Quantifying Differential Privacy under Temporal Correlations

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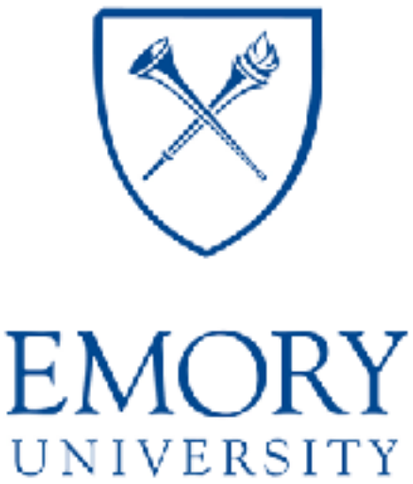
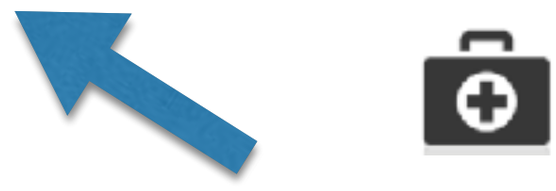


Outline

- What is Differential Privacy (DP)?
- What is Problem of DP under Temporal Correlations?
  - unexpected privacy loss
- How to solve this?
  - we **analyze**, **calculate** and **prevent** such privacy loss
- Experiments

Privacy Preserving Data Release

Company



Institute

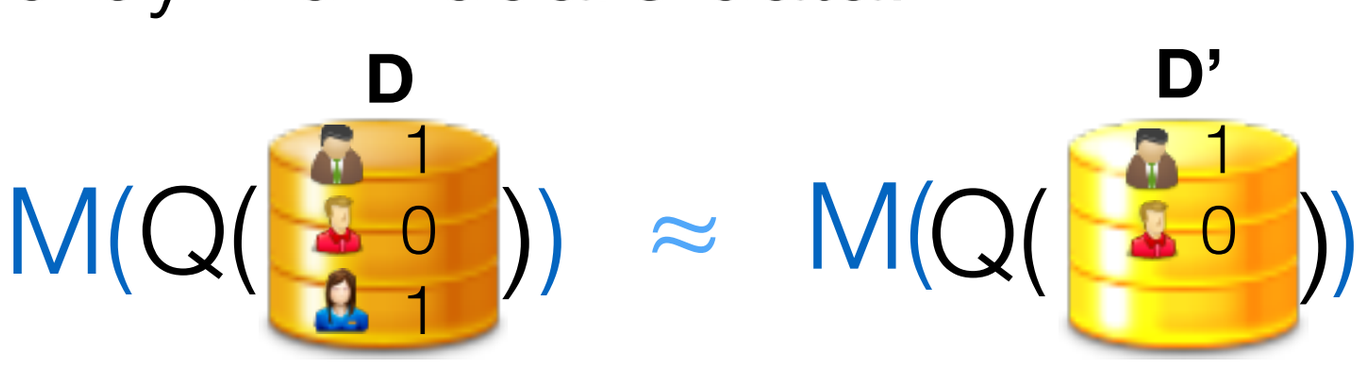
sensitive
database D

Public

Attacker

What is Differential Privacy

- Privacy: the right to be forgotten.
- DP: output of an algorithm should not be significantly affected by individual's data.



- Formally, M satisfies ε-DP if…

$$\log \frac{\Pr(M(Q(D)) = r)}{\Pr(M(Q(D')) = r)} \leq \varepsilon$$

ε ⬆️, privacy ⬇️.
e.g. **2ε**-DP means **more privacy loss** than **ε**-DP.

- e.g., Laplace mechanism: add Lap(1/ε) noise to Q(D)
- Sequential Composition. e.g., run **M** twice → **2ε**-DP

The Problem of DP under Temporal Correlation

- Our setting: *continuous data release with DP*

2ε-DP

ε-DP ~~ε-DP~~ ε-DP

r^1 r^2 r^3 …

D^1 D^2 D^3 …

t=	1	2	3	…
u1	loc_3	loc_1	loc_1	…
u2	loc_2	loc_4	loc_5	…
u3	loc_2	loc_4	loc_5	…
u4	loc_4	loc_5	loc_3	…

(a) Location Data

Count Query

t=	1	2	3	..
loc1	0	2	2	..
loc2	2	0	0	..
loc3	1	0	1	..
loc4	1	2	0	..
loc5	0	1	2	..

(b) True Counts

Laplace Noise

Lap(1/ε)

t=	1	2	3	..
loc1	0	1	3	..
loc2	3	1	0	..
loc3	1	0	1	..
loc4	2	1	0	..
loc5	1	3	3	..

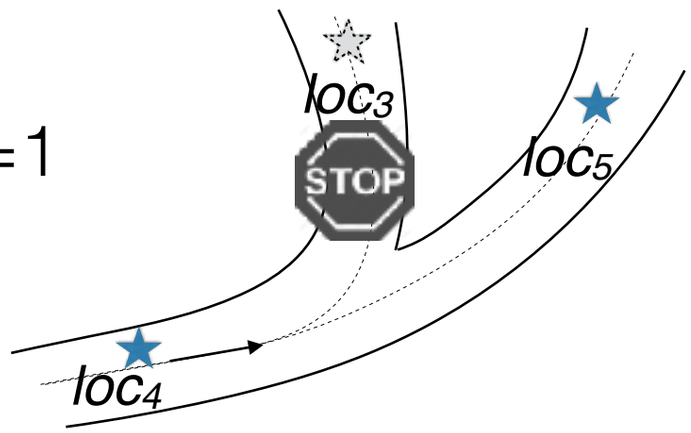
(c) Private Counts

- Temporal correlations degrade the privacy guarantee!

$Pr(l^t=loc_5 \mid l^{t-1}=loc_4)=1$

↓

2ε-DP at time 2



Road Network

$Pr(l^t=loc_5 \mid l^{t-1}=loc_4)=0.5$

↓

?-DP at time 2

Related work

- This scenario, ***continuous data release with DP,*** has been extensively studied for different issues:
  - high dimension[5][6][13],sliding window queries[7][8],infinite stream data[12], real-time publishing[11]
    - but none of them considered the effect of temporal correlations on privacy loss.
- Few works studied **potential privacy loss of DP on correlated** data, but no study investigated “DP under temporal correlations”.
  - Group DP[1][2] — not finely
  - Bayesian DP[4] ,Wasserstein Mechanism[16] — static database

Our contributions

We satisfy DP on temporally correlated data by …

- Analyzing Temporal Privacy Leakage (TPL).
  ⇒ the privacy loss may increase over time!

- Calculating TPL
  ⇒ Linear-Fractional Programing

  Simplex Algorithm: $O(2^n)$

  Our Algorithm: $O(n^2)$

- Preventing TPL
  ⇒ by carefully calibrating ε at each time point

Analyzing TPL

Model Attacker → **Define TPL** → **Find structure of TPL**

- Model temporal correlations using **Markov Chain**

e.g., user **i** : $loc_1 \rightarrow loc_3 \rightarrow loc_2 \rightarrow \ldots$

(a) Transition Matrix $\Pr(l_i^{t-1} | l_i^t)$

time t-1

time t	loc_1	loc_2	loc_3
loc_1	0.1	0.2	**0.7**
loc_2	0	0	1
loc_3	0.3	0.3	0.4

Backward Temporal Correlation P_i^B

(b) Transition Matrix $\Pr(l_i^t | l_i^{t-1})$

time t

time t-1	loc_1	loc_2	loc_3
loc_1	0.2	0.3	0.5
loc_2	0.1	0.1	0.8
loc_3	**0.6**	0.2	0.2

Forward Temporal Correlation P_i^F

Analyzing TPL

Model Attacker → **Define TPL** → **Find structure of TPL**

- DP can protect against the attacker with knowledge of all tuples except the one of victim + Temporal Correlation ?

D

t=	1
u1	? loc_3
u2	loc_2
u3	loc_2
u4	loc_4

l_i

D_K

$A_i(D_{\mathcal{K}})$

$A_i^{\mathcal{T}}(D_{\mathcal{K}}, P_i^B, P_i^F)$

(i) $A_i^{\mathrm{T}}(D_{\mathrm{K}}, P_i^B, \varnothing)$

(ii) $A_i^{\mathrm{T}}(D_{\mathrm{K}}, \varnothing, P_i^F)$

(iii) $A_i^{\mathrm{T}}(D_{\mathrm{K}}, P_i^B, P_i^F)$

Analyzing TPL

Model Attacker → **Define TPL** → **Find structure of TPL**

- Recall the definition of DP:

$$PL_0(\mathcal{M}) \overset{\text{def}}{=\!=} \max_{\forall A_i, i \in \boldsymbol{U}} PL_0(A_i, \mathcal{M}) = \sup_{\boldsymbol{r}, D, D'} \log \frac{\Pr(\boldsymbol{r}|D)}{\Pr(\boldsymbol{r}|D')}$$

if $PL_0(\mathcal{M}) \leq \varepsilon$, then $\mathcal{M}$ satisfies ε-DP.

- Definition of TPL:

$$TPL(A_i^{\mathcal{T}}, \mathcal{M}^t) \overset{\text{def}}{=\!=} \sup_{l^t, l_i^{t\prime}, \boldsymbol{r}^1, \ldots, \boldsymbol{r}^T} \log \frac{\Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^T | l_i^t, D_{\mathcal{K}}^t)}{\Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^T | l_i^{t\prime}, D_{\mathcal{K}}^t)}. \quad (2)$$

$$TPL(\mathcal{M}^t) \overset{\text{def}}{=\!=} \max_{\forall A_i^{\mathcal{T}}, i \in \boldsymbol{U}} TPL(A_i^{\mathcal{T}}, \mathcal{M}^t) \quad (3)$$

$$= \sup_{D^t, D^{t\prime}, \boldsymbol{r}^1, \ldots, \boldsymbol{r}^T} \log \frac{\Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^T | D^t)}{\Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^T | D^{t\prime})}. \quad (4)$$

Analyzing TPL

Model Attacker → **Define TPL** → **Find structure of TPL**

- Definition of TPL:

$$TPL(A_i^{\mathcal{T}}, \mathcal{M}^t) \overset{\text{def}}{=\!=} \sup_{l^t, l_i^{t\prime}, \boldsymbol{r}^1, \ldots, \boldsymbol{r}^T} \log \frac{\Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^T | l_i^t, D_{\mathcal{K}}^t)}{\Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^T | l_i^{t\prime}, D_{\mathcal{K}}^t)}. \quad (2)$$

$$TPL(\mathcal{M}^t) \overset{\text{def}}{=\!=} \max_{\forall A_i^{\mathcal{T}}, i \in \boldsymbol{U}} TPL(A_i^{\mathcal{T}}, \mathcal{M}^t) \quad (3)$$

$$= \sup_{D^t, D^{t\prime}, r^1, \ldots, r^T} \log \frac{\Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^T | D^t)}{\Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^T | D^{t\prime})}. \quad (4)$$

- If no temporal correlation… **TPL = PL_0**

$$\text{Eqn(2)} = \underbrace{\log \frac{\Pr(r^1 | l_i^t, D_k{}^t)}{\Pr(r^1 | l_i^{t'}, D_k{}^t)}}_{0} + \ldots + \underbrace{\log \frac{\Pr(r^t | l_i^t, D_k{}^t)}{\Pr(r^t | l_i^{t'}, D_k{}^t)}}_{PL_0} + \ldots + \underbrace{\log \frac{\Pr(r^T | l_i^t, D_k{}^t)}{\Pr(r^T | l_i^{t'}, D_k{}^t)}}_{0}$$

Analyzing TPL

Model Attacker → **Define TPL** → **Find structure of TPL**

- Definition of TPL:

$$TPL(A_i^{\mathcal{T}}, \mathcal{M}^t) \overset{\text{def}}{=\!=} \sup_{l^t, l_i^{t\prime}, \boldsymbol{r}^1, \ldots, \boldsymbol{r}^T} \log \frac{\Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^T | l_i^t, D_{\mathcal{K}}^t)}{\Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^T | l_i^{t\prime}, D_{\mathcal{K}}^t)}. \quad (2)$$

$$TPL(\mathcal{M}^t) \overset{\text{def}}{=\!=} \max_{\forall A_i^{\mathcal{T}}, i \in \boldsymbol{U}} TPL(A_i^{\mathcal{T}}, \mathcal{M}^t) \quad (3)$$

$$= \sup_{D^t, D^{t\prime}, \boldsymbol{r}^1, \ldots, \boldsymbol{r}^T} \log \frac{\Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^T | D^t)}{\Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^T | D^{t\prime})}. \quad (4)$$

- If with temporal correlation…**TPL = ?**

Hard to quantify Eqn(2)…

$$\text{Eqn(2)} = \underbrace{\log \frac{\Pr(r^1 | l_i^t, D_k^t)}{\Pr(r^1 | l_i^{t\prime}, D_k^t)}}_{?} + \ldots + \underbrace{\log \frac{\Pr(r^t | l_i^t, D_k^t)}{\Pr(r^t | l_i^{t\prime}, D_k^t)}}_{PL_0} + \ldots + \underbrace{\log \frac{\Pr(r^T | l_i^t, D_k^t)}{\Pr(r^T | l_i^{t\prime}, D_k^t)}}_{?}$$

Analyzing TPL

Model Attacker → **Define TPL** → **Find structure of TPL**

$$\text{Eqn.(2)} = \sup_{l^t, l_i^{t\prime}, \boldsymbol{r}^1, \ldots, \boldsymbol{r}^T} \log \frac{\Pr(\boldsymbol{r}^1 | l_i^t, D_{\mathcal{K}}^t)}{\Pr(\boldsymbol{r}^1 | l_i^t, D_{\mathcal{K}}^t)} * \cdots * \frac{\Pr(\boldsymbol{r}^T | l_i^t, D_{\mathcal{K}}^t)}{\Pr(\boldsymbol{r}^T | l_i^t, D_{\mathcal{K}}^t)}$$

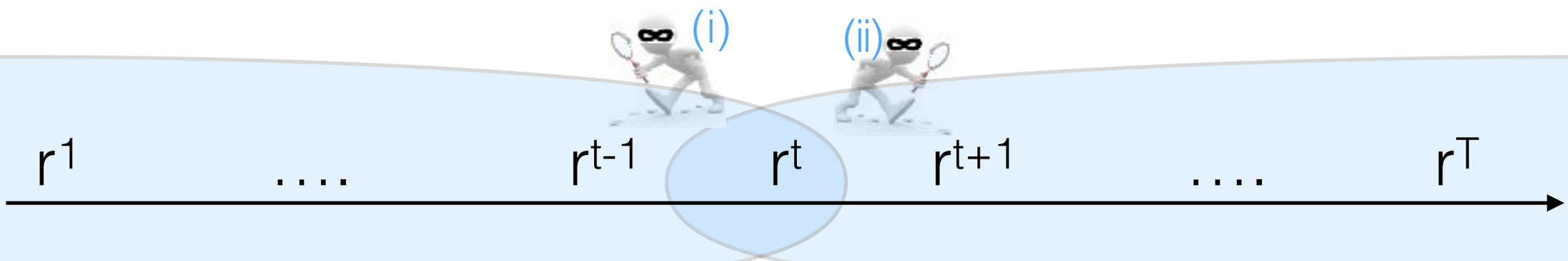
$$= \underbrace{\sup_{\substack{\boldsymbol{r}^1, \ldots, \boldsymbol{r}^t, \\ l_i, l_i'}} \log \frac{\Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^t | l_i^t, D_{\mathcal{K}}^t)}{\Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^t | l_i^t, D_{\mathcal{K}}^t)}}_{\text{(i) } A_i^{\mathrm{T}}(D_{\mathrm{K}}, P_i^B, \varnothing)} + \underbrace{\sup_{\substack{\boldsymbol{r}^t, \ldots, \boldsymbol{r}^T, \\ l_i, l_i'}} \log \frac{\Pr(\boldsymbol{r}^t, \ldots, \boldsymbol{r}^T | l_i^t, D_{\mathcal{K}}^t)}{\Pr(\boldsymbol{r}^t, \ldots, \boldsymbol{r}^T | l_i^t, D_{\mathcal{K}}^t)}}_{\text{(ii) } A_i^{\mathrm{T}}(D_{\mathrm{K}}, \varnothing, P_i^F)}$$

backward privacy leakage (BPL) | forward privacy leakage (FPL)

$$- \underbrace{\sup_{\boldsymbol{r}^t, l_i, l_i'} \log \frac{\Pr(\boldsymbol{r}^t | l_i^t, D_{\mathcal{K}}^t)}{\Pr(\boldsymbol{r}^t | l_i^t, D_{\mathcal{K}}^t)}}_{PL_0(A_i^{\mathcal{T}}, \mathcal{M}^t)} \tag{5}$$

(iii) $A_i^{\mathrm{T}}(D_{\mathrm{K}}, P_i^B, P_i^F)$

$$\Rightarrow \quad TPL(A_i^{\mathcal{T}}, \mathcal{M}^t) = BPL(A_i^{\mathcal{T}}, \mathcal{M}^t) + FPL(A_i^{\mathcal{T}}, \mathcal{M}^t) - PL_0(A_i^{\mathcal{T}}, \mathcal{M}^t). \tag{10}$$



Analyzing TPL

BPL

Model Attacker → **Define TPL** → **Find structure of TPL**

$$BPL(A_i^{\mathcal{T}}, \mathcal{M}^t) \overset{\text{def}}{=\!=} \sup_{l_i^t, l_i^{t\prime}, \boldsymbol{r}^1, \ldots, \boldsymbol{r}^t} \log \frac{\Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^t | l_i^t, D_{\mathcal{K}}^t)}{\Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^t | l_i^{t\prime}, D_{\mathcal{K}}^t)}. \quad (6)$$

- Analyze BPL

Backward *temporal correlations*

Eqn(6)=

$$\sup_{\substack{l_i^t, l_i^{t\prime}, \\ \boldsymbol{r}^1, \ldots, \boldsymbol{r}^{t-1}}} \log \frac{\sum_{l_i^{t-1}} \underbrace{\Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^{t-1} | l_i^{t-1}, D_{\mathcal{K}}^{t-1})}_{(i) BPL(A_i^{\mathcal{T}}, \mathcal{M}^{t-1})} \underbrace{\Pr(l_i^{t-1} | l_i^t)}_{(ii) P_i^B}}{\sum_{l_i^{t-1\prime}} \Pr(\boldsymbol{r}^1, \ldots, \boldsymbol{r}^{t-1} | l_i^{t-1\prime}, D_{\mathcal{K}}^{t-1}) \Pr(l_i^{t-1\prime} | l_i^{t\prime})}$$

$$+ \sup_{l_i^t, l_i^{t\prime}, \boldsymbol{r}^t} \log \underbrace{\frac{\Pr(\boldsymbol{r}^t | l_i^t, D_{\mathcal{K}}^t)}{\Pr(\boldsymbol{r}^t | l_i^{t\prime}, D_{\mathcal{K}}^t)}}_{(iii) PL_0(A_i^{\mathcal{T}}, \mathcal{M}^t)}. \quad (12)$$

Backward privacy loss function.
how to calculate it?

$$\Rightarrow \quad BPL(A_i^{\mathcal{T}}, \mathcal{M}^t) = \mathcal{L}^B\big(BPL(A_i^{\mathcal{T}}, \mathcal{M}^{t-1})\big) + PL_0(A_i, \mathcal{M}^t) \quad (13)$$

Analyzing TPL

FPL

Model Attacker → **Define TPL** → **Find structure of TPL**

$$FPL(A_i^{\mathcal{T}}, \mathcal{M}^t) \overset{\text{def}}{=\!=} \sup_{l_i^t, l_i^{t\prime}, \boldsymbol{r}^t, \ldots, \boldsymbol{r}^T} \log \frac{\Pr(\boldsymbol{r}^t, \ldots, \boldsymbol{r}^T | l_i^t, D_{\mathcal{K}}^t)}{\Pr(\boldsymbol{r}^t, \ldots, \boldsymbol{r}^T | l_i^{t\prime}, D_{\mathcal{K}}^t)}. \quad (8)$$

- Analyze FPL

Forward *temporal correlations*

$$\sup_{\substack{l_i^t, l_i^{t\prime}, \\ \boldsymbol{r}^{t+1}, \ldots, \boldsymbol{r}^T}} \log \frac{\sum_{l_i^{t+1}} \underbrace{\Pr(\boldsymbol{r}^{t+1}, \ldots, \boldsymbol{r}^T | l_i^{t+1}, D_{\mathcal{K}}^{t+1})}_{(i)FPL(A_i^{\mathcal{T}}, \mathcal{M}^{t+1})} \underbrace{\Pr(l_i^{t+1} | l_i^t)}_{(ii)P_i^F}}{\sum_{l_i^{t+1\prime}} \Pr(\boldsymbol{r}^{t+1}, \ldots, \boldsymbol{r}^T | l_i^{t+1\prime}, D_{\mathcal{K}}^{t+1}) \Pr(l_i^{t+1\prime} | l_i^{t\prime})}$$

$$+ \sup_{l_i^t, l_i^{t\prime}, \boldsymbol{r}^t} \log \underbrace{\frac{\Pr(\boldsymbol{r}^t | l_i^t, D_{\mathcal{K}}^t)}{\Pr(\boldsymbol{r}^t | l_i^{t\prime}, D_{\mathcal{K}}^t)}}_{(iii)PL_0(A_i^{\mathcal{T}}, \mathcal{M}^t)}.$$

Forward *privacy loss function.*
how to calculate it?

$$\Rightarrow \quad FPL(A_i^{\mathcal{T}}, \mathcal{M}^t) = \mathcal{L}^F\left(FPL(A_i^{\mathcal{T}}, \mathcal{M}^{t+1})\right) + PL_0(A_i, \mathcal{M}^t) \quad (15)$$

Calculating BPL & FPL

Privacy Quantification → Upper bound

- We convert the problem of BPL/FPL calculation to **finding an optimal solution of a linear-fractional programming problem.**

$$\mathcal{L}^B\left(BPL(A_i^{\mathcal{T}}, \mathcal{M}^{t-1})\right) = \sup_{\boldsymbol{q},\boldsymbol{d}\in P_i^B} \log \frac{q_1 x_1 + \cdots + q_n x_n}{d_1 x_1 + \cdots + d_n x_n}$$

$$= \sup_{\boldsymbol{q},\boldsymbol{d}\in P_i^B} \log \frac{\boldsymbol{qx}}{\boldsymbol{dx}}$$

$$\text{maximize} \quad \frac{\boldsymbol{qx}}{\boldsymbol{dx}} \tag{18}$$

$$\text{subject to} \quad e^{-\alpha_{t-1}^B} \leq \frac{x_j}{x_k} \leq e^{\alpha_{t-1}^B}, \tag{19}$$

$$0 < x_j < 1 \text{ and } 0 < x_k < 1, \tag{20}$$

$$\text{where } x_j, x_k \in \boldsymbol{x},\ j, k \in [1, n].$$

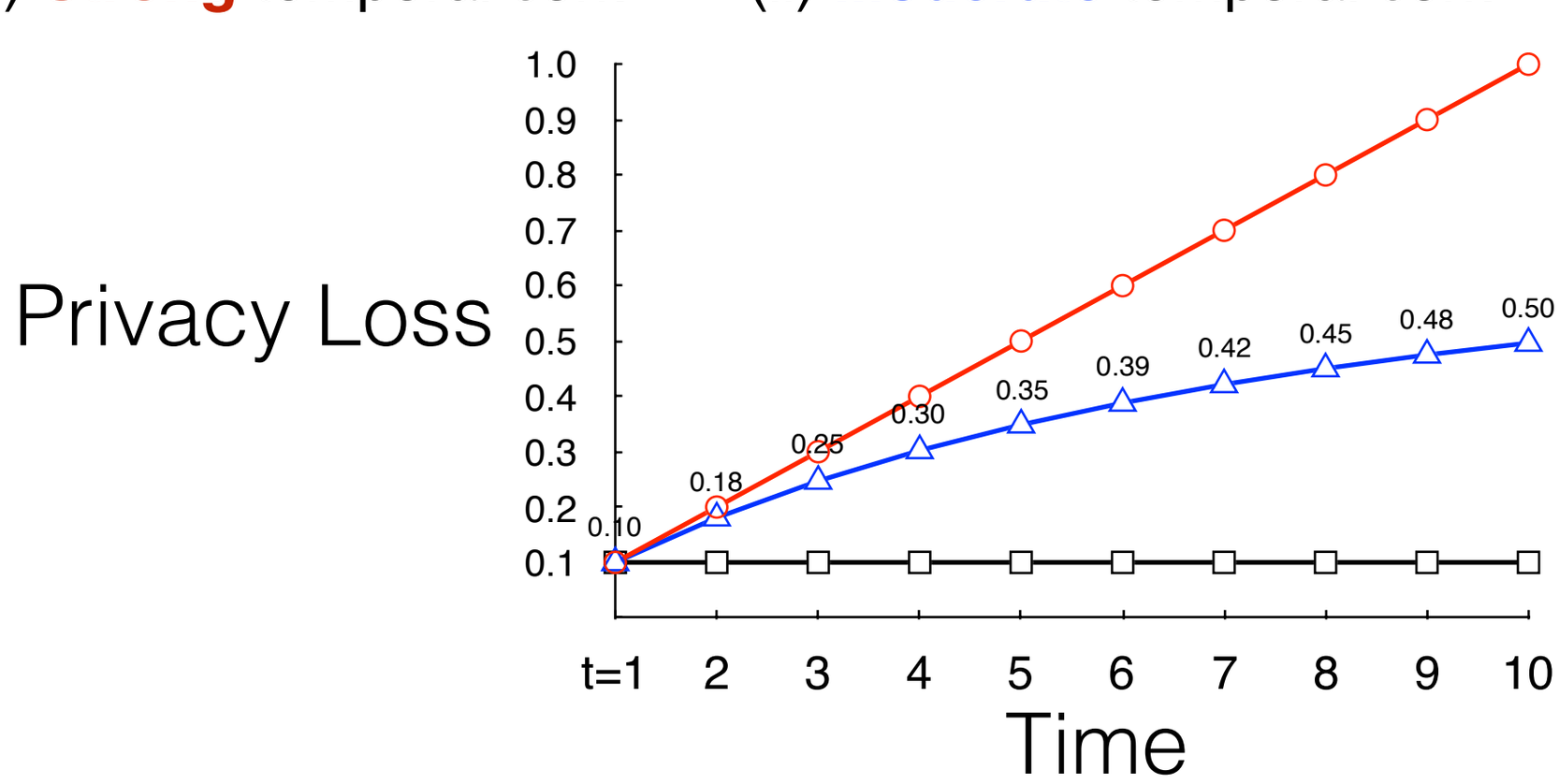
- This problem can be solved by simplex algorithm in $O(2^n)$.
- We designed a $O(n^2)$ algorithm for quantifying BPL/FPL.

Calculating BPL & FPL

Privacy Quantification → Upper bound

- Example of **BPL** under different temporal corr.

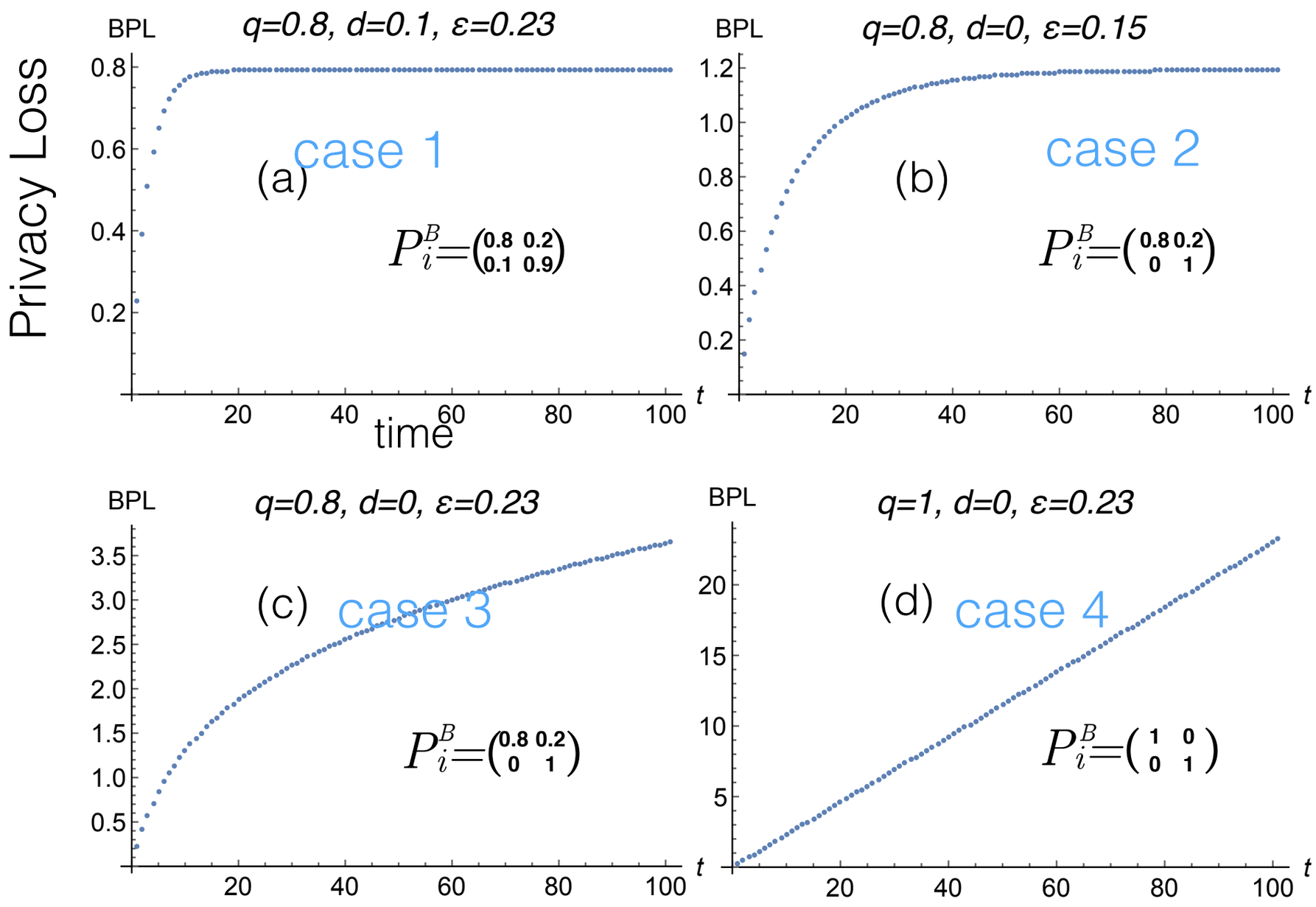
(i) **Strong** temporal corr. (ii) **Moderate** temporal corr. (iii) **No** temporal corr.



$$\Rightarrow \quad TPL(A_i^{\mathcal{T}}, \mathcal{M}^t) = BPL(A_i^{\mathcal{T}}, \mathcal{M}^t) + FPL(A_i^{\mathcal{T}}, \mathcal{M}^t) - PL_0(A_i^{\mathcal{T}}, \mathcal{M}^t). \qquad (10)$$

Calculating BPL & FPL

Privacy Quantification → Upper bound

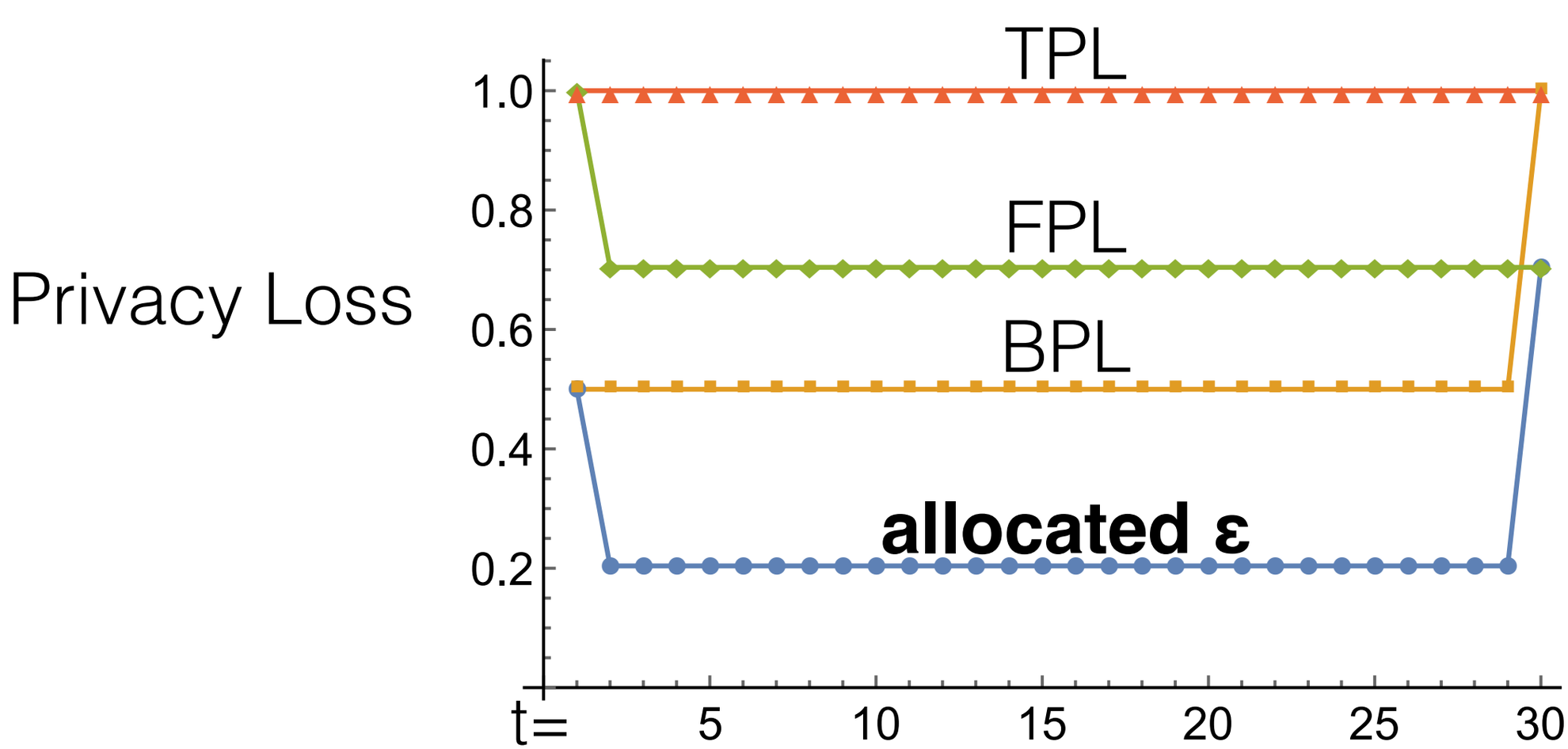


Refer to **Theorem 5** in our paper

Preventing BPL & FPL

by Quantification → **by Upper Bound**

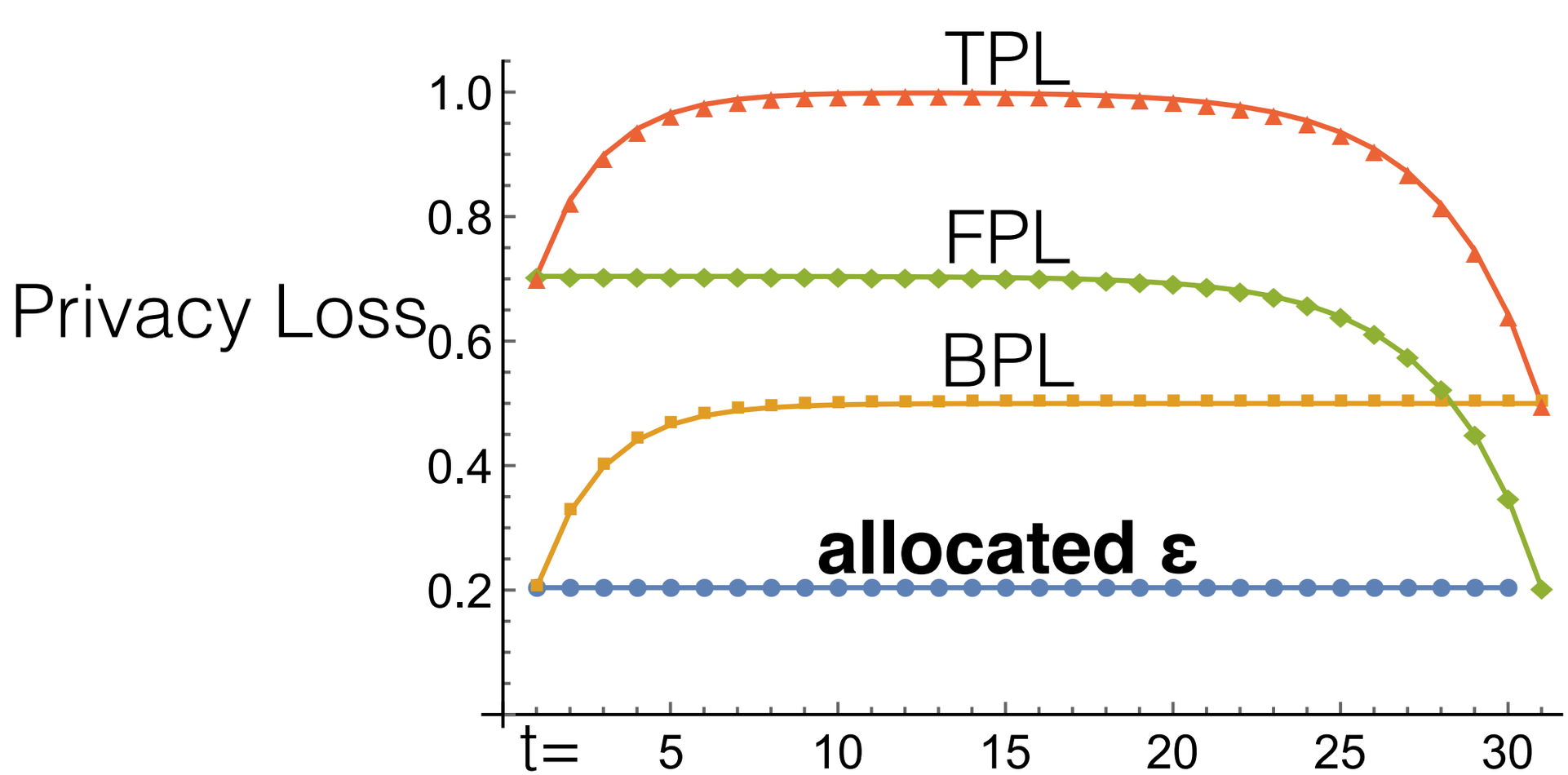
- If T is known, we can assign proper ε at each t,
  to make sure that TPL always equal to a specific value.



Preventing BPL & FPL

by Quantification → **by Upper Bound**

- If T is unknown, we can assign proper ε at each t, to make sure that TPL never exceeds a specific value.



Experiments

- Goals
  - (1) Runtime of privacy quantification algorithm
  - (2) Impact of temporal correlations on privacy
- Synthetic datasets
  - Generate transition matrix randomly.
  - Generate the strongest temporal correlation $P_i=\begin{pmatrix}1 & 0\\ 0 & 1\end{pmatrix}$
  - Uniformize the strongest temporal correlation by Laplace smoothing:

$$\hat{p_{jk}} = \frac{p_{jk} + s}{\sum_{u=1}^{n} (p_{ju} + s)} \qquad (25)$$

A smaller **s** results in a stronger temporal correlation.

e.g., s=0 $P_i=\begin{pmatrix}1 & 0\\ 0 & 1\end{pmatrix}$

e.g., s=0.1 $P_i=\begin{pmatrix}0.92 & 0.08\\ 0.08 & 0.92\end{pmatrix}$

e.g., s=0.5 $P_i=\begin{pmatrix}0.75 & 0.25\\ 0.25 & 0.75\end{pmatrix}$

Runtime Evaluation

- **lp_solve** and **Gurobi** are two well-known software for solving optimization problems (e.g., Linear-Fractional Program in our setting)

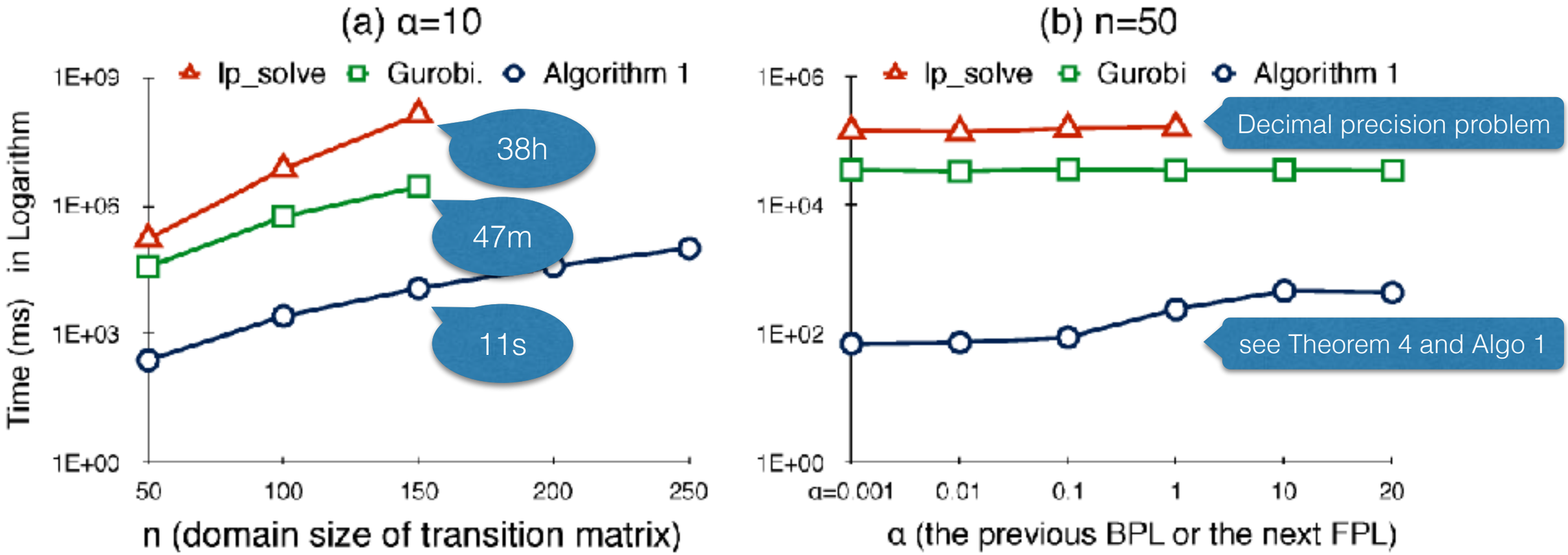


Fig. 5: Runtime of Privacy Quantification Algorithms.

Impact of Temporal Corr. on Privacy Leakage

- temporal correlation ⬆️ (s ⬇️), privacy leakage ⬆️
- ε significantly delayed the growth of privacy leakage
- value domain n ⬆️, privacy leakage ⬇️

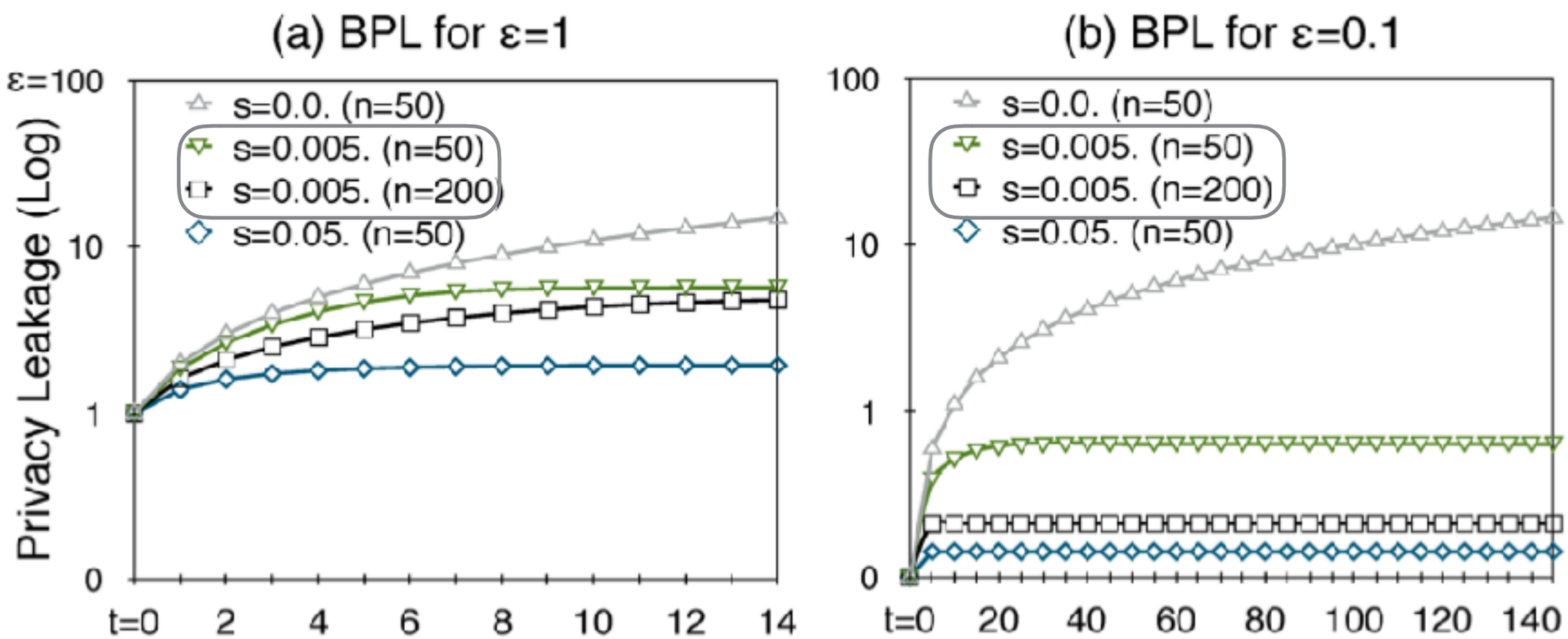


Fig. 6: Evaluation of BPL.

Future work

- **Applications**

- Convert a traditional DP mechanism into one prevent against TPL under temporal correlations.
- Using our new sequential composition theorem, to Design complicated algorithms against TPL

- **Extensions**

- How to learn appropriate temporal correlations?
- How to model/quantify DP under other types of correlations?
- Is there a better way to prevent TPL (e.g., utilize temporal corr.)?

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Thank you!

Calculating BPL & FPL

Privacy Quantification → Upper bound

- Example of BPL/FPL/TPL under different temporal corr.

(i) **Strong** temporal corr. (ii) **Moderate** temporal corr. (iii) **No** temporal corr.