

QUALITY ASSESSMENT IN PRODUCTION

Christian Kaestner

Required Reading:

- Hulten, Geoff. "[Building Intelligent Systems: A Guide to Machine Learning Engineering.](#)" Apress, 2018, Chapters 14 and 15 (Intelligence Management and Intelligent Telemetry).

Suggested Readings:

- Alec Warner and Štěpán Davidovič. "[Canary Releases.](#)" in [The Site Reliability Workbook](#), O'Reilly 2018
- Georgi Georgiev. "[Statistical Significance in A/B Testing – a Complete Guide.](#)" Blog 2018



Changelog
@changelog



“Don’t worry, our users will notify us if there’s a problem”



2:03 PM · Jun 8, 2019



2.3K 688 Copy link to Tweet

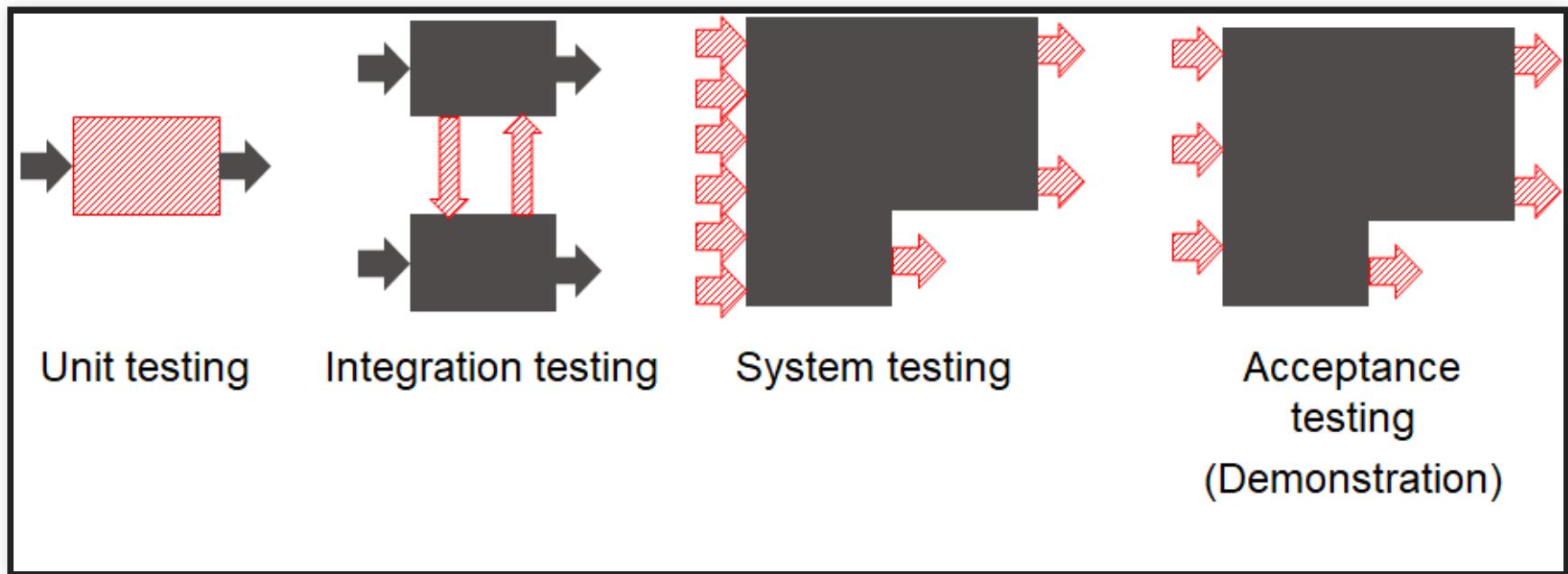
LEARNING GOALS

- Design telemetry for evaluation in practice
- Understand the rationale for beta tests and chaos experiments
- Plan and execute experiments (chaos, A/B, shadow releases, ...) in production
- Conduct and evaluate multiple concurrent A/B tests in a system
- Perform canary releases
- Examine experimental results with statistical rigor
- Support data scientists with monitoring platforms providing insights from production data

FROM UNIT TESTS TO TESTING IN PRODUCTION

(in traditional software systems)

UNIT TEST, INTEGRATION TESTS, SYSTEM TESTS



Speaker notes

Testing before release. Manual or automated.

BETA TESTING



Speaker notes

Early release to select users, asking them to send feedback or report issues. No telemetry in early days.

CRASH TELEMETRY

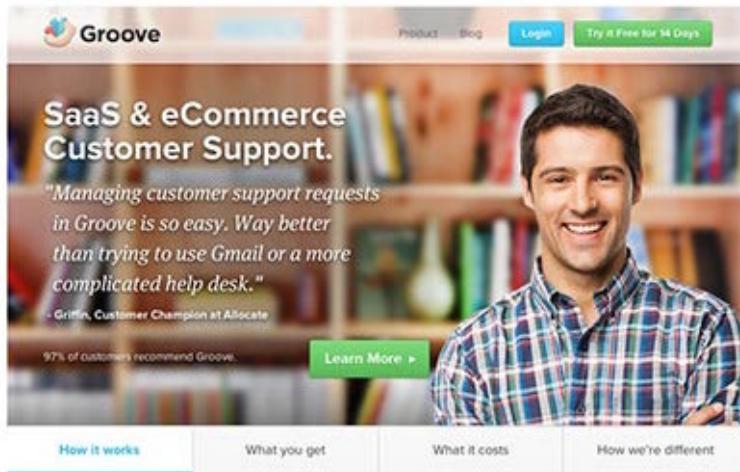


Speaker notes

With internet availability, send crash reports home to identify problems "in production". Most ML-based systems are online in some form and allow telemetry.

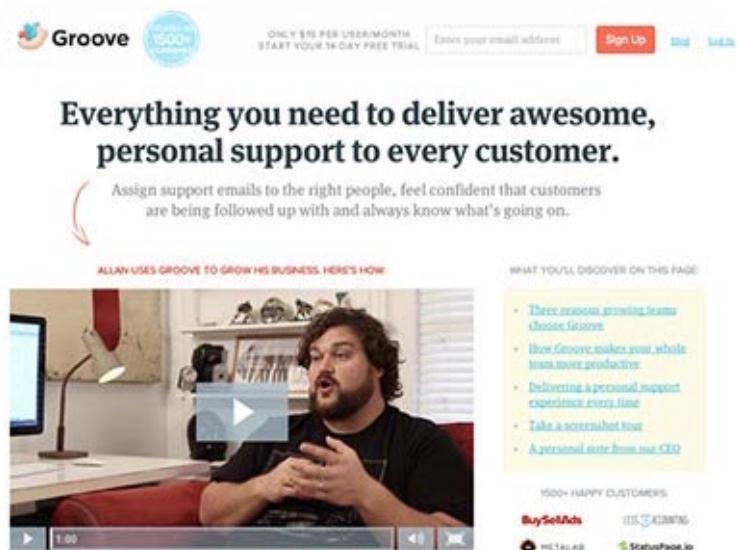
A/B TESTING

Original: 2.3%



The original landing page for Groove features a large image of a smiling man in a plaid shirt. Headlines include "SaaS & eCommerce Customer Support." and "Managing customer support requests in Groove is so easy. Way better than trying to use Gmail or a more complicated help desk." A testimonial from "Griffin, Customer Champion at Allocacoo" is present. Call-to-action buttons include "Learn More" and "How it works".

Long Form: 4.3%



The long-form landing page for Groove includes a headline: "Everything you need to deliver awesome, personal support to every customer." It features a video player showing a man speaking, with the caption "ALLAN USES GROOVE TO GROW HIS BUSINESS. HERE'S HOW." Below the video, a list of what visitors will discover on the page includes: "Three reasons growing teams choose Groove", "How Groove makes your whole team more productive", "Delivering a personal support experience every time", "Take a screenshot tour", and "A personal note from our CEO". Logos for "1500+ HAPPY CUSTOMERS" and various partners like BuySellAds, Clicking, Metalab, and StatusPage.io are at the bottom.

Speaker notes

Usage observable online, telemetry allows testing in production. Picture source: <https://www.designforfounders.com/ab-testing-examples/>

CHAOS EXPERIMENTS



Speaker notes

Deliberate introduction of faults in production to test robustness.

MODEL ASSESSMENT IN PRODUCTION

Ultimate held-out evaluation data: Unseen real user data

LIMITATIONS OF OFFLINE MODEL EVALUATION

- Training and test data drawn from the same population
 - i.i.d.: independent and identically distributed
- Is the population representative of production data?
- If not or only partially or not anymore: Does the model generalize beyond training data?

IDENTIFY FEEDBACK MECHANISM IN PRODUCTION

- Live observation in the running system
- Potentially on subpopulation (A/B testing)
- Need telemetry to evaluate quality -- challenges:
 - Gather feedback without being intrusive (i.e., labeling outcomes), without harming user experience
 - Manage amount of data
 - Isolating feedback for specific AI component + version

DISCUSS HOW TO COLLECT FEEDBACK

- Was the house price predicted correctly?
- Did the profanity filter remove the right blog comments?
- Was there cancer in the image?
- Was a Spotify playlist good?
- Was the ranking of search results good?
- Was the weather prediction good?
- Was the translation correct?
- Did the self-driving car break at the right moment? Did it detect the pedestrians?



Speaker notes

More:

- SmartHome: Does it automatically turn off the lights/lock the doors/close the window at the right time?
- Profanity filter: Does it block the right blog comments?
- News website: Does it pick the headline alternative that attracts a user's attention most?
- Autonomous vehicles: Does it detect pedestrians in the street?

Skype for Business

How was the call quality?

Good

Audio Issues

- Distorted speech
- Electronic feedback
- Background noise
- Muffled speech
- Echo

Video Issues

- Frozen video
- Pixelated video
- Blurry image
- Poor color
- Dark video

blog post demo

Privacy Statement

Submit Close

Matt Millman
Because I'm happy 😊

Settings

Help and feedback

Report a problem

RECENT CHATS

Besties 10/10/2018

EN Elena Nilsson, Anna Davie... 7/27/2018
It was great talking to all of ...

Anna Davies 6/26/2018
coffee awaits!

Maarten Smenk 5/25/2018
Missed call

MS Maarten Smenk, Anna Davie... 5/21/2018
Hi, happy Monday!

Speaker notes

Expect only sparse feedback and expect negative feedback over-proportionally

A screenshot of a flight search interface. At the top, there's a green line graph icon followed by the text "DFW ↔ SFO" and "Nov 16". Below this, it says "1659 of 1687 flights" and "Wednesday". A red oval highlights a yellow callout box containing the following text:

Prices may fall within 7 days – Watch

Our model strongly indicates that fares will fall during the next 7 days. This forecast is based on analysis of historical price changes and is not a guarantee of future results.

The interface includes a "Create a price alert" button, a "Stops" section with checkboxes for "nonstop", "1 stop", and "2+ stops" (all checked), and a "Times" section with a dropdown menu showing "Take-off Dallas" and "Arrival San Francisco".

Speaker notes

Can just wait 7 days to see actual outcome for all predictions

A screenshot of a transcription software interface. At the top, there's a header with the project name 'the-changelog-318', a link to 'Dashboard', and a 'Quality' setting at 'High'. To the right are buttons for 'Last saved a few seconds ago', three dots for more options, and a yellow 'Share' button. Below the header is a timeline bar with markers at 00:00, Offset, 00:00, and 01:31:27. Underneath the timeline are four buttons: 'Play', 'Back 5s', '1x Speed', and 'Volume'. The main area contains the transcribed text.

NOTES

Write your notes here

Speaker 5 ► 07:44

Yeah. So there's a slight story behind that. So back when I was in, uh, Undergrad, I wrote a program for myself to measure a, the amount of time I did data entry from my father's business and I was on windows at the time and there wasn't a function called time dot [inaudible] time, uh, which I needed to parse dates to get back to time, top of representation, uh, I figured out a way to do it and I gave it to what's called the python cookbook because it just seemed like something other people could use. So it was just trying to be helpful. Uh, subsequently I had to figure out how to make it work because I didn't really have to. Basically, it bothered me that you had to input all the locale information and I figured out how to do it over the subsequent months. And actually as a graduation gift from my Undergrad, the week following, I solved it and wrote it all out.

Speaker 5 ► 08:38

And I asked, uh, Alex Martelli, the editor of the Python Cookbook, which had published my original recipe, a, how do I get this into python? I think it might help

How did we do on your transcript?

Speaker notes

Clever UI design allows users to edit transcripts. UI already highlights low-confidence words, can

MANUALLY LABEL PRODUCTION SAMPLES

Similar to labeling learning and testing data, have human annotators



SUMMARY: TELEMETRY STRATEGIES

- Wait and see
- Ask users
- Manual/crowd-source labeling, shadow execution
- Allow users to complain
- Observe user reaction

EXERCISE: DESIGN TELEMETRY IN PRODUCTION

Discuss how to collect telemetry (Wait and see, ask users, manual/crowd-source labeling, shadow execution, allow users to complain, observe user reaction)

Scenarios:

- Group 1: Amazon: Shopping app feature that detects the shoe brand from photos
- Group 2: Google: Tagging uploaded photos with friends' names
- Group 3: Spotify: Recommended personalized playlists
- Group 4: Wordpress: Profanity filter to moderate blog posts

Summarize results on a slide

MEASURING MODEL QUALITY WITH TELEMETRY

- Three steps:
 - Metric: Identify quality of concern
 - Telemetry: Describe data collection procedure
 - Operationalization: Measure quality metric in terms of data
- Telemetry can provide insights for correctness
 - sometimes very accurate labels for real unseen data
 - sometimes only mistakes
 - sometimes delayed
 - often just samples
 - often just weak proxies for correctness
- Often sufficient to *approximate* precision/recall or other model-quality measures
- Mismatch to (static) evaluation set may indicate stale or unrepresentative data
- Trend analysis can provide insights even for inaccurate proxy measures

MONITORING MODEL QUALITY IN PRODUCTION

- Monitor model quality together with other quality attributes (e.g., uptime, response time, load)
- Set up automatic alerts when model quality drops
- Watch for jumps after releases
 - roll back after negative jump
- Watch for slow degradation
 - Stale models, data drift, feedback loops, adversaries
- Debug common or important problems
 - Monitor characteristics of requests
 - Mistakes uniform across populations?
 - Challenging problems -> refine training, add regression tests

Average rating last 15min



PROMETHEUS AND GRAFANA





Website Overview

Zoom Out

Last 3 hours



Logins

190

Sign ups

269

Sign outs

273

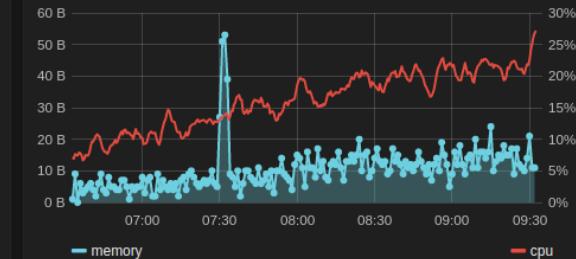
Memory / CPU



logins



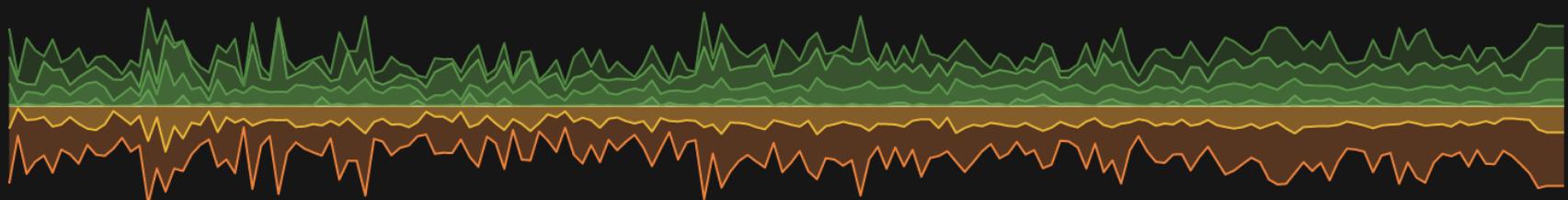
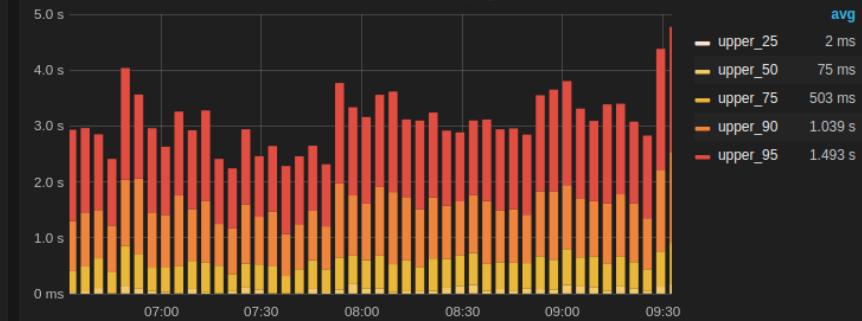
Memory / CPU



server requests



client side full page load



MANY COMMERCIAL SOLUTIONS

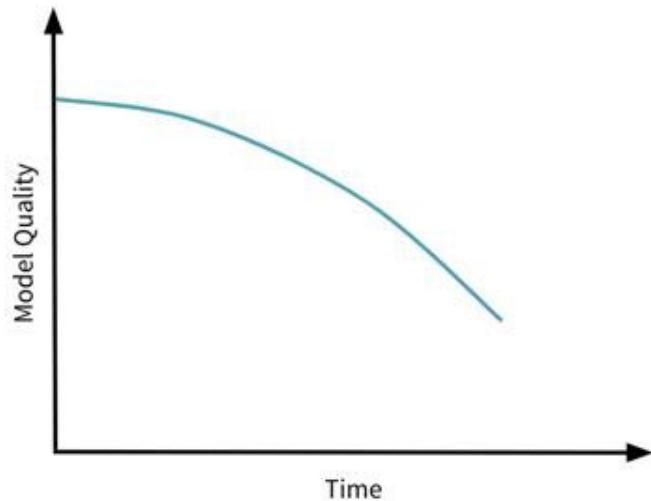


e.g. <https://www.datarobot.com/platform/mlops/>

Many pointers: Ori Cohen "Monitor! Stop Being A Blind Data-Scientist." Blog 2019

DETECTING DRIFT

Static models



Refreshed models



Image source: Joel Thomas and Clemens Mewald. [Productionizing Machine Learning: From Deployment to Drift Detection](#). Databricks Blog, 2019

ENGINEERING CHALLENGES FOR TELEMETRY

TRENDING

Buying Guides

Note 10

Best Laptops

iOS 13

Best Phones

Amazon Alexa stores voice recordings for as long as it likes (and shares them too)

By Olivia Tambini 21 days ago Digital Home

A letter from Amazon reveals all



ENGINEERING CHALLENGES FOR TELEMETRY

- Data volume and operating cost
 - e.g., record "all AR live translations"?
 - reduce data through sampling
 - reduce data through summarization (e.g., extracted features rather than raw data; extraction client vs server side)
- Adaptive targeting
- Biased sampling
- Rare events
- Privacy
- Offline deployments?

EXERCISE: DESIGN TELEMETRY IN PRODUCTION

Discuss: Quality measure, telemetry, operationalization, false positives/negatives, cost, privacy, rare events

Scenarios:

- Group 1: Amazon: Shopping app feature that detects the shoe brand from photos
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Summarize results on a slide

TELEMETRY FOR TRAINING: THE ML FLYWHEEL



graphic by [CBInsights](#)

MODEL QUALITY VS SYSTEM GOALS

MODEL QUALITY VS SYSTEM GOALS

- Telemetry can approximate model accuracy
- Telemetry can directly measure system qualities, leading indicators, user outcomes
 - define measures for "key performance indicators"
 - clicks, buys, signups, engagement time, ratings
 - operationalize with telemetry

MODEL QUALITY VS SYSTEM QUALITY



Bernardi, Lucas, Themistoklis Mavridis, and Pablo Estevez. "150 successful machine learning models: 6 lessons learned at Booking.com." In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 1743-1751. 2019.

MODEL QUALITY VS SYSTEM QUALITY



Possible causes?

Bernardi et al. "150 successful machine learning models: 6 lessons learned at Booking.com." In Proc KDD, 2019.

Speaker notes

hypothesized

- model value saturated, little more value to be expected
- segment saturation: only very few users benefit from further improvement
- overoptimization on proxy metrics not real target metrics
- uncanny valley effect from "creepy AIs"

EXERCISE: DESIGN TELEMETRY IN PRODUCTION

Discuss: What key performance indicator of the system to collect?

Scenarios:

- Group 1: Amazon: Shopping app feature that detects the shoe brand from photos
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- Group 3: Spotify: Recommended personalized playlists
- Group 4: Wordpress: Profanity filter to moderate blog posts

Summarize results on a slide

EXPERIMENTING IN PRODUCTION

- A/B experiments
- Shadow releases / traffic teeing
- Blue/green deployment
- Canary releases
- Chaos experiments



Changelog
@changelog



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2.3K 688 Copy link to Tweet

A/B EXPERIMENTS

WHAT IF...?

- ... we had plenty of subjects for experiments
 - ... we could randomly assign subjects to treatment and control group without them knowing
 - ... we could analyze small individual changes and keep everything else constant
- Ideal conditions for controlled experiments



SEE SOMETHING NEW, EVERY DAY.

TAKE A LOOK



amazon
Try Prime

All ▾



Deliver to
Pittsburgh 15213

Your Amazon.com

Today's Deals

Gift Cards

Whole Foods

Registry

Sell

EN
GLISH

Hello, Sign in
Account & Lists ▾

Orders

Try Prime ▾

Cart 0

Valentine's Day deals

Amazon Devices



echo



fire tv stick 4K
2-pack



echospot



fire 7
3-pack

\$99⁹⁹ \$69⁹⁹

\$99⁹⁹ \$84⁹⁸

\$129⁹⁹ \$99⁹⁹

\$149⁹² \$109⁹⁷

Bargain finds



Explore live plants



New year, new records



Sign in for the best
experience

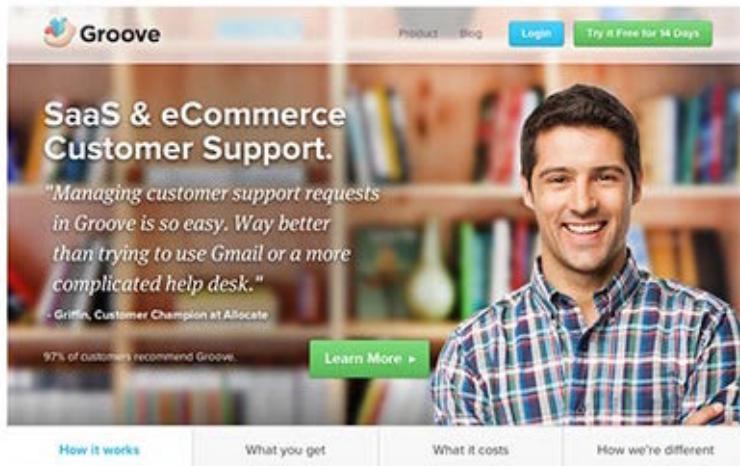
Sign in securely

https://www.amazon.com/Low-Price-With-Free-Shipping/bb?category=/electronics&ref=bb_bb_a77114_in_db_w_ur_en_US&linenumber=8078H77S6K&of_rd_p=39b36ea0-aa36-484b-adef-e16d0468b38f&of_rd_r=6R617PT5...

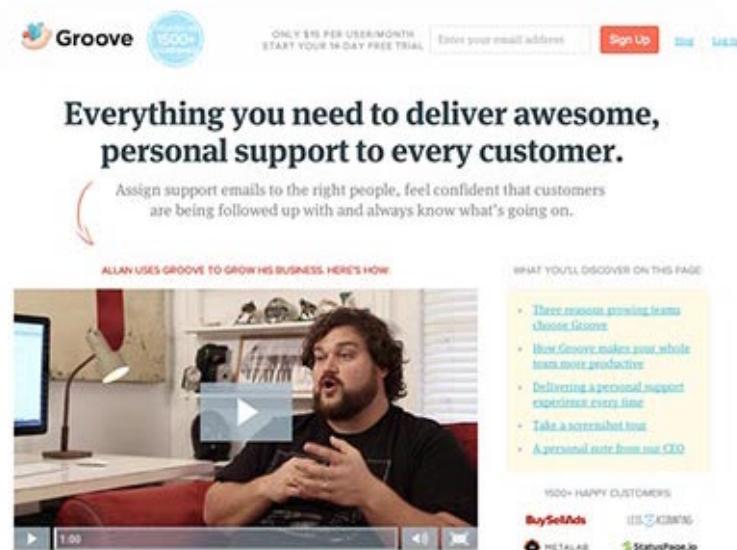
A/B TESTING FOR USABILITY

- In running system, random sample of X users are shown modified version
- Outcomes (e.g., sales, time on site) compared among groups

Original: 2.3%



Long Form: 4.3%



Speaker notes

Picture source: <https://www.designforfounders.com/ab-testing-examples/>

Save on prescription drugs - over \$3,637* a year!

Last year, Humana's Medicare Advantage plan members saved, on average, \$3,637* on prescription drugs!

Choose your Humana Medicare Advantage plan and you could enjoy savings on prescription drugs, plus:

- Hospital, doctor AND drug coverage combined into one easy-to-use plan
- Extra benefits not offered by Original Medicare
- Affordable or no monthly plan premiums

[Shop 2014 Medicare Plans](#)

Control



Explore Humana's Medicare plans

Let us help you determine the Humana plan that's best for your needs.

[Get started now](#)



1 2 3

Treatment

Speaker notes

Picture source: <https://www.designforfounders.com/ab-testing-examples/>

A/B EXPERIMENT FOR AI COMPONENTS?

- New product recommendation algorithm for web store?
- New language model in audio transcription service?
- New (offline) model to detect falls on smart watch



EXPERIMENT SIZE

- With enough subjects (users), we can run many many experiments
- Even very small experiments become feasible
- Toward causal inference



IMPLEMENTING A/B TESTING

- Implement alternative versions of the system
 - using feature flags (decisions in implementation)
 - separate deployments (decision in router/load balancer)
- Map users to treatment group
 - Randomly from distribution
 - Static user - group mapping
 - Online service (e.g., [launchdarkly](#), [split](#))
- Monitor outcomes *per group*
 - Telemetry, sales, time on site, server load, crash rate

FEATURE FLAGS

```
if (features.enabled(userId, "one_click_checkout")) {  
    // new one click checkout function  
} else {  
    // old checkout functionality  
}
```

- Boolean options
- Good practices: tracked explicitly, documented, keep them localized and independent
- External mapping of flags to customers
 - who should see what configuration
 - e.g., 1% of users sees `one_click_checkout`, but always the same users; or 50% of beta-users and 90% of developers and 0.1% of all users

```
def isEnabled(user): Boolean = (hash(user.id) % 100) < 10
```

Treatments ⓘ | 2 treatments, if Split is killed serve the default treatment of "off"

Treatment	Default	Description
on		The new version of registration process is enabled.
off		The old version of registration process is enabled.

[+ Add treatment](#) | [Learn more about multivariate treatments](#).

Whitelist ⓘ | 0 user(s) or segments individually targeted.

[+ Add whitelist](#)

Traffic Allocation ⓘ | 100% of user included in Split rules evaluation below.

Total Traffic Allocation: 100 % total User in Split

Targeting Rules ⓘ | 2 rules created for targeting.

```

graph TD
    If1((if)) --> Cond1["user is in segment qa"]
    Cond1 --> Then1["Then serve on"]
    ElseIf2((else if)) --> Cond2["user is in segment beta_testers"]
    Cond2 --> Then2["Then serve percentage"]
    Then2 --> On50["on 50"]
    Then2 --> Off50["off 50"]
  
```

[+ Add rule](#)

Default Rule ⓘ | Serve treatment of "off".

serve off

CONFIDENCE IN A/B EXPERIMENTS

(statistical tests)

COMPARING AVERAGES

Group A

*classic personalized content
recommendation model*

2158 Users

average 3:13 min time on site

Group B

*updated personalized content
recommendation model*

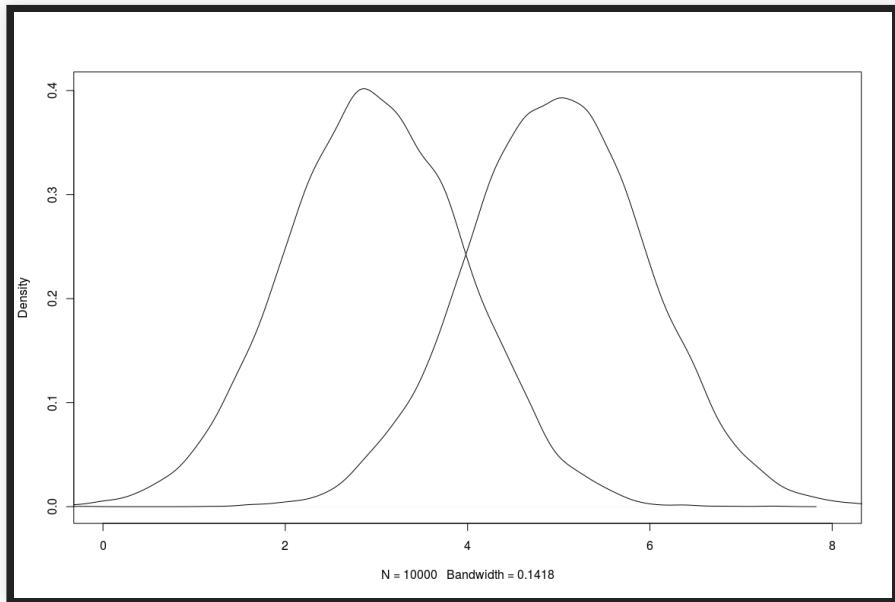
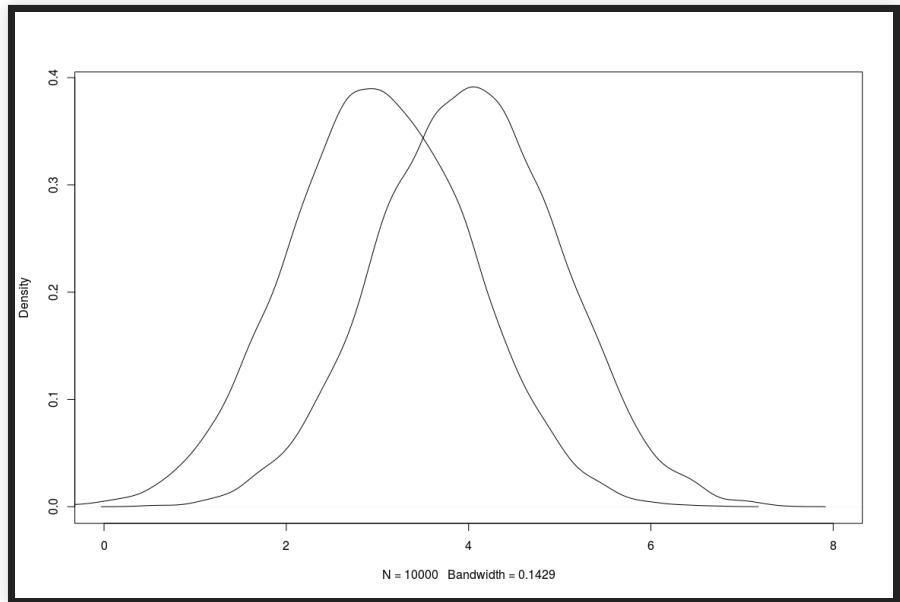
10 Users

average 3:24 min time on site

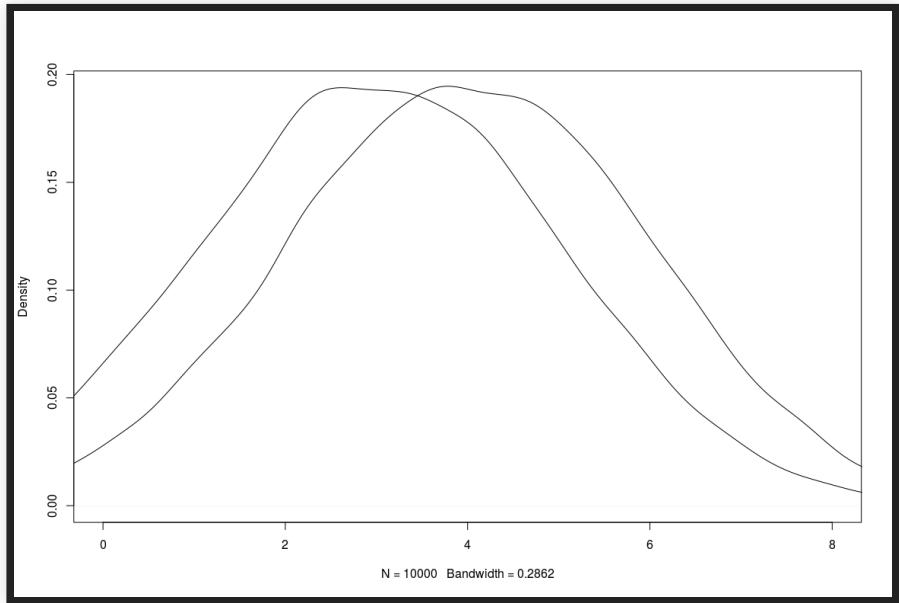
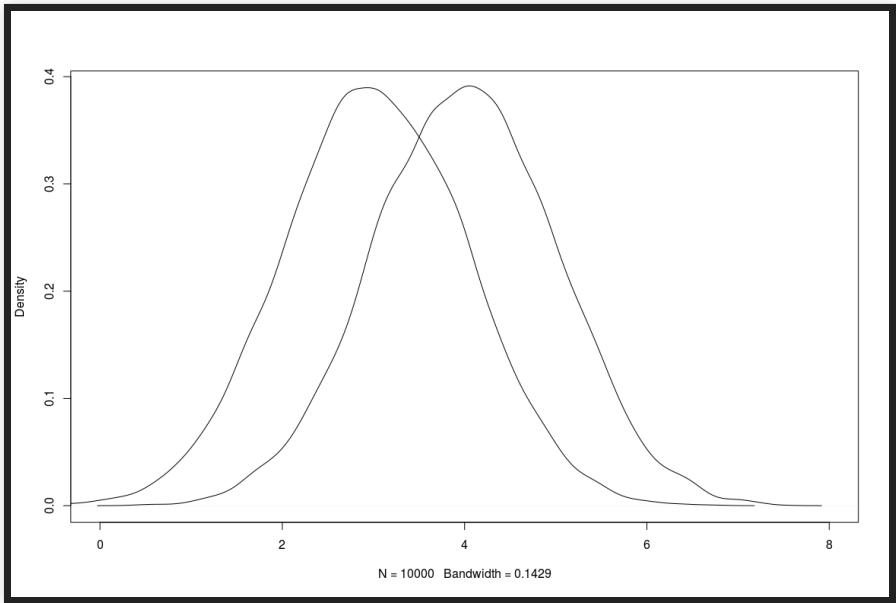
COMPARING DISTRIBUTIONS



DIFFERENT EFFECT SIZE, SAME DEVIATIONS



SAME EFFECT SIZE, DIFFERENT DEVIATIONS



Less noise --> Easier to recognize

DEPENDENT VS. INDEPENDENT MEASUREMENTS

- Pairwise (dependent) measurements
 - Before/after comparison
 - With same benchmark + environment
 - e.g., new operating system/disc drive faster
- Independent measurements
 - Repeated measurements
 - Input data regenerated for each measurement

SIGNIFICANCE LEVEL

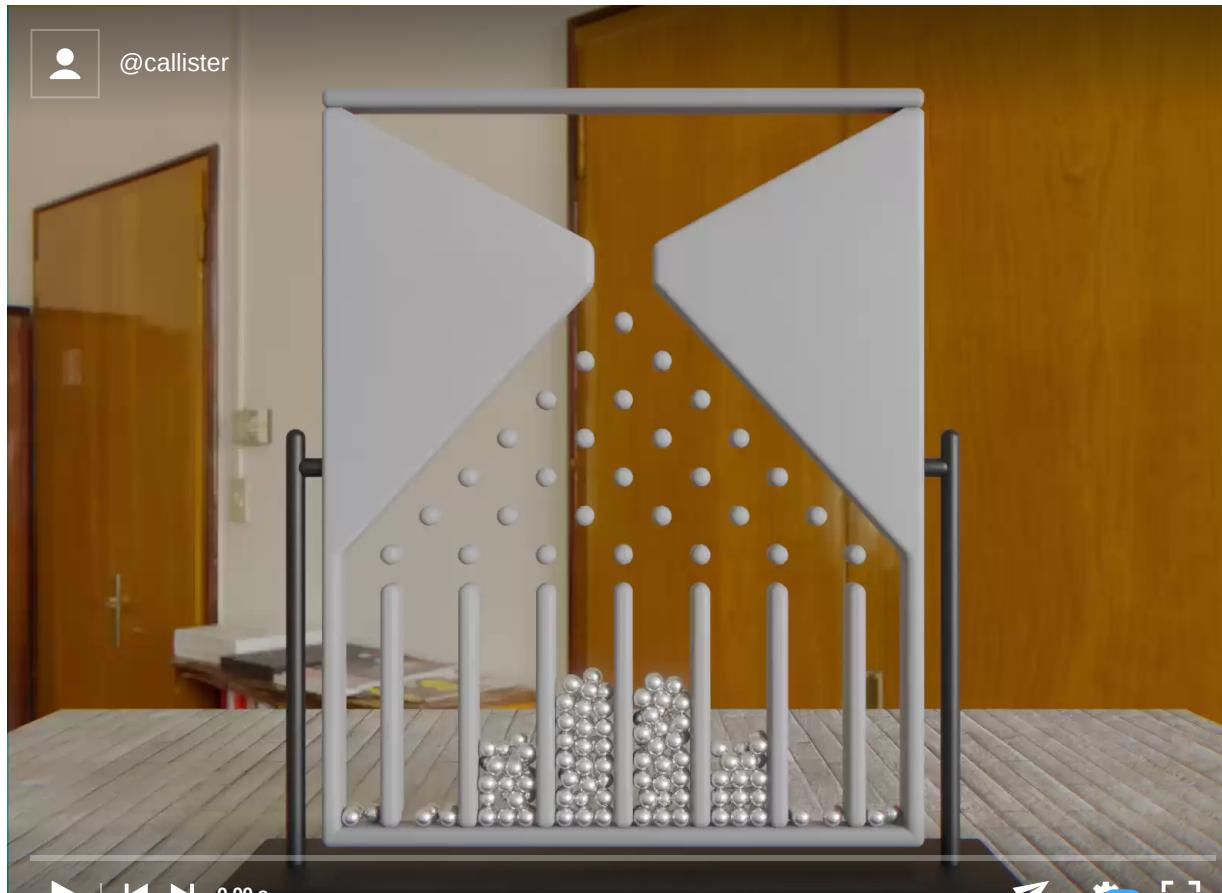
- Statistical change of an error
- Define before executing the experiment
 - use commonly accepted values
 - based on cost of a wrong decision
- Common:
 - 0.05 significant
 - 0.01 very significant
- Statistically significant result =!> proof
- Statistically significant result =!> important result
- Covers only alpha error (more later)

INTUITION: ERROR MODEL

- 1 random error, influence +/- 1
 - Real mean: 10
 - Measurements: 9 (50%) und 11 (50%)
-
- 2 random errors, each +/- 1
 - Measurements: 8 (25%), 10 (50%) und 12 (25%)
-
- 3 random errors, each +/- 1
 - Measurements : 7 (12.5%), 9 (37.5), 11 (37.5), 12 (12.5)



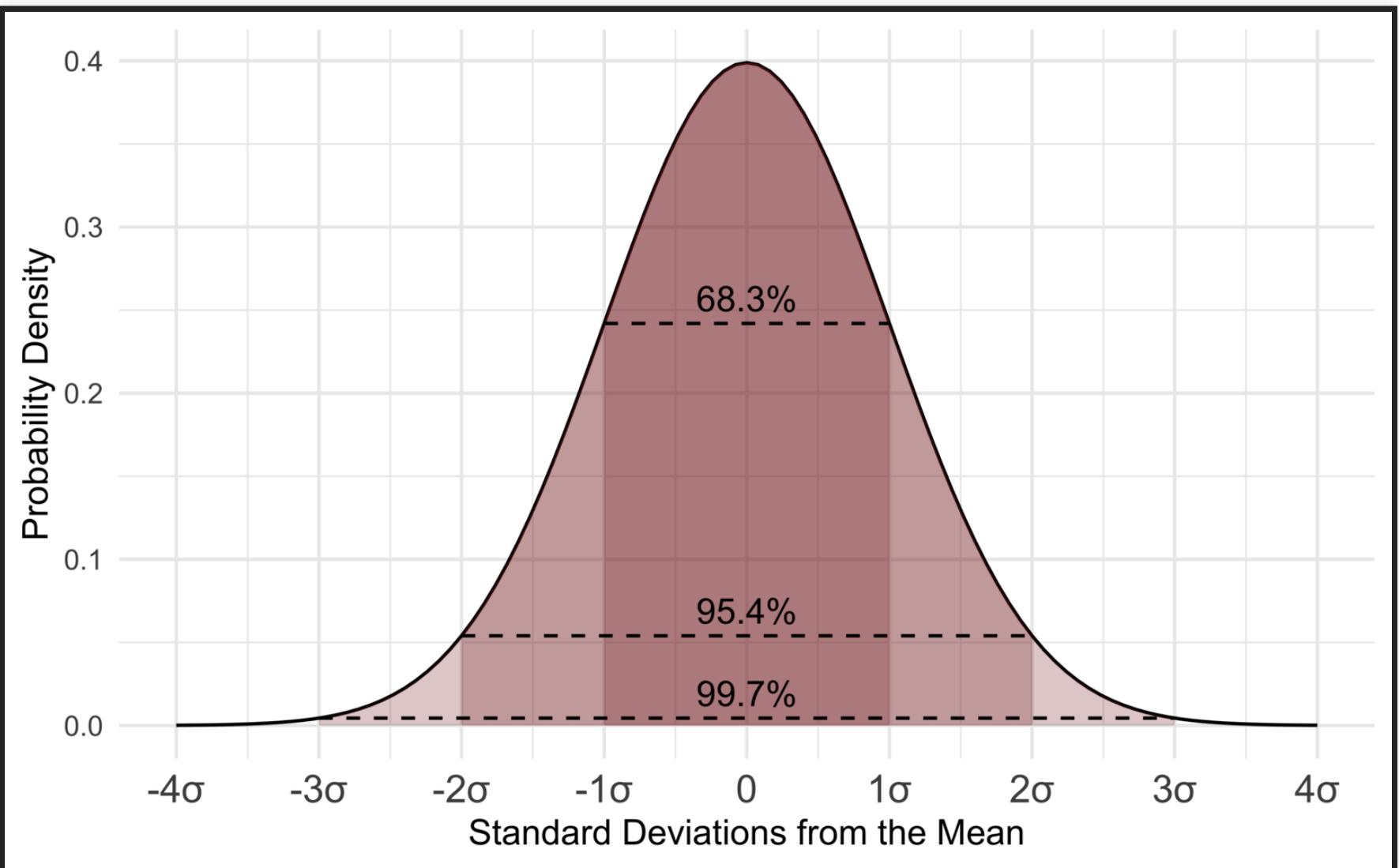
@callister



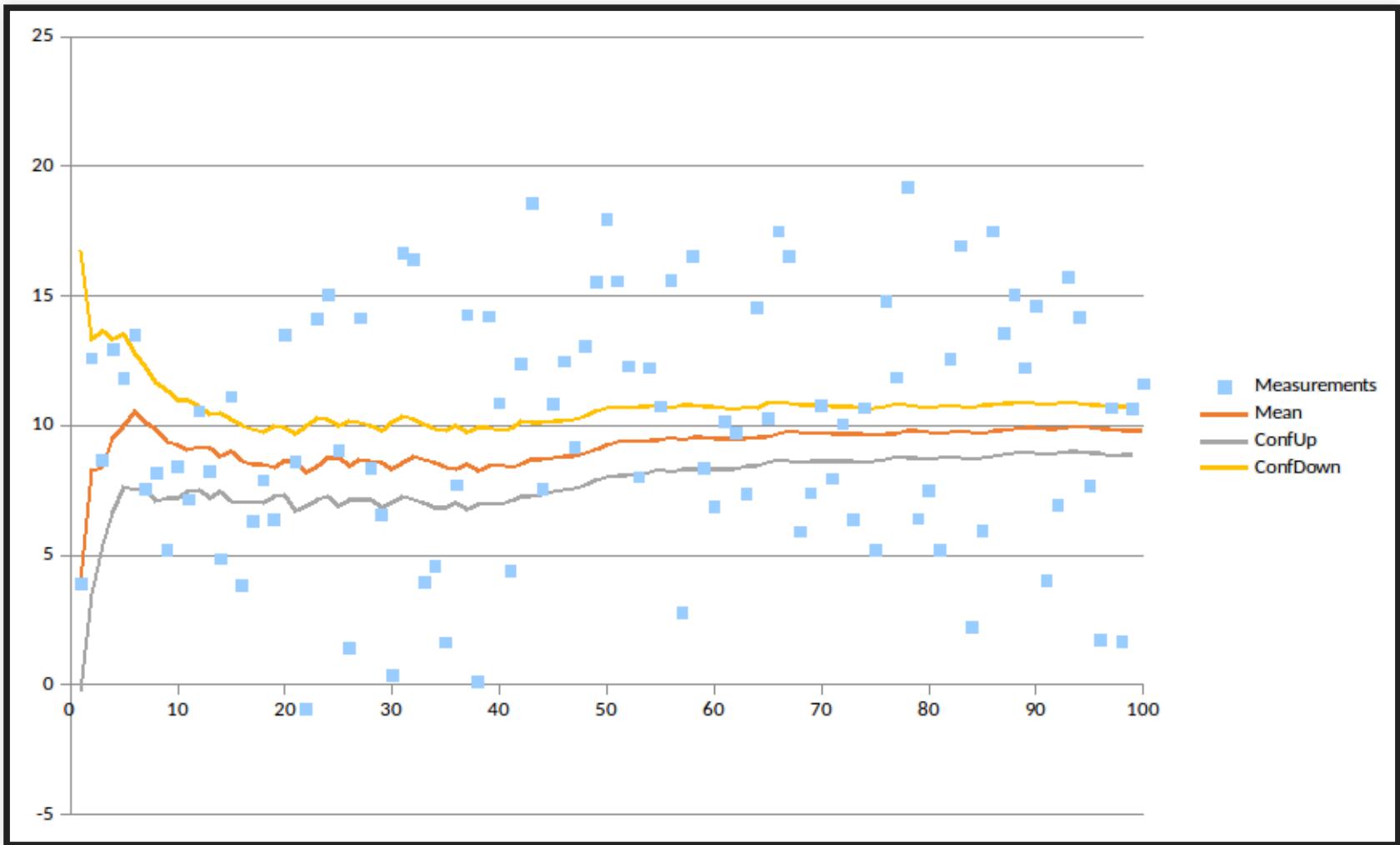
12.5K views

gfycat

NORMAL DISTRIBUTION

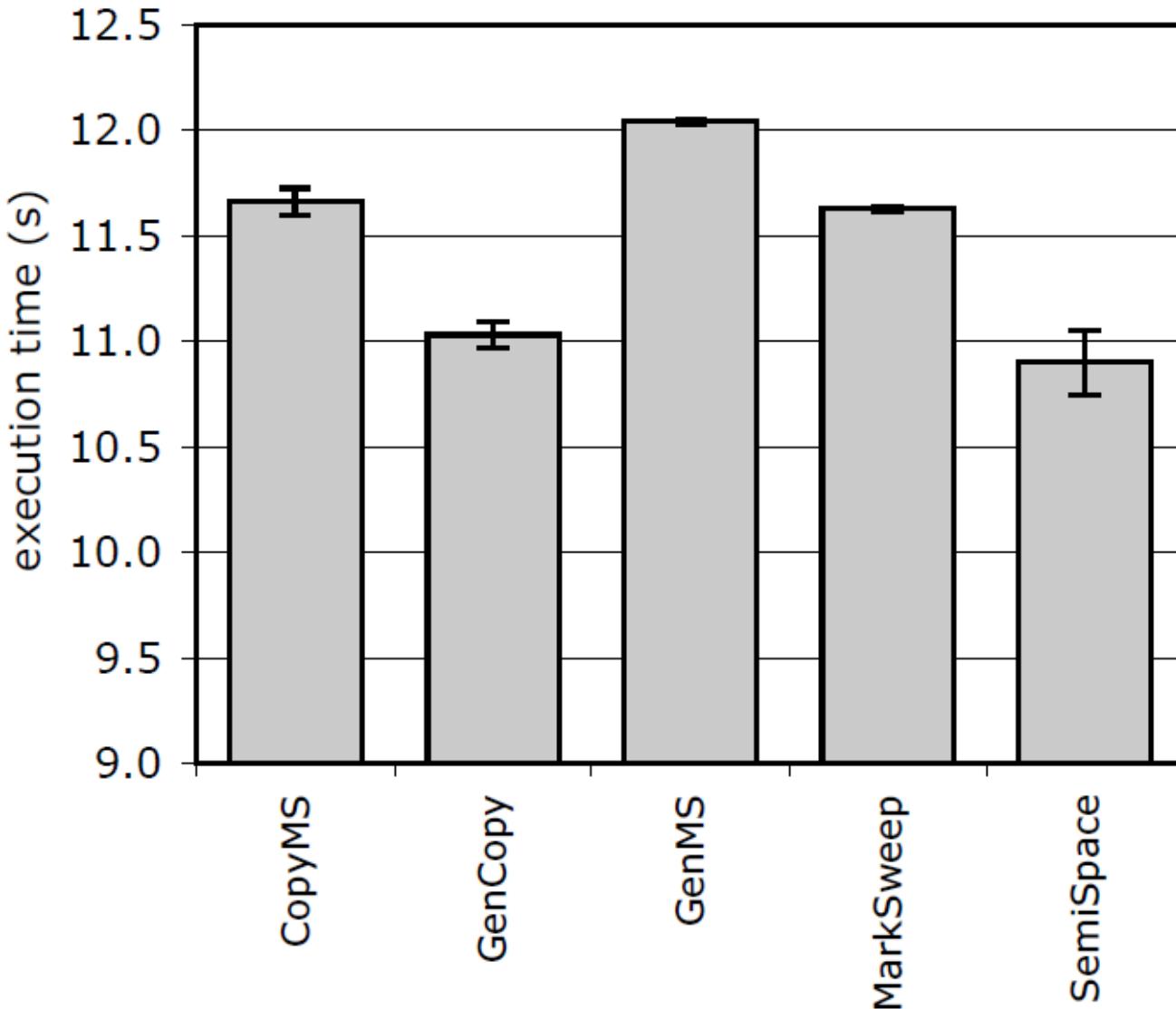


CONFIDENCE INTERVALS



COMPARISON WITH CONFIDENCE INTERVALS

mean w/ 95% confidence interval



T-TEST

```
> t.test(x, y, conf.level=0.9)

Welch Two Sample t-test

t = 1.9988, df = 95.801, p-value = 0.04846
alternative hypothesis: true difference in means is
not equal to 0
90 percent confidence interval:
 0.3464147 3.7520619
sample estimates:
mean of x mean of y
 51.42307 49.37383

> # paired t-test:
> t.test(x-y, conf.level=0.9)
```

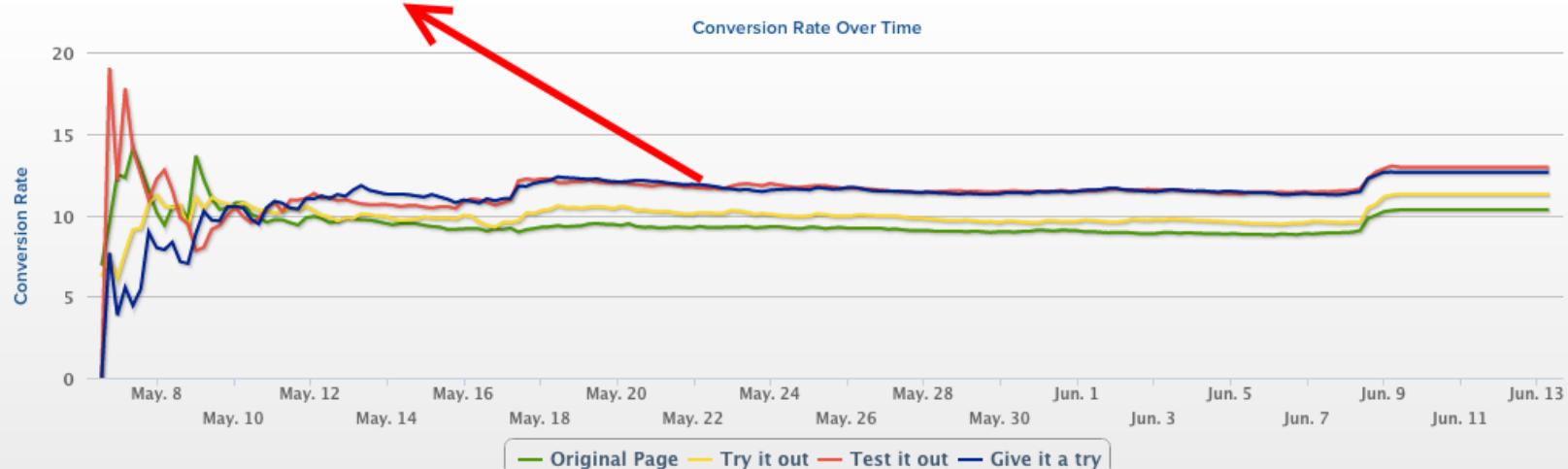
Experiment Created

[Edit](#) [Remove](#) [Delete](#)

✓ Test it out is beating Original Page by +25.4%.

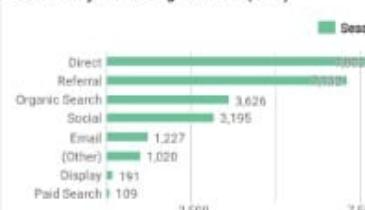
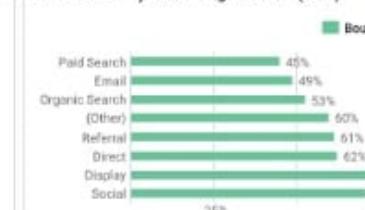
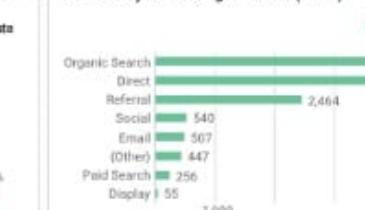
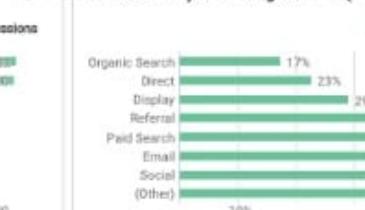
The percentage of visitors who clicked on a tracked element.

Variations	Conversions / Visitors	Conversion Rate	Baseline	Chance to beat Baseline	Improvement
Test it out	462 / 3,568	12.9% ($\pm 1.1\%$)		✓ 100.0%	+25.4%
Give it a try	440 / 3,479	12.6% ($\pm 1.1\%$)		✓ 99.9%	+22.5%
Try it out	395 / 3,504	11.3% ($\pm 1.0\%$)		90.2%	+9.2%
Original Page	378 / 3,662	10.3% ($\pm 1.0\%$)		---	---



Source: <https://conversionsciences.com/ab-testing-statistics/>

01/23/2017 - 01/31/2017

V1 (Old Design)		V2 (New Design)	
Sessions (OLD) 24,301	Pageviews (OLD) 59,987	Sessions (NEW) 13,091	Pageviews (NEW) 100,623
New Visitor vs Returning Visitor (OLD)	Pageviews Trend (OLD)	New Visitor vs Returning Visitor (NEW)	Pageviews Trend (NEW)
 New Visitor: 5,856 (24%) Returning Visitor: 18,445 (76%)	 Pageviews 5,000 01/11/2017 02/09/2017	 New Visitor: 1,009 (8%) Returning Visitor: 12,082 (92%)	 Pageviews 20,000 01/11/2017 02/09/2017
Bounce Rate (OLD) 62.19%	Time on Site in seconds (OLD) 187	Bounce Rate (NEW) 25.03%	Time on Site in seconds (NEW) 443
Pages / Session (OLD) 2.47	Sessions w. Search (OLD) 5.61%	Pages / Session (NEW) 7.69	Sessions w. Search (NEW) 42.23%
List Through Rate (OLD) 2.10%	Contact Through Rate (OLD) 4.12%	List Through Rate (NEW) 2.09%	Contact Through Rate (NEW) 5.43%
Sessions by Marketing Channel (OLD)	Bounce Rate by Marketing Channel (OLD)	Sessions by Marketing Channel (NEW)	Bounce Rate by Marketing Channel (NEW)
 Sessions Direct: 18,445 Referral: 3,195 Organic Search: 3,626 Social: 3,195 Email: 1,227 (Other): 1,020 Display: 191 Paid Search: 109 2,500 7,500	 Bounce Rate Paid Search: 45% Email: 49% Organic Search: 53% (Other): 60% Referral: 61% Direct: 62% Display: 74% Social: 75% 25% 75%	 Sessions Organic Search: 13,091 Direct: 12,082 Referral: 2,464 Social: 540 Email: 507 (Other): 447 Paid Search: 256 Display: 55 1,000 4,000	 Bounce Rate Organic Search: 17% Direct: 23% Display: 29% Referral: 33% Paid Search: 36% Email: 36% Social: 40% (Other): 42% 10% 40%
Sessions by Landing Page (OLD)	Bounce Rate by Landing Page (OLD)	Sessions by Landing Page (NEW)	Bounce Rate by Landing Page (NEW)
LANDING PAGE GROUP 1 VIP: 14,792 eVIP: 3,206 Homepage: 2,464 ActivateAdSuccess: 1,080	SESSIONS Login: 21.05% ResultsBrowse: 23.77% Homepage: 30.32% ResultsSearch: 35.31% (NULL): 49.32%	SESSIONS VIP: 4,329 Homepage: 2,582 ResultsSearch: 2,666 ResultsBrowse: 1,598	SESSIONS UserRegistrationForm: 0.00% EditAdForm: 4.39% Homepage: 6.94% Login: 14.47% MyAds: 15.15%
Search Pages / Session (OLD)	Search Pageviews Trend (OLD)	Search Pages / Session (NEW)	Search Pageviews Trend (NEW)

HOW MANY SAMPLES NEEDED?

Too few?

Too many?



A/B TESTING AUTOMATION

- Experiment configuration through DSLs/scripts
- Queue experiments
- Stop experiments when confident in results
- Stop experiments resulting in bad outcomes (crashes, very low sales)
- Automated reporting, dashboards

Further readings:

- Tang, Diane, et al. [Overlapping experiment infrastructure: More, better, faster experimentation.](#)
Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining.
ACM, 2010. (Google)
- Bakshy, Eytan, Dean Eckles, and Michael S. Bernstein. [Designing and deploying online field experiments.](#)
Proceedings of the 23rd International Conference on World Wide Web. ACM, 2014. (Facebook)

DSL FOR SCRIPTING A/B TESTS AT FACEBOOK

```
button_color = uniformChoice(  
    choices=['#3c539a', '#5f9647', '#b33316'],  
    unit=cookieid);  
  
button_text = weightedChoice(  
    choices=['Sign up', 'Join now'],  
    weights=[0.8, 0.2],  
    unit=cookieid);  
  
if (country == 'US') {  
    has_translate = bernoulliTrial(p=0.2, unit=userid);  
} else {  
    has_translate = bernoulliTrial(p=0.05, unit=userid);  
}
```

Further readings:

- Bakshy, Eytan, Dean Eckles, and Michael S. Bernstein. [Designing and deploying online field experiments](#). Proceedings of the 23rd International Conference on World Wide Web. ACM, 2014. (Facebook)

CONCURRENT A/B TESTING

- Multiple experiments at the same time
 - Independent experiments on different populations -- interactions not explored
 - Multi-factorial designs, well understood but typically too complex, e.g., not all combinations valid or interesting
 - Grouping in sets of experiments

Further readings:

- Tang, Diane, et al. [Overlapping experiment infrastructure: More, better, faster experimentation.](#)
Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining.
ACM, 2010. (Google)
- Bakshy, Eytan, Dean Eckles, and Michael S. Bernstein. [Designing and deploying online field experiments.](#)
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OTHER EXPERIMENTS IN PRODUCTION

- Shadow releases / traffic teeing
- Blue/green deployment
- Canary releases
- Chaos experiments

SHADOW RELEASES / TRAFFIC TEEING

- Run both models in parallel
- Report outcome of old model
- Compare differences between model predictions
- If possible, compare against ground truth labels/telemetry

Examples?

BLUE/GREEN DEPLOYMENT

- Provision service both with old and new model (e.g., services)
- Support immediate switch with load-balancer
- Allows to undo release rapidly

Advantages/disadvantages?

CANARY RELEASES

- Release new version to small percentage of population (like A/B testing)
- Automatically roll back if quality measures degrade
- Automatically and incrementally increase deployment to 100% otherwise



CHAOS EXPERIMENTS



CHAOS EXPERIMENTS FOR AI COMPONENTS?



Speaker notes

Artifically reduce model quality, add delays, insert bias, etc to test monitoring and alerting infrastructure

ADVICE FOR EXPERIMENTING IN PRODUCTION

- Minimize *blast radius* (canary, A/B, chaos expr)
- Automate experiments and deployments
- Allow for quick rollback of poor models (continuous delivery, containers, loadbalancers, versioning)
- Make decisions with confidence, compare distributions
- Monitor, monitor, monitor

MLOps



<https://ml-ops.org/>

ON TERMINOLOGY

- Many vague buzzwords, often not clearly defined
- *MLOps*: Collaboration and communication between data scientists and operators, e.g.,
 - Automate model deployment
 - Model training and versioning infrastructure
 - Model deployment and monitoring
- *AIOps*: Using AI/ML to make operations decision, e.g. in a data center
- *DataOps*: Data analytics, often business setting and reporting
 - Infrastructure to collect data (ETL) and support reporting
 - Monitor data analytics pipelines
 - Combines agile, DevOps, Lean Manufacturing ideas

MLOPS OVERVIEW

- Integrate ML artifacts into software release process, unify process
- Automated data and model validation (continuous deployment)
- Data engineering, data programming
- Continuous deployment for ML models
 - From experimenting in notebooks to quick feedback in production
- Versioning of models and datasets
- Monitoring in production

Further reading: [MLOps principles](#)

BONUS: MONITORING WITHOUT GROUND TRUTH

INVARIANTS/ASSERTIONS TO ASSURE WITH TELEMETRY

- Consistency between multiple sources
 - e.g., multiple models agree, multiple sensors agree
 - e.g., text and image agree
- Physical domain knowledge
 - e.g., cars in video shall not flicker,
 - e.g., earthquakes should appear in sensors grouped by geography
- Domain knowledge about unlikely events
 - e.g., unlikely to have 3 cars in same location
- Stability
 - e.g., object detection should not change with video noise
- Input conforms to schema (e.g. boolean features)
- And all invariants from model quality lecture, including capabilities

Kang, Daniel, Deepti Raghavan, Peter Bailis, and Matei Zaharia. "Model Assertions for Monitoring and Improving ML Model." In Proceedings of MLSys 2020.

SUMMARY

- Production data is ultimate unseen validation data
- Telemetry is key and challenging (design problem and opportunity)
- Monitoring and dashboards
- Many forms of experimentation and release (A/B testing, shadow releases, canary releases, chaos experiments, ...) to minimize "blast radius"
- Gain confidence in results with statistical tests
- MLOps: DevOps-like infrastructure to support data scientists

