

Personalized Marketing with Latent Confounders

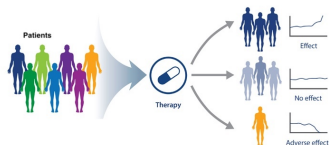
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RBC Royal Bank

Inspiration for Personalized Marketing

- Personalization is founded on the premise that individuals have heterogeneous response to actions.
- Personalization algorithms aim to improve decision-making by identifying and exploiting this heterogeneity.

One Treatment Fits All

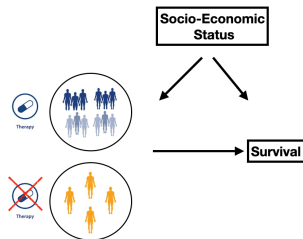


Personalized Treatments



Estimating Treatment Effects: **Non**-Personalized Paradigm

A/B Tests are 'gold standard' in the One-Treatment-Fits-All paradigm because they remove the influence of unobserved confounders (variables that influence both the treatment and the outcome).



Estimating Treatment Effects: **Non-Personalized Paradigm**

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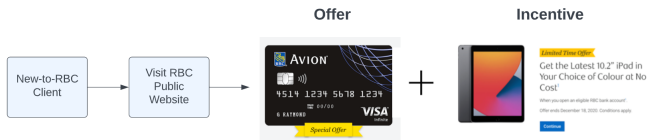


Estimating Treatment Effects: Personalized Paradigm

- In the presence of unobserved confounders (most plausible scenario), experimental data is likely not 'gold standard' for estimating heterogeneous treatment effects.
- A coherent fusion of experimental and observational data that results from a *counterfactual*-based decision criterion is likely to outperform other approaches.
- In what follows, I'll use a Personalized Marketing problem as a motivating example to discuss the statements above.

The Business Setting

- **Business objective:** Sell a credit card to new-to-RBC clients.
- **Current campaign: One-Treatment-Fits-All paradigm.** All new-to-RBC clients who visited the RBC public site, get a credit card offer + iPad incentive.



- **Future campaign: 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

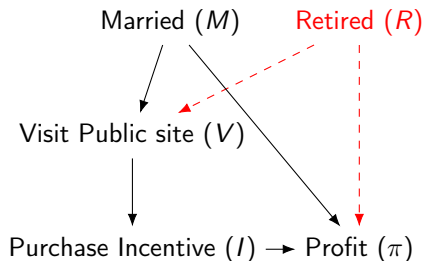


Figure: 'True' Causal Graph (current campaign).

Data Generating Process

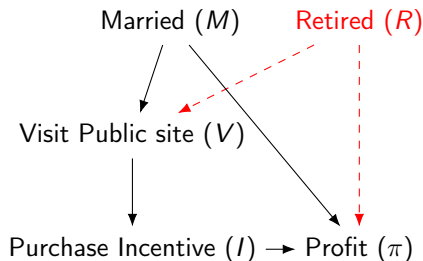


Figure: 'True' Causal Graph (current campaign).

$$P(m, r) = 0.25 \quad \forall m \in M, r \in R$$

$$V := M \oplus R$$

$$I := V$$

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

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

Four Approaches to Personalizing the Incentive

Data Scientist 1



Data Scientist 2



Data Scientist 3



Data Scientist 4



DS #1: Empirical Decision Criterion (EDC)

Associational Inference

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

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

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

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

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

	$R = 0$		$R = 1$	
	$M = 1$	$M = 0$	$M = 1$	$M = 0$
$I = 1$	0.25	0.50	0.45	0.05
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DS #1: Empirical Decision Criterion (EDC)

Associational Inference

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	$M = 1$	$M = 0$	$M = 1$	$M = 0$
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Table: $E[\pi|M, R, I]$.

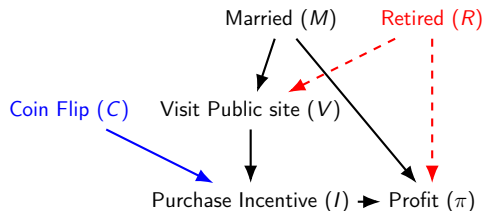
Decision Rule:

- If Visit Site \wedge Married \rightarrow Purchase Incentive $\rightarrow E[\pi] = 0.25$
- If Visit Site \wedge Not Married \rightarrow No Purchase Incentive $\rightarrow E[\pi] = 0.30$

Expected profit = 0.275 = $(0.25 + 0.30)/2$.

DS #2: Post-Visit Randomization (PVR)

Interventional Inference



$$V := M \oplus R$$

$$I := V \wedge C$$

Figure: Causal DAG with post-visit randomization.

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

Interventional Inference

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

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

Interventional Inference

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

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

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

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

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

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

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

Interventional Inference

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

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

	$R = 0$		$R = 1$	
	$M = 1$	$M = 0$	$M = 1$	$M = 0$
$I = 1$	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 $\rightarrow E[\pi] = \mathbf{0.30}$

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

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

Interventional Inference

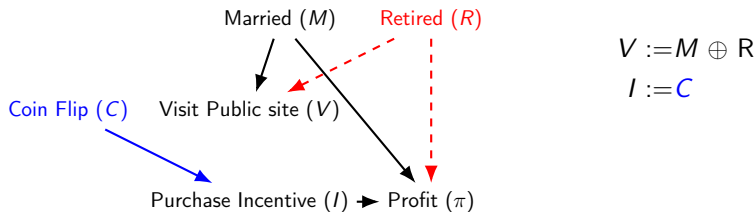


Figure: Causal DAG with A/B Test on all New-to-RBC clients.

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

Interventional Inference

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

$$E[\pi | \text{do}(I = 1), M = 1] = 0.350 = (0.25 + 0.45)/2$$

$$E[\pi | \text{do}(I = 0), M = 1] = 0.275 = (0.50 + 0.05)/2$$

$$E[\pi | \text{do}(I = 1), M = 0] = 0.275 = (0.50 + 0.05)/2$$

$$E[\pi | \text{do}(I = 0), M = 0] = 0.200 = (0.10 + 0.30)/2$$

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

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

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

Interventional Inference

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

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

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

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

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

	$R = 0$		$R = 1$	
	$M = 1$	$M = 0$	$M = 1$	$M = 0$
$I = 1$	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 \rightarrow Purchase Incentive $\rightarrow E[\pi] = 0.35$
- If Not Married \rightarrow Purchase Incentive $\rightarrow E[\pi] = 0.275$

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

DS #4: Regret Decision Criterion (RDC)

Counterfactual Inference

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

DS #4: Regret Decision Criterion (RDC)

Counterfactual Inference

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

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

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

$$P(\pi_{a'} | M, a) = \frac{1}{P(a | M)} \left[P(\pi_{a'} | M) - P(\pi | M, a') P(a' | M) \right]$$

$$= \underbrace{\frac{1}{P(a | M)}}_{\text{observational}} \left[\overbrace{P(\pi | M, do(a'))}^{\text{experimental}} - \underbrace{P(\pi | M, a') P(a' | M)}_{\text{observational}} \right]$$

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

Counterfactual Inference

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

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

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

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

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

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

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

Counterfactual Inference

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

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

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

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

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

	R = 0		R = 1	
	M = 1	M = 0	M = 1	M = 0
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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 $\rightarrow E[\pi] = \mathbf{0.30}$
- 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 $\rightarrow E[\pi] = \mathbf{0.50}$

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

Summary of Methods

Criterion	Decision Rule	$E[\pi]$
EDC	<ul style="list-style-type: none">• If Visit Site \wedge Married \rightarrow Purchase Incentive• If Visit Site \wedge Not Married \rightarrow No Purchase Incentive	.2750
PVR	Never Purchase Incentive	.4000
ABT	Always Purchase Incentive	.3150
RDC	<ul style="list-style-type: none">• 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

Remarks

- If the goal is to learn personalized actions, experimental data alone is sub-optimal in the presence of unobserved confounders.
- Combining experimental and observational data under a Regret Decision Criterion (RDC) can provide information about the unobserved confounders, and hence outperform alternative optimization criteria.
- The expression derived from RDC works only in the binary treatment case. RDC-type randomization (Forney et al., 2017) was proposed to estimate 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