Foundations of machine learning

Experiments for policy choice

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Outline

- Alternative objectives for the design of experiments.
- Exploration sampling as a modification of Thompson sampling.
- The oracle optimal allocation for the policy choice problem.
- Exploration sampling converges to the oracle optimal allocation.
- Simulations and empirical application.

Takeaways for this part of class

- Adaptive designs improve expected welfare.
- Features of the optimal treatment assignment:
  - Shift toward better performing treatments over time.
  - But don't shift as much as for Bandit problems:
    We have no "exploitation" motive!
  - Asymptotically: Equalize power for comparisons
    of each suboptimal treatment to the optimal one.
- Fully optimal assignment is computationally challenging in large samples.
- We propose a simple **exploration sampling** algorithm.
  - Argue that it is rate-optimal for our problem,
    because it equalizes power across suboptimal treatments.
  - Show that it dominates alternatives in calibrated simulations.

Introduction

The goal of many experiments is to inform policy choices:

1. **Job search assistance** for refugees:
   - Treatments: Information, incentives, counseling, ...
   - Goal: Find a policy that helps as many refugees as possible to find a job.
2. **Clinical trials**:
   - Treatments: Alternative drugs, surgery, ...
   - Goal: Find the treatment that maximizes the survival rate of patients.
3. Online **A/B testing**:
   - Treatments: Website layout, design, search filtering, ...
   - Goal: Find the design that maximizes purchases or clicks.
4. Testing **product design**:
   - Treatments: Various alternative designs of a product.
   - Goal: Find the best design in terms of user willingness to pay.

What is the objective of your experiment?

1. Getting precise treatment effect estimators, powerful tests:

$$\min \sum_d (\hat{\theta}^d - \theta^d)^2$$

   $\Rightarrow$ Standard experimental design recommendations.

2. Maximizing the outcomes of experimental participants:

$$\max \sum_i \theta^{D_i}$$

   $\Rightarrow$ Multi-armed bandit problems.

3. Picking a welfare maximizing policy after the experiment:

$$\max \theta^{d^*},$$

   where d^* is chosen after the experiment.
   $\Rightarrow$ This lecture.

Setup

- Waves $t = 1, \ldots, T$, sample sizes N_t.
- Treatment $D \in \{1, \ldots, k\}$, outcomes $Y \in \{0, 1\}$.
- Potential outcomes Y^d.
- Repeated cross-sections:
  $(Y_{it}^0, \ldots, Y_{it}^k)$ are i.i.d. across both i and t.
- Average potential outcome:
  $$\theta^d = E[Y_{it}^d].$$
- Key choice variable:
  Number of units n_t^d assigned to $D = d$ in wave t.
- Outcomes:
  Number of units s_t^d having a "success" (outcome $Y = 1$).

Treatment assignment, outcomes, state space

- Treatment assignment in wave t: $n_t = (n_t^1, \ldots, n_t^k)$.
- Outcomes of wave t: $s_t = (s_t^1, \ldots, s_t^k)$.
- Cumulative versions:

$$M_t = \sum_{t' \leq t} N_{t'}, \qquad m_t = \sum_{t' \leq t} n_t, \qquad r_t = \sum_{t' \leq t} s_t.$$

- Relevant information for the experimenter in period $t+1$ is summarized by m_t and r_t.
- Total trials for each treatment, total successes.

Design objective and Bayesian prior

- **Policy objective** $\theta^{d_T^*}$.
  - where d_T^* is chosen after the experiment.
- **Prior**
  - $\theta^d \sim Beta(\alpha_0^d, \beta_0^d)$, independent across d.
  - Posterior after period t: $\theta^d | m_t, r_t \sim Beta(\alpha_t^d, \beta_t^d)$

$$\alpha_t^d = \alpha_0^d + r_t^d$$
$$\beta_t^d = \beta_0^d + m_t^d - r_t^d.$$

- **Posterior expected social welfare**
  as a function of d:

$$SW_T(d) = E[\theta^d | m_T, r_T],$$
$$= \frac{\alpha_T^d}{\alpha_T^d + \beta_T^d},$$
$$d_T^* \in \underset{d}{\text{argmax}}\ SW_T(d).$$

Regret

- True optimal treatment: $d^{(1)} \in \arg\max_{d'} \theta^{d'}$.
- **Policy regret** when choosing treatment d:

$$\Delta^d = \theta^{d^{(1)}} - \theta^d.$$

- Maximizing expected social welfare is equivalent to minimizing the expected policy regret at T,

$$E[\Delta^d | m_T, r_T] = \theta^{d^{(1)}} - SW_T(d)$$

- **In-sample regret**: Objective considered in the bandit literature,

$$\frac{1}{M} \sum_{i,t} \Delta^{D_{it}}.$$

Different from policy regret $\Delta^{d_T^*}$!

Reminder: Thompson sampling

- **Thompson sampling**
  Assign each treatment with probability equal to the posterior probability that it is optimal.

$$p_t^d = P\left(d = \underset{d'}{\operatorname{argmax}}\ \theta^{d'} | m_{t-1}, r_{t-1}\right).$$

- Easily implemented: Sample draws $\widehat{\theta}_{it}$ from the posterior, assign

$$D_{it} = \underset{d}{\operatorname{argmax}}\ \hat{\theta}_{it}^d.$$

- **Expected Thompson sampling**
  - Straightforward modification for the batched setting.
  - Assign non-random shares p_t^d of each wave to treatment d.

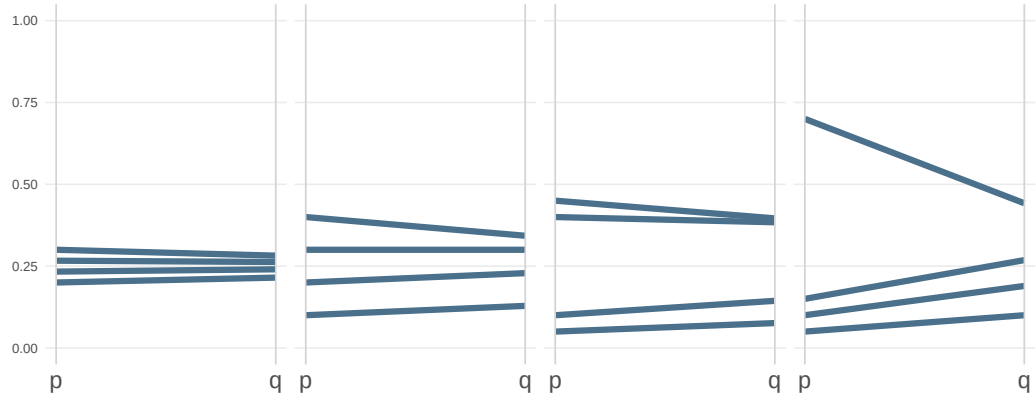
Exploration sampling

- Agrawal and Goyal (2012) proved that Thompson-sampling is rate-optimal for the multi-armed bandit problem.
- It is not for our policy choice problem!
- We propose the following modification.
- **Exploration sampling**:
  Assign shares q_t^d of each wave to treatment d, where

$$q_t^d = S_t \cdot p_t^d \cdot (1 - p_t^d),$$
$$S_t = \frac{1}{\sum_d p_t^d \cdot (1 - p_t^d)}.$$

- This modification
  1. yields rate-optimality, and
  2. improves performance in our simulations.

Illustration of the mapping from Thompson to exploration sampling



Calibrated simulations

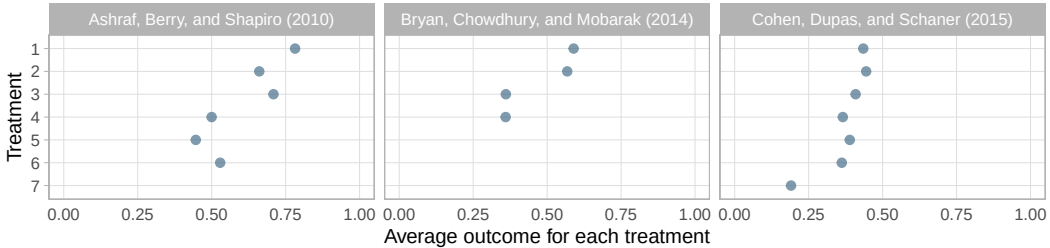
- Simulate data calibrated to estimates of 3 published experiments.
- Set θ equal to observed average outcomes for each stratum and treatment.
- Total sample size same as original.

Ashraf, N., Berry, J., and Shapiro, J. M. (2010). Can higher prices stimulate product use? Evidence from a field experiment in Zambia. *American Economic Review*, 100(5):2383–2413

Bryan, G., Chowdhury, S., and Mobarak, A. M. (2014). Underinvestment in a profitable technology: The case of seasonal migration in Bangladesh. *Econometrica*, 82(5):1671–1748

Cohen, J., Dupas, P., and Schaner, S. (2015). Price subsidies, diagnostic tests, and targeting of malaria treatment: evidence from a randomized controlled trial. *American Economic Review*, 105(2):609–45

Calibrated parameter values



Treatment arms labeled 1 up to 7:

- Ashraf et al. (2010): Kw 300 - 800 price for water disinfectant.
- Bryan et al. (2014): Migration incentives - cash, credit, information, and control.
- Cohen et al. (2015): Price of Ksh 40, 60, and 100 for malaria tablets, each with and without free malaria test, and control of Ksh 500.

Summary of simulation findings

- With two waves, relative to non-adaptive assignment:
  - Thompson reduces average policy regret by 15-58 %,
  - exploration sampling by 21-67 %.
- Similar pattern for the probability of choosing the optimal treatment.
- Gains increase with the number of waves, given total sample size.
  - Up to 85% for exploration sampling with 10 waves for Ashraf et al. (2010).
- Gains largest for Ashraf et al. (2010),
  followed by Cohen et al. (2015),
  and smallest for Bryan et al. (2014).
- For in-sample regret, Thompson is best,
  followed closely by exploration sampling.

Ashraf, Berry, and Shapiro (2010)

Statistic	2 waves	4 waves	10 waves
Average policy regret			
exploration sampling	0.0017	0.0010	0.0008
expected Thompson	0.0022	0.0014	0.0013
non-adaptive	0.0051	0.0050	0.0051
Share optimal			
exploration sampling	0.978	0.987	0.989
expected Thompson	0.971	0.981	0.982
non-adaptive	0.933	0.935	0.933
Average in-sample regret			
exploration sampling	0.1126	0.0828	0.0701
expected Thompson	0.1007	0.0617	0.0416
non-adaptive	0.1776	0.1776	0.1776
Units per wave	502	251	100

Bryan, Chowdhury, and Mobarak (2014)

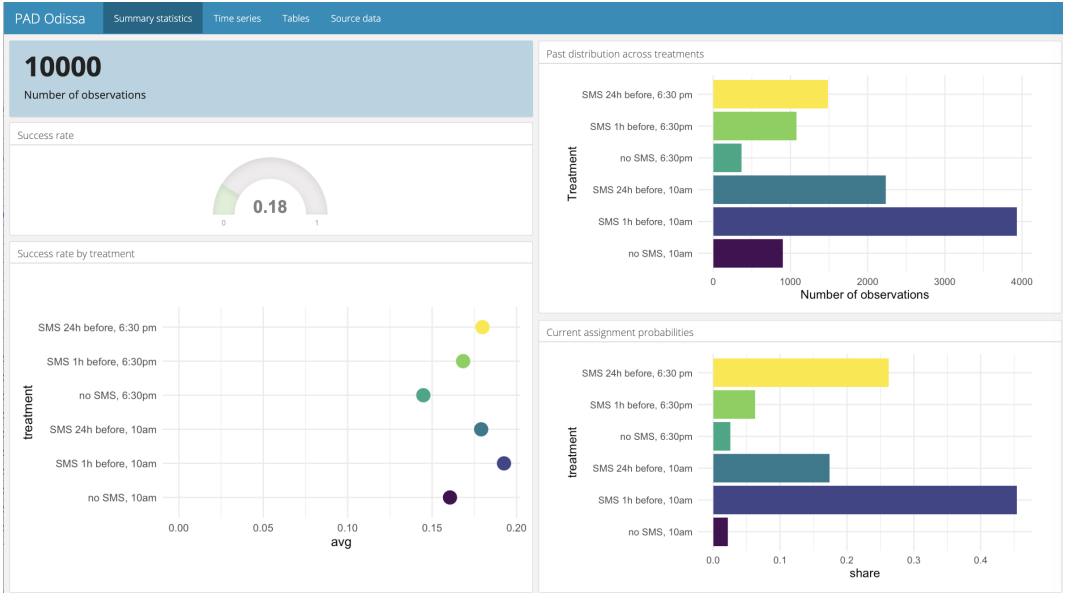
Statistic	2 waves	4 waves	10 waves
Average policy regret			
exploration sampling	0.0045	0.0041	0.0039
expected Thompson	0.0048	0.0044	0.0043
non-adaptive	0.0055	0.0054	0.0054
Share optimal			
exploration sampling	0.792	0.812	0.820
expected Thompson	0.777	0.795	0.801
non-adaptive	0.747	0.748	0.749
Average in-sample regret			
exploration sampling	0.0655	0.0386	0.0254
expected Thompson	0.0641	0.0359	0.0205
non-adaptive	0.1201	0.1201	0.1201
Units per wave	935	467	187

Cohen, Dupas, and Schaner (2015)

Statistic	2 waves	4 waves	10 waves
Average policy regret			
exploration sampling	0.0070	0.0063	0.0060
expected Thompson	0.0074	0.0065	0.0061
non-adaptive	0.0086	0.0087	0.0085
Share optimal			
exploration sampling	0.567	0.586	0.592
expected Thompson	0.560	0.582	0.589
non-adaptive	0.526	0.524	0.529
Average in-sample regret			
exploration sampling	0.0489	0.0374	0.0314
expected Thompson	0.0467	0.0345	0.0278
non-adaptive	0.0737	0.0737	0.0737
Units per wave	1080	540	216

Implementation in the field

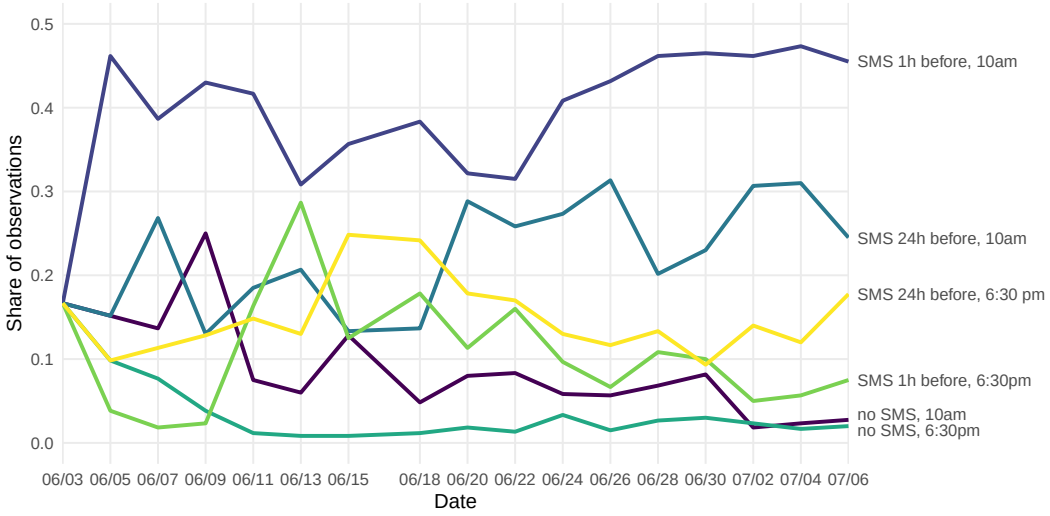
- NGO Precision Agriculture for Development (PAD),
  and Government of Odisha, India.
- Enrolling rice farmers into customized advice service by mobile phone.
- Waves of 600 farmers called through automated service; total of 10K calls.
- Outcome: did the respondent answer the enrollment questions?


PAD Odissa
Summary statistics
Time series
Tables
Source data
10000
Number of observations
Success rate
0.18
0
1
Success rate by treatment
SMS 24h before, 6:30 pm
SMS 1h before, 6:30pm
no SMS, 6:30pm
SMS 24h before, 10am
SMS 1h before, 10am
no SMS, 10am
treatment
0.00
0.05
0.10
0.15
0.20
avg
Past distribution across treatments
SMS 24h before, 6:30 pm
SMS 1h before, 6:30pm
no SMS, 6:30pm
SMS 24h before, 10am
SMS 1h before, 10am
no SMS, 10am
Treatment
0
1000
2000
3000
4000
Number of observations
Current assignment probabilities
SMS 24h before, 6:30 pm
SMS 1h before, 6:30pm
no SMS, 6:30pm
SMS 24h before, 10am
SMS 1h before, 10am
no SMS, 10am
treatment
0.0
0.1
0.2
0.3
0.4
share

Outcomes and posterior parameters

Treatment		Outcomes			Posterior		
Call time	SMS alert	m_T^d	r_T^d	r_T^d/m_T^d	mean	SD	p_T^d
10am	-	903	145	0.161	0.161	0.012	0.009
10am	1h ahead	3931	757	0.193	0.193	0.006	0.754
10am	24h ahead	2234	400	0.179	0.179	0.008	0.073
6:30pm	-	366	53	0.145	0.147	0.018	0.011
6:30pm	1h ahead	1081	182	0.168	0.169	0.011	0.027
6:30 pm	24h ahead	1485	267	0.180	0.180	0.010	0.126

Assignment shares over time



References

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- *Russo, D. (2016). Simple bayesian algorithms for best arm identification. In* Conference on Learning Theory*, pages 1417–1418.*
- *Kasy, M. and Sautmann, A. (2021). Adaptive treatment assignment in experiments for policy choice.* Econometrica*, 89(1):113–132.*

- Interactive dashboard for treatment assignment:
  `https://maxkasy.shinyapps.io/exploration_sampling_dashboard/`