o




Human responses (from Prolific)

# Experiment 2.1: Use LLM to optimize framing $c$

| **Framing for the "Henry" Instance** | **Utility** |
|---|---|
| No framing - receiver prior equal to sender prior | 0.28 |
| Realtor Jeremy Profile from the Instance Description | 0.30 |
| Best LLM Framing: *Meet Jeremy Hammond, a dedicated realtor with over 8 years of experience, specializing in finding the perfect homes for outdoor enthusiasts like you. Living in Downtown Boston, Jeremy understands the balance between city life and access to nature. With a background as a contractor, he ensures that every property meets your low-maintenance needs. When he's not helping clients, you can find him hiking local trails or enjoying his backyard garden. Trust Jeremy to help you discover a home that complements your active lifestyle while staying within your budget.* | 0.40 |
| Analytical Upper Bound (Optimal Joint Strategy when $B = \Delta(\Omega)$) | 0.41 |

LLM generates sentences not in the given realtor profile, tailored to Henry

# Experiment 2.2: Use LLM to optimize framing $c$

| **Framing for the "Lilly" Instance** | **Utility** |
|---|---|
| No framing - receiver prior equal to sender prior | 0.33 |
| Realtor Jeremy Profile from the Instance Description | 0.33 |
| Best LLM Framing: *Introducing Jeremy Hammond, a seasoned realtor with 8 years dedicated to helping families find their dream homes in Boston's suburbs. With a rich background as a contractor, Jeremy excels in identifying spacious, family-friendly properties with excellent school districts—just what you need for your kids. As a fellow dog owner, he knows the importance of a great yard and a welcoming neighborhood. Trust Jeremy to leverage his local expertise and commitment to family values as he guides you to affordable yet quality homes that fit your family's lifestyle.* | 0.42 |
| Analytical Upper Bound (Optimal Joint Strategy when $B = \Delta(\Omega)$) | 0.46 |

LLM generates a different realtor description for another house-buyer

# Outline

- Background on a Classical Information Design Model: “Bayesian Persuasion” [Kamenica & Gentzkow, 2011]
- Information Design with a Learning Receiver
- Information Design with Large Language Models
- Summary and one more thing

# Summary: Information Design + Learning & LLM

- **Commitment**: *Learning outcomes might differ from classic outcomes*
  - Sender can commit to a randomized mapping ("signaling scheme") $\pi: \Omega \to \Delta(S)$ before state realization.
- **Bayesian receiver:**
  - Knowing the prior $\mu$ and signaling scheme $\pi$, the receiver does Bayes update after receiving signal $s$ (and best responds)

- **Abstract signal space:**
  - Language doesn't matter – only the correlation between signal and state matters. *Capture framing effect by theory and LLM*

***Many research opportunities!***

# My Research Interests

"Learning-Based Incentive Design":

- *Information Design*
- *Mechanism Design*
- *Algorithmic Game Theory*
- *Multi-Agent Learning*
- ……