



<https://arxiv.org/abs/2009.12920>

# Privacy and Fairness in Data-driven Personalized Revenue Management

**Yining Wang**

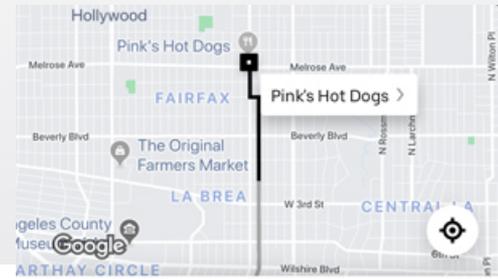
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# Data-driven revenue management

- Using **data analytics** to help **revenue / profit** decisions.

*Dynamic pricing*



## Best flights ⓘ

Total price includes taxes + fees for 1 adult. [Additional bag fees](#) and other fees may apply.

Sort by:

Choose a ride, or swipe up for more



7:20 AM – 12:59 PM

United · Operated by Air Wisconsin DBA United Express

5 hr 39 min

MCO–YUL

1 stop

1 hr 38 min IAD

\$141



10:40 AM – 4:58 PM

American · Operated by PSA Airlines as American Eagle

6 hr 18 min

MCO–YUL

1 stop

1 hr 54 min PHL

\$141



1:10 PM – 7:16 PM

Air Canada · Operated by Air Canada Rouge, Air Canada...

6 hr 6 min

MCO–YUL

1 stop

2 hr 10 min YYZ

\$174



UberX 4

\$8-10

11:14am dropoff



UberXL

\$11-13

11:16am



Comfort **New**

\$10-11

11:14am

**Uber in California shows a range of prices instead of up-front prices**

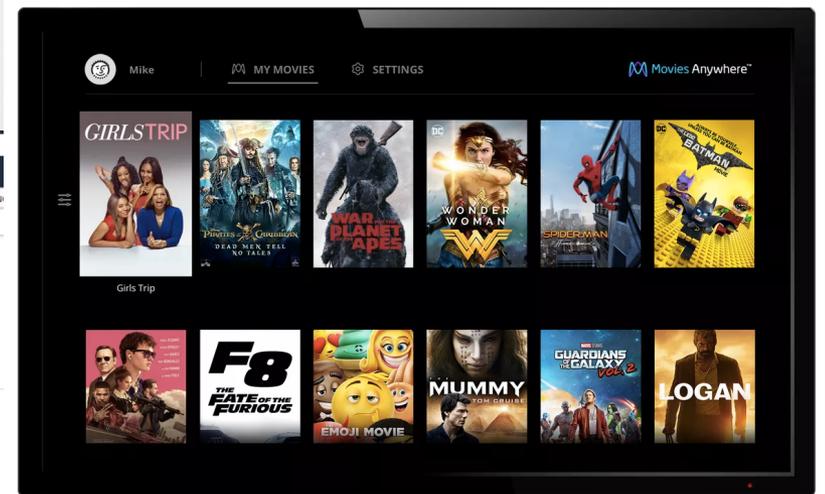
# Data-driven revenue management

- Using **data analytics** to help **revenue / profit** decisions.

## Dynamic Assortment Planning

The screenshot shows the Amazon.com search results for 'headphones'. The search bar at the top contains 'Audio Headphones' and 'headphones'. The results are filtered to show '1-24 of over 8,000 results for Electronics : Headphones : Prime Eligible : Wireless : "headphones"'. The left sidebar includes navigation options like 'FREE One-Day Shipping', 'Any Category', and 'Refine by'. The main content area displays several headphone products with their prices, ratings, and special features.

Product	Price	Rating	Special Features
COWIN E9 [Upgraded] Active Noise Cancelling Headphone Bluetooth Headphones with Microphone HI-Fi Deep Bass Wireless Headphones Over Ear 20 Hour Playtime for Travel/Work/TV/Computer/Phone - Orange by cowin	\$14999	★★★★☆ - 210	Special Feature: Stereo Headphones Form Factor: Over-ear
Beats Solo3 Wireless On-Ear Headphones - Rose Gold by Beats	\$29995	★★★★☆ - 2,889	Special Feature: wireless Wireless Communication Technology: bluetooth Headphones Form Factor: On Ear
Mpow 059 Bluetooth Headphones Over Ear, Hi-Fi Stereo Wireless Headset, Foldable, Soft Memory-Protein Earmuffs, w/Built-in Mic Wired Mode PC/Cell Phones/TV by Mpow	\$3599	★★★★☆ - 8,766	Promotion Available and 3 more promotions Special Feature: Foldable Wireless Communication Technology: bluetooth Headphones Form Factor: In Ear
COWIN E7 Active Noise Cancelling Headphones Bluetooth Headphones with Mic Deep Bass Wireless Headphones Over Ear, Comfortable Protein Earpads, 30H Playtime for Travel Work TV PC Cellphone - Black by cowin	\$6899	★★★★☆ - 7,232	





# Data-driven revenue management

- The **population** approach:
  - Use *population data* such as the average demand or click-through rates over a region to make general price, promotion and inventory decisions.
- The **personalized** approach
  - Use *personalized data* to make individualized price/promotion/recommendation decisions.
  - More detailed, refined with higher profits

# Personalized revenue management

- Example: **Yamibuy.com** (online retail)



# Personalized revenue management

- Example: **Yamibuy.com** (online retail)

The screenshot shows a social media post from a user named 'Food Queen' dated Saturday, June 13, 2020. The post text reads: 'The summer vacation came quietly. This year because of the epidemic. So I have to accompany the children online classes. When I wake up late in the morning, I always eat this bread +milk. I really...'. The post includes three images: a large pile of various packaged breads, a single round bread next to a 'Beauty OK' magazine, and two close-up photos of breads with dark fillings. To the right of the post is a 'You might be interested' sidebar with four recommendations: 'Pancake', 'Food Queen', 'Baa baa baa baa ...', and '@九九'. Each recommendation has an 'unsubscribe' or 'attention' button and a close 'X' icon.



# Personalized revenue management

- Example: **Yamibuy.com** (online retail)
  - Personalized price decisions: set higher prices for those who **target higher brands**?
  - Personalized recommendation/promotion decisions: promote new/emerging items to **social influencers (i.e. many posts / followers)**?





# Data privacy in Personalized revenue management

- Personalized data involved in data-driven decision making are sensitive and private.
  - Example: age, gender, telephone number
  - More serious: medical history (drug stores), credit history (credit cards/loans)
- **Privacy breaches** of personalized data can have serious ethical and legal consequences!



# Personalized revenue management

- **Question.** When using personalized data to make decisions, how to avoid inadvertently leaking private data of the users?

# Data-driven personalized pricing

- The model.



- $T$  consumers, arriving sequentially.



$y_1$        $y_2$        $y_3$

- Personal info. (age, gender, etc.)
- History (purchase, credit, medical, etc.)
- Social network (e.g., page-rank)

Customer  $t$  profile:  
Posted price:  $p_t$



Vector representation  
 $\phi_t = \phi(x_t, p_t)$

$$E[y_t | x_t, p_t] = f(\langle \phi_t, \theta^* \rangle)$$

# Data-driven personalized pricing

- The “learning-while-doing” framework: learning the model  $\theta^*$  while optimizing prices  $\{p_t\}_{t=1}^T$ 
  - Many existing works in the literature. Zeevi & Besbes’09,15, Broder & Rusmevichientong’12, Chen & Gallego’19, Wang et al.’14, Keskin & Zeevi’14
  - The key principle: “**Optimism in the Face of Uncertainty**” (OFU), by Abbasi-Yadkori *et al.* in *NeurIPS, 2011*.

$$\hat{p}_t = \arg \max_p p \times \left[ f(\phi_t, \hat{\theta}_{t-1}) + \gamma \sqrt{\phi_t^T \Lambda_{t-1}^{-1} \phi_t} \right]$$

The predicted demand at  $p$

Confidence interval of the prediction

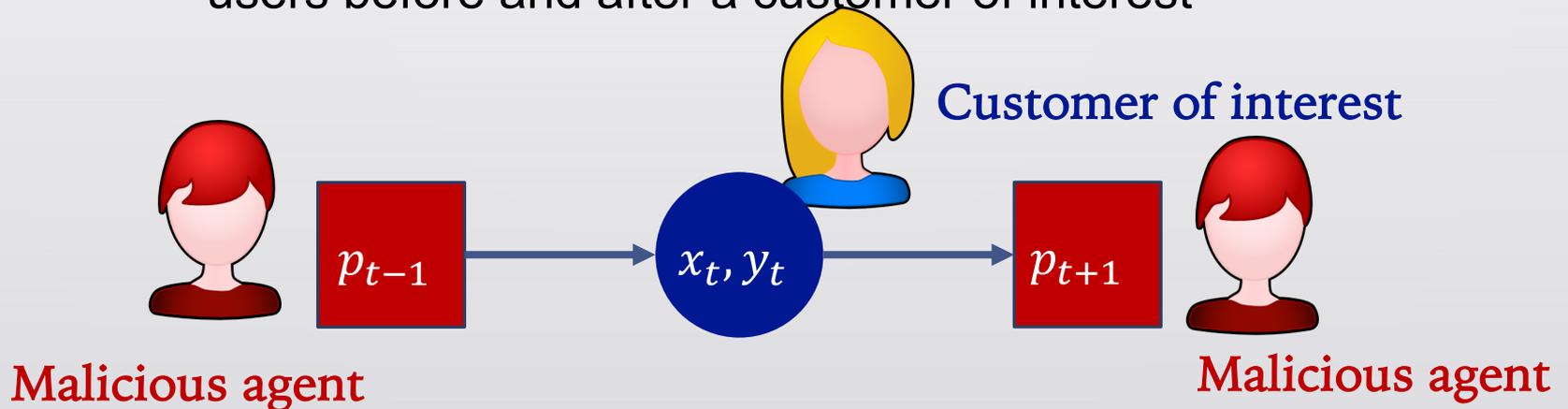


# Concerns over privacy leakage

- The customer's profile  $x_t$  contains many sensitive information that shouldn't be published.
- The customer's purchase decision  $y_t$  is sometimes also sensitive information.
  - Whether the customer purchased certain medication
- **Concerns:** even if the pricing algorithm doesn't release  $x_t, y_t$ , could other people still **infer** these sensitive data, from the posted prices?

# Concerns over privacy leakage

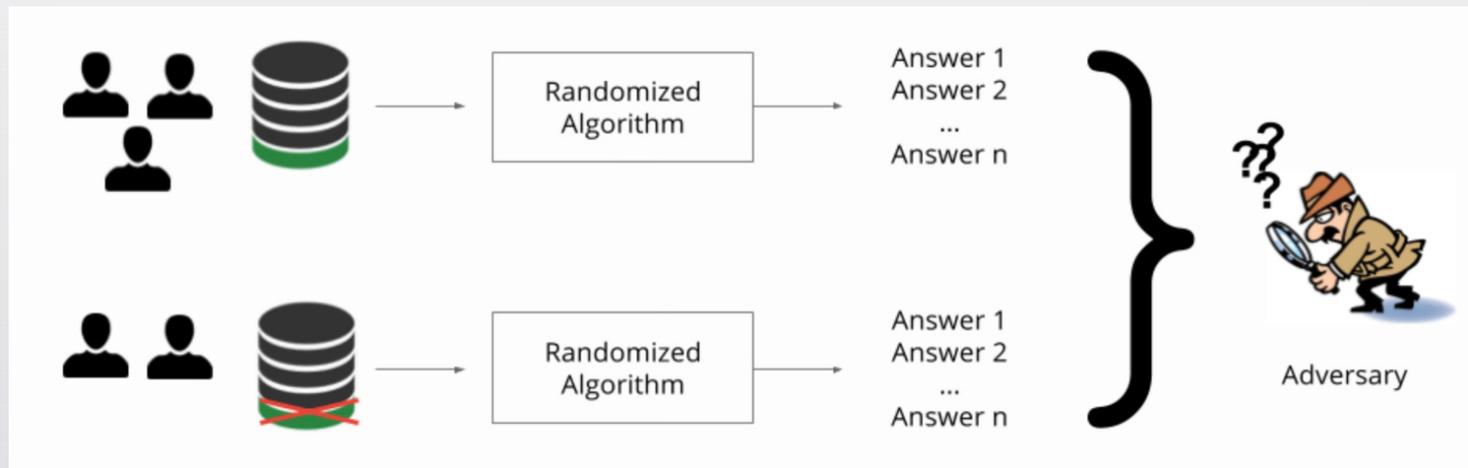
- **Example:** Privacy breach of purchase activity  $y_t$ .
  - Frequently, with active recent purchase activities the retailer spikes the price for larger profit margins.
  - A potential attack by a malicious agent: pretend as legitimate users before and after a customer of interest



If the agents see a price increase  $p_{t-1} < p_{t+1}$ , it's more likely the person of interest made purchases.

# Differentially private personalized pricing

- **Differential privacy**: a mathematically rigorous way to quantify privacy leakage. [Dwork et al.'06](#)





# Differentially private personalized pricing

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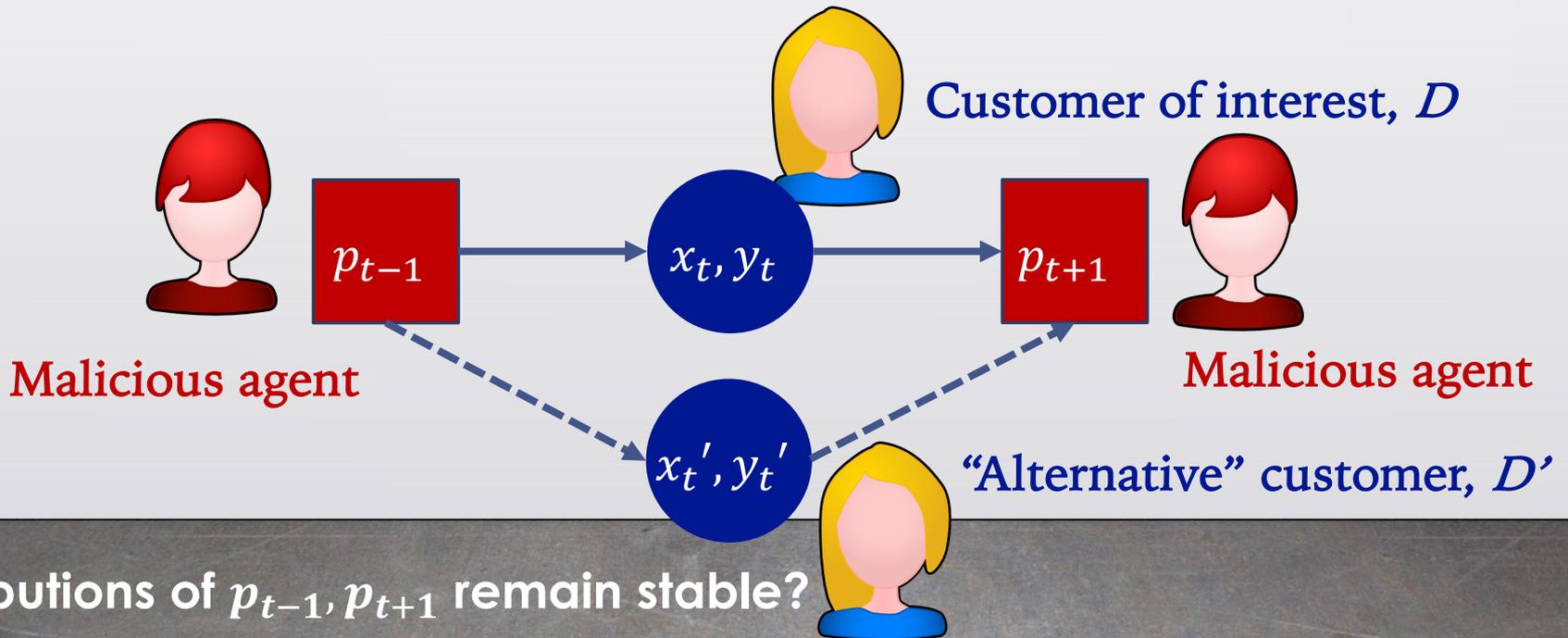
$$\Pr[O|D] \leq e^\epsilon \Pr[O|D'] + \delta$$

- Interpretation: the probability of certain outcomes from the policy  $O$  does not change much, when a user's sensitive information changes ( $D \rightarrow D'$ ).

# Differentially private personalized pricing

- **Differential privacy:** a mathematically rigorous way to quantify privacy leakage. [Dwork et al.'06](#)

$$\Pr[O|D] \leq e^\epsilon \Pr[O|D'] + \delta$$





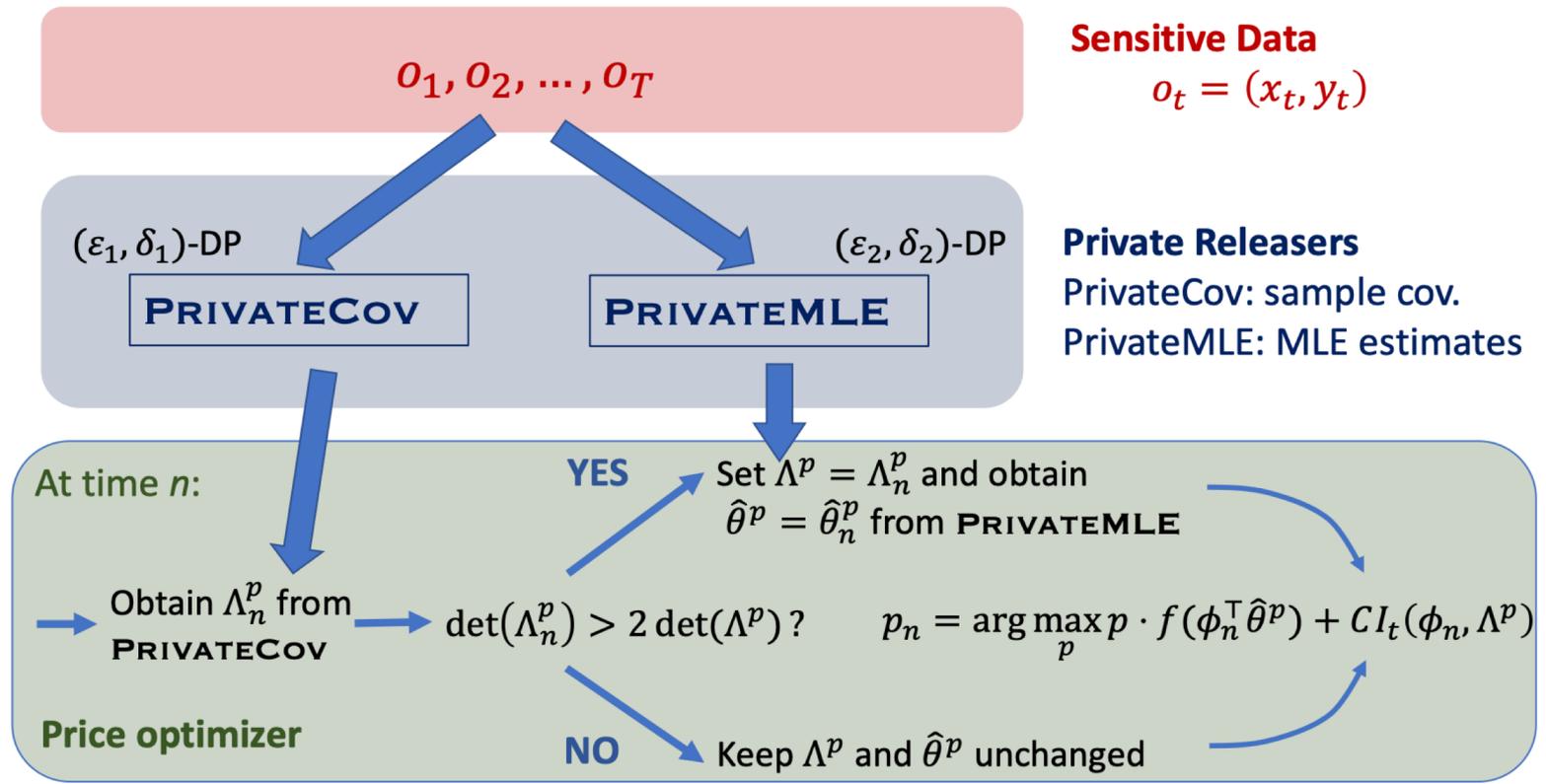
# Differentially private personalized pricing

- **Differential privacy:** a mathematically rigorous way to quantify privacy leakage. [Dwork et al.'06](#)

$$\Pr[O|D] \leq e^\varepsilon \Pr[O|D'] + \delta$$

- **The  $(\varepsilon, \delta)$ -differential privacy:** the smaller  $\varepsilon, \delta$  are, the stronger privacy demands are requested by the firms/practitioners
- **Objective:** design **differentially private** algorithms without **sacrificing too much profits**.

# Algorithm framework





# Algorithm details

- The **PrivateMLE** routine: produce privacy-aware model estimates using data prior to time  $t$
- Key idea: “objective perturbation”

$$\max_{\theta} \sum_{\tau < t} \log P(y_{\tau} | x_{\tau}, p_{\tau}; \theta) - \underbrace{w_t^{\top} \theta}_{\text{The calibrated noise}} \quad w_t \sim N(0, v_{\epsilon, \delta}^2)$$

- Privacy arguments in [Kifer et al.'12](#), [Chaudhuri et al.'11](#)
- Utility (error) analysis of  $\hat{\theta}_t - \theta^*$  available by analyzing the first-order KKT condition of the perturbed objective.

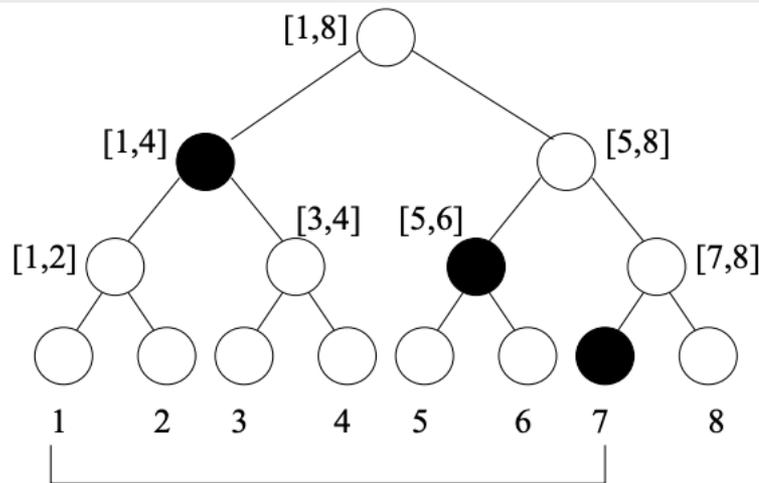


# Algorithm details

- The **PrivateCov** routine: give signals to invoke PrivateMLE for estimates, as few as possible.
- Approach: sequentially releasing differentially private sample covariance estimates.
  - “Tree-based” protocol in releasing consecutive sample covariances to facilitate frequent PrivateCov checks.  
Dwork et al.’10, 14, Chan et al.’11

# Algorithm details

- At each time  $t$ , report **privatized** version  $\tilde{\Lambda}_t$  of the sample covariance  $\Lambda_t = \sum_{\tau < t} x_\tau x_\tau^T$  using **tree-based aggregation**



**Example:**  $\sum_{\tau=1}^7 x_\tau x_\tau^T$  is calculated

$$\sum_{\tau=1}^4 x_\tau x_\tau^T + \text{noise}$$

$$\sum_{\tau=5}^6 x_\tau x_\tau^T + \text{noise}$$

$$\sum_{\tau=7} x_\tau x_\tau^T + \text{noise}$$



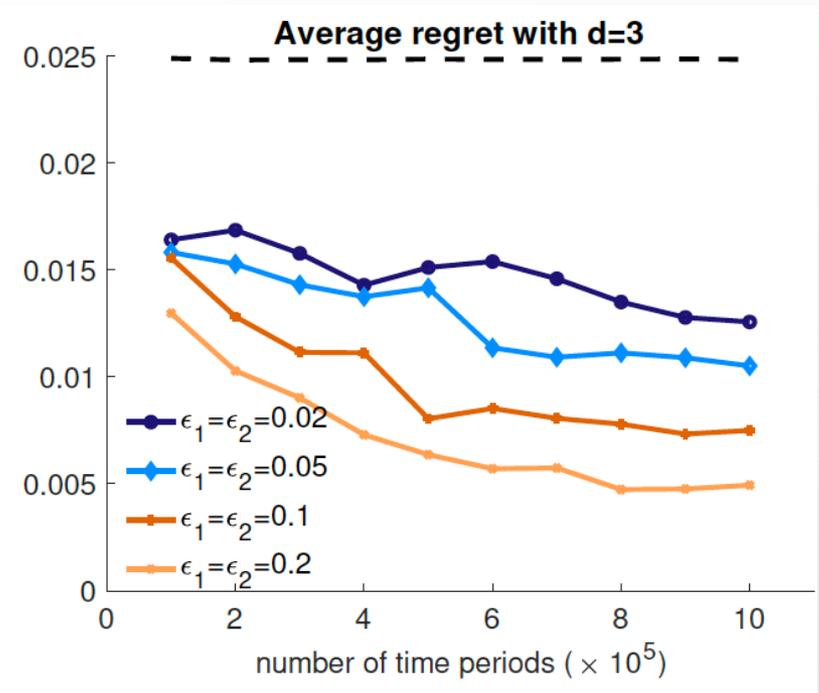
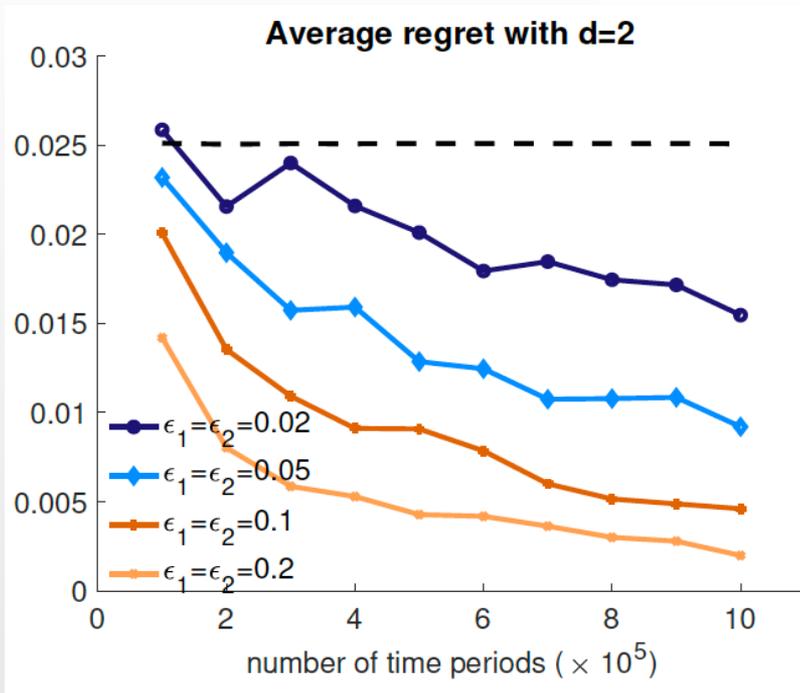
# Regret analysis

- **Regret measure:** performance of a (privacy-aware) policy  $\pi$  measured by  $E^\pi[\sum_{t=1}^T r_t(p_t^*) - r_t(p_t)]$ 
  - $p_t$  is the price offer by  $\pi$  and  $r_t(p) = p \times E[y_t|p, x_t]$
  - $p_t^*$  is the **optimal** price maximizing  $r_t(\cdot)$
- Without privacy concerns, the best algorithm has regret  $\tilde{O}(d\sqrt{T})$ . Filippi et al.'10, Abbasi-Yadkori et al.'11
- What does the regret look like for our proposed algorithm, subject to  $(\epsilon, \delta)$ -privacy constraints?



# Regret analysis

- Without privacy concerns, the best algorithm has regret  $\tilde{O}(d\sqrt{T})$ . Filippi et al.'10, Abbasi-Yadkori et al.'11
- Subject to  $(\epsilon, \delta)$ -differential privacy constraints, our algorithm has regret  $\tilde{O}(\epsilon^{-1}\sqrt{d^3T \ln^5(\delta^{-1})})$ 
  - Matches  $\tilde{O}(\sqrt{T})$  regret, with slightly worse  $d$  dependency.
  - In practice  $d$  is usually small (few #. of covariates).
- If the contexts  $x_t$  are i.i.d. and non-degenerate, the regret can be improved to  $\tilde{O}(d\sqrt{T} + \epsilon^{-2}d^2 \ln^{10}(\delta^{-1}))$ 
  - Completely matches  $\tilde{O}(d\sqrt{T})$  in the dominating term.



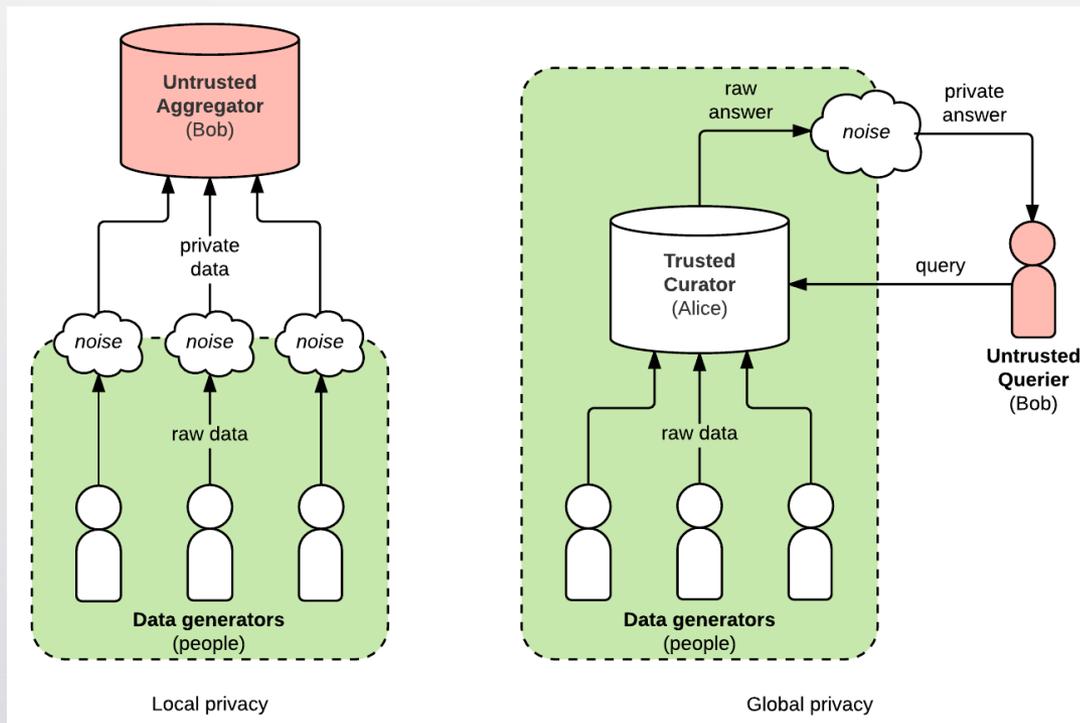
# Numerical results

Average regret, with  $\delta = 1/T^2$  and changing  $T$

Additional results available in the paper

# Future directions

- **Centralized (global) privacy** vs. **Local privacy**



Key question:  
Do I (as users) trust the *outside queriers (other users)*, or the *data curator (the company)*, or neither?



## Future directions

- **Centralized (global) privacy** vs. **Local privacy**
- For **local privacy**, the users do **not** trust the company and requires their profiles  $\{x_t\}$  to be anonymized *first* before storing at the company's database.
- Idea: first-order methods with perturbed gradients

$$x_t, y_t \Rightarrow g_t = \nabla_{\theta} \log P(y_t, x_t; \hat{\theta}_{t-1}) \Rightarrow \tilde{g}_t = g_t + \xi$$



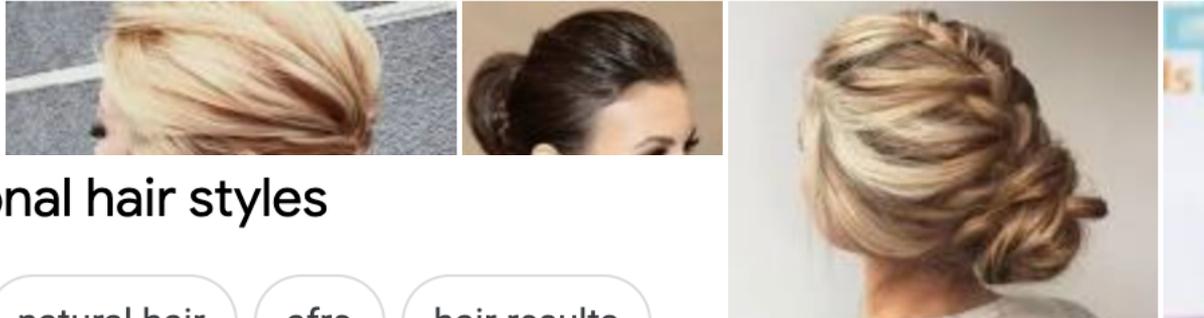
# Future directions

- **Data privacy** vs. **Decision fairness**
- **Data privacy** requires the platform to avoid privacy leakage of users' data, through data storage or revenue decisions.
- **Decision fairness**, on the other hand, requires the firm to *not discriminate against* users inadvertently with their personalized data.

# Decision fa

## Images for professional hair styles

long hair female short job interview



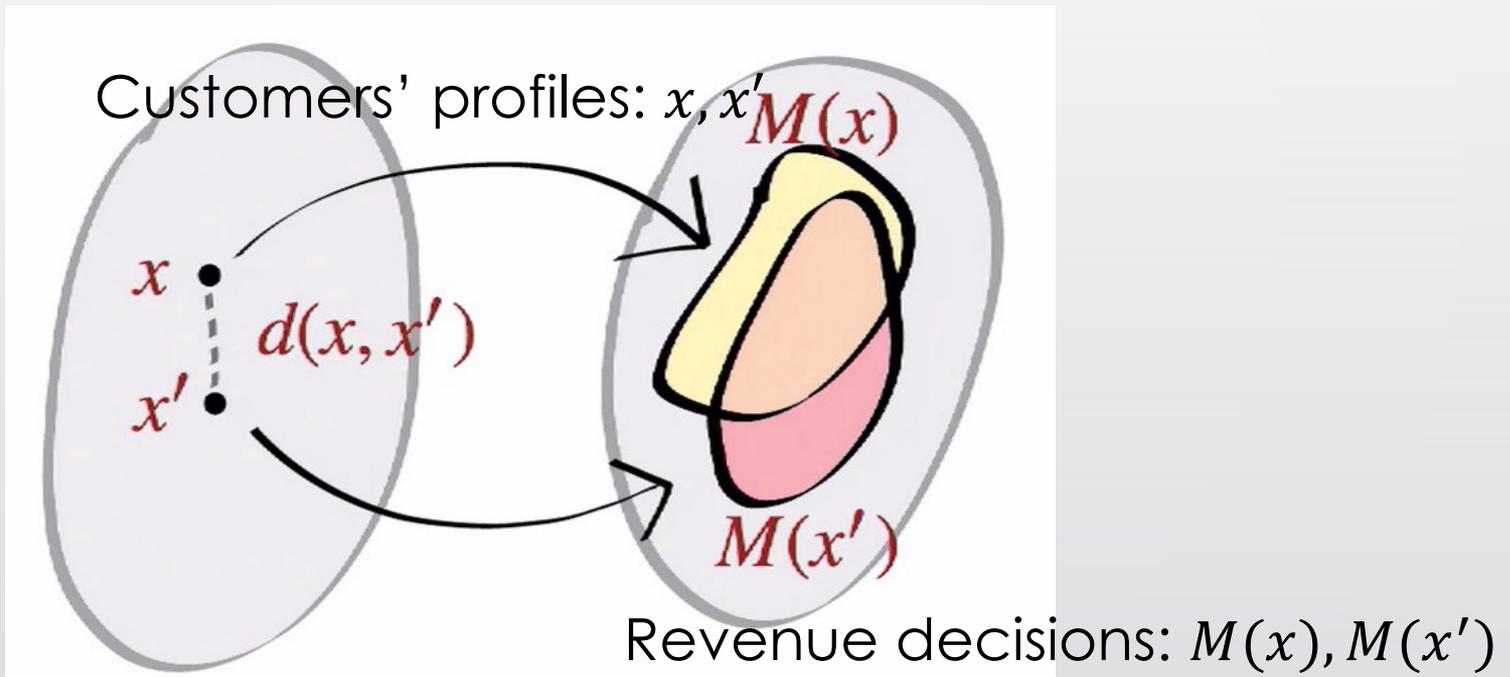
## Images for unprofessional hair styles

google unprofessional black natural hair afro hair results



# Decision fairness

- “Individual fairness” or “Meritocratic fairness”.





# Decision fairness

- “**Individual fairness**” or “**Meritocratic fairness**”.
- “**Group fairness**”: many times, fairness across user groups is more important/visible.

	WHITE	AFRICAN AMERICAN
Labeled Higher Risk, But Didn't Re-Offend	23.5%	44.9%
Labeled Lower Risk, Yet Did Re-Offend	47.7%	28.0%

*Overall, Northpointe's assessment tool correctly predicts recidivism 61 percent of the time. But blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend. It makes the opposite mistake among whites: They are much more likely than blacks to be labeled lower risk but go on to commit other crimes. (Source: ProPublica analysis of data from Broward County, Fla.)*



## Decision fairness

- Suppose users come from  $K$  **sensitive groups**, which are observable to the firm (racial, financial, demographical, etc.)
- The revenue decisions are required to solicit similar **average demands** across all **sensitive groups**.

# Group fairness in personalized pricing

- Customer has profile  $x \in X$ , belongs to group  $k$ 
  - Finite profile set  $|X| < \infty$ ;
  - Personalized price decision  $p_t: X \rightarrow [\underline{p}, \bar{p}]$ ;
- Revenue maximization with fairness constraints:

Distrb. Of profiles for ALL consumers

$$\bar{G} = \frac{1}{K} \sum_{k=1}^K \pi_k G_k$$

$$\max E_{x \sim \bar{G}} [p_t(x) D(p_t(x))]$$

Discrepancy between sensitive groups  $\forall k \neq k'$

$$s. t. \quad \left| E_{x \sim G_k} [D(p_t(x))] - E_{x \sim G_{k'}} [D(p_t(x))] \right| \leq \varepsilon$$



# Group fairness in personalized pricing

- Customer has profile  $x \in X$ , belongs to group  $k$ 
  - Finite profile set  $|X| < \infty$ ;
  - Personalized price decision  $p_t: X \rightarrow [\underline{p}, \bar{p}]$ ;
- Revenue maximization with fairness constraints:

$$\begin{aligned} & \max E_{x \sim \bar{G}} [p_t(x) D(p_t(x))] \\ & \text{s. t.} \quad \left| E_{x \sim G_k} [D(p_t(x))] - E_{x \sim G_{k'}} [D(p_t(x))] \right| \leq \varepsilon \end{aligned}$$

- **Learning-While-Doing:**

- Replace  $D(\cdot)$  with  $\bar{D}_t$  (UCB) or  $\hat{D}_t \sim Q(\cdot | y_{<t})$  (TS)



Thank you!  
Questions?

# Personalized revenue management

- Example: **Booking.com** (hotel reservations)

The screenshot displays a user's profile and trip history on the Booking.com dashboard. The profile section for Yining Wang shows 43% completion with options to add a photo, location, and display name. The trip history section lists two completed trips: Charlotte (Jun 17 - Jun 18) at Holiday Inn Charlotte Airport and San Diego (Jan 1 - Jan 5) at Comfort Inn Gaslamp Convention Center.

My Dashboard Bookings Reviews Your trips

Yining Wang  
Edit your profile

43% complete

- + Add a Photo  
This is the first thing people see, so show them your best side!
- + Add Where You Live  
We'll fill this in for you the next time you book or leave a review.
- + Add a Display Name  
This can be updated as often as you want and is shown with your reviews.

**Charlotte**  
Jun 17 - Jun 18

 Holiday Inn Charlotte Airport  
Jun 17 - Jun 18 · 2 rooms · Charlotte  
Completed

**San Diego**  
Jan 1 - Jan 5

 Comfort Inn Gaslamp Convention Center  
Jan 1 - Jan 5 · San Diego  
Completed

Can we use the user's

- *home address*, or
- *past booking history*, to

1. **promote** certain hotels (destinations closer to the user's home address), or
2. **price** stays at differently (set high prices for high-end or frequent business travelers)



## Technical comment

- Why not perturb the user profiles  $x_t$  directly?
- Imagine a simple task of releasing the **sample**

**average** of  $x_1, \dots, x_n$ ,  $\bar{x} = (x_1 + \dots + x_n)/n$

- If I add noise first:  $\tilde{x}_i = x_i + \xi_i$ , and then report the average  $\hat{x}^1 = (\tilde{x}_1 + \dots + \tilde{x}_n)/n$ , we have that

$$|\hat{x}^1 - \bar{x}| = \tilde{O}(1/\varepsilon\sqrt{n})$$

- If I compute  $\bar{x} = (x_1 + \dots + x_n)/n$  first and then report  $\hat{x}^2 = \bar{x} + \bar{\xi}$ , then we have that

$$|\hat{x}^2 - \bar{x}| = \tilde{O}(1/\varepsilon n)$$



# Machine learning for revenue management

- Machine learning and big-data analytics
  - Supervised, unsupervised and semi-supervised learning
  - Active learning, online learning, design of experiments
  - Reinforcement learning and multi-agent learning
  - Deep learning and learning representations
  - Resource-constrained learning (communications, computations, privacy, fairness, etc.)
- Many of the above techniques can be adapted to solve challenges in data-driven revenue management!

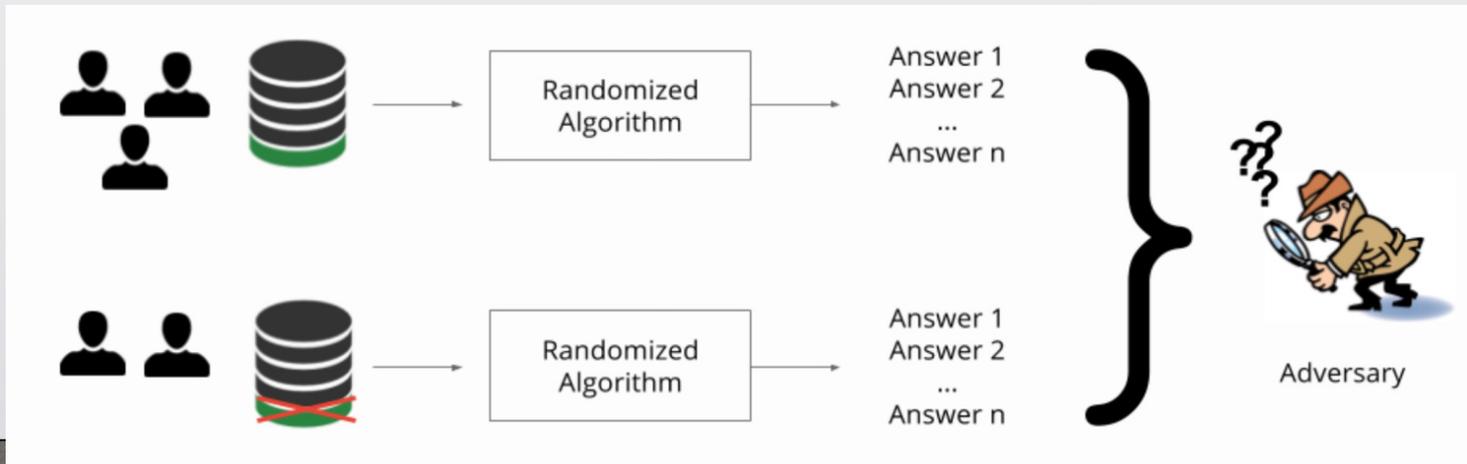
# Machine learning for revenue management

- **Question 1.** How to systematically incorporate personalized data to maximize revenue/profit performances as much as possible?
- *Applicable ML techniques:* **online and bandit learning**



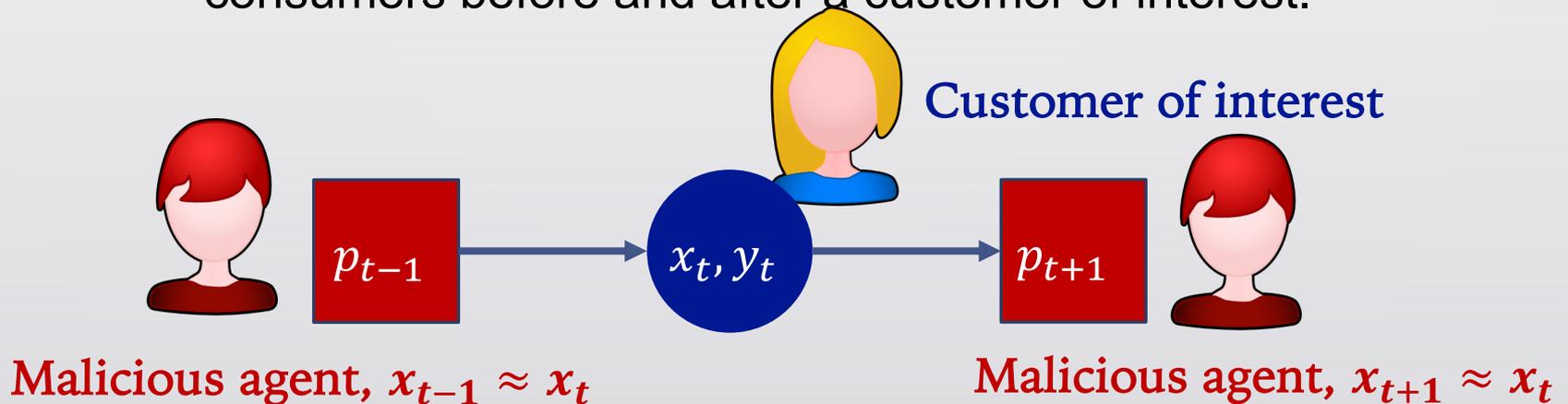
# Machine learning for revenue management

- **Question 2.** When using personalized data to make decisions, how to avoid inadvertently leaking private data of the users?
- *Applicable ML techniques:* **differential privacy**



# Concerns over privacy leakage

- **Example:** Privacy breach of customer profile  $x_t$ .
  - Most pricing systems post similar prices to consumers with similar profiles in the future (i.e., similar  $x_t$ )
  - A potential attack by a malicious agent: pretend as consumers before and after a customer of interest.



If the agents see similar prices  $p_{t-1} \approx p_{t+1}$ , it is more likely that the customer of interest has similar profiles.



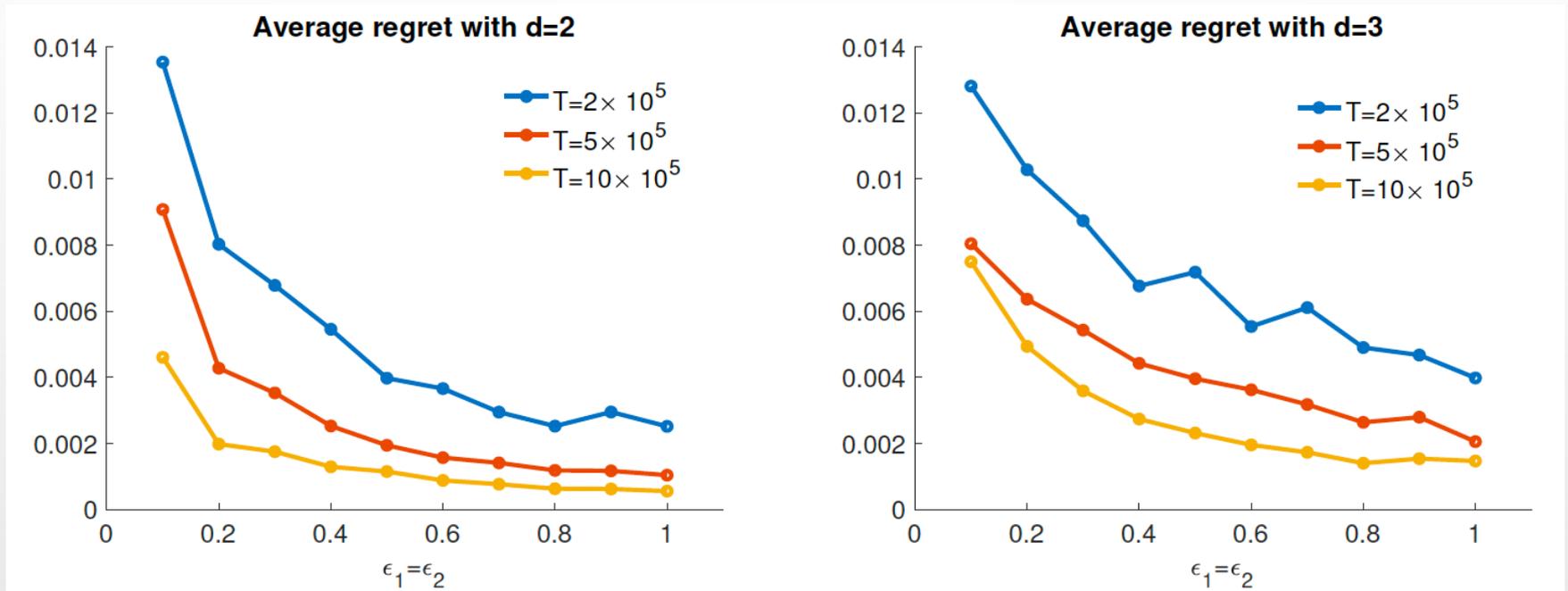
# Technical challenges

- **Challenge 1.** General demand models do not admit *sufficient statistics* like the linear regression.
  - Cannot directly apply [Shariff & Sheffet'18](#) which simply perturbs the sample covariance and average demand.
  - **Solution: privacy-aware maximum likelihood estimation with a concave/convex formulation**
  - Privacy analysis comes from [Kifer et al.'12](#), [Chaudhuri et al.'11](#), but utility/error analysis is re-done and novel.



# Technical challenges

- **Challenge 2.** the “curse of composition”:  
releasing too many statistics in DP formulation.
  - Cannot update demand model **after every customer**. That leaks too much privacy through composition.
  - **Solution: infrequent private model updates, with private protocols signaling updates as well.**
  - Ideas drawn from non-private low-switching policies [Abbasi-Yadkori et al.’11](#) and private protocols for sample covariance and sequence releases. [Dwork et al.’10, 14](#), [Chan et al.’11](#)



# Numerical results

Average regret, with  $\delta = 1/T^2$  and changing  $\epsilon$