A/B Tests: The Essentials

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Learning Goals

1. Explain the basic principles of an A/B Test
2. Analyze A/B test data to draw causal conclusions about a treatment
3. Determine the appropriate sample size for an experiment
4. Discuss challenges of shifting to an “experimentation first” company culture

Where Are We Now?

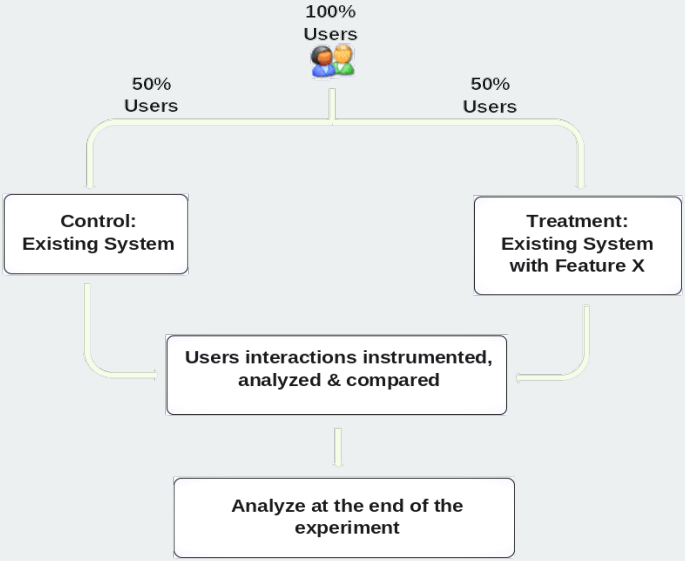
So far we've discussed:

- What makes a **good research question**
- The importance of **research design** and thinking through the **identification** problem to find the "right variation" to estimate casual effects
- **Randomized Control Trials** as a means to generate the right variation

Today: A/B tests $\leftrightarrow$ Randomized Control Trials online!

- aka Online Controlled Experiments

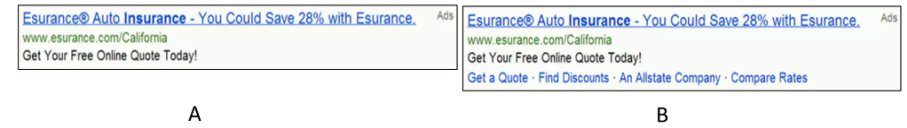
A/B Tests: The Basic Idea



Source: Kohavi (2019)

Example: Bing Ads with Site Links

Shound Bing add site links to ads that allow advertisers to offer multiple destinations on an ad?

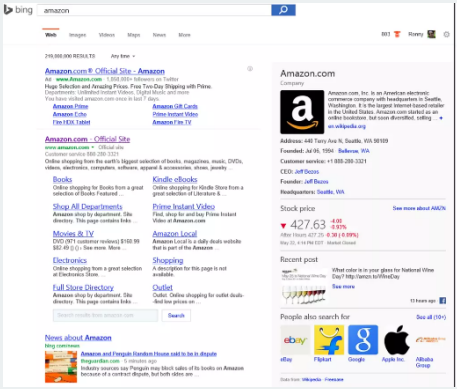


Question: What are the pros and cons of each design?

Question: Which one created more revenue for Bing?

Example: Bing Search with Underlined Links

Does underlining a link impact clickthrough?

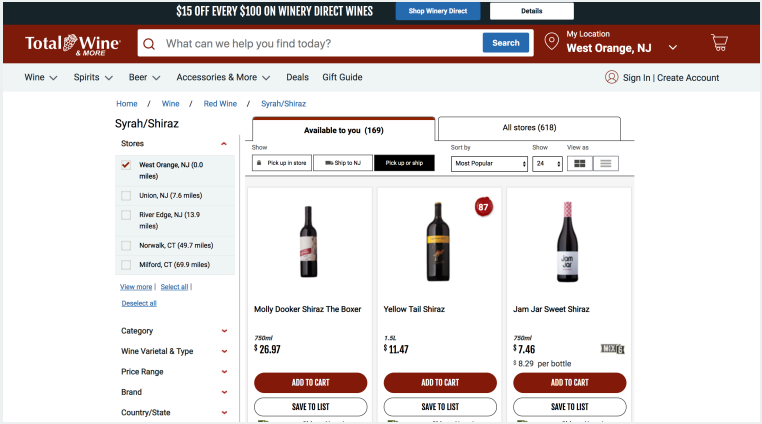


Question: Which one created more revenue for Bing?

1/ Working Example: Email Marketing

An Email A/B Test

The email A/B test we will analyze was conducted by an online wine store.



Source: Total Wine & More

Wine retailer email test

Test setting: email to retailer email list

Unit: email address

Treatments: email version A, email version B, holdout

Reponse: open, click on link and 1-month purchase ($)

Selection: all active customers

Assignment: randomly assigned (1/3 each)

Loading & Inspecting the Data

```
Rows: 123,988
Columns: 14
$ user_id   <dbl> 1000001, 1000002, 1000003, 1000004, 1000005, 1000006, 10000~
$ cpgn_id   <chr> "1901Email", "1901Email", "1901Email", "1901Email", "1901Em~
$ group     <chr> "ctrl", "email_B", "email_A", "email_A", "email_A", "email_~
$ email     <lgl> FALSE, TRUE, TRUE, TRUE, TRUE, TRUE, TRUE, TRUE, FALSE, TRU~
$ open      <dbl> 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0,~
$ click     <dbl> 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,~
$ purch     <dbl> 0.00, 0.00, 200.51, 0.00, 158.30, 0.00, 26.52, 0.00, 0.00, ~
$ chard     <dbl> 0.00, 0.00, 516.39, 0.00, 426.53, 0.00, 0.00, 0.00, 0.00, 0~
$ sav_blanc <dbl> 0.00, 0.00, 0.00, 0.00, 1222.48, 0.00, 0.00, 0.00, 0.00, 0.~
$ syrah     <dbl> 33.94, 16.23, 16.63, 0.00, 0.00, 0.00, 124.31, 32.12, 148.5~
$ cab       <dbl> 0.00, 76.31, 0.00, 41.21, 0.00, 0.00, 58.19, 62.67, 0.00, 0~
$ past_purch <dbl> 33.94, 92.54, 533.02, 41.21, 1649.01, 0.00, 182.50, 94.79, ~
$ days_since <dbl> 119, 60, 9, 195, 48, 149, 118, 125, 100, 50, 192, 27, 41, 4~
$ visits    <dbl> 11, 3, 9, 6, 9, 6, 8, 7, 7, 6, 0, 4, 9, 8, 6, 6, 5, 7, 7, 9~
```

Variables associated with the Test

Treatment indicator (T_i)

- Which (randomized) treatment was received

Outcomes (Y_i)

- Outcome(s) measured for each customer, i.e. the outcome variable

Baseline variables (Z_i)

- Other stuff we know about customers **prior** to the randomization
- Sometimes called “pre-randomization covariates” or “observables”

Question: For each variable in the dataset, which one of these categories does it fall into?

2/ Analysis of A/B tests

The First Question

What is the first question you should ask about an A/B test?

The First Question

What is the first question you should ask about an A/B test?

~~Did the treatment affect the response?~~

Was the randomization done correctly?

How can we check randomization with the data at hand?

Randomization checks

Randomization checks confirm that the **baseline variables** are **distributed similarly** for the **treatment and control groups**.

- Also known as "**Balance tests**"

Randomization checks: Our data

```
# A tibble: 3 x 8
  group  days_since_mean visits_mean past_purch_mean chard_mean sav_blanc_mean
  <chr>            <dbl>       <dbl>           <dbl>      <dbl>          <dbl>
1 ctrl              90.0        5.95            188.       71.7           73.6
2 email_A           90.2        5.95            188.       73.5           72.1
3 email_B           89.8        5.94            190.       74.8           71.6
# i 2 more variables: syrah_mean <dbl>, cab_mean <dbl>
```

Randomization checks

We can **test for balance** across treatments for each of our baseline variables:

```
# note: output omitted
df %>%
    select(group, days_since, visits, past_purch,
           chard, sav_blanc, syrah, cab) %>%
    st(group = 'group', group.test = TRUE)
```

Randomization checks

Randomization seems to check out!

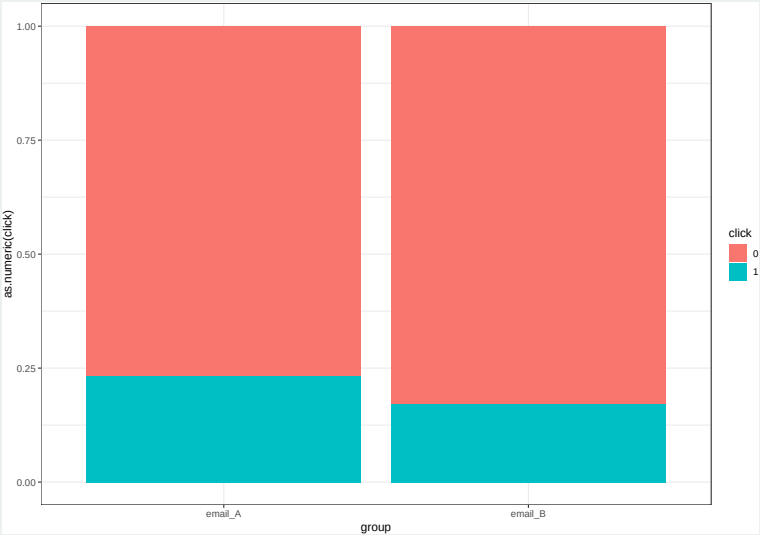
... onto average treatment effects

Did the treatments affect the responses?

Look at the means of outcome variables between treatments:

```
# A tibble: 3 x 4
  group   open_mean click_mean purch_mean
  <chr>       <dbl>      <dbl>      <dbl>
1 ctrl        0          0           12.4
2 email_A     0.718      0.132       25.6
3 email_B     0.652      0.0934      25.9
```

Question: What differences do you observe?


1.00
0.75
0.50
0.25
0.00
as.numeric(click)
email_A
email_B
group
click
0
1

Does email A have higher open rate than B?

```
# A tibble: 1 x 6
  statistic chisq_df  p_value alternative lower_ci upper_ci
      <dbl>    <dbl>    <dbl> <chr>          <dbl>    <dbl>
1      424.        1 1.40e-94 greater       0.0613        1
```

Does email A have higher open rate than B?

```
# A tibble: 2 x 5
  term         estimate std.error statistic  p.value
  <chr>           <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept)    0.718    0.00228     315.  0
2 groupemail_B  -0.0666   0.00322     -20.7 1.40e-94
```

Does email A have higher click rate than B?

```
# A tibble: 2 x 5
  term         estimate std.error statistic  p.value
  <chr>           <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept)    0.132    0.00155      84.9 0
2 groupemail_B  -0.0383   0.00219     -17.4 6.28e-68
```

Doing it all at once with regression

```
# A tibble: 3 x 5
  term          estimate std.error statistic p.value
  <chr>            <dbl>     <dbl>     <dbl>   <dbl>
1 (Intercept)    0         0.00127       0      1.00
2 groupemail_A   0.132     0.00179      73.5    0
3 groupemail_B   0.0934    0.00179      52.1    0
```

Does email A lead to different click thru than B?

```
Linear hypothesis test

Hypothesis:
groupemail_A - groupemail_B = 0

Model 1: restricted model
Model 2: click ~ group

  Res.Df    RSS Df Sum of Sq     F    Pr(>F)
1 123986 8256.0
2 123985 8225.7  1     30.24 455.8 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Pairwise testing with `rstatix`

The **no** regression version, **uses proportions tests**

```
# A tibble: 3 x 5
  group1  group2      p p.adj p.adj.signif
* <chr>   <chr>   <dbl> <dbl> <chr>
1 ctrl    email_A 0     0     ****
2 ctrl    email_B 0     0     ****
3 email_A email_B 1e-67 1e-67 ****
```

Does email A lead to higher average purchases than B?

```
# A tibble: 2 x 5
  term         estimate std.error statistic p.value
  <chr>           <dbl>     <dbl>     <dbl>   <dbl>
1 (Intercept)    25.6       0.291    88.1     0
2 groupemail_B    0.243     0.411     0.592   0.554
```

Do the emails lead to higher average purchases?

```
# A tibble: 3 x 5
  term          estimate std.error statistic   p.value
  <chr>            <dbl>     <dbl>     <dbl>     <dbl>
1 (Intercept)      12.4      0.268      46.4 0
2 groupemail_A     13.2      0.379      34.8 9.47e-265
3 groupemail_B     13.4      0.379      35.5 1.79e-274
```

Does email A lead to higher average purchases than B?

```
Linear hypothesis test

Hypothesis:
groupemail_A - groupemail_B = 0

Model 1: restricted model
Model 2: purch ~ group

  Res.Df       RSS Df Sum of Sq      F Pr(>F)
1 123986 367801404
2 123985 367800179  1    1224.8 0.4129 0.5205
```

Pairwise testing with `rstatix`

The **no** regression version, **uses t-tests**

```
# A tibble: 3 x 9
  .y.   group1  group2     n1    n2          p p.signif     p.adj p
* <chr> <chr>   <chr>   <int> <int>      <dbl> <chr>        <dbl> <
1 purch ctrl    email_A 41330 41329 9.47e-265 ****     1.89e-264 *
2 purch ctrl    email_B 41330 41329 1.79e-274 ****     5.36e-274 *
3 purch email_A email_B 41329 41329 5.21e-  1 ns       5.21e-  1 n
```

Summary of findings

Email A has significantly higher opens and clicks than email B,

- But purchase are similar for both emails $\rightarrow$ Send email A!

Both emails generate higher average purchases than the control $\rightarrow$ Send emails!

3/ Design of A/B tests

Seven key questions

1. Business question
2. Test setting (lab vs. field)
3. Unit of analysis (visit, customer, store)
4. Treatments
5. Response variable(s)
6. Selection of units
7. Assignment to treatments
8. Sample size

If you can answer these questions, you have a test plan

Email test

Business questions: Does email work? If so which email is better?

Test setting: email to retailer customers

Unit: email address

Treatments: email version A, email version B, holdout

Reponse: open, click and 30-day purchase ($)

Selection: all active emails on email list (open in last 12 months)

Assignment: randomly assigned (1/3 each)

Sample size: 123,988 emails

Sample size planning

The standard recommendation is to set the sample size **in advance** and not test for significance until the data comes in.

- The recommended sample size is:

$$n_1 = n_2 \approx (z_{1-\alpha/2} + z_\beta)^2 \left(\frac{2s^2}{d^2} \right)$$

Interpreting the sample size formula

$$n_1 = n_2 \approx (z_{1-\alpha/2} + z_\beta)^2 \left(\frac{2s^2}{d^2} \right)$$

- More noise, $s^2 \rightarrow$ larger sample size
- Smaller difference to detect, $d \rightarrow$ larger sample size
- Lower error rates, $(z_{1-\alpha/2} + z_\beta) \rightarrow$ larger sample size

Sample size planning: Key ideas

Data is noisy, so the group with the higher average in the test not always have the higher true response.

There are **two mistakes** you can make:

- **Type I error**: Declare the treatments different, when they are the same (α)
- **Type II error**: Declare the treatment the same, when they are different (β)

I want a low probability of both of those mistakes (α, β) given a specific known difference between treatments (d) and noise in my response (s)

$$n_1 = n_2 \approx (z_{1-\alpha/2} + z_\beta)^2 \left(\frac{2s^2}{d^2}\right)$$

Sample size calculator in R

Sample size to detect at $1 difference in average 30-day purchases:

```
power.t.test(sd = sd(df$purch), # ideally using
                                # pre-experiment data!
             delta = 1, # minimum detectable effect
             sig.level = 0.95, # alpha: industry standard
             power=0.80 # 1 - beta: industry standard
             )
```

Sample size planning

- **Continous response** (e.g. money, time on website)

$$n_1 = n_2 \approx (z_{1-\alpha/2} + z_\beta)^2 \left(\frac{2s^2}{d^2} \right)$$

- **Binary response** (e.g. conversions)

$$n_1 = n_2 \approx (z_{1-\alpha/2} + z_\beta)^2 \left(\frac{2p(1-p)}{d^2} \right)$$

Sample size calculator in R

Binary response

```
power.prop.test(p1=0.07,
                p2=0.07 + 0.01, # d = 0.01
                sig.level=0.05,
                power=0.80
                )
```

A word of caution about sample size calculators

There are **different sample size formulas floating around**.

- These formulas differ on what assumptions they may about what you are trying to do,
- It **can be very hard to figure out what assumptions are being made**
- ... even for experts
- So use some care before plugging numbers into an online calculator

A sample size calculation will help you identify the right amount of data you need for the problem at hand.

Choosing Outcome Variables

Agreeing on **outcome variables** is **not** as **easy** as it sounds

- Should be defined using short-term metrics that predict long-term value
- (and hard to game)
- Think about customer lifetime value, not immediate revenue
- Use few but key metrics Conversion funnels use Pirate metrics: AARRR: acquisition, activation, retention, revenue, and referral

Most Ideas Fail

Experiments at Microsoft (paper):

- 1/3 of ideas were positive ideas and statistically significant
- 1/3 of ideas were flat, with no statistically significant difference
- 1/3 of ideas were negative and statistically significant

At Bing (well optimized), the success rate is lower: 10-20%.

Implication: **Aim for small continuous improvements**

Twyman's Law

Any figure that looks interesting or different is usually wrong

- Check before celebrating

Cultural Challenges

”Experimentation is the least arrogant method of gaining knowledge”

- Isaac Asimov

Some folks believe controlled experiments threaten their jobs

- “we know what to do and we’re sure of it”
- Reflex-like rejection of new knowledge because it contradicts entrenched norms, beliefs or paradigm

Ethical Issues

Controversy in treatment design

- Facebook's emotional contagion experiment
- Amazon and early pricing experiments
- OK Cupid (Tinder for the previous generation) with deception on match score

Minimal Risk Experimentation:

> *"the probability and magnitude of harm or discomfort anticipated in the research are not greater in and of themselves than those ordinarily encountered in daily life or during the performance of routine physical or psychological examinations or tests"*

When in doubt have an Institutional Review Board

4/ Recap

Summary

- A/B testing is running Randomized Control Trials online
- Balance tests help confirm that randomization into treatment is indeed random
- Statistical inference toolkit and linear regression enable us to estimate the treatment effects
- The correct sample size for detecting a treatment effect is a crucial aspect of test design
- There are challenges beyond the analysis of data that are important obstacles in implementation

Acknowledgements

I have borrowed content and inspiration from the following sources:

- Elea Feit's "Advanced A/B testing workshop"
- Ronny Kohavi's "A/B Testing at Scale: Accelerating Software Innovation"

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```

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