

Discussion of:
“Increasing the uptake of long-acting reversible
contraceptives among adolescents and young women in
Cameroon”

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Summary and discussion of the paper

Choosing the objective for adaptive experiments in economics

- Surrogates and value alignment
- Social welfare
- Resource constraints

Summary

- Contraceptive counseling in a hospital in Cameroon.
 - **Treatments:**
Subsidy rate (1 of 4) for long-acting reversible contraceptives, presentation format (1 of 2).
 - **Primary objective:**
Minimize probability of unwanted pregnancy for chosen contraceptive, net of the (weighted) cost of subsidy.
- A four stage experimental design:
 1. **Pilot:** Non-adaptive.
Partition covariate space for targeting, choose tuning parameters.
 2. **Exploration sampling:** Adaptively shift to better-performing treatment, within each of 4 cells, to maximize information for treatment choice.
 3. **Evaluation:** Non-adaptive.
Most weight on the best policy from stage 2, and the control.
 4. **Follow-up** interviews.

Discussion

- An impressive, pioneering study.
 - Important real-world setting.
 - Balancing numerous objectives:
Policy choice, participant welfare, several estimands and hypothesis tests.
 - Multi-stage, “human in the loop” procedure.

Q: Motivation for the multi-stage procedure?

- Could a simpler algorithm achieve the same objectives better?
- E.g. Exploration sampling throughout, or some similar algorithm?

Q: Why restrict to targeting on 4 sets, based on pilot?

- No information sharing across cells; coarse representation of context.
- Alternative: (non-parametric) Bayesian prior \Rightarrow information-sharing across covariate values, and richer targeting?

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Getting the objective function right

- Key issue here, and for adaptive experiments generally!
 1. Measuring the right outcome.
 2. What about welfare (utility)?
 3. What about resource constraints?
- Remainder of this discussion:
Elaborating in the context of the [present paper](#), and my own work.

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Measuring the right outcome: Surrogates.

Q: Can we **measure** what we really care about?

- Unwanted pregnancy rates for the chosen contraceptive
= ? actual unwanted pregnancies = ? participant welfare?
- Maximizing short-term formal employment
= ? maximizing longer-term employment of any kind?

(As in our own experiment on **Job search assistance for refugees in Jordan**.)

A: Under some conditions, yes: “**Surrogate outcomes**.”

Condition: No unobserved causal pathways
to the ultimate outcome of interest.

Athey, S., Chetty, R., Imbens, G. W., and Kang, H. (2019).

The surrogate index: Combining short-term proxies to estimate long-term treatment effects more rapidly and precisely.

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Measuring the right outcome: Value alignment.

- More generally: Things can go very wrong – “Value alignment.”

Russell, S. (2019).

Human compatible: Artificial intelligence and the problem of control.

Thought experiment:

“The robot programmed to produce as many paperclips as possible, ends up eliminating humanity, since otherwise it could be switched off, which would limit paperclip production...”

- Interesting parallels to contract theory / mechanism design:
 - Picking observable outcome for the algorithm to maximize
 - ≈ designing an **incentive pay** scheme for an agent.

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What about welfare? Bandits and the social planner.

- Bandit algorithms, exploration sampling:
Maximize **observable outcomes**.
- Welfare economics, optimal tax theory:
Maximize **social welfare** – weighted sum of realized **utility**.
 - Subsidy for contraceptives:
Why not assume that the Cameroonian women are maximizing their welfare, subject to constraints?
- Tax rate x , demand function G :

$$\text{Social welfare} = \underbrace{x \cdot G(x)}_{\text{Public revenue}} + \lambda \cdot \underbrace{\int_x^1 G(x') dx'}_{\text{Consumer surplus}} .$$

- Welfare at policy x depends on demand for other policies x' !

Adaptive maximization of social welfare

⇒ Exploration needs to take a different form than for bandits.

- Welfare maximizing algorithms:

- Need to explore more, away from the optimal policy.
- Worst-case regret rate of $T^{2/3}$, versus $T^{1/2}$ for bandits.

- Work in progress:

Taking this to the field with the NGO “Mein Grundeinkommen” in Germany:

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What about resource constraints?

Combinatorial semi bandits

- Many settings: **Resource constraints** / matching problems.
- Giving a “treatment” to one unit means we can not give it to another.
 - Monetary budget constraint for contraceptive subsidies?
 - Limited doctor availability?
- Allocations need to be chosen jointly.
- Surprisingly: No cost for worst-case regret rates, relative to unconstrained bandits.

Thank you!

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Matching with semi-bandits.