

# Design and Analysis of Panel Data Experiments

Ruoxuan Xiong

Emory University

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[Optimal experimental design for staggered rollouts](#) with Susan Athey, Mohsen Bayati, Guido Imbens (XABI'19)

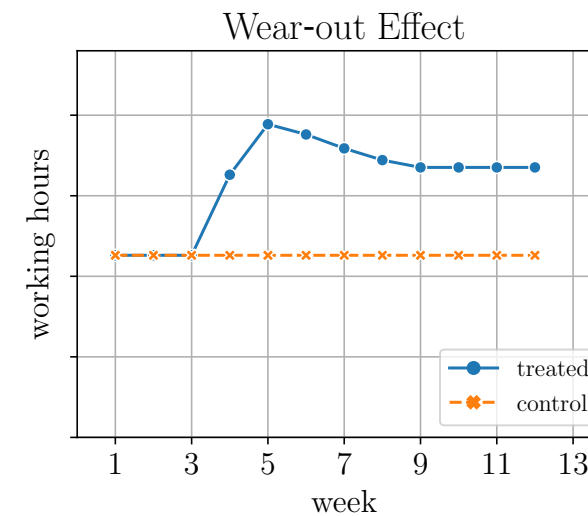
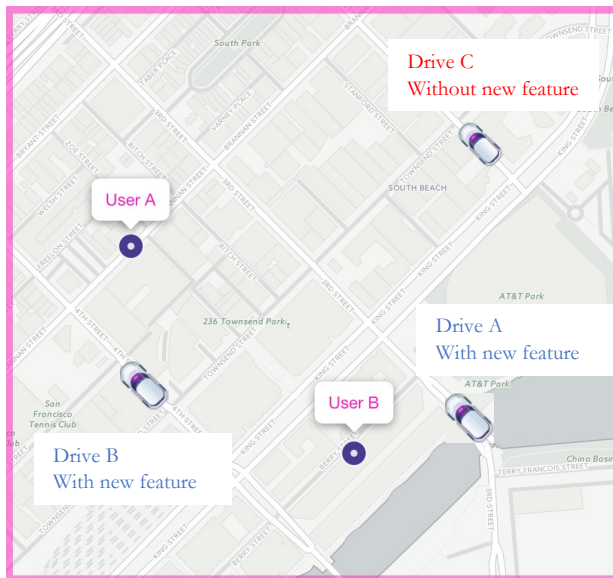
[Bias-variance tradeoffs for designing simultaneous temporal experiments](#) with Alex Chin, Sean Taylor, Susan Athey (XCTA'22)



# Example: Marketplace experiments

A ridesharing platform tests an app feature to improve driver experience

- Conventional A/B testing suffers from network or contamination effect
- The impact of the feature may fade over time



# Two key challenges

1. **Interference** and network effects
2. **Carryover** effects (instantaneous and lagged effects)

Panel data experiments can help  
addressing **both** challenges



# Panel data experiments

- Run an experiment on  $N$  units (e.g. cities) for  $T$  time periods (e.g. days, weeks)
  - Repeated treatment decisions for the same  $N$  units
  - Repeated observations on the same  $N$  units

	day 1	day 2	day 3	day 4
NY	Control	Control	Treatment	Treatment
SF	Treatment	Treatment	Treatment	Treatment
ATL	Control	Treatment	Treatment	Treatment
:				

- Three main advantages

- Increase sample size
- Allow for heterogeneity in unit means and common time shocks
- Study the impact of sustaining treatment over multiple periods



# Treatment allocation schemes

## Switchback experiments

	day 1	day 2	day 3	day 4
NY	Treatment	Treatment	Control	Control
SF	Treatment	Control	Control	Treatment
ATL	Control	Treatment	Control	Treatment
:				

**Pro:** Flexible

**Con:** Some practical constraints to switch back

[Bojinov, Simchi-Levi, Zhao'20]

## Irreversible treatment adoption experiments

	day 1	day 2	day 3	day 4
NY	Control	Control	Treatment	Treatment
SF	Treatment	Treatment	Treatment	Treatment
ATL	Control	Treatment	Treatment	Treatment
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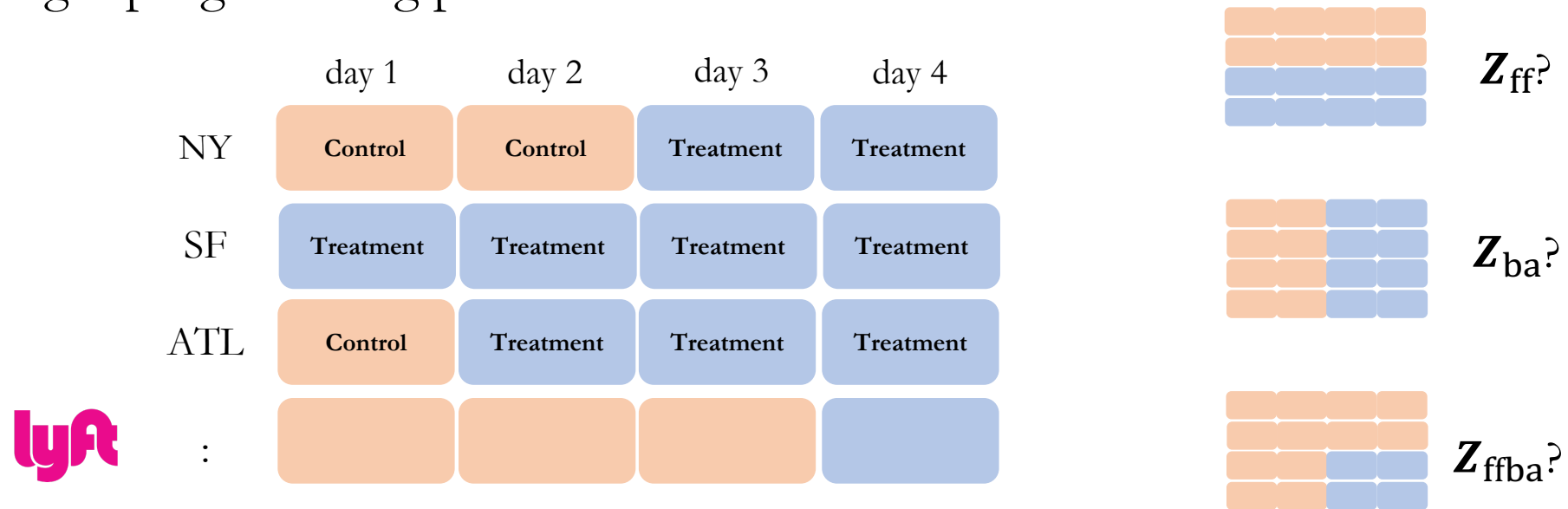
*Simultaneous* or *staggered* adoption pattern

Optimal design is a challenging problem!

[Hussey and Hughes'07, Hemming et al.'15, Li, Turner and Preisser'18]

# Decision making problem

- **Objective:** Most **precisely** estimate instantaneous and lagged effects
  - Can reduce sample size requirement and experimental cost!
- **Decision variables:** Optimally choose the **treatment times** for each unit
  - Integer programming problem



# Fixed-sample-size experiments

- $N$  and  $T$  are set pre-experiment
- Consider a flexible outcome model
  - Nonstationarity and heterogeneity

$$Y_{it}(Z) = \alpha_i + \beta_t + X_i^\top \cdot \theta_t + U_i^\top \cdot V_t + \tau_0 \cdot Z_{it} + \tau_1 \cdot Z_{i,t-1} + \dots + \tau_\ell \cdot Z_{i,t-\ell} + \varepsilon_{it}$$

Two-way fixed effects  
(**unknown**)

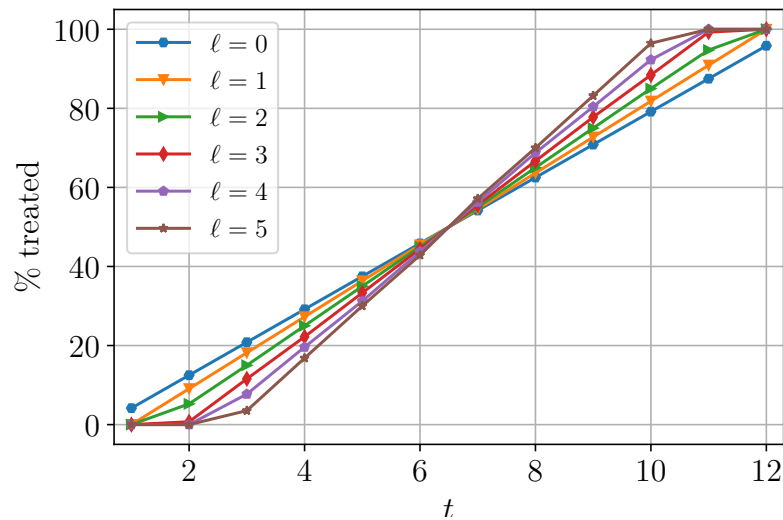
Observed and latent covariates  
with **unknown** time-varying  
coefficients

Binary treatment variables with  
**unknown** treatment effect parameters

- Formulate an integer program to solve  $Z$  that maximizes the estimation precision of instantaneous effect  $\hat{\tau}_0$  and lagged effects  $\hat{\tau}_1, \dots, \hat{\tau}_\ell$ , post-experiment

# Optimality conditions and choosing a design

- Provide the **optimal conditions** for the integer program [XABI'19]
  - Optimal treated fraction at every time period
  - Covariate conditions
- Develop an algorithm to choose a design with **provably guarantee** to the optimal integer solution (within  $1 + O(1/N^2)$ ) [XABI'19]



Optimal treated fraction for a 12-period experiment

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Algorithm 2: Choose a treatment design for each stratum  $g$

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1 Inputs:  $|\mathcal{O}_g|, \{\omega_{i,t}^*\}_{i \in [T]}$ 
2 for  $t = 1, \dots, T$  do
3   if  $\text{frac}(\frac{|\mathcal{O}_g| \cdot (1 + \omega_{i,t}^*)}{2T}) < \frac{1}{2}$  or  $\text{frac}(\frac{|\mathcal{O}_g| \cdot (1 + \omega_{i,t}^*)}{2T}) = \frac{1}{2}$  with  $\frac{1 + \omega_{i,t}^*}{2T} < \frac{1}{2}$  then
4      $N_{g,t} \leftarrow \lceil \frac{|\mathcal{O}_g| \cdot (1 + \omega_{i,t}^*)}{2T} \rceil$ ;
5   else
6      $N_{g,t} \leftarrow \lceil \frac{|\mathcal{O}_g| \cdot (1 + \omega_{i,t}^*)}{2T} \rceil$ ;
7   end
8   end
9    $f(\cdot) \leftarrow$  a random function that shuffles  $\{1, 2, \dots, |\mathcal{O}_g|\}$ ;
10   $Z_g \leftarrow [-1]^{|\mathcal{O}_g| \times T}$ ;
11  for  $i = 1, \dots, |\mathcal{O}_g|$  do
12    for  $t = 1, \dots, T$  do
13      if  $f(i) \leq N_{g,t}$  then
14         $z_{g,it} \leftarrow 1$ ;
15      else
16         $z_{g,it} \leftarrow -1$ ;
17      end
18    end
19  end
20 end
21 return  $Z_g$ ;

```

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# Sequential experiments

- $N$  is fixed and  $T$  varies (we can early stop the experiment)
- More flexible and cost-effective!
- Key challenges
  - Experiment **termination rule**
    - What is an appropriate rule and how to implement the rule
  - **Peeking** challenge [Johari, Koomen, Pekelis, Walsh'17]
    - Treatment effect estimation based by experiment termination rule
  - **Infeasibility to optimize** treatment times **pre-experiment**
    - Optimal solution depends on  $T$

# An initial stab at the problem

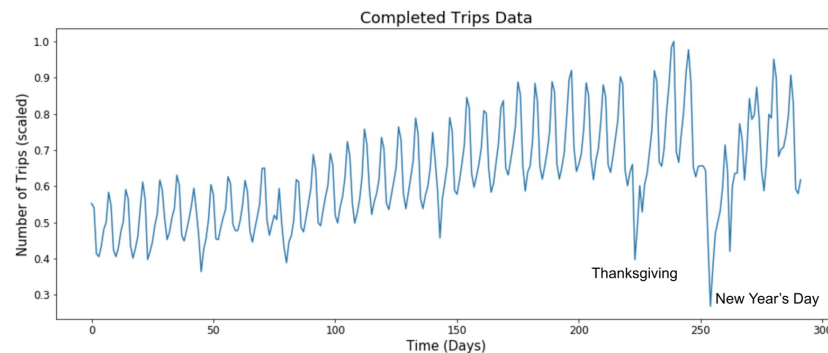
- We propose the Precision-Guided Adaptive Experimentation (P-GAE) algorithm [XABI'19]
  - Leverage ideas from [dynamic programming](#), [empirical Bayes](#), and [sample splitting](#)
  - [Key features](#)
    - [Adaptive](#) treatment decisions
    - [Precision](#)-based experiment termination rule
    - [Valid](#) statistical [inference](#) post-experiment
  - We provide [theoretical guarantees](#) for P-GAE
    - Asymptotic: consistency, normality, and efficiency



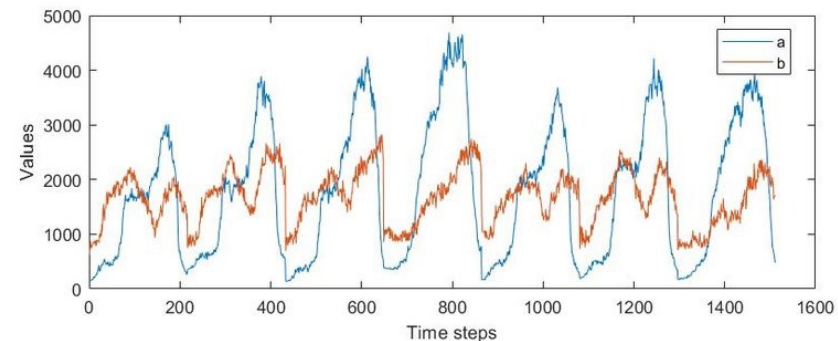
# Micro-level perspective

- Micro-level data: raw data are **events**, like rider checking price, outcome is whether rider requested a ride
  - Large sample size, but analysis is more challenging [Johari, Li, Liskovich, Weintraub'21]
- Additional considerations when analyzing event data

Irregular event density



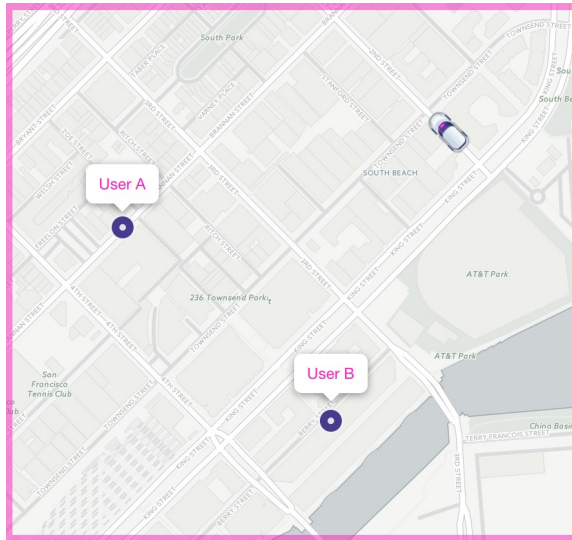
Correlation in event outcomes



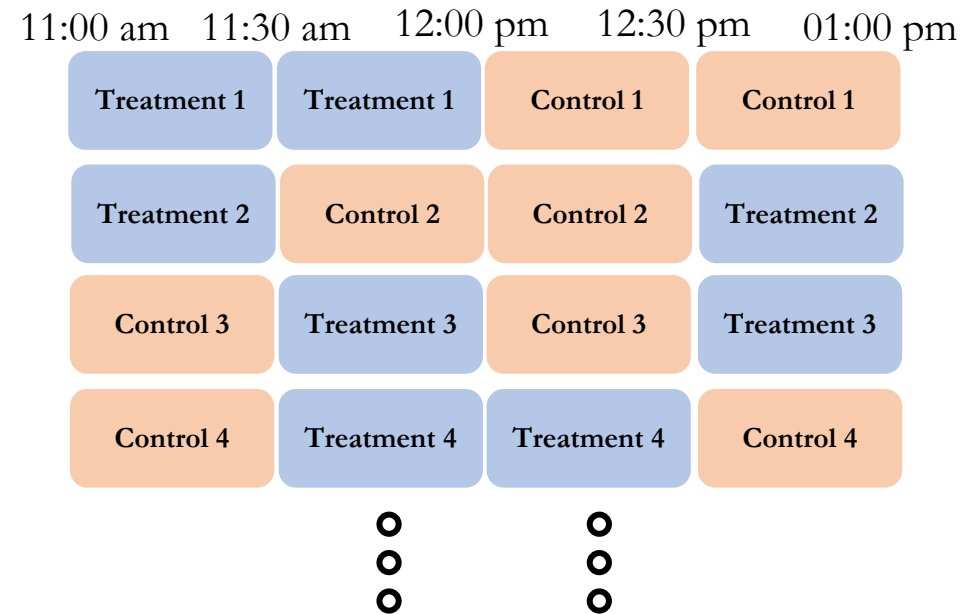
# Additional considerations

- Additional considerations when analyzing event data

## Spillover effects



## Simultaneous experiments



# Error analysis and design of experiments

- Analyze the **mean-squared error** (MSE) in treatment effect estimation [XCTA'22]
  - **Bias** affected by event density, spillover effects, simultaneous experiments
  - **Variance** affected by event density, correlation in event outcomes
- Study how **partition** time and space (irregularly) to minimize MSE [XCTA'22]



Thank you!

