

Personalization with Unobserved Heterogeneity

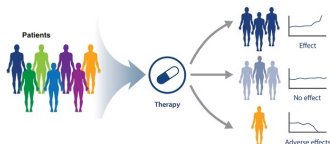
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RBC Royal Bank

Motivation for Personalization

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

Non-Personalized Paradigm



Personalized Paradigm



Unobserved and Heterogeneous Confounder (UHC)

- Treatment effect (T) varies according to the value of an unobserved confounder (U).

$$T := f(U) + N_T$$

$$Y := f(T, U, \mathbf{T} \times \mathbf{U}) + N_Y$$

- Presence of UHCs is arguably the most sensible assumption in practice.
- UHCs introduce challenges to personalization.

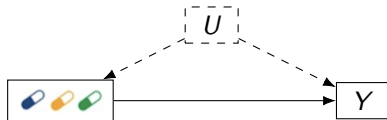


Figure: Observational setting.

Motivating Questions

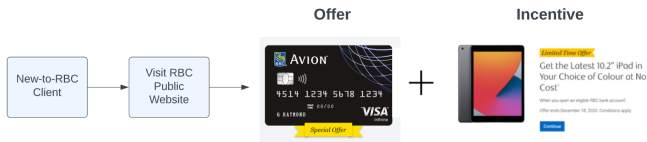
Given the high-level goal of personalization, and the context of UHCs:

- How should I express my objective function? What is a suitable causal estimand?
- What data do I need for identification?
- Is experimental data 'gold standard'?

Out-of-scope: Estimation (e.g., compare different estimators for personalization).

Business Setting

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



- **Business Goal: 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

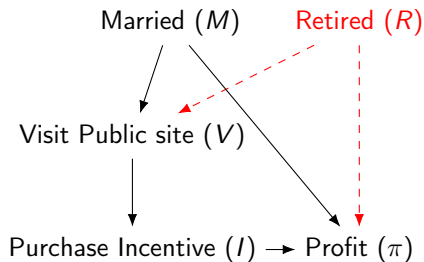


Figure: Observational setting.

Data Generating Process

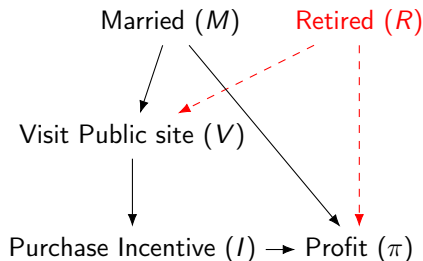


Figure: Observational setting.

$$P(R = 1) = 0.5, \quad P(M = 1) = 0.5$$

$$V := M \oplus R$$

$$I := V$$

	$R = 0$		$R = 1$	
	$M = 1$	$M = 0$	$M = 1$	$M = 0$
$I = 1$	25	50	45	5
$I = 0$	50	10	5	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

Business Goal: Identify which new-to-RBC clients should receive an iPad incentive in the future to maximize the expected profitability of the campaign.

Data Scientist 1



Data Scientist 2



Data Scientist 3



Data Scientist 4



1. Associational Inference



$$\mathcal{D}_{\text{AI}}^*(M) = \operatorname{argmax}_{I \in \{0,1\}} E[\pi|I, M]$$

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$$E[\pi|I = 1, M = 1] = 25$$

$$E[\pi|I = 0, M = 1] = 5$$

$$E[\pi|I = 1, M = 0] = 5$$

$$E[\pi|I = 0, M = 0] = 10$$

	$R = 0$		$R = 1$	
	$M = 1$	$M = 0$	$M = 1$	$M = 0$
$I = 1$	25	50	45	5
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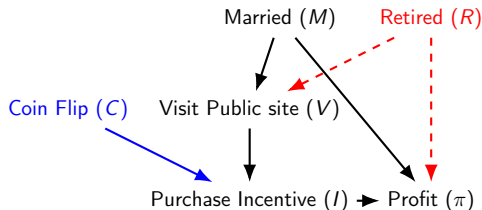
Table: $E[\pi|M, R, I]$.

Decision Rule:

- If Visit Site \wedge Married \rightarrow Purchase Incentive $\rightarrow E[\pi] = 25$
- If Visit Site \wedge Not Married \rightarrow No Purchase Incentive $\rightarrow E[\pi] = 30$

Expected profit = $\boxed{27.5} = (25+30)/2$.

2. Interventional Inference + Post-Visit Randomization



$$V := M \oplus R$$

$$I := V \wedge C$$

Figure: Causal DAG with post-visit randomization.

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$$\mathcal{D}_{\text{IPVR}}^*(M) = \operatorname{argmax}_{I \in \{0,1\}} E[\pi | do(I), M, V = 1]$$

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$$E[\pi | do(I = 0), M = 1, V = 1] = 50$$

$$E[\pi | do(I = 1), M = 0, V = 1] = 5$$

$$E[\pi | do(I = 0), M = 0, V = 1] = 30$$

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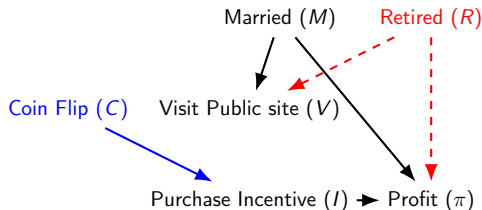
Table: $E[\pi | M, R, I]$.

Decision Rule:

- If Visit Site \wedge Married \rightarrow No Purchase Incentive $\rightarrow E[\pi] = 50$
- If Visit Site \wedge Not Married \rightarrow No Purchase Incentive $\rightarrow E[\pi] = 30$

Expected profit = $\boxed{40} = (50+30)/2$.

3. Interventional Inference + Full Randomization



$$V := M \oplus R$$

$$I := C$$

Figure: Causal DAG with Full Randomization.

3. Interventional Inference + Full Randomization



$$\mathcal{D}_{\text{IFR}}^*(M) = \operatorname{argmax}_{I \in \{0,1\}} E[\pi | \text{do}(I), M]$$

$$E[\pi | \text{do}(I = 1), M = 1] = 35.0 = (25 + 45)/2$$

$$E[\pi | \text{do}(I = 0), M = 1] = 27.5 = (50 + 5)/2$$

$$E[\pi | \text{do}(I = 1), M = 0] = 27.5 = (50 + 5)/2$$

$$E[\pi | \text{do}(I = 0), M = 0] = 20.0 = (10 + 30)/2$$

	$R = 0$		$R = 1$	
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$$E[\pi | do(I = 0), M = 0] = 20.0 = (10 + 30)/2$$

	$R = 0$		$R = 1$	
	$M = 1$	$M = 0$	$M = 1$	$M = 0$
$I = 1$	25	50	45	5
$I = 0$	50	10	5	30

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

Decision Rule:

- If Married \rightarrow Purchase Incentive $\rightarrow E[\pi] = 35$
- If Not Married \rightarrow Purchase Incentive $\rightarrow E[\pi] = 27.5$

$$\text{Expected profit} = \boxed{31.5} = (35 + 27.5)/2.$$

4. Regret Decision Criterion



Puzzled by $E[\pi|I, M] \neq E[\pi|do(I), M]$.

4. Regret Decision Criterion



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$$\mathcal{D}_{\text{RDC}}^*(M, I) = \operatorname{argmax}_{a' \in \{0,1\}} E[\pi_{I=a'} | I = a, M]$$

4. Regret Decision Criterion



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$$\mathcal{D}_{\text{RDC}}^*(M, I) = \operatorname{argmax}_{a' \in \{0,1\}} E[\pi_{I=a'} | I = a, M]$$

- 1 Do we need to assume a parametric SCM to identify this causal estimand?

4. Regret Decision Criterion



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$$\mathcal{D}_{\text{RDC}}^*(M, I) = \operatorname{argmax}_{a' \in \{0,1\}} E[\pi_{I=a'} | I = a, M]$$

- ❶ Do we need to assume a parametric SCM to identify this causal estimand?
 - ▶ No. Only unit-level counterfactuals require a parametric model for identification.
 - ▶ There is nothing personal about personalization!

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- ❶ Do we need to assume a parametric SCM to identify this causal estimand?
 - ▶ No. Only unit-level counterfactuals require a parametric model for identification.
 - ▶ There is nothing personal about personalization!
- ❷ Do we need the causal graph to non-parametrically identify this causal estimand?

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$$\mathcal{D}_{\text{RDC}}^*(M, I) = \underset{a' \in \{0,1\}}{\operatorname{argmax}} E[\pi_{I=a'} | I = a, M]$$

- ❶ Do we need to assume a parametric SCM to identify this causal estimand?
 - ▶ No. Only unit-level counterfactuals require a parametric model for identification.
 - ▶ There is nothing personal about personalization!
- ❷ Do we need the causal graph to non-parametrically identify this causal estimand?
 - ▶ In general, yes. Population-level counterfactuals require the causal graph.
 - ▶ An exception is when the treatment is binary and both experimental and observational data are available.

4. Regret Decision Criterion



$$\mathcal{D}_{\text{RDC}}^*(M, I) = \operatorname{argmax}_{a' \in 0,1} E[\pi_{a'} | I = a, M]$$

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

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

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

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

4. Regret Decision Criterion



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

$$\begin{aligned} & \frac{1}{P(I=0|M=1)} \left[E(\pi|M=1, do(I=1)) - \right. \\ & \quad \left. E(\pi|M=1, I=1)P(I=1|M=1) \right]. \\ & = \frac{1}{1/2} (35 - 25 \times 1/2) = 45 \\ & > 5 = E(\pi_{I=0}|M=1, I=0). \end{aligned}$$

$$E(\pi_{I=1}|M=0, I=0) = 50$$

$$E(\pi_{I=0}|M=1, I=1) = 50$$

$$E(\pi_{I=0}|M=0, I=1) = 30$$

	$R=0$		$R=1$	
	$M=1$	$M=0$	$M=1$	$M=0$
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4. Regret Decision Criterion



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$$E(\pi_{I=1}|M=0, I=0) = 50$$

$$E(\pi_{I=0}|M=1, I=1) = 50$$

$$E(\pi_{I=0}|M=0, I=1) = 30$$

Decision Rule:

- If Not Visit Site \wedge Married \rightarrow Purchase Incentive $\rightarrow E[\pi] = 45$
- If Not Visit Site \wedge Not Married \rightarrow Purchase Incentive $\rightarrow E[\pi] = 50$
- If Visit Site \wedge Married \rightarrow No Purchase Incentive $\rightarrow E[\pi] = 50$
- If Visit Site \wedge Not Married \rightarrow No Purchase Incentive $\rightarrow E[\pi] = 30$

$$\text{Expected profit} = \boxed{43.75} = (45 + 50 + 50 + 30)/4.$$

	R = 0		R = 1	
	M = 1	M = 0	M = 1	M = 0
I = 1	25	50	45	5
I = 0	50	10	5	30

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

Summary of Methods

Criterion	Decision Rule	$E[\pi]$
\mathcal{D}_{AI}	<ul style="list-style-type: none"> • If Visit Site \wedge Married \rightarrow Purchase Incentive • If Visit Site \wedge Not Married \rightarrow No Purchase Incentive 	27.50
\mathcal{D}_{IPVR}	Never Purchase Incentive	40.0
\mathcal{D}_{IFR}	Always Purchase Incentive	31.50
\mathcal{D}_{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 	43.75
\mathcal{D}_{Oracle}		43.75

Remarks

- Experimental data are ‘gold standard’ in the non-personalized paradigm because they remove the influence of unobserved confounders.
- In the personalization paradigm with UHCs, experimental data are not necessarily ‘gold standard’ for identifying heterogeneous treatment effects:
 - ▶ Experiments ‘destroy’ uncoded knowledge about these confounders.
 - ▶ Interventional inference does not capture the information required to maximize payout.
- Counterfactual-based decision-making leads to a fusion of experimental and observational data, which might capture additional information about UHCs required to maximize payout.

Further Reading

- This presentation is fundamentally inspired by this paper:
 - ▶ 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>.
- 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.