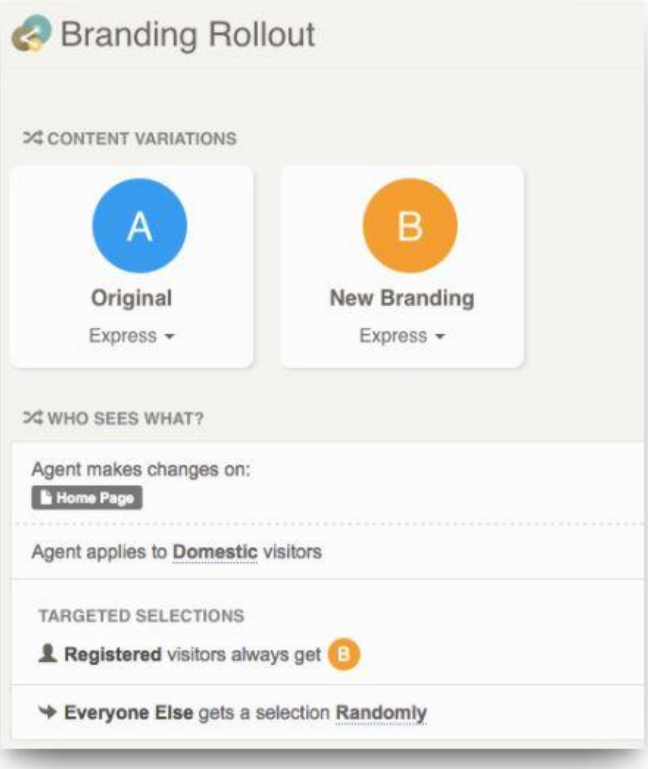
CONDUCTRICS STUDY

FEI WU

产品

What Can You Do With Your Variations?

Learn about them, validate assumptions, serve your visitors better ...



Select Them via Machine Learning

Automatically present the best variation for each visitor, in real time.

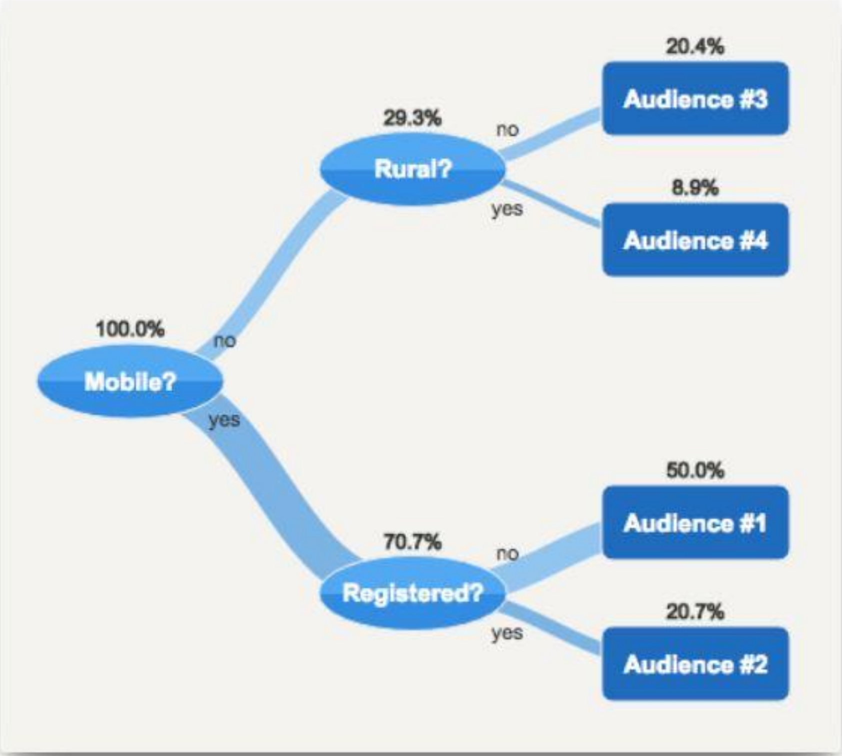
Target Them via Business Rules

Create your own rules to present content or functionality to certain visitors.

Test Them via A/B and MVT Testing

Use industry-standard testing methods to randomly select variations for each visitor, to learn which works best for whom.

算法



Audience Decision Trees

Our audience decision tree report shows which audiences our ML algorithms have discovered to be most informative, and why.

Used by AI and Humans Alike

Your Conductrics "agents" use the same audience trees when actually selecting variations for your visitors.

Don't Settle for Black Boxes

Now you no longer have to worry about not being able to understand why some customers receive different experiences.

DO NO HARM OR AB TESTING WITHOUT P-VALUES

Go For It: Tests with no P-Values: This test guarantees that if there is a true difference of the minimum discernible effect (MDE), or larger, **one will choose the better-performing arm X% of the time, where X is the power of the test.**

steps:

1. Calculate the sample size-----------------------计算 epsilon（explore）

2. Collect data----------------------计算2个版本的conversion rate

3. **Pick whichever option has the highest raw conversion value**. If a tie, flip a coin (exploit)

Input:

```
power.prop.test(n = NULL, p1 = 0.04, p2 = 0.05, sig.level = 0.5, power = .95,
alternative ="one.sided", strict = FALSE)
```

minimum detectable effect (effect size) : 多大的区别可以鉴定为A与B不同

statistics power of the test (1-beta)：不出现type II error（false negative）错误的概率

Significance level: type I error（false positive）错误的概率

Sample size, effect size, statistics power, Significance level这四个值知其三可推出剩下的[1]

1. Paul.D.ELLIS, *“The essential guide to effect sizes”*

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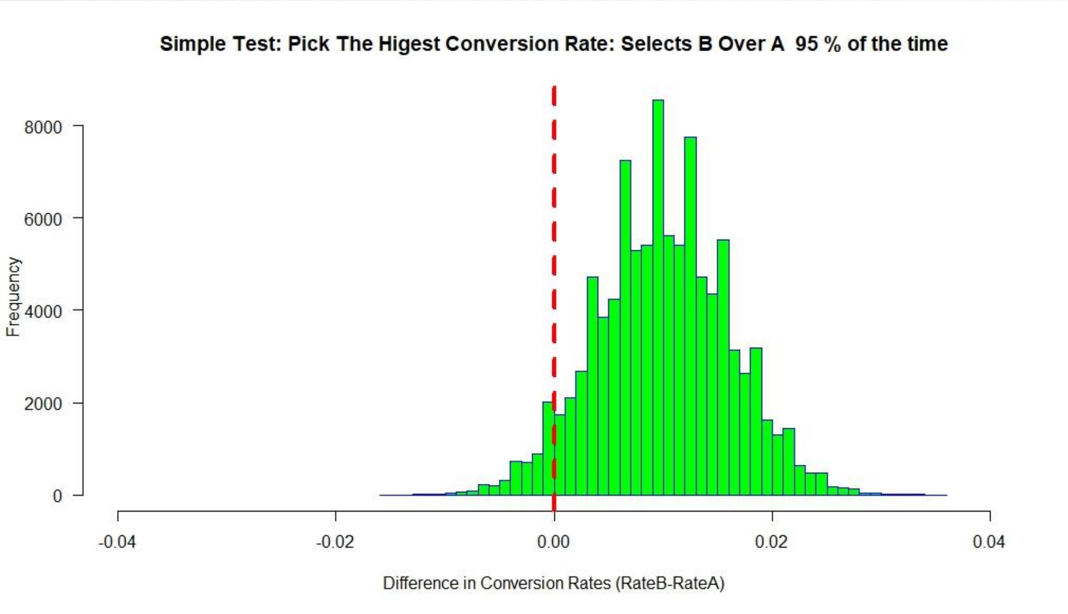
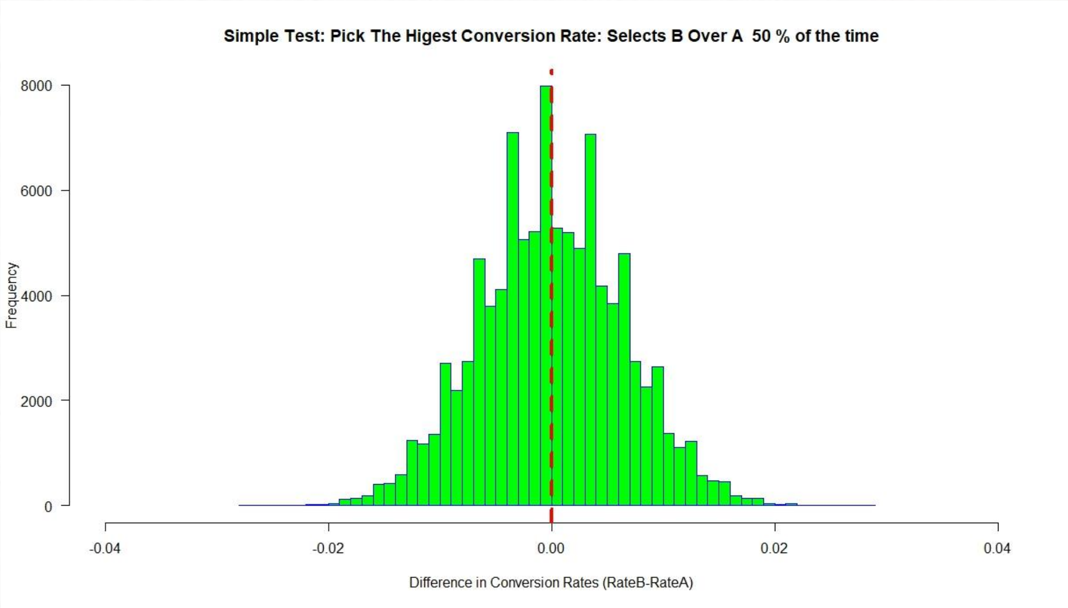
Output: Difference in conversion rate





p1=0.04, p2=0.05

p1=0.04, p2=0.04

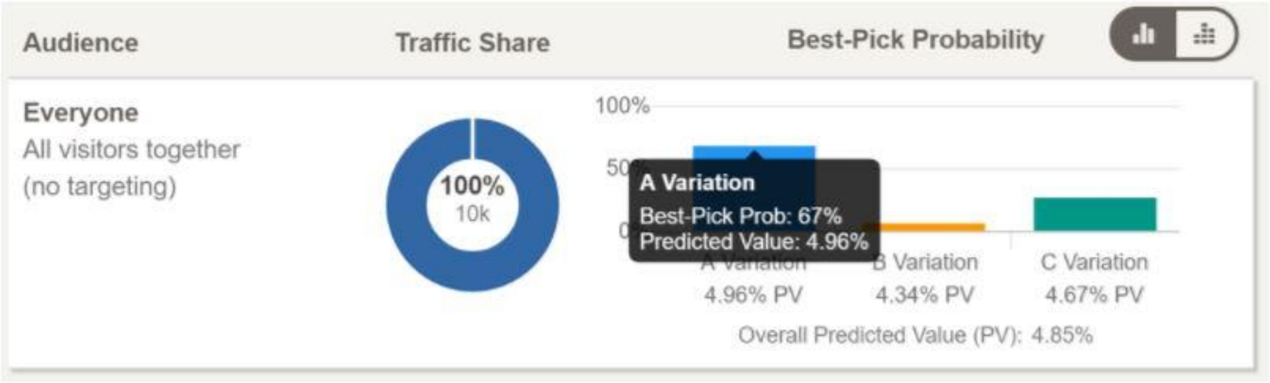
DO NO HARM OR AB TESTING WITHOUT P-VALUES

Proof:

"Find N such that $P(meanA-meanB < 0 \mid A = B + MDE) < 0.05$. This is equal to the N needed to have 95% power for a one-sided test with alpha = 0.5.

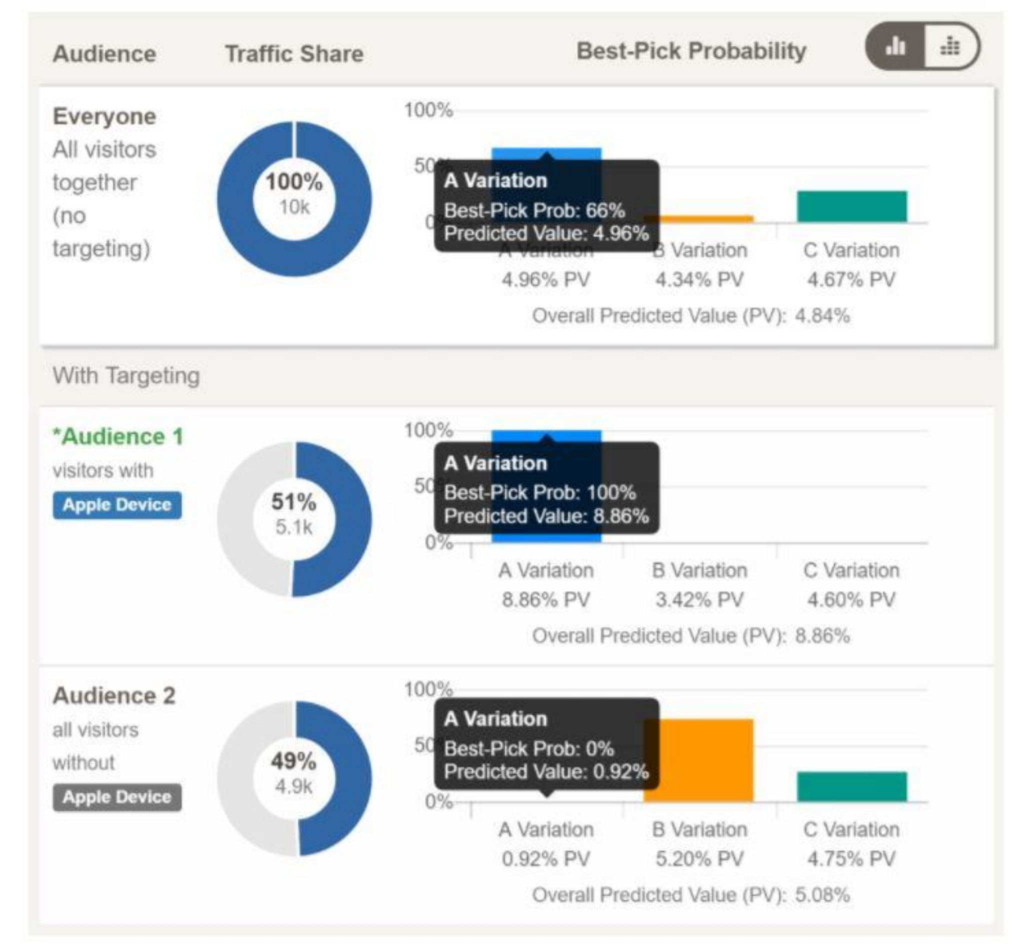
Proof: Setting alpha = 0.5 sets the rejection threshold at 0. So a 95% power means that the test statistic is greater than zero 95% of the time under the alternative ($A = B + MDE$). The test statistic has the same sign as meanA-meanB. So, at this sample size, $P(meanA - meanB > 0 \mid A = B + MDE) = 0.95$."

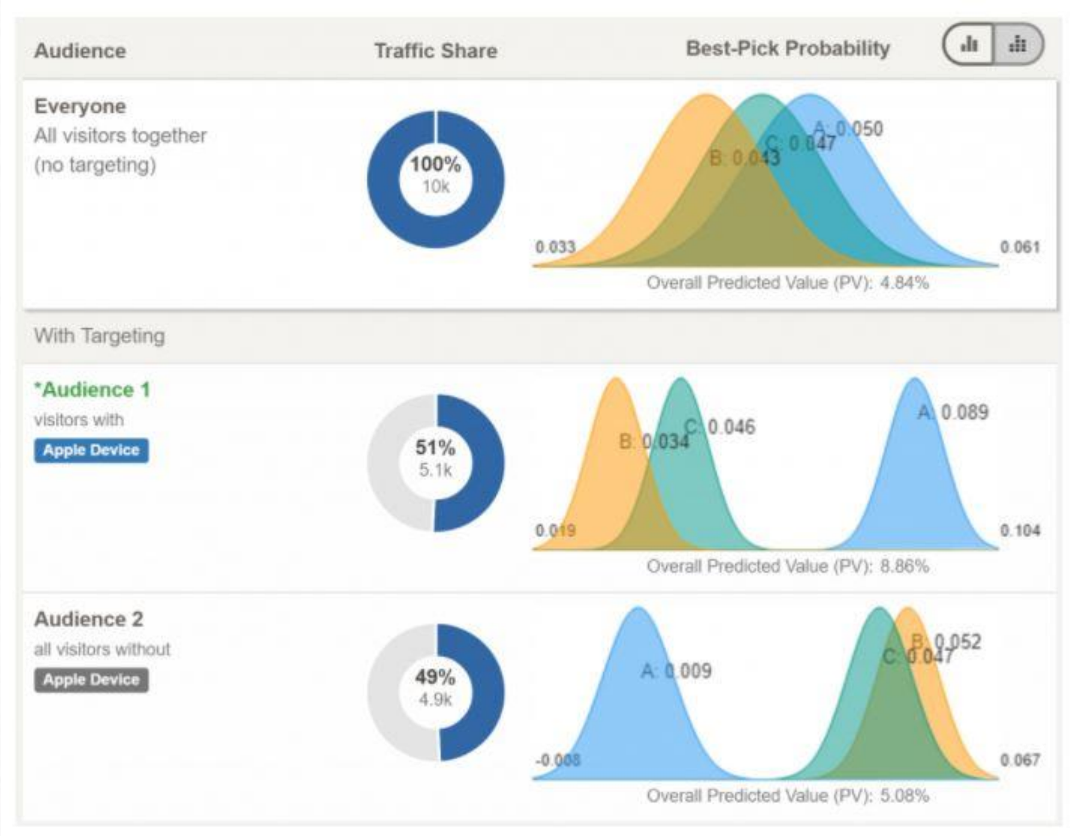
THOMPSON SAMPLING OR HOW I LEARNED TO LOVE ROULETTE



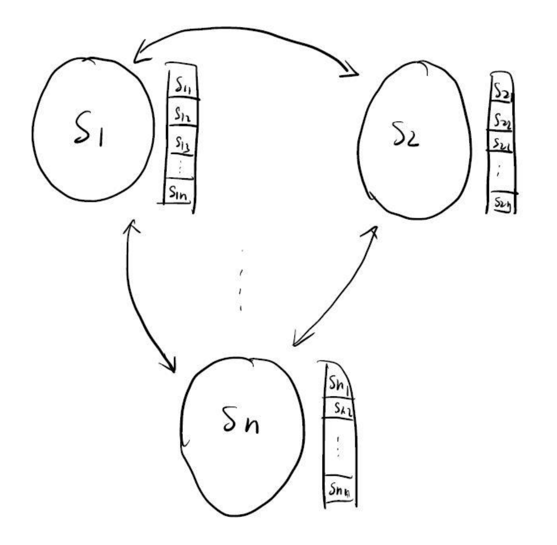
But wait, there is more. We even provide a data visualization view that displays the posterio
Thompson Sampling draws.

THOMPSON SAMPLING OR HOW I LEARNED TO LOVE ROULETTE





GOING FROM AB TESTING TO AI: OPTIMIZATION AS REINFORCEMENT LEARNING



Q-learning: learning though markov state transition

1. Agent在众多的state之间转移（action），直到达到最终的目标状态（goal state）

2. Agent每次使用action i离开一个state j 时，更新对应分数

Q（sj, ai）

$$Q(s_t,a_t) \leftarrow (1-\alpha)\cdot \underbrace{Q(s_t,a_t)}_{\text{old value}} + \underbrace{\alpha}_{\text{learning rate}} \cdot \overbrace{\Big(\underbrace{r_t}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(s_{t+1},a)}_{\text{estimate of optimal future value}}\Big)}^{\text{learned value}}$$

括号内可写为：R(state, action) + Gamma * Max[Q(next state, all actions)]

其中R(state, action) 是已知的，要更新的是Q

$$\begin{array}{ccc} & & \text{Action} \\ & \text{State} & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ R= & \begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} & \begin{bmatrix} -1 & -1 & -1 & -1 & 0 & -1 \\ -1 & -1 & -1 & 0 & -1 & 100 \\ -1 & -1 & -1 & 0 & -1 & -1 \\ -1 & 0 & 0 & -1 & 0 & -1 \\ 0 & -1 & -1 & 0 & -1 & 100 \\ -1 & 0 & -1 & -1 & 0 & 100 \end{bmatrix} \end{array}$$

GOING FROM AB TESTING TO AI: OPTIMIZATION AS REINFORCEMENT LEARNING

Q-learning在conversion rate optimization的应用

每个页面的每个variation都有其相应的quality score（Q）。 算法通过用户在该页的行为更新该页的分数：

算法包括两部分：

1. 当用户到达某一页，选取对应的layout （variation）；
2. 当用户离开某一页（特定的layout）， 更新这个layout的分数

一个简单的分数更新公式： $\mathrm{Reward}_{(t+1)} + \gamma * \mathrm{Max}_a\, Q(s_{(t+1)}, a_t)$.

分数更新时有三种情况：

1). 用户直接购买（convert）

2). 用户转到其他页

3）用户离开

Q-learning 可以融合personalization，在选择layout时加入用户分类的权重。（个人看法）