Uplift modeling
from Causal Inference to Personalization

The Web Conference 2021 Tutorial (WWW '21) - Ljubljana, Slovenia

THE WEB CONFERENCE

https://booking.ai/uplift-modeling-f9759e3fb51e

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Who are we?

Irene Teinemaa

- **Machine Learning Scientist** at Booking.com Amsterdam for about 2 years
- Prior to Booking: Ph.D. in Applied ML at University of Tartu, Estonia

Javier Albert

- **Machine Learning Scientist** at Booking.com Tel Aviv for about 2 years
- Prior to Booking: M.Sc. in Electrical Engineering at Tel Aviv University

Dima Goldenberg

- **Machine Learning Team Lead** at Booking.com Tel Aviv
- Prior to Booking: M.Sc. in Industrial Engineering at Tel Aviv University

Agenda

Tuesday, April 13th 2021, GMT+1

- 09:00 - Recommenders & Causality
- 09:30 - Introduction to Causality
- 09:50 - Uplift Modeling
- 10:30 - Constrained Uplift Modeling
- 11:10 - Applications
- 11:40 - Q&A

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Recommenders and Causality

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Company Highlights

29+ M
listings including
6+M homes, apartments and other unique places

Offices in over
70 countries

10,000,000,000
Model predictions per day

300+
Models Running Live

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€ | List your property | Register | Sign in

Accommodation | Flights | Car rental | Airport taxis

Amsterdam

3 reasons to visit: **Van Gogh Museum, Coffee Shops, Red Light District**

Amsterdam's intriguing history spans seven centuries. From humble beginnings as a small village to a world power in the seventeenth century, Amsterdam today is a beguiling mix of history and commerce.... Show more

Map view

Search

Destination/property name:

Amsterdam

Check-in date

Monday 17 June 2019

Check-out date

Thursday 20 June 2019

3-night stay

2 adults

No children | 1 room

I'm travelling for work

Search

Amsterdam is a top pick amongst travellers on your selected dates (74% reserved).
Tip: Prices may be higher than usual for the dates you have selected, why not try again with these alternatives?

74% reserved

15 Jun - 18 Jun	16 Jun - 19 Jun	17 Jun - 20 Jun	18 Jun - 21 Jun	19 Jun - 22 Jun
From ₪ 314 per night	₪ 23 less per night	From ₪ 209 per night	From ₪ 219 per night	From ₪ 316 per night
85% reserved	75% reserved	74% reserved	78% reserved	81% reserved

Amsterdam: 384 properties found

Our top picks | Price (lowest first) | Review score and price | Stars | Star rating and price | •••

Bestseller

Hotel Casa Amsterdam ★★★

Oost, Amsterdam – Show on map (3.1 km from centre) – Metro access

1 other person looked for your dates in the last 10 minutes
Booked 4 times for your dates in the last 6 hours

Twin Room –
Only 2 rooms left on our site!

Very good 8.4
6,979 reviews

3 nights, 2 adults
~~€ 547~~ € 479
+€ 31 taxes and charges

See our last available rooms ›

Hotel Tamara ★

Amsterdam City Centre, Amsterdam – Show on map (300 m from centre) – Metro access

Family Room with Shared Bathroom – × 5
Only 1 room left on our site!

Review score 5.4
1,119 reviews

3 nights, 2 adults
€ 600
+€ 39 taxes and charges

Choose your room ›

Filter by:

Your budget

- € 50 - € 100 per night 31
- € 100 - € 150 per night 106
- € 150 - € 200 per night 159
- € 200 + per night 242

Popular filters

- Amsterdam City Centre 190
- Breakfast included 162

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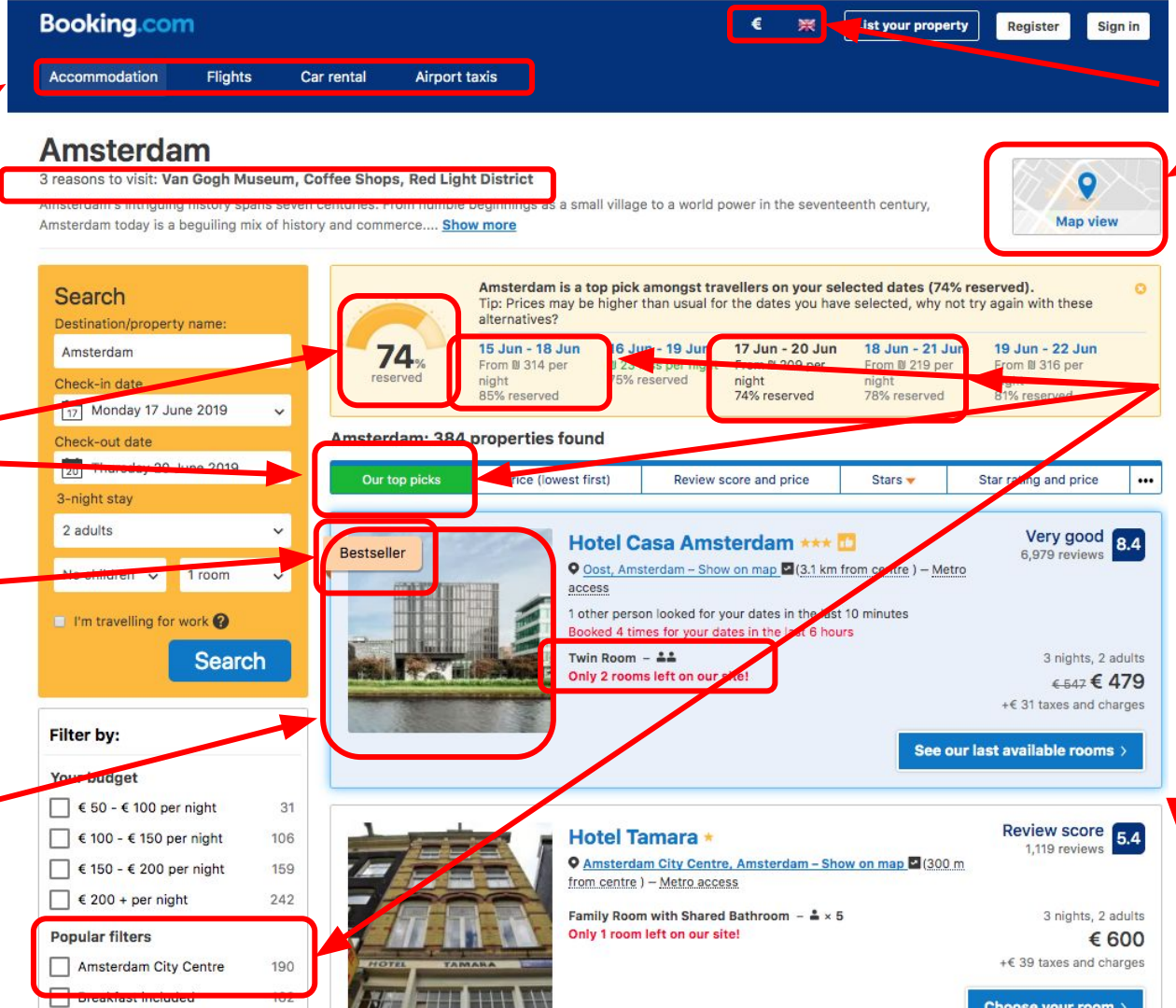

Product types

Topic modelling

Metrics definition

Automatic detection of high-demand properties

Content selection

website settings

Personalized elements

Recommendations

Ranking

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Recommender Systems are Complex.

Target Item	Audience	Framing	KPI	Data	Feedback
What do we want to recommend?	Who are we recommending? When?	What is the role of the recs?	How do we measure effectiveness?	What data are we going to use?	How do we define user satisfaction?

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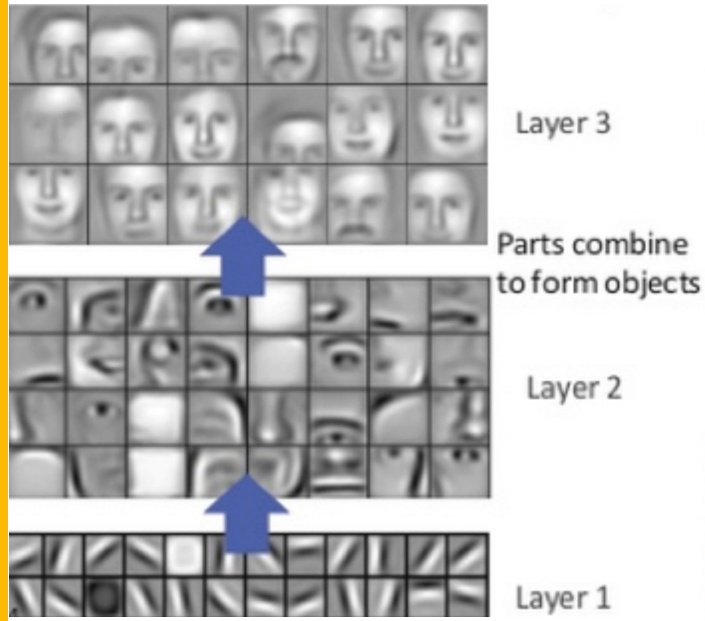
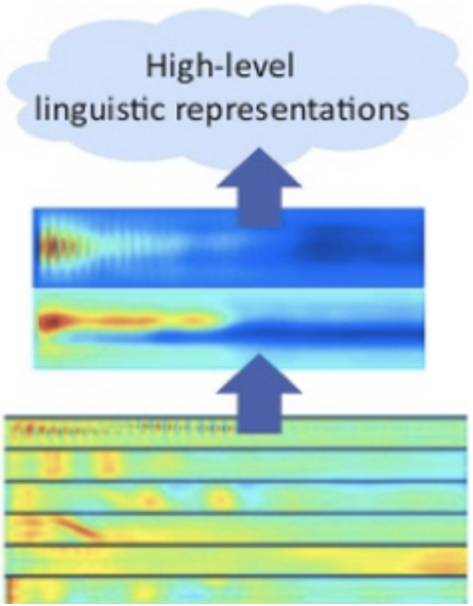
Deep learning solving "human" problems





	Problem	Superhuman?
Vision	Understand objects in images	2015
	Visual question answering	No
Language	Speech recognition	2016
	Reading comprehension	No
	Translation	No
Games	Abstract strategy	2017 (Go)
	Real-time video games	Mixed

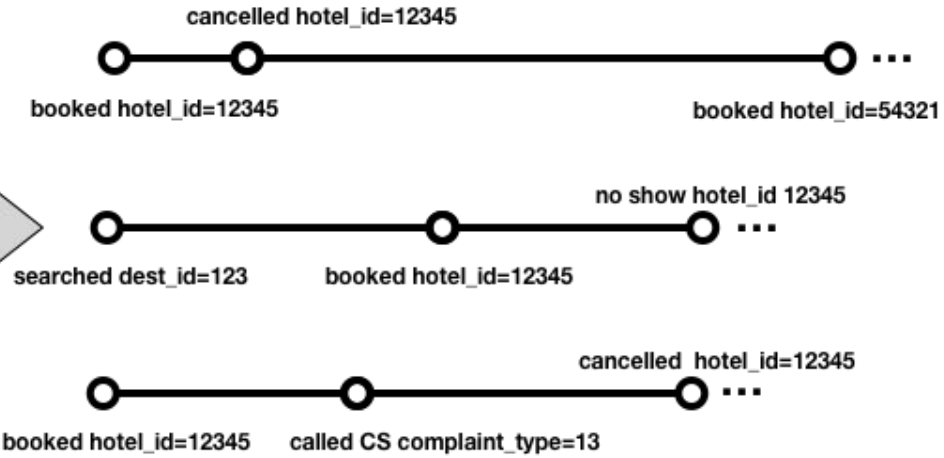
Source: Electronic Frontier Foundation AI Progress Measurement

Sequence learning

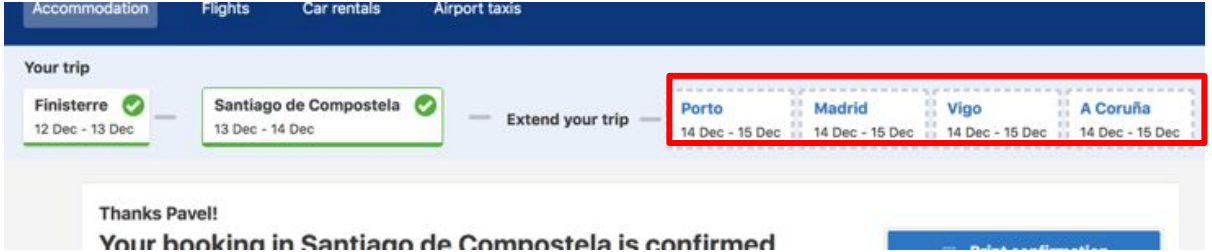
Rectangular data view

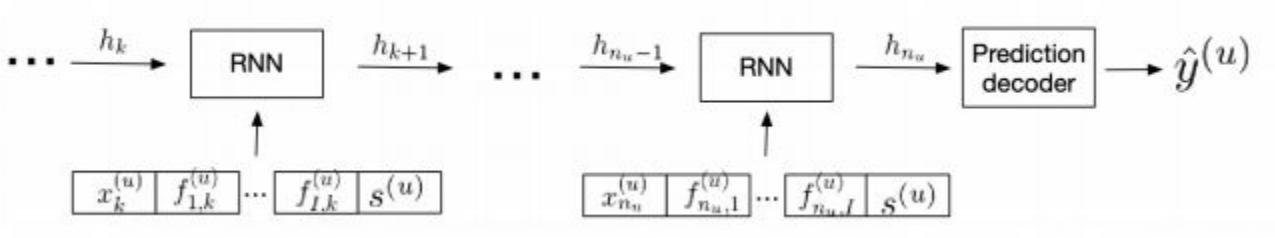
booker_cc1	n_res_past_year	frac_cancelled	had_cs_contact
nl	4	0.25	TRUE
us	2	0	FALSE
us	1	1.0	FALSE
de	8	0.125	TRUE
...	...	...	...

Sequence data view



At Booking.com:





https://booking.ai/combining-context-features-in-sequence-aware-recommender-systems-b6691bdd2f2d

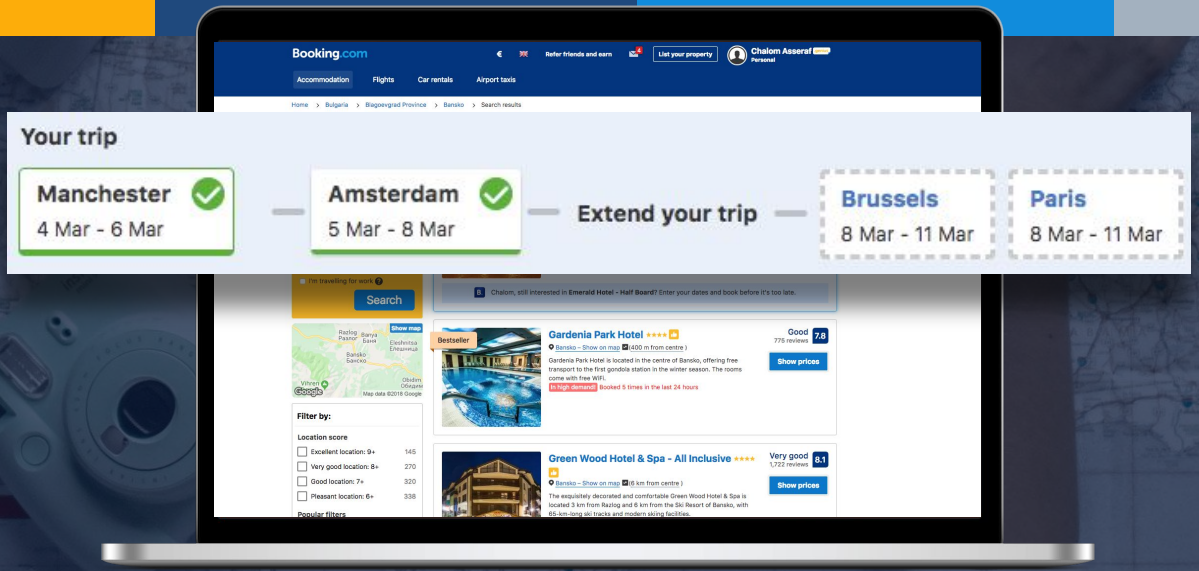
More improvements around.

Copywriting.

User Experience.

Infrastructure.

Retraining.



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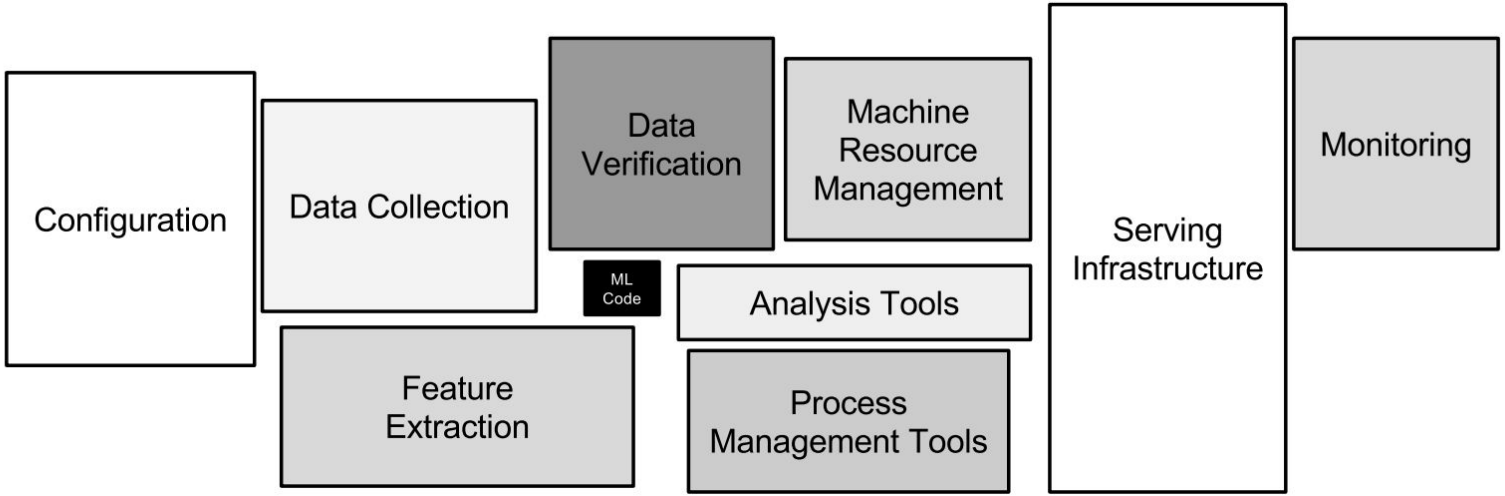
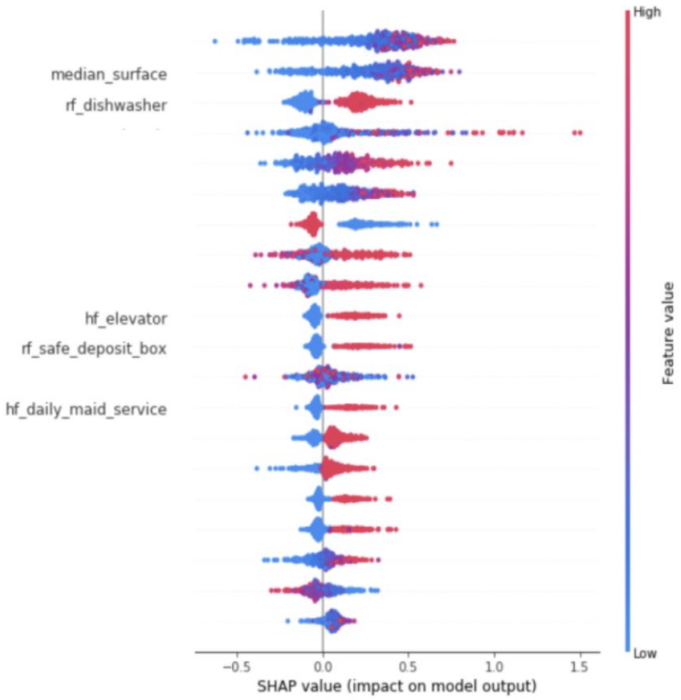
ML Ops



Sculley, David, et al. "Hidden technical debt in machine learning systems." *Advances in neural information processing systems* 28 (2015): 2503-2511.

Models Explanation Methods



Local Interpretability:

- **Shapley Values** - NIPS 2018, ICML 2020, NMI 2020
- **LIME -** Local Surrogate by Ribeiro et al. 2016
- **Anchors** - Ribeiro et al. 2018

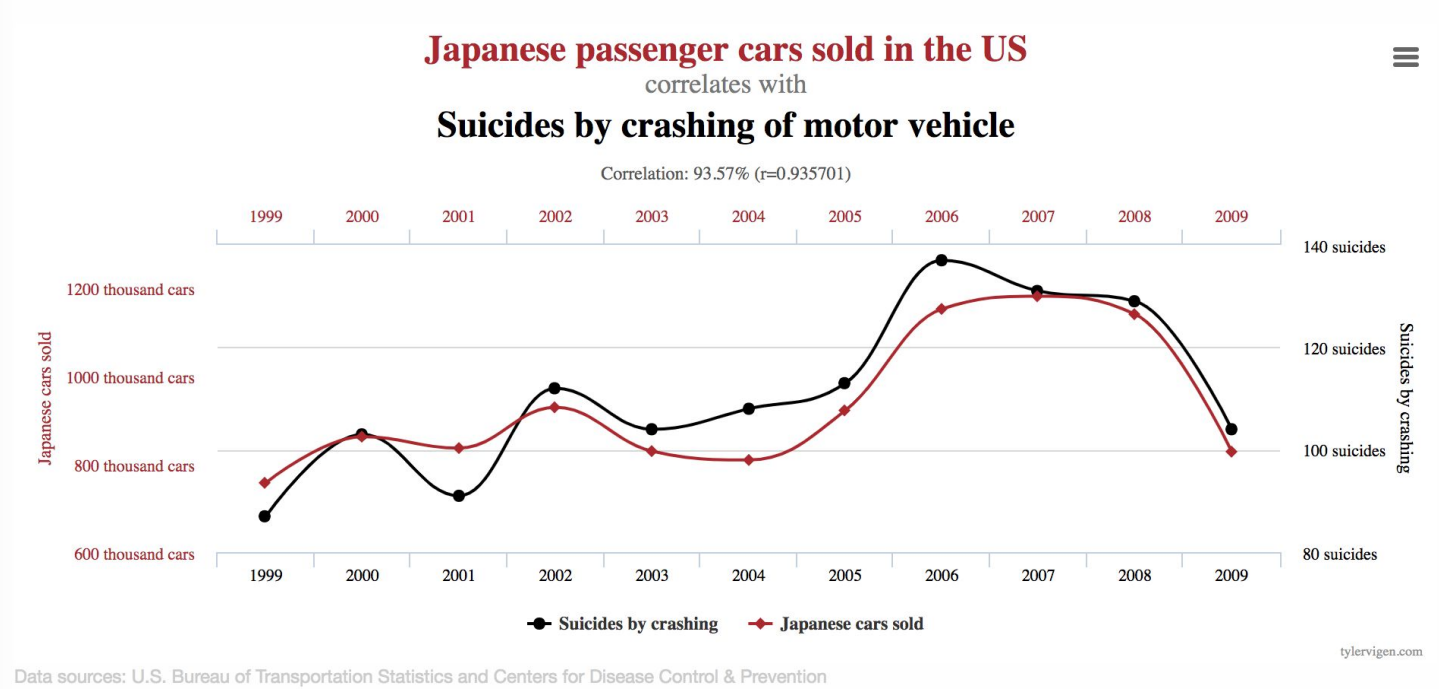
Global Interpretability:

- PDP, ICE, SHAP dependence plots, ALE
- Surrogate model (linear regression, decision tree)
- Shapley Values

Inherently Interpretable models:

- Decision Trees
- Linear / Logistic Regression
- Naive Bayes

Move from Correlation to Causality



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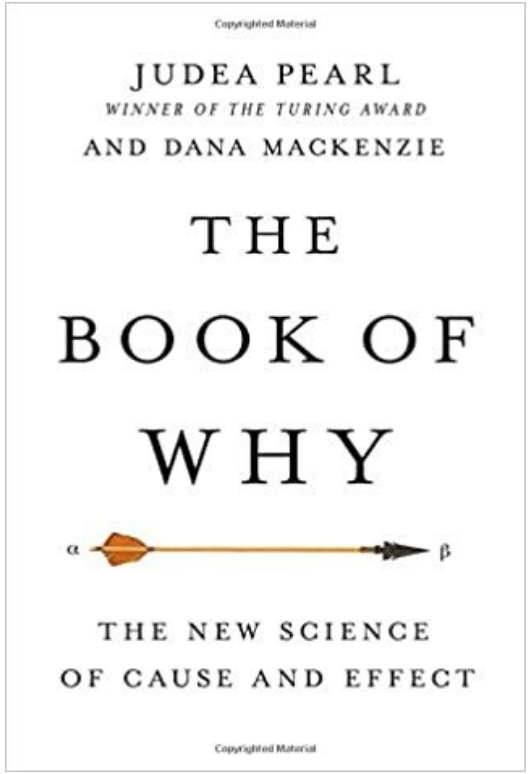
Move from Correlation to Causality

NOX HOTELS- Baker Street
London

Starting from ₪ 279

8.4 Very good · 1,398 reviews

?



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Biases in Models

Data Proxy

Selection Bias

Model Bias

Online vs Offline

Business Metrics

Selection Bias

How representative is the data we're using?

- Filter sorting/position might affect the usage
- Bias towards users who interact more with the site
- Supply availability

Online vs Offline

How good is our online performance?

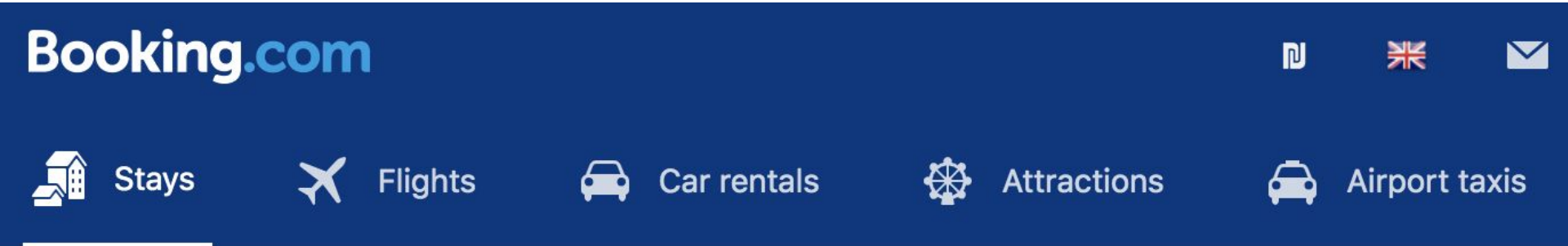
- Data Consistency (features and labels)
- Behavior change
- Target Audience change

Business Metrics

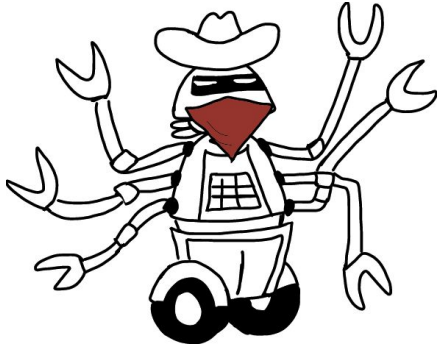
What is the effect on users our business metrics?

- Correlation vs Causation
- Cannibalism and Distraction
- True Positives vs False Positives

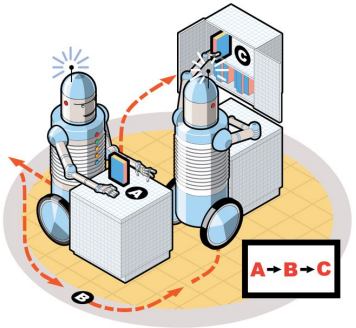
Feedback Loops



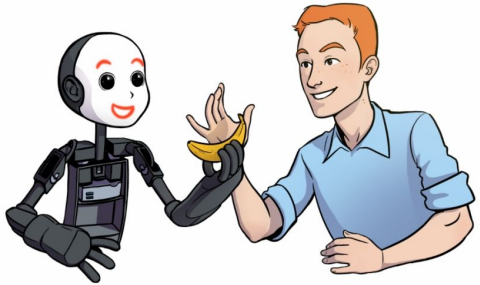
Active Exploration



Contextual Bandits



Reinforcement Learning

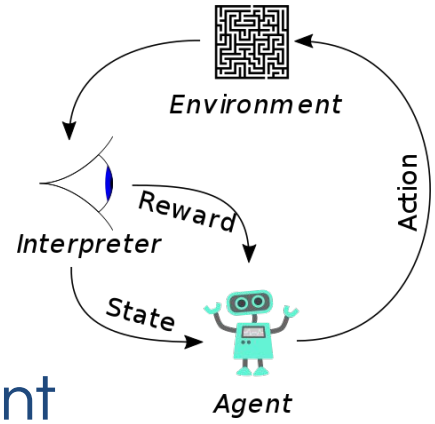


Human in the Loop

Multi-Armed Bandits

- Comes from “one-armed bandit” in casino
- Our goal is to **maximize total payout (reward)**.
- **exploration/exploitation tradeoff**
- Contextual Bandit learns the reward Based on the feature space

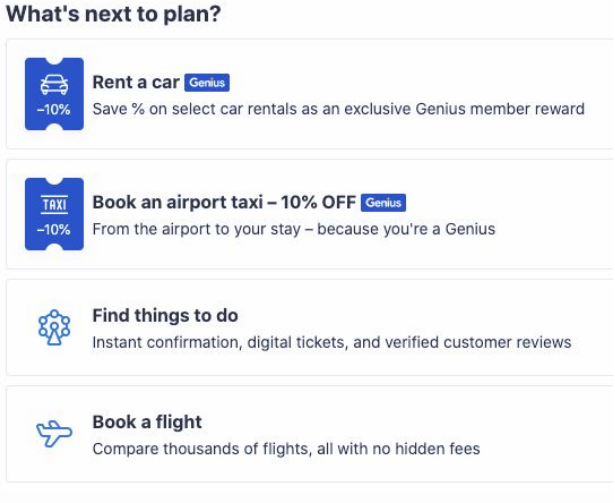
Reinforcement Learning



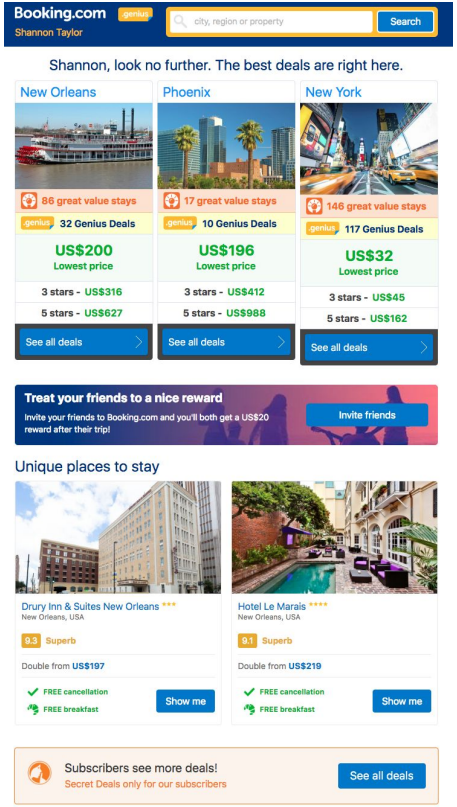
- Similarly to bandits **maximize total reward**.
- Maintains state in a agent-based environment
- Very common in games, driving and robotics
- Special applications for dynamic environment and long-term reward

Searching for the best filters

Products personalization



which emails *not* to send

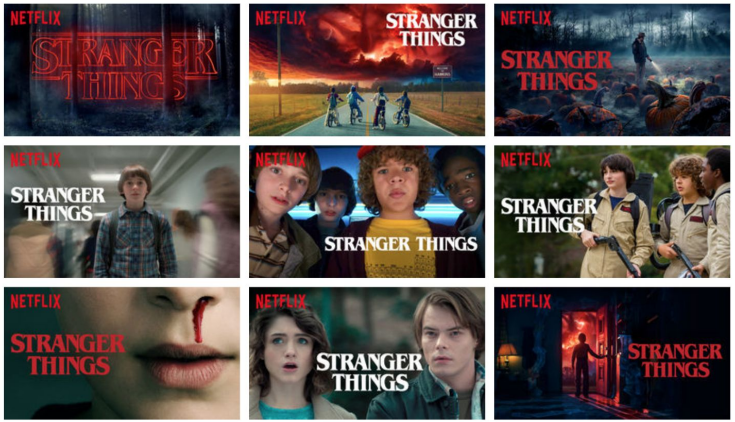


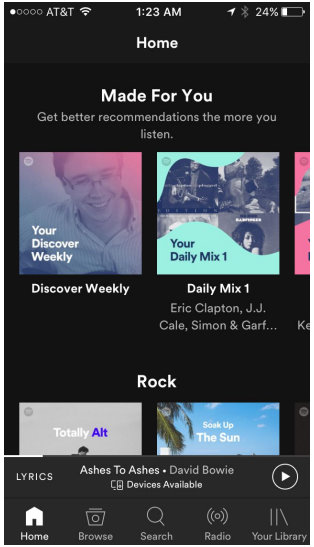
Recommending Accommodation Filters with Online Learning

Lucas Bernardi, Pablo Estevez, Matias Eidis and Eqbal Osama - ORSUM @ RecSys'20

Industry Examples

Netflix and Spotify recommendations: all about exploration

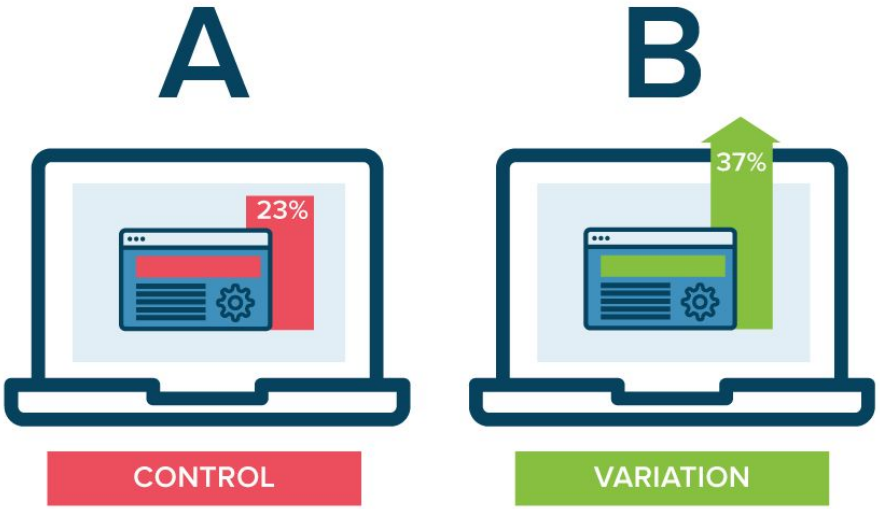




Chandrashekar, Ashok et al. “Artwork Personalization at Netflix” https://medium.com/netflix-techblog/artwork-personalization-c589f074ad76, 2017

Dimakopoulou, Maria, et al. "Marginal Posterior Sampling for Slate Bandits." IJCAI. 2019.

A/B Testing



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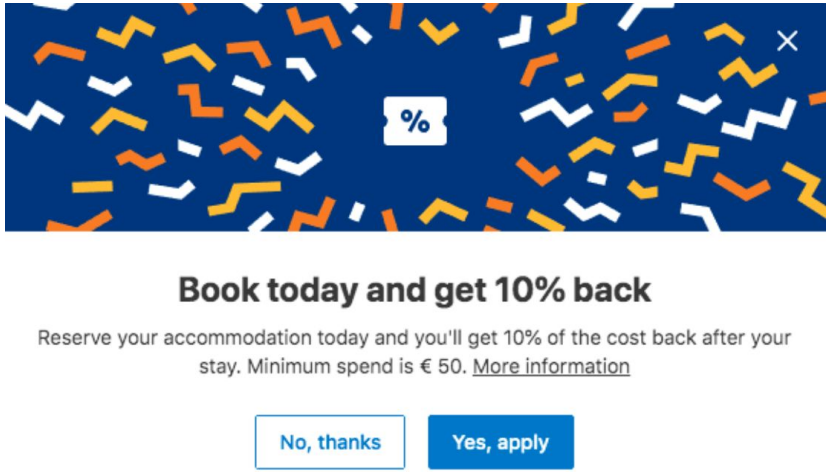
A/B Testing

Thousands of experiments are running simultaneously

Any site change is going through testing (Copy, UI, Bugfix and ML models)

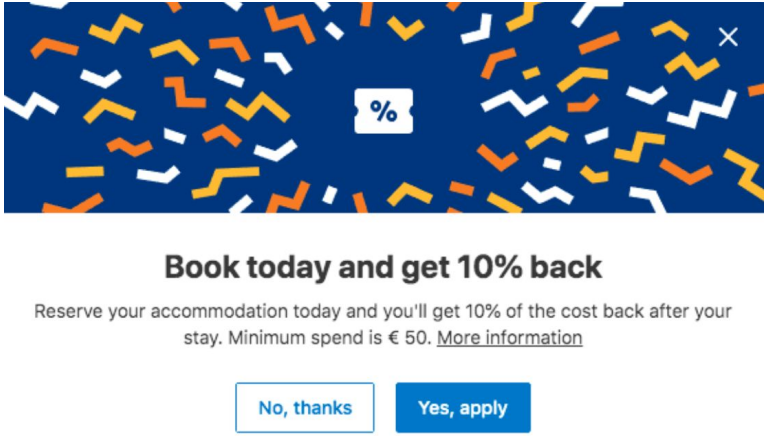
Experimentation is focused on hypothesis validation by statistical tests on metrics

Causal Models - Uplift



Causal Models - Uplift

	No Discount	Discount
	✓	✓
	✗	✗
	✓	✗
	✗	✓



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Causality

Recent work:

Booking: Dmitri Goldenberg, Javier Albert, Lucas Bernardi, and Pablo Estevez. 2020.Free Lunch! Retrospective Uplift Modeling for Dynamic Promotions Recommendation within ROI Constraints. (RecSys ’20), Virtual Event, Brazil.ACM

Princeton: Chaney, Allison JB, Brandon M. Stewart, and Barbara E. Engelhardt. "How algorithmic confounding in recommendation systems increases homogeneity and decreases utility." arXiv preprint arXiv:1710.11214 (2017).

Cornell: Schnabel, Tobias, et al. "Recommendations as treatments: Debiasing learning and evaluation." arXiv preprint arXiv:1602.05352 (2016).

Spotify: McInerney, James, et al. "Explore, exploit, and explain: personalizing explainable recommendations with bandits." Proceedings of the 12th ACM Conference on Recommender Systems. ACM, 2018.

Debiasing:

Inverse Propensity Weighting: Austin, Peter C., and Elizabeth A. Stuart. "Moving towards best practice when using inverse probability of treatment weighting (IPTW) using the propensity score to estimate causal treatment effects in observational studies." *Statistics in medicine* 2015

Causal Embeddings: Bonner, Stephen, and Flavian Vasile. "Causal embeddings for recommendation." *Proceedings of the 12th ACM Conference on Recommender Systems*. 2018

Doubly Robust Estimation: Bang, Heejung, and James M. Robins. "Doubly robust estimation in missing data and causal inference models." *Biometrics* 61.4 2005

Intro to Causality

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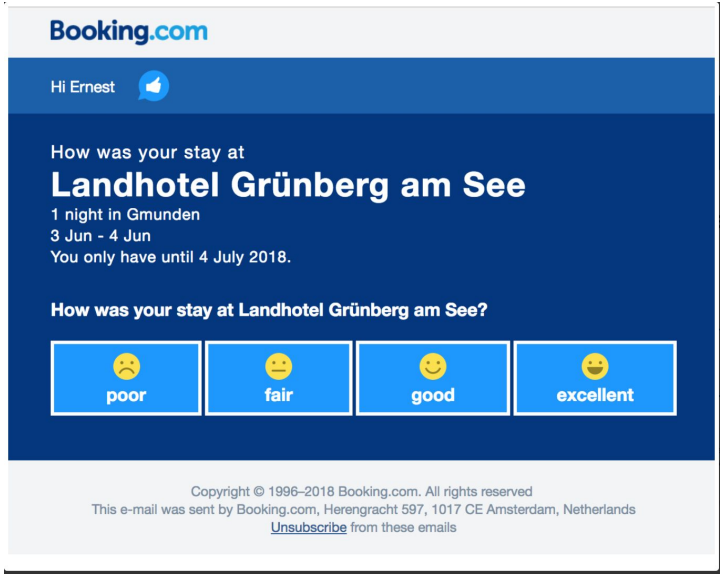
A/B testing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1 night in Gmunden
3 Jun - 4 Jun
You only have until 4 July 2018.
How was your stay at Landhotel Grünberg am See?
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fair
good
excellent
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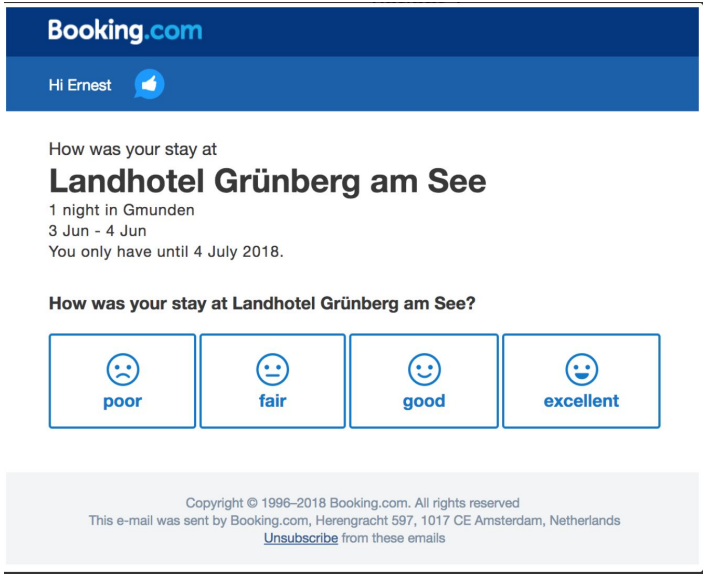
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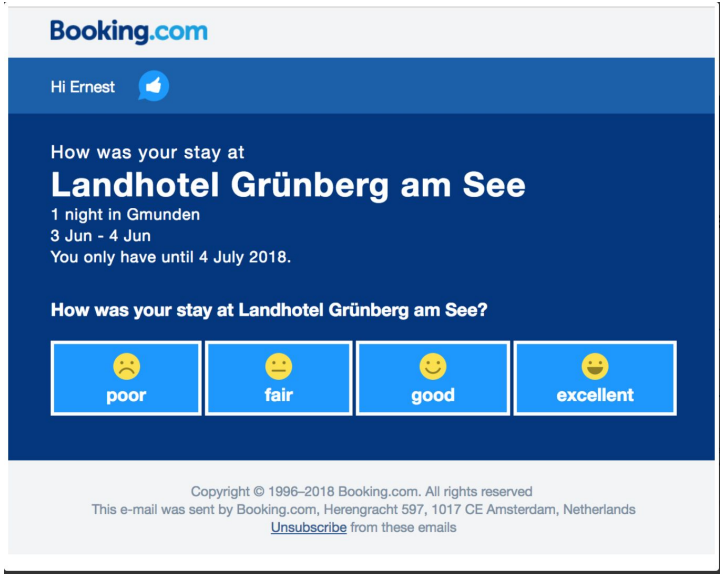
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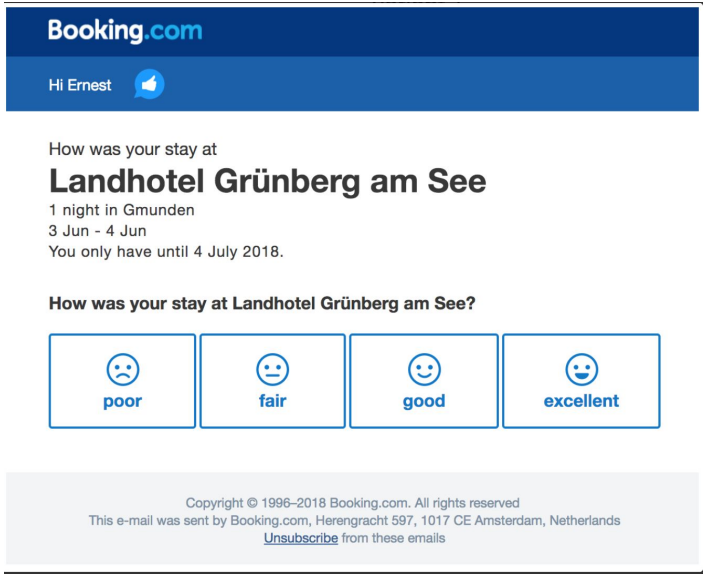
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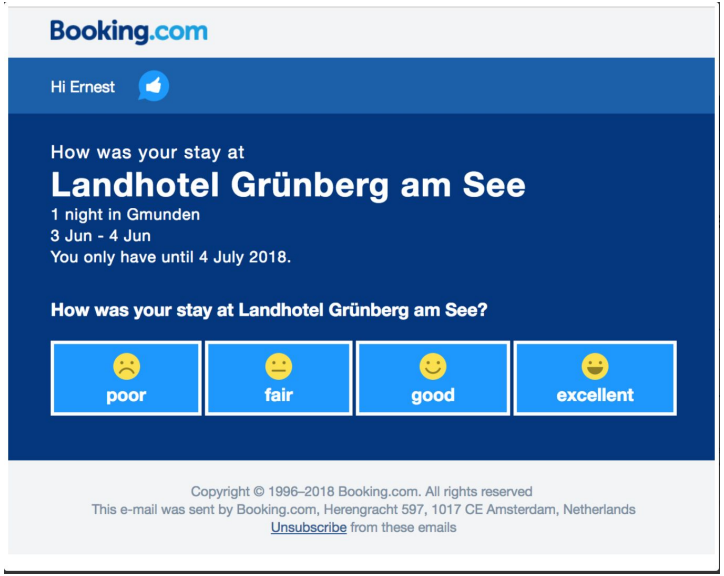
A/B testing

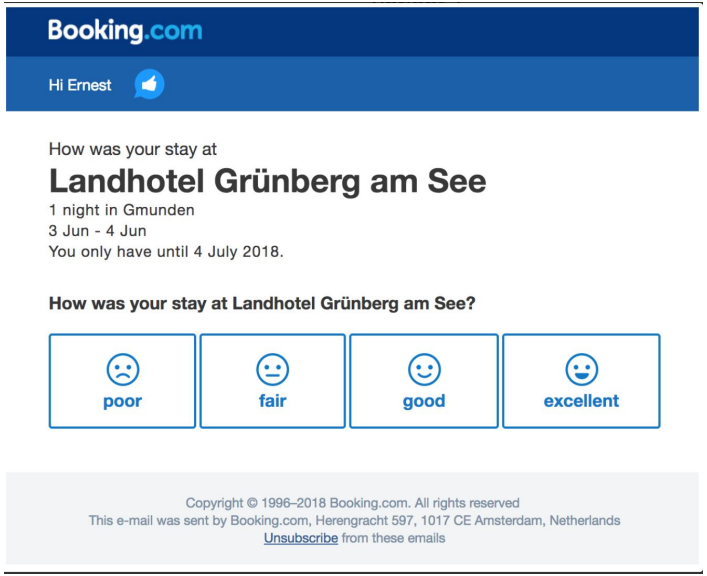
50%

50%

A/ Base/ Control



B/ Variant/ Treatment

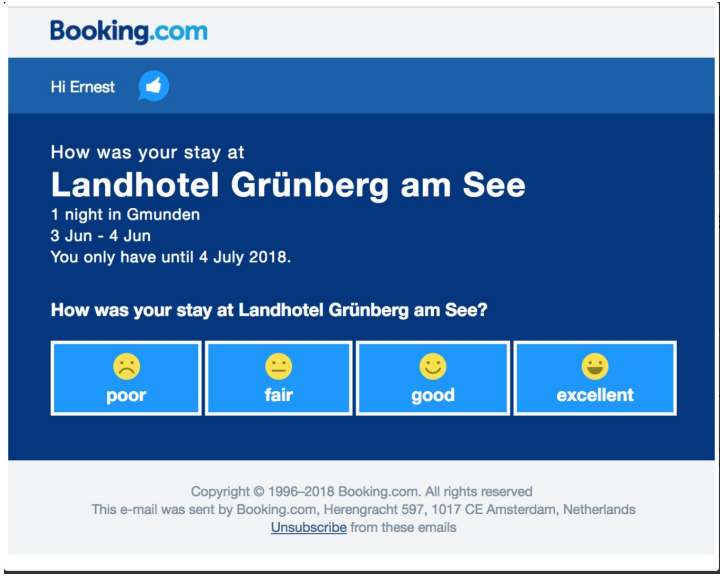


A/B testing

50%

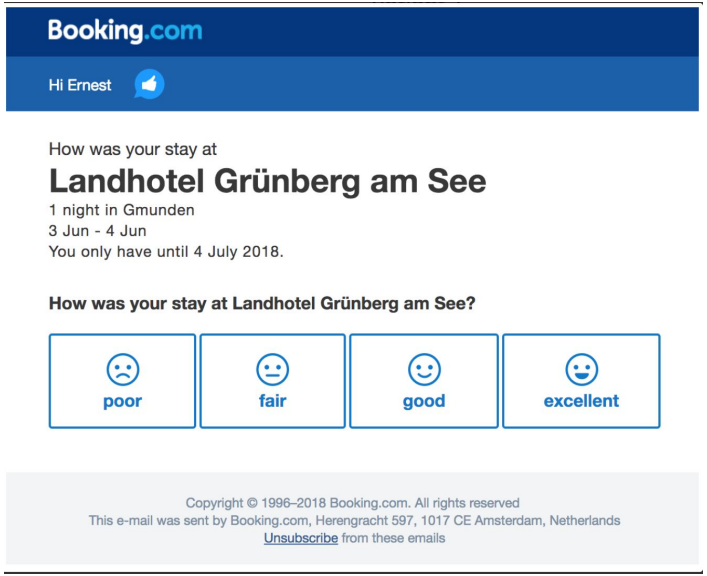
50%

A/ Base/ Control



Review Submission Rate:
13.71%

B/ Variant/ Treatment



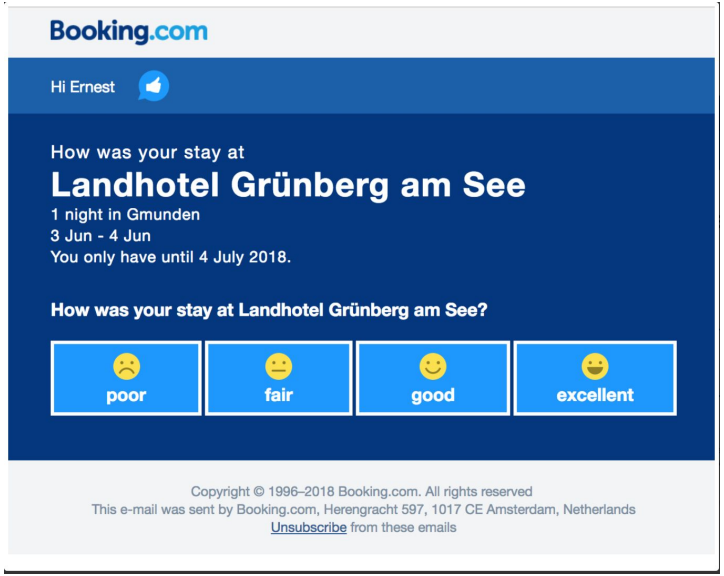
Review Submission Rate:
13.75%

A/B testing

50%

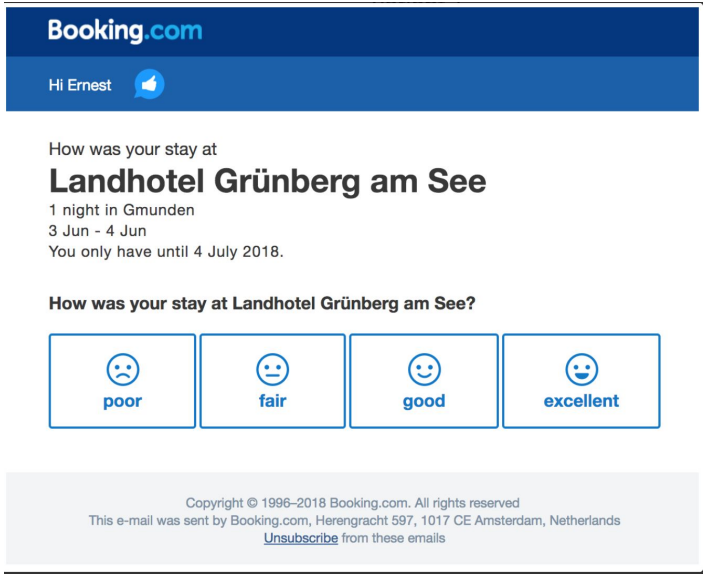
50%

A/ Base/ Control



Review Submission Rate:
13.71%

B/ Variant/ Treatment



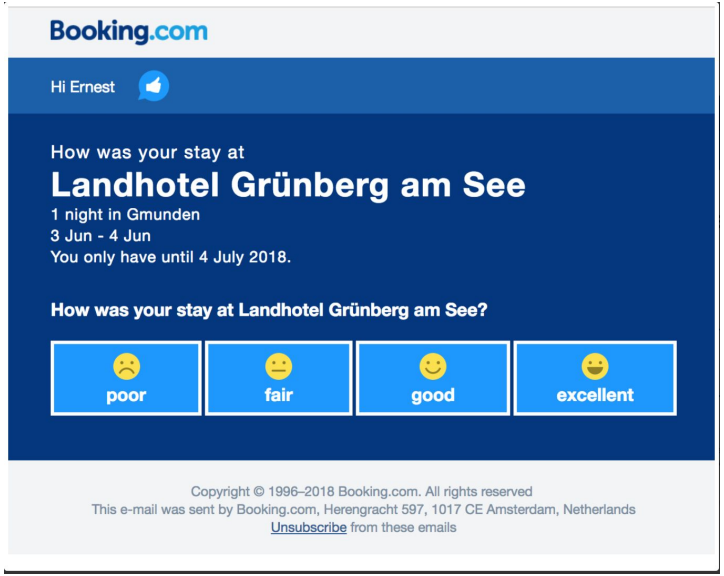
Review Submission Rate:
13.75% ✓

A/B testing

50%

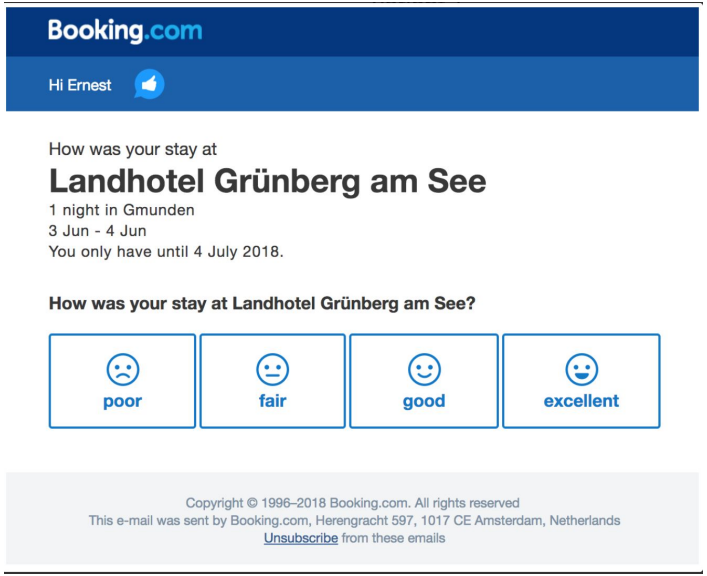
50%

A/ Base/ Control



Review Submission Rate:
13.71%

B/ Variant/ Treatment



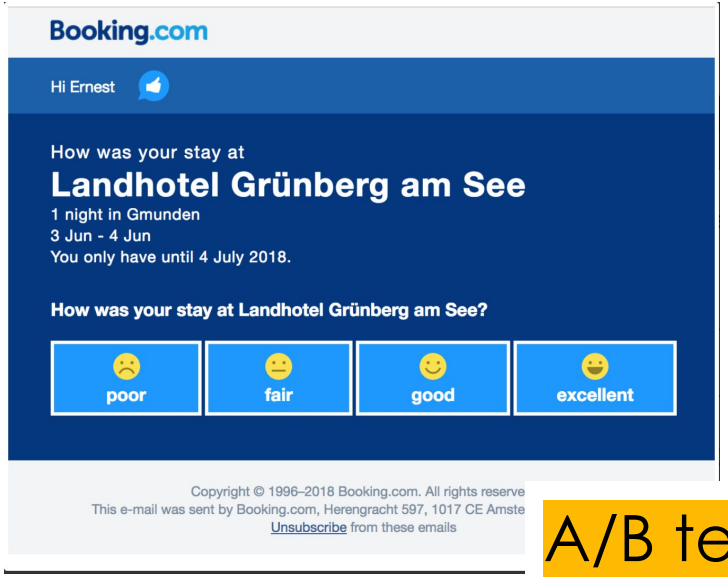
Review Submission Rate:
13.71%

A/B testing

50%

50%

A/ Base/ Control



B/ Variant/ Treatment

A/B test inconclusive

Review Submission Rate:
13.71%

Review Submission Rate:
13.71%

A/B testing

A/B test inconclusive

Users don’t care

Some users loved it and some hated it

Users don’t care

How was your stay?

How was your stay?

Some users loved it, some hated it

	How was your stay?	How was your stay?
	✓	✗
	✗	✓

Individual treatment effect

Potential outcome if treated

Individual treatment effect

	Y(1)	Y(0)	Y(1) - Y(0)
	1	1	0
	0	0	0
	1	0	1
	0	1	-1

Average treatment effect

	Y(1)	Y(0)	Y(1) - Y(0)
	1	1	0
	0	0	0
	1	0	1
	0	1	-1

ATE: $\tau = E[Y(1) - Y(0)]$

Conditional average treatment effect

Pre-exposure covariate(s)

	Y(1)	Y(0)	Y(1) - Y(0)	X
	1	1	0	1
	0	0	0	0
	1	0	1	0
	0	1	-1	1

ATE: $\tau = E[Y(1) - Y(0)]$

CATE: $\tau(x) = E[Y(1) - Y(0) \mid X=x]$

In reality, we observe only one outcome

	Y(1)	Y(0)	Y(1) - Y(0)
	1	?	?
	0	?	?
	?	0	?
	?	1	?

Can we estimate the causal effect from data?

	Y(1)	Y(0)	Y(1) - Y(0)	Received treatment T	Observed outcome Y = Y(T)
	1	?	?	1	1
	0	?	?	1	0
	?	0	?	0	0
	?	1	?	0	1

$$\underbrace{\qquad\qquad}_{E[Y(1) - Y(0)]}$$

Can we estimate the causal effect from data?

	Y(1)	Y(0)	Y(1) - Y(0)	T	Y = Y(T)
	1	?	?	1	1
	0	?	?	1	0
		0	?	0	0
		1	?	0	1

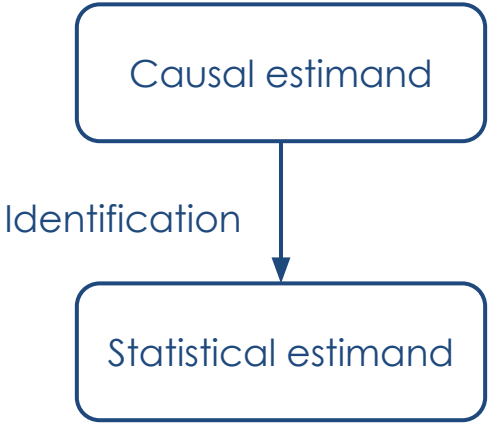
$E[Y \mid T=1]$ $E[Y(1) - Y(0)]$

Can we estimate the causal effect from data?

	Y(1)	Y(0)	Y(1) - Y(0)	T	Y = Y(T)
	1		?	1	1
	0		?	1	0
		0	?	0	0
		1	?	0	1

$$E[Y \mid T=1] - E[Y \mid T=0] \overset{?}{=} E[Y(1) - Y(0)]$$

Identification



$$E[Y(1) - Y(0)]$$

?

$$=$$

$$E[Y \mid T=1] - E[Y \mid T=0]$$

Only if some **conditions** hold:

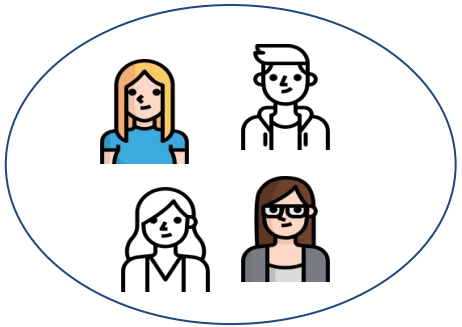
1. Exchangeability
2. Positivity
3. Consistency
4. No interference

Condition 1: Exchangeability

How was your stay?

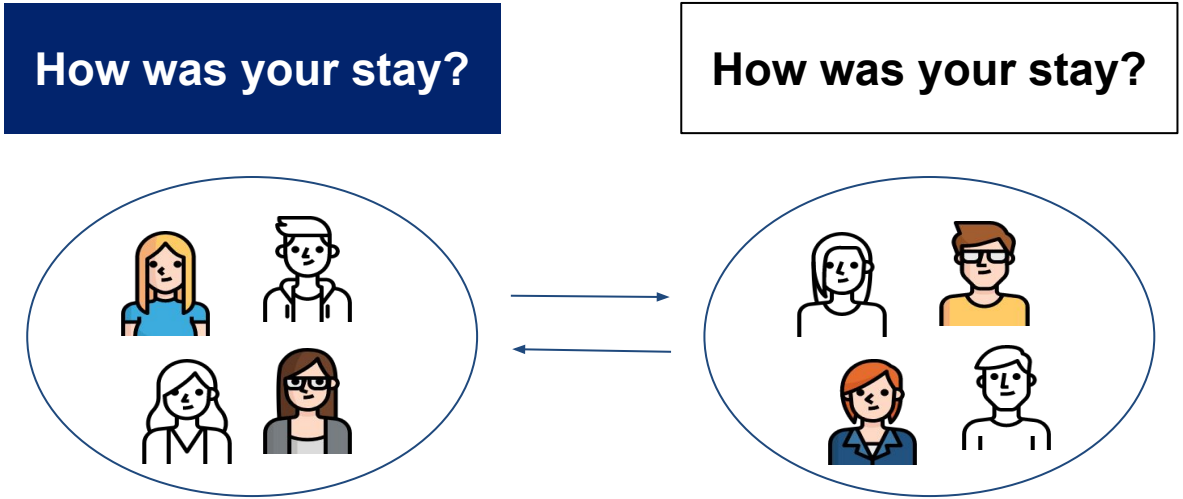
$E[Y(1) \mid \mathbf{T=1}]$

How was your stay?



$E[Y(0) \mid \mathbf{T=0}]$

Condition 1: Exchangeability



$E[Y(1) \mid \mathbf{T=1}]$

$E[Y(0) \mid \mathbf{T=0}]$

Swapping the groups **wouldn't change** the expected value!

Condition 1: Exchangeability

$E[Y(1) \mid \mathbf{T=1}] = E[Y(1) \mid \mathbf{T=0}]$

Condition 1: Exchangeability

$E[Y(1) \mid \mathbf{T=1}] = E[Y(1) \mid \mathbf{T=0}] = E[Y(1)]$

$E[Y(0) \mid \mathbf{T=0}] = E[Y(0) \mid \mathbf{T=1}] = E[Y(0)]$

Potential outcomes are independent of T: $\boxed{\{Y(0), Y(1)\} \perp\!\!\!\perp T}$

This holds in **randomized** experiments!

Condition 2: Positivity

All subgroups have some prob. of receiving any value of treatment:

$$0 < P(T \mid X=x) < 1$$

<u>Violation example</u>: if users from Germany **always receive treatment T=1**, we cannot estimate the counterfactual under T=0 for this group

Condition 3: Consistency

The observed outcome Y corresponds to the potential outcome under the observed treatment T:

$$\boxed{Y = Y(T)}$$

<u>Violation example</u>: if treatment **T=1 has multiple variants**, the potential outcome Y(1) is not well defined

How was your stay?	T=1 => **Y=1**
How was your stay?	T=1 => **Y=0**
How was your stay?	T=1 => **Y=0**

Condition 4: No interference

A given user's outcome $\mathbf{Y_i}$ is **unaffected** by anyone else's treatment $\mathbf{T_j}$

<u>Violation example</u>: users "compete" for the same supply of accommodations

T=1 => books => **Y=1**

T=1 => can't book because unavailable => **Y=0**

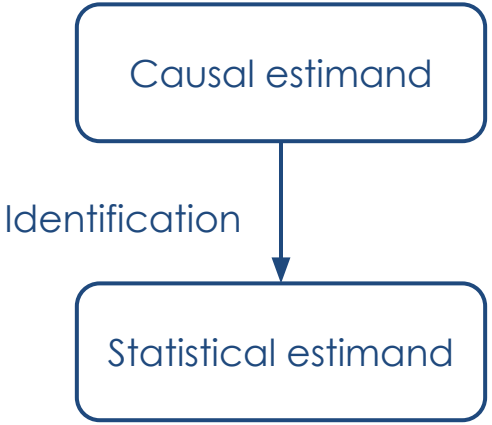
Condition 4: No interference

A given user's outcome $\mathbf{Y_i}$ is **unaffected** by anyone else's treatment $\mathbf{T_j}$

<u>Violation example</u>: users are connected in the social network

[1] Saint-Jacques, G., Varshney, M., Simpson, J. and Xu, Y., 2019. Using ego-clusters to measure network effects at LinkedIn. arXiv preprint arXiv:1903.08755.
[2] Saveski, M., Pouget-Abadie, J., Saint-Jacques, G., Duan, W., Ghosh, S., Xu, Y. and Airoldi, E.M., 2017, August. Detecting network effects: Randomizing over randomized experiments. In Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining (pp. 1027-1035).
[3] Pouget-Abadie, J., Saint-Jacques, G., Saveski, M., Duan, W., Ghosh, S., Xu, Y. and Airoldi, E.M., 2019. Testing for arbitrary interference on experimentation platforms. Biometrika, 106(4), pp.929-940.

Identification



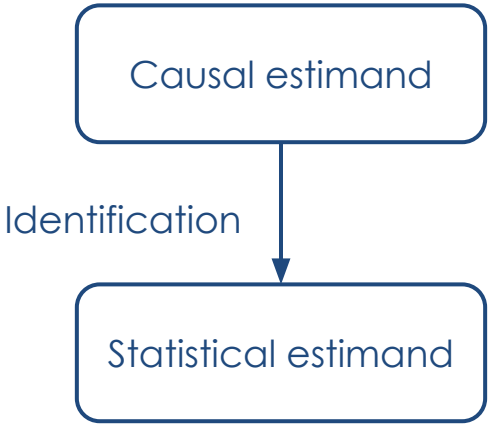
$$E[Y(1) - Y(0)]$$

$$=$$

$$E[Y \mid T=1] - E[Y \mid T=0]$$

- Exchangeability
- Positivity
- Consistency
- No interference

Identification from observational data



$$E[Y(1) - Y(0)]$$

$$=$$

$$?$$

Unconfoundedness
Positivity
Consistency
No interference

Useful resources:

- Online course and textbook on Causal Inference by Brady Neal
- "What if" book by Hernan and Robins
- Causal inference in statistics: A primer by Judea Pearl et al.
- Youtube tutorial by Jonas Peters

Conditional exchangeability (unconfoundedness)

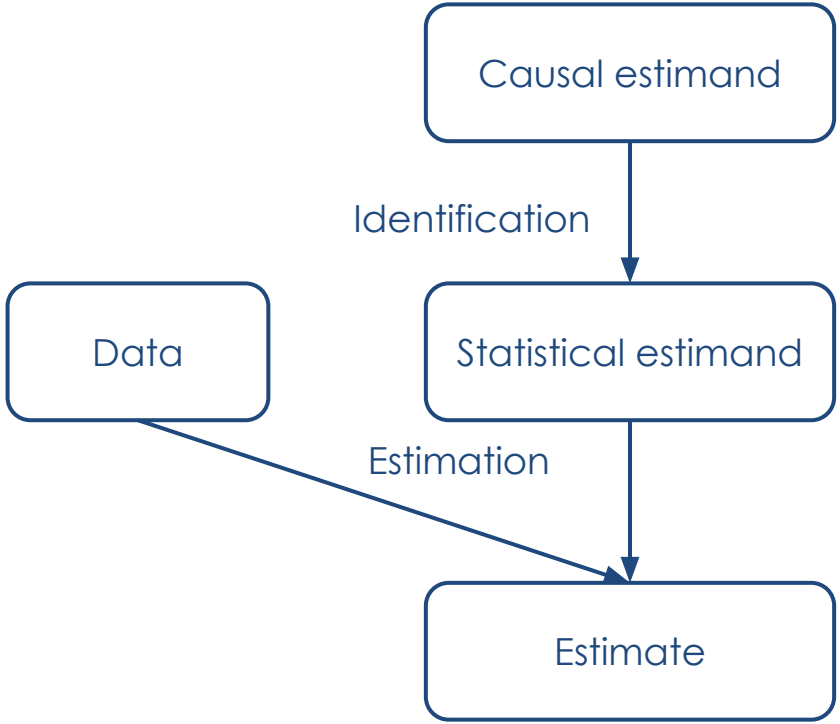
$E[Y(1) \mid \mathbf{T=1}, \mathbf{X=x}] = E[Y(1) \mid \mathbf{T=0}, \mathbf{X=x}] = E[Y(1) \mid \mathbf{X=x}]$

$E[Y(0) \mid \mathbf{T=0}, \mathbf{X=x}] = E[Y(0) \mid \mathbf{T=1}, \mathbf{X=x}] = E[Y(0) \mid \mathbf{X=x}]$

Potential outcomes are independent of **T**, given **X**: $\{Y(0), Y(1)\} \perp\!\!\!\perp T \mid X$

This is a **milder** assumption and also **sufficient**!

Identification and estimation



$$E[Y(1) - Y(0)]$$

$$E[Y \mid T=1] - E[Y \mid T=0]$$

$$\hat{E}[Y \mid T=1] - \hat{E}[Y \mid T=0]$$

Estimating treatment effect: all users

How was your stay?

How was your stay?

ATE = E[Y|T=1] − E[Y|T=0]

Estimating treatment effect: all users

How was your stay?

How was your stay?

ATE = E[Y|T=1] − E[Y|T=0]

Can use simple averages

Estimating treatment effect: users from Germany

How was your stay?

How was your stay?

CATE = $E[Y|T=1, X=\{de\}]$ − $E[Y|T=0, X=\{de\}]$

Estimating treatment effect: leisure travellers from Germany

How was your stay?

How was your stay?

CATE = $E[Y|T=1, X=\{de, leisure\}]$ − $E[Y|T=0, X=\{de, leisure\}]$

Estimating treatment effect: leisure travellers from Germany, doing a last minute reservation on their mobile, ...

How was your stay?

How was your stay?

CATE $=$ $E[Y|T=1, X=x]$ $-$ $E[Y|T=0, X=x]$

Can't use simple averages anymore!

Uplift Modeling

Booking.com
Machine Learning

Uplift modeling

Estimating CATE using **machine learning**.

Model the **change in the outcome** **due to the treatment**.

Uplift modeling

Methods

Metalearners

- Two-model
- Single model
- Transformed Outcome
- R-learner
- …

Tailored methods

- Uplift Trees, Causal Trees
- Causal Forests, Uplift RF
- …

Uplift modeling

Methods

Metalearners

- Two-model
- Single model
- Transformed Outcome [1, 2]
- R-learner [8]
- …

Tailored methods

- Uplift Trees [3], Causal Trees [4]
- Causal Forests [5, 6], Uplift RF [7]
- …

[1] Jaskowski, M. and Jaroszewicz, S., 2012, June. Uplift modeling for clinical trial data. In ICML Workshop on Clinical Data Analysis (Vol. 46).
[2] Athey, S. and Imbens, G.W., 2015. Machine learning methods for estimating heterogeneous causal effects. stat, 1050(5), pp.1-26.
[3] Rzepakowski, P. and Jaroszewicz, S., 2012. Decision trees for uplift modeling with single and multiple treatments. *Knowledge and Information Systems*, *32*(2), pp.303-327.
[4] Athey, S. and Imbens, G., 2016. Recursive partitioning for heterogeneous causal effects. Proceedings of the National Academy of Sciences, 113(27), pp.7353-7360.
[5] Wager, S. and Athey, S., 2018. Estimation and inference of heterogeneous treatment effects using random forests. Journal of the American Statistical Association, 113(523), pp.1228-1242.
[6] Athey, S., Tibshirani, J. and Wager, S., 2019. Generalized random forests. Annals of Statistics, 47(2), pp.1148-1178.
[7] Guelman, L., Guillén, M. and Pérez-Marín, A.M., 2015. Uplift random forests. Cybernetics and Systems, 46(3-4), pp.230-248.
[8] Nie, X. and Wager, S., 2017. Quasi-oracle estimation of heterogeneous treatment effects. arXiv preprint arXiv:1712.04912.
[9] Devriendt, F., Moldovan, D. and Verbeke, W., 2018. A literature survey and experimental evaluation of the state-of-the-art in uplift modeling: A stepping stone toward the development of prescriptive analytics. Big data, 6(1), pp.13-41.
[10] Zhang, Weijia, Jiuyong Li, and Lin Liu. "A unified survey on treatment effect heterogeneity modeling and uplift modeling." arXiv preprint arXiv:2007.12769 (2020).

Two-model approach

How was your stay?

How was your stay?

Logistic regression,
RF, NN, ...

$$\hat{\mu}_1(x)$$

$$\hat{\mu}_0(x)$$

Two-model approach

How was your stay?

How was your stay?

Logistic regression,
RF, NN, ...

$$\hat{\mu}_1(x)$$

$$\hat{\mu}_0(x)$$

Predict Y from X

Two-model approach

How was your stay?

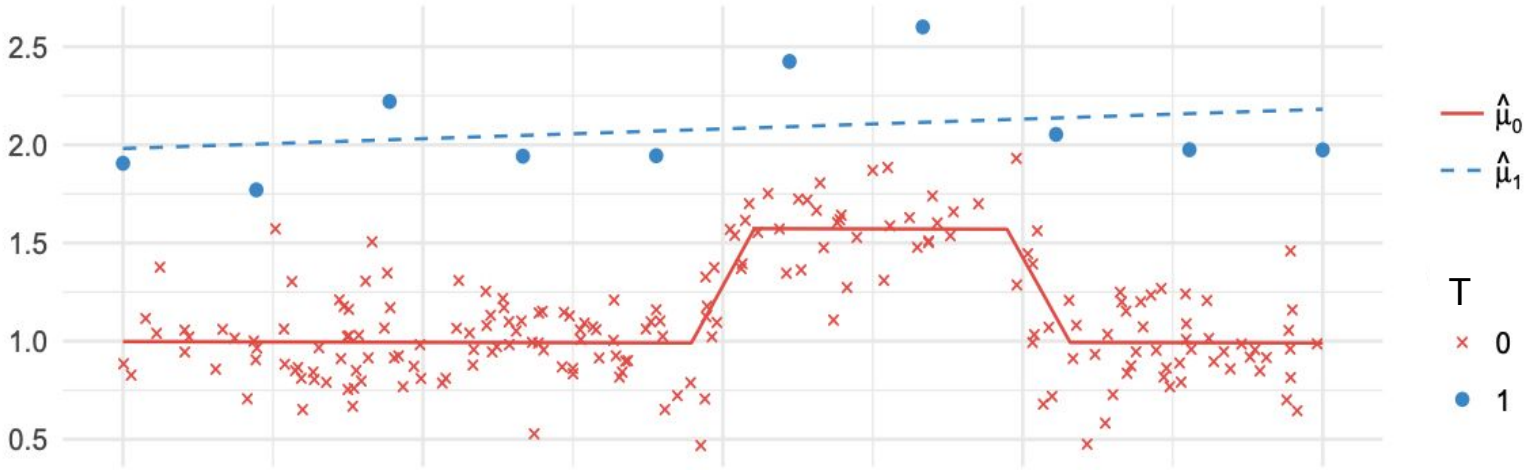
How was your stay?

Logistic regression,
RF, NN, ...

$$\hat{\tau}(x) = \hat{\mu}_1(x) - \hat{\mu}_0(x)$$

Two-model approach: drawbacks

Models are trained **independently** -> might predict **spurious** effects



[1] Künzel, S.R., Sekhon, J.S., Bickel, P.J. and Yu, B., 2019. Metalearners for estimating heterogeneous treatment effects using machine learning. *Proceedings of the national academy of sciences*, *116*(10), pp.4156-4165.

Single model approach

How was your stay?

How was your stay?

Logistic regression,
RF, NN, ...

$$\hat{\mu}(t, x)$$

Predict Y from X and T

Single model approach

How was your stay?

How was your stay?

Logistic regression,
RF, NN, ...

$$\hat{\mu}(t, x)$$

Predict Y from X and T

$$\hat{\tau}(x) = \hat{\mu}(1, x) - \hat{\mu}(0, x)$$

Single model approach: drawbacks

What if the model learns to **ignore** T?

$$\hat{\tau}(x) = \hat{\mu}(\boxed{1}, x) - \hat{\mu}(\boxed{0}, x)$$

Single model approach: drawbacks

What if the model learns to **ignore** T?

$$\hat{\tau}(x) = \hat{\mu}(\quad x) - \hat{\mu}(\quad x)$$

Single model approach: drawbacks

What if the model learns to **ignore** T?

$$\hat{\tau}(x) = \hat{\mu}(\square\, x) - \hat{\mu}(\square\, x)$$

Treatment effect is usually very small!

Class Variable Transformation

	Received treatment	Observed outcome
	T	**Y**
	1	1
	1	0
	0	0
	0	1

Class Variable Transformation

	Received treatment	Observed outcome	Transformed outcome
	T	**Y**	**Y***
	1	1	1
	1	0	0
	0	0	1
	0	1	0

$$Y^* = \begin{cases} 1 & \text{if } T = 1 \text{ and } Y = 1, \\ 1 & \text{if } T = 0 \text{ and } Y = 0, \\ 0 & \text{otherwise} \end{cases}$$

[1] Jaskowski, M. and Jaroszewicz, S., 2012, June. Uplift modeling for clinical trial data. In ICML Workshop on Clinical Data Analysis (Vol. 46).

Class Variable Transformation

	Received treatment	Observed outcome	Transformed outcome
	T	**Y**	**Y***
	1	1	1
	1	0	0
	0	0	1
	0	1	0

$$Y^* = \begin{cases} 1 & \text{if } T = 1 \text{ and } Y = 1, \\ 1 & \text{if } T = 0 \text{ and } Y = 0, \\ 0 & \text{otherwise} \end{cases}$$

$$\boxed{2 \cdot \mathbb{E}[Y^* | X = \boldsymbol{x}] - 1 = \tau(\boldsymbol{x})}$$

[1] Jaskowski, M. and Jaroszewicz, S., 2012, June. Uplift modeling for clinical trial data. In ICML Workshop on Clinical Data Analysis (Vol. 46).

Class Variable Transformation: drawbacks

Assumes $P(T=1 \mid X) = 0.5$ for all X!

Transformed outcome

$$Y^* = \frac{Y}{e(\boldsymbol{x})} \cdot T - \frac{Y}{(1 - e(\boldsymbol{x}))} \cdot (1 - T)$$

$$\boxed{\mathbb{E}[Y^* | X = \boldsymbol{x}] = \tau(\boldsymbol{x})}$$

Propensity: P(T=1 | X)

[1] Athey, S. and Imbens, G.W., 2015. Machine learning methods for estimating heterogeneous causal effects. stat, 1050(5), pp.1-26.

Class Variable Transformation: drawbacks

Assumes $P(T=1 \mid X) = 0.5$ for all X!

Solved by a more generic approach that takes **propensity score** into account.

[1] Athey, S. and Imbens, G.W., 2015. Machine learning methods for estimating heterogeneous causal effects. stat, 1050(5), pp.1-26.

Evaluating uplift models

Predicted treatment effect

Actual treatment effect

$$\frac{1}{n}\sum_{i}^{n}(\hat{\tau}(\boldsymbol{x}_i) - \tau(\boldsymbol{x}_i))^2$$

[1] Shalit, U., Johansson, F.D. and Sontag, D., 2017, July. Estimating individual treatment effect: generalization bounds and algorithms. In International Conference on Machine Learning (pp. 3076-3085). PMLR.
[2] Saito, Y. and Yasui, S., 2020, November. Counterfactual Cross-Validation: Stable Model Selection Procedure for Causal Inference Models. In International Conference on Machine Learning (pp. 8398-8407). PMLR.

Evaluating uplift models

MSE-type loss **cannot be calculated**!

$$\frac{1}{n}\sum_{i}^{n}(\hat{\tau}(\boldsymbol{x}_i) - \tau(\boldsymbol{x}_i))^2$$

No ground truth available

[1] Shalit, U., Johansson, F.D. and Sontag, D., 2017, July. Estimating individual treatment effect: generalization bounds and algorithms. In International Conference on Machine Learning (pp. 3076-3085). PMLR.
[2] Saito, Y. and Yasui, S., 2020, November. Counterfactual Cross-Validation: Stable Model Selection Procedure for Causal Inference Models. In International Conference on Machine Learning (pp. 8398-8407). PMLR.

Evaluating uplift models: uplift per segment

High predicted CATE

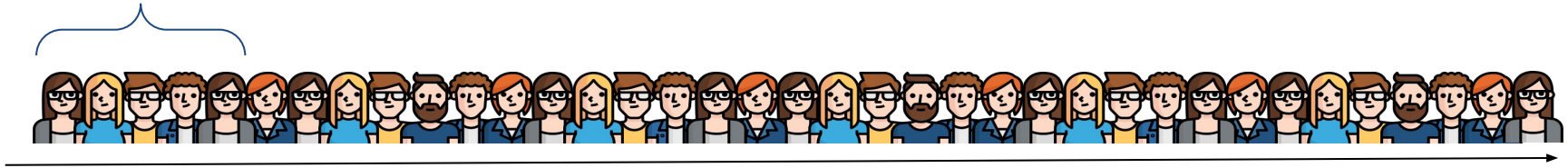
Low predicted CATE

[1] Radcliffe, N.J., 2007. Using control groups to target on predicted lift: Building and assessing uplift models. Direct Marketing Analytics Journal, 1(3), pp.14-21.
[2] Gutierrez, P. and Gérardy, J.Y., 2017, July. Causal inference and uplift modelling: A review of the literature. In International Conference on Predictive Applications and APIs (pp. 1-13). PMLR.

Evaluating uplift models: uplift per segment

Sample means

$$E[Y|T=1] - E[Y|T=0]$$



High predicted CATE

Low predicted CATE

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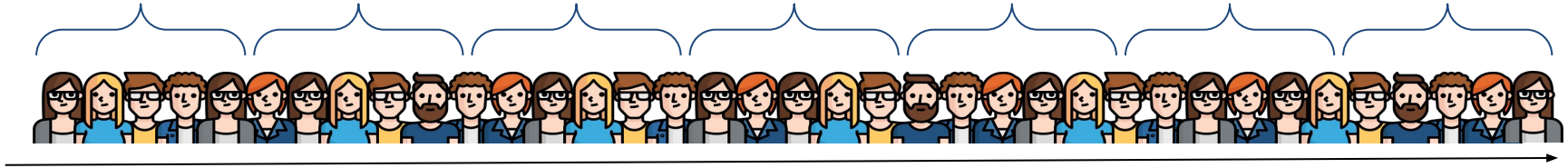
Evaluating uplift models: uplift per segment

$E[Y|T=1] - E[Y|T=0]$



High predicted CATE

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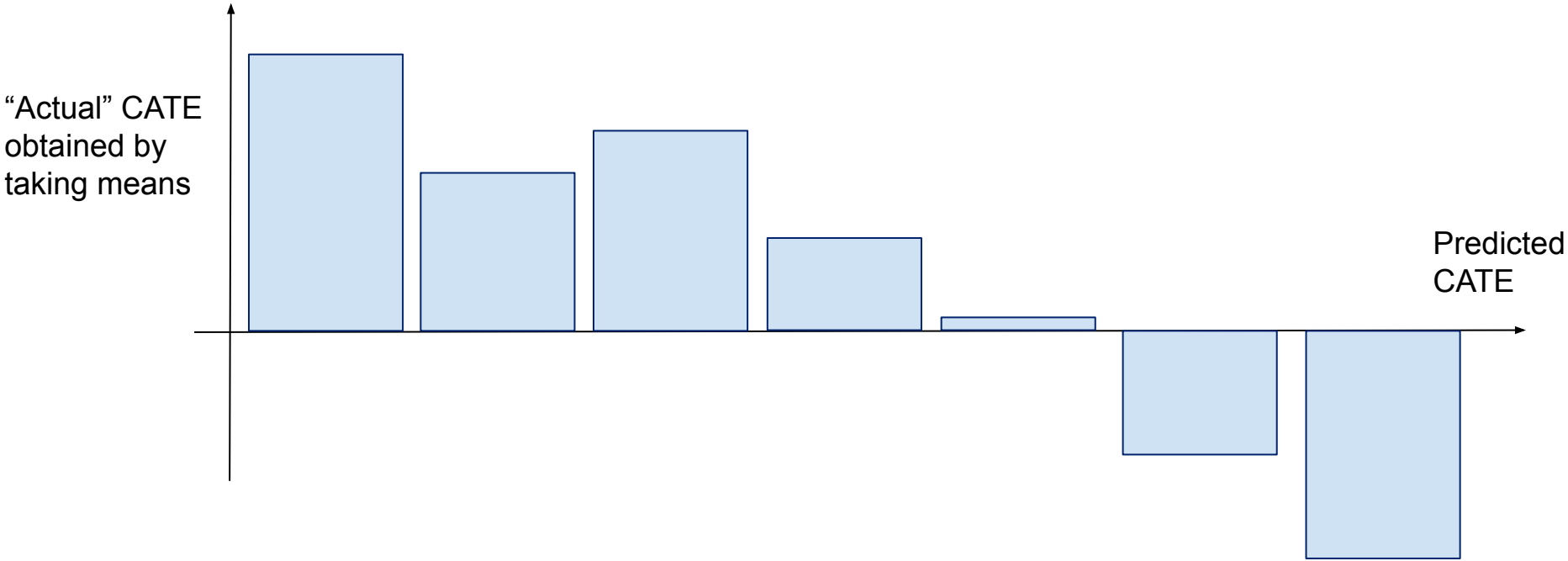
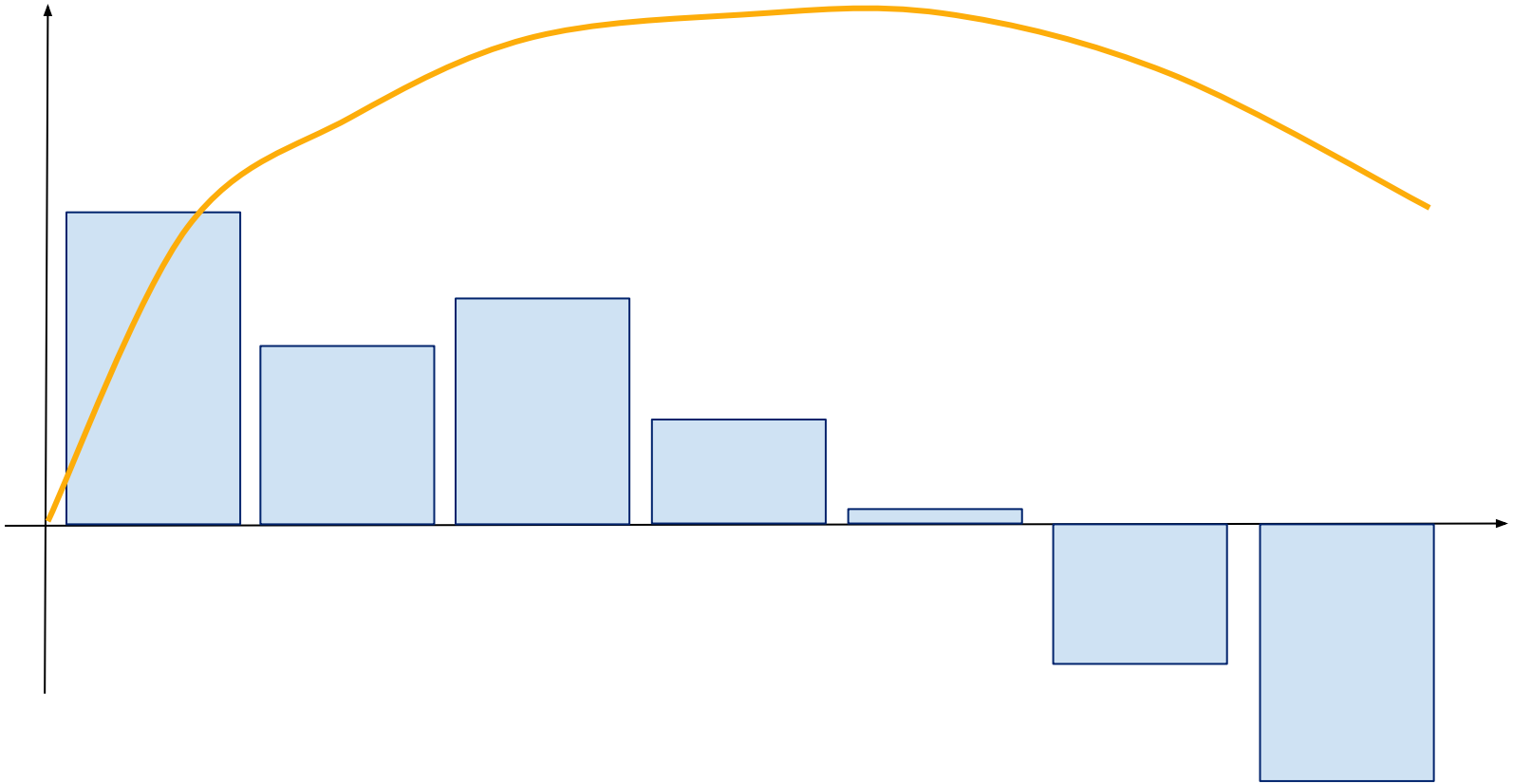
Uplift per segment



[1] Radcliffe, N.J., 2007. Using control groups to target on predicted lift: Building and assessing uplift models. Direct Marketing Analytics Journal, 1(3), pp.14-21.
[2] Gutierrez, P. and Gérardy, J.Y., 2017, July. Causal inference and uplift modelling: A review of the literature. In International Conference on Predictive Applications and APIs (pp. 1-13). PMLR.

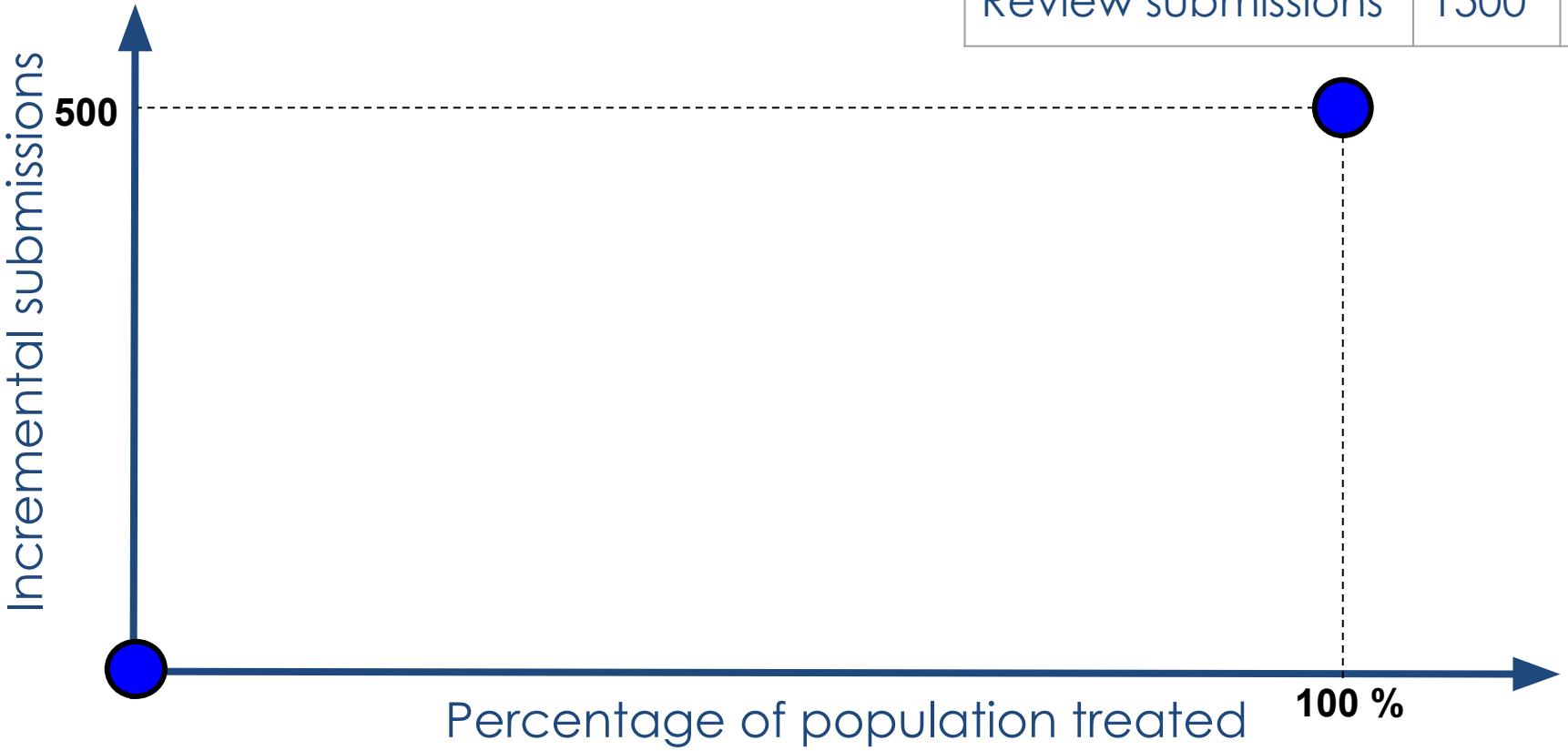
Cumulative curve



[1] Radcliffe, N.J., 2007. Using control groups to target on predicted lift: Building and assessing uplift models. Direct Marketing Analytics Journal, 1(3), pp.14-21.
[2] Gutierrez, P. and Gérardy, J.Y., 2017, July. Causal inference and uplift modelling: A review of the literature. In International Conference on Predictive Applications and APIs (pp. 1-13). PMLR.

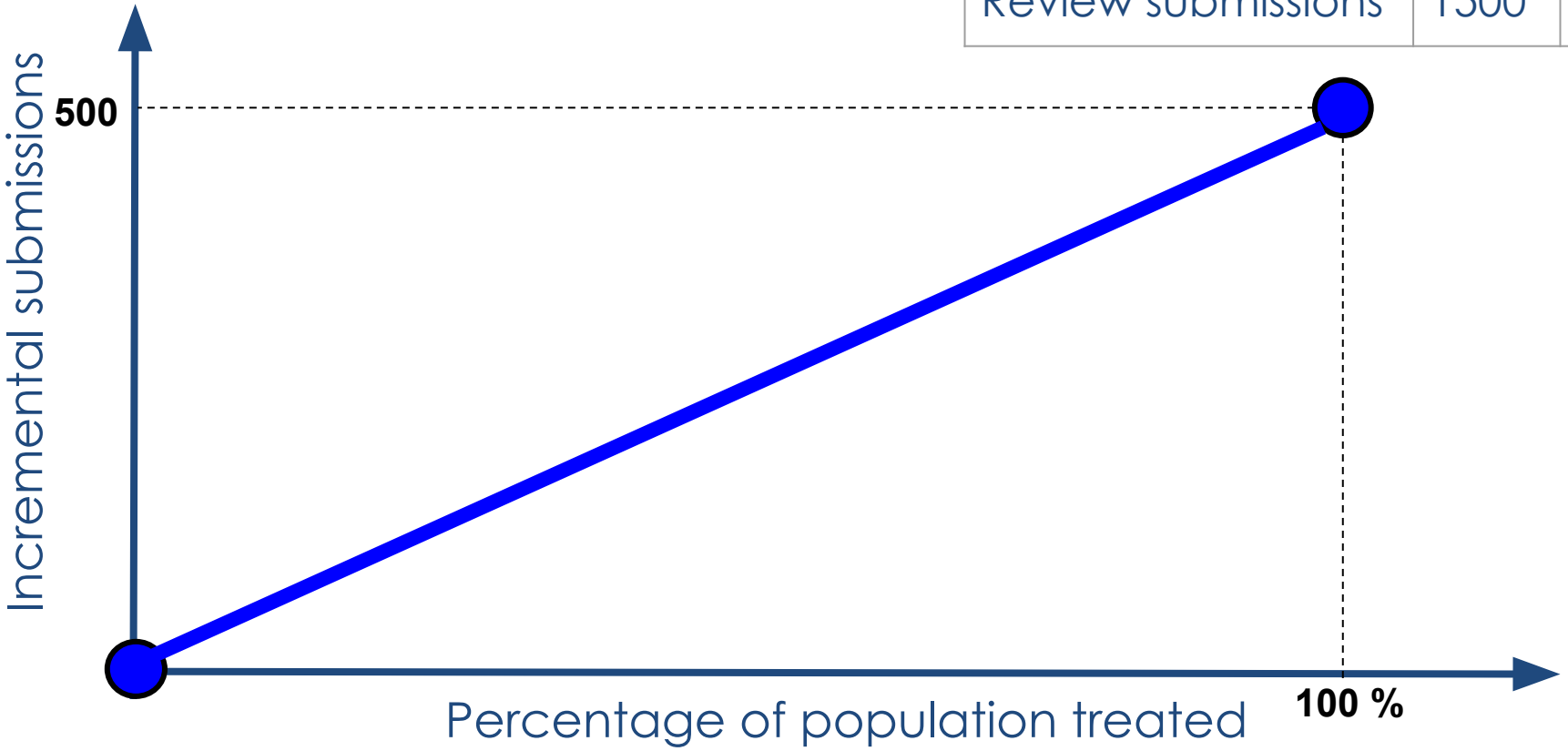
Uplift curve

	T=1	T=0
Review submissions	1500	1000



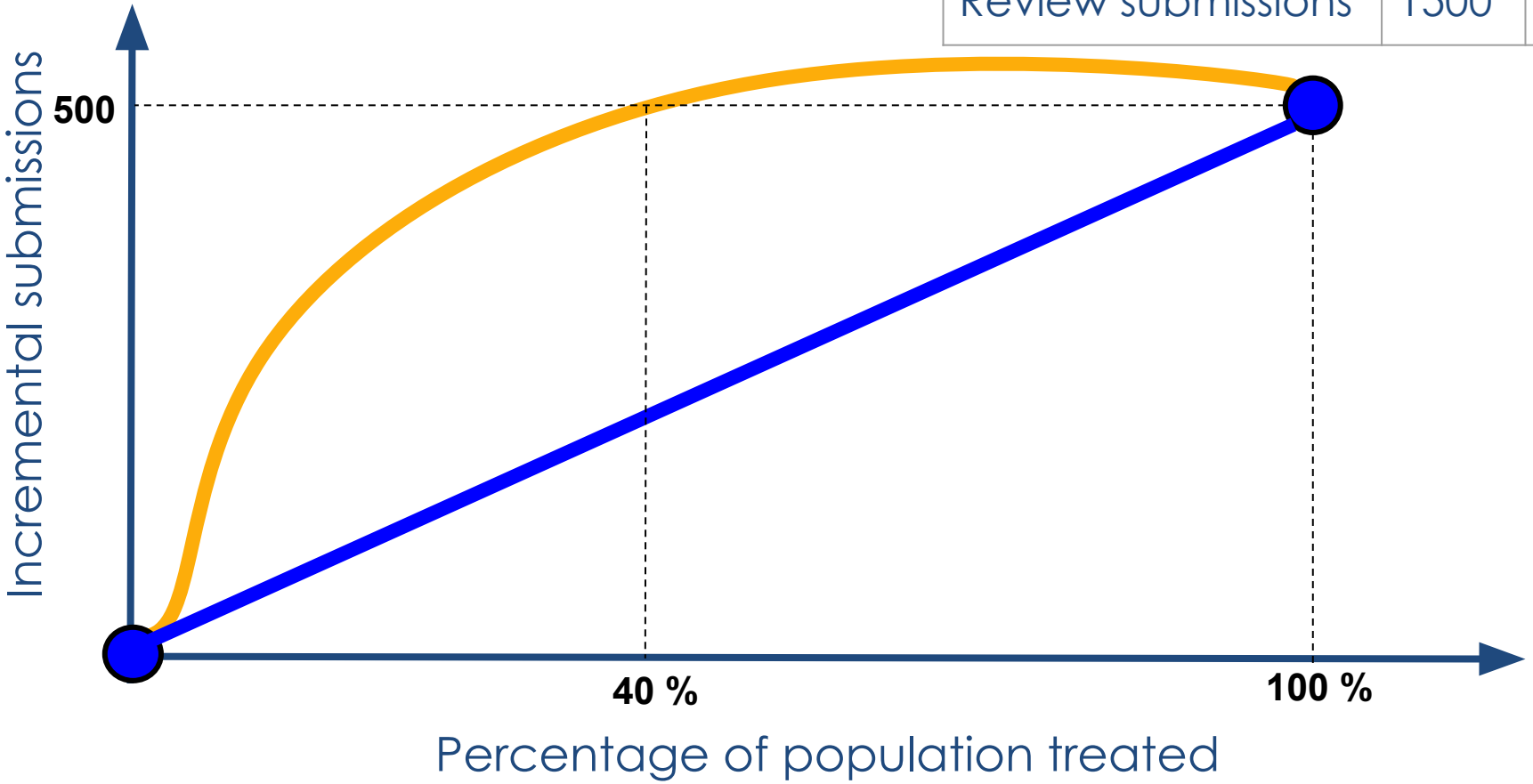
Uplift curve

	T=1	T=0
Review submissions	1500	1000

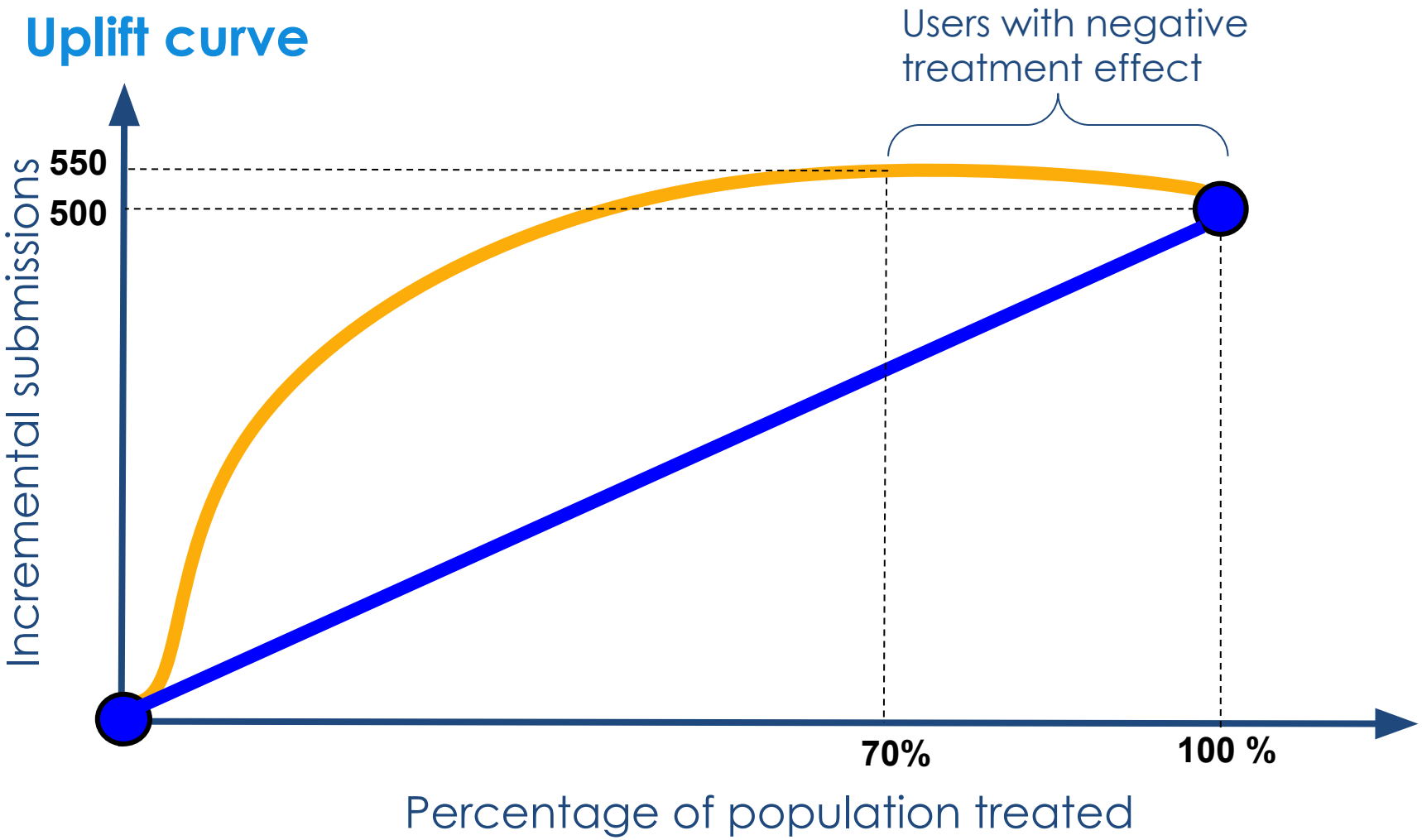


Uplift curve

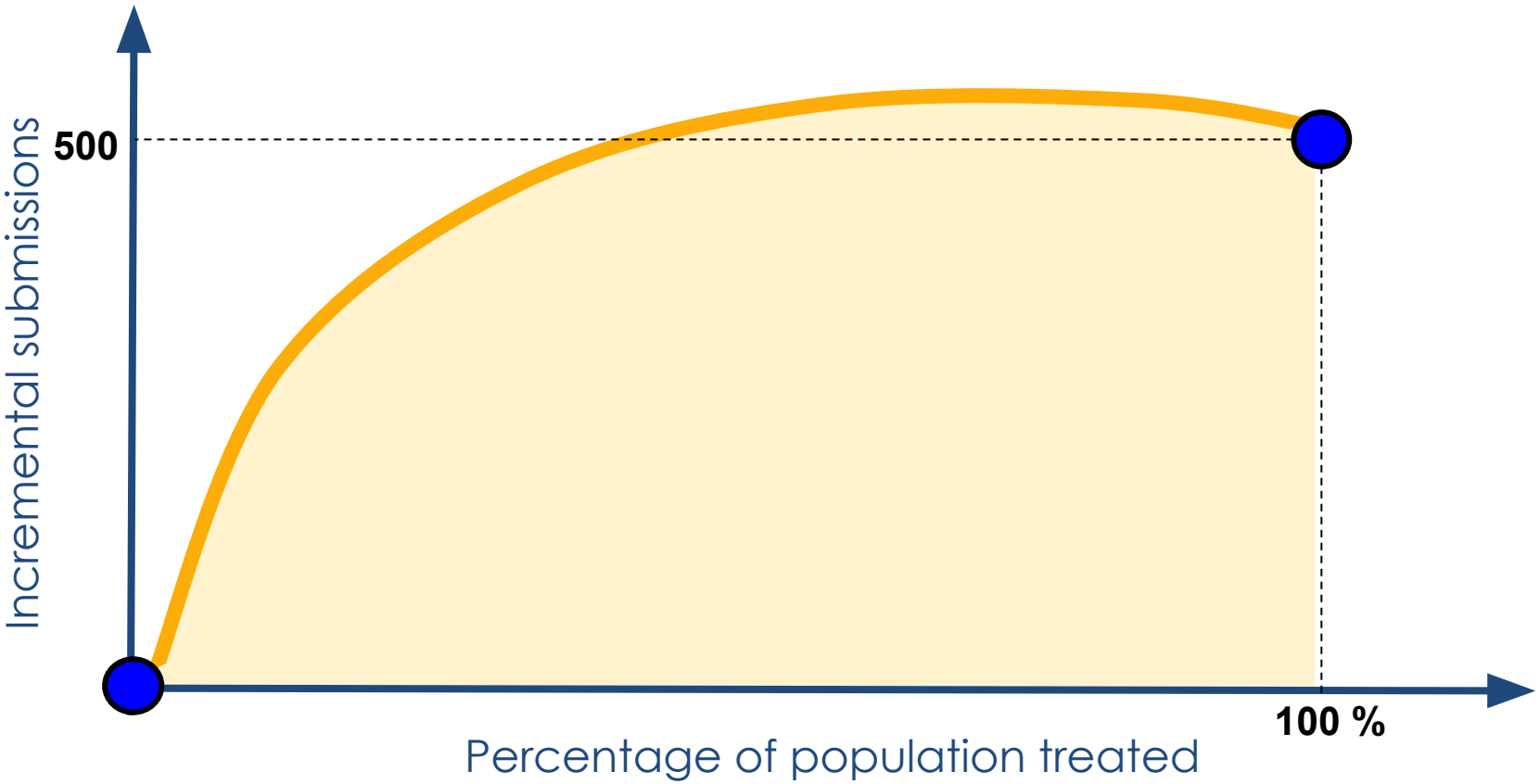
	T=1	T=0
Review submissions	1500	1000



Uplift curve



Area under the uplift curve (AUUC)



[1] Betlei, A., Diemert, E. and Amini, M.R., 2020. Treatment Targeting by AUUC Maximization with Generalization Guarantees. arXiv preprint arXiv:2012.09897.

Constrained Uplift

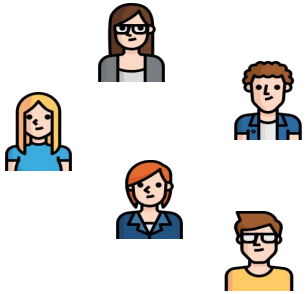
Booking.com
Machine Learning

Treatment Personalization

Y : Form Submissions

How was your stay?

How was your stay?



$$CATE_Y(x_i)$$

Treatment Personalization

Y : Form Submissions

How was your stay?

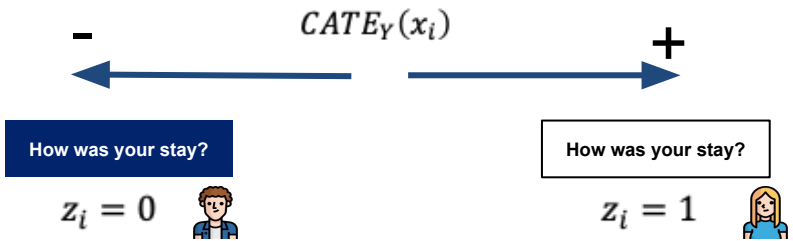
How was your stay?

$$Maximize \sum_{i \in U} z_i \,.\, CATE_Y(x_i)$$

$Y : Metric$

$CATE_Y(x_i) : Uplift\ for\ user\ i\ with\ features\ x_i$

$z_i : Assignment\ variable\ \{0,1\}$



No-cost Treatments

How was your stay?

How was your stay?

No cost

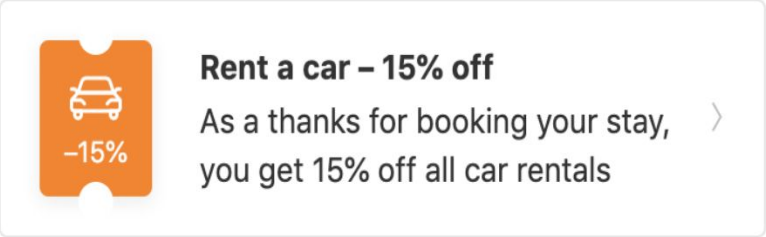
Treatments can have a fixed cost

$1 for every letter sent

[1] Zhao, Z. and Harinen, T., 2019, October. Uplift modeling for multiple treatments with cost optimization. In *2019 IEEE International Conference on Data Science and Advanced Analytics (DSAA)* (pp. 422-431). IEEE.
[2] Li, A. and Pearl, J., 2019, August. Unit selection based on counterfactual logic. In Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence.
[3] Verbeke, W., Olaya, D., Berrevoets, J. and Maldonado, S., 2020. The foundations of cost-sensitive causal classification. arXiv preprint arXiv:2007.12582.

Treatments can have a triggered cost

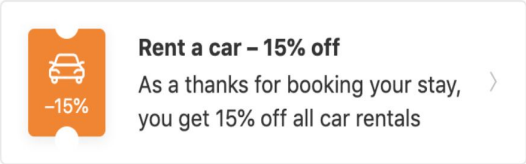
Triggered only if user converts



[1] Zhao, Z. and Harinen, T., 2019, October. Uplift modeling for multiple treatments with cost optimization. In *2019 IEEE International Conference on Data Science and Advanced Analytics (DSAA)* (pp. 422-431). IEEE.
[2] Li, A. and Pearl, J., 2019, August. Unit selection based on counterfactual logic. In Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence.
[3] Verbeke, W., Olaya, D., Berrevoets, J. and Maldonado, S., 2020. The foundations of cost-sensitive causal classification. arXiv preprint arXiv:2007.12582.

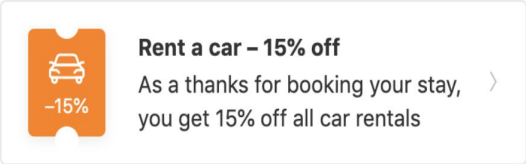
Uplift in Conversion & Uplift in Revenue

	Y(0)	R(0)
Bob	0	0
Amy	1	180

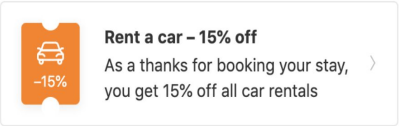


Uplift in Conversion & Uplift in Revenue

	Y(0)	Y(1)	R(0)	R(1)
Bob	0		0	
Amy	1		180	



Uplift in Conversion & Uplift in Revenue



	Y(0)	Y(1)	R(0)	R(1)
Bob	0	1	0	150
Amy	1	1	180	140

Y ↑

R ↑

Y –

R ↓

Uplift in Conversion (Y)

$$CATE_Y(x_i) = E[Y(1) - Y(0) \mid X = x_i]$$

Uplift in Revenue (R)

$$CATE_R(x_i) = E[R(1) - R(0) \mid X = x_i]$$

Decide which user to treat in order to:

- Maximize the treatment effect (Y)
- Hurt revenue until some budget (B)

Decide which user to treat in order to:

- Maximize conversion (booking rate)
- Don’t hurt revenue (B=0)

Personalization under cost constraints

$$Maximize \quad \sum_{i \in U} z_i \,.\, CATE_Y(x_i)$$

$$subject\ to \quad \sum_{i \in U} -z_i \,.\, CATE_R(x_i) \leq B$$

$Y : Metric$

$CATE_Y(x_i) : Uplift\ for\ user\ i\ with\ features\ x_i$

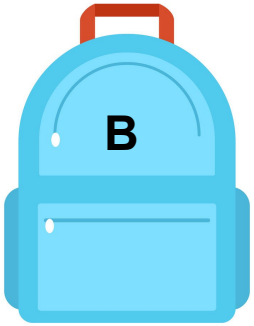
$CATE_R(x_i) : Uplift\ in\ revenue\ for\ user\ i\ with\ features\ x_i$

$z_i : Assignment\ variable\ \{0,1\}$

$B : Budget$

[1] Lo, V.S. and Pachamanova, D.A., 2015. From predictive uplift modeling to prescriptive uplift analytics: A practical approach to treatment optimization while accounting for estimation risk. Journal of Marketing Analytics, 3(2), pp.79-95.
[2] Goldenberg, D., Albert, J., Bernardi, L. and Estevez, P., 2020, September. Free Lunch! Retrospective Uplift Modeling for Dynamic Promotions Recommendation within ROI Constraints. In Fourteenth ACM Conference on Recommender Systems (pp. 486-491).
[3] Zou, W.Y., Du, S., Lee, J. and Pedersen, J., 2020. Heterogeneous Causal Learning for Effectiveness Optimization in User Marketing. *arXiv preprint arXiv:2004.09702.*
[4] Du, S., Lee, J. and Ghaffarizadeh, F., 2019, July. Improve User Retention with Causal Learning. In The 2019 ACM SIGKDD Workshop on Causal Discovery (pp. 34-49). PMLR.

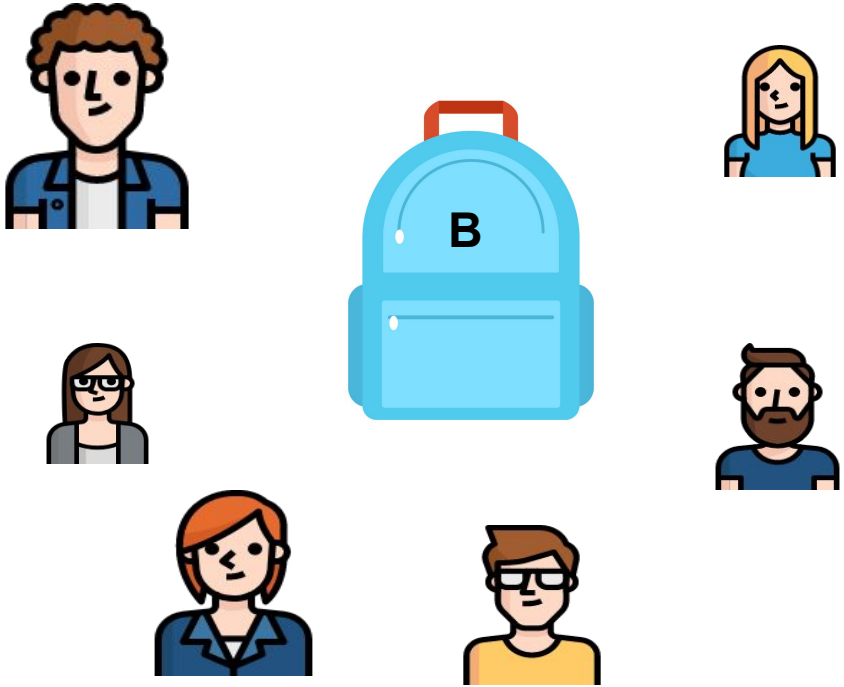
A Knapsack formulation



$Value_i$

$Weight_i$

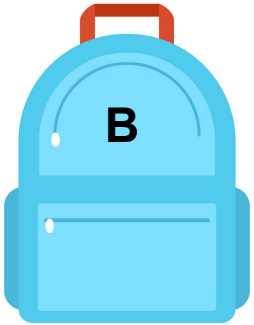
A Knapsack formulation

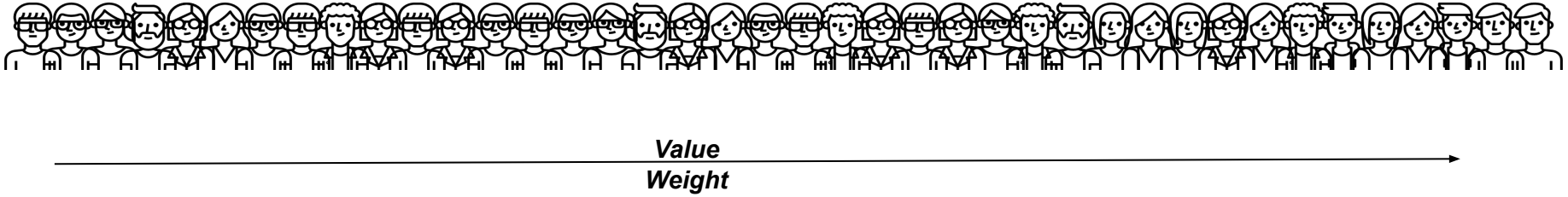


$$Value_i = CATE_Y(x_i)$$

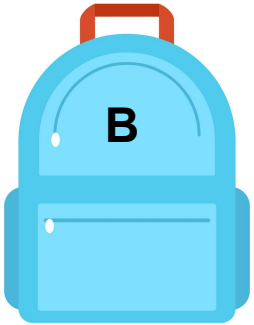
$$Weight_i = -CATE_R(x_i)$$

A knapsack approximation solution

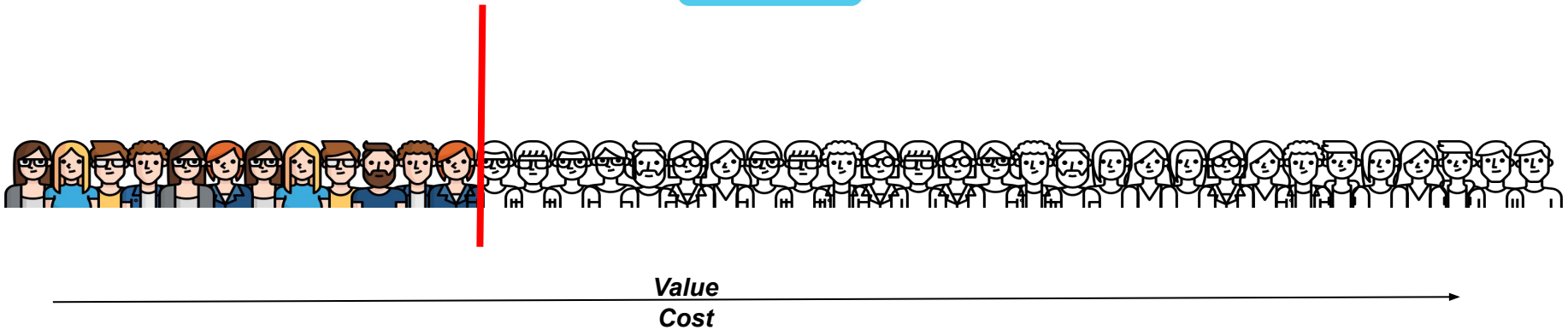




A knapsack approximation solution



Also an online solution!



Retrospective Estimation

Too much noise

$$CATE_Y(x_i) = E(Y \mid x_i, T = 1) - E(Y \mid x_i, T = 0)$$

$$P(Y \mid x_i, T = 1) = \frac{P(T = 1 \mid x_i, Y = 1) \; P(Y = 1 \mid x_i)}{P(T = 1 \mid x_i)}$$

$$S(x_i) = P(T = 1 \mid x_i, Y = 1)$$

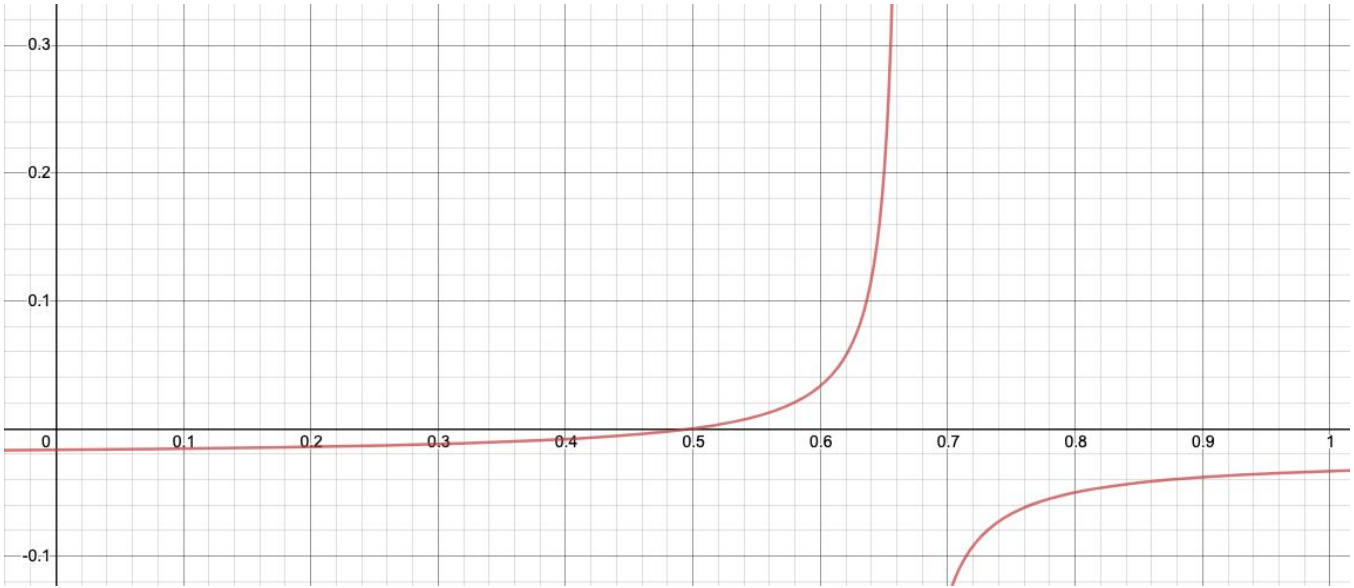
Retrospective Estimation

$$\frac{value}{weight} = \frac{CATE_Y(x_i)}{-CATE_R(x_i)} = \frac{2 \cdot S(x_i) - 1}{a \cdot S(x_i) + b}$$

[1] Goldenberg, D., Albert, J., Bernardi, L. and Estevez, P., 2020, September. Free Lunch! Retrospective Uplift Modeling for Dynamic Promotions Recommendation within ROI Constraints. In Fourteenth ACM Conference on Recommender Systems (pp. 486-491).

Retrospective Estimation

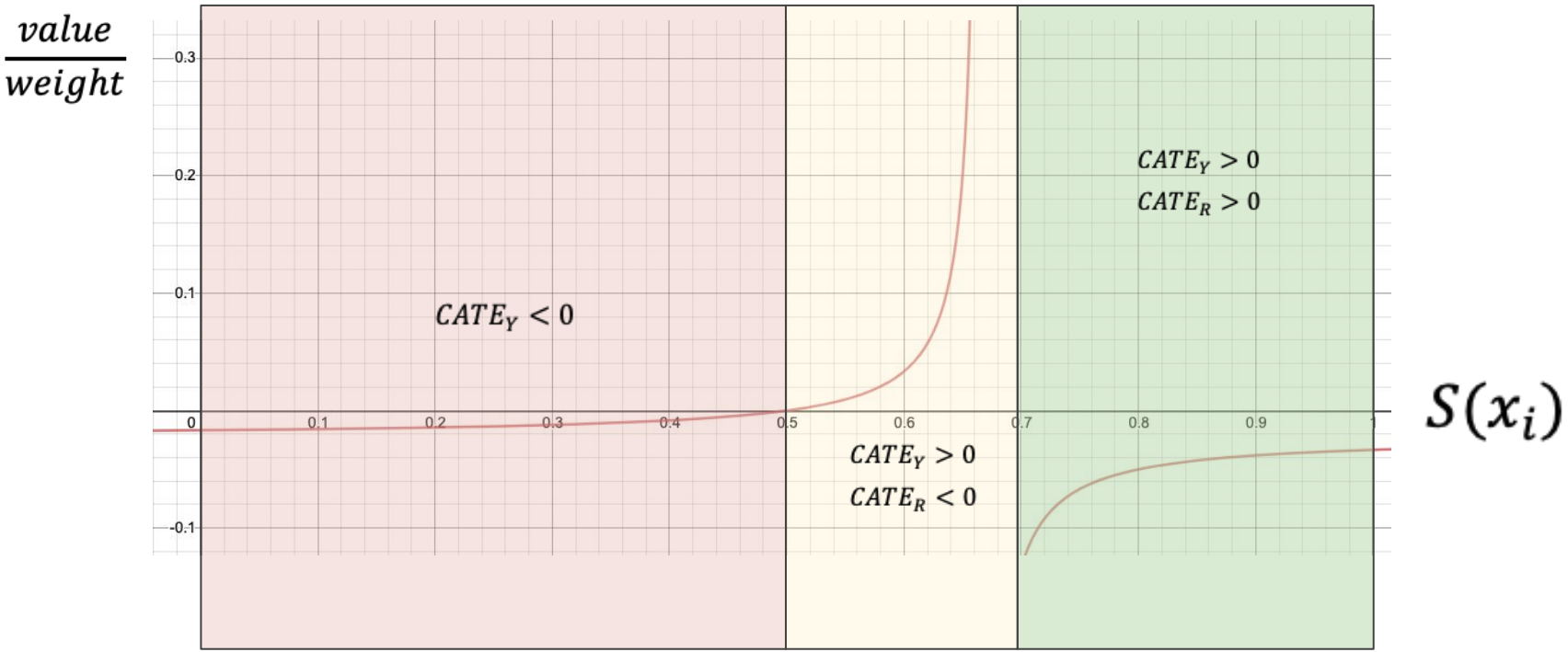
$$\frac{value}{weight}$$



$$S(x_i)$$

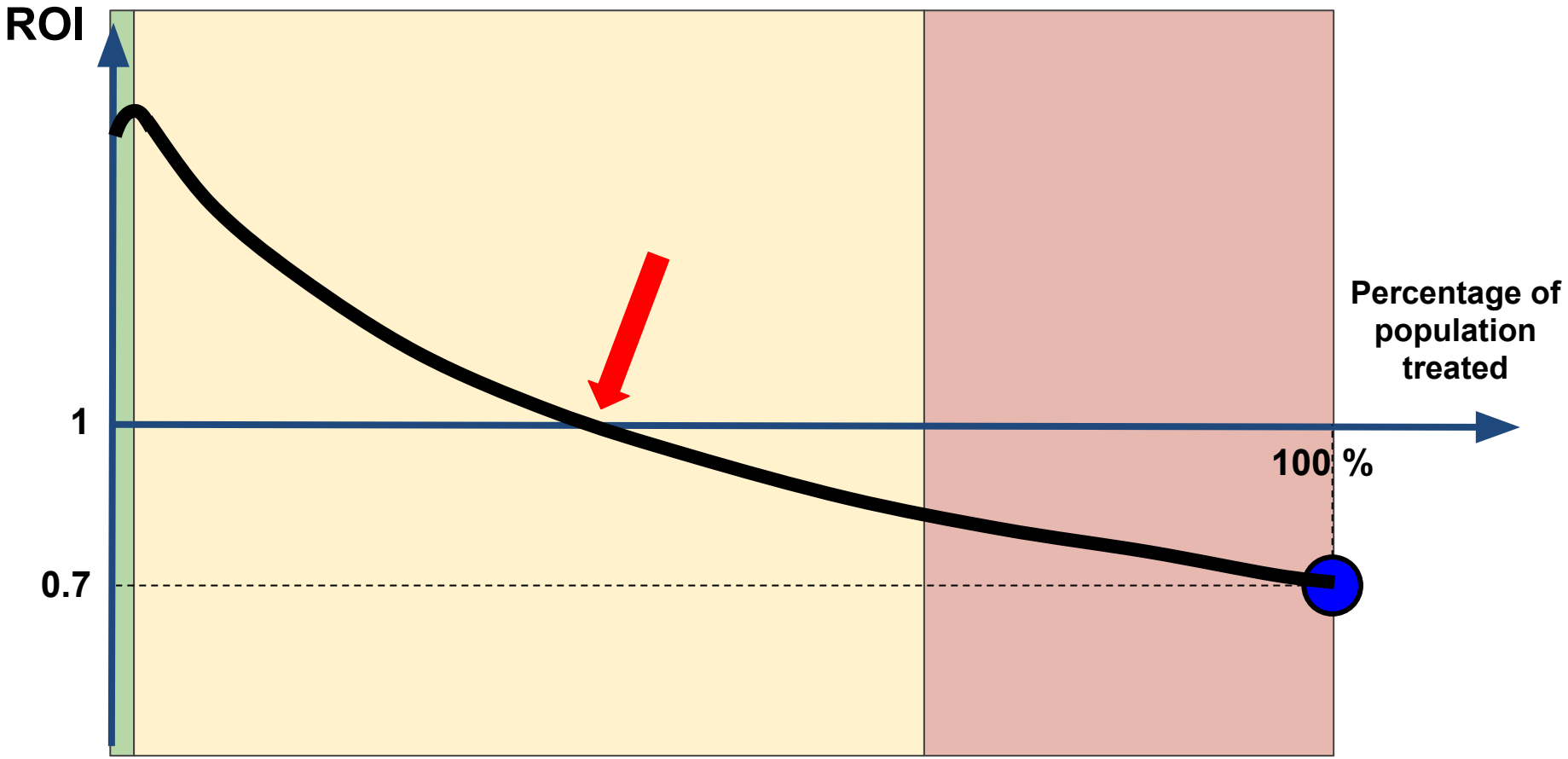
[1] Goldenberg, D., Albert, J., Bernardi, L. and Estevez, P., 2020, September. Free Lunch! Retrospective Uplift Modeling for Dynamic Promotions Recommendation within ROI Constraints. In Fourteenth ACM Conference on Recommender Systems (pp. 486-491).

Retrospective Estimation



[1] Goldenberg, D., Albert, J., Bernardi, L. and Estevez, P., 2020, September. Free Lunch! Retrospective Uplift Modeling for Dynamic Promotions Recommendation within ROI Constraints. In Fourteenth ACM Conference on Recommender Systems (pp. 486-491).

ROI curve



Retrospective Estimation

$$\frac{value}{weight} = \frac{CATE_Y(x_i)}{-CATE_R(x_i)} = \frac{2 \cdot S(x_i) - 1}{a \cdot S(x_i) + b} \quad \sim \quad S(x_i)$$

$$S(x_i) = P(T = 1 \mid x_i, Y = 1)$$

[1] Goldenberg, D., Albert, J., Bernardi, L. and Estevez, P., 2020, September. Free Lunch! Retrospective Uplift Modeling for Dynamic Promotions Recommendation within ROI Constraints. In Fourteenth ACM Conference on Recommender Systems (pp. 486-491).

Multi-level personalization under cost constraints

$$CATE_Y(x_i, t) = E[Y(t) - Y(0) \mid X = x_i]$$

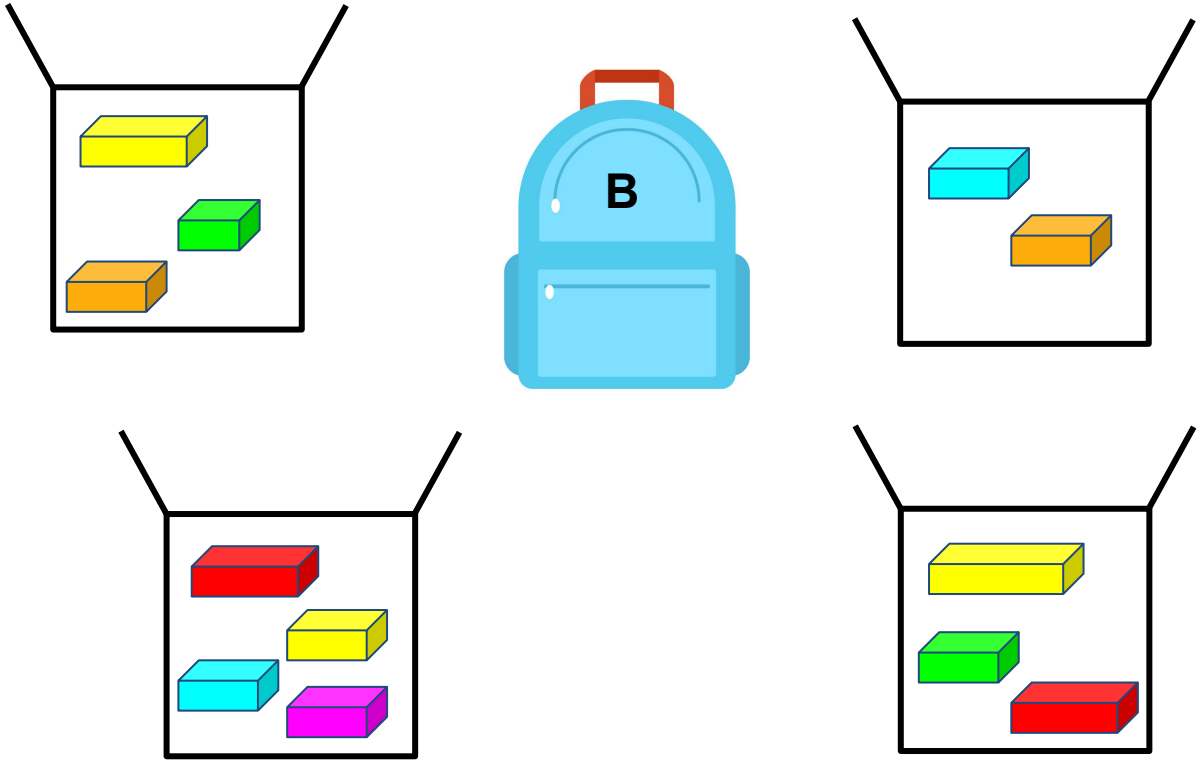
$$CATE_R(x_i, t) = E[R(t) - R(0) \mid X = x_i]$$

[1] Olaya, D., Coussement, K. and Verbeke, W., 2020. A survey and benchmarking study of multitreatment uplift modeling. *Data Mining and Knowledge Discovery*, *34*(2), pp.273-308.
[2] Makhijani, R., Chakrabarti, S., Struble, D. and Liu, Y., LORE: A Large-Scale Offer Recommendation Engine through the lens of an Online Subscription Service.

Multiple-Choice Knapsack

$Value_i$

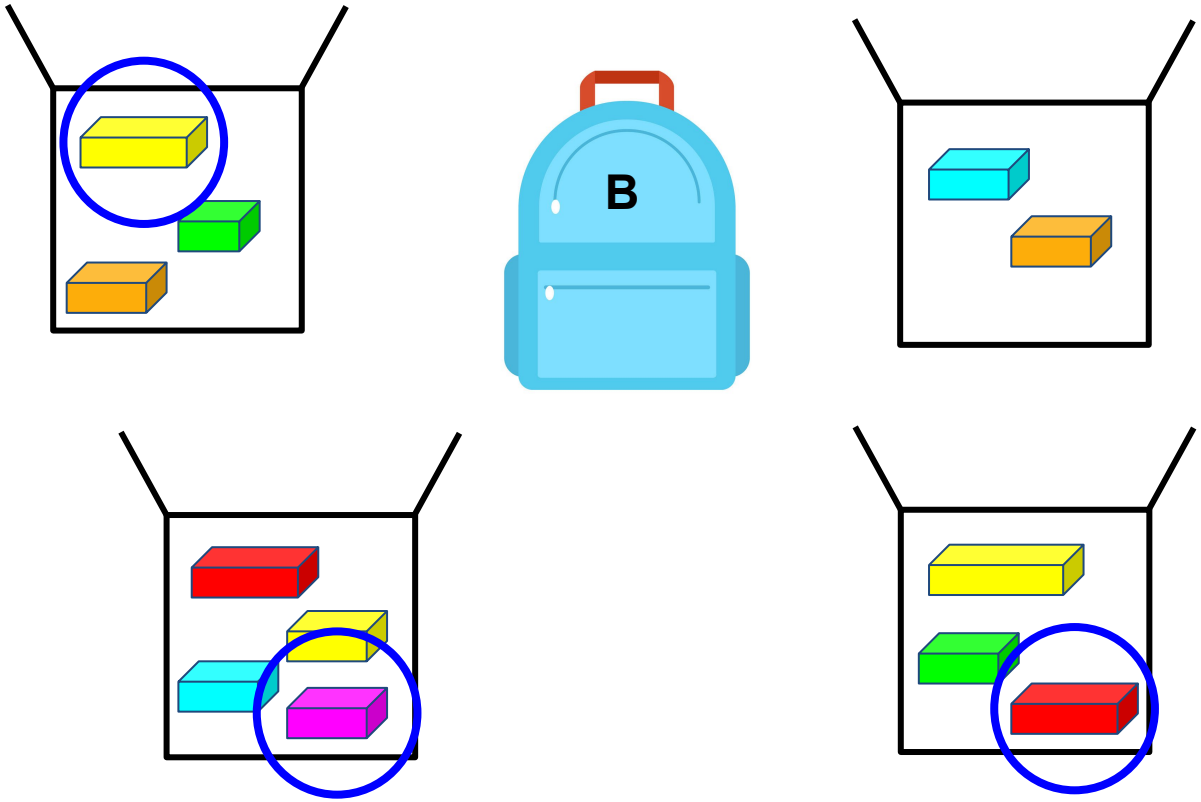
$Weight_i$



Multiple-Choice Knapsack

$Value_i$

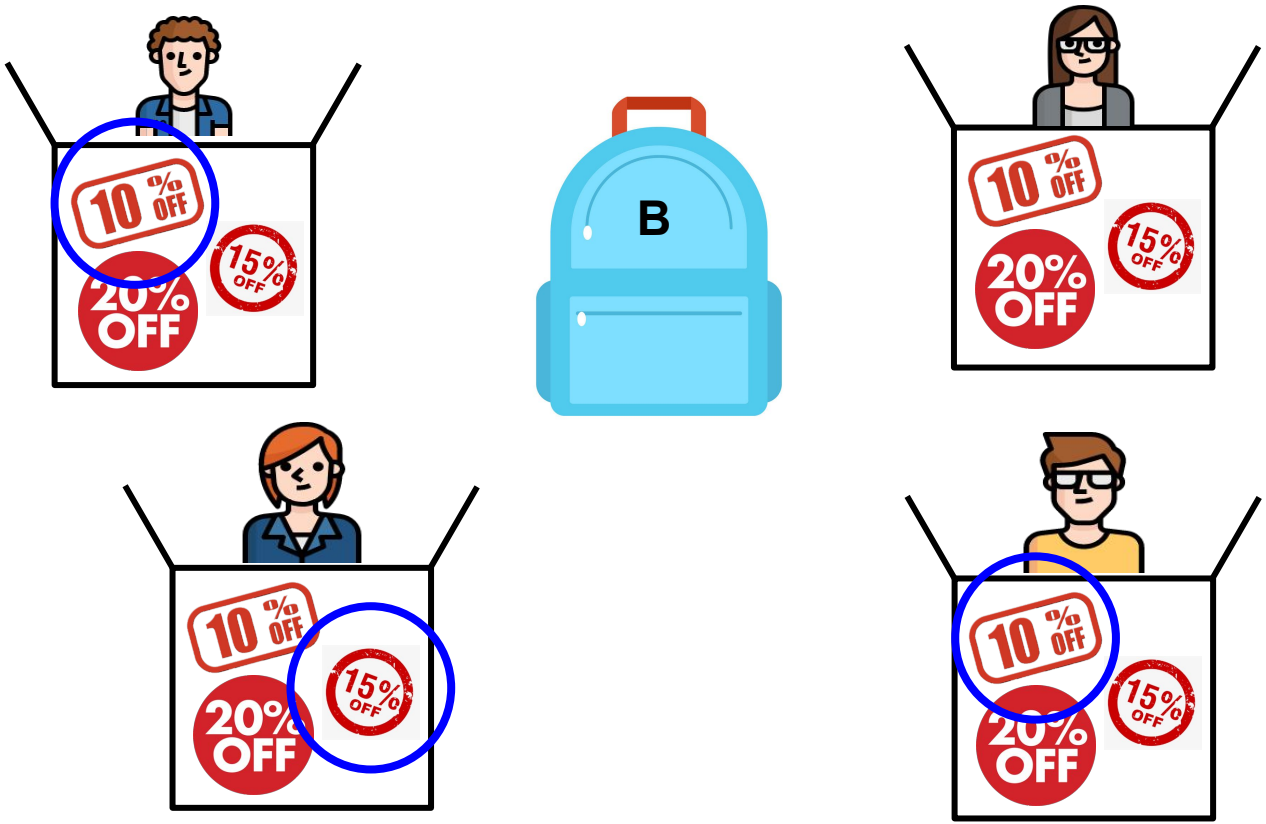
$Weight_i$



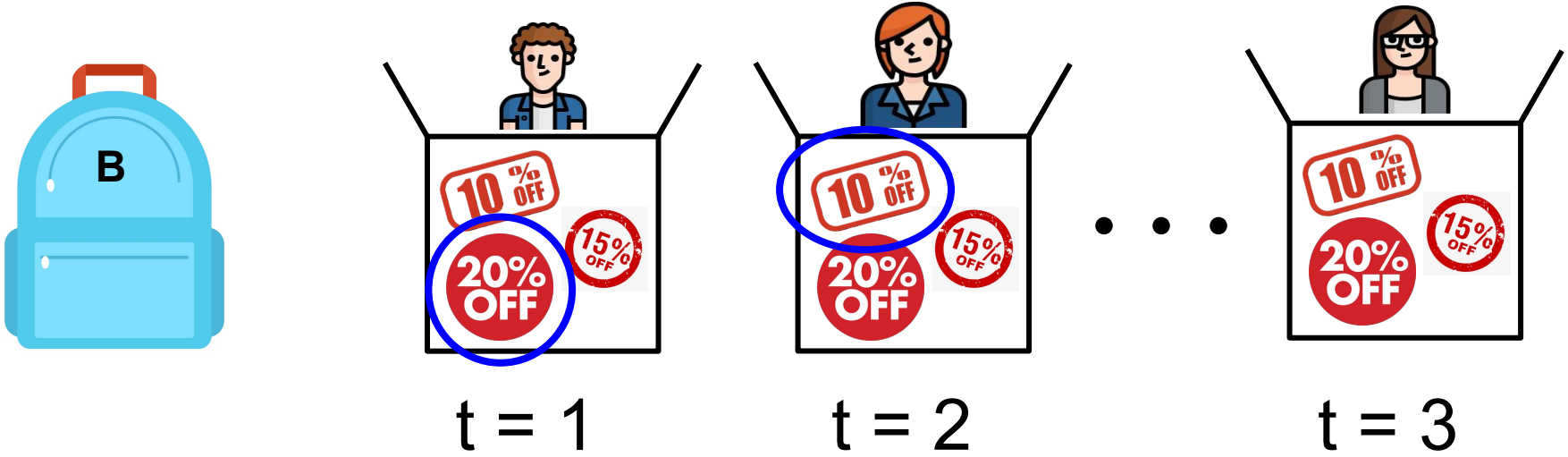
Multiple-Choice Knapsack

$$Value_i = CATE_Y(x_i)$$

$$Weight_i = -CATE_R(x_i)$$

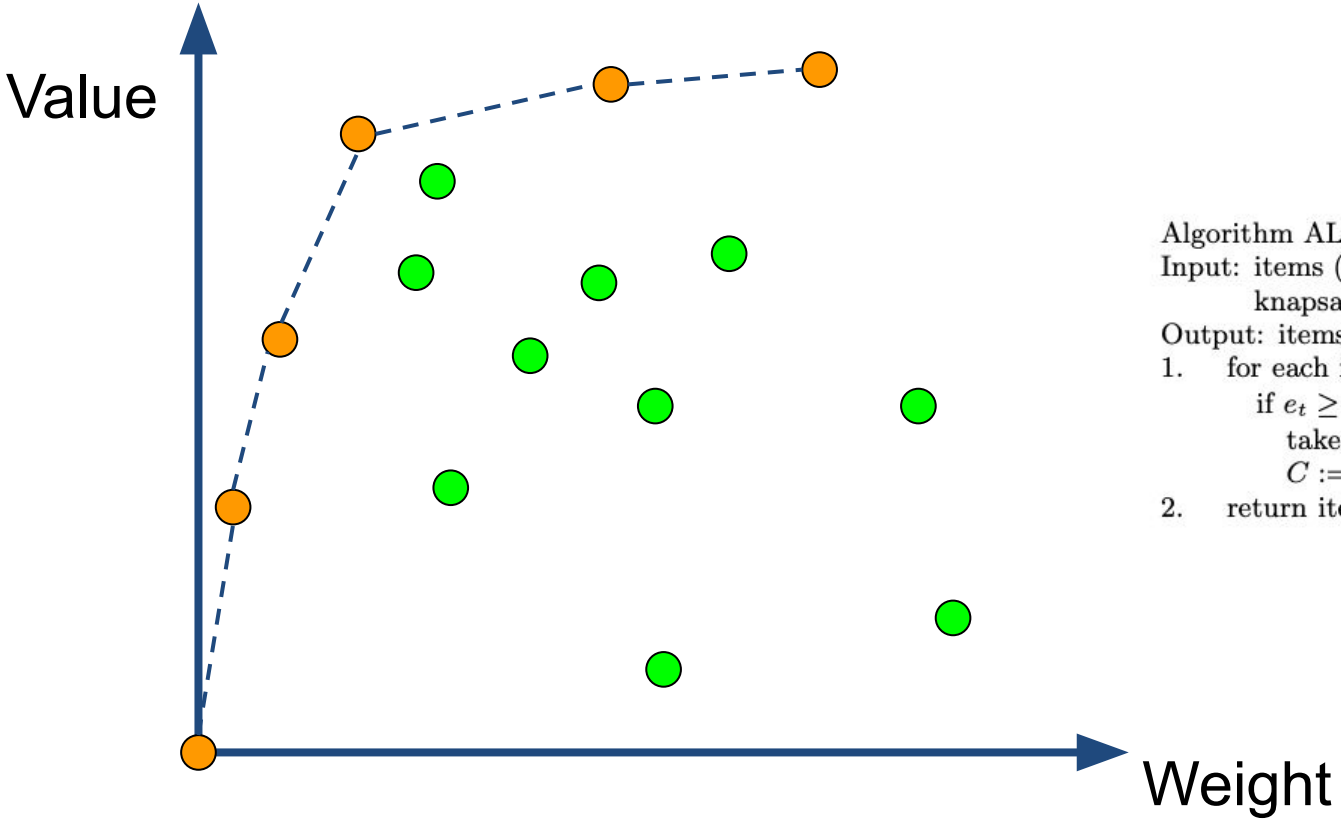


Online Multiple-Choice Knapsack



An Algorithm for Stochastic Multiple-Choice Knapsack Problem and Keywords Bidding

Yunhong Zhou, Victor Naroditskiy



Algorithm ALG-Lueker-OKP
Input: items (w_t, v_t) for $t = 1, \ldots, n$;
knapsack capacity C; threshold function g
Output: items to take
1. for each item t from 1 to n
if $e_t \geq g(\frac{C}{n-t+1})$ and $w_t \leq C$
take item t
$C := C - w_t$
2. return items taken

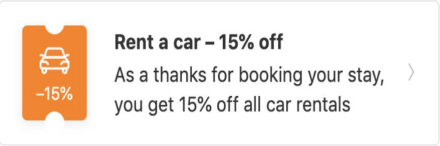
Yunhong Zhou, Victor Naroditskiy 2008: An Algorithm for Stochastic Multiple-Choice Knapsack Problem and Keywords Bidding

Treatment Personalization

How was your stay?

How was your stay?

Treatment Personalization Under ROI Constraints



Multi Treatment Personalization Under ROI Constraints

Uplift Applications

Booking.com
Machine Learning

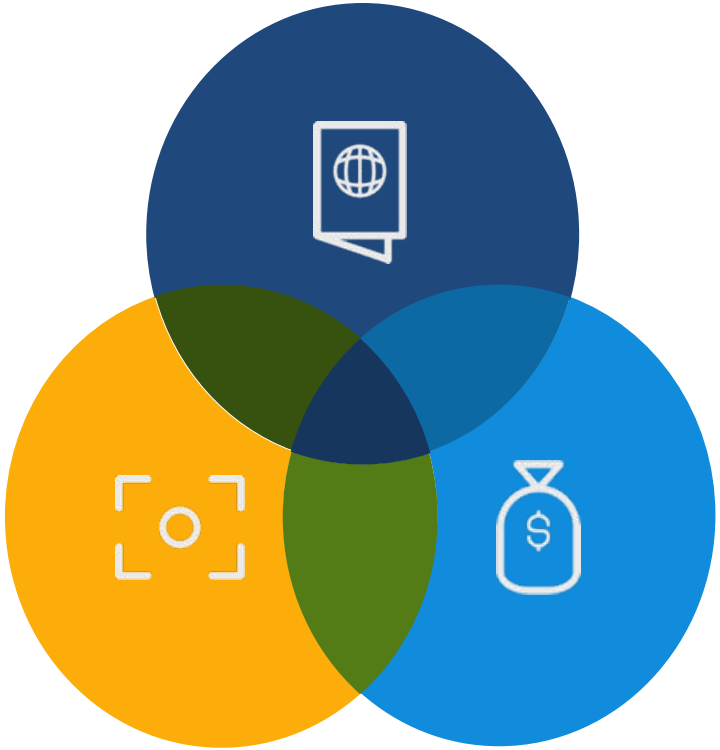
Industry Applications

Global Marketing Budget Allocation

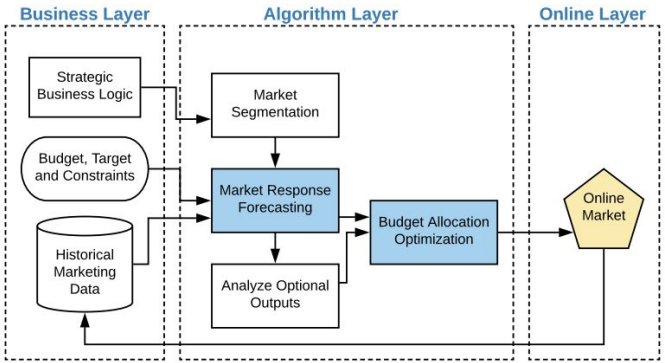
Cost-Aware Modeling

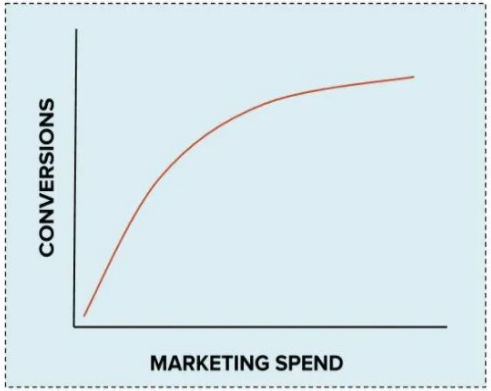
Meta-Learners Techniques

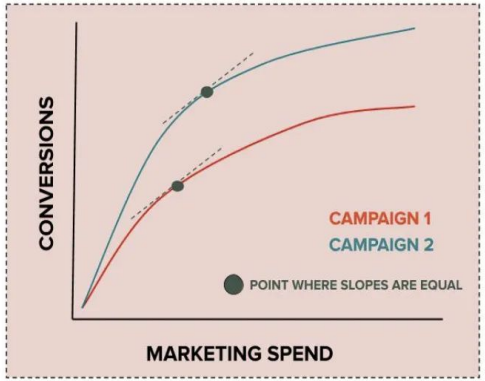
Industry Applications



Global Marketing Budget Allocation



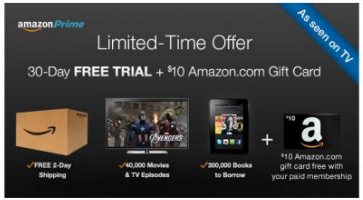




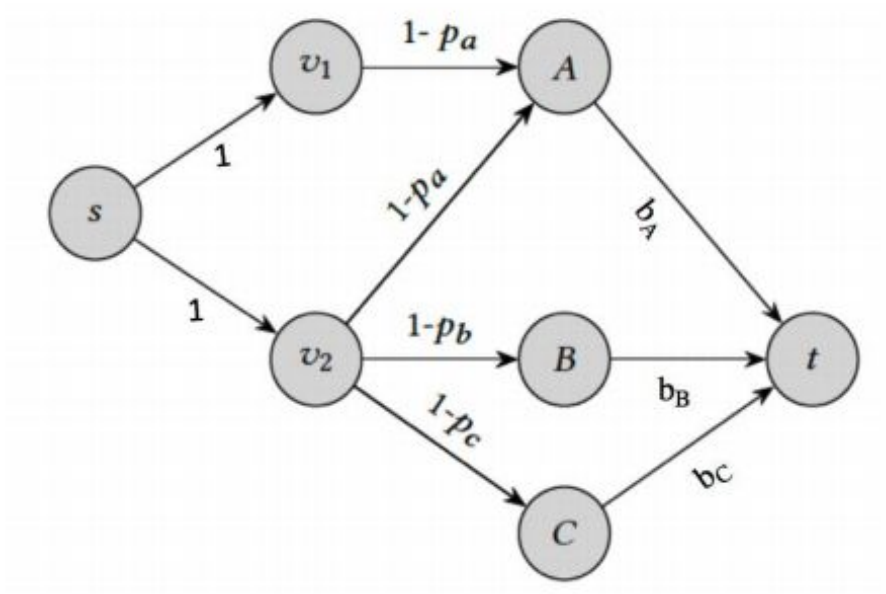
A Unified Framework for Marketing Budget Allocation - Zhao et al. @ KDD 2019 - Alibaba
https://blogboard.io/blog/data-science-in-marketing-optimization/amp/ - DoorDash, AirBnB

Global Marketing Budget Allocation

(a) Amazon Prime subscription Offer 1



(b) Amazon Prime subscription Offer 2



Rahul Makhijani, Shreya Chakrabarti, Dale Struble and Yi Liu. 2019. LORE: A Large-Scale Offer Recommendation Engine with Eligibility and Capacity Constraints. In Thirteenth ACM Conference on Recommender Systems (RecSys '19), September 16–20, 2019, Copenhagen, Denmark. ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3298689.3347027

Cost-Aware Modeling

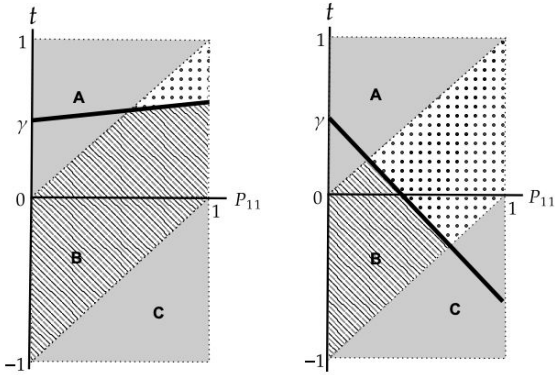


Figure 2: The cost-sensitive causal classification decision boundary (solid line) with a positive (panel a) or negative (panel b) slope.

$$Maximize \ \sum_i x_i * CATE_i$$

$$Subject\ to \ \sum_i x_i * Profit_i \geq 0$$

$$max\ g = \sum_{i=1}^{n} \tau^r(x_i) z_i + \lambda(B - \sum_{i=1}^{n} \tau^c(x_i) z_i) \quad s.t.\ 0 \leq z_i \leq 1$$

$$\tau^r(x_i) - \lambda \tau^c(x_i) > 0,\ z_i = 1,\ o/w,\ z_i = 0$$

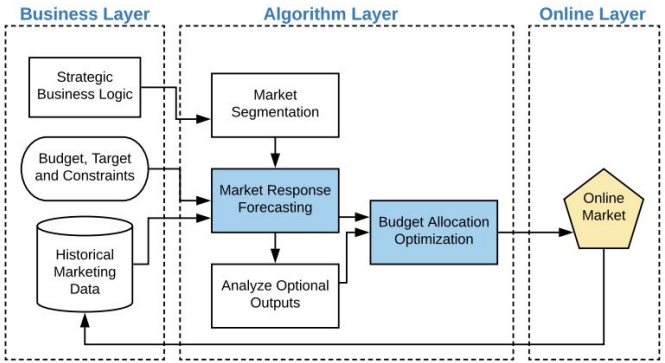
$$\lambda \rightarrow \lambda + \alpha(B - \sum_{i=1}^{n} \tau^c(x_i))$$

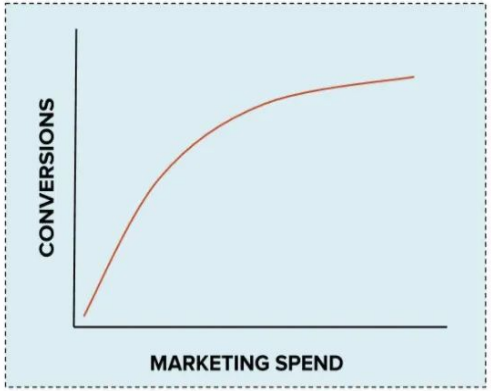
$$Y^S = Y^r - \lambda Y^c$$

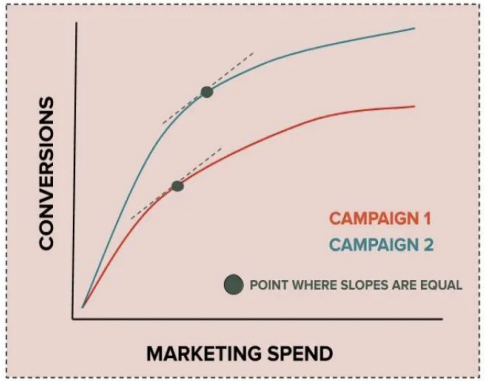
To do or not to do: cost-sensitive causal decision-making - Olaya et. al 2021

Improve User Retention with Causal Learning - Du et al. 2019

Global Marketing Budget Allocation







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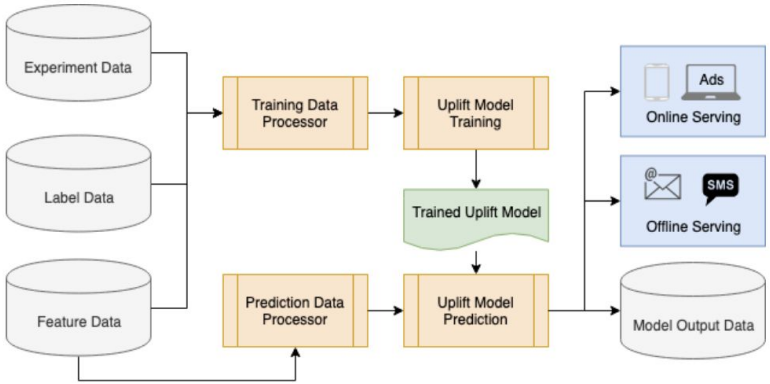
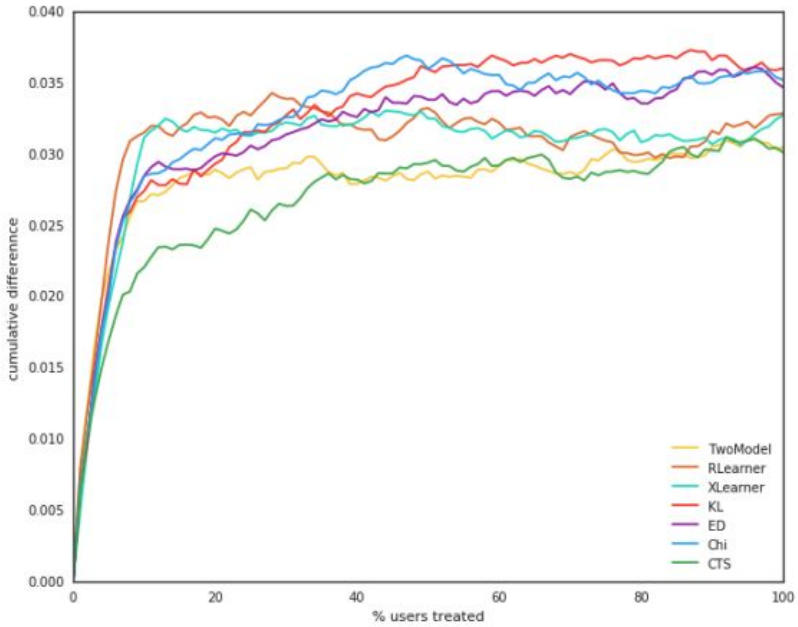
https://blogboard.io/blog/data-science-in-marketing-optimization/amp/ - DoorDash, AirBnB

Meta Learners

Modified Meta-Learners (NVX, NVR):

- Conversion value
- Impression cost
- Triggered cost





Zhenyu Zhao, Totte Harinen - Uplift Modeling for Multiple Treatments with Cost Optimization, DSAA 2019

Open Source Projects:

CausalML

EconML

scikit-uplift

Causal Impact

pylift

JustCause

DoWhy

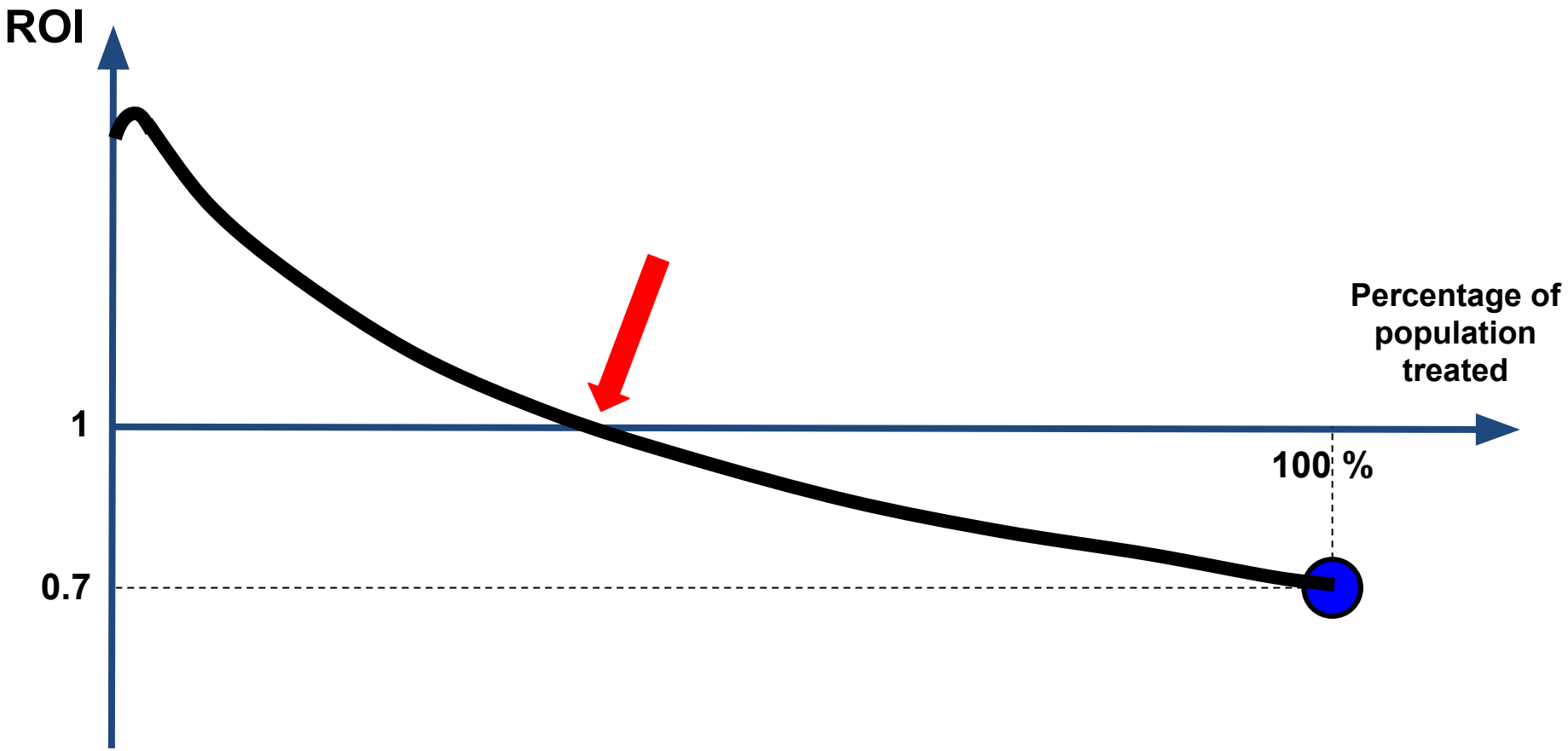
Implementation Challenges

Booking.com
Machine Learning

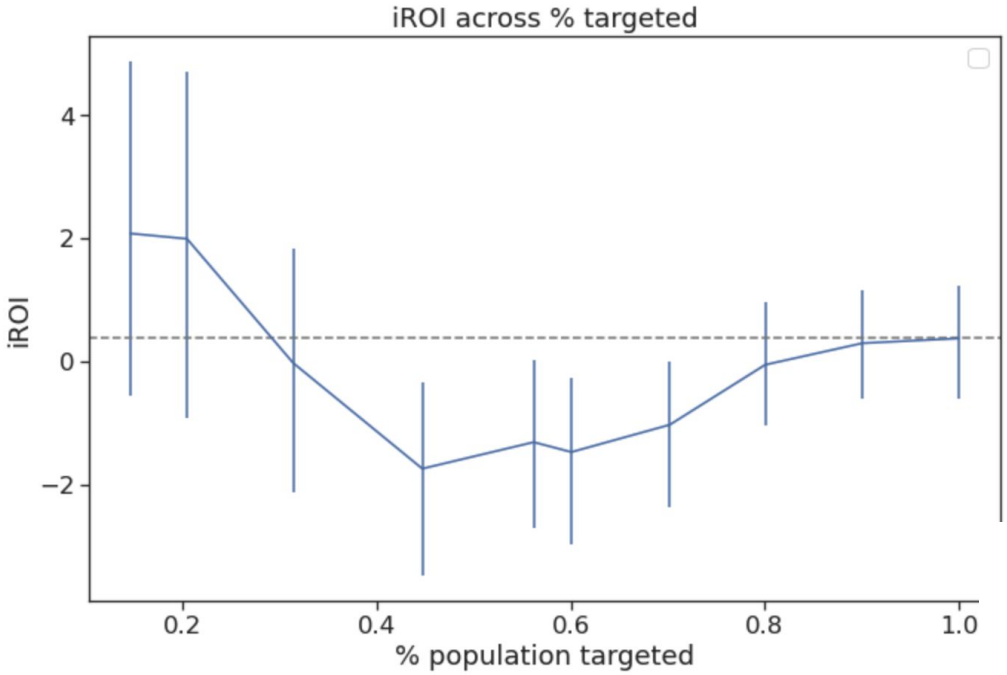
Implementation Challenges:

- Uncertainty
- Drift and Calibration
- Iterative Experimentation
- Exploration
- Persistency

Uncertainty



Controlling Uncertainty



Controlling Uncertainty

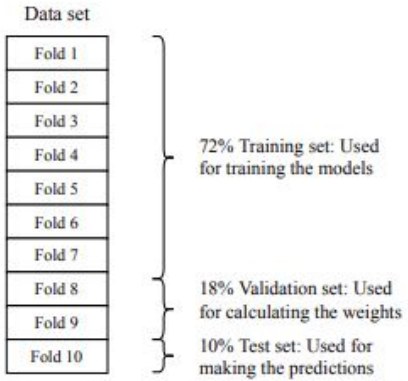


Figure 1. Illustration of training, validation and test split

Table 3. Average qini coefficient for each approach across different data sets

Approach	Hillstrom	Hillstrom/Women	Starbucks	Churn Prevention	Churn Prevention/A	Churn Prevention/B	Customer Acquisition	Criteo Resampled	Criteo	Average
Ensemble	0.836	0.917	0.981	1.000	0.730	1.000	0.610	0.912	0.996	0.887
Direct uplift	1.000	1.000	1.000	0.000	0.000	0.154	1.000	0.705	0.839	0.633
Two-model	0.000	0.174	0.600	0.731	1.000	0.000	0.000	1.000	1.000	0.501
Class transformation	0.128	0.000	0.000	0.082	0.634	0.931	0.392	0.000	0.000	0.241

Note: Higher values are better

first second

Table 4. Standard deviation of qini coefficient for each approach and data set

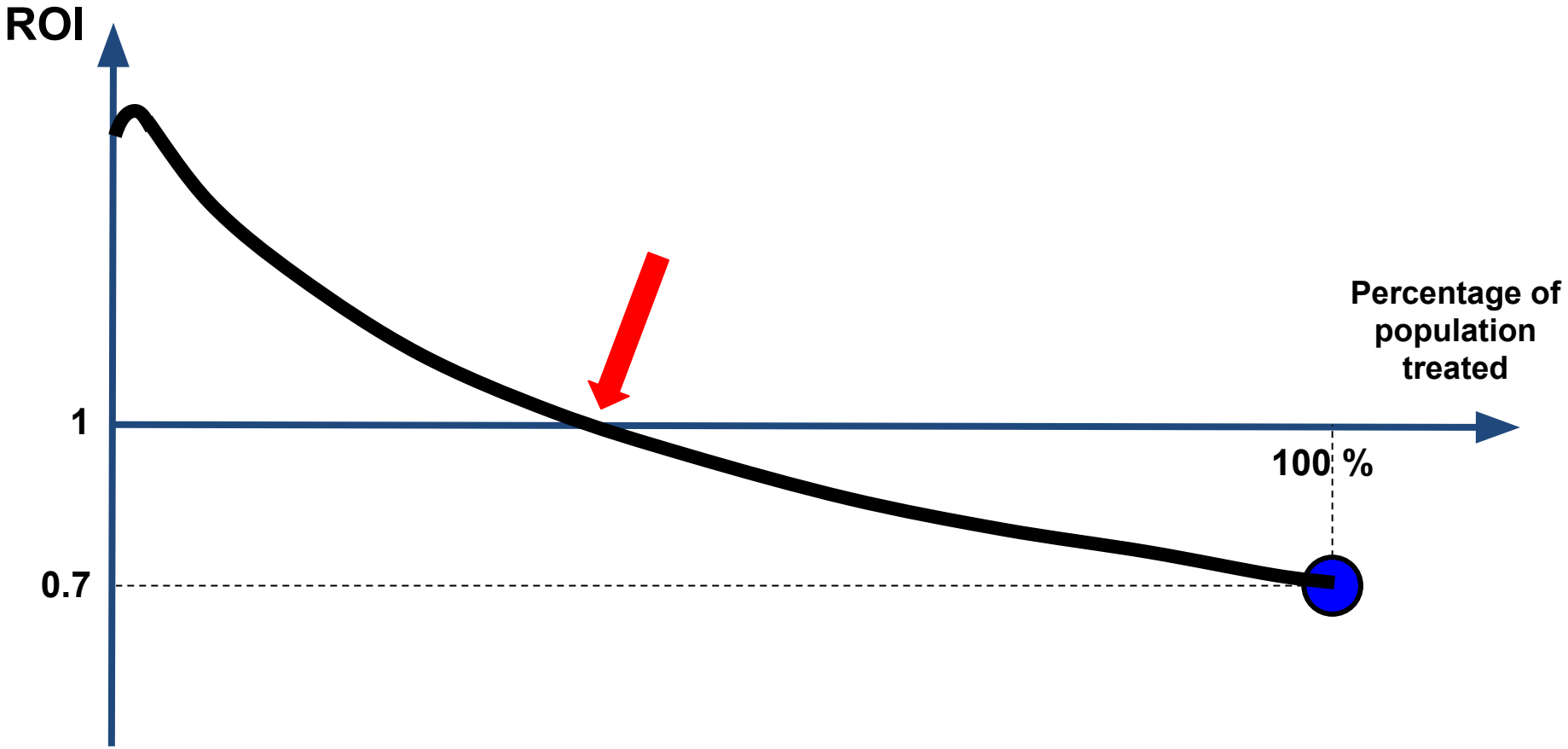
Approach	Hillstrom	Hillstrom/Women	Starbucks	Churn Prevention	Churn Prevention/A	Churn Prevention/B	Customer Acquisition	Criteo Resampled	Criteo	Average
Ensemble	0.000	0.017	0.439	0.000	0.000	0.156	0.301	0.298	*n/a*	0.151
Direct uplift	0.767	0.000	0.356	0.972	0.315	0.502	0.000	0.000	*n/a*	0.364
Two-model	0.115	0.222	0.000	1.000	0.024	1.000	1.000	1.000	*n/a*	0.545
Class transformation	1.000	1.000	1.000	0.177	1.000	0.000	0.843	0.007	*n/a*	0.628

Note: Lower values are better

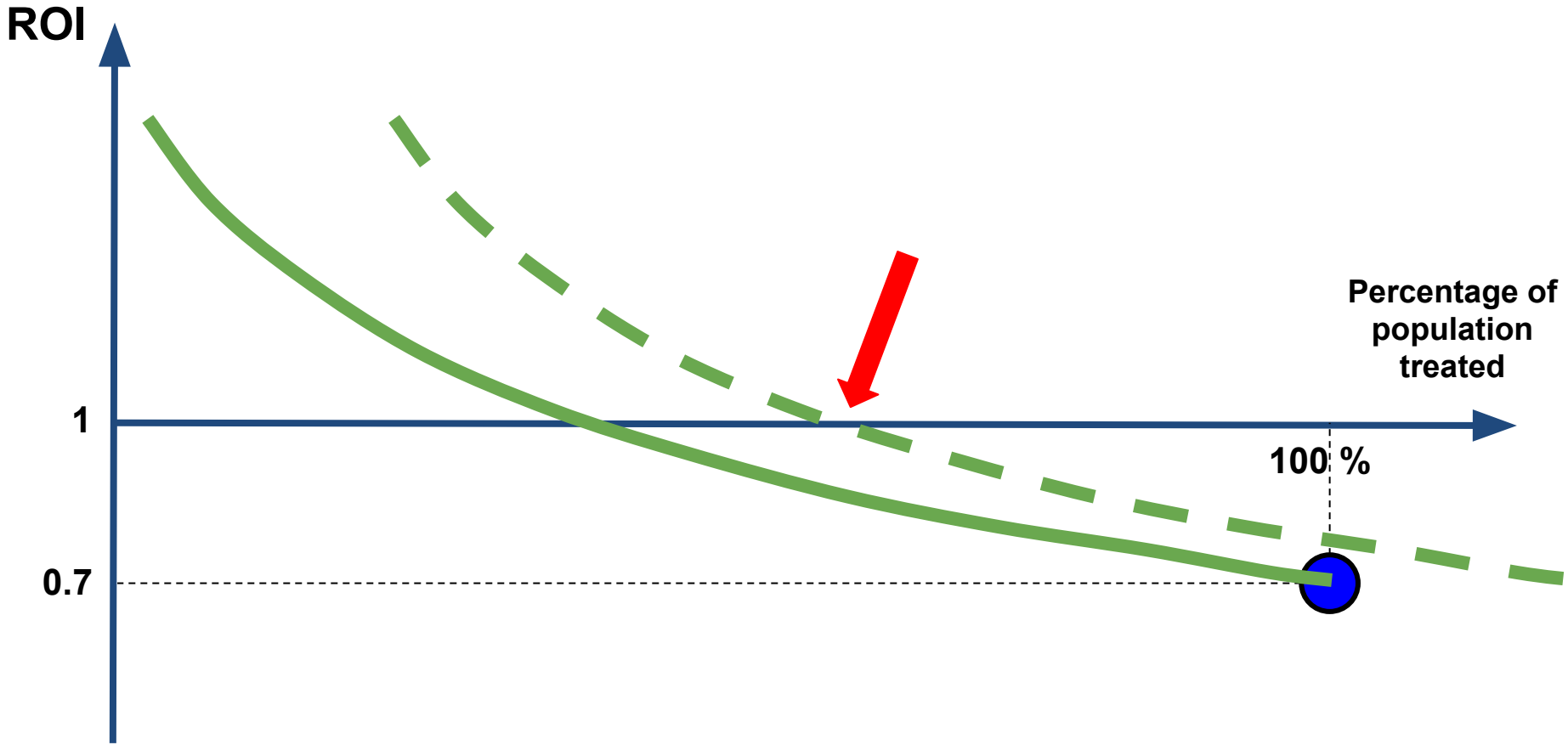
first second

- Rößler, Jannik, Roman Tilly, and Detlef Schoder. "To Treat, or Not to Treat: Reducing Volatility in Uplift Modeling Through Weighted Ensembles." *Proceedings of the 54th Hawaii International Conference on System Sciences*. 2021.
-Saito, Yuta, and Shota Yasui. "Counterfactual Cross-Validation: Stable Model Selection Procedure for Causal Inference Models." *International Conference on Machine Learning*. PMLR, 2020.

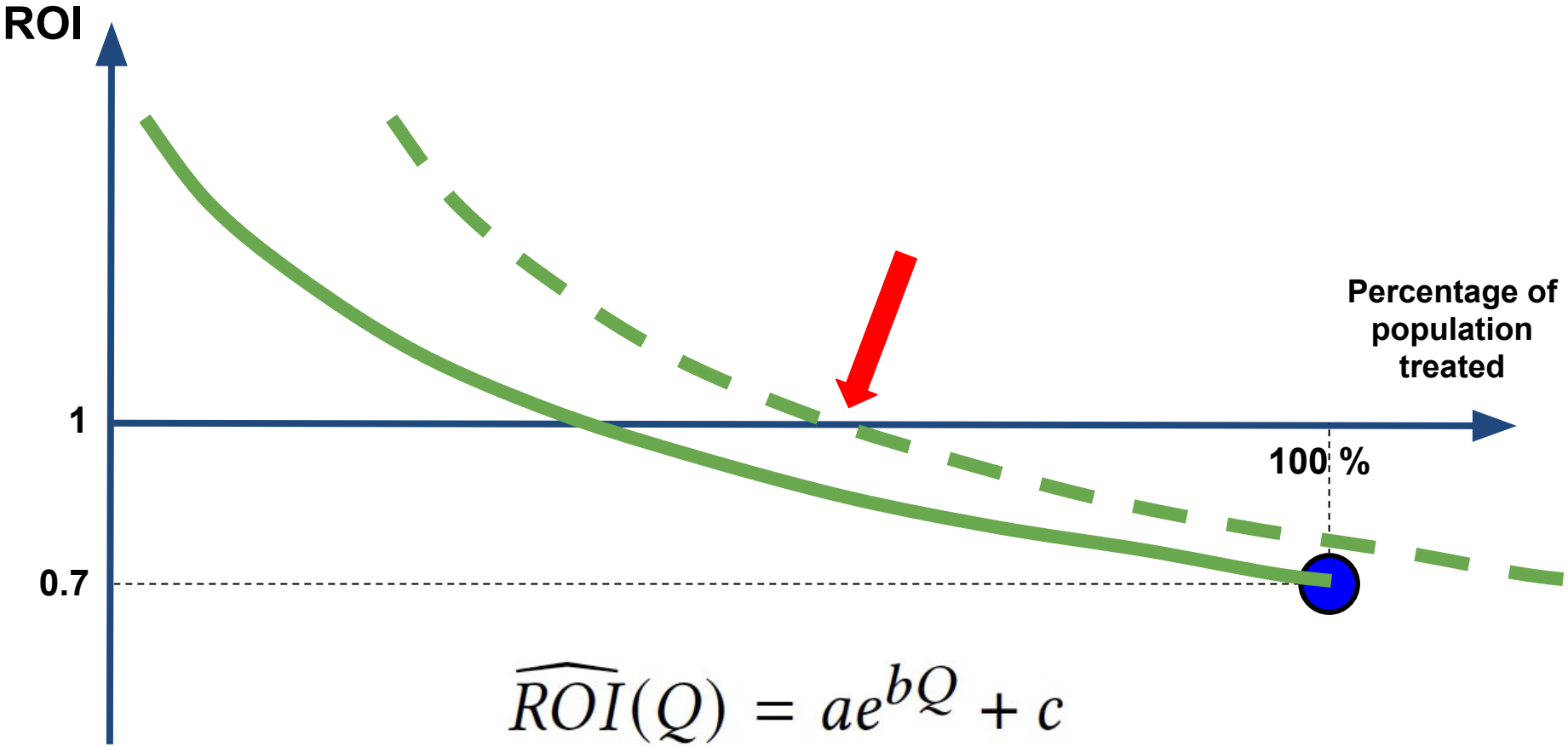
Drift and Calibration



Drift and Calibration

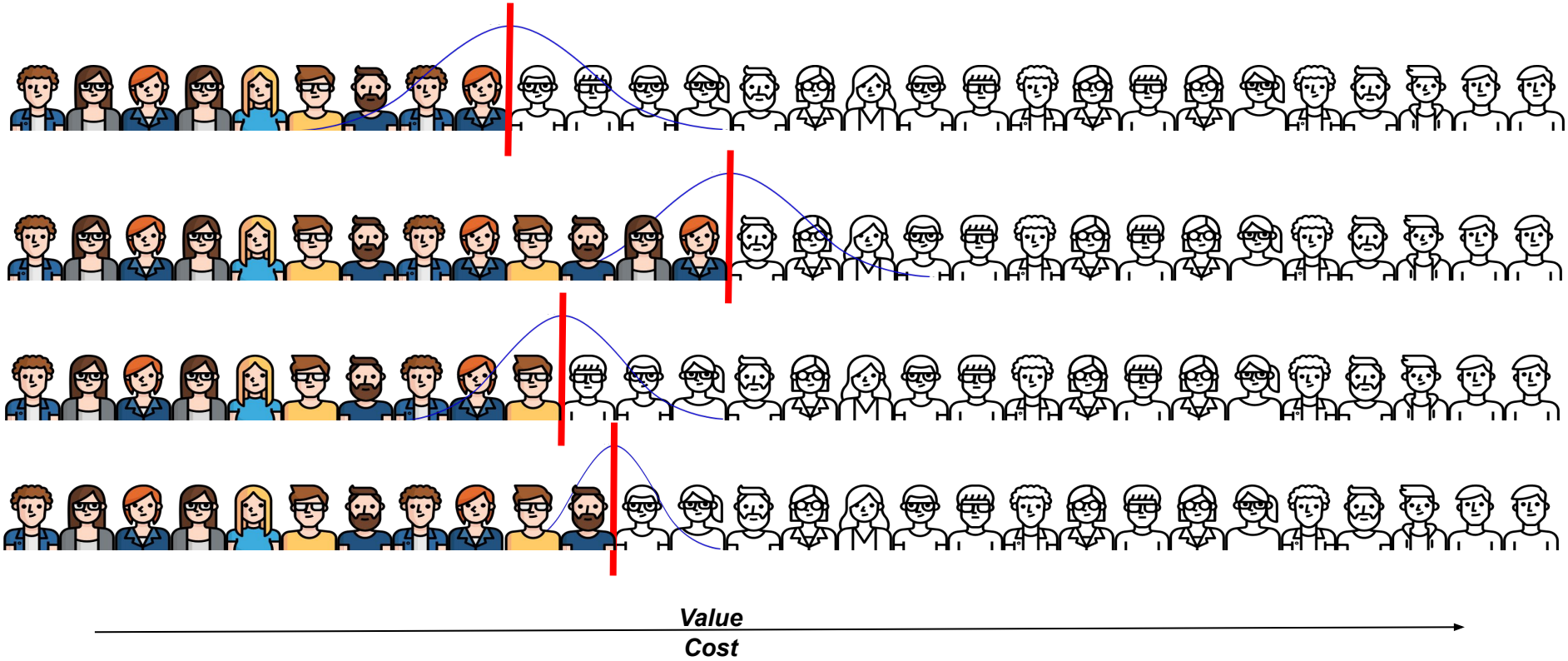


Drift and Calibration



$$\widehat{ROI}(Q) = ae^{bQ} + c$$

Drift and Calibration



Drift and Calibration

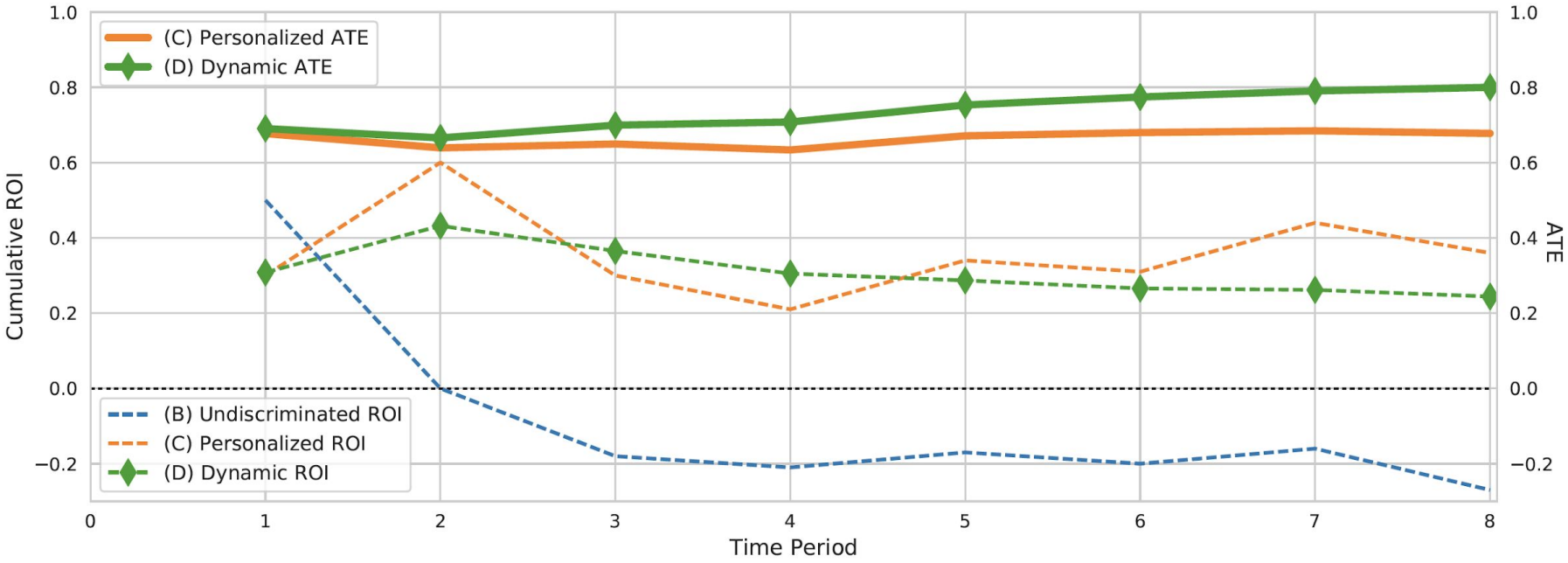
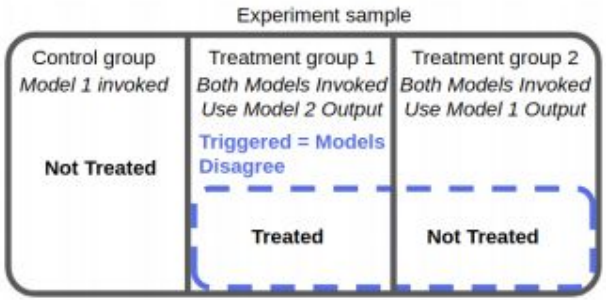


Fig. 3. Experimental results (achieved ROI and portion of ATE) of personalized promotions assignment

Free Lunch! Retrospective Uplift Modeling for Dynamic Promotions Recommendation within ROI Constraints

Dmitri Goldenberg, Javier Albert, Lucas Bernardi, Pablo Estevez @ RecSys'20

Iterative Experimentation



150 successful machine learning models: 6 lessons learned at booking.com

Lucas Bernardi, Themis Mavridis, Pablo Estevez @ KDD ‘19

Iterative Experimentation

A- No Treatment

B- Treatment

A- No Treatment

B- Treatment

C - Selective

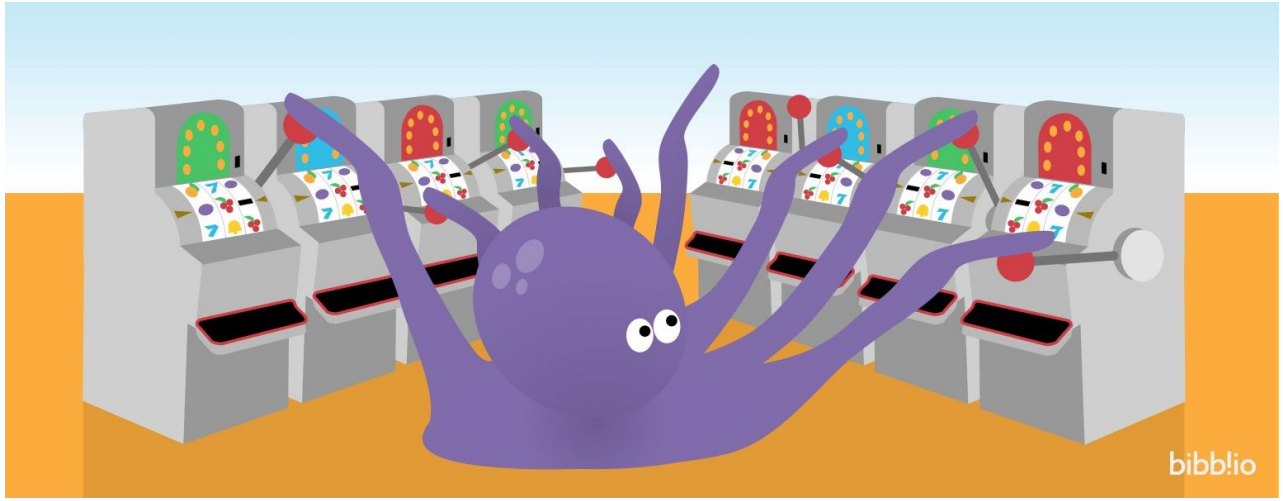
A- No Treatment

B- Treatment

C - Selective

- Costly Exploration
- No Monitoring
- Static Model
- Treatment Leakage
- Long-Term Effects

Bandit-Based Models



Recommending Accommodation Filters with Online Learning

Lucas Bernardi, Pablo Estevez, Matias Eidis and Eqbal Osama - ORSUM @ RecSys'20

Cost Aware Bandits

1. Budget limited policy learning methods
   a. Knapsack Based Upper Confidence Bound Explore/Exploit (KUBE)
   b. Fractional KUBE as direct policy learning method
   c. KUBE for adversarial Bandits
2. Bandits with Knapsack
   a. Primal-Dual Bandits with knapsack
   b. Lagrange BwK

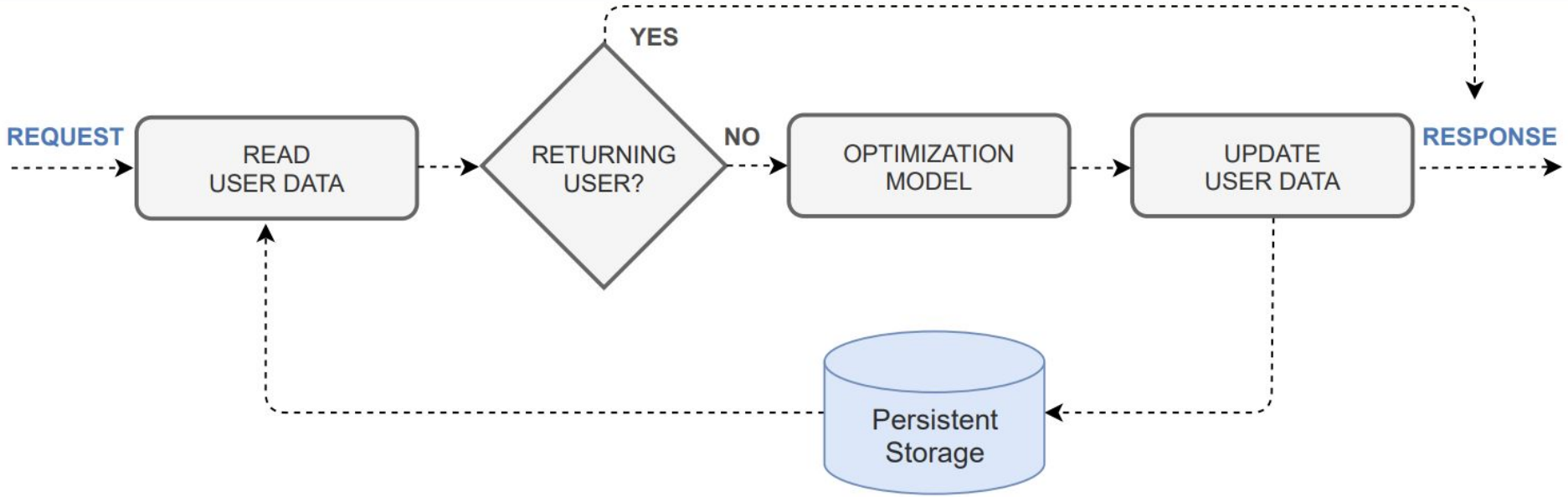
Bandits with Knapsacks - Badanidiyuru, Ashwinkumar, Robert Kleinberg, and Aleksandrs Slivkins - IEEE SFCS 2013
Knapsack based optimal policies for budget–limited multi–armed bandits - Tran-Thanh, A Chapman, A Rogers, N Jennings - AAAI 2012

Repetitive Model Calls

When is it ok to replace offers?

Every Page-load?
Every day? Week?
Every search query?
Every Destination?
Never?

Persistency



Learning to Persist: Exploring the Tradeoff Between Model Optimization and Experience Consistency
Goldenberg, Tsype, Spivak, Albert, Tzur - *TemporalWeb @ Web Conference 2021*

Uplift modeling
from Causal Inference to Personalization

The Web Conference 2021 Tutorial (WWW '21) - Ljubljana, Slovenia

THE WEB CONFERENCE

https://booking.ai/uplift-modeling-f9759e3fb51e

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