To Save Crowdsourcing from Cheap-talk: Strategic Learning from Biased Users

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Pillar of Engineering Systems and Design
Singapore University of Technology and Design (SUTD)

September 9th, 2023

About SUTD

- A new public university established in 2009.
- Was established in collaboration with MIT.
- Ranking in the world: 21th in Telecommunication Engineering according to ShanghaiRanking 2023.

Acknowledgement

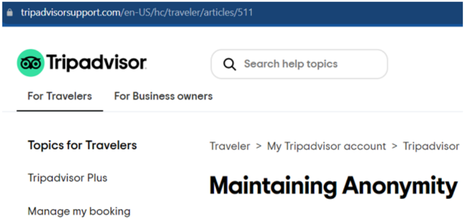
- This is a joint work with Associate Professor Lingjie Duan.
- Part of results here are to appear in IEEE WiOpt 2023.
- **Shugang Hao** and Lingjie Duan, "To Save Crowdsourcing from Cheap-talk: Game Theoretic Learning from Biased Users," working paper.
- **Shugang Hao** and Lingjie Duan, "To Save Crowdsourcing from Cheap-talk: Strategic Learning from Biased Users," in Proc. IEEE WiOpt 2023 (**IEEE WiOpt**), Singapore, August 24-27, 2023.

Overview

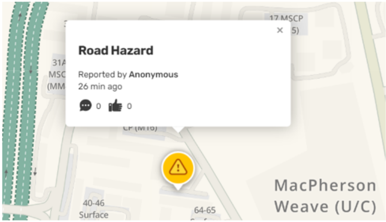
Background: Crowdsourcing Users' Reviews

Crowdsourcing: platforms invite many users to submit anonymous reviews to rate their experienced services. For example,

- TripAdvisor for hotel and restaurant experiences,
- Waze for navigation.



Anonymity on TripAdvisor



Anonymous reports on Waze live map

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+ TripAdvisor: investigation shows that anonymous users posted 79% of the five-star fraudulent hotel reviews.
– Yelp: carpet-cleaning company Hadeed was targeted by many anonymous negative reviews.


Home » Travel Tips » What's Wrong with TripAdvisor, and What to Do About It

What's Wrong with TripAdvisor, and What to Do About It

By Lance Longwell

Last updated: April 6, 2022


The Washington Post

Democracy Dies in Darkness

Exposing anonymous Yelp reviewers

By David Post

April 23, 2015 at 1:26 p.m. EDT

Share

Paul Levy, over at Public Citizen, has an interesting discussion of a recent decision by the Virginia Supreme Court in a case (*Yelp v Hadeed Carpet Cleaning*) involving the right to speak anonymously.

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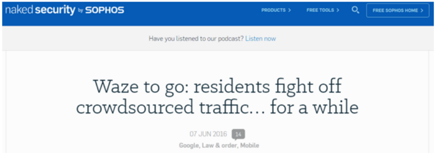

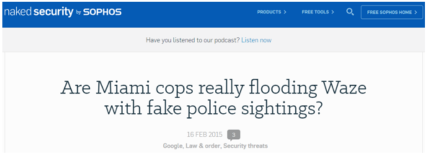

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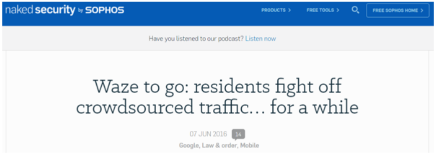

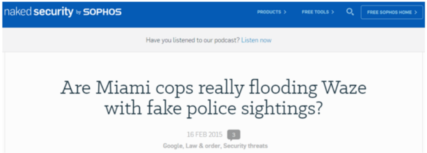

It is critical for crowdsourcing platforms to strategically learn from these biased reviews to infer actual service state.

Research Questions

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Is it always beneficial for the platform to learn from multiple users?

Related Work on Crowdsourcing

Detecting malicious attackers in the crowdsourcing systems

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Such works

- consider malicious data attackers who send fake reports to maximally reduce systems' inference accuracy,

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To our best knowledge, we are the first to

- study how to save crowdsourcing from cheap-talk,
- and strategically learn from biased users.

Related Work on Cheap-talk

Cheap-talk games in the economics & game theory literature

- Battaggion et al. (2022), Karakoc et al. (2021), McGee et al. (2013), Lu et al. (2017).
- Biased senders observe the nature state and adaptively send messages to the receiver.
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- is not limited to one or two users, and
- allows the users' uncertain biases to be extremely positive or negative.

References

J. James, “Sybil attack identification for crowdsourced navigation: A self-supervised deep learning approach,” IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 7, pp. 4622–4634, 2020

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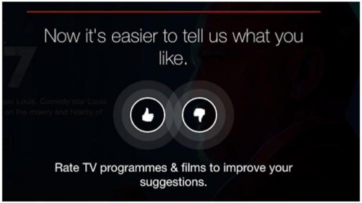
System Model: Binary Rating Systems

In practice, binary rating systems are prevailing and widely deployed.

- Netflix: binary like or dislike to rate movies,
- Reddit and Twitter: upvote and downvote to highlight replies.

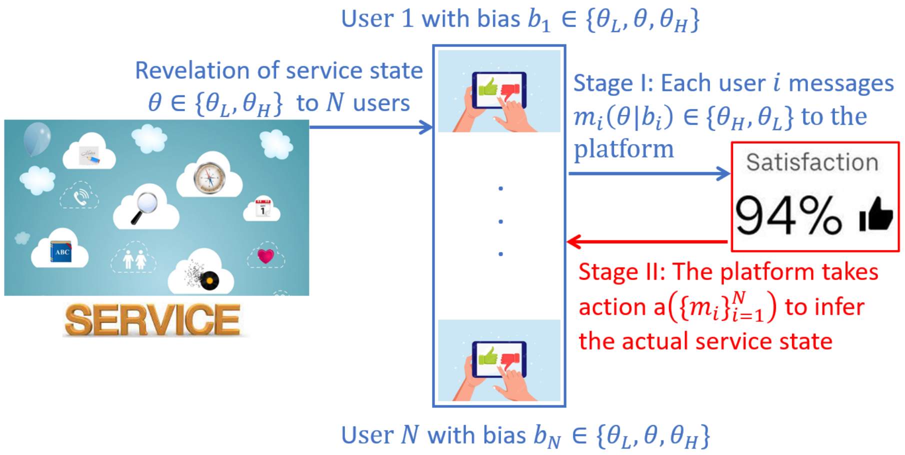


Binary rating in Netflix

Binary rating in Twitter

System Model: Big Picture

Dynamic Bayesan Game Modelling



System Model on Crowdsourcing Users and the Platform

High or low service state $\theta \in \{\theta_H, \theta_L\} = \Theta$

- probability distribution: $Pr(\theta{=}\theta_H){=}p_H$ and $Pr(\theta{=}\theta_L){=}1{-}p_H$.

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II. After receiving all the users' messages $\{m_i\}_{i=1}^N$, the platform takes recommendation action $a(\{m_i\}_{i=1}^N)$ to infer the actual service state.

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His expected cost depends on the service state and the other users' bias distribution:

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Its expected cost under a given inference strategy is thus

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The platform's best strategy of inference action to minimize its expected cost is

$$\begin{aligned} a^*(\{m_i\}_{i=1}^N) =& E[\theta | \{m_i\}_{i=1}^N] \\ =& \arg\min_a \sum_{j \in \{\theta_L, \theta_H\}} Pr\big(\theta = j | \{m_i\}_{i=1}^N\big) u_R(a, \theta = j). \end{aligned}$$

Perfect Bayesian Equilibrium

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Definition (Perfect Bayesian Equilibrium)

A PBE is a set of strategies, $\{m_i^*\}_{i=1}^N$ and $a^*(\{m_i\}_{i=1}^N)$, with beliefs $Pr(\theta|\{m_i^*\}_{i=1}^N)$ such that

- $m_i^*(\theta|b_i)$ minimizes $\bar{u}_{S_i}(b_i)$, given $\{m_j^*\}_{j\neq i}$, $a^*(\{m_i\}_{i=1}^N)$ and $Pr(\theta|\{m_i^*\}_{i=1}^N)$.
- $a^*(\{m_i\}_{i=1}^N)$ minimizes $\bar{u}_R$, given $\{m_i^*\}_{i=1}^N$ and $Pr(\theta|\{m_i^*\}_{i=1}^N)$.

Social Cost and Expected Social Cost at a PBE

We define social cost as the sum of N users' and the platform's costs as follows:

$$U(a, \theta, \{b_i\}_{i=1}^{N}) = \sum_{i=1}^{N} u_{S_i}(a, b_i) + u_R(a, \theta).$$

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Define $\bar{U}_e^*$ as the expected social cost at a particular PBE e out of PBE set E of the Bayesian game as follows:

$$\bar{U}_e^*(N, p_H, q, \theta_H, \theta_L) = \sum_{i=1}^{N} \sum_{\{b_i\}_{i=1}^{N} \in B} Pr(\{b_i\}_{i=1}^{N}) \bar{u}_{S_i}^e(b_i) + \bar{u}_R^e, e \in E.$$

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It decides the platform's inference as the average of all users' biases and the actual service state:

$$a^{**} = \arg\min_{a} U(a, \theta, \{b_i\}_{i=1}^{N}) = \frac{\theta + \sum_{i=1}^{N} b_i}{N+1}.$$

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The minimum expected social cost $\bar{U}^{**}$ is then

$$\bar{U}^{**}(N, p_H, q, \theta_H, \theta_L) = \frac{Nq(N+q-Nq)}{N+1}(\theta_H - \theta_L)^2.$$

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We then finally define PoA as the maximum ratio between expected social costs under the worst PBE and the social optimum:

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We will examine it against different user number N.

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Thus, the platform aims to blindly minimize its expected cost according to its initial belief on service state as follows:

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Lemma (Infinite Efficiency Loss at the benchmark)

At "babbling equilibrium" of the benchmark case, the platform's recommendation action is $\bar{a}=p_H\theta_H+(1-p_H)\theta_L$ with expected cost $\bar{u}_R=p_H(1-p_H)(\theta_H-\theta_L)^2$. Besides, $PoA\to\infty$ happens as $q\to 0$.

Need to remedy the huge efficiency loss!

User's Strategy Simplification

Lemma (Simplifying User's Strategy Space)

At the PBE of the dynamic Bayesian game, we have $m^*(\theta = \theta_L | b = \theta_L) = \theta_L$, $m^*(\theta | b = \theta) = \theta$, *and* $m^*(\theta = \theta_H | b = \theta_H) = \theta_H$.

- If state realization is equal to his bias, the b-biased user never cheats with same cost function.
- The unbiased user type is always honest.

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- If state realization is equal to his bias, the b-biased user never cheats with same cost function.
- The unbiased user type is always honest.

User's Strategy Candidates

- *User's honest strategy 1*: $m(\theta | b) = \theta$.
- *User's maximum dishonest strategy 2*: $m(\theta | b = \theta_L) = \theta_L$ and $m(\theta | b = \theta_H) = \theta_H$.
- *User's dishonest* $b = \theta_L$ *only strategy 3*: $m(\theta | b = \theta_L) = \theta_L$ and $m(\theta | b = \theta_H) = \theta$.
- *User's dishonest* $b = \theta_H$ *only strategy 4*: $m(\theta | b = \theta_L) = \theta$ and $m(\theta | b = \theta_H) = \theta_H$.

The Platform's Strategic Learning

After receiving the user's message m, the platform updates its posterior state belief according to Bayes' theorem:

$$Pr(\theta = \theta_i | m = \theta_i) = \frac{Pr(m = \theta_i | \theta = \theta_i) Pr(\theta = \theta_i)}{\sum_{j \in \{H,L\}} Pr(m = \theta_i | \theta = \theta_j) Pr(\theta = \theta_j)}, i \in \{H, L\},$$

where the truthful reporting probability is:

$$\begin{aligned} Pr(m = \theta_i | \theta = \theta_i) =& \sum_{j \in \{\theta_L, \theta, \theta_H\}} Pr(m = \theta_i, b = j | \theta = \theta_i) \\ =& \sum_{j \in \{\theta_L, \theta, \theta_H\}} Pr(m = \theta_i | \theta = \theta_i, b = j) Pr(b = j). \end{aligned}$$

To Finalize PBE

Assuming the user will adopt honest strategy 1, the platform expects:

$$Pr(m = \theta_i | \theta = \theta_i, b) = 1, \ i \in \{H, L\}.$$

According to its strategic learning, the platform's best-response action to user's strategy 1 is to predict

$$a_1^*(m) = m, \ m \in \{\theta_H, \theta_L\}.$$

Similarly, we can obtain the platform's best-response actions to user's strategy 2-4, respectively.

User's expected costs under strategy 1-4 can be obtained under the platform's best responses, respectively.

We are then able to compare his expected costs to finalize the PBE.

PBE in the Small Bias-Probability Regime (1)

Proposition. PBE in the small bias-probability regime of one-user case

In the one-user case, if the user has small bias probability (i.e., $q \leq \frac{\sqrt{1+2\sqrt{2}}-1}{2}$), we have $p_{1,L} \leq \frac{1}{2} \leq p_{1,H}$. PBE is given in closed-form in the following table with three high-state probability p_H regimes. If $q{=}\frac{\sqrt{1+2\sqrt{2}}-1}{2}$, $p_{1,L}{=}p_{1,H}{=}\frac{1}{2}$ and the medium p_H regime with maximum dishonest strategy diminishes.

p_H REGIME	PBE
SMALL $p_H \in [0, p_{1,L}]$	DISHONEST $b=\theta_H$ ONLY STRATEGY 4: $m^*(\theta \mid b{=}\theta_L){=}\theta,\ m^*(\theta \mid b{=}\theta_H){=}\theta_H$;
MEDIUM $p_H \in [p_{1,L}, p_{1,H}]$	MAXIMUM DISHONEST STRATEGY 2: $m^*(\theta \mid b{=}\theta_L){=}\theta_L,\ m^*(\theta \mid b{=}\theta_H){=}\theta_H$;
LARGE $p_H \in [p_{1,H}, 1]$	DISHONEST $b=\theta_L$ ONLY STRATEGY 3: $m^*(\theta \mid b{=}\theta_L){=}\theta_L,\ m^*(\theta \mid b{=}\theta_H){=}\theta$.

PBE in the Small Bias-Probability Regime (2)

Dishonest $b = \theta_H$ Only:
$m^*(\theta|b = \theta_L) = \theta$,
$m^*(\theta|b = \theta_H) = \theta_H$

Maximum Dishonest:
$m^*(\theta|b = \theta_L) = \theta_L$,
$m^*(\theta|b = \theta_H) = \theta_H$

Dishonest $b = \theta_L$ Only:
$m^*(\theta|b = \theta_L) = \theta_L$,
$m^*(\theta|b = \theta_H) = \theta$

0 $\quad p_{1,L} \quad p_{1,H} \quad$ **1** $\quad p_H$

At the PBE, the biased user's cheap-talk does not happen in most cases.

PBE in the Small Bias-Probability Regime (2)

Dishonest $b = \theta_H$ Only: $m^*(\theta|b = \theta_L) = \theta$, $m^*(\theta|b = \theta_H) = \theta_H$

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Dishonest $b = \theta_L$ Only: $m^*(\theta|b = \theta_L) = \theta_L$, $m^*(\theta|b = \theta_H) = \theta$

0 — $p_{1,L}$ — $p_{1,H}$ — 1 $\quad p_H$

At the PBE, the biased user's cheap-talk does not happen in most cases.

If $p_H > p_{1,H}$ (or $p_H < p_{1,L}$),

- the $b = \theta_H$ (or $b = \theta_L$) user type truthfully messages to convince the platform of no cheap-talk,

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If $p_H > p_{1,H}$ (or $p_H < p_{1,L}$),

- the $b = \theta_H$ (or $b = \theta_L$) user type truthfully messages to convince the platform of no cheap-talk,
- without losing much as state $\theta = \theta_L$ (or $\theta = \theta_H$) does not happen frequently to incur his cost.

PBE in the Small Bias-Probability Regime (2)

Dishonest $b = \theta_H$ Only: $m^*(\theta|b=\theta_L)=\theta$, $m^*(\theta|b=\theta_H)=\theta_H$

Maximum Dishonest: $m^*(\theta|b=\theta_L)=\theta_L$, $m^*(\theta|b=\theta_H)=\theta_H$

Dishonest $b = \theta_L$ Only: $m^*(\theta|b=\theta_L)=\theta_L$, $m^*(\theta|b=\theta_H)=\theta$

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If $p_H > p_{1,H}$ (or $p_H < p_{1,L}$),

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- without losing much as state $\theta = \theta_L$ (or $\theta = \theta_H$) does not happen frequently to incur his cost.

For medium p_H,

- the cost in honest reporting is non-small,
- and the user chooses maximum dishonest messaging.

PBE in the Large Bias-Probability Regime (1)

Proposition. PBE in the large bias-probability regime of one-user case

In the one-user case, if the user has large bias probability (i.e., $q \in (\frac{\sqrt{1+2\sqrt{2}}-1}{2}, \frac{1}{2})$), we have $0 \leq p_{1,H} < \frac{1}{2}$ and $\frac{1}{2} < p_{1,L} \leq 1$. PBE is given in closed-form in the following with three high-state probability p_H regimes.

p_H REGIME	PBE
SMALL $p_H \in [0, p_{1,H}]$	DISHONEST $b = \theta_H$ ONLY STRATEGY 4: $m^*(\theta \mid b=\theta_L)=\theta,\ m^*(\theta \mid b=\theta_H)=\theta_H;$
MEDIUM $p_H \in [p_{1,H}, p_{1,L}]$	DISHONEST $b = \theta_H$ ONLY STRATEGY 4: $m^*(\theta \mid b=\theta_L)=\theta,\ m^*(\theta \mid b=\theta_H)=\theta_H;$
	DISHONEST $b = \theta_L$ ONLY STRATEGY 3: $m^*(\theta \mid b=\theta_L)=\theta_L,\ m^*(\theta \mid b=\theta_H)=\theta;$
LARGE $p_H \in [p_{1,L}, 1]$	DISHONEST $b = \theta_L$ ONLY STRATEGY 3: $m^*(\theta \mid b=\theta_L)=\theta_L,\ m^*(s \mid b=\theta_H)=\theta;$

PBE in the Large Bias-Probability Regime (2)

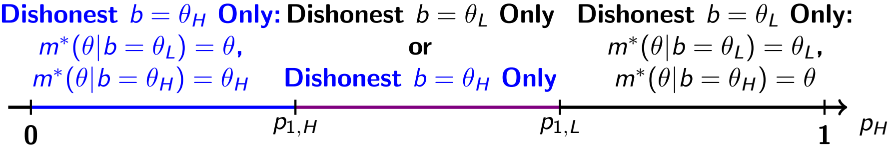
Dishonest $b = \theta_H$ **Only:**
$m^*(\theta|b = \theta_L) = \theta$,
$m^*(\theta|b = \theta_H) = \theta_H$

Dishonest $b = \theta_L$ **Only**
or
Dishonest $b = \theta_H$ **Only**

Dishonest $b = \theta_L$ **Only:**
$m^*(\theta|b = \theta_L) = \theta_L$,
$m^*(\theta|b = \theta_H) = \theta$

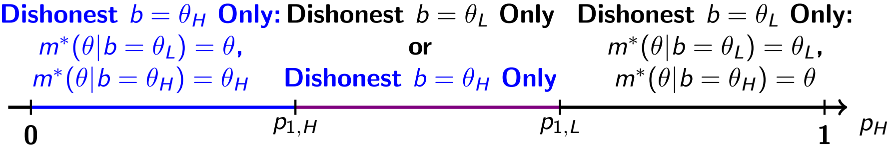
0 $p_{1,H}$ $p_{1,L}$ **1** p_H

PBE in the Large Bias-Probability Regime (2)



At the PBE, the biased user's cheap-talk never happens.

PBE in the Large Bias-Probability Regime (2)



At the PBE, the biased user's cheap-talk never happens.

With non-small bias-probability q,

- the biased user tries to be more honest to convince the platform,
- and skips maximum dishonest strategy 2.

PoA Analysis in the One-User Case

Proposition. PoA in the One-User Case

In the one-user case, we have $PoA = 2$ in the worst case, telling that the social cost can at most be doubled in the worst-case. This is obtained when the user exhibits maximum dishonest strategy 2 with $m^*(\theta|b = \theta_L) = \theta_L$ and $m^*(\theta|b = \theta_H) = \theta_H$.

- The user does not use honest strategy 1 at all times.
- The maximum efficiency loss is incurred when the user exhibits the maximum dishonest strategy 2 to confuse the platform.

Learning from Multiple Users

By asking multiple users,

- each user needs to take the others' possible biases/messages into consideration when deciding his own messaging strategy,

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By asking multiple users,

- each user needs to take the others' possible biases/messages into consideration when deciding his own messaging strategy,
- involves competition among biased users to persuade the platform on their own messages,
- leading to more involved message combinations for the platform to strategically learn from.

The Platform's Best Responses

Either biased-user i still choose one out of strategies 2-4.

By applying similar strategic learning as in the one-user case, we can obtain the platform's best-response learning action under users' strategy 2-4 as follows:

$$a_2^*(|I_H|=k) = \frac{p_H(1-q)^k q^{N-k}\theta_H + (1-p_H)q^k(1-q)^{N-k}\theta_L}{p_H(1-q)^k q^{N-k} + (1-p_H)q^k(1-q)^{N-k}},$$

$$a_3^*(|I_H|=k) = \begin{cases} \theta_H, & \text{if } k>0, \\ \frac{p_H q^N \theta_H + (1-p_H)\theta_L}{p_H q^N + 1 - p_H}, & \text{if } k=0, \end{cases}$$

$$a_4^*(|I_H|=k) = \begin{cases} \theta_L, & \text{if } k<N, \\ \frac{p_H \theta_H + (1-p_H) q^N \theta_L}{p_H + (1-p_H) q^N}, & \text{if } k=N, \end{cases}$$

where set $I_j=\{i|m_i=\theta_j, 0\leq i\leq N\}$ denotes all users for messaging θ_j with $j\in\{L,H\}$.

PBE in the Two-User Case (1)

Let us investigate $N=2$-user case to find more insights.

Proposition. PBE in the two-user case

In the two-user case, $p_{2,L} < \frac{1}{2} < p_{2,H}$ always holds. Users' strategies at the unique PBE are given in closed-form in the following with three high-state probability p_H regimes.

p_H REGIME	PBE
SMALL $p_H \in [0, p_{2,L}]$	DISHONEST $b_i = \theta_H$ ONLY STRATEGY 4: $m_i^*(\theta \vert b_i = \theta_L) = \theta,\ m_i^*(\theta \vert b_i = \theta_H) = \theta_H.$
MEDIUM $p_H \in [p_{2,L}, p_{2,H}]$	MAXIMUM DISHONEST STRATEGY 2: $m_i^*(\theta \vert b_i = \theta_L) = \theta_L,\ m_i^*(\theta \vert b_i = \theta_H) = \theta_H.$
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PBE in the Two-User Case (2)

Dishonest $b_i = \theta_H$ Only:	**Maximum Dishonest:**	Dishonest $b_i = \theta_L$ Only:
$m_i^*(\theta \mid b_i = \theta_L) = \theta$,	$m_i^*(\theta \mid b_i = \theta_L) = \theta_L$,	$m_i^*(\theta \mid b_i = \theta_L) = \theta_L$,
$m_i^*(\theta \mid b_i = \theta_H) = \theta_H$	$m_i^*(\theta \mid b_i = \theta_H) = \theta_H$	$m_i^*(\theta \mid b_i = \theta_H) = \theta$

$0 \quad\quad p_{2,L} \quad\quad p_{2,H} \quad\quad 1 \quad p_H$

At the PBE, biased users' cheap-talks do not happen in most cases.

Similar to one-user case,

- each θ_L-biased user misreports state $\theta = \theta_H$ to θ_L if $p_H > p_{2,L}$,

PBE in the Two-User Case (2)

Dishonest $b_i = \theta_H$ Only:
$m_i^*(\theta|b_i = \theta_L) = \theta$,
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At the PBE, biased users' cheap-talks do not happen in most cases.

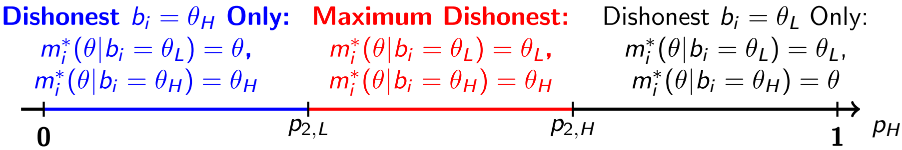
Similar to one-user case,

- each θ_L-biased user misreports state $\theta = \theta_H$ to θ_L if $p_H > p_{2,L}$,
- each θ_H-biased user misreports state $\theta = \theta_L$ to θ_H if $p_H < p_{2,H}$.

As the other user to message may be likely to have opposite bias,

- a user with different bias from the state $(b_i \neq \theta)$ has greater cost to message truthfully,

PBE in the Two-User Case (2)



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As the other user to message may be likely to have opposite bias,

- a user with different bias from the state $(b_i \neq \theta)$ has greater cost to message truthfully,
- and choose maximum dishonest strategy 2 as cheap-talk.

PoA Analysis in the Two-User Case

Proposition. PoA in the Two-User Case

In the two-user case, we have $PoA = 2$ in the worst case, telling that the social cost can at most be doubled in the worst-case. This is obtained when $p_H \in [p_{2,L}, p_{2,H}]$ for each user i's maximum dishonest strategy 2 with $m_i^*(\theta|b_i = \theta_L) = \theta_L$ and $m_i^*(\theta|b_i = \theta_H) = \theta_H$.

- Each user does not use honest strategy 1 anyway.
- The maximum efficiency loss is incurred when each exhibits the maximum dishonest strategy 2 to confuse the platform.

Learning from Two Users May Not be Better than One

Corollary. Learning from two may not be better than one.

The platform's expected cost decreases with one more random user if high-state probability $p_H \in [0, p_{2,L}] \cup [p_{2,H}, 1]$ and bias probability $q \leq \frac{\sqrt{1+2\sqrt{2}}-1}{2}$, but increases if $p_H \in (p_{2,L}, p_{2,H})$ and $q > \frac{\sqrt{1+2\sqrt{2}}-1}{2}$.

- In the one-user case, cheap-talk does not happen at the PBE in the large regime of bias probability $q > \frac{\sqrt{1+2\sqrt{2}}-1}{2}$,
- but may still occur in the two-user case.

Learning from Arbitrary Users

For arbitrary N users,

- it includes many combinations of users' biases,

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- and the analysis is more involved.

Nonetheless, we manage to

- provide asymptotic analysis as $N \to \infty$,
- and numerically study the case of finite N.

Asymptotic Analysis on PBE

Proposition. PBE with $N \to \infty$ users.

Given user number $N \to \infty$, at the PBE each biased user i may arbitrarily choose any strategy 1-4. The platform can always learn the actual service state, and its equilibrium action is $a^* = \theta, \ \theta \in \{\theta_H, \theta_L\}$.

As $N \to \infty$,

- positively and negatively biased users' reviews well negate each other,

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As $N \to \infty$,

- positively and negatively biased users' reviews well negate each other,
- and the platform always learns the actual service state from the majority including unbiased user(s).

Numerical Results on PBE with Finite Users (1)

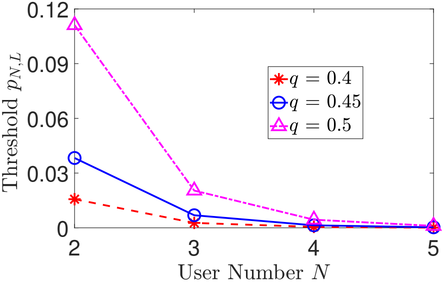

Figure: Threshold $p_{N,L}$ versus user number N and bias probability q. If $p_H > p_{N,L}$, a user of bias θ_L misreports state $\theta = \theta_H$ to bias θ_L.

As N increases, each $b_i = \theta_L$ user is less likely to truthfully message.

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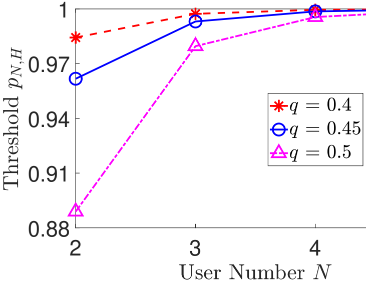


Figure: Threshold $p_{N,H}$ versus user number N and bias probability q. If $p_H < p_{N,H}$, a user of bias θ_H misreports state $\theta = \theta_L$ to bias θ_H.

As N increases, each $b_i = \theta_H$ user is less likely to truthfully message.

Numerical Results on The Platform's Expected Cost

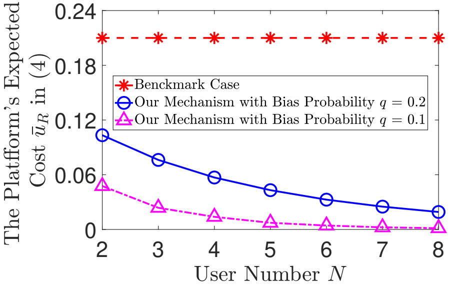


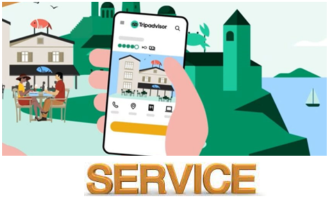
Figure: The platform's expected cost $\bar{u}_R^*$ versus user number N and bias probability q, respectively. Here we set $(\theta_H - \theta_L)^2 = 1$ and $p_H = 0.3$.

At the PBE of our dynamic Bayesian game, the platform's expected cost $\bar{u}_R^*$ decreases with N and approaches zero.

Journal Extension: System Model

User 1 with bias $b_1 \in \{-,+\}$

Realized service type $\phi(\theta) \in \{\phi_H(\theta), \phi_L(\theta)\}$ of service state θ to N users



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Stage I: Each user i messages $m_i(\phi(\theta)|b_i) \in \{\phi_H(\theta), \phi_L(\theta)\}$ to the platform

Stage II: The platform takes action $a(\{m_i\}_{i=1}^N)$ to best learn the future service state

User N with bias $b_N \in \{-,+\}$

Each user observes service type $\phi(\theta)$ instead of service state $\theta \in \Theta \subseteq R$.

The Platform's One-Shot Commitment Mechanism

Thanks to the Revelation Principle,
we focus on the platform's commitment mechanism.

Definition (The Platform's One-Shot Commitment Mechanism)

The platform commits to action a_i, $i \in \{H, L\}$, when observing $m = \phi_i(\theta)$. The actions (a_L, a_H) ensure that neither-biased user type obtains more expected utility by deviating from truthfully messaging.

Unfortunately, it fails to distinguish with Babbling Equilibrium.

$$a_L = a_H.$$

The Platform's Time-Evolving Mechanism

Definition (The Platform's Time-Evolving Commitment Mechanism)

The platform designs its time-evolving mechanism in its interaction with the user over multiple $T{\geq}2$ periods as follows:

- Period 0: the user with private bias $b \in \{-, +\}$ observes realized PDF $\phi(\theta) \in \{\phi_H(\theta), \phi_L(\theta)\}$ of service state θ and truthfully messages $m(\phi_i(\theta)|b){=}\phi_i(\theta)$ to the platform.
- Period $k \in \{1, 2, \cdots, T\}$: the platform commits to an action $a_i(h_{k-1})$ in the beginning of period k according to its past observations on service states $h_{k-1}{=}(\theta_1, \cdots, \theta_{k-1}) \in \Theta_{k-1}$ and its received message $m = \phi_i(\theta)$, $i \in \{H, L\}$. Its objective is to minimize its expected cost over T periods. After that the actual service state θ_k in period k is revealed to the public.

The Platform's Time-Evolving Mechanism

$$\min_{\{a_L(h_{k-1})\}_{k=1}^N, \{a_H(h_{k-1})\}_{k=1}^N} \bar{u}_R^M$$

$$s.t. \sum_{k=1}^{T} \int_{\Theta_{k-1}} (a_L(h_{k-1}) - a_H(h_{k-1}))\phi_L(h_{k-1}) dh_{k-1} \geq 0, \text{ (I.C.L+)}$$

$$\sum_{k=1}^{T} \int_{\Theta_{k-1}} (a_H(h_{k-1}) - a_L(h_{k-1}))\phi_H(h_{k-1}) dh_{k-1} \geq 0, \text{ (I.C.H+)}$$

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The Platform's Time-Evolving Mechanism (Cont.)

Proposition. The Platform's Optimal Commitment Actions

Our time-evolving mechanism for the platform can ensure the biased user's truthfully messaging in period 0, by choosing the following commitment actions $a_L^*(h_{k-1})$ and $a_H^*(h_{k-1})$, $k \in \{1, \cdots, T\}$:

$$a_L^*(h_{k-1}) = \mu_L + w(h_{k-1})\,(\mu_H - \mu_L) > \mu_L,$$

$$a_H^*(h_{k-1}) = \mu_H - w(h_{k-1})\frac{1-p_H}{\Lambda(h_{k-1})p_H}\,(\mu_H - \mu_L) < \mu_H.$$

The platform's loss per period is

$$\hat{L}_1 = \frac{(1-p_H)p_H T(\mu_H-\mu_L)^2((p_H-1)s_\alpha - p_H s_\beta + T)}{p_H^2(s_\alpha - T)(s_\beta - T) - p_H(s_\alpha(s_\beta - 2T) + T^2) + T(T - s_\alpha)},$$

which is reduced from that of Babbling Equilibrium.

Performance of Time-Evolving Mechanism

Proposition.

Under the platform's time-evolving mechanism with normally-distributed service state $\theta \sim N(\mu_i, \sigma^2)$, $i \in \{H, L\}$, the platform's loss is

$$\hat{L}_1 = \frac{1}{\frac{e^{T(\mu_H-\mu_L)^2/\sigma^2}-1}{T(\mu_H-\mu_L)^2(e^{(\mu_H-\mu_L)^2/\sigma^2}-1)} - \frac{1}{(\mu_H-\mu_L)^2} + \frac{1/(p_H(1-p_H))}{(\mu_H-\mu_L)^2}}.$$

It decreases with period number T. Besides, we have $\lim_{T\to\infty} \hat{L}_1 = 0$ and $\lim_{(\mu_H-\mu_L)\to\infty} \hat{L}_1 = 0$, improving from $\lim_{(\mu_H-\mu_L)\to\infty} L_1 = \infty$ at the PBE, and $\lim_{(\mu_H-\mu_L)\to\infty} \bar{L}_2 = \infty$ at the benchmark 2.

Conclusion

- The first work to study how to save crowdsourcing from cheap-talk and strategically learn the actual service state from biased users' reviews.
- With our dynamic Bayesian game design, the platform's strategic learning can successfully prevent biased users from cheap-talk in most cases.
- It may not be better for the platform to learn from two users than one.
- The platform's truthful mechanism design to enable truthfulness all the time.

Thank You! Q & A