Motivation

✗ So many features to recommend!
✗ Not all such messages are useful for every individual!
✗ Unaffordable or detrimental to run active experiments on all of them!
✓ Split-Treatment!

Use logged behavioral data to identify who are likely to benefit from a novel intervention.

Identification of Split-Treatment

Assumption 1 (Ignorability): $P(Y|do(a), x) = P(Y|a, x)$
Assumption 2 (Compliance): $E(x|compliance(x)) > 0$

$$\text{ITE}(x) = \mathbf{E}(Y|do(a) = 1, x) - \mathbf{E}(Y|do(a) = 0, x)$$
$$\text{CATE}_W^{\mathbf{ITE}} = E_W[\text{ITE}(x)]$$

We pick a proxy treatment $A$ such that:

- $A$ exists, with some natural variation, in our observational logs.
- The effect of $Z$ on $Y$ should be mediated through $A$.

Estimation using Split-Treatment

1. Data processing and setup
2. Estimate ITE models
3. Refine/ sensitivity analysis

Validation via active experiment

Likely best models

Message/variable targeting

Experiments and Results

Simulation

Violation of the two assumptions: Comparison between the ground-truth rank and the proxy-estimated rank in simulations with and without violation of the assumptions.

Unobserved-confounding analysis: Comparison between estimated causal effect with and without unobserved confounding, for two causal models.

Real-world data

• RMSE of outcome prediction from the baseline models.

• Validation on experimental data

Conclusion

We presented a practical, observational analysis pipeline for:

- Identifying individuals likely to benefit from a novel treatment $Z$.
- Using proper causal analysis of existing logs that contain proxy treatment $A$.

A key contribution:

- Refutation tests and sensitivity analyses enable a principled a priori identification of the feature selection and elimination of unreliable algorithmic design.

We validated our analysis with an A/B experiment in a large real-world setting.