Uplift Modeling

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Special topic

Domain specific: marketing.

Marketing meets statistics!

Uplift modeling

Politics

“How Hillary’s Campaign Is (Almost Certainly) Using Big Data” Scientific American, September 2016

“The Obama Camp Persuaded Millions of Voters with Uplift Modeling” Predictive Analytics World, 2013

Uplift modeling

Background

"Predictive analytics"

Estimating probabilities of outcomes for future events, typically for individual people.

More granular than forecasting, which is the prediction of aggregate trends or events.

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Predictive analytics examples:

- Capacity planning
- Retail purchasing
- Actuarial science (some insurance products are based on probabilities of individual actions)
- Credit scoring
- "Customer relationship management" (changing customer behavior)
- "Influencer marketing"

Uplift modeling

History

Uplift modeling is a relatively new technique in predictive analytics.

First paper: 1999.

"Differential Response Analysis: Modeling True Response by Isolating the Effect of a Single Action", Credit Scoring & Credit Control VI, 1999

Uplift modeling

Define: Uplift

The difference in response between a *treated* group and a *control* group.

Treatment group: group of users subjected to an intervention.

Control group: held out group of users.

Example: Pre-approved credit card offer.

Example: 40% discount offer to shop at a retail store for a certain day.

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Treatment and control groups

Same population, randomly sampled. (Important for correctness.)

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Traditional response modeling:

For a given intervention, what is the response rate?

Example:

"When we sent out this 50% off coupon to 10000 customers, 3% of those customers bought the item."

"When we did not send out this 50% off coupon to another 10000 customers, 1% of those customers bought the item."

Response rate uplift: 3% - 1% = 2%.

Treatment vs control

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"When we sent out this 50% off coupon to 10000 customers, 3% of those customers bought the item."

Modeling problem? Think about the real world. Does everyone want a coupon?

(Who are those customers?)

This method of analysis can work as a baseline but it is not complete:

Example: What if a recipient would have bought without the coupon?

Example: What if a recipient loathes getting promotional emails, and they decided to buy *less*?

Example: What if we sent a promotion to a recipient who doesn't care at all and will not be influenced?

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To try to solve these issues, we separate customers into four groups:

- Persuadables: Customers who can be persuaded to purchase, but will only buy if contacted.
- Sure Things: Customers who will buy, regardless of contact.
- Lost Causes: Customers who will not buy, regardless of contact.
- Do Not Disturbs: Customers whom you should not contact. Contacting them may cause a negative response like provoking them to cancel a subscription, return a product, or ask for a price adjustment.

Uplift modeling only targets the persuadables.

Uplift modeling

Uplift modeling only targets the persuadables.

Why is this hard?

It requires segmenting users before conducting interventions.

Is this really that hard or groundbreaking?

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Comparison with bandit optimization.

Bandit optimization can be used within a user segment..

But, bandit methods do not necessarily help in finding those user segments.

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Synthesis / Discussion