Personalized Ads Using ML

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Lecturer

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Lecture Outline

1. **Economics of Advertising**
   - Why firms advertise: information, persuasion, heterogeneity
   - Limits of mass and rule-based targeting
2. **Prediction with Machine Learning for Ads**
   - ML as a tool for predicting individual outcomes
   - Decision trees and random forests
   - Using prediction models to personalize advertising
3. **From Prediction to Causal Effects (Uplift)**
   - Prediction vs. treatment effects
   - Causal forests for personalized advertising
   - Policy learning for targeting

(Some) References

- Ascarza (2018): "Retention Futility: Targeting High-Risk Customers Might be Ineffective" Journal of Marketing Research, 55(1), 80-98, download.
- Strittmatter (2025): "Machine Learning for Causal Inference in Economics", IZA World of Labor, No. 516, download.
- Mullainathan and Spiess (2017): "Machine Learning: An Applied Econometric Approach", Journal of Economic Perspectives, 31 (2), pp. 87-106, download.
- Athey (2017): "Beyond Prediction: Using Big Data for Policy Problems", Science, 355 (6324), pp. 483-485, download.
- Cagala, Rincke, Glogowsky, Strittmatter (2021): "Optimal Targeting in Fundraising: A Machine Learning Approach", download.
- James, Witten, Hastie, Tibshirani (2023): "An Introduction to Statistical Learning", 2nd edition, Springer, download.

PC Lab Exercises for Self-Study

- I provide code for three use cases covered in the lecture
- The exercises let you replicate, explore, and extend these use cases independently

- All course materials (slides, data, and code) are available on GitHub: github.com/AStrittmatter/Tech-Economics
- PC labs are based on interactive Jupyter notebooks that run directly in your browser: mybinder.org

General

- Feel free to interrupt me at any time when you have questions.
- Tell me when I'm too slow or too fast. Ask me to repeat material in case something was not clear.
- You can also send me an email with questions: anthony.strittmatter@unidistance.ch
- Proposals to improve the lecture are also welcome.

Economics of Advertising

From demand shifts to the economic rationale for personalized advertising

What Is Advertising?

- Advertising is a firm's instrument to influence consumer demand
- It operates by affecting:
  - information (what consumers know)
  - beliefs (how consumers evaluate products)
  - attention (which options are considered)
- It differs from pricing and product design

Economic Definition

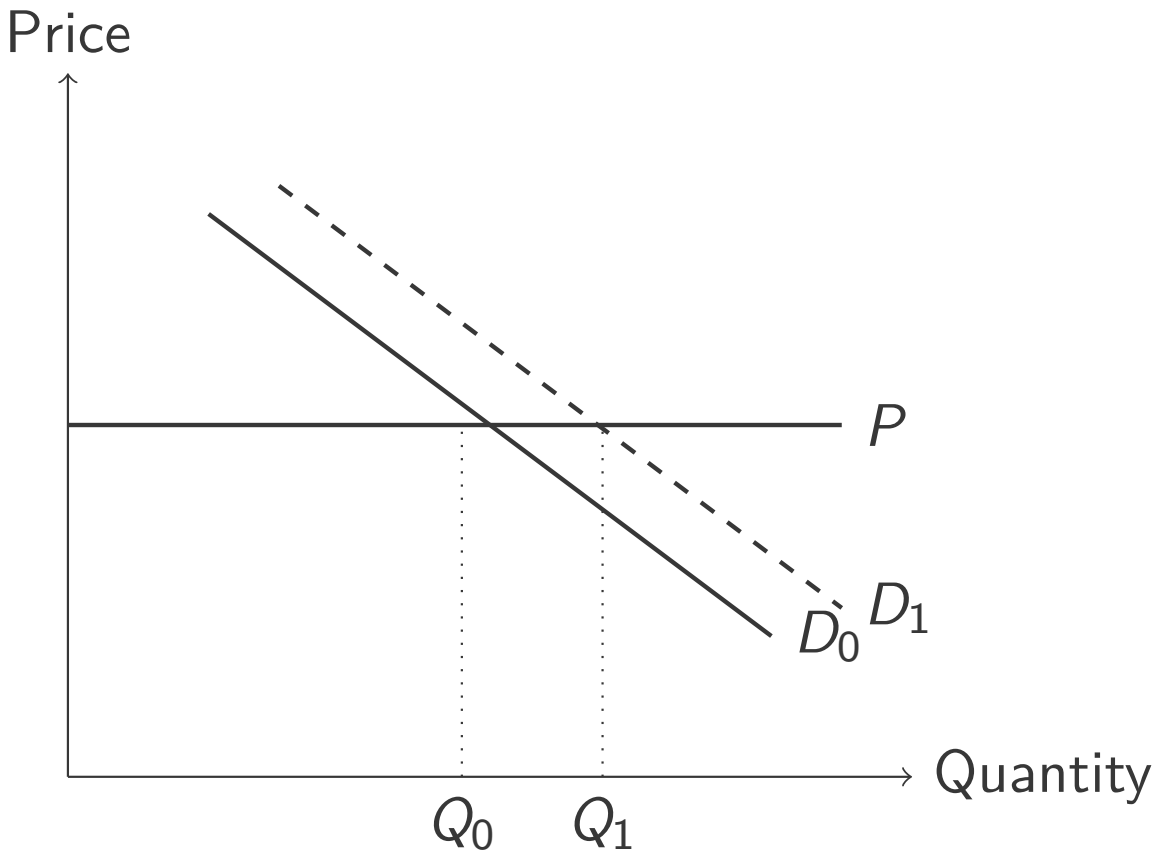
Advertising shifts demand by changing information or salience, without directly changing prices or product characteristics.

Why Do Firms Advertise?

1. **Reduce information frictions**
   - Consumers may not know that a product exists
   - They may be uncertain about price, quality, or fit
2. **Create awareness among potential buyers**
   - A product cannot be purchased if consumers are unaware of it
   - Advertising moves consumers into the "consideration set"
3. **Influence marginal purchase decisions**
   - Advertising can tip decisions when consumers are almost indifferent
   - Small effects on many consumers can generate large revenues

Economic implication: Advertising shifts or rotates demand by increasing willingness to buy at a given price.

Advertising as a Demand Shift



- Advertising shifts demand from D_0 to D_1
- Prices P are fixed in the short run
- Sales increase from Q_0 to Q_1

Example: Amazon Prime

- Some Prime subscribers consider canceling their membership
- They underestimate how often they use Prime benefits (delivery, video, music)
- Amazon sends personalized emails and in-app reminders about recent usage

Economic mechanisms:

- Consumers have imperfect recall of past usage and benefits (information frictions)
- Personalized summaries make benefits more visible at decision time
- Better information raises perceived surplus from staying subscribed

Why this matters economically:

- Reducing information frictions stabilizes demand without lowering prices
- Small reductions in churn have large effects on lifetime customer value

Example: Google Search Ads

- A consumer searches for *"running shoes"* on Google
- Sponsored ads appear above organic search results

Economic mechanisms:

- Ads make consumers aware of brands and products they did not know
- Only visible products enter the consideration set of consumers
- Higher placement in search results increases click probability
- Ads reduce the effort required to find relevant offers

Why this matters economically:

- Products not seen are effectively not demanded
- Advertising shifts demand by expanding and reshaping choice sets
- Even without changing prices, firms can reallocate market shares

Example: Netflix

- Netflix advertises a new flagship series (e.g. *Stranger Things*) on Instagram and YouTube
- Subscription price and overall catalog remain unchanged
- A modest increase in new subscriptions is observed after the campaign

Economic mechanism:

- Many consumers are *almost indifferent* between subscribing and not
- Advertising increases awareness and salience of specific content
- This slightly raises perceived value and willingness to pay
- For some consumers, willingness to pay crosses the subscription price

Why this matters economically:

- Individual effects are small, but applied to millions of users, they generate substantial revenue

Heterogeneous Consumers

- Consumers differ systematically in:
  - **preferences** (needs, tastes, brands)
  - **price sensitivity** (budget constraints, urgency)
  - **attention and responsiveness** to advertising

Example: Same Ad, Different Effects

- Customer already planning to buy running shoes $\rightarrow$ ad accelerates purchase
- Casual browser $\rightarrow$ ignores the ad
- Loyal customer of another brand $\rightarrow$ ad has no effect

Key insight: The same ad can increase demand for some consumers and have no (or even negative) effect for others

Different Responses to the Same Ad

Scenario: Online ad for a luxury watch shown to all users

High-income consumer

- Already interested in luxury brands
- High willingness to pay
- Ad increases purchase probability

Low-income consumer

- Budget constrained
- Low relevance of the product
- Ad has no effect on behavior

Economic implication:
Showing the same ad to everyone wastes budget and reduces effectiveness.

Traditional (Mass) Advertising

How advertising used to work

- One ad message shown to everyone
- No individual-level information used
- Common channels:
  - TV commercials
  - newspapers
  - billboards

Problem:
Most impressions go to consumers with low or zero responsiveness.

Inefficiency of Mass Advertising

Scenario: TV advertising for the PlayStation 5

Relevant audience

- households without a current-generation console
- active video game players
- parents considering a console purchase for children

Irrelevant audience

- households that already own a PlayStation 5
- viewers with no interest in video games
- individuals with budget or age constraints

Economic problem:
Mass advertising reaches many consumers with zero probability of purchase, leading to wasted advertising expenditure and low average returns.

Why Do Firms Use Targeting?

Advertising as an investment decision

- Each ad impression has a cost
- Consumers differ in their probability of responding
- Showing ads to low-response users wastes budget

Economic objective

Maximize expected returns by allocating ads to consumers with higher expected response.

Rule-Based Targeting

Early approach to personalized advertising

- Advertising decisions based on simple if–then rules
- Rules designed manually by marketers
- Consumers grouped into a small number of predefined segments

Typical decision logic

IF user satisfies the rule $\rightarrow$ show ad
ELSE $\rightarrow$ do not show ad

Key feature: The same rule is applied to all users within a segment.

Example: Gym Membership Advertising

Example: Planet Fitness / Anytime Fitness

- Facebook ad campaign to acquire new gym members
- Rule-based targeting:
  - Age between 20 and 40
  - Lives within 10 km of a gym
- Users satisfying the rule differ strongly in:
  - interest in fitness
  - past exercise behavior
  - likelihood of signing up

Economic insight: Rules improve targeting relative to mass advertising, but still treat unequal users equally.

Common Types of Rule-Based Targeting

- **Demographic targeting**
  - age, gender, income, location
  - e.g. ads for student loans shown to young adults
- **Behavioral targeting**
  - past purchases, browsing history
  - e.g. retargeting users who visited a product page
- **Interest-based targeting**
  - broad categories inferred from activity
  - e.g. “fitness enthusiasts”, “travel lovers”

Common feature: Rules rely on coarse groupings rather than individual-level predictions.

Why Rule-Based Targeting Is Limited

Economic problem of coarse segmentation

- Large heterogeneity within segments
- Rules ignore interactions and nonlinearities
- Manual rules do not scale to rich user data

Economic consequence

Ads are shown to many low-response users and withheld from some high-response users.

Implication: There are large gains from individual-level, data-driven targeting.

From Rules to Data-Driven Targeting

What has changed in advertising markets?

- Platforms observe rich, high-dimensional user data
  - browsing behavior, search queries, app usage, location, time
- Simple if–then rules cannot exploit this information
- Manually designing rules does not scale

Economic shift

Targeting moves from hand-crafted rules to data-driven decision problems.

Next step: Prediction and causal inference with machine learning

Key Takeaways: Economics of Advertising

- Advertising shifts demand by changing information and attention
- Consumers respond heterogeneously to ads
- Uniform advertising is inefficient in heterogeneous markets
- Targeting improves efficiency by matching ads to responsive consumers
- The complexity of targeting decisions motivates ML-based personalization

Prediction with Machine Learning for Ads

Using data to predict individual advertising outcomes

The Core Decision Problem in Digital Advertising

Think like an advertiser:

- You can potentially show ads to **many** users, but:
  - ads cost money
  - user attention is limited
  - users differ in how likely they are to respond

Example: Online shoe retailer

The firm wants to decide:

- who should see an ad,
- how much to bid for an impression,
- which message to show.

Where Machine Learning Appears in Practice

- **Google Search Ads**
  - *Who should see the ad:* predict which queries and users are likely to click
  - *How much to bid:* estimate expected value of an impression to guide bids
  - *Which message to show:* select ad text matching the search intent
- **Uber**
  - *Who should see the message:* predict which riders are likely to stop using Uber
  - *How much to spend:* choose the minimum incentive needed to prevent churn
  - *Which message to show:* decide between a price discount, ride reminder, or feature highlight

What Exactly Do Firms Predict in Advertising?

- Firms do not predict actions directly – they predict **probabilities and expected values**
- Common prediction targets:
  - **Click through rate (CTR):** $Pr(\text{click} \mid X)$
  - **Conversion rate:** $Pr(\text{purchase} \mid \text{click}, X)$
  - **Expected revenue:** $E(\text{value} \mid X)$
  - **Churn risk:** $Pr(\text{churn} \mid X)$

Interpretation

Each user receives a *score* summarizing how valuable or responsive they are expected to be.

Machine Learning for Advertising: What Does It Do?

- **Machine learning (ML)** builds predictive models from data

$$\widehat{Y} = \hat{f}(X)$$

- In digital advertising:
  - Y: clicks, purchases, revenue, or churn
  - X: user characteristics, past behavior, context
- The output is a **score for each user**:
  - how likely they are to click
  - how likely they are to buy
  - how much revenue they are expected to generate

Interpretation: ML turns rich user data into predictions that can be used to target users.

Why Use Machine Learning in Advertising?

Why ML works well in practice:

- handles many variables at once (high-dimensional data)
- captures nonlinearities and interactions automatically
- often delivers strong **out-of-sample** prediction accuracy

Important limitations:

- many ML models are hard to interpret ("black box")
- good prediction does *not* imply causal relationship

Key takeaway: ML is excellent for predicting users behaviour, but prediction alone does not answer whether ads *change* behavior.

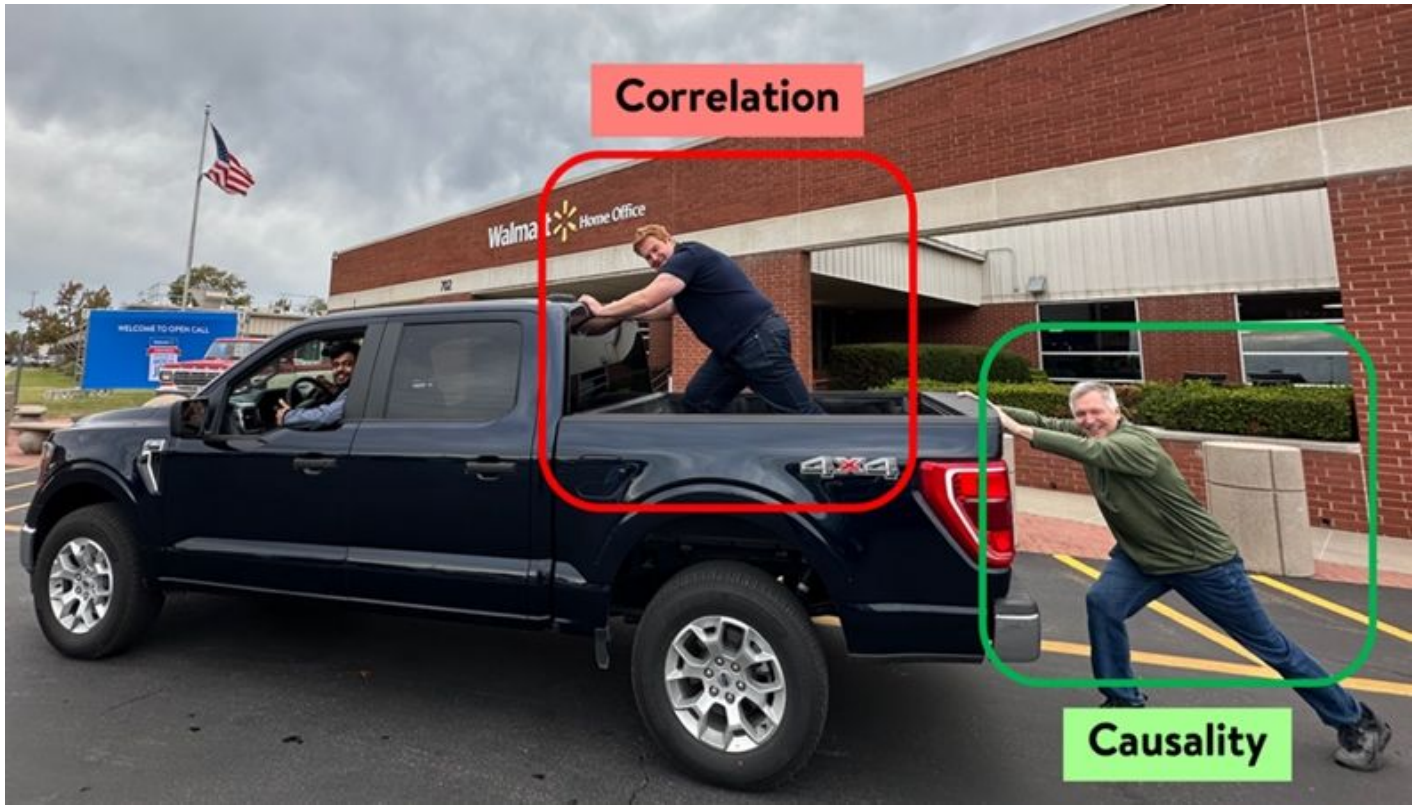
Prediction vs. Causality in Advertising

- **Prediction answers:**
  - Who is likely to buy?
  - Who has high expected spending?
- **Causality answers:**
  - Who buys *because* of the ad?
  - For whom does the ad change behavior?

Why this matters

A user with a high predicted purchase probability may have bought anyway. Prediction success does not imply that advertising caused the purchase.

Prediction vs. Causality in Advertising



John List and Jeffrey Lachman

When Prediction Is Still Useful for Advertising

- Prediction alone does not identify causal effects
- But real-world advertising decisions rely on **economic assumptions**

Common assumptions used in practice

- Users with very low churn risk do not need advertising
- Only high-spending users are worth persuading
- Users close to a purchase decision are more responsive to ads

Key message: Prediction becomes decision-relevant once combined with explicit behavioral assumptions.

How Do Trees Make Predictions?

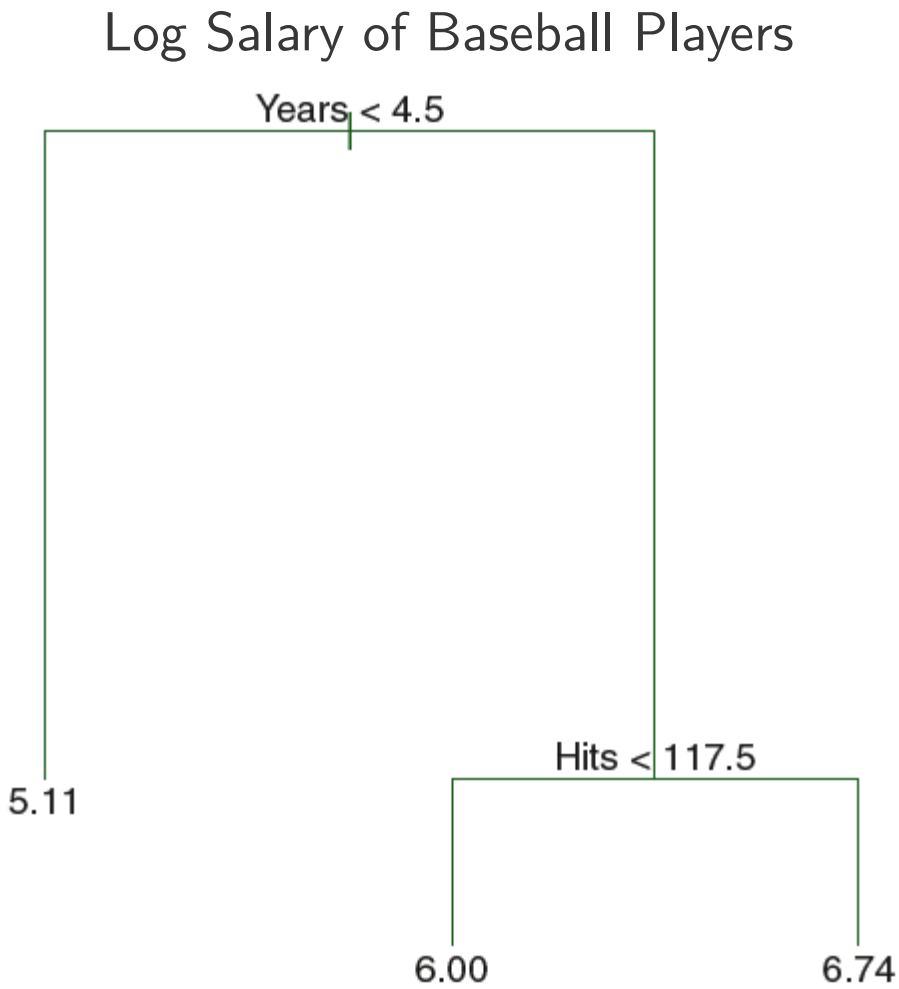
Idea: partition the market into "if–then" segments

1. Start with all consumers in one group
2. Pick a split (e.g., *visited sports sites?*) that best reduces prediction error
3. Repeat inside each subgroup until the tree is "good enough"

What the tree outputs at the end

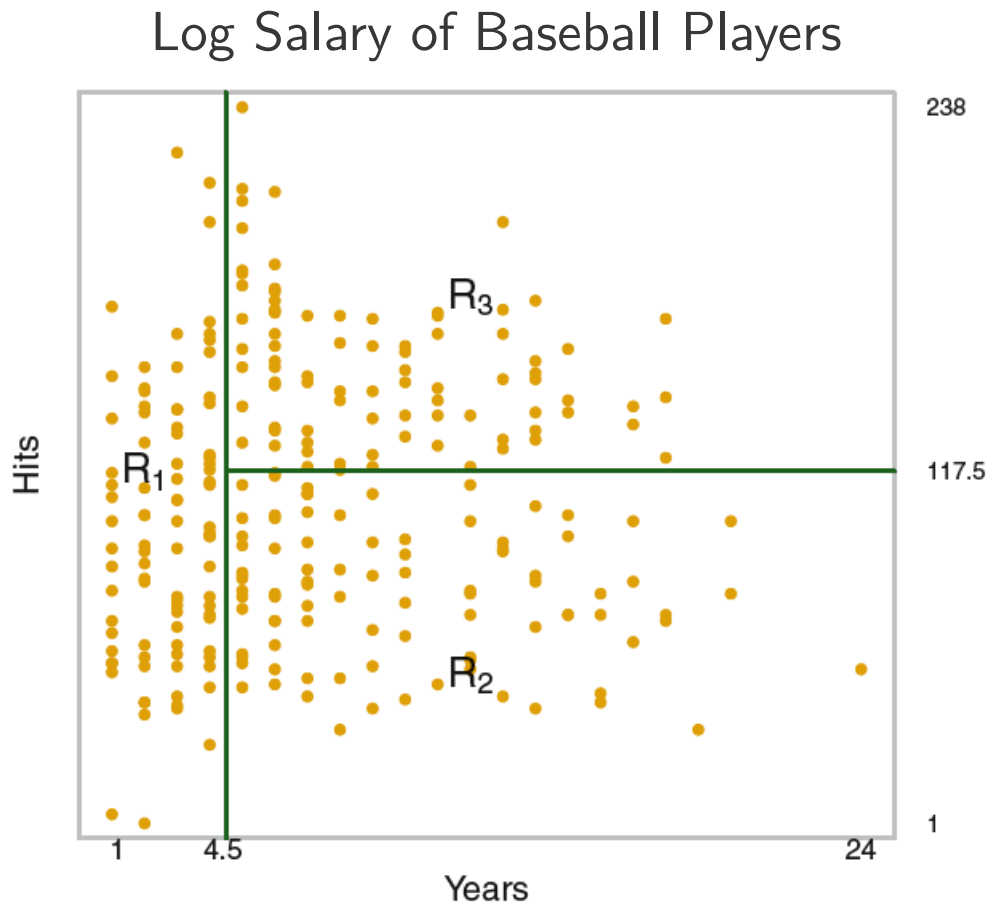
Each terminal node (leaf) stores a **predicted outcome**, e.g.
$\widehat{E}[Y \mid X]$ = predicted spending / purchase probability.

Example: Shallow Tree



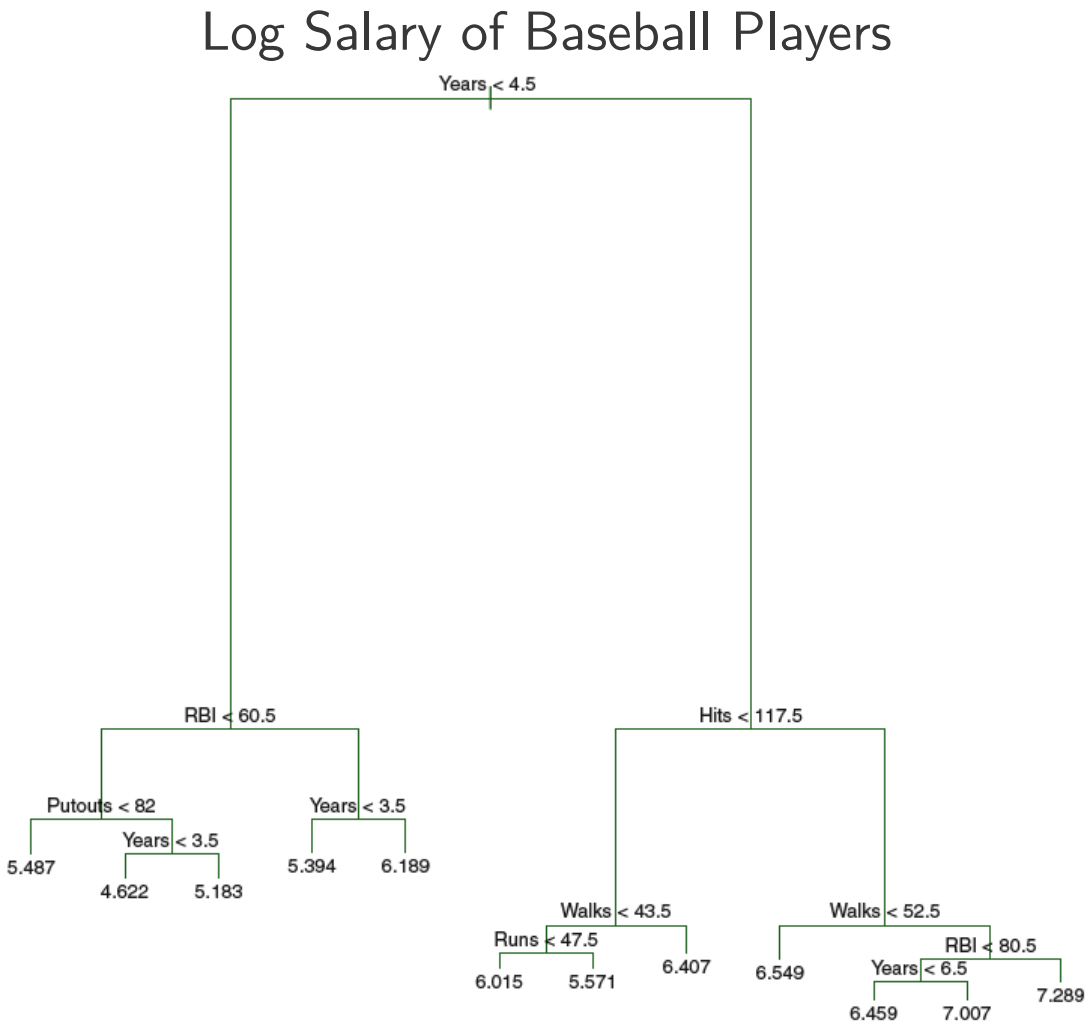
Source: James, Witten, Hastie, Tibshirani (2013)
Interpretation: Each terminal node defines a group of players with similar characteristics; the model predicts their log salary as the average log salary observed in that segment.

Example: Shallow Tree (cont.)



Source: James, Witten, Hastie, Tibshirani (2013)

Example: Deep Tree



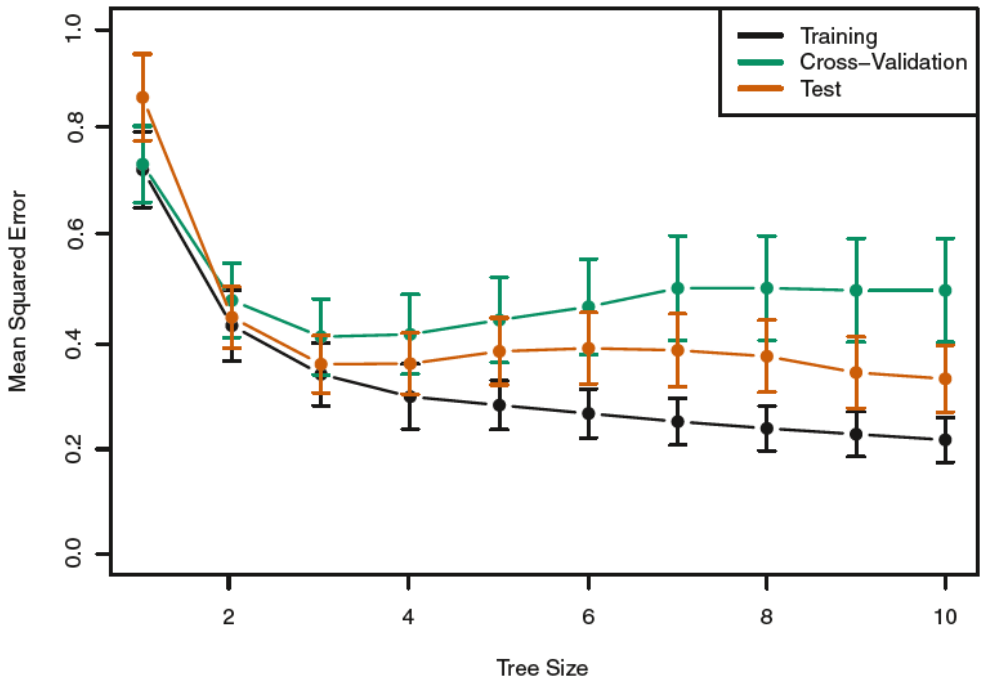
Source: James, Witten, Hastie, Tibshirani (2013)

Shallow vs. Deep Trees

- Shallow trees:
  - easy to explain and communicate
  - may miss important patterns (underfitting)
- Deep trees:
  - very flexible
  - can overfit noise (poor out-of-sample performance)

Trade-off: interpretability vs. predictive accuracy

Selecting Optimal Tree Size



→ Very large trees can fit past data extremely well.

→ But they may perform poorly on new, unseen data.

→ Choose the tree size that predicts *future outcomes* most accurately.

Source: James, Witten, Hastie, Tibshirani (2013)

Limitations of Single Trees

- Small data changes can lead to very different trees
- Predictions may be unstable
- This may limits out-of-sample performance

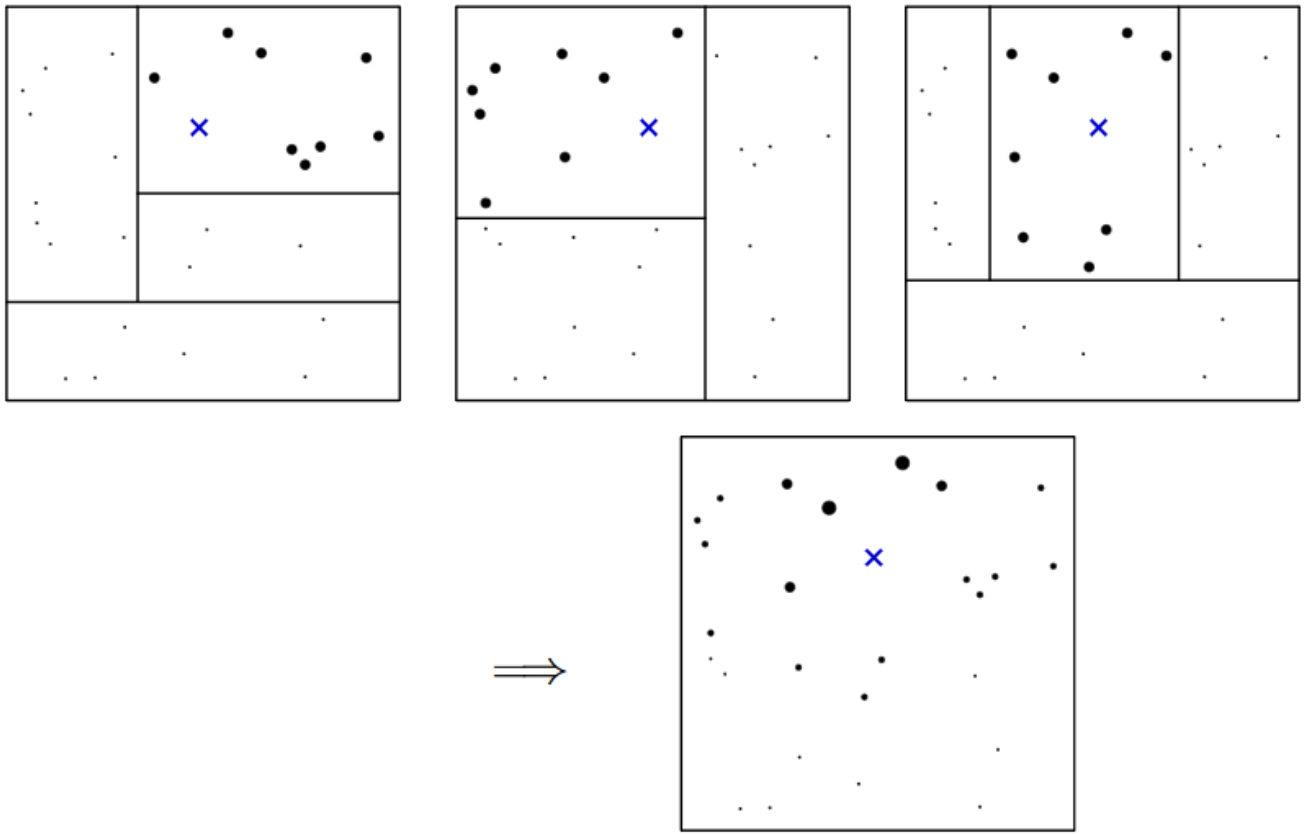
Idea: Combine many trees to improve prediction

Random Forests: Core Idea

- Build many trees on different subsamples of the data (and different candidate predictors)
- Each tree makes a prediction
- Final prediction is the average across trees
- Lower variance than single trees

Economic intuition: Aggregation reduces noise and improves predictive accuracy

Random Forest: Weighted Representation



Source: Athey, Tibshirani, Wager (2018)

Use Case: Comscore Data for Digital Advertising

- We use **real household-level data** collected by **Comscore**
- Comscore is a global analytics company measuring:
  - online purchases,
  - website traffic,
  - digital advertising exposure
- Its data are widely used by:
  - advertisers,
  - media companies,
  - large digital platforms

Why this matters

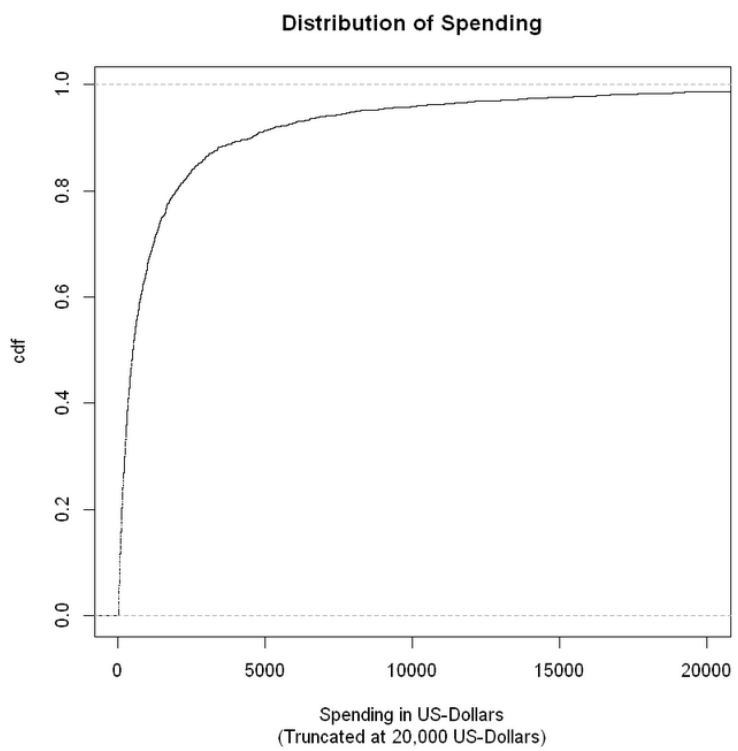
This is the type of data firms actually use to make targeting, bidding, and personalization decisions in digital advertising.

What Do We Observe in the Comscore Data?

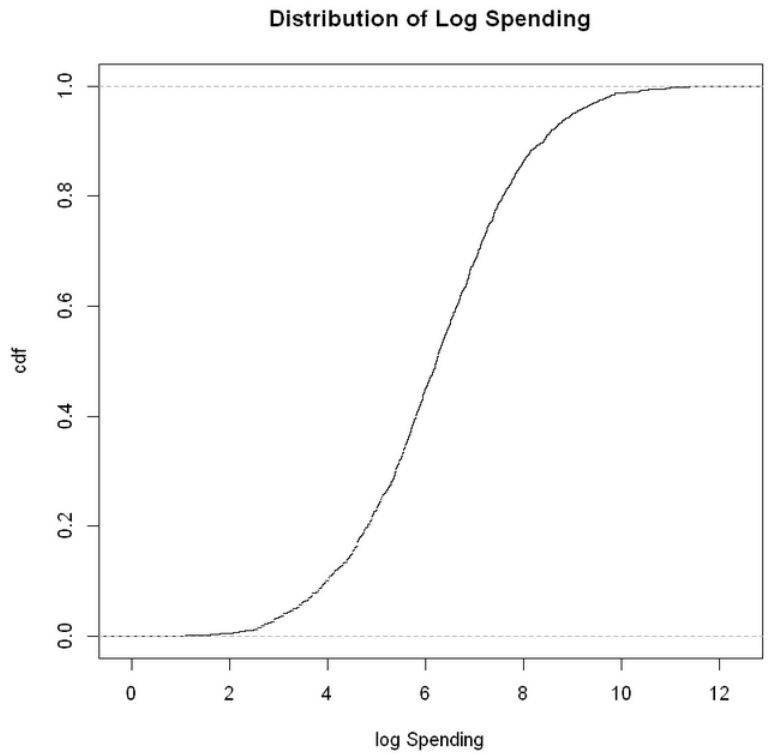
- For each household, we observe:
  - **Annual online spending** (observed in historical data)
  - **Browsing behavior** across the **1,000 most visited websites**
- Browsing data are measured as:
  - share of total online time spent on each website
- Two groups of households:
  - **Historical users:** browsing + spending observed
  - **New users:** browsing observed, spending not yet observed

Goal: Use historical browsing behavior to predict the value of new users for advertising.

Outcome Distribution: Spending Is Highly Skewed



Spending (USD)



Log spending (more symmetric)

- Many households spend little; a few spend a lot

Decision Trees with Comscore Data

- Consider an advertiser selling products online
- The advertiser wants to identify high-value households for advertising

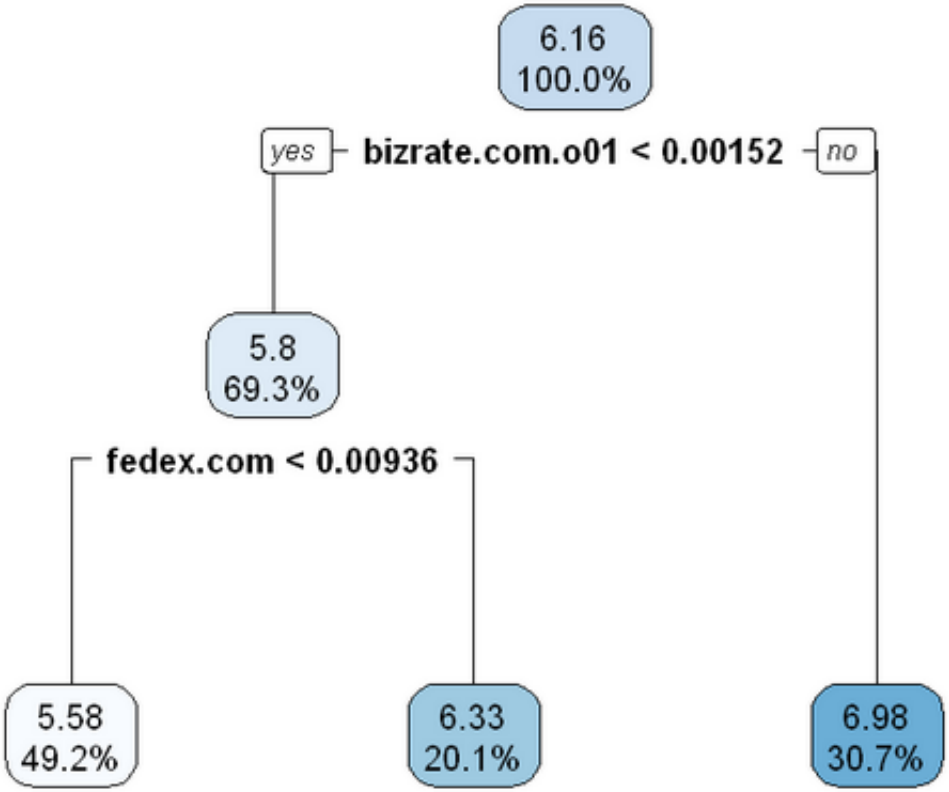
What the decision tree learns

- The tree uses detailed web browsing behavior across many websites
- It splits households into segments with similar browsing patterns
- Each terminal node corresponds to a group with similar *predicted online spending*

Key idea

Households with similar browsing behavior tend to have similar online spending patterns.

Example Tree: Browsing Predicts Spending



- Splits are based on browsing shares of particular websites
- Each leaf corresponds to a segment with different predicted spending

From Prediction to Advertising Decisions

- For new households, only browsing behavior is observed
- A tree predicts expected online spending

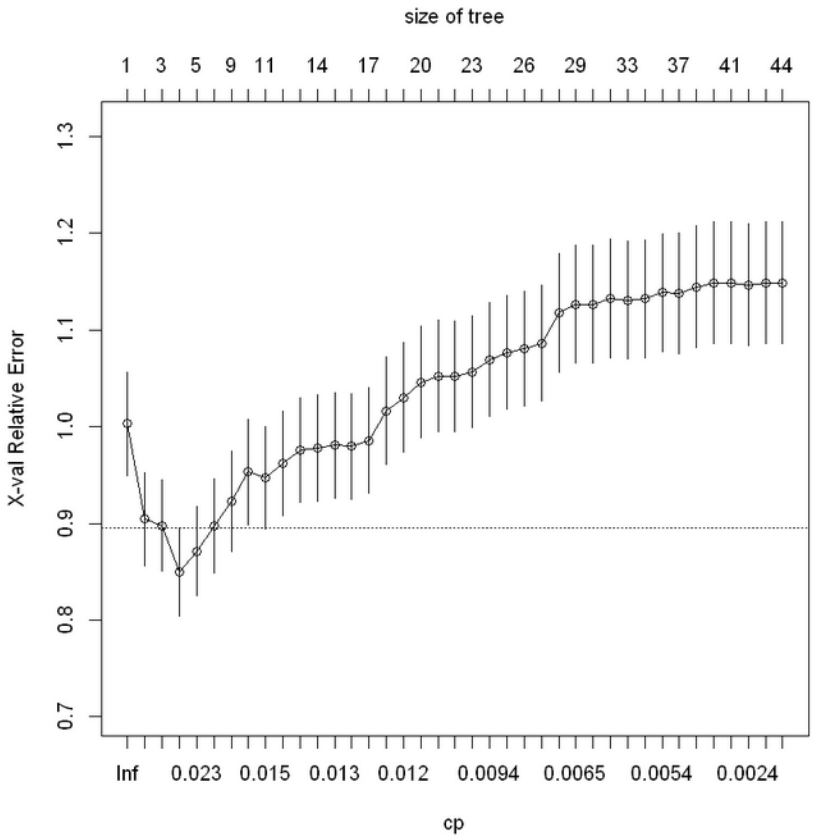
How advertisers act on predictions

- **High predicted spending:** bid more, show premium ads
- **Medium predicted spending:** show standard ads or promotions
- **Low predicted spending:** limit exposure or show no ads

Behavioral assumption

Households with higher online spending tend to be more responsive to advertising.

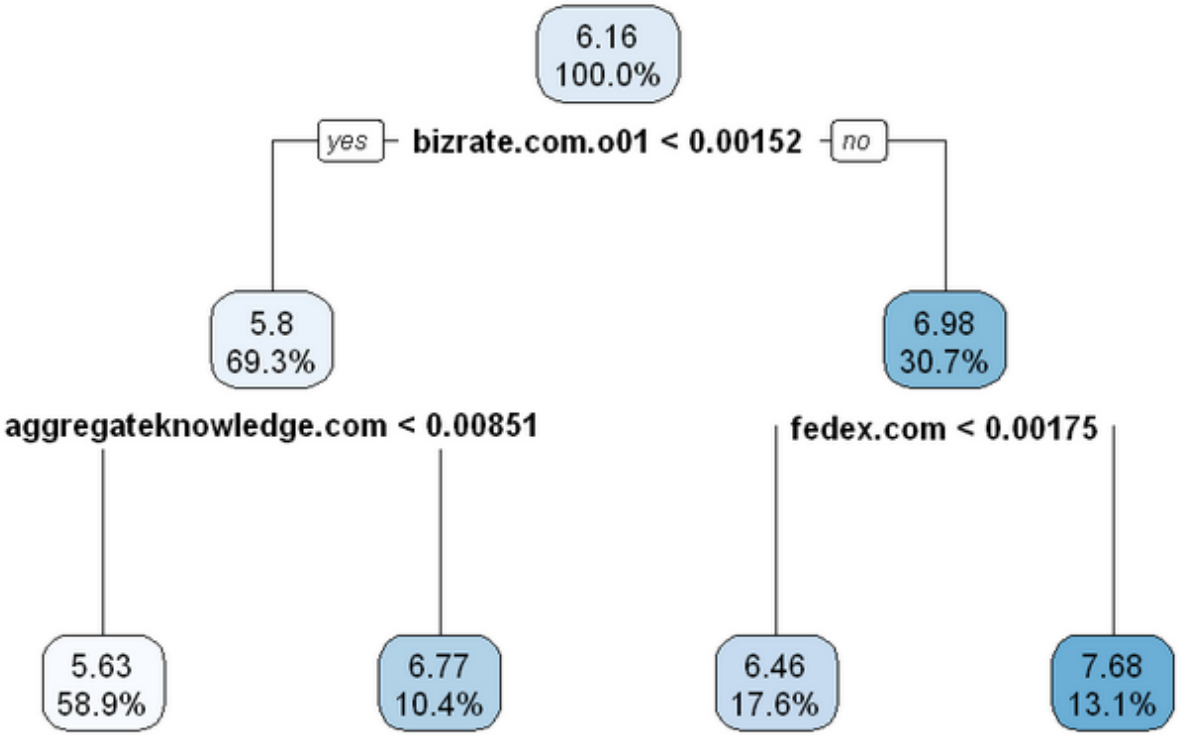
Avoiding Overfitting: Pruning with Cross-Validation



Cross-validation error vs. tree complexity

- Deep trees can fit noise (training accuracy looks great)
- Pruning improves stability and generalization
- Cross-validation chooses complexity that predicts well on new users

Optimized Tree Size



Why Stop at One Tree?

- A single tree can be unstable: small data changes $\Rightarrow$ different splits
- This instability can change the ranking of users (bad for targeting/bidding)

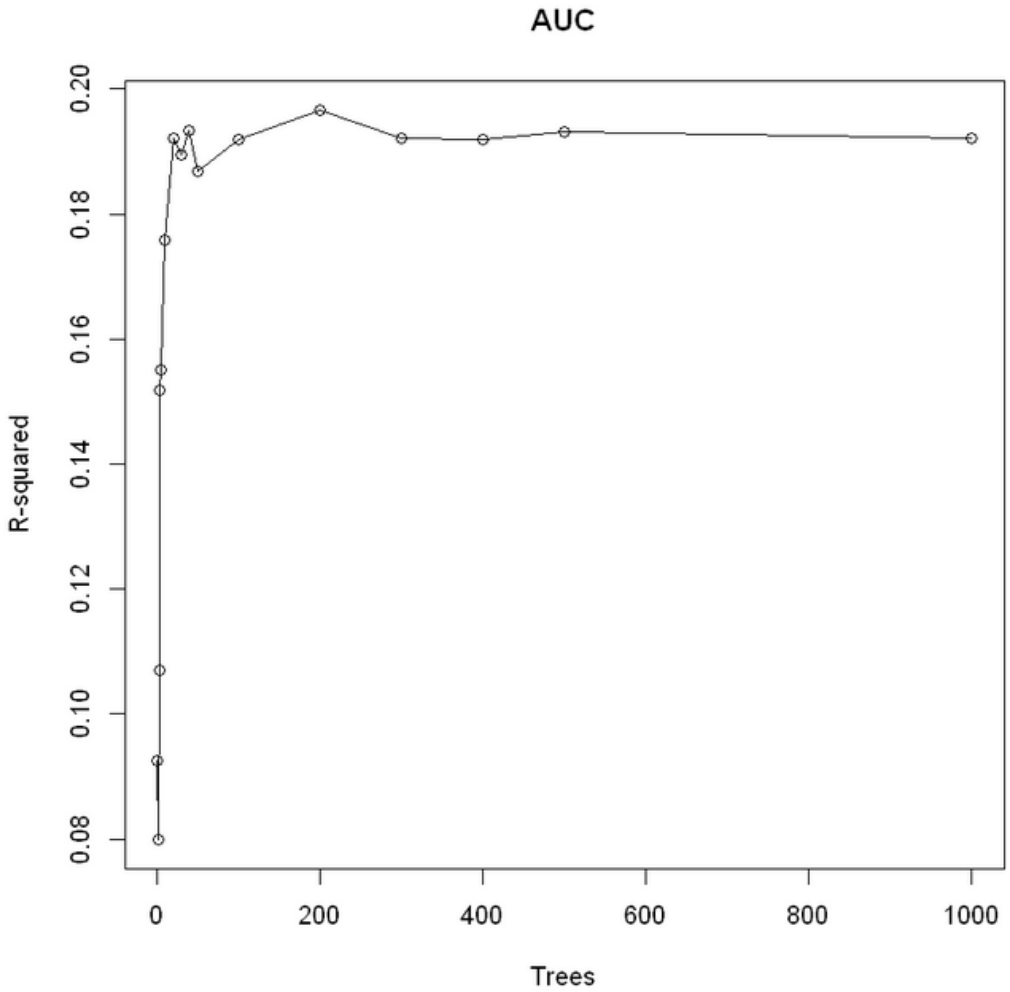
Solution: build many trees and average them (random forests).

Random Forests: Many Trees, Better Prediction

- Build many trees on different subsamples (and different candidate predictors)
- Each tree is noisy; averaging reduces variance
- Compared to a single tree:
  - higher predictive accuracy
  - more stable rankings of consumers
  - less interpretability

Economic intuition: better prediction $\Rightarrow$ better budget allocation.

Predictive Performance Improves with More Trees



- Performance improves quickly as we add trees
- Returns diminish: after some point, more trees add little

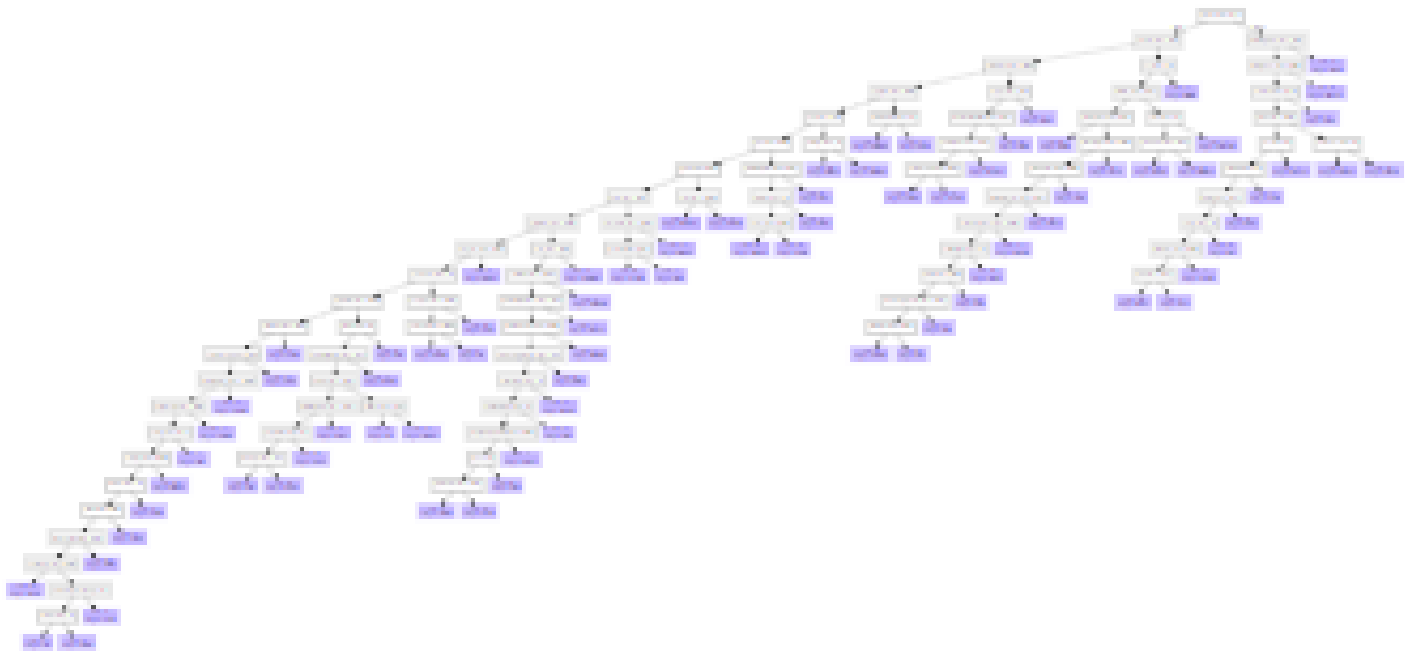
Why Random Forests Are Hard to Interpret

- A forest aggregates predictions from many deep trees
- Each tree uses different subsamples and different candidate splits
- There is no single, simple set of rules explaining the final score

Black-box intuition

A single tree gives one transparent segmentation rule. A forest gives a highly accurate score, but the "rule" is the average of many rules.

A Single Tree Inside a Random Forest (Illustration)



Variable Importance: Which Browsing Variables Matter?

- Even if the model is complex, we can summarize it
- Variable importance: which predictors frequently help create informative splits
- Two versions (as in our code):
  - importance from early splits (max.depth $= 1$)
  - importance from first few levels (discounted, max.depth $= 4$)

Variable Importance (Top Predictors)

Website	Importance
bizrate.com.o01	0.264
aggregateknowledge.com	0.180
fedex.com	0.142
ups.com	0.087
liveperson.net	0.039
marriott.com	0.033
jcpenney.com	0.025
searchmarketing.com	0.023

Note: Importance based on early splits (max.depth = 1)

Variable Importance (First Four Splits)

Website	Importance
bizrate.com.o01	0.220
aggregateknowledge.com	0.140
fedex.com	0.113
ups.com	0.069
liveperson.net	0.036
marriott.com	0.029
jcpenney.com	0.022

Note: Discounted importance from early levels (max.depth = 4)

Variable Importance (Why Be Cautious?)

- **Not causal:** importance $\neq$ "this site causes spending"
- **Correlation:** correlated variables can substitute for each other
- **Measurement:** variables with more variation/split opportunities can look more important

Takeaway: variable importance is useful for summarizing prediction, not for identifying mechanisms.

Deployment: Personalized Ads for New Households

1. Train the model on historical data (spending observed)
2. Predict spending for new households (only browsing observed)
3. Rank households by predicted value (model score)
4. Implement an ad policy:
   - target top $K\%$ (budget constraint)
   - bid more for high-value users in the auction
   - match premium vs. discount messaging

Key point: Prediction enables personalization *before* observing purchases.

Prediction and Personalized Advertising

- Trees and random forests predict **individual outcomes**
  - expected spending,
  - purchase probability,
  - user value

- Firms use these predictions to:
  - rank users,
  - allocate ads,
  - reduce waste compared to broad targeting rules

Key limitation

A user with high predicted spending may have purchased even without seeing the ad. Prediction alone does not measure *ad effectiveness*. To optimize advertising, we need to measure **incremental effects**.

Key Takeaways: Prediction for Personalized Ads

- Prediction is central to modern digital advertising
- Machine learning turns rich user data into **individual-level scores**
- These scores guide:
  - targeting,
  - bidding,
  - ad selection
- Prediction improves efficiency, but:
  - it does not answer whether ads *change* behavior

Looking ahead

To decide *who should be shown an ad*, we must move from prediction to causal effects (uplift and policy learning).

From Prediction to Causal Effects (Uplift)

Why predicting outcomes is not enough for personalized advertising

Prediction Is Not the Same as Advertising Impact

- In prediction, we learn $E[Y \mid X]$ (e.g., spending, purchase probability)
- In advertising, the key object is the **incremental effect** of showing the ad

Key distinction

- **Prediction:** Who is likely to buy?
- **Causality/Uplift:** Who buys *because of the ad*?

Implication: High predicted buyers can be *wasted budget* if they would buy anyway.

Why Causal Modeling Is Better for Targeting

- If you target based only on prediction, you need extra assumptions like:
  - "High predicted buyers are also the most persuadable"
  - "Low churn risk $\Rightarrow$ no need to advertise"
- Causal modeling is designed to answer the question directly:

What changes if we show the ad?

Takeaway

Causal estimates reduce the reliance on ad-hoc behavioral assumptions when choosing who to target.

Simple Example: Three Types of Consumers

Three stylized types

- **Sure buyers:** buy with or without the ad (uplift ≈ 0)
- **Persuadables:** buy only if they see the ad (uplift > 0)
- **Never buyers:** do not buy even with the ad (uplift ≈ 0)

- **Targeting goal:** spend budget on **persuadables**.
- **Prediction failure mode:** sure buyers often look "best" in predicted conversion.

Advertising as a Treatment: Potential Outcomes

- Let $D_i \in \{0, 1\}$ indicate whether user i is shown an ad
- Potential outcomes:
  - $Y_i(1)$: outcome if shown the ad (purchase, spending, churn, etc.)
  - $Y_i(0)$: outcome if not shown the ad

Individual ad effect (uplift)

$$\tau_i = Y_i(1) - Y_i(0)$$

Fundamental problem: we never observe both $Y_i(1)$ and $Y_i(0)$ for the same user.

Observed Outcomes and SUTVA

- Observed outcome:

$$Y_i = D_i Y_i(1) + (1 - D_i) Y_i(0)$$

- **SUTVA** (stable unit treatment value assumption):
  - no interference between users (one user's ad exposure doesn't change others' outcomes)
  - well-defined treatment (how often do consumers see the ad?)

In advertising

SUTVA can be blured by spillovers (word-of-mouth), market-level effects, or auction dynamics.

Treatment Effects: ATE and CATE

- **ATE (average treatment effect):**

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

- **CATE (conditional average treatment effect):**

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

- **Targeting** is about heterogeneity: who has large $\tau(x)$?

Why CATE is the natural object for personalization

It formalizes "uplift varies with user features" (socio-economic characteristics, prior purchases, etc.).

Identification: Randomized Experiments

If D is randomized (A/B test), then:

$$(Y(1), Y(0)) \perp D$$

and we can identify:

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

In ads

Platforms routinely run experiments:

- holdout groups (no ads)
- randomized ad exposure / randomized bids / randomized creatives

Identification: Observational Data (Harder)

Without randomization we need assumptions, e.g. **unconfoundedness**:

$$(Y(1), Y(0)) \perp D \mid X$$

plus overlap:

$$0 < P(D = 1 \mid X) < 1$$

Why ads are tricky observationally

Users who get ads often differ systematically (intent, browsing, retargeting exposure), so confounding can be severe.

Decision Rules for Uplift Targeting

- $\tau(x) = E[Y(1) - Y(0) \mid X = x)$ is the **personalized uplift**
- Let v_i be the value of a conversion and c_i the cost of showing an ad.

Profit-based targeting

Show ad to i if $v_i \cdot \tau(X_i) > c_i$

Uplift ranking

Rank users by $v_i \cdot \tau(X_i)$ and target the top group.

Budget-constrained targeting

Rank users by $v_i \cdot \tau(X_i)$ and target until the budget is exhausted.

Where Uplift Matters in Practice

- **Retargeting:** high baseline purchase $\neq$ high incremental effect
- **Discount ads:** uplift must exceed margin loss
- **Ad fatigue:** some users can have *negative* uplift
- **Creative choice:** different messages produce different treatment effects
- **Bidding:** impressions are worth more if incremental value is higher

Transition

To personalize, we need methods for estimating heterogeneous treatment effects instead of predicted purchases.

Methods to Estimate Heterogeneous Effects

Classic idea: estimate $E[Y \mid D = 1, X]$ and $E[Y \mid D = 0, X]$ then difference.

- Meta-learners (T-learner, S-learner, X-learner)
- Doubly robust / orthogonalized learners (R-learner / AIPW-based)
- **Causal trees and causal forests** (tree-based CATE estimation)

Why trees/forests?

They capture nonlinearities and interactions and produce flexible heterogeneity patterns without manual specification.

Why Not Use Off-the-Shelf Prediction Trees?

- Prediction trees split to improve fit of $E[Y \mid X]$
- For treatment effects we need splits that maximize differences in *uplift*

Causal splitting intuition

Choose splits that create groups with different estimates of

$$E[Y(1) - Y(0) \mid X \in \text{leaf}]$$

not simply different levels of $E[Y \mid X]$.

Causal Forest: Intuition

- Like random forests, but targeted at treatment effects
- Build many "causal trees" on subsamples
- Each tree creates local neighborhoods; estimate treatment effect locally
- Average across many causal trees for stability and accuracy

Output

A prediction $\hat{\tau}(X_i)$ for each user i (estimated CATE / uplift).

Orthogonalization: Deconfounding

In observational (or stratified) settings, we estimate **nuisance functions**:

$$\mu(x) = E[Y \mid X = x], \qquad e(x) = P(D = 1 \mid X = x).$$

Orthogonalized signals (core idea)

Transform outcomes and treatments to

$$Y_i - \mu(X_i), \qquad D_i - e(X_i),$$

which removes sensitivity to errors in nuisance estimation and allows more robust learning of $\tau(x)$ (*double machine learning* logic).

Practical takeaway: Orthogonalization yields more stable and reliable causal ML estimates.

Use Case 2: Fundraising for Charity (*Freedom from Hunger*)

- Fundraising campaigns face the same economic problem as advertising
- The goal is to persuade individuals to take an action
  - in advertising: buy a product
  - in fundraising: make a donation

Key analogy

- Fundraising letter $\leftrightarrow$ advertisement
- Donation $\leftrightarrow$ conversion
- Message content $\leftrightarrow$ ad creative

Experimental Design

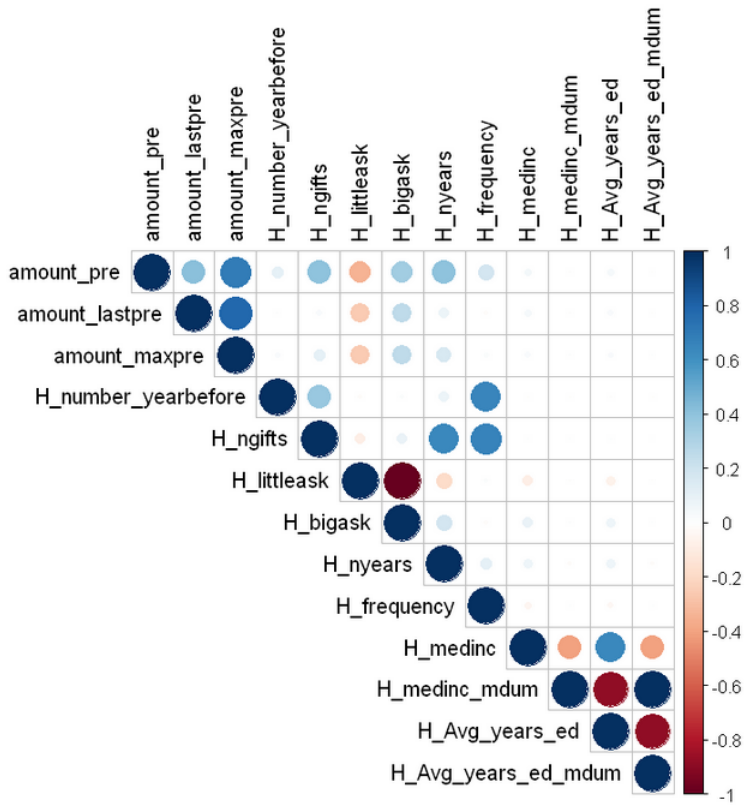
- The charity **Freedom from Hunger** runs a direct-mail fundraising campaign (Karlan and Wood, 2017)
- Potential donors receive one of two solicitation letters supporting a microcredit and education program

Randomized message variation

- **Control (emotional appeal):**
  - A narrative about a single mother and her son
  - Designed to trigger emotions and *warm-glow* giving
- **Treatment (informational appeal):**
  - Scientific evidence on the long-run effectiveness of the program
  - Designed to appeal to more *altruistic*, impact-oriented donors

Business question: Do informational messages increase donations relative to emotional appeals – and for whom?

Rich Covariates



- Detailed donation histories
- Recency, frequency, and spending measures
- Many correlated predictors

Why ML helps

Causal forests scale to many correlated predictors and capture complex heterogeneity.

Average Effect (ATE): Often Not the Main Story

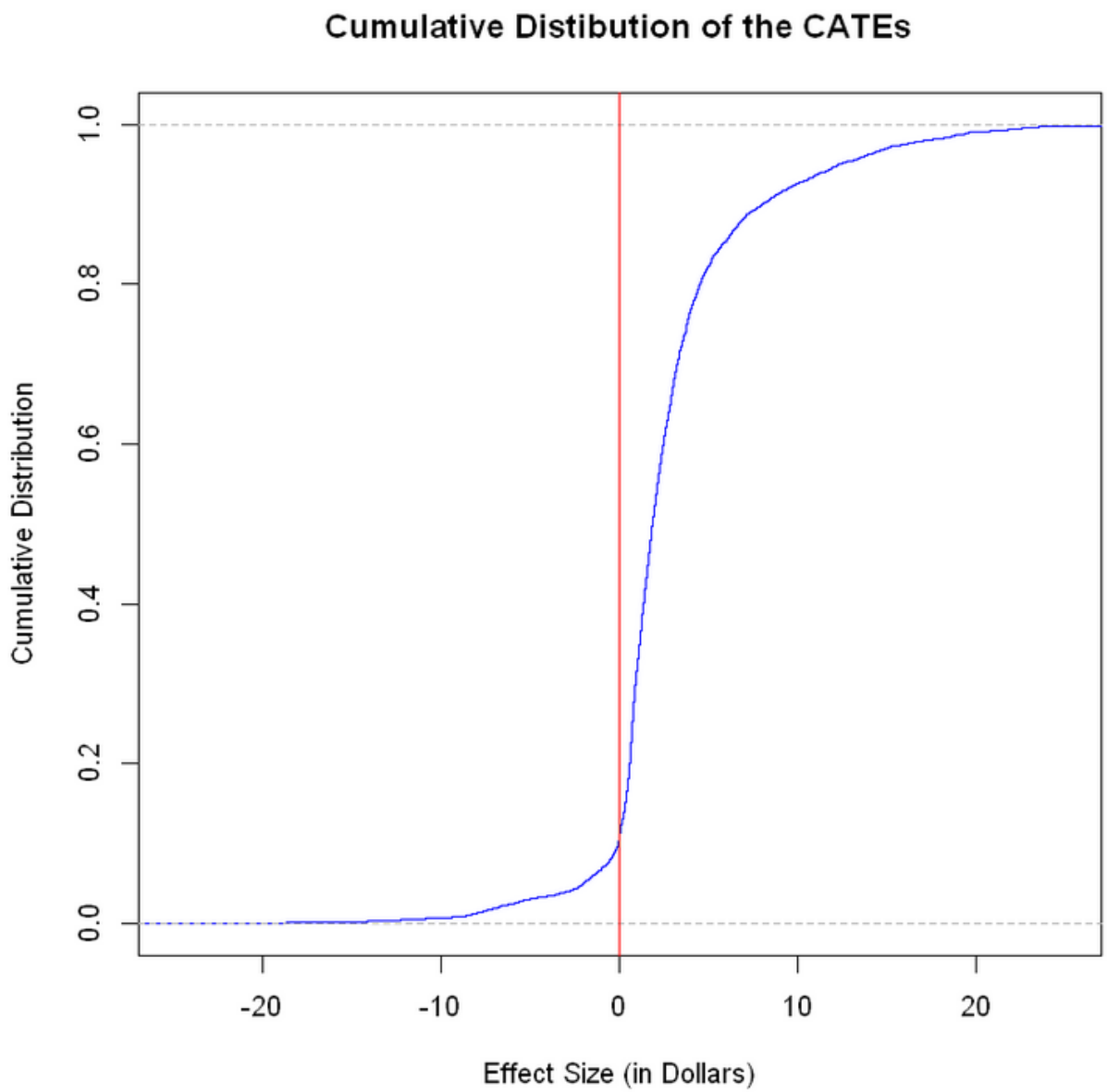
- Even with strong heterogeneity, the **average** effect can be small or imprecise
- In the causal forest output we obtain an ATE estimate:

Average treatment effect (from the estimation output)

$$\widehat{\text{ATE}} = 3.54 \quad \text{(s.e. } 4.32\text{)}, \quad p = 0.413$$

Key message: for targeting, we care less about the average and more about **who gains** (CATEs).

Distribution of Estimated CATEs (Uplift)



Estimated CATE distribution (uplift per person or individual)

Positive vs. Negative Uplift: Interpretation

- Estimated treatment-effect heterogeneity:
  - **Positive uplift:** 88.6% of donors
  - **Negative uplift:** 11.4% of donors

Interpretation in the fundraising context

- **Positive uplift:** altruistic donors value information on effectiveness
- **Negative uplift:** warm-glow donors respond better to emotional stories

Implication: Target informational messages to altruists and emotional messages to warm-glow donors.

What Drives Heterogeneity? (Split Frequencies)

- Causal forests search for splits that maximize **treatment effect heterogeneity**
- A simple summary is how often variables are used for splits (depth $= 4$)

Feature (examples)	**Split count**
`amount_maxpre`	1986
`amount_pre`	1736
`amount_lastpre`	1557
`H_number_yearbefore`	1292
`H_frequency`	714

Interpretation: uplift depends strongly on past donation amount.

From CATEs to Targeting: Empirical Success Rule

- CATEs answer: *"Which message works better for this donor?"*

Empirical success rule

For each donor i:

- Send informational letter if $\widehat{\tau}(X_i) > 0$,
- send emotional letter if $\widehat{\tau}(X_i) < 0$.

Interpretation

- Positive uplift $\Rightarrow$ donor responds better to scientific evidence (altruism)
- Negative uplift $\Rightarrow$ donor responds better to emotional narratives (warm glow)

CATEs Measure Effects — Not Decisions

- $\hat{\tau}(x)$ estimates the causal effect of a treatment
- Effects describe *what would happen*, not *what to do*

What firms still need to decide

- whether to treat or not
- which message to show
- how frequently to intervene

Decision layer

Actions are chosen by combining estimated effects with costs and constraints (e.g. budgets, margins, fatigue, capacity). This requires a **nonlinear decision rule**: an effect estimate is an input, not an action.

Policy Learning: Learning Actions Directly

- A **policy** $\pi(x)$ maps features to an action

$$\pi(x) \in \mathcal{A}$$

- Examples in ads:
  - $\mathcal{A} = \{0, 1\}$: show ad vs no ad
  - $\mathcal{A} = \{\text{brand}, \text{discount}\}$: choose creative
  - $\mathcal{A} = \{0, 1, 2, 3\}$: frequency caps

Goal

Choose π to maximize expected objective (profit, donations, welfare), not just to estimate $\tau(x)$.

The Policy Value (Objective)

For binary treatment $D \in \{-1, 1\}$ and policy $\pi(x) \in \{-1, 1\}$:

$$V(\pi) = E\big[Y(\pi(X))\big]$$

With costs (ad cost, coupon cost), we often maximize:

$$V(\pi) = E\big[Y(\pi(X)) - c(\pi(X)) \cdot \frac{1 + \pi(X)}{2}\big]$$

Economic interpretation

This is the "choose who to treat" problem under costs and constraints.

Why Learn Policies Directly (Rather Than CATE Then Threshold)?

- Converting CATEs into actions requires extra steps:
  - choose a threshold
  - incorporate costs correctly
  - handle constraints (budget, limited capacity)
- A policy learner can be **targeted** to the objective:
  - maximize net donations
  - maximize profit
  - minimize churn risk

Takeaway

Good effect estimation does not automatically imply a good decision rule.

Use Case 3: Optimal Targeting with Fundraising Gifts

- Fundraisers use many instruments (e.g. matching grants, gifts, lotteries).
- Donors differ in how they evaluate fundraising practices and costs.
- Effects of any instrument are therefore likely to be **heterogeneous**.
- **Goal:** maximize *net donations* (= donations − costs) by targeting gifts using observable characteristics.

Field Experiment with Gifts

- Field experiment with small unconditional gifts (Dürrer's flower postcards) accompanied by a solicitation letter ($N \approx 20{,}000$).

- Individuals in the randomly selected treatment group received a mailer with the gift and solicitation letter.
- Individuals in the randomly selected control group received the solicitation letter, but not the gift.
- Reference: Cagala, Rincke, Glogowsky, Strittmatter (2021)

Why Gifts May Help or Hurt Donations

- Gifts can **increase** giving if they trigger reciprocity or social norms (e.g. Benabou & Tirole, 2006; Dufwenberg & Kirchsteiger, 2004; Falk, 2007).
- Gifts can also **reduce** giving if donors infer **ineffective fundraising**:
  - "Money spent on gifts could have gone to the cause."
  - Altruistic donors may dislike high overhead / low effectiveness signals.
- Evidence is mixed:
  - Backfiring: Landry et al. (2010); Yin et al. (2020)
  - Too costly to justify: Alpizar et al. (2008)

$\Rightarrow$ Gifts are a setting with strong scope for **heterogeneity** and **targeting**.

Two Donor Populations: Warm vs. Cold List

- **Warm list:** donors with prior giving history (relationship already exists)
- **Cold list:** donors without prior giving history (no established relationship)
- Same treatment can perform differently across lists because:
  - baseline donation probability differs strongly
  - gift costs matter more when baseline response is low
  - perceptions of effectiveness may differ across donor types

Experimental Data

- Field experiment in cooperation with a fundraiser operating within the structure of the Catholic church in an urban area in Germany in 2014.
- All experimental participants received a letter with information about the fundraiser's cause (maintaining clergy houses, parish centers, and churches) and a donation request.
- A randomly selected treatment group additionally received a small unconditional gift.
- Attached to the letter is a bank transfer form pre-filled with the fundraiser's bank account information and the recipient's name.
- Donations are made exclusively via bank transfer, and the fundraiser does not provide any information about individual donations to the church parishes.

Heterogeneity Variables

- **Socio-economic characteristics:**
  Gender, age, marital status, years residency.
- **Donation history:**
  Number of previous donation, total previous donations, maximum previous donations, yearly donations of the previous 5 years.
- **Geo-spatial information of home address:**
  Number of restaurants, supermarkets, medical facilities, cultural facilities, and churches in the proximity (300 meters radius), distance to city hall, main station, main church, and airport, travel distance to main station, elevation.

Descriptive Statistics

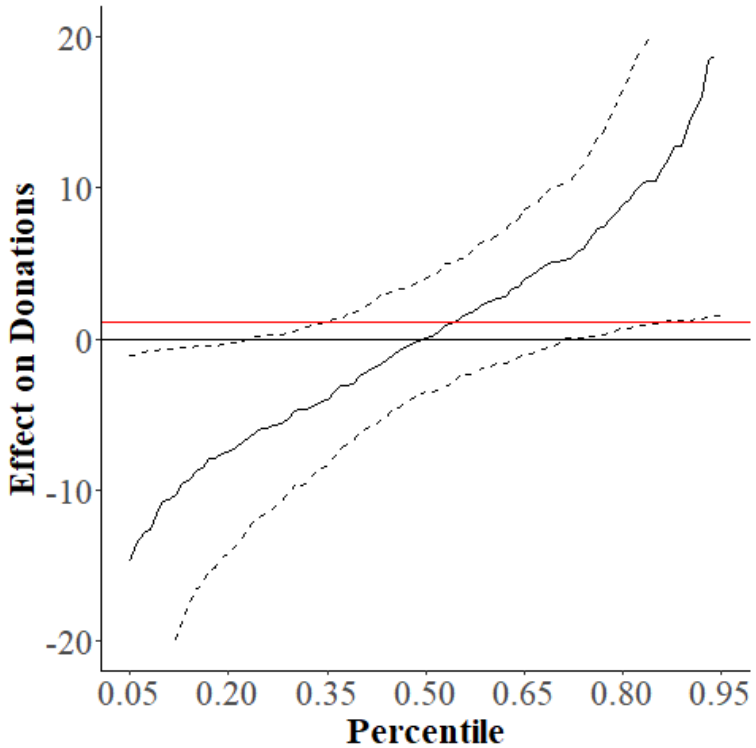
	Warm-list		Cold-list	
	Mean	Std. Dev.	Mean	Std. Dev.
	(1)	(2)	(3)	(4)
Socio-economic characteristics				
Female dummy	0.53		0.50	
Single dummy	0.50		0.64	
Widowed dummy	0.05		0.02	
Age (in years)	68.51	18.30	48.40	19.32
Duration residency in urban area (in years)	7.43	1.67	5.97	2.82
Donation history before the experiment				
Number of donations previous 8 years	3.97	2.83	0	
Max. donations previous 8 years (in Euro)	36.02	42.90	0	
Total donations previous 8 years (in Euro)	125.9	176.0	0	
Observations	2,354		17,425	

Average Effects

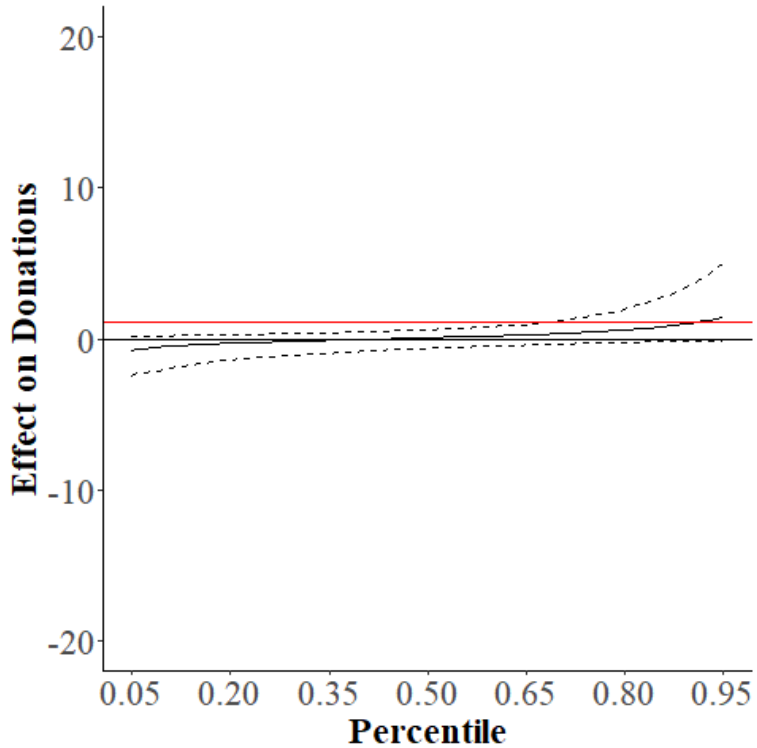
	Warm list	Cold list
	(1)	(4)
ATE	1.22	0.19*
	(1.15)	(0.10)
ATE - costs	0.06	-0.97***
	(1.15)	(0.10)
Strata controls	Yes	Yes
Observations	2'354	17'425

Notes: Outcome is donation amount (Euro) during the first year after the gift was sent.

Effect Heterogeneity



Warm list



Cold list

Notes: Figure based on the sorted effects model of Chernozhukov, Fernández-Val, and Luo (2018).

Targeting Rule

- A targeting rule $\pi(x) \in \{-1, 1\}$ allocates the gift based on observable X_i:
  - Individuals with $\pi(X_i) = 1$ receive the mailer with the gift
  - Individuals with $\pi(X_i) = -1$ receive the mailer without the gift

- Expected net donations (= expected donations - costs of gift),

$$
\begin{aligned}
P(\pi(X_i)) &= E\left[Y_i(\pi(X_i)) - \frac{1+\pi(X_i)}{2}c\right], \\
&= \begin{cases} E\left[Y_i(-1)\right] & \text{if } \pi(X_i) = -1, \\ E\left[Y_i(1)\right] - c & \text{if } \pi(X_i) = 1, \end{cases}
\end{aligned}
$$

where c are the variable costs of the gift.

Benchmarks

- Everybody receives the gift:

$$P(\pi_1) = E[Y_i(1)] - c$$

- Nobody receives the gift:

$$P(\pi_{-1}) = E[Y_i(-1)]$$

- 50/50 randomization:

$$P(\pi_R) = \tfrac{1}{2}\left(E[Y_i(1) + Y_i(-1)] - c\right)$$

From Heterogeneity to an Implementable Policy

- We cannot observe individual gift effects δ_i directly
- But we can construct an **unbiased score** that summarizes "how valuable the gift is" for each person
- This score is the input for **policy learning** (who gets the gift)

Advertising analogy

A coupon is sent only if its expected incremental value exceeds its cost.

Augmented Inverse Probability Weighting (AIPW)

- δ_i is crucial for targeting but unobservable.
- Replace δ_i with an approximation score Γ_i.
- AIPW score (Robins et al., 1994; Chernozhukov et al., 2018):

$$\hat{\Gamma}_i = \hat{\Gamma}_i(1) - \hat{\Gamma}_i(-1)$$

with

$$\hat{\Gamma}_i(1) = \hat{\mu}_1(Z_i) + \frac{1 + D_i}{2} \cdot \frac{Y_i - \hat{\mu}_1(Z_i)}{\hat{p}(Z_i)},$$
$$\hat{\Gamma}_i(-1) = \hat{\mu}_{-1}(Z_i) - \frac{D_i - 1}{2} \cdot \frac{Y_i - \hat{\mu}_{-1}(Z_i)}{1 - \hat{p}(Z_i)}.$$

Estimation of the Optimal Targeting Rule

- Athey and Wager (2019): maximize sample analog of $Q_R(\pi)$:

$$\pi^* = \arg\max_{\pi} \left\{ \frac{1}{2N} \sum_{i=1}^{N} \pi(X_i)(\hat{\Gamma}_i - c) \right\}.$$

- Equivalent weighted classification problem:

$$\pi^* = \text{argmax}_{\pi} \left\{ \frac{1}{2N} \sum_{i=1}^{N} \underbrace{\pi(X_i) sign(\hat{\Gamma}_i - c)}_{\text{max if sign equal}} \underbrace{|\hat{\Gamma}_i - c|}_{+} \right\},$$

Value Added of Machine Learning

- We could estimate π^* with a weighted logit (or any weighted classifier).
- But then we must choose X manually.
- Bias-variance trade-off:
  - too few features $\Rightarrow$ miss relevant heterogeneity
  - too many features $\Rightarrow$ overfit, poor out-of-sample policy value
- ML can balance this in a data-driven way.
- In the main specs we use optimal policy trees (Zhou et al., 2019).

Out-of-Sample Off-Policy Evaluation

- Once we have obtained π^*, estimate:

$$\hat{P}(\pi^*) = \frac{1}{N} \sum_{i=1}^{N} \left(\hat{\Gamma}_i(\pi^*(X_i)) - \frac{1 + \pi^*(X_i)}{2} c \right).$$

- Estimators are consistent and semiparametrically efficient (Chernozhukov et al., 2018).
- We apply cross-fitting to assess targeting rules out-of-sample.

Out-of-Sample Results for the Warm List

	Share Treated	Net Donations	Optimal Targeting Rule vs. Everybody	Nobody	Random
	(1)	(2)	(3)	(4)	(5)
Panel A: Results for Target Variable					
Net Donation Amount (1st year)	0.334	17.61*** (0.971)	2.141*** (0.817)	2.199*** (0.813)	2.170*** (0.575)
Panel B: Second Order Effects					
Net Donation Amount (1st and 2nd year)		32.94*** (1.661)	2.328* (1.405)	3.753*** (1.412)	3.040*** (0.995)
Donation Probability (1st year)		0.503*** (0.013)	0.007 (0.013)	0.025** (0.010)	0.016* (0.008)
Donation Probability (1st and 2nd year)		0.582*** (0.013)	0.001 (0.013)	0.017* (0.009)	0.009 (0.008)

Notes: Donation amounts in Euro. Standard errors in parentheses.

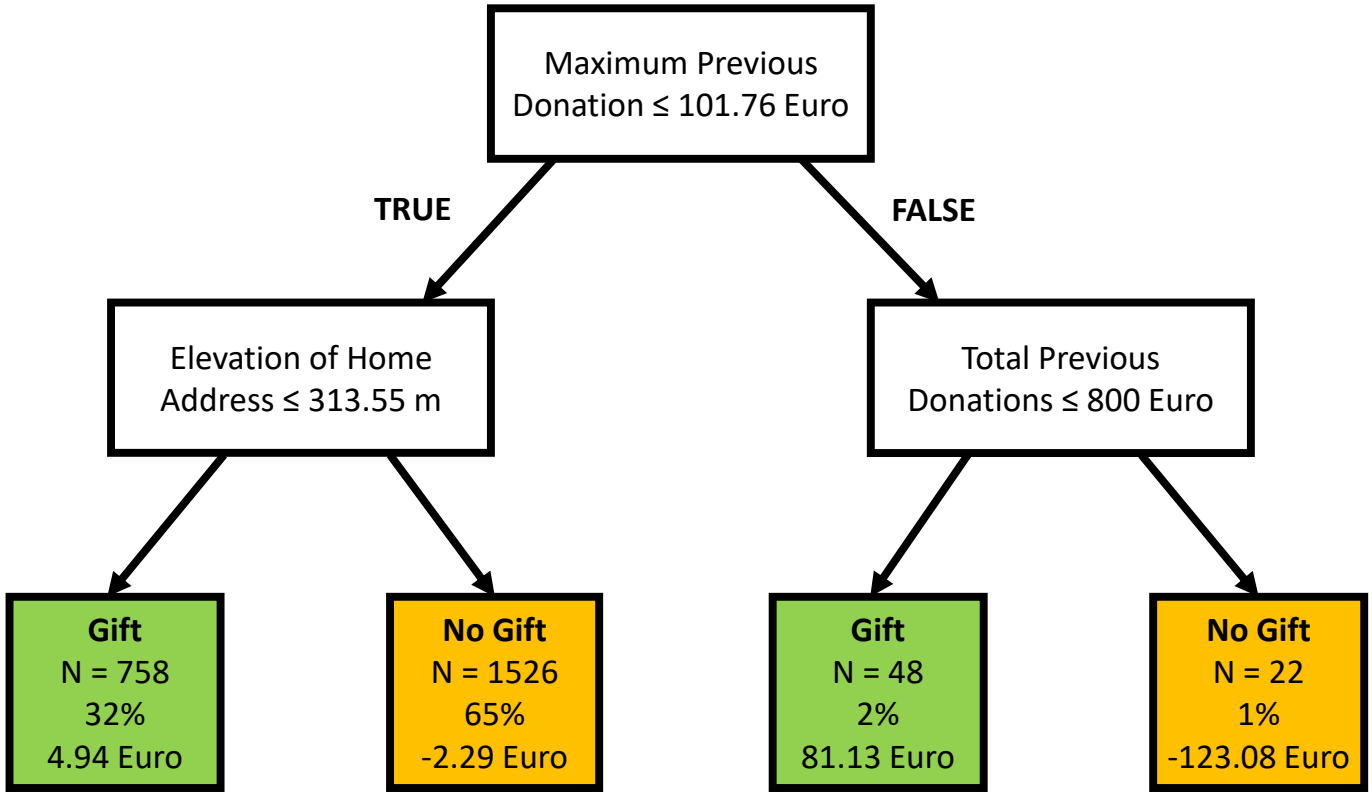
$\Rightarrow$ 14% increase in donations during 1st year.

Out-of-Sample Results for the Cold List

	Share Treated	Net Donations	Optimal Targeting vs. Everybody	Nobody	Random
	(1)	(2)	(3)	(4)	(5)
Panel A: Results for Target Variable					
Net Donation Amount (1st year)	0.014	0.15*** (0.02)	0.97*** (0.10)	-0.005 (0.012)	0.48*** (0.05)
Panel B: Second Order Effects					
Net Donation Amount (1st and 2nd year)		0.44*** (0.07)	0.96*** (0.13)	0.04 (0.06)	0.50*** (0.07)
Donation Probability (1st year)		0.009*** (0.001)	-0.007*** (0.003)	0.001 (0.001)	-0.003** (0.001)
Donation Probability (1st and 2nd year)		0.017*** (0.001)	-0.006* (0.003)	0.001 (0.001)	-0.003 (0.002)

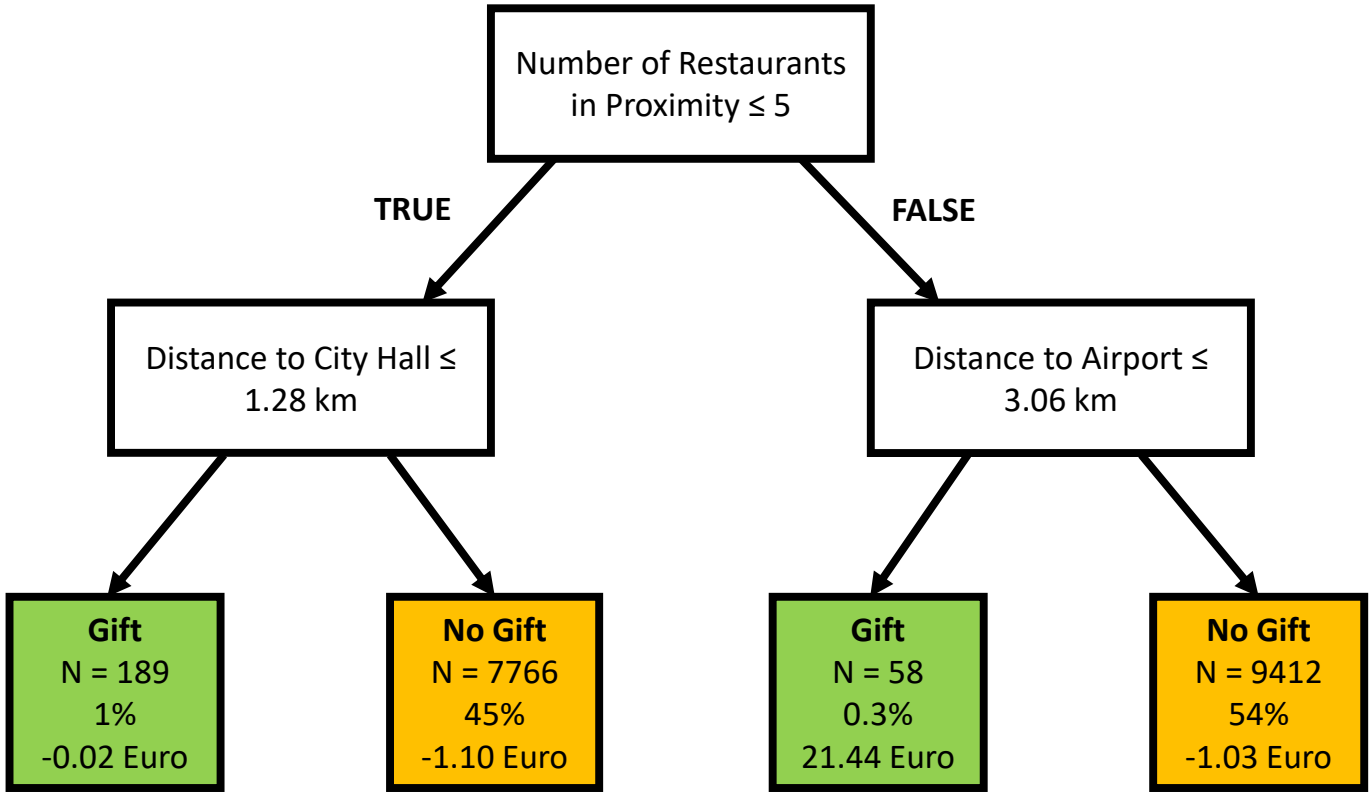
Notes: Donation amounts in Euro. Standard errors in parentheses.

Exact Policy Tree: Warm List



Note: Figure based on the optimal policy tree of Zhou et al. (2019) and Sverdrup et al. (2020).

Exact Policy Tree: Cold List



Note: Figure based on the optimal policy tree of Zhou et al. (2019) and Sverdrup et al. (2020).

Interpreting the Fundraising Results

- Warm list: the optimal targeting rule treats about one-third of donors and increases net donations
- Cold list: optimal rule treats a very small share (because gifts are costly and baseline response is tiny)
- Policy learning naturally incorporates:
  - treatment effect heterogeneity
  - costs of treatment

Key Takeaway: From Uplift to Decisions

What changes relative to "prediction-based targeting"?

- **Goal shifts:** from finding *high baseline responders* to finding *high incremental responders*.
- **Object shifts:** from $E[Y \mid X]$ to **uplift** $\tau(x) = E[Y(1) - Y(0) \mid X = x]$.
- **Decision shifts:** from ranking users to choosing actions that maximize **net value** (value minus costs).

Economic message

Personalization should target **persuadables** (high uplift), not **sure buyers**. Costs and constraints determine *who gets treated* and *how many get treated*.

Conclusions (1/4): The Core Problem

Modern advertising is a decision problem

Limited budgets | Costly impressions | Heterogeneous users

- Platforms observe rich data X (behavior, context, history)
- The advertiser must decide: **who to target**, **what to show**, **how much to bid**
- A good model is valuable only if it improves **economic outcomes**

Bottom line

The key question is not "Who buys?" but "**What changes if we intervene?**"

Conclusions (2/4): Prediction

Prediction

$$\widehat{Y} = \hat{f}(X) \qquad \Rightarrow \qquad \text{rank users by } E[Y \mid X]$$

- Turns user data into **scores**
- Used for bidding, ranking, and targeting
- Works well with trees and random forests

Key limitation

High predicted buyers may have bought anyway.

Prediction ranks outcomes, not causal impact.

Conclusions (3/4): Uplift and Policy

Uplift = incremental effect of the intervention

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

- Uplift answers: **who is persuadable?**
- Policy learning turns effects into **actions** under constraints

Decision layer

Actions combine estimated effects with costs and constraints (e.g. budgets, capacity).

Conclusions (4/4): Economic Takeaway

What ML adds

- Handles rich user data
- Captures nonlinear heterogeneity
- Individualized estimates

What economics adds

- Causal identification
- Objectives (profit / welfare)
- Economic rationale for decisions

Final takeaway

Prediction ranks users. Uplift measures impact. Policy chooses actions.
The same logic applies beyond advertising: fundraising, health, labor markets, and public policy.

Thank You for Your Attention

Questions and discussion are very welcome.

Contact

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