

Personalization with Latent Confounders

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- However, latent confounders (i.e., unobserved variables affecting both the actions and the outcome variables) pose a unique challenge to personalization.
- In contrast to the general notion that Randomized Controlled Experiments (a.k.a. A/B Tests) are 'gold standard', in this setting they might actually result in loss of information.

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- Personalization algorithms aim to improve decision-making by identifying and exploiting this heterogeneity.
- However, latent confounders (i.e., unobserved variables affecting both the actions and the outcome variables) pose a unique challenge to personalization.
- In contrast to the general notion that Randomized Controlled Experiments (a.k.a. A/B Tests) are 'gold standard', in this setting they might actually result in loss of information.
- Counterfactual-based decision-making can address these problems and lead to a coherent fusion of observational and experimental data.

The Business Setting

- **Business objective:** Cross-sell a credit card to new-to-RBC clients.
- **Past campaign:** All new-to-RBC clients who visited the RBC public site, get a credit card offer + iPad incentive.



- **The goal is to personalize the incentive:** Identify which new-to-RBC clients should receive an iPad incentive in the future to maximize the expected profitability of the campaign.

Data Generating Process

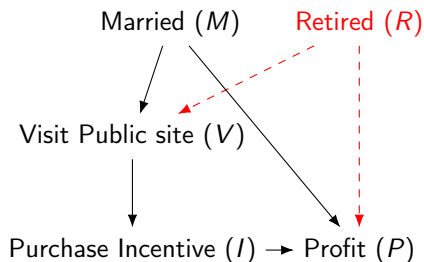


Figure: Past campaign 'true' causal DAG.

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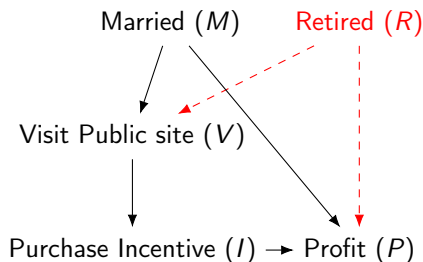


Figure: Past campaign 'true' causal DAG.

$$V := M \oplus R$$

$$I := V$$

	$R = 0$		$R = 1$	
	$M = 1$	$M = 0$	$M = 1$	$M = 0$
$I = 1$	0.25	0.50	0.45	0.05
$I = 0$	0.50	0.10	0.05	0.30

Table: $E[P|M, R, I]$. Highlighted cells reflect (new-to-RBC) client's 'natural' choice to visit the Public site or not.

Approach 1: Empirical Decision Criterion (EDC)

$$\text{EDC} \rightarrow \operatorname{argmax}_{I \in \{0,1\}} E[P|I, M]$$

$$E[P|I = 1, M = 1] = 0.25$$

$$E[P|I = 0, M = 1] = 0.05$$

$$E[P|I = 1, M = 0] = 0.05$$

$$E[P|I = 0, M = 0] = 0.10$$

	$R = 0$		$R = 1$	
	$M = 1$	$M = 0$	$M = 1$	$M = 0$
$I = 1$	0.25	0.50	0.45	0.05
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Table: $E[P|M, R, I]$.

Approach 1: Empirical Decision Criterion (EDC)

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$$E[P|I = 0, M = 0] = 0.10$$

	$R = 0$		$R = 1$	
	$M = 1$	$M = 0$	$M = 1$	$M = 0$
$I = 1$	0.25	0.50	0.45	0.05
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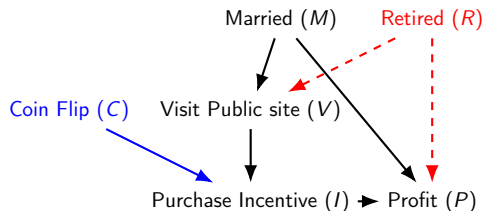
Table: $E[P|M, R, I]$.

Decision Rule:

- If Visit Site \wedge Married \rightarrow Purchase Incentive $\rightarrow E[P] = 0.25$
- If Visit Site \wedge Not Married \rightarrow No Purchase Incentive $\rightarrow E[P] = 0.05$

Expected profit = 0.15 = $(0.25 + 0.05)/2$.

Approach 2: Post-Visit Randomization (PVR)



$$V := M \oplus R$$

$$I := V \wedge C$$

Figure: Causal DAG with post-visit randomization.

Approach 2: Post-Visit Randomization (PVR) - cont'd

$$\text{PVR} \rightarrow \arg\max_{I \in \{0,1\}} E[P|do(I), M, V = 1]$$

$$E[P|do(I = 1), M = 1, V = 1] = 0.25$$

$$E[P|do(I = 0), M = 1, V = 1] = 0.50$$

$$E[P|do(I = 1), M = 0, V = 1] = 0.05$$

$$E[P|do(I = 0), M = 0, V = 1] = 0.30$$

	$R = 0$		$R = 1$	
	$M = 1$	$M = 0$	$M = 1$	$M = 0$
$I = 1$	0.25	0.50	0.45	0.05
$I = 0$	0.50	0.10	0.05	0.30

Table: $E[P|M, R, I]$.

Approach 2: Post-Visit Randomization (PVR) - cont'd

$$\text{PVR} \rightarrow \operatorname{argmax}_{I \in \{0,1\}} E[P | do(I), M, V = 1]$$

$$E[P | do(I = 1), M = 1, V = 1] = 0.25$$

$$E[P | do(I = 0), M = 1, V = 1] = 0.50$$

$$E[P | do(I = 1), M = 0, V = 1] = 0.05$$

$$E[P | do(I = 0), M = 0, V = 1] = 0.30$$

	$R = 0$		$R = 1$	
	$M = 1$	$M = 0$	$M = 1$	$M = 0$
$I = 1$	0.25	0.50	0.45	0.05
$I = 0$	0.50	0.10	0.05	0.30

Table: $E[P | M, R, I]$.

Decision Rule:

- If Visit Site \wedge Married \rightarrow No Purchase Incentive $\rightarrow E[P] = 0.50$
- If Visit Site \wedge Not Married \rightarrow No Purchase Incentive $\rightarrow E[P] = 0.30$

$$\text{Expected profit} = \boxed{0.40} = (0.50 + 0.30) / 2.$$

Approach 3: RCT on All New-to-RBC Clients

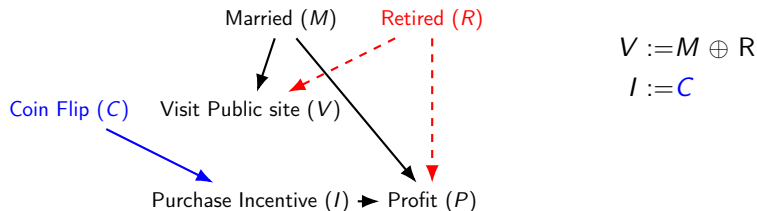


Figure: Causal DAG with RCT on All New-to-Bank Clients.

Approach 3: RCT on All New-to-RBC Clients - cont'd

$$\text{RCT} \rightarrow \operatorname{argmax}_{I \in \{0,1\}} E[P|do(I), M]$$

$$E[P|do(I = 1), M = 1] = 0.350 = (0.25 + 0.45)/2$$

$$E[P|do(I = 0), M = 1] = 0.275 = (0.50 + 0.05)/2$$

$$E[P|do(I = 1), M = 0] = 0.275 = (0.50 + 0.05)/2$$

$$E[P|do(I = 0), M = 0] = 0.200 = (0.10 + 0.30)/2$$

	$R = 0$		$R = 1$	
	$M = 1$	$M = 0$	$M = 1$	$M = 0$
$I = 1$	0.25	0.50	0.45	0.05
$I = 0$	0.50	0.10	0.05	0.30

Table: $E[P|M, R, I]$.

Approach 3: RCT on All New-to-RBC Clients - cont'd

$$\text{RCT} \rightarrow \operatorname{argmax}_{I \in \{0,1\}} E[P|do(I), M]$$

$$E[P|do(I=1), M=1] = 0.350 = (0.25 + 0.45)/2$$

$$E[P|do(I=0), M=1] = 0.275 = (0.50 + 0.05)/2$$

$$E[P|do(I=1), M=0] = 0.275 = (0.50 + 0.05)/2$$

$$E[P|do(I=0), M=0] = 0.200 = (0.10 + 0.30)/2$$

	$R = 0$		$R = 1$	
	$M = 1$	$M = 0$	$M = 1$	$M = 0$
$I = 1$	0.25	0.50	0.45	0.05
$I = 0$	0.50	0.10	0.05	0.30

Table: $E[P|M, R, I]$.

Decision Rule:

- If Married \rightarrow Purchase Incentive $\rightarrow E[P] = 0.35$
- If Not Married \rightarrow Purchase Incentive $\rightarrow E[P] = 0.275$

$$\text{Expected profit} = \boxed{0.315} = (0.35 + 0.275)/2.$$

Approach 4: Regret Decision Criterion (RDC)

$$\text{RDC} \rightarrow \operatorname{argmax}_{a' \in 0,1} E[P_{a'} | I = a, M]$$

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$$\text{RDC} \rightarrow \operatorname{argmax}_{a' \in 0,1} E[P_{a'} | I = a, M]$$

$$\begin{aligned} P(\pi_{a'}, M) &= P(\pi_{a'}, M, a') + P(\pi_{a'}, M, a) \\ &= P(\pi_{a'} | M, a') P(M, a') + P(\pi_{a'} | M, a) P(M, a) \end{aligned}$$

$$\begin{aligned} P(\pi_{a'} | M) &= P(\pi_{a'} | M, a') P(a' | M) + P(\pi_{a'} | M, a) P(a | M) \\ &= P(\pi | M, a') P(a' | M) + P(\pi_{a'} | M, a) P(a | M) \text{ (Consistency)} \end{aligned}$$

$$\begin{aligned} P(\pi_{a'} | M, a) &= \frac{1}{P(a | M)} \left[P(\pi_{a'} | M) - P(\pi | M, a') P(a' | M) \right] \\ &= \boxed{\frac{1}{P(a | M)} \left[P(\pi | M, do(a')) - P(\pi | M, a') P(a' | M) \right]} \end{aligned}$$

Approach 4: Regret Decision Criterion (RDC) - cont'd

$$P(\pi_{I=1} | M = 1, I = 0) =$$

$$\begin{aligned} & \frac{1}{P(I = 0 | M = 1)} \left[P(\pi | M = 1, do(I = 1)) - \right. \\ & \quad \left. P(\pi | M = 1, I = 1) P(I = 1 | M = 1) \right] \\ &= \frac{1}{1/2} (0.350 - 0.25 \times \frac{1}{2}) = \mathbf{0.45} \end{aligned}$$

	R = 0		R = 1	
	M = 1	M = 0	M = 1	M = 0
I = 1	0.25	0.50	0.45	0.05
I = 0	0.50	0.10	0.05	0.30

$$P(\pi_{I=1} | M = 0, I = 0) = \mathbf{0.50}$$

$$P(\pi_{I=0} | M = 1, I = 1) = \mathbf{0.50}$$

$$P(\pi_{I=0} | M = 0, I = 1) = \mathbf{0.30}$$

Table: $E[P | M, R, I]$.

Decision Rule:

- If Visit Site \wedge Married \rightarrow No Purchase Incentive $\rightarrow E[P] = \mathbf{0.50}$
- If Visit Site \wedge Not Married \rightarrow No Purchase Incentive $\rightarrow E[P] = \mathbf{0.30}$
- If Not Visit Site \wedge Married \rightarrow Purchase Incentive $\rightarrow E[P] = \mathbf{0.45}$
- If Not Visit Site \wedge Not Married \rightarrow Purchase Incentive $\rightarrow E[P] = \mathbf{0.50}$

$$\text{Expected profit} = \boxed{0.4375} = (0.50 + 0.30 + 0.45 + 0.50)/4.$$

Summary

- Summarize results so far from the various criteria and emphasize no result is right or wrong, they answer different questions, but some questions are more preferable than others in specific context.
- Compare to oracle
- Profit = 0.4375

Extensions

- Multiple Actions
- Online policy optimization (e.g., MABUC)

The Personalization Paradigm

- Illustration that shows that what is good for person 1 might be neutral or even harmful for person 2.
- Motivating illustration in healthcare, marketing, client-level decision making.

Notes

For each Data Science articulate what is the question being asked!!!!
The conclusion should be that although DS 4 achieves highest reward, whether that is the right solution, depends on the question being asked.