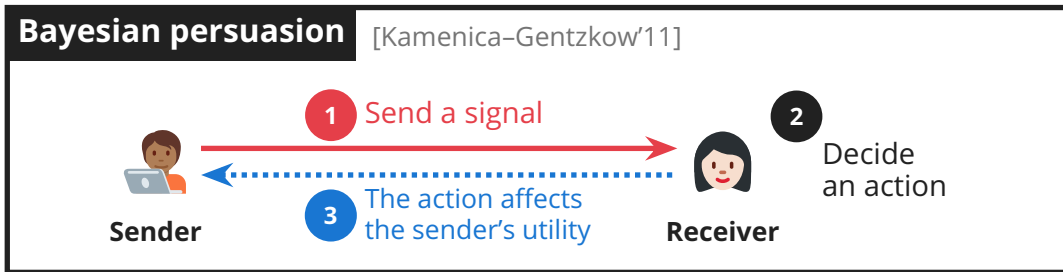


# Algorithmic Bayesian persuasion with combinatorial actions

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(joint work with **Shinsaku Sakaue** (UTokyo))

A game-theoretic model of strategic information revelation for how to lead an agent to a preferred action

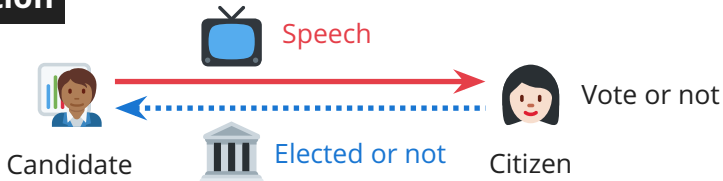


How to compute an optimal signaling strategy?

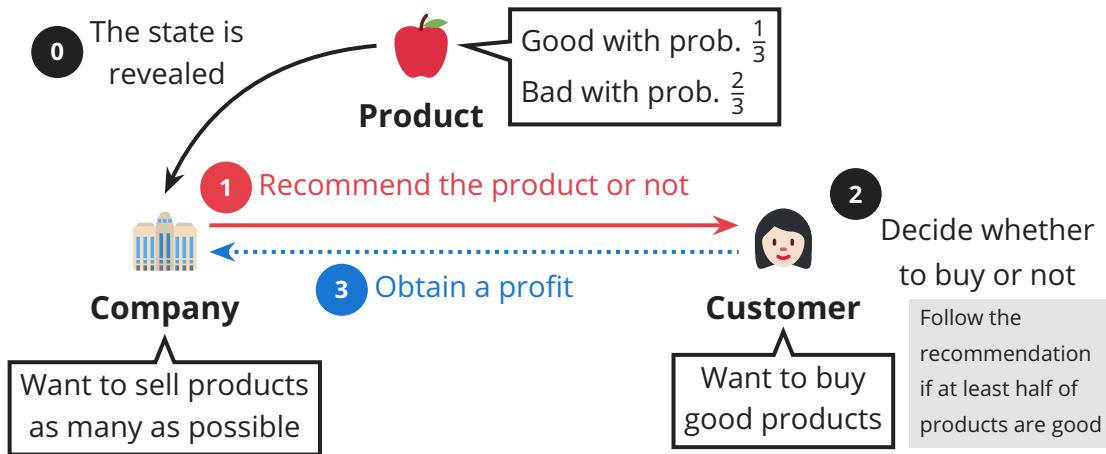
## (1) Ads



## (2) Election



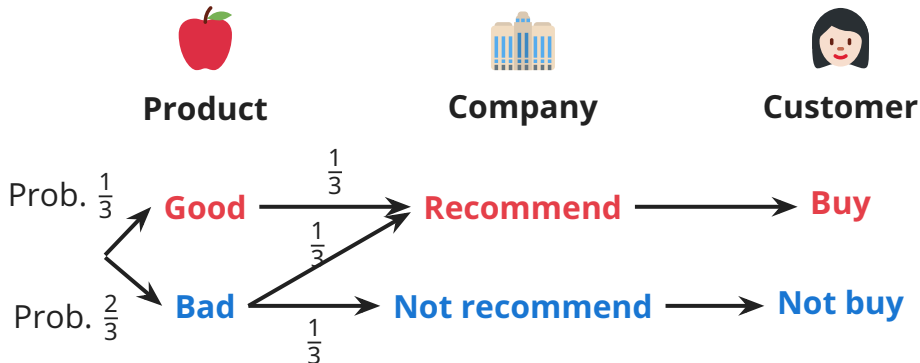
**Q** What is an optimal signaling strategy for the company?

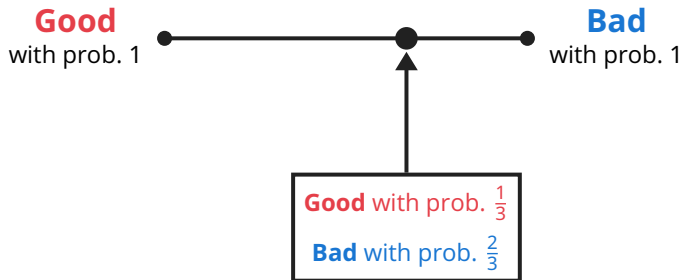


**Optimal**

**Recommend all good products and half of bad products**

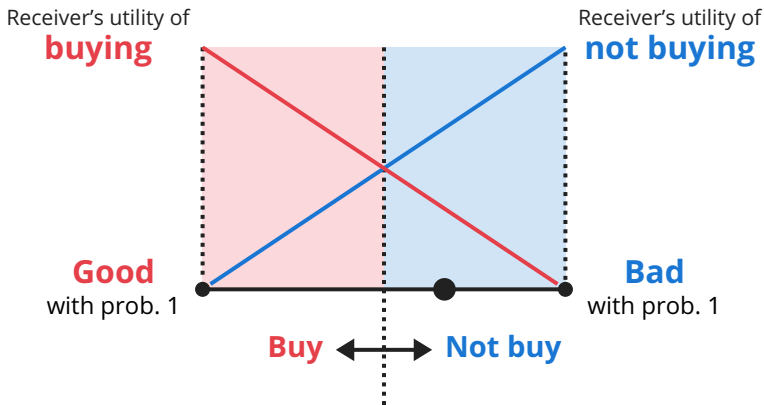
→ Customer buys  $\frac{2}{3}$  of all products

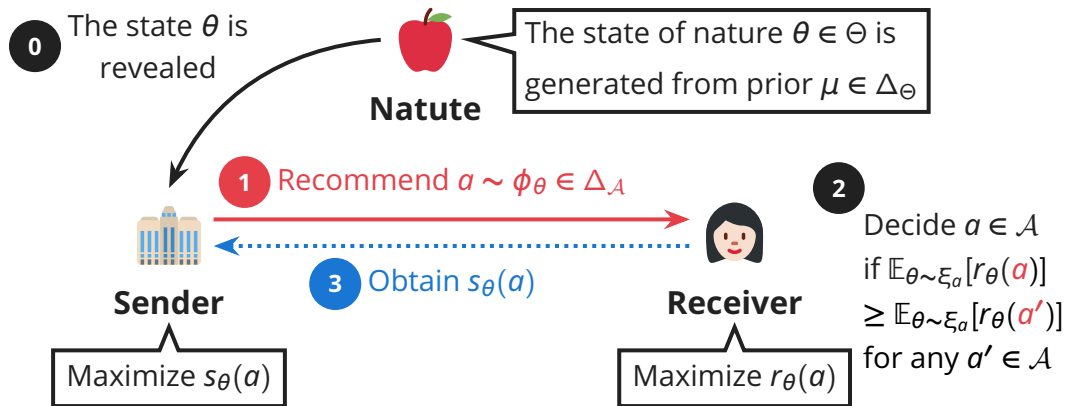




# Example of Bayesian persuasion [Kamenica-Gentzkow'11]

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✳ signaling scheme  $(\phi_\theta)_{\theta \in \Theta}$  is declared in advance

(commitment assumption)



Computation of an optimal strategy can be formulated as LP

$$\text{maximize}_{(\phi_\theta)_{\theta \in \Theta}} \sum_{\theta \in \Theta} \sum_{a \in \mathcal{A}} \mu(\theta) \phi_\theta(a) s_\theta(a)$$

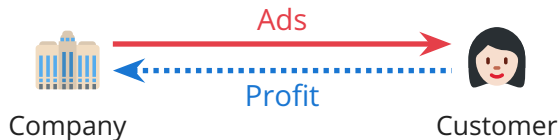
$$= \mathbb{E}_{\theta \sim \mu, a \sim \phi_\theta} [s_\theta(a)] \quad \text{Sender's expected utility}$$

$$\text{subject to } \sum_{\theta \in \Theta} \mu(\theta) \phi_\theta(a) (r_\theta(a) - r_\theta(a')) \geq 0 \quad (a, a' \in \mathcal{A})$$

$$\Leftrightarrow \mathbb{E}_{\theta \sim \xi_a} [r_\theta(a)] \geq \mathbb{E}_{\theta \sim \xi_a} [r_\theta(a')] \quad \text{persuasiveness constraints}$$

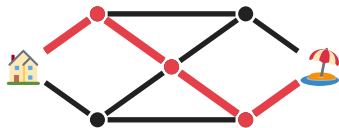
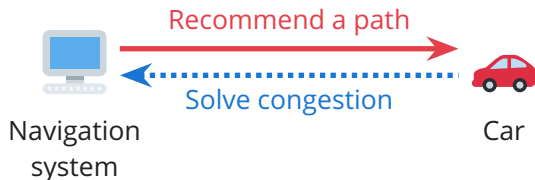
$$\phi_\theta \in \Delta_{\mathcal{A}} \quad (\theta \in \Theta)$$

## (1) Buy multiple products



Buy  $k$  products

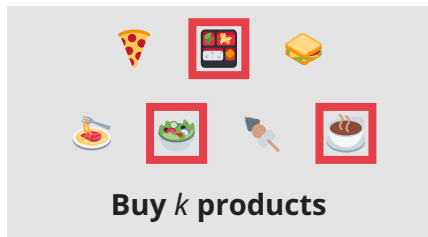
## (2) Choose a path



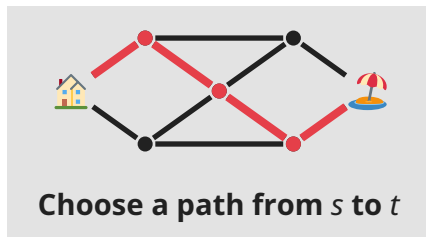
Choose a path from  $s$  to  $t$

# Bayesian persuasion with combinatorial actions 10/23

Receiver's action is a combination of elements in a finite set  $E$   
i.e.,  $\mathcal{A} = \mathcal{I}$ , where  $\mathcal{I} \subseteq 2^E$  is a set family

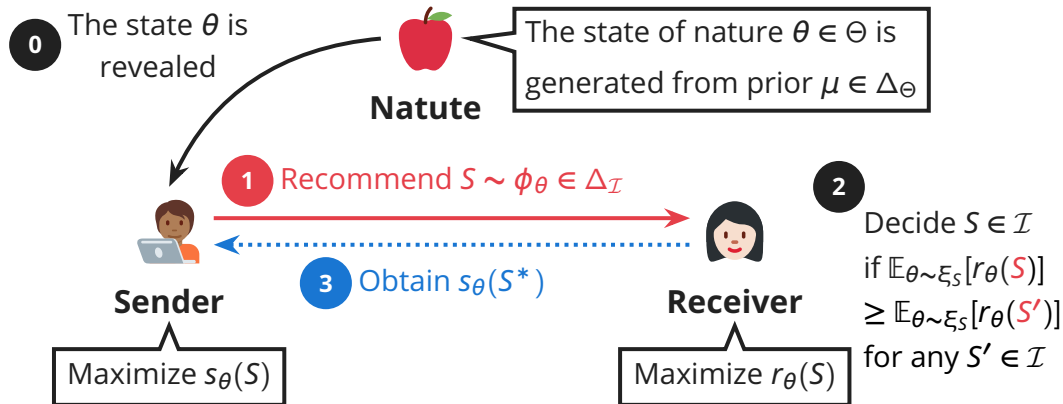


$E$  is the set of products  
 $\mathcal{I} = \{S \subseteq E \mid |S| \leq k\}$   
uniform matroid constraints



$E$  is the set of edges  
 $\mathcal{I} = \{S \subseteq E \mid s-t \text{ path}\}$   
path constraints

Consider a recommendation of combinatorial action  $S \in \mathcal{I} \subseteq 2^E$



## LP with exponentially many variables and constraints

$$\text{maximize}_{(\phi_\theta)_{\theta \in \Theta}} \sum_{\theta \in \Theta} \sum_{S \in \mathcal{I}} \mu(\theta) \phi_\theta(S) s_\theta(S) \quad \text{Sender's expected utility}$$

$$\text{subject to} \quad \sum_{\theta \in \Theta} \mu(\theta) \phi_\theta(S) (r_\theta(S) - r_\theta(S')) \geq 0 \quad (S, S' \in \mathcal{I})$$

persuasiveness constraints

$$\phi_\theta \in \Delta_{\mathcal{I}} \quad (\theta \in \Theta)$$



Is it possible to solve this LP in time polynomial in  $|E|$ ?

**Q** Is it possible to efficiently compute an optimal signaling strategy for Bayesian persuasion with combinatorial actions?

## Our results

- 1** **NP-hardness** of constant-factor approximations
- 2** Poly-time algorithms when **the number of states is a constant**
- 3** Poly-time algorithms for **CCE-persuasiveness**

## Constant-factor approximation is NP-hard for simple constraints

### Theorem

For any  $\alpha \in (0, 1]$ , it is NP-hard to compute an  $\alpha$ -approximate signaling scheme for Bayesian persuasion with any of

- uniform matroid constraints
- partition matroid constraints
- graphic matroids constraints
- path constraints

if the utility functions are linear, i.e.,  $s_\theta(S) = \sum_{i \in S} s_\theta(\{i\})$  and  $r_\theta(S) = \sum_{i \in S} r_\theta(\{i\})$

## ■ Partition matroids

Reduction from **public Bayesian persuasion with no externalities**

[Dughmi-Xu'17]

## ■ Uniform matroids, Graphic matroids, Paths

Reduction from **LINEQ-MA**( $1 - \zeta, \delta$ ) [Guruswami-Raghavendra'09]

Given a linear system  $Ax = c$ , the promise problem of distinguishing

- there exists  $x \in \{0, 1\}^n$  that satisfies at least a  $1 - \zeta$  fraction of the equations
- every  $x \in \mathbb{Q}^n$  satisfies less than a  $\delta$  fraction of the equations

based on the reduction for OptSignal [Castiglioni-Celli-Marchesi-Gatti'20]



We need to consider combinations that can be a best response

$$\sum_{\theta \in \Theta} \mu(\theta) \phi_{\theta}(S) (r_{\theta}(S) - r_{\theta}(S')) \geq 0 \quad (S, S' \in \mathcal{I})$$

persuasiveness constraints

$$\Leftrightarrow S \in \operatorname{argmax}_{S \in \mathcal{I}} \sum_{\theta \in \Theta} \mu(\theta) \phi_{\theta}(S) r_{\theta}(S) \text{ for each } S \in \mathcal{I}$$

$S$  is a best response for posterior  $\xi_S(\theta) \propto \mu(\theta) \phi_{\theta}(S)$

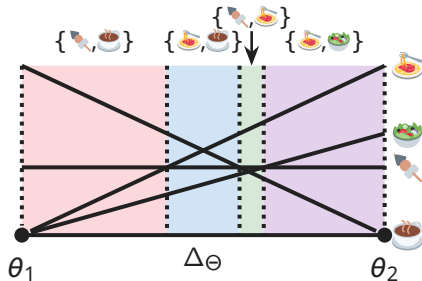
## Observation

In the LP formulation, instead of  $\mathcal{I}$ , it is sufficient to consider

$$\mathcal{I}^* = \left\{ S \in \mathcal{I} \mid \exists \xi \in \Delta_{\Theta} : S \in \operatorname{argmax}_{S \in \mathcal{I}} \sum_{\theta \in \Theta} \xi(\theta) r_{\theta}(S) \right\}$$

Assume  $r_\theta(\cdot)$  is linear, i.e.,  $r_\theta(S) = \sum_{i \in S} r_\theta(\{i\})$  and  $s_\theta(\cdot)$  is given by a value oracle

## Uniform matroids



For each posterior  $\xi \in \Delta_\Theta$ ,  
selecting top- $k$  elements is best

↓

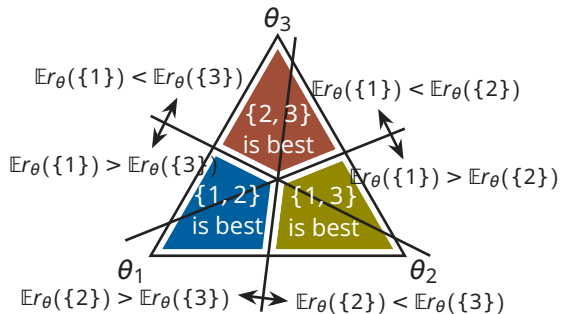
$k$ -level faces enumeration [Mulmuley'91]

studied in computational geometry

## Lemma

Under a certain degeneracy assumption,  $|\mathcal{I}^*| = O(|E|^{|\Theta|-1})$

## ■ General matroids



For each posterior  $\xi \in \Delta_\Theta$ ,  
the ranking of  $\mathbb{E}_\theta(\{\cdot\})$  determines the  
best response

↓  
cell enumeration in an arrangement of  
hyperplanes [Edelsbrunner'87]

### Lemma

Under a certain degeneracy assumption,  $|\mathcal{I}^*| = O(|E|^{2(|\Theta|-1)})$

## ■ Partition matroids

It is sufficient to consider the ranking in each partition

→  $|\mathcal{I}^*| = O(|E|^{2(|\Theta|-1)}/P^{(|\Theta|-1)})$ , where  $P$  is the number of partitions

## ■ Graphic matroids

The enumeration is reduced to the parametric spanning tree problem

$|\mathcal{I}^*| = O(|E||V|^{1/3})$  when  $|\Theta| = 2$ , where  $V$  is the set of vertices [Dey'98]

## ■ Paths

Even if  $|\Theta| = 2$ , there exists an instance such that  $|\mathcal{I}^*| = |E|^{\Omega(\log |E|)}$

[Carstensen'83]

In the CCE-persuasiveness setting, the receiver selects either of:

- following the signal (the expected utility is  $\sum_{\theta \in \Theta} \sum_{S \in \mathcal{I}} \mu(\theta) \phi_{\theta}(S) r_{\theta}(S)$ )
- not receiving the signal (the expected utility is  $\max_{S \in \mathcal{I}} \sum_{\theta \in \Theta} \mu(\theta) r_{\theta}(S)$ )

$$\text{maximize } \sum_{\theta \in \Theta} \sum_{S \in \mathcal{I}} \mu(\theta) \phi_{\theta}(S) s_{\theta}(S)$$

$$\text{subject to } \sum_{\theta \in \Theta} \sum_{S \in \mathcal{I}} \mu(\theta) \phi_{\theta}(S) r_{\theta}(S) \geq \max_{S \in \mathcal{I}} \sum_{\theta \in \Theta} \mu(\theta) r_{\theta}(S)$$

**CCE-persuasiveness constraints**

$$\phi_{\theta} \in \Delta_{\mathcal{I}} \quad (\theta \in \Theta)$$

## Theorem (informal)

If we have an oracle that, for any  $y \geq 0$  and  $\theta \in \Theta$ , returns  $S \in \mathcal{I}$  s.t.

$$s_{\theta}(S) + y \cdot r_{\theta}(S) \geq \max_{S' \in \mathcal{I}} \alpha \cdot s_{\theta}(S') + y \cdot r_{\theta}(S'),$$

then we can compute an  $(\alpha - \epsilon)$ -approximation for any  $\epsilon \in (0, \alpha)$

**Proof** Consider a separation oracle for the dual LP

## Applications

- $s_{\theta}, r_{\theta}$ : linear,  $\mathcal{I}$ : matroid,  $\alpha = 1$
- $s_{\theta}$ : monotone submodular,  $r_{\theta}$ : linear,  $\mathcal{I}$ : matroid,  $\alpha = 1 - 1/e$

**Q** Is it possible to efficiently compute an optimal signaling strategy for Bayesian persuasion with combinatorial actions?

## Our results

- 1** **NP-hardness** of constant-factor approximations
- 2** Poly-time algorithms when **the number of states is a constant**
- 3** Poly-time algorithms for **CCE-persuasiveness**

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