**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**

- **Prospective data**
- **Observational data**

- Target treatment
- A: Proxy treatment
- Y: Outcome
- U: Natural variation

- Assumption 1 (Ignorability): $P(Y|do(a), x) = P(Y|a, x)$
- Assumption 2 (Compliance): $E_x[E_a[1_{Z(a = 1)}]] > 0$

$ITE_{Y|X}(a) = E_x[E_{do(Y|X)}(1|x) - E_x[E_{do(Y|X)}(0|x)]$  

$CATE_Y = E_x[E_{do(Y|X)}(1|x) - E_x[E_{do(Y|X)}(0|x)] = 0$  

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. Refutation/sensitivity analysis

- Placebo test
  - Place a random variable as the treatment A
  - Test if estimator returns zero causal effect

- Unobserved confounding test
  - Add a new confounder to the feature set with varying degrees of its effect on A and Y
  - Test if an estimator is less sensitive to the varying degrees of effect of the new confounder

**Experiments and Results**

**Simulation**

- RMSE of outcome prediction from the baseline models.
- Validation on experimental data

**Real-world data**

- Sensitivity analysis (unobserved confounding)

**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.