Data Driven Design: A/B Testing

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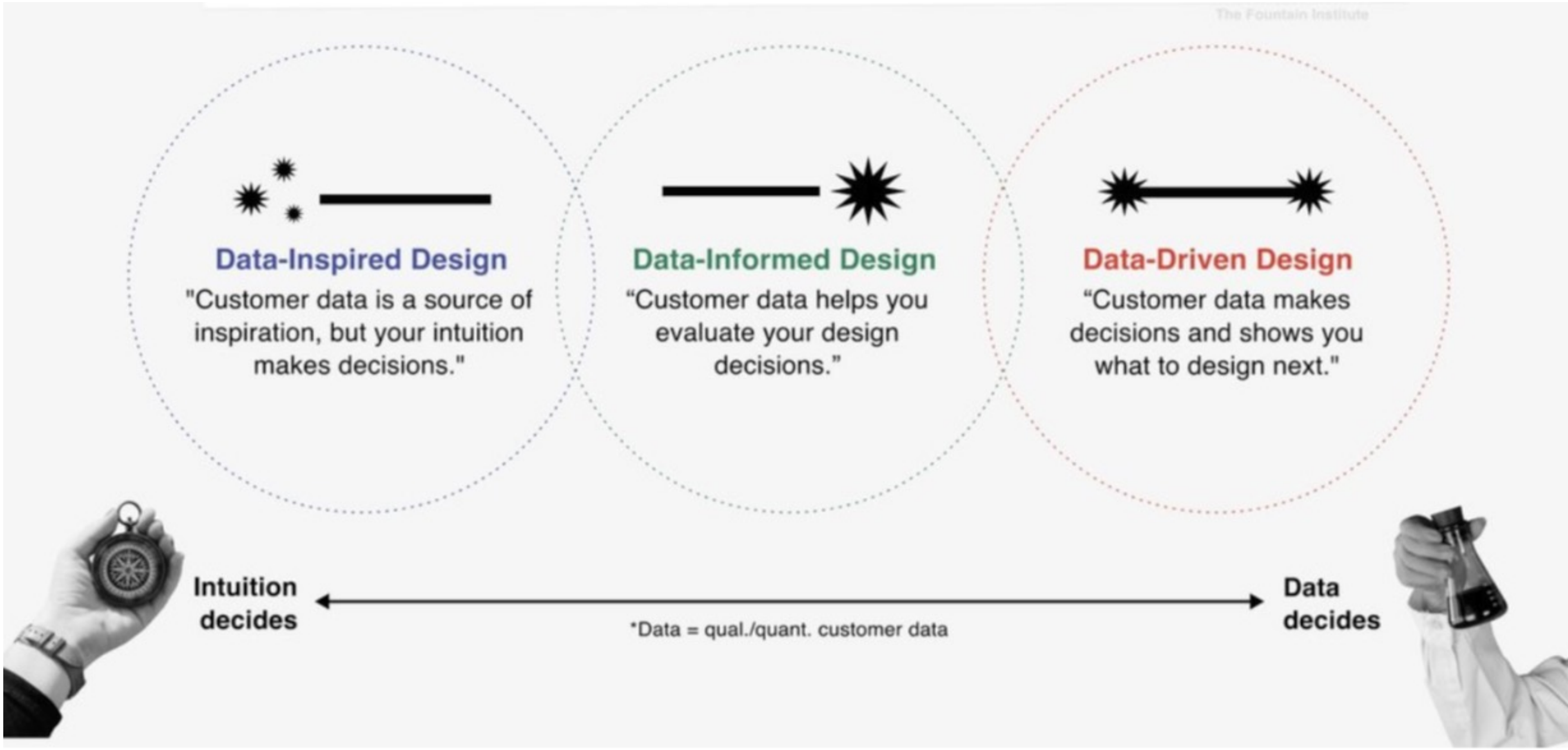
[Adapted from ID430B Data Analytics for Designers, KAIST]

Agenda

- Definition of A/B test
- Case studies and Examples
- Steps of running A/B test
- A/B Testing practice

The Influence of Data on Design



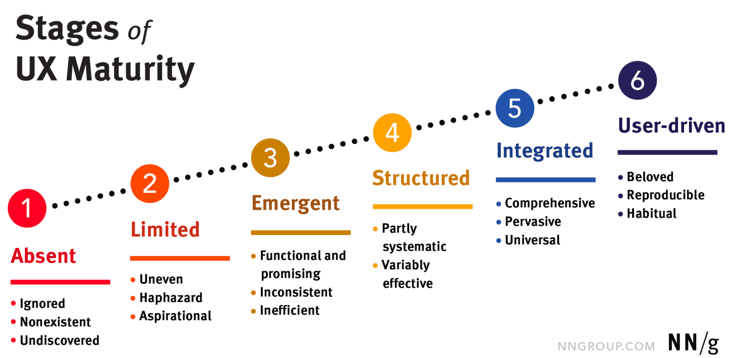
Data Driven Design

Pros:

Data-driven product designers are human-centered since they let the customer directly influence what gets built.

Customers decide through their behavior in various research and testing activities.

Intuition can still play a role in interpreting the data, but you should submit your decisions to the results of customer behavior.



Cons:

The iterative nature of letting data make decisions can mean you sometimes miss out on the big-picture view and trends that also have a part to play in design.

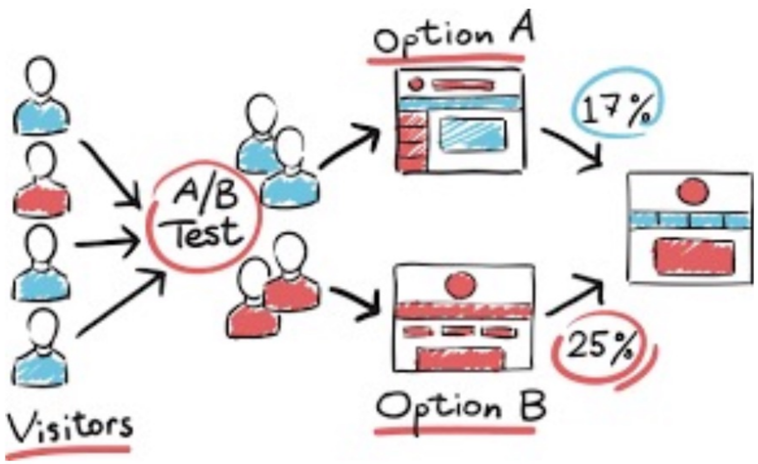
Sometimes customers don't show their ideal behaviors in their actions. When we base our decisions on behaviors, we can end up with products that provide what customers want but don't need. Addictive online shopping is an example where you might want to mix research data with experiment data to ensure that you address the entire landscape of customer needs…

What is A/B Testing?

- **Compare two or more variations** of an experience to see which one performs the best for a single / multiple objective measure(s)
- **Test on a small fraction** of the entire user population (in order to minimize the side-effect of contaminating users with experimental designs)
- **Causal analysis** of the variations to user behavior; to understand how your design will affect user experience if launched

Why do we study A/B testing?

- Empirical evidences are more persuasive than design authority
- Testing improves your understanding of the users
- Data-driven decision making can become a part of the product



https://www.diggintravel.com/airline-ab-testing/

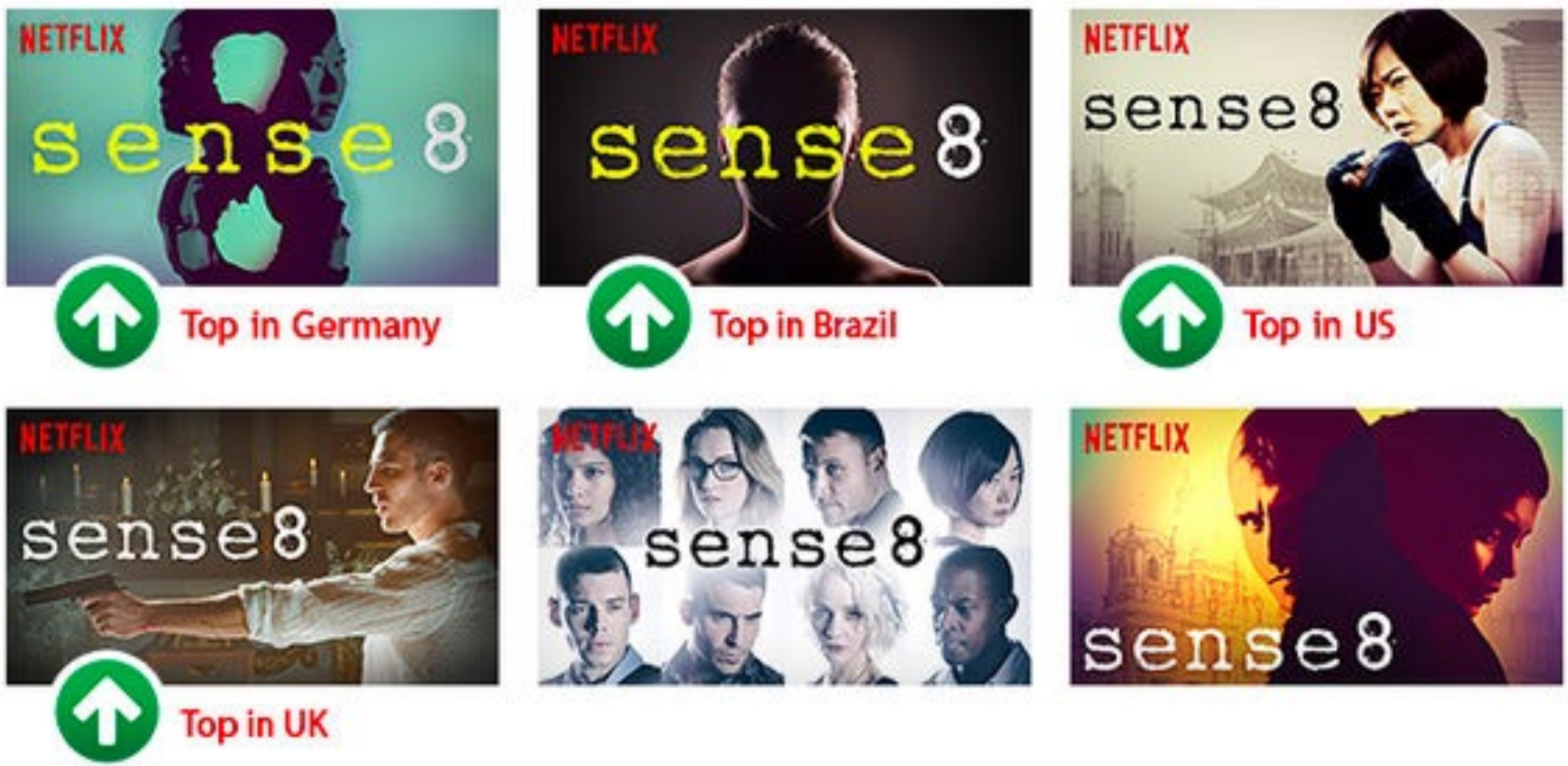
Ronald Fisher
It's me again. Back in 1920s, I created **randomized controlled experiment**, the core concept of A/B testing. I wish I could run A/B testing for the smoking-cancer causality.

1950s- clinical trials adopted A/B testing
1960s- markerters evaluate whether postcard or letter would gather more customers?
1990s- online experiments
2020s- AI-driven, continuous and highly-automated experiments

When can you use A/B testing

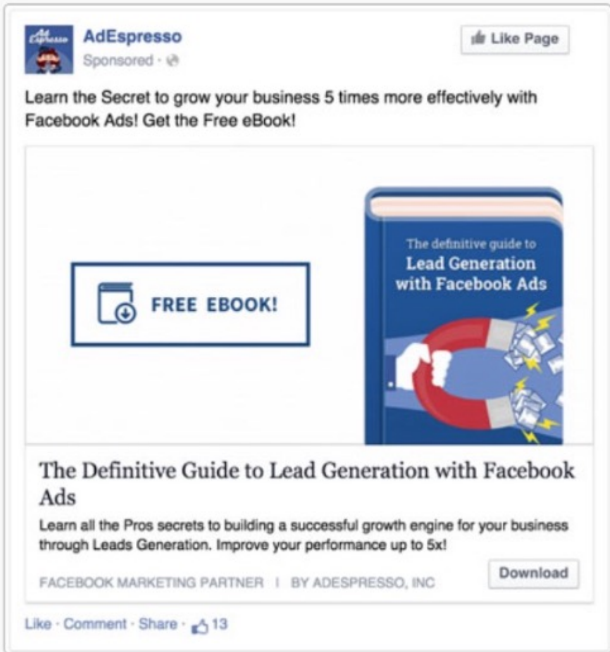
- Online shopping company: Is my site complete?
- Add Premium service
- Movie recommendation site: new ranking algorithms
- Change backend: page loading time, results user see, etc
- Website selling cars: will a change increase repeat customers of referrals?
- Update brand, including main logo
- Test layout of initial page

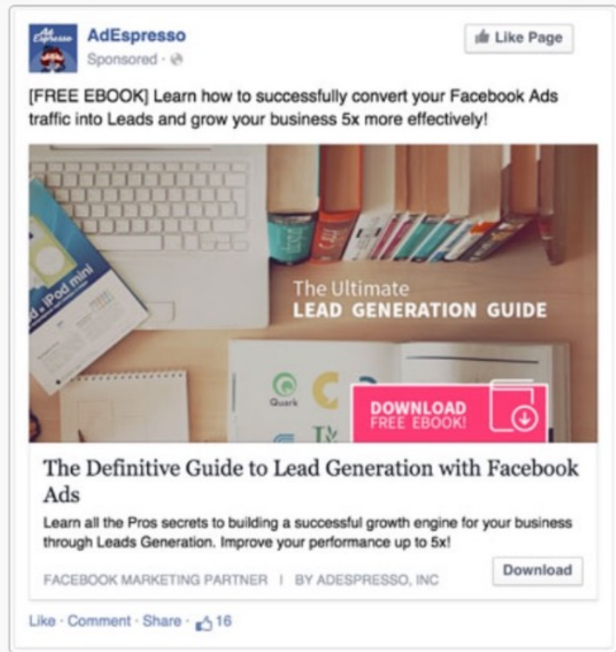
Netflix thumbnail experiments



https://medium.com/@sdhrshn/netflix-a-b-testing-5d7c8216853f

Advertisement lead (title and thumbnail) on Facebook





Titles

Thumbnail images

10,000 Impression	10,000 Impression
237 Clicks *(CTR: 2.37%)*	187 Clicks *(CTR: 1.87%)*
28 Sales *(Conversion rate: 11.81%)*	16 Sales *(Conversion rate: 8.55%)*
Spent: $150	Spent: $150
Cost per Sale: $5.35	Cost per Sale: $9.37 (+75.14%)

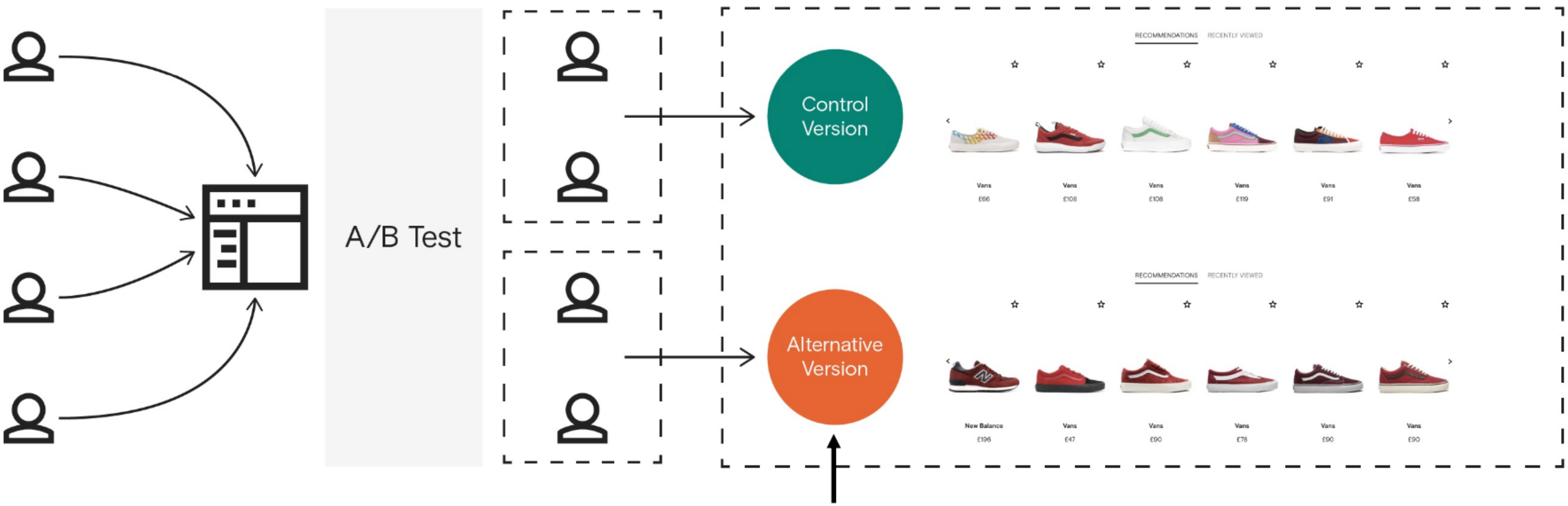
Same # observations

Two stage results

1. Click-through rate
2. Conversion rate

Test 1 has almost double ROI per dollar

Recommender System



Two different AI models are randomly assigned to each user

https://www.farfetchtechblog.com/en/blog/post/how-to-swiftly-a-b-test-recommendations-from-the-inside-rocket-style/

Examples of A/B Testing

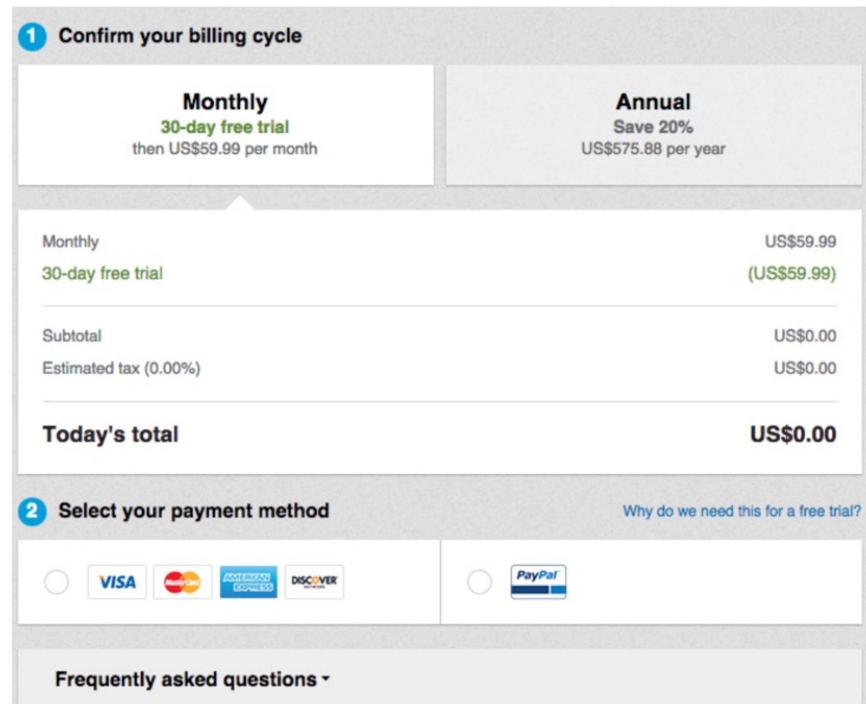
- (At LinkedIn) we have hundreds of experiments running in parallel

LinkedIn's Profile Edit

The **movitational text** boosted up 14% of the profile edits

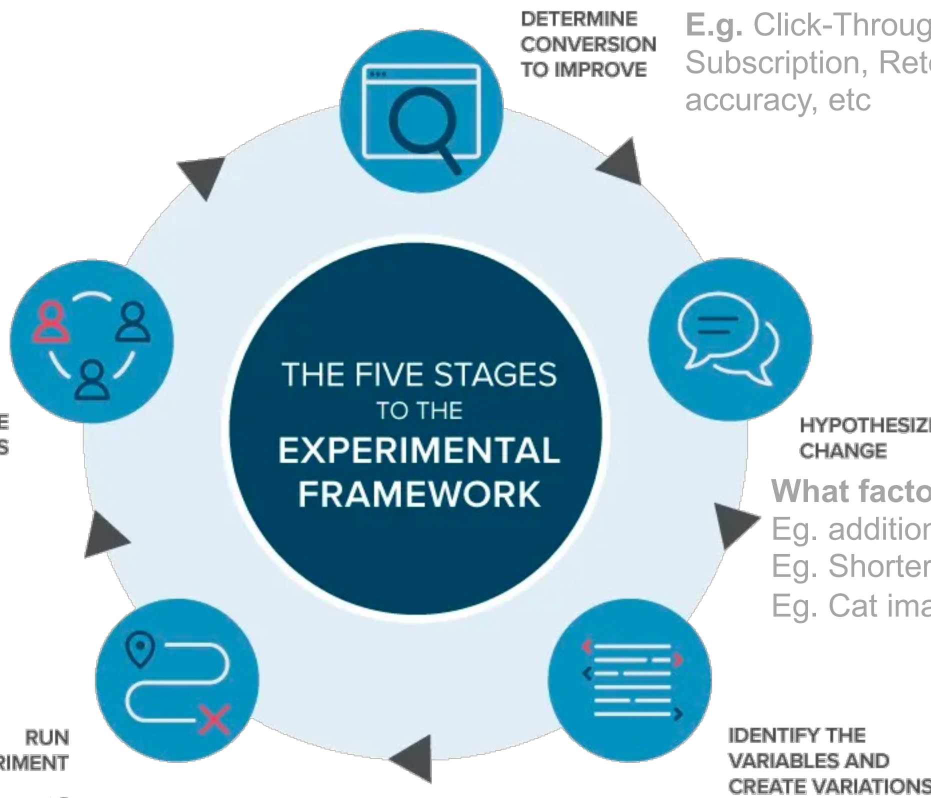
https://content.linkedin.com/content/dam/engineering/site- assets/pdfs/ABTestingSocialNetwork_share.pdf

LinkedIn's Premium Subscription Payment flow



The new payment flow merges two pages into one; and provides FAQs → 30% less refunding orders and 10% more free trial orders

Interative cycles



E.g. Click-Through-Rate (CTR), Purchase, Subscription, Retention, # use, # friends, # likes, accuracy, etc

What factor will affect the conversion?
Eg. additional text -> More # uses
Eg. Shorter flow -> More # completion
Eg. Cat image in the banner -> Higher CTR

What are design A and B?
(!) Can they help testing hypothesis?
(!) Beware of confounding factors
(!) Avoid obvious comparisons

How to run experiment?
(!) Start with tiny fraction of users
(!) Randomly assign who will get what
(!) Keep one's experience consistent
(!) Log additional signals for EDA

What to analyze?
(!) Test correlation between factors and conversion metrics
(!) EDA for explanation and potential issues

Step 1. Set the Goal

- A/B testing usually focuses on a single (or couple) quantifiable measures of user behavior. While the below examples are commonly used, you may create custom measures.

Examples of Common Measures to optimize

Click-Through Rates (CTR)
- Ratio of users who click on a specific link
- A KPI (Key Performance Indicator) of an online banner / email advertising campaign

Conversion Rates
- Ratio of users who did the desired action such as product purchase, subscription, signing up, sharing with others, and so on.

Retention Rates
- Ratio of users who keep using the service within a specific period of time (and other conditions such as minimum # of usage, etc)
- An inverse of retention rates would be unsubscription rates

Task Completion Rate
- Ratio of users who complete the given task (e.g. form fill-in, survey, tutorial)

Error Rate
- Ratio of users who see any error message or make mistakes
- Unlike the others, we optimize a system to lower the error rate

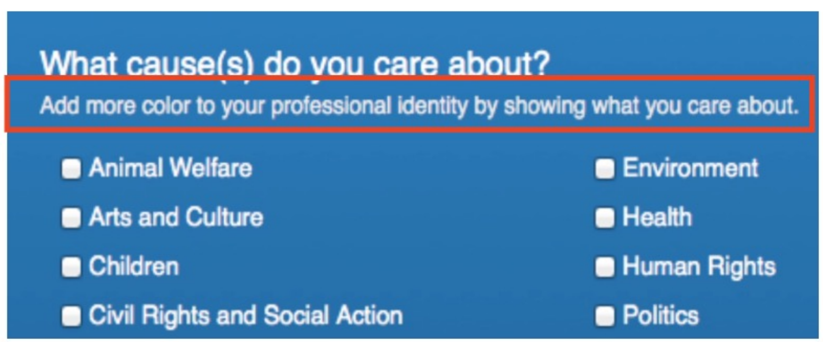
Satisfaction Rate
- Ratio of users who give positive answers via a survey or other communication channels

Cost
- Amount of money spent for specific returns (e.g. AD banner for clicks)
- businesses can find the option that offers better returns and get rid of the process that offers lower returns

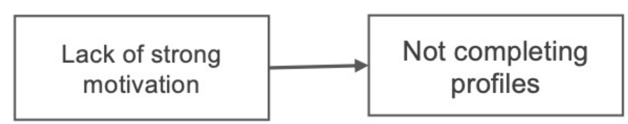
Step 2. Construct Hypothesis

- Prior to designing variations, you need to clarify the hypothesis to be tested. A hypothesis is usually a combination of cause(s) and the effect(s) that describes the current situation. They tend to be more abstract than design variations and measurements.

E.g. LinkedIn Profile Edit Case



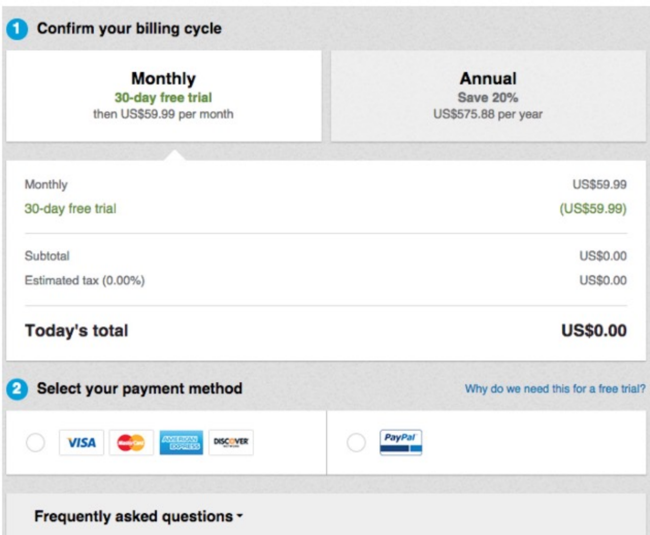
H: Users are not completing their profiles because they do not have strong motivation



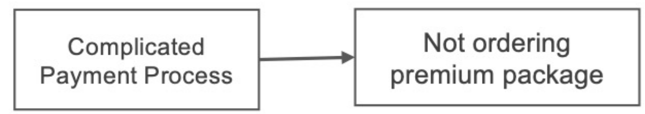
Note that the hypothesis is more abstract than the design variations and measurements in your mind. For instance, “lack of motivation” is not a concrete design yet. Adding a motivational sentence is one of many design choices. Also “not completing profiles” is not a specific measure yet. “# users completed their profiles” is one of many possible measurements.

Step 2. Construct Hypothesis

E.g. LinkedIn Payment Page Case



H: Users are not ordering the premium package because the current process is too complicated



(Similar with the profile edit case) “complicated payment process” is not your design variation yet (i.e. single-page process and the link to FAQ are concrete design choices) Also, “not ordering premium package” is not a concrete measure yet (i.e. “# free trial orders” and “# refunding orders” are the corresponding measures)

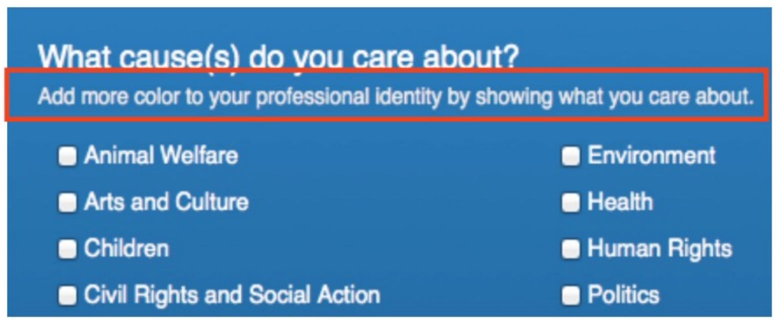
There are two reasons of creating hypotheses:

(1) If designers create concrete variations without hypotheses, they might overlook confounding factors
(2) By testing hypotheses, designers can gain generalizable understanding of the issue and the users

Step 3. Create Design Variations

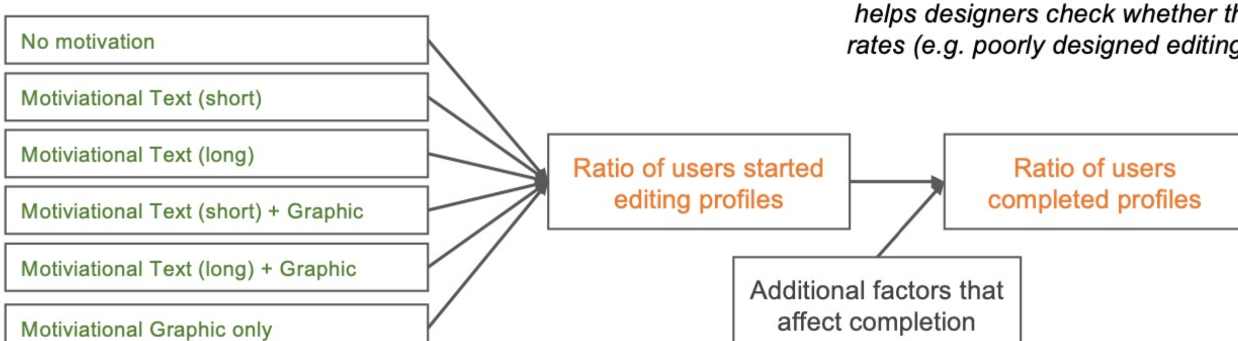
- It's time to create design variations to test your hypothesis. Variations may include a control and a single or multiple experimental condition(s). Variations must be evaluated via the measurement.

E.g. LinkedIn Profile Edit Case



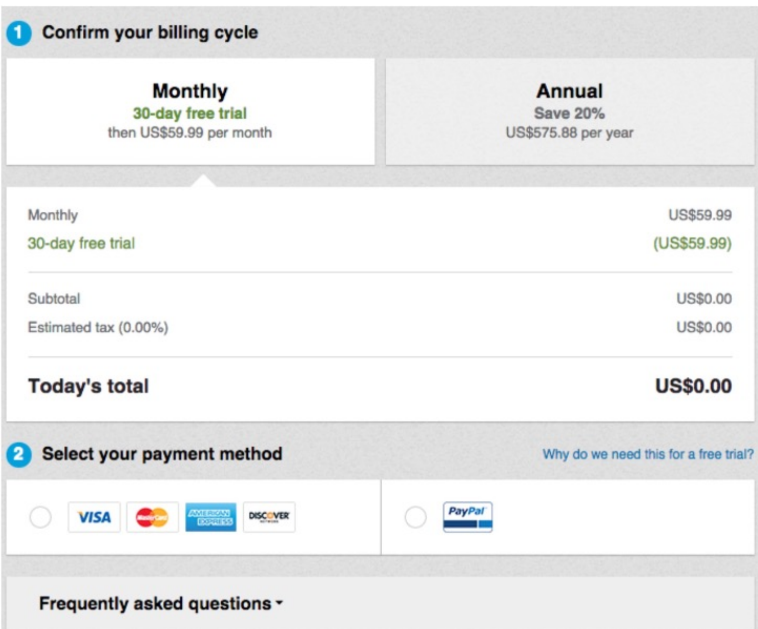
Control. Showing no motivational text
Experimental. Showing "Add more color to …"
To get further insights, designers may create more than one experimental conditions. For instance, there could be variations of motivational text content, graphical and/or textual motivation, and so on.

Measurement. Ratio of users completed profiles
To get more detailed insights, designers are advised to create additional measurements. In this example, measuring "ratio of users start editing their profiles helps designers check whether there are additional factors affecting the completion rates (e.g. poorly designed editing UI)



Step 3. Create Design Variations

E.g. LinkedIn Payment Page Case



Experimental design

- Two-page payment flow is compressed into a single-page
- A link to the FAQ page is added

Control. Original payment flow (2-pages)
Experimental. Redesigned payment flow (1-page; link to FAQ)
To get further insights, designers may create more than one experimental conditions. LinkedIn people created four conditions (including the original condition)

	2 page	1 page
No FAQ	**E0.** Original	**E1.** 1 page flow
FAQ	**E2.** 2 page + FAQ	**E3.** 1 page + FAQ

Measurement. # free trial orders; # refunded orders
To get more detailed insights, designers are advised to create additional measurements:

(m1) Ratio of users who clicked both “Monthly” and “Annual” buttons
(m2) Ratio of users who selected at least one payment method
(m3) Ratio of users who clicked “Why do we need this for a free trial?”
(m4) Ratio of users who clicked “Frequently asked questions”
(m5) Ratio of users who started the payment process
(m6) Ratio of users who completed / did not complete the payment process
(m7) Ratio of users who refunded within a week after completion

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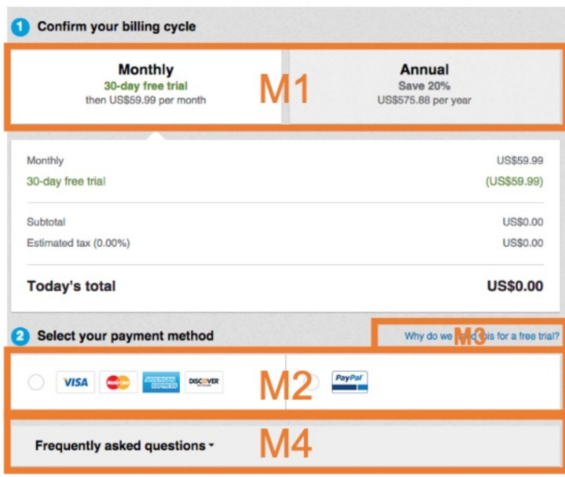
Step 3. Create Design Variations

Design Variations

- **E0.** Original
- **E2.** 2 page + FAQ
- **E1.** 1 page flow
- **E3.** 1 page + FAQ

Detailed Measurements



M1-M4 are useful measurements to gain insights about how # pages and FAQ affect user's engagement to start the payment process. In specific, M3 and M4 indicate user's need for detailed information, and might lead to further experiments about "what information should be shown upfront?"

M5. Ratio of users who started the payment process

M6. Ratio of users who completed the payment process

M7. Ratio of users who refunded within a week after completion

M5-M7 are measurements of sequential events (i.e. how many users start / complete / refund their payments). M5 measures the immediate effect of design variables. The difference of M5 and M6 indicates the impact of other factors between starting and completing payment process. M7 could indicate how clearly users understood the details of the service.

Step 4. Running Experiment

- A/B testing is usually conducted with a small fraction of randomly-selected users. There is no fixed sample size or percentage, but you should consider the following rule-of-thumbs.

1. Equally allocate users to design variations (if possible)

I.e. Don't assign majority of users to specific conditions. It will slow down the experiment by increasing the minimum sample sizes to get statistical significance. (additional reading)

2. Get sufficient samples to get statistical significance of at least 95% ($p<0.05$)

300-400 samples per variation is usually considered enough. If you cannot reach the 95% ($p=0.05$) with 300-400 samples * # variations, it is very unlikely that the variations have strong impact on the measured goal.

3. Run the experiment for multiple behavioral cycles

Lots of user behaviors tend to have weekly patterns (e.g. on Monday, people tend to be quite busy). To minimize the risk of weekly biases, run the experiment for at least one week (preferably two weeks or a month). However, it depends on what the task is and who the users are.

4. Pay attention to external factors

If it is Christmas or Valentine's day, an online marketing campaign might be highly affected by the external factor. If your users have been constantly exposed to similar experiments, user's prior experience might skew your test results. While it's impossible to get a perfectly clean environment, consider external factors in your interpretation.

Step 5. Analysis

- Once you get the numbers, the first thing to do is EDA focusing on the validity of the experiment. Then you find the winner by comparing the goal measurements. Finally, you test the hypotheses that you set beforehand.

1. **Perform EDA for validating the experimental result**
   - Did you get the planned # samples per variation?
   - Is every data point complete and accurately collected?
   - Is there any unexpected bias or confounding factor?

2. **Finding the winning variation**
   - Which variation achieved the highest measurement?
   - Drill down to smaller subgroups of people. For instance, does the global winner also outperform for more specific user groups / situations? Remember the Simpson's paradox.
   - If you set multiple measurements, try to characterize pros and cons of each variation. For instance, a variation that achieved the highest conversion ratio may have a high ratio of refunding too.

Step 5. Analysis

3. Test Hypothesis

- After finding a winner you should investigate further – in order to gain generalizable design knowledge, and to get ideas for follow-up tests.
- E.g. (For the LinkedIn Payment Flow case) Were users not ordering the premium package because of the overly complicated payment process?
- Yes, by applying both of the 1-page flow and the FAQ link, we significantly ($p<0.03$) increased # free trial orders and decreased # refunding orders. In specific, users seem to be interested in either the summarized list of benefits and the cancellation policy. We also observed higher # orders during the first week of month. Does it mean that users are concerned about the meaning of 1 month trial?

4. Plan for the next A/B test

- Note that results from A/B tests cannot guarantee reproducibility (i.e. you may not get the same result the next time), and it is likely that the first test will give more questions than concrete answers. (e.g. "Why did the winner perform so well?")
- Therefore you need to repeat the same study at least once more. You may refine the test plan though (e.g. smaller # variations; more measurements; etc). A good news is that you will feel follow-up tests much easier than the first test and become more and more confident about user's behavior.
- Actual goals of A/B testing is not just finding winners but also developing a platform for continuously gaining insights from the real users.

Summary

- **A/B testing is a special kind of quantitative experiments**
  - where “A” representing the old control, and “B” representing a single / multiple experimental changes
  - where the goal is to maximize single/multiple measurements of user behavior
  - A/B testing is most useful when combined with qualitative methods (e.g. observation, survey, interview)

- **A/B testing has multiple goals as listed below**
  - Finding a winner among many design variations
  - Testing hypotheses of cause (design) and effect (user behavior)
  - Gaining generalizable understanding of the task and the user population
  - Developing a reusable platform for continuously running a series of A/B tests

- **A/B testing consists of five big steps**
  1. Choose a single (or couple) quantifiable measure(s) of user behavior
  2. Construct hypotheses
  3. Create design variations
  4. Run the experiment
  5. Analyze the results

Summary

- A/B testing is not silver bullet. It has a lot of limitations and pitfalls.

When A/B testing is not worth	What's the problem? How can we make it worth again?
You don't have meaningful traffic (i.e. # users)	• Without meaningful traffic you won't be able to tell anything about statistical significance. • Reduce # variations • Wait until you have a big enough population • Construct a hypothesis that you can indirectly test on a similar platform (e.g. running A/B test of your streaming platform on YouTube users), crowdsourcing platform (e.g. Amazon Mechanical Turk), or as a lab experiment
You don't have enough resources for running A/B test – which is a management-intensive task.	• You will regret, "We should've finished our design first." • Wait until you have enough time • Consider using existing tools for A/B testing. They are not mature yet, but still useful for marketing.
You don't have an informed hypothesis.	• Gather more information and perform EDA • Treat A/B test like real science. Learn from lectures, case studies, and tutorials. Ask psychologists and data scientists who have conducted randomized controlled experiments what hypothesis you can test for the given situation

Summary

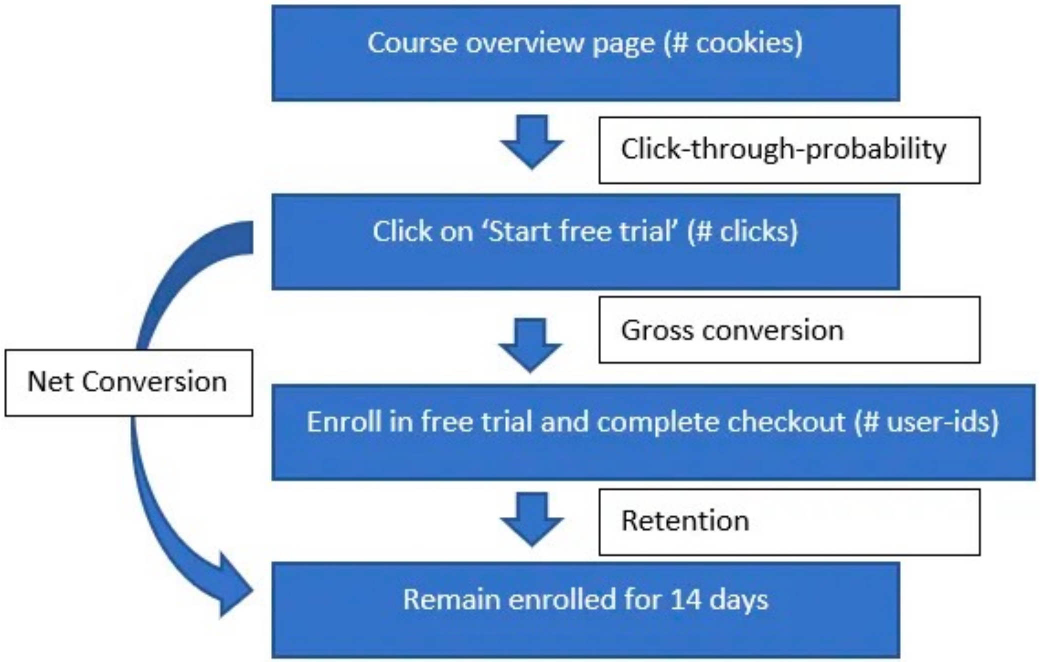
- A/B testing is not silver bullet. It has a lot of limitations and pitfalls.

When A/B testing is not worth	What's the problem? How can we make it worth again?
You have an obvious winner.	• It's waste of resources to find an obvious winner. • Diversify the winner into multiple variations as the LinkedIn purchase flow case. You will learn a lot more than "who's the winner".
Your design variations have serious side-effects on user's mindset.	• Users may get confused by inconsistent usages, and even lose their trust on your service. For instance, if a company assigns different prices randomly assigned for each customer, customers may become angry. • Test with a small fraction of users, or on a closed-beta system. Some companies test price variations not on their official market but through a 3rd party discount platforms (e.g. limited-time deal)
Your variations are not suitable for fair comparison	• A common scenario is UI redesign where users are already familiar with the original design. Your new design variation is unfairly undervalued by its learning curve. • Construct a hypothesis that does not involve familiarity. I.e. make all the variations familiar / unfamiliar. • Run A/B test on newbies only, or even create a new service.

A/B Testing practice

- Udacity Free Trial Screener

Please scan the following code to access the Feishu Doc for the practice project.



Thank you~

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