Personalization with Latent Confounders

Leo Guelman

RBC Royal Bank

Figure: Ronald Fisher (1890-1962)

A/B Testing is likely NOT 'gold standard' for Personalized Decision-Making.

Personalization with Unobserved Confounders

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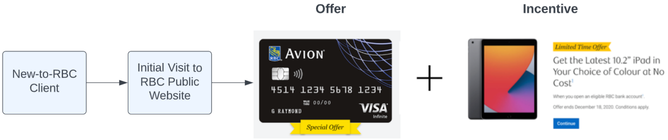
- The value of Personalization is founded on the premise that individuals have heterogenous response to actions.
- Personalization algorithms aim to improve decision-making by identifying and exploiting this heterogeneity.
- However, latent confounders (i.e., unobserved variables affecting both the actions 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

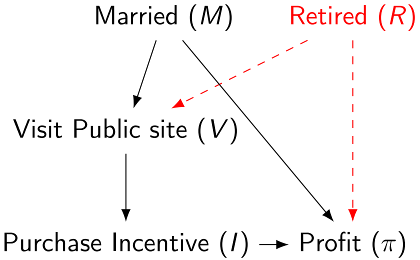


Figure: Past campaign 'true' causal DAG.

Data Generating Process

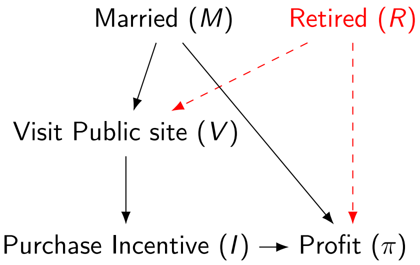


Figure: Past campaign ‘true’ causal DAG.

$$V := M \oplus \mathrm{R}$$
$$I := V$$

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

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

Approach 1: Empirical Decision Criterion (EDC)

$$\text{EDC} \rightarrow \underset{I \in 0,1}{\operatorname{argmax}} \; E[\pi | I, M]$$

$$E[\pi | I = 1, M = 1] = 0.25$$
$$E[\pi | I = 0, M = 1] = 0.05$$
$$E[\pi | I = 1, M = 0] = 0.05$$
$$E[\pi | I = 0, M = 0] = 0.10$$

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

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

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$$E[\pi|I=1, M=0] = 0.05$$
$$E[\pi|I=0, M=0] = 0.10$$

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

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

Decision Rule:

- If Visit Site $\wedge$ Married $\rightarrow$ Purchase Incentive $\rightarrow$ $E[\pi] = \mathbf{0.25}$
- If Visit Site $\wedge$ Not Married $\rightarrow$ No Purchase Incentive $\rightarrow$ $E[\pi] = \mathbf{0.05}$

Expected profit $= \boxed{0.15} = (0.25+0.05)/2$.

Approach 2: Post-Visit Randomization (PVR)

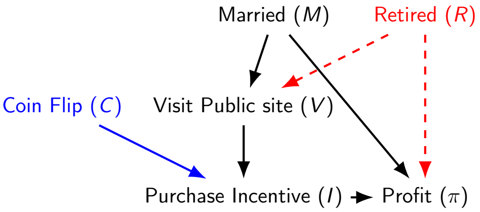

Figure: Causal DAG with post-visit randomization.

$$V := M \oplus \mathrm{R}$$
$$I := V \wedge C$$

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

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

$$E[\pi | do(I = 1), M = 1, V = 1] = 0.25$$
$$E[\pi | do(I = 0), M = 1, V = 1] = 0.50$$
$$E[\pi | do(I = 1), M = 0, V = 1] = 0.05$$
$$E[\pi | do(I = 0), M = 0, V = 1] = 0.30$$

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

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

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

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

$$E[\pi|do(I = 1), M = 1, V = 1] = 0.25$$
$$E[\pi|do(I = 0), M = 1, V = 1] = 0.50$$
$$E[\pi|do(I = 1), M = 0, V = 1] = 0.05$$
$$E[\pi|do(I = 0), M = 0, V = 1] = 0.30$$

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

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

Decision Rule:

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

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

Approach 3: A/B Test on All New-to-RBC Clients

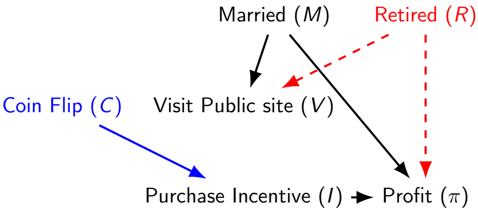

Figure: Causal DAG with A/B Test on All New-to-Bank Clients.

$$V := M \oplus R$$

$$I := C$$

Approach 3: A/B Test on All New-to-RBC Clients - cont'd

$$\text{ABT} \rightarrow \underset{I \in 0,1}{\text{argmax}}\ E[\pi | do(I), M]$$

$$E[\pi | do(I=1), M=1] = 0.350 = (0.25 + 0.45)/2$$
$$E[\pi | do(I=0), M=1] = 0.275 = (0.50 + 0.05)/2$$
$$E[\pi | do(I=1), M=0] = 0.275 = (0.50 + 0.05)/2$$
$$E[\pi | do(I=0), M=0] = 0.200 = (0.10 + 0.30)/2$$

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

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

Approach 3: A/B Test on All New-to-RBC Clients - cont'd

$$\text{ABT} \rightarrow \underset{I \in 0,1}{\operatorname{argmax}}\; E[\pi | do(I), M]$$

$$E[\pi|do(I=1), M=1] = 0.350 = (0.25 + 0.45)/2$$
$$E[\pi|do(I=0), M=1] = 0.275 = (0.50 + 0.05)/2$$
$$E[\pi|do(I=1), M=0] = 0.275 = (0.50 + 0.05)/2$$
$$E[\pi|do(I=0), M=0] = 0.200 = (0.10 + 0.30)/2$$

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

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

Decision Rule:

- If Married → Purchase Incentive → $E[\pi] = \mathbf{0.35}$
- If Not Married → Purchase Incentive → $E[\pi] = \mathbf{0.275}$

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

Approach 4: Regret Decision Criterion (RDC)

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

Approach 4: Regret Decision Criterion (RDC)

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

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

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

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

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

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

$$\frac{1}{P(I=0|M=1)}\Big[P\Big(\pi|M=1, do(I=1)\Big)-$$
$$P(\pi|M=1, I=1)P(I=1|M=1)\Big].$$
$$= \frac{1}{1/2}(0.350 - 0.25 \times \frac{1}{1/2}) = \mathbf{0.45}$$

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

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

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

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

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

Decision Rule:

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

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

Summary of Methods

Criterion	Decision Rule	$E[\pi]$
EDC	• If Visit Site $\wedge$ Married $\rightarrow$ **Purchase Incentive** • If Visit Site $\wedge$ Not Married $\rightarrow$ **No Purchase Incentive**	.1500
PVR	**Never Purchase Incentive**	.4000
ABT	**Always Purchase Incentive**	.3150
RDC	• If Visit Site $\wedge$ Married $\rightarrow$ **No Purchase Incentive** • If Visit Site $\wedge$ Not Married $\rightarrow$ **No Purchase Incentive** • If Not Visit Site $\wedge$ Married $\rightarrow$ **Purchase Incentive** • If Not Visit Site $\wedge$ Not Married $\rightarrow$ **Purchase Incentive**	**.4375**
Oracle		**.4375**

Key Takeaways

- A/B testing is not always the 'Gold Standard' for learning causal effects
- If (i) the goal is to learn optimal personalized actions, and (ii) we have unobserved confounders (very likely!), and (iii) these confounders interact with the action: then Counterfactual-based decision-making may outperform Causal-decision making.
- The expression derived from RDC works only in the binary treatment case. RDC-type randomization (Forney et al., 2017) was proposed to estimate the counterfactual expressions empirically from an arbitrary number of treatments.

References

- Elias Bareinboim, Andrew Forney, and Judea Pearl. 2015. Bandits with unobserved confounders: a causal approach. In Proceedings of the 28th International Conference on Neural Information Processing Systems - Volume 1 (NIPS'15).
  - Implementation: https://github.com/leoguelman/mabuc
- Forney, A., Pearl, J. ; Bareinboim, E.. (2017). Counterfactual Data-Fusion for Online Reinforcement Learners. Proceedings of the 34th International Conference on Machine Learning, in Proceedings of Machine Learning Research 70:1156-1164