# 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

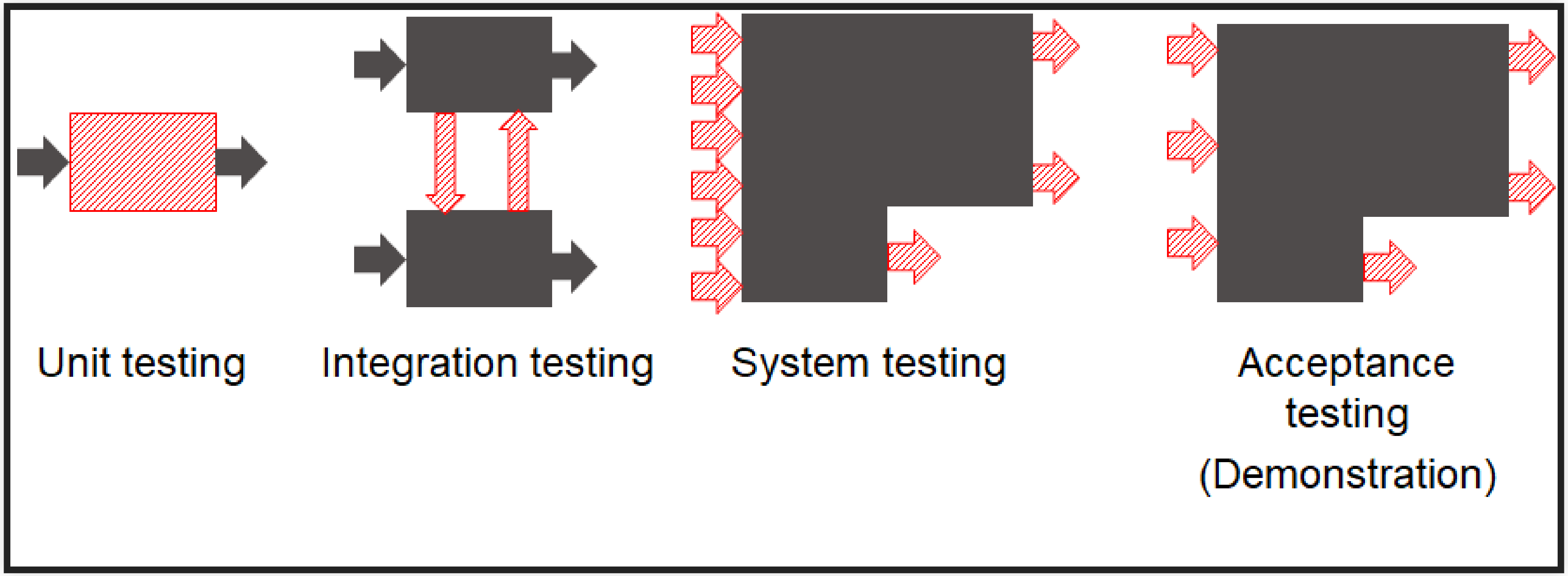
# LEARNING GOALS

- 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

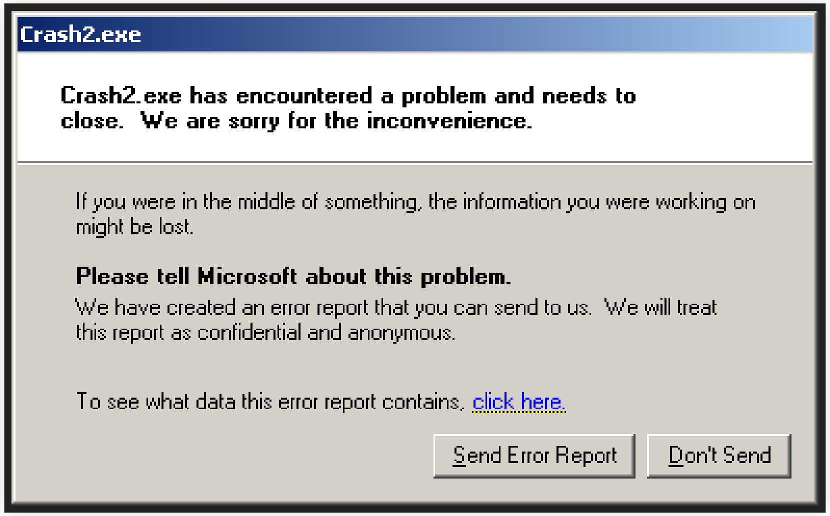
Testing before release. Manual or automated.

# BETA TESTING

Speaker notes

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

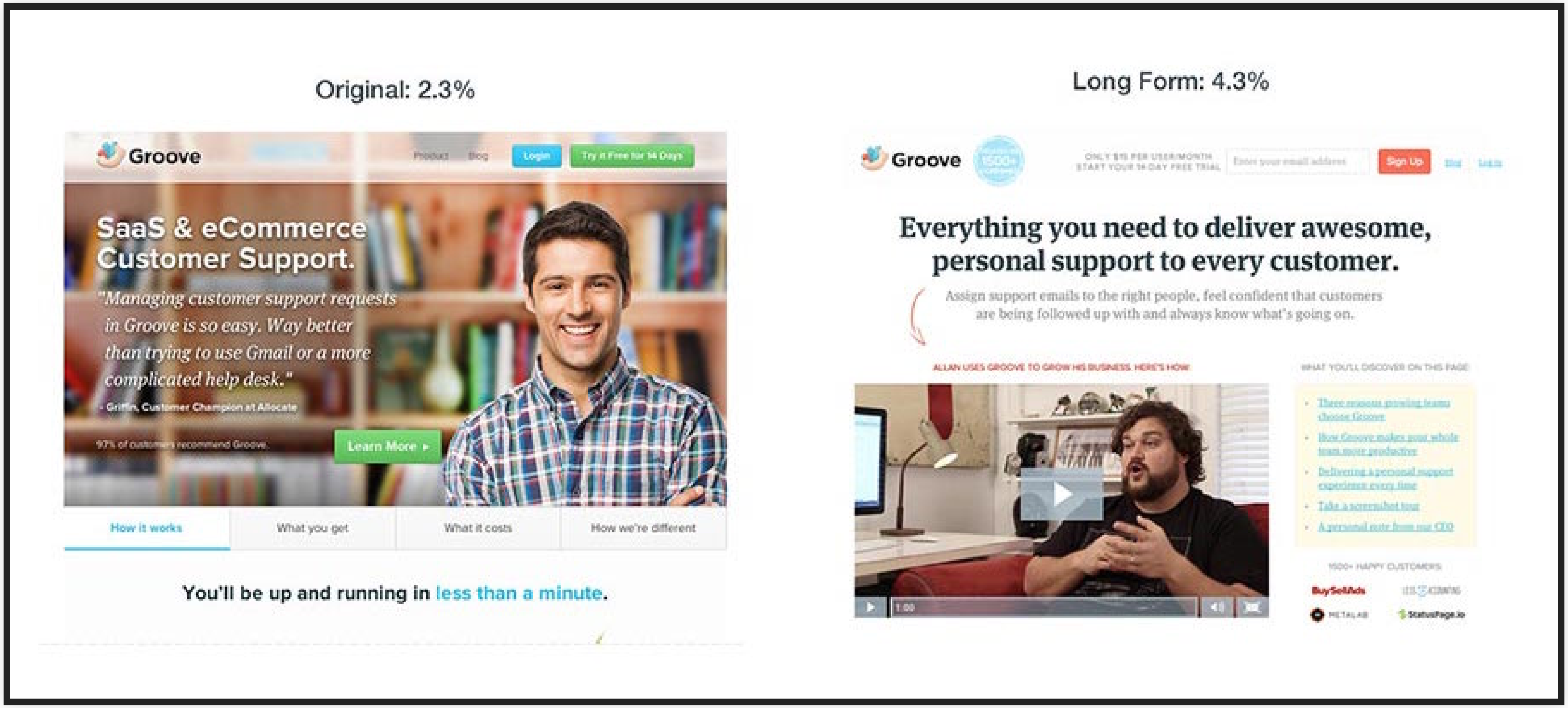
# CRASH TELEMETRY



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



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Long Form: 4.3%
Groove
SaaS & eCommerce Customer Support.
"Managing customer support requests in Groove is so easy. Way better than trying to use Gmail or a more complicated help desk."
- Griffin, Customer Champion at Allocate
Learn More
How it works
What you get
What it costs
How we're different
You'll be up and running in less than a minute.
Groove
Sign Up
Everything you need to deliver awesome, personal support to every customer.
Assign support emails to the right people, feel confident that customers are being followed up with and always know what's going on.
ALLAN USES GROOVE TO GROW HIS BUSINESS. HERE'S HOW
WHAT YOU'LL DISCOVER ON THIS PAGE
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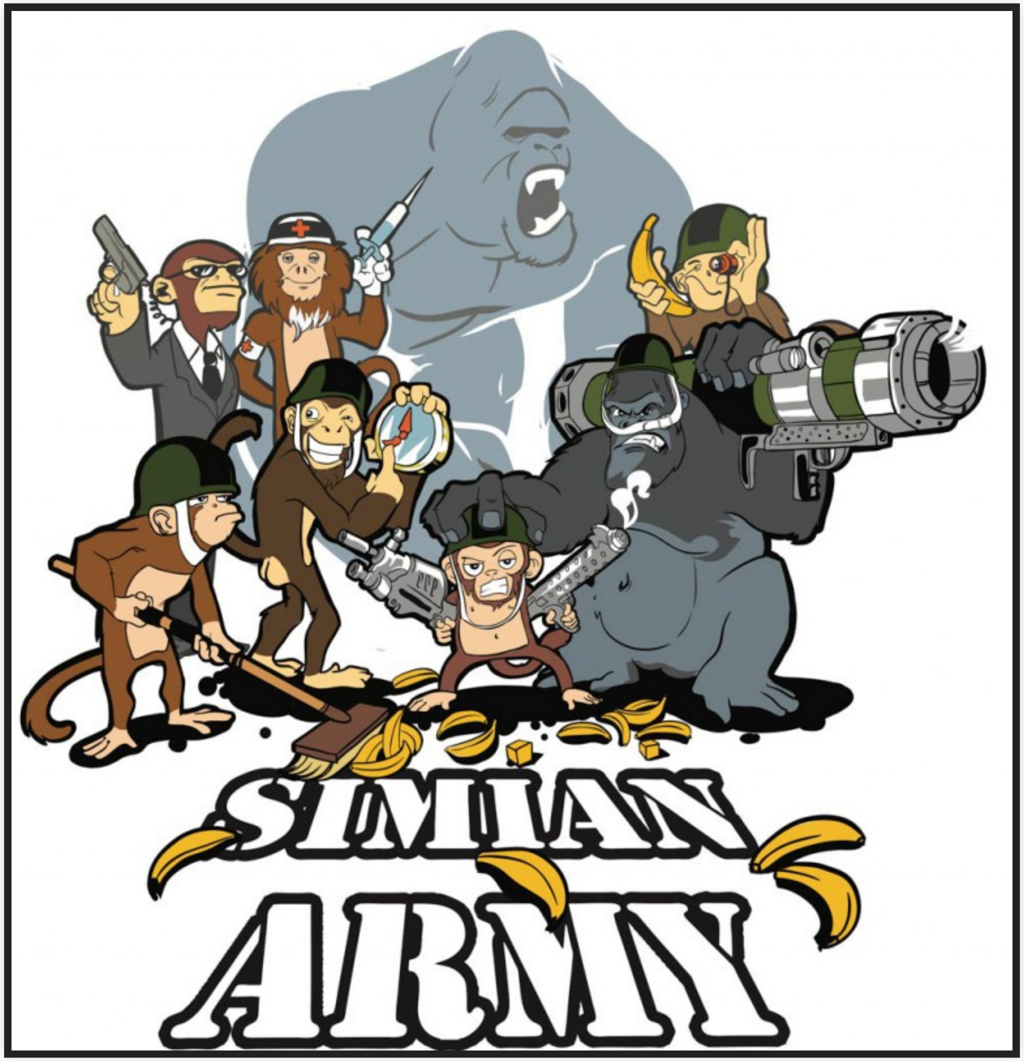
Delivering a personal support experience every time
Take a screenshot tour
A personal note from our CEO
1500+ HAPPY CUSTOMERS
BuySellAds
StatusPage.io

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

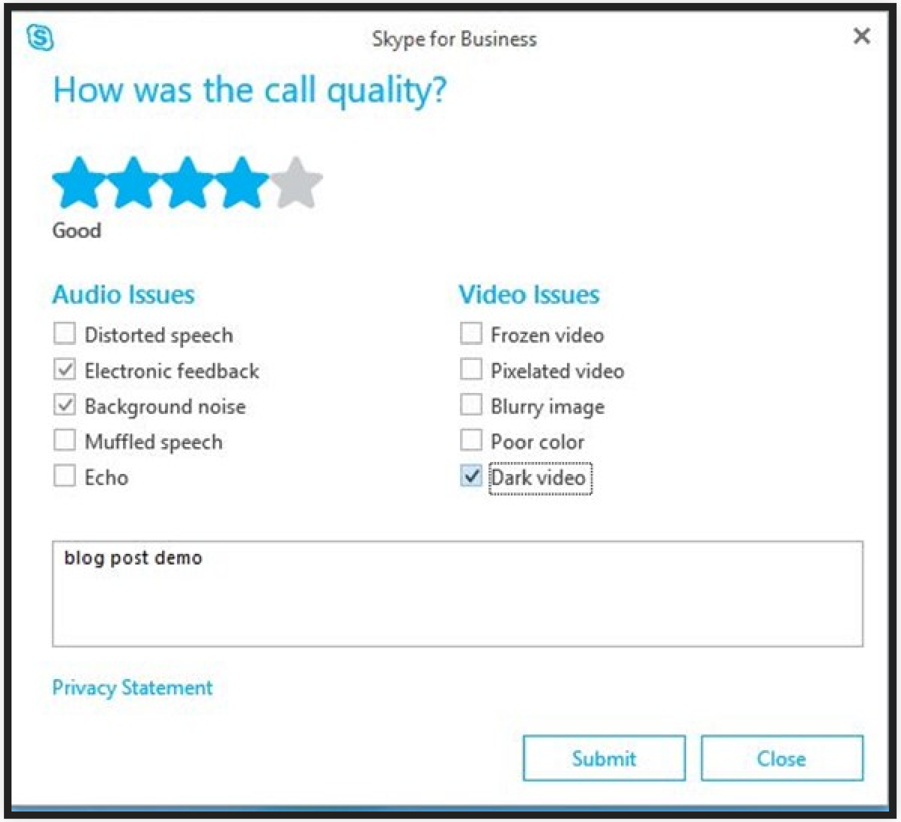
# DISCUSS HOW TO COLLECT FEEDBACK

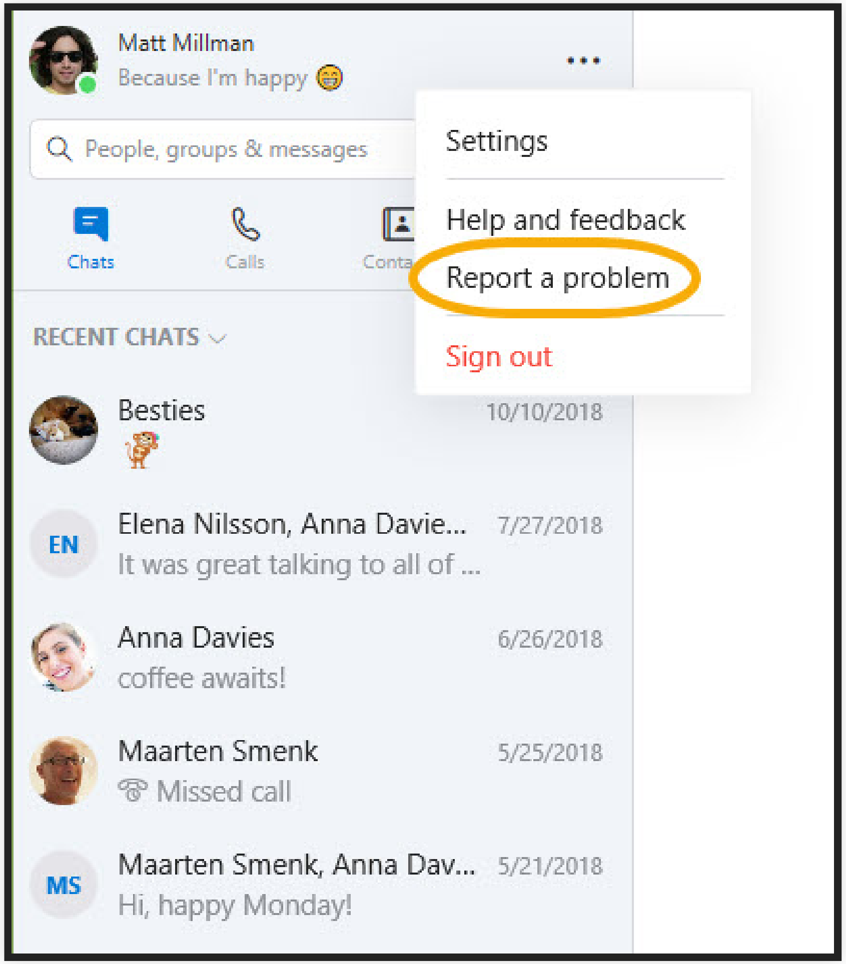
- Was the house price predicted correctly?
- Did the profanity filter remove the right blog comments?
- Was there cancer in the image?
- Was a Spotify playlist good?
- Was the ranking of search results good?
- Was the weather prediction good?
- Was the translation correct?
- Did the self-driving car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

Speaker notes

More:

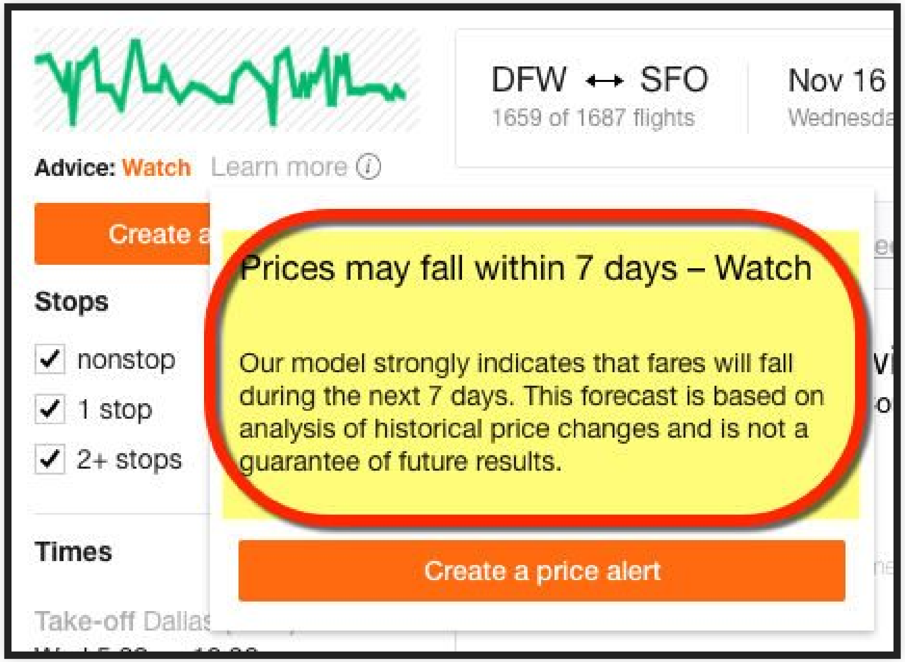
- SmartHome: Does it automatically turn of the lights/lock the doors/close the window at the right time?
- Profanity filter: Does it block the right blog comments?
- News website: Does it pick the headline alternative that attracts a user’s attention most?
- Autonomous vehicles: Does it detect pedestrians 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
People, groups & messages
Chats
Calls
Settings
Help and feedback
Report a problem
Sign out
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 Dav...
5/21/2018
Hi, happy Monday!

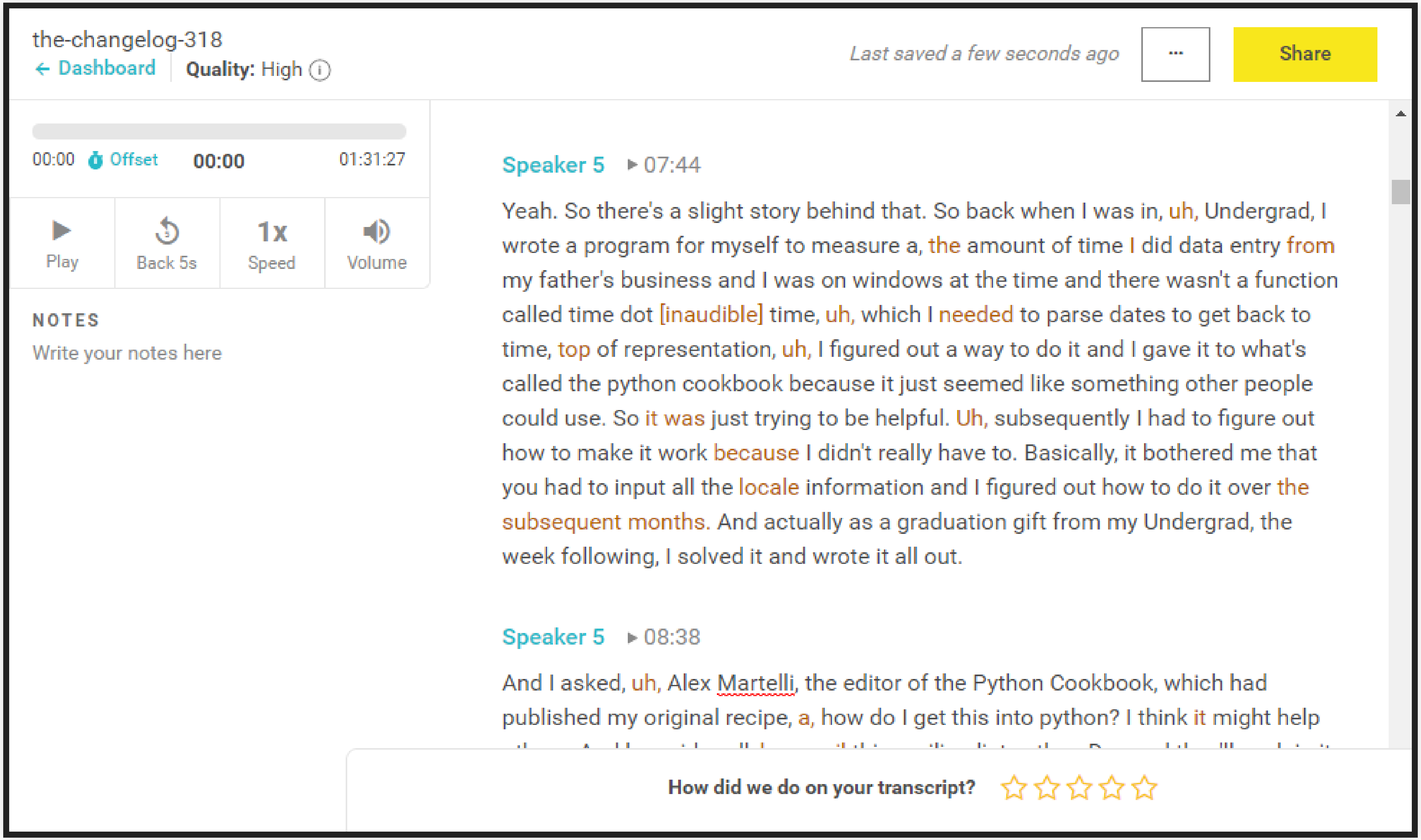
Speaker notes

Expect only sparse feedback and expect negative feedback over-proportionally


DFW ↔ SFO
1659 of 1687 flights
Nov 16
Advice: Watch
Learn more
Stops
nonstop
1 stop
2+ stops
Times
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.
Create a price alert

Speaker notes

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


the-changelog-318
← Dashboard
Quality: High
Last saved a few seconds ago
···
Share
00:00
Offset
00:00
01:31:27
Play
Back 5s
1x
Speed
Volume
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

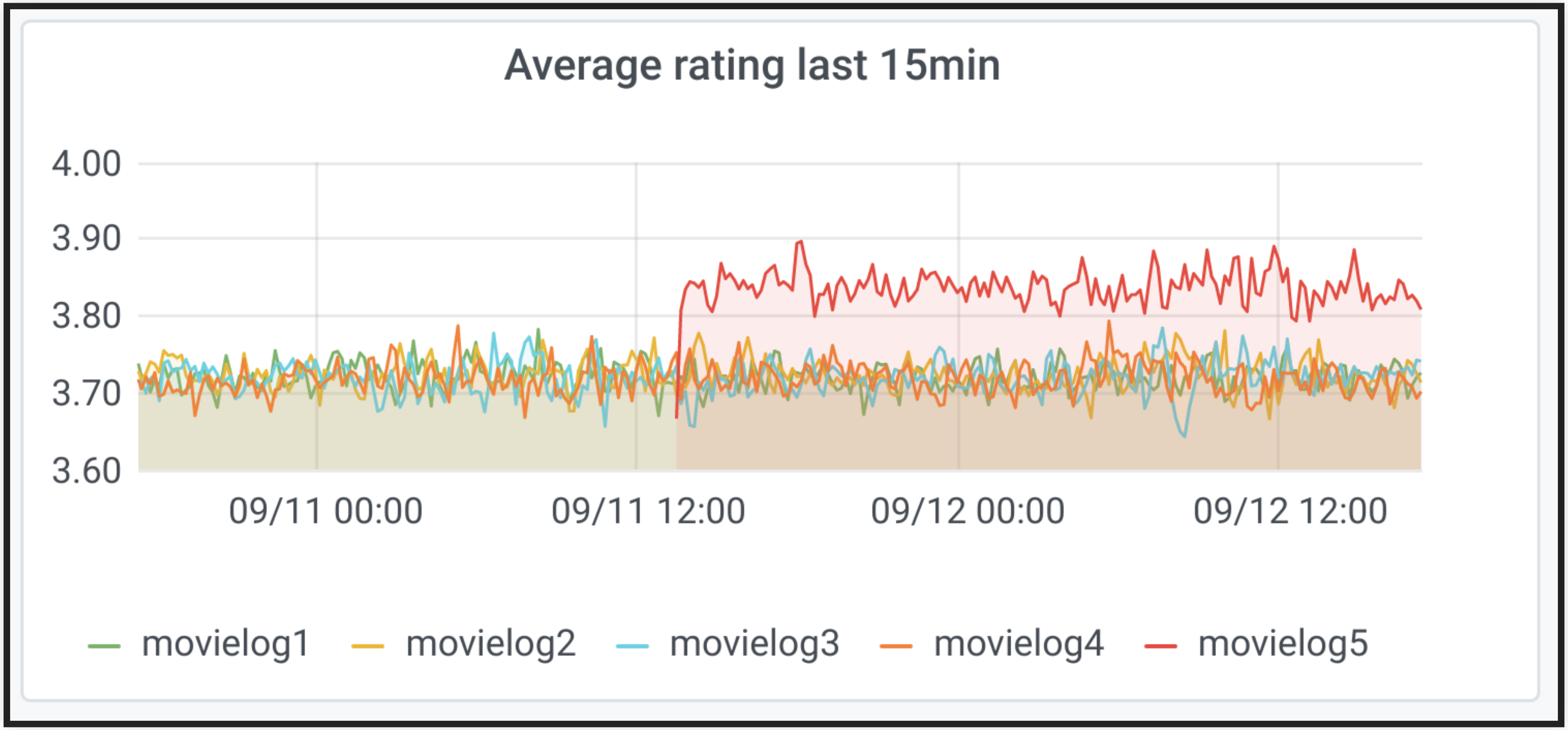
Summarize results on a slide

# MEASURING MODEL QUALITY WITH TELEMETRY

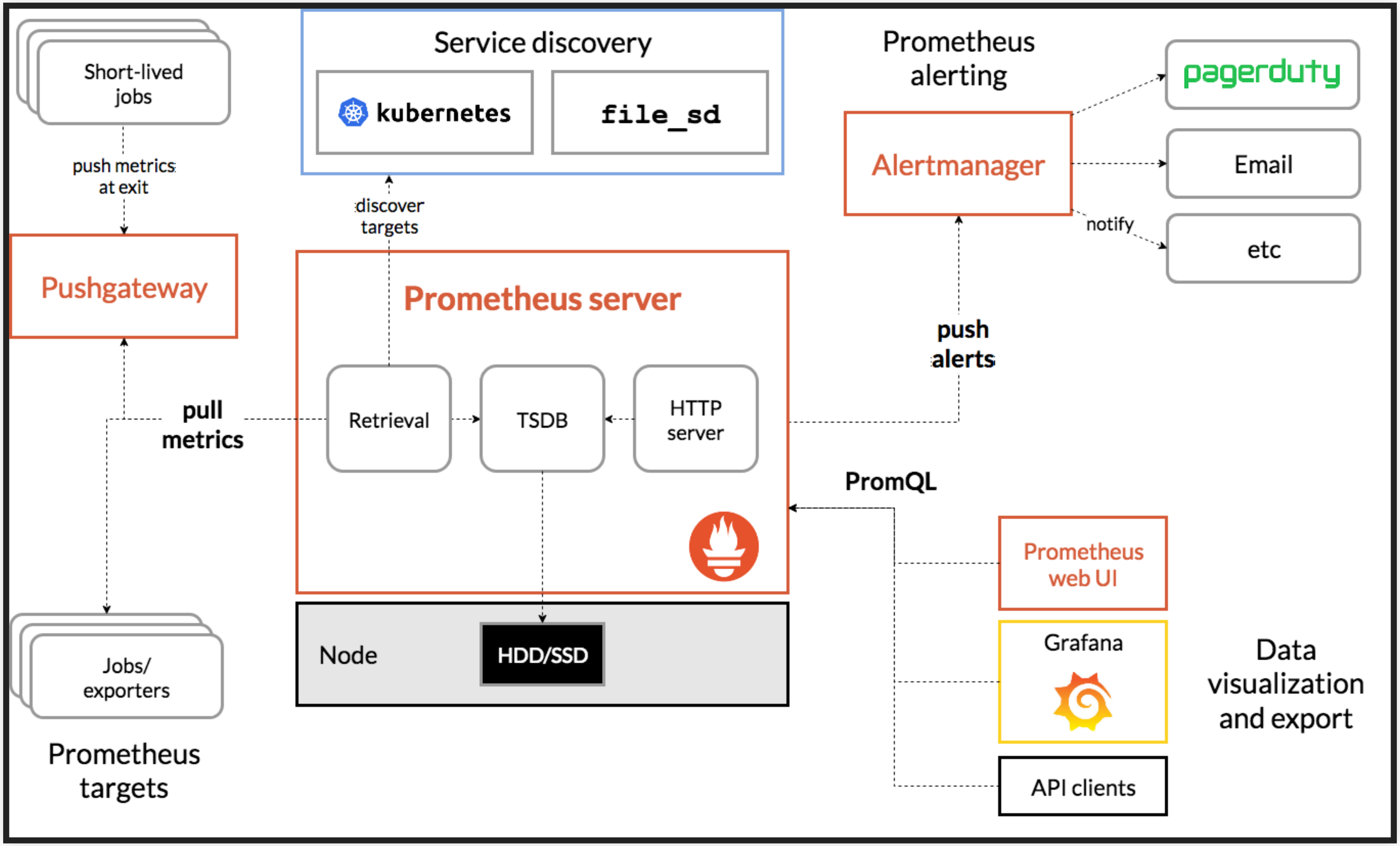
- Three steps:
  - Metric: Identify quality of concern
  - Telemetry: Describe data collection procedure
  - Operationalization: Measure quality metric in terms of data
- Telemetry can provide insights for correctness
  - sometimes very accurate labels for real unseen data
  - sometimes only mistakes
  - 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

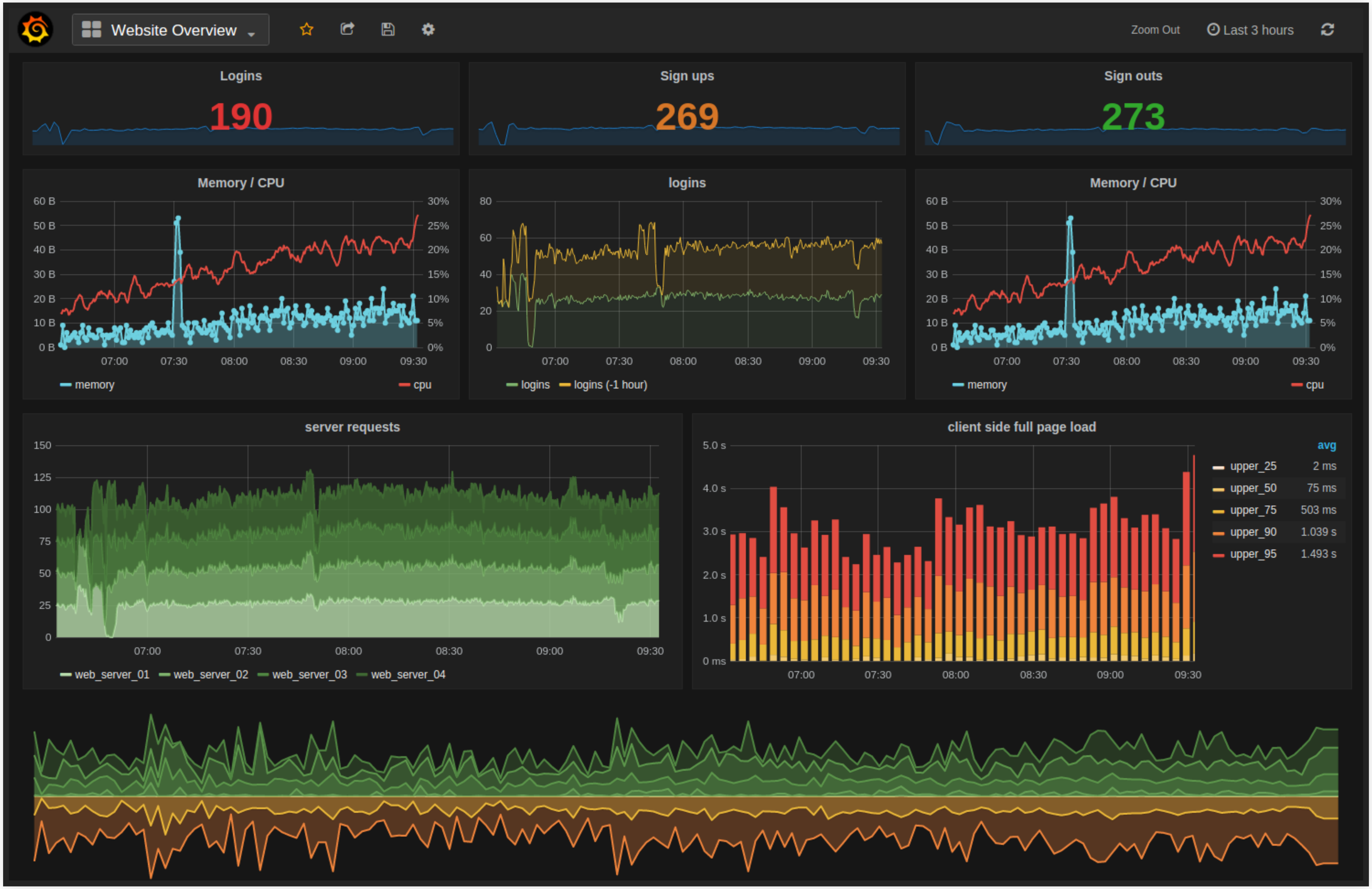
# MONITORING MODEL QUALITY IN PRODUCTION

- 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
4.00
3.90
3.80
3.70
3.60
09/11 00:00
09/11 12:00
09/12 00:00
09/12 12:00
movielog1
movielog2
movielog3
movielog4
movielog5

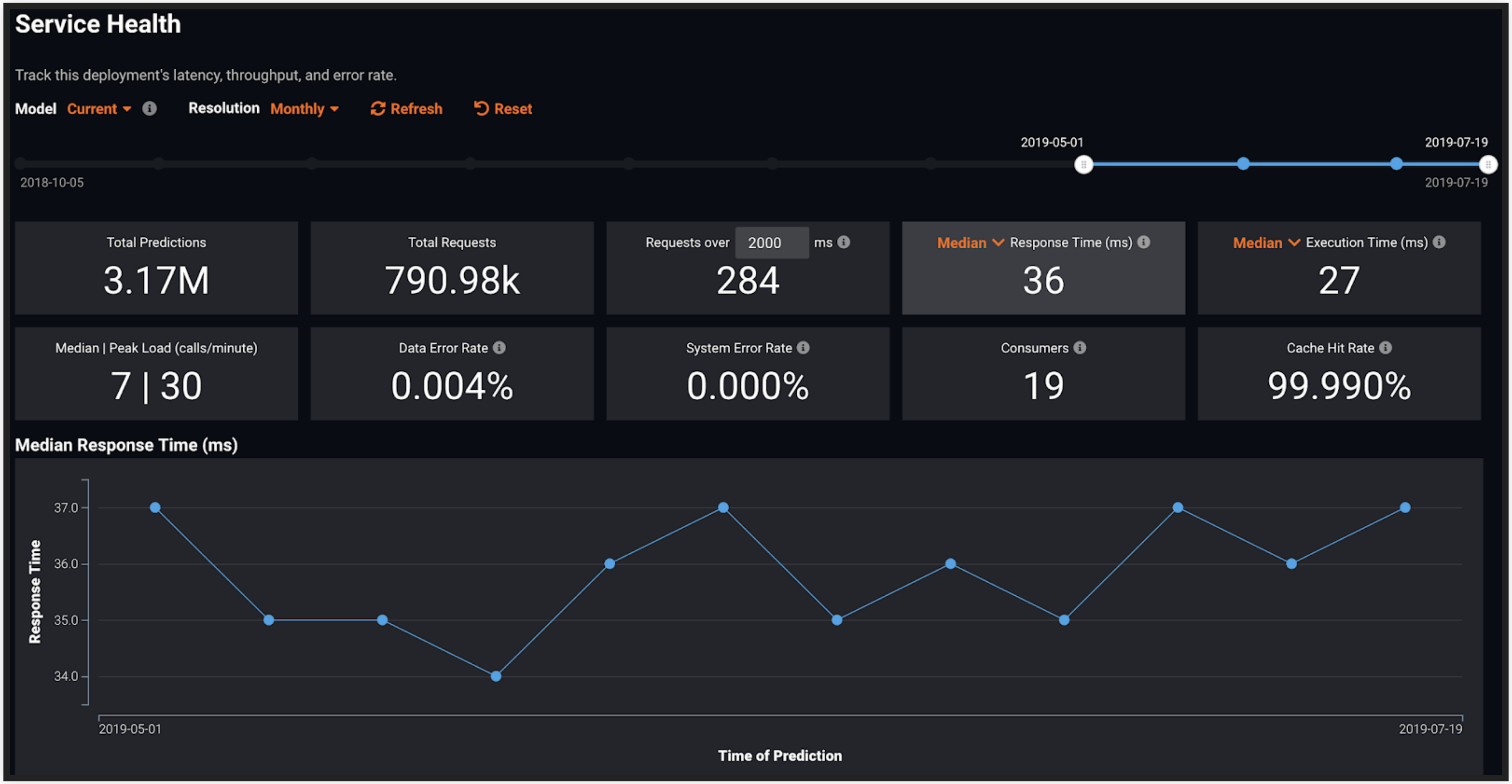
# PROMETHEUS AND GRAFANA





Website Overview
Zoom Out
Last 3 hours
Logins
190
Sign ups
269
Sign outs
273
Memory / CPU
memory
cpu
logins
logins
logins (-1 hour)
Memory / CPU
memory
cpu
server requests
web_server_01
web_server_02
web_server_03
web_server_04
client side full page load
avg
upper_25 2 ms
upper_50 75 ms
upper_75 503 ms
upper_90 1.039 s
upper_95 1.493 s

# 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

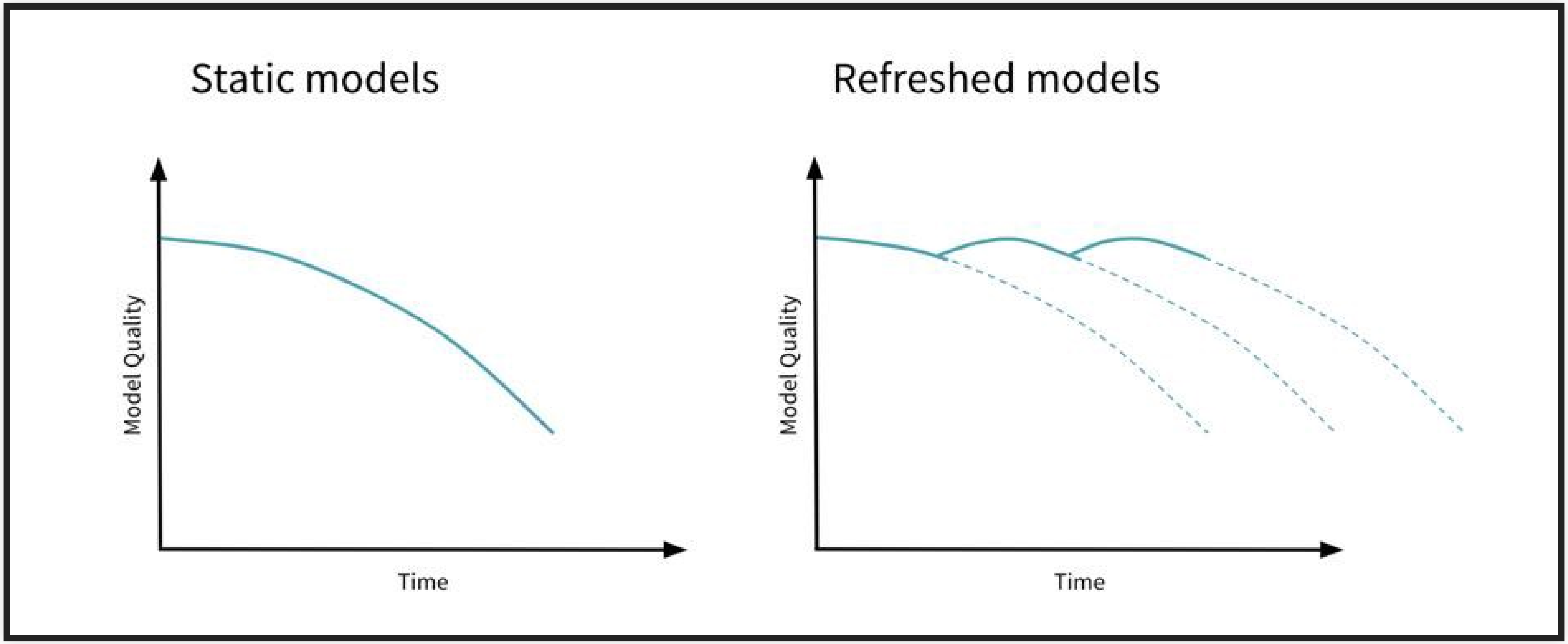



Image source: Joel Thomas and Clemens Mewald. Productionizing Machine Learning: From Deployment to Drift Detection. Databricks Blog, 2019

# ENGINEERING CHALLENGES FOR TELEMETRY

techradar

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

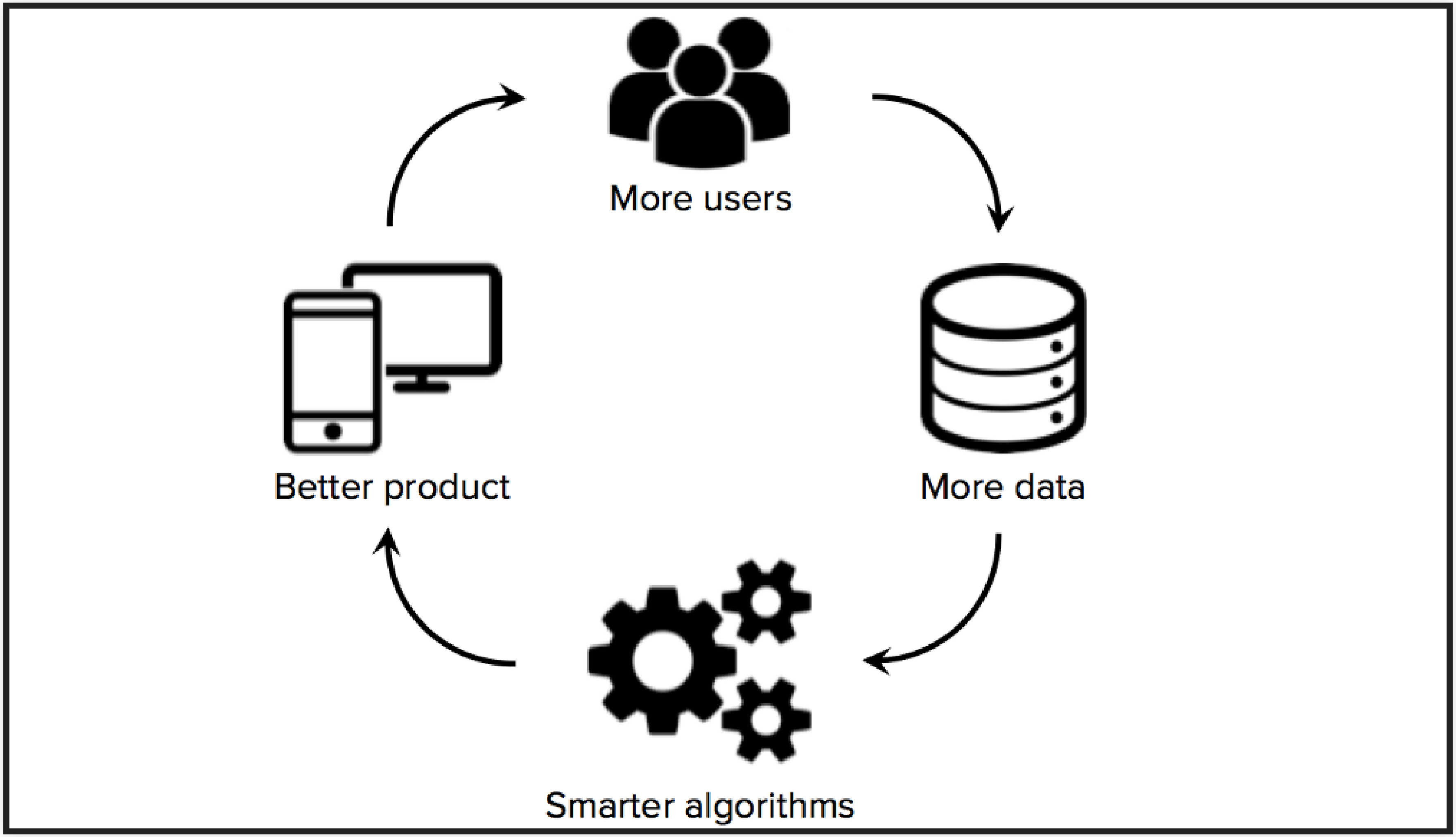
Discuss: Quality measure, telemetry, operationalization, false positives/negatives, cost, privacy, rare events

Scenarios:

- Group 1: Amazon: Shopping app feature that detects the shoe brand from photos
- 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

# TELEMETRY FOR TRAINING: THE ML FLYWHEEL



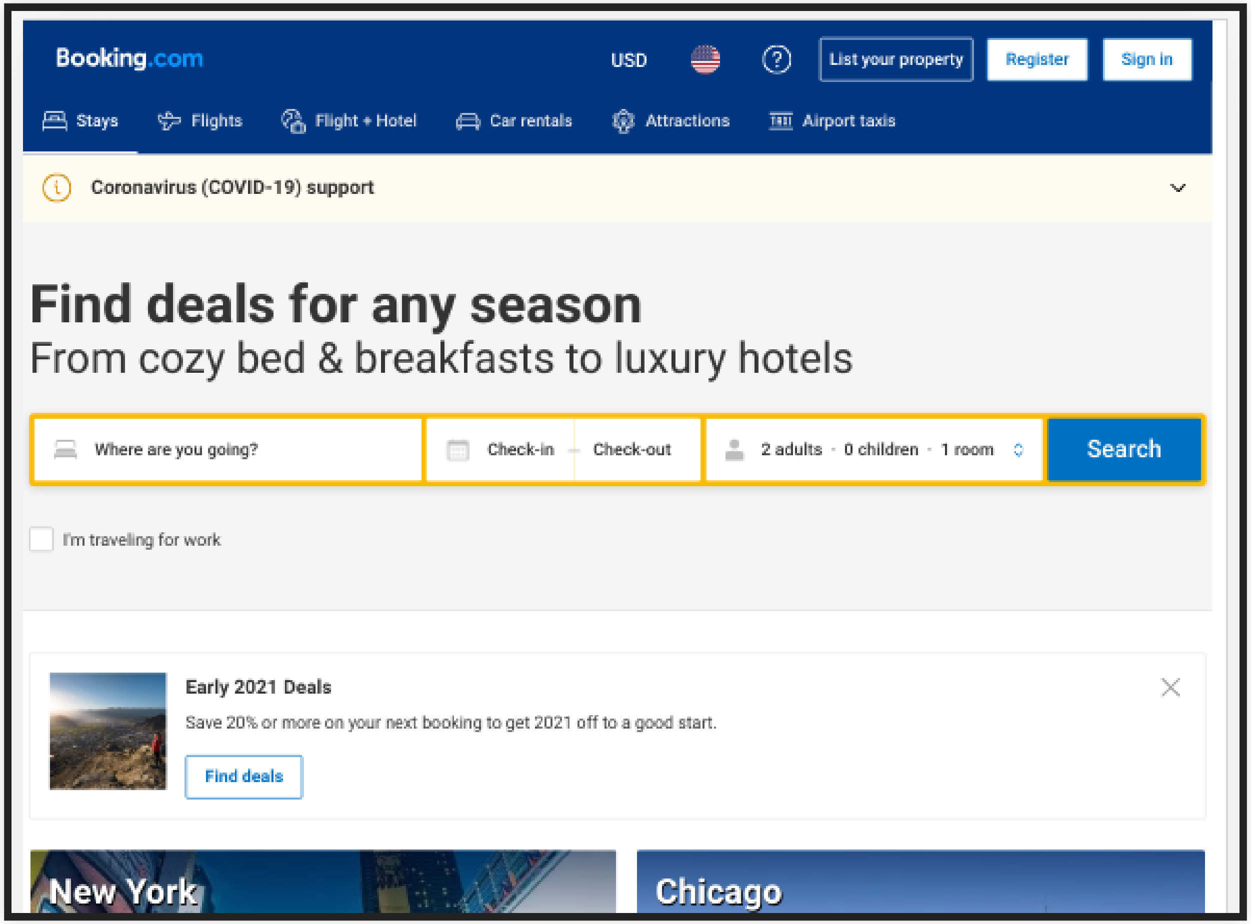

graphic by CBInsights

# MODEL QUALITY VS SYSTEM GOALS

# MODEL QUALITY VS SYSTEM GOALS

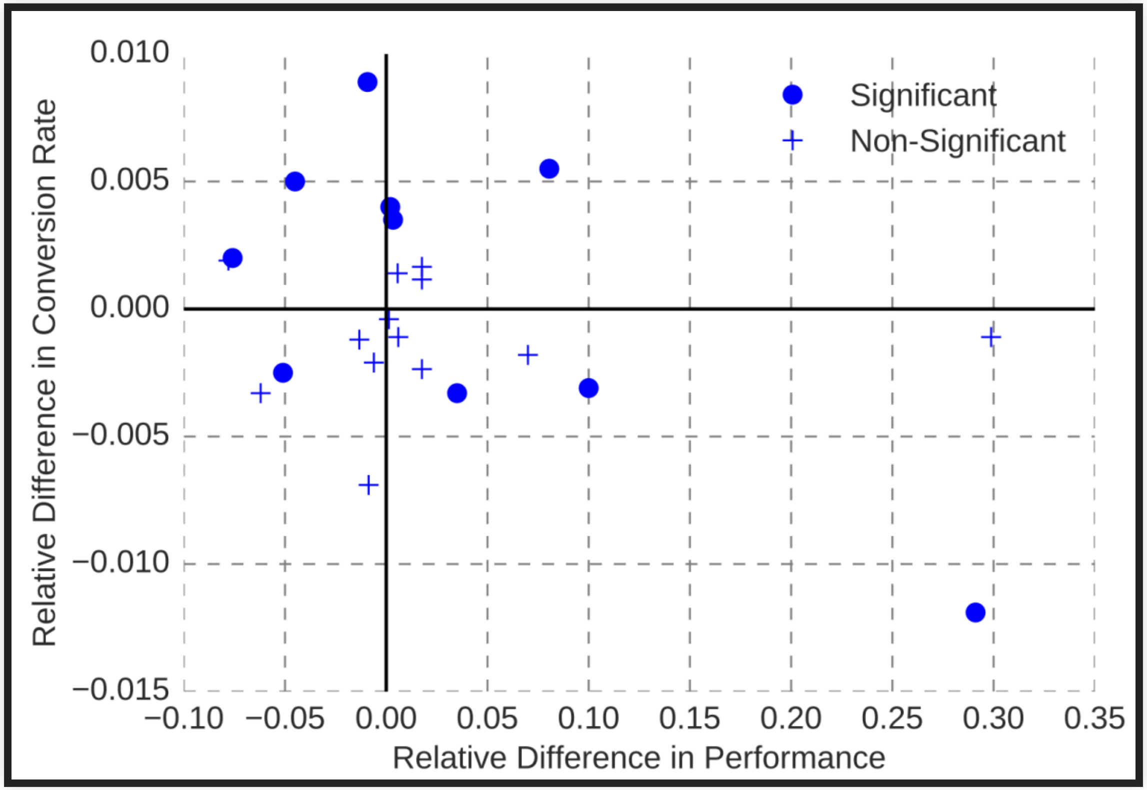
- Telemetry can approximate model accuracy
- Telemetry can directly measure system qualities, leading indicators, user outcomes
    - define measures for "key performance indicators"
    - clicks, buys, signups, engagement time, ratings
    - operationalize with telemetry

# 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
- 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

# EXPERIMENTING IN PRODUCTION

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

**Changelog**
@changelog

"Don't worry, our users will notify us if there's a problem"


2:03 PM · Jun 8, 2019

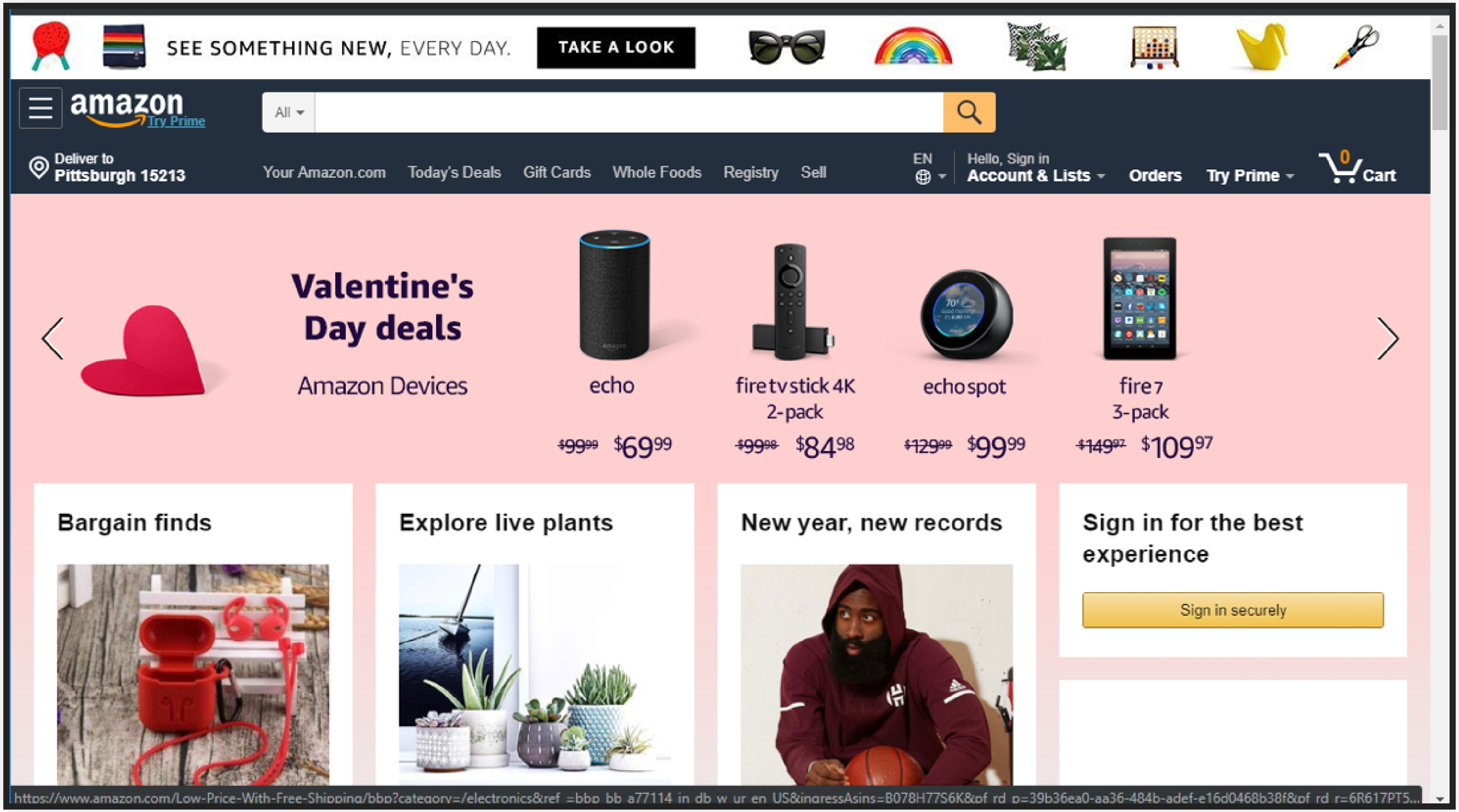
♡ 2.3K 688 Copy link to Tweet

# A/B EXPERIMENTS

# WHAT IF...?

- ... we hand 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

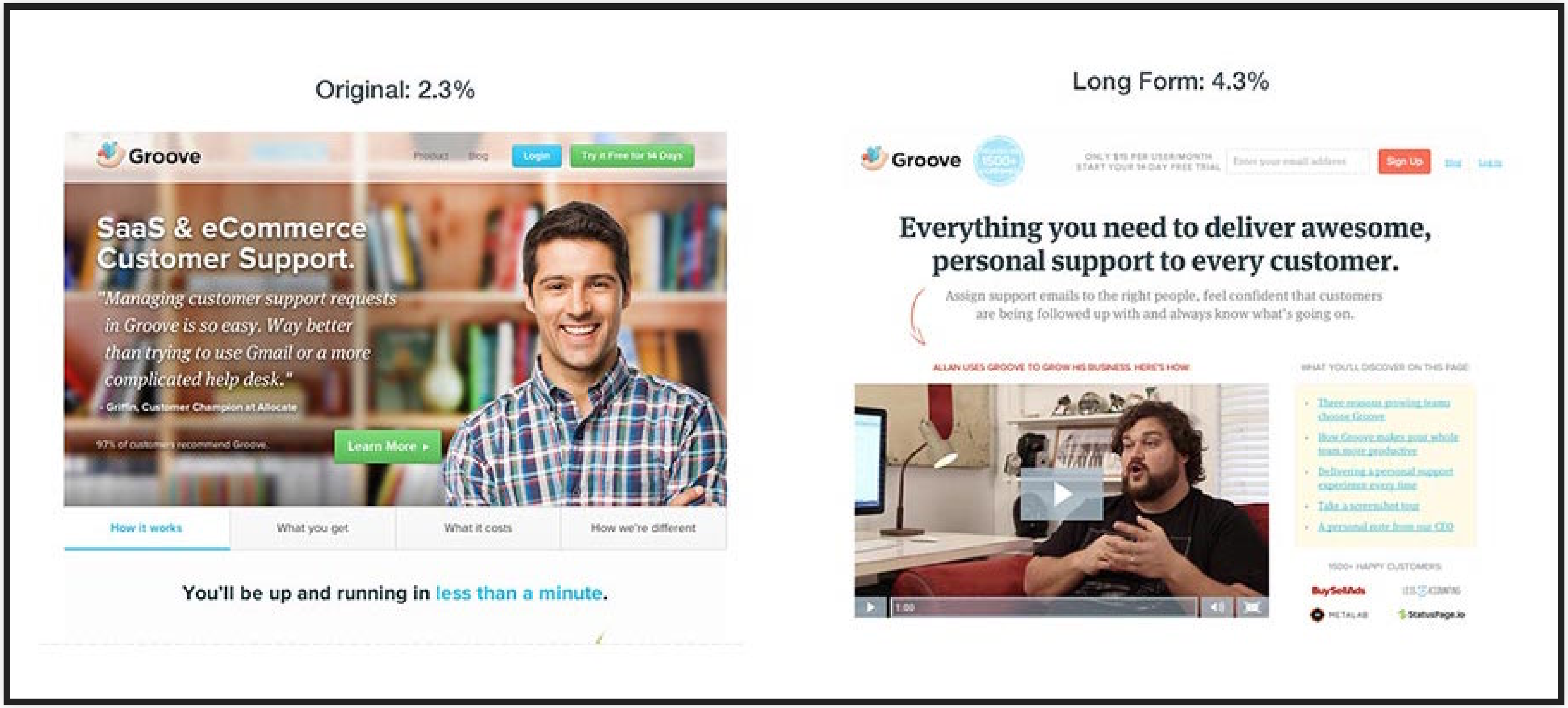
▸ Ideal conditions for controlled experiments


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
Hello, Sign in
Account & Lists
Orders
Try Prime
0
Cart
Valentine's Day deals
Amazon Devices
echo
$99.99 $69.99
fire tv stick 4K 2-pack
$99.98 $84.98
echo spot
$129.99 $99.99
fire 7 3-pack
$149.97 $109.97
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/bbp?category=/electronics&ref_=bbp_bb_a77114_in_db_w_ur_en_US&ingressAsins=B078H77S6K&pf_rd_p=39b36ea0-aa36-484b-adef-e16d0468b38f&pf_rd_r=6R617PT5...

8.2

# 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



Speaker notes

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


Control


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

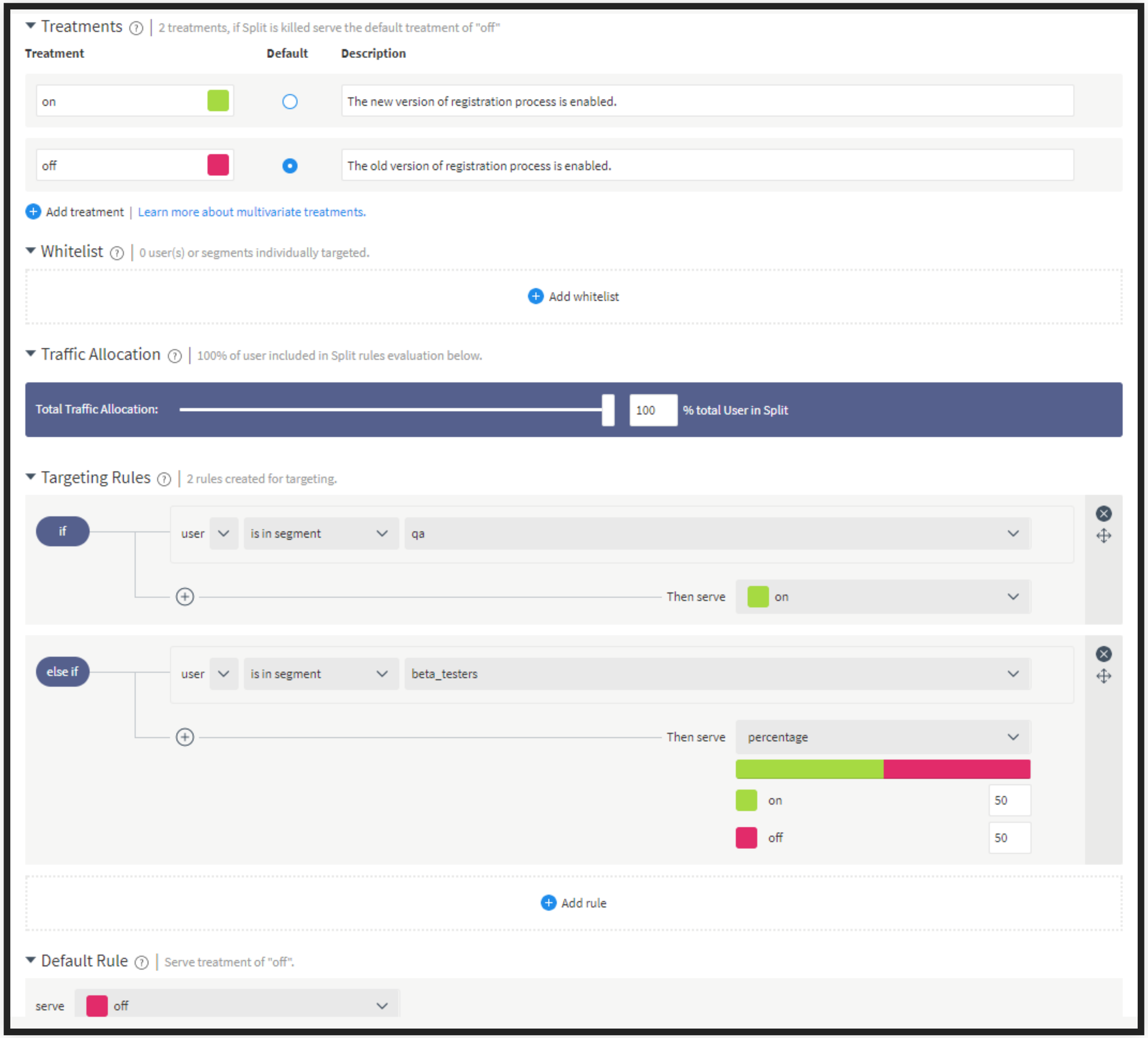
- Implement alternative versions of the system
  - using feature flags (decisions in implementation)
  - separate deployments (decision in router/load balancer)
- Map users to treatment group
  - Randomly from distribution
  - Static user - group mapping
  - Online service (e.g., launchdarkly, split)
- 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.
if
user
is in segment
qa
Then serve
on
else if
user
is in segment
beta_testers
Then serve
percentage
on
50
off
50
Add rule
Default Rule
Serve treatment of "off".
serve
off

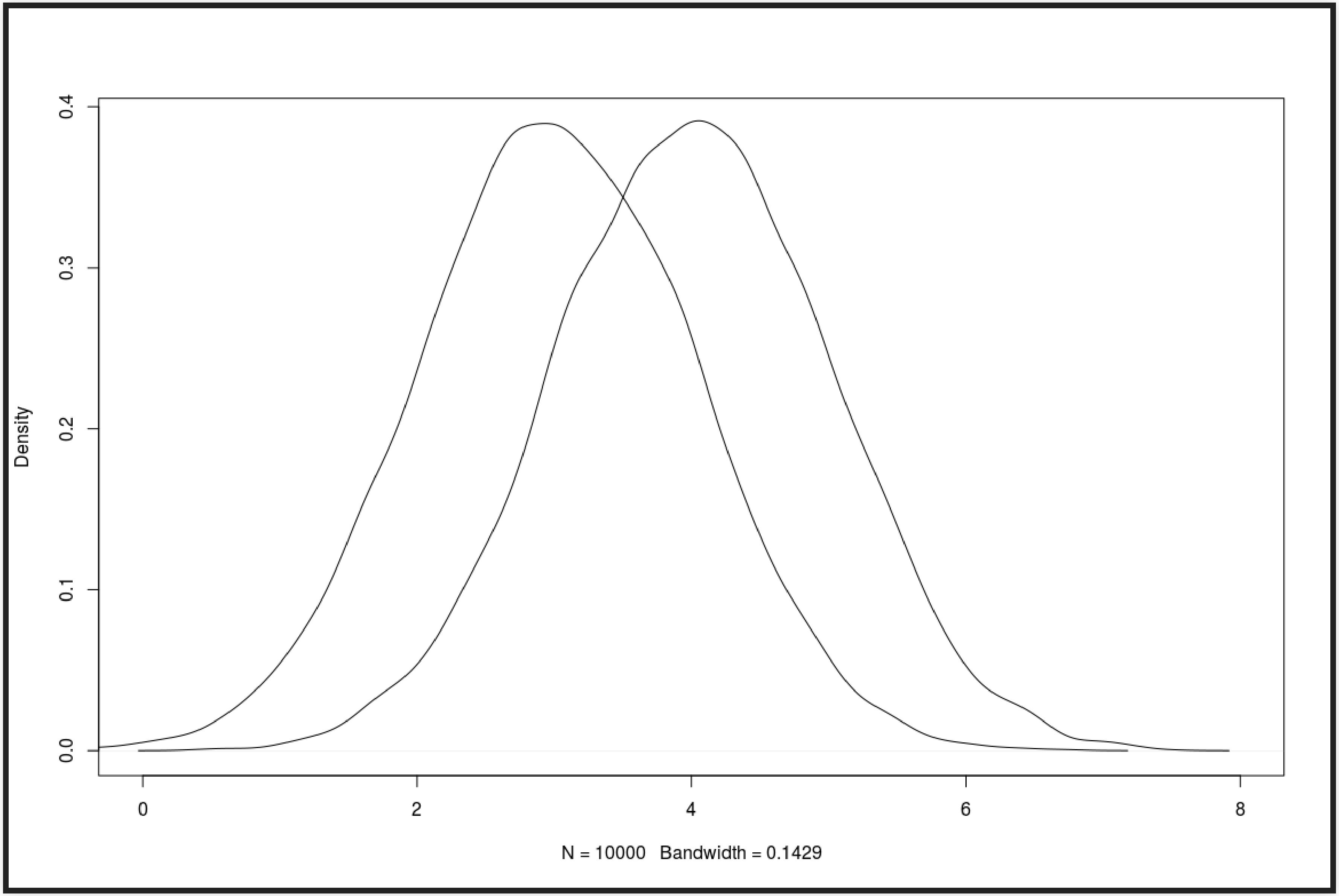
# CONFIDENCE IN A/B EXPERIMENTS

(statistical tests)

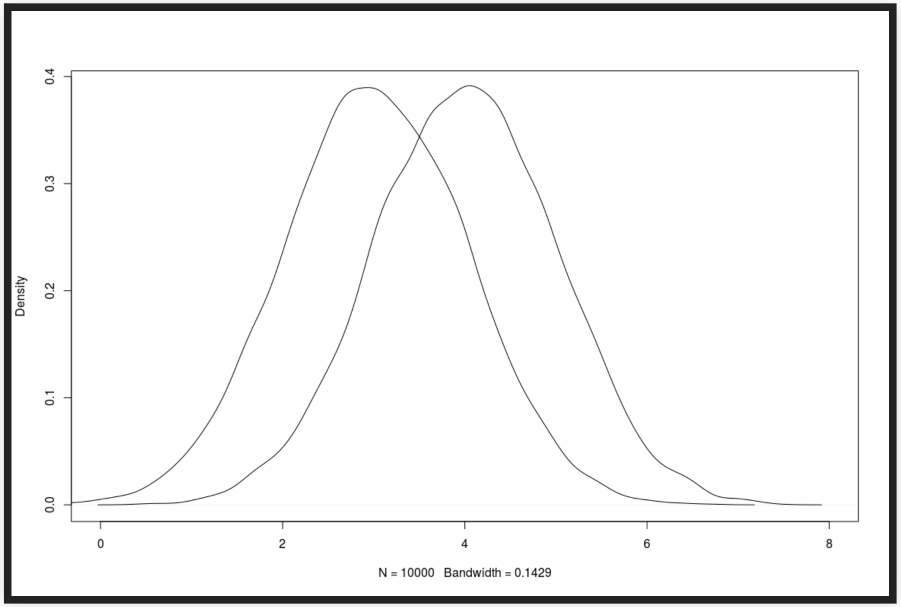
# COMPARING AVERAGES

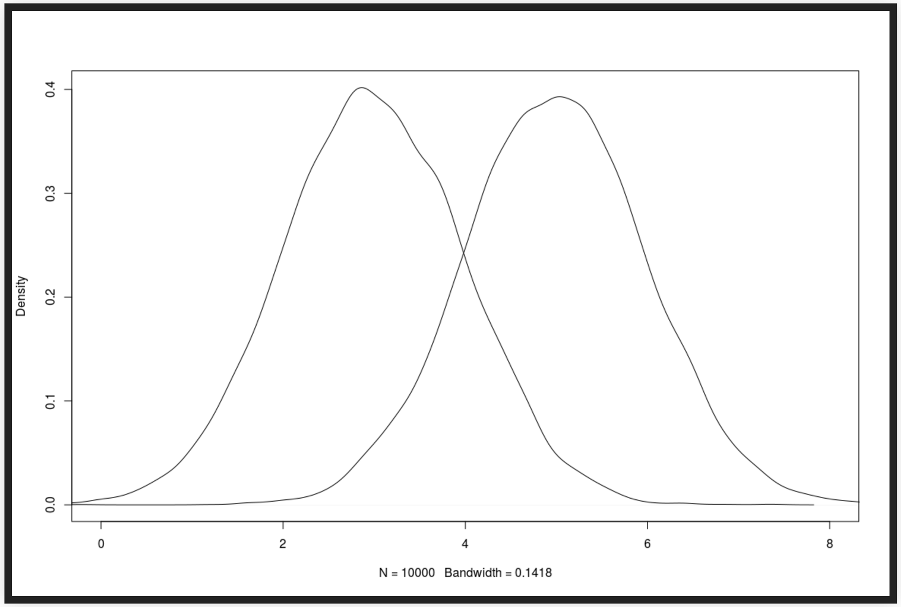
| Group A | Group B |
| --- | --- |
| *classic personalized content recommendation model* | *updated personalized content recommendation model* |
| 2158 Users | 10 Users |
| average 3:13 min time on site | average 3:24 min time on site |

# COMPARING DISTRIBUTIONS

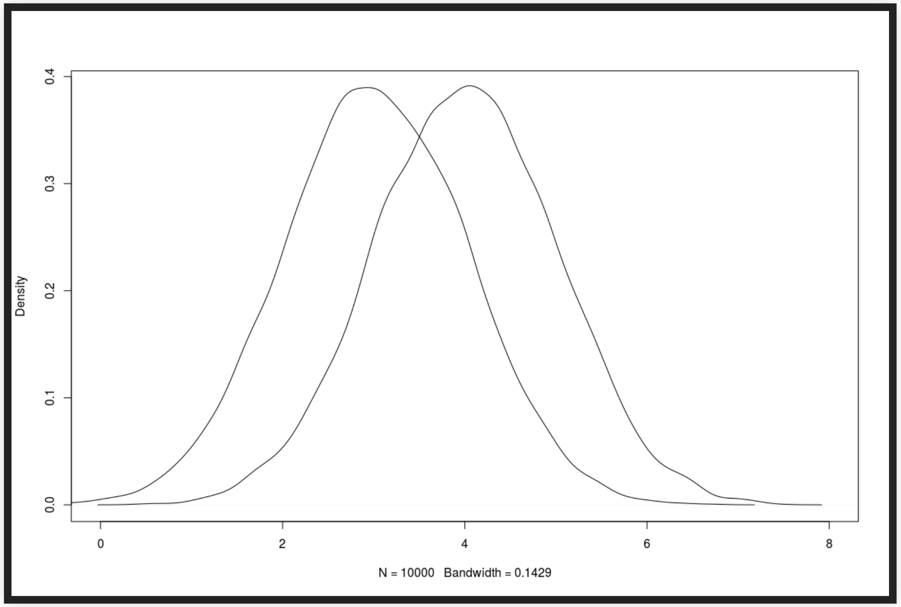

0.0
0.1
0.2
0.3
0.4
Density
0
2
4
6
8
N = 10000 Bandwidth = 0.1429

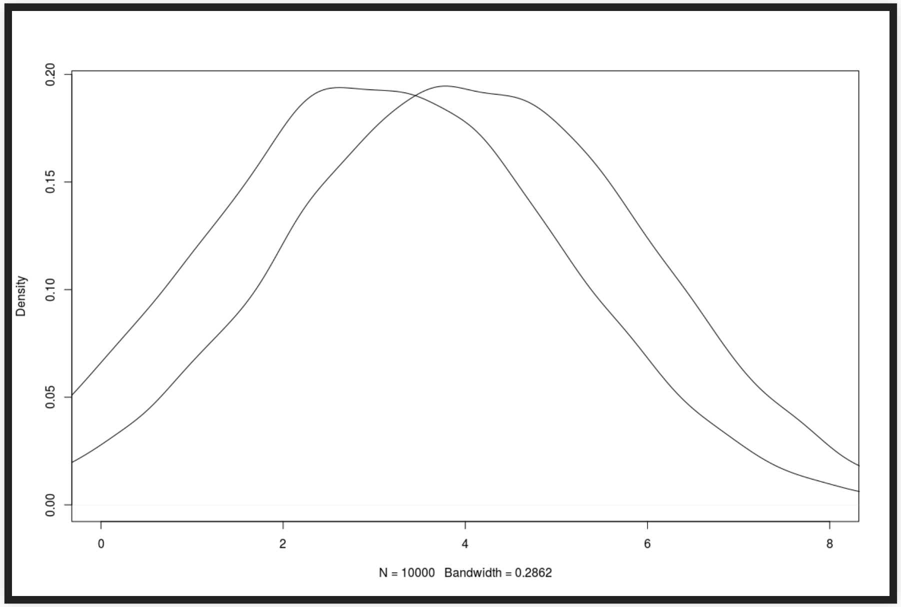
# DIFFERENT EFFECT SIZE, SAME DEVIATIONS



# 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

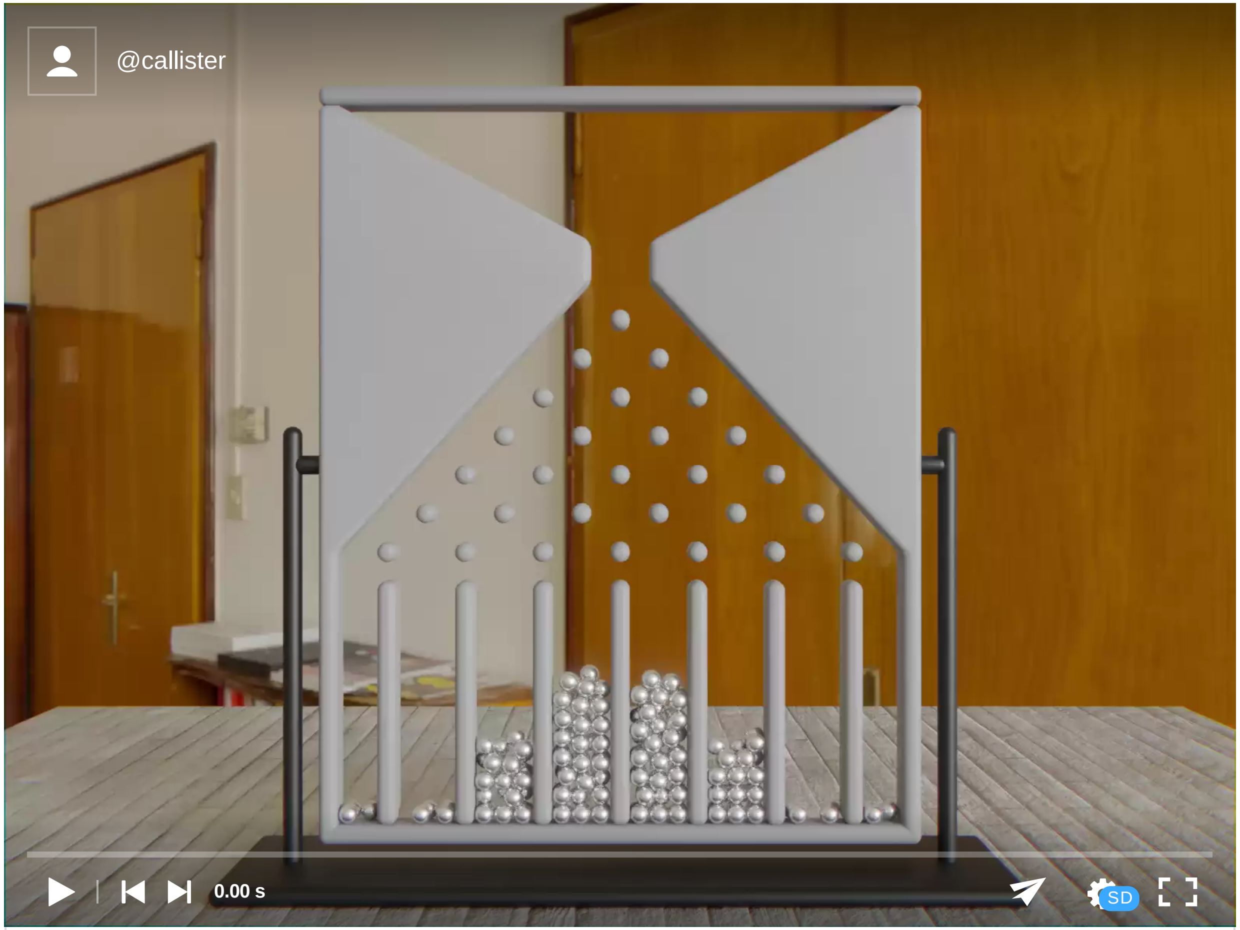
- Statistical change of an error
- Define before executing the experiment
    - use commonly accepted values
    - based on cost of a wrong decision
- Common:
    - 0.05 significant
    - 0.01 very significant
- Statistically significant result =!> proof
- Statistically significant result =!> important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

# INTUITION: ERROR MODEL

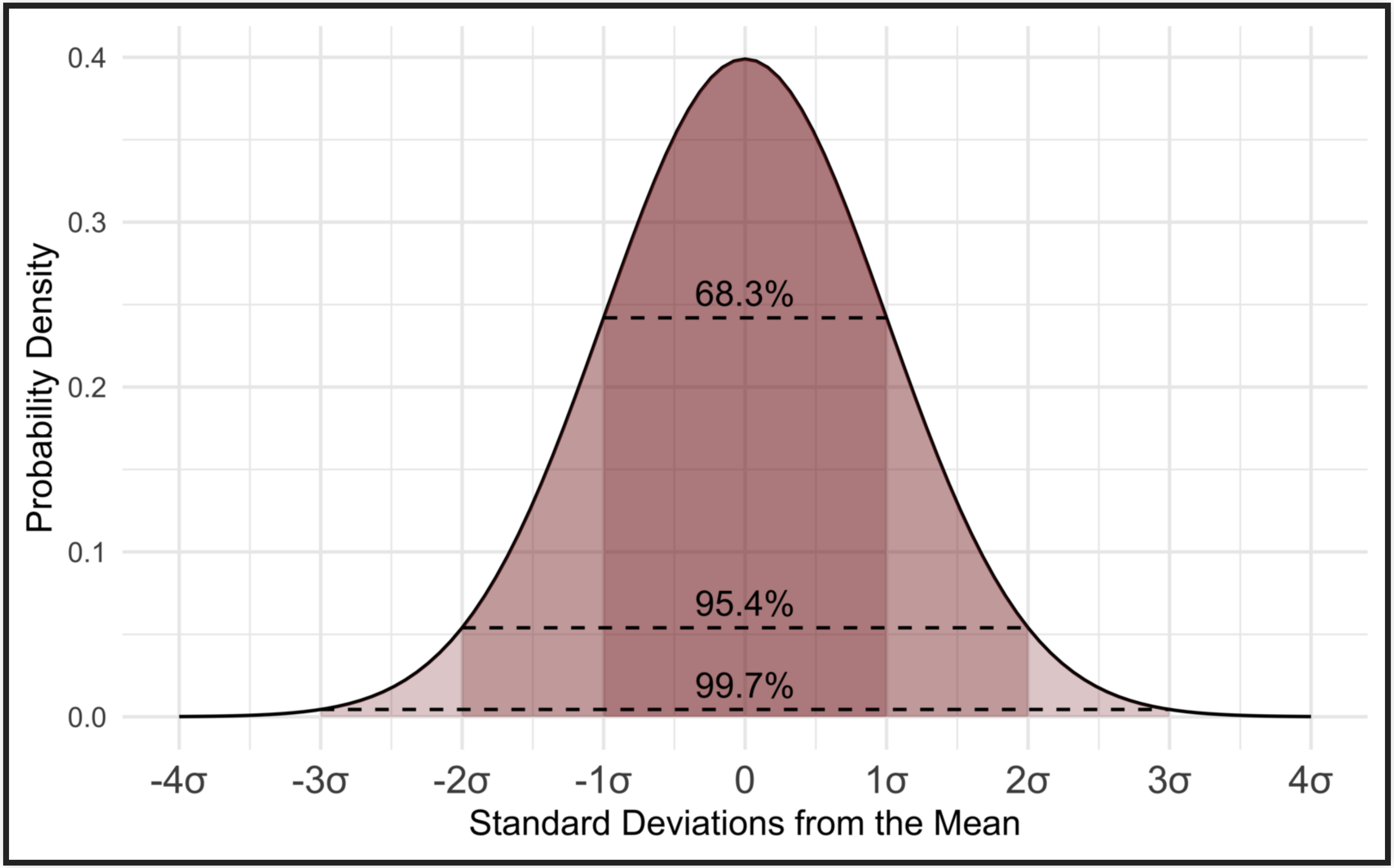
- 1 random error, influence +/- 1
- Real mean: 10
- Measurements: 9 (50%) und 11 (50%)

- 2 random errors, each +/- 1
- Measurements: 8 (25%), 10 (50%) und 12 (25%)

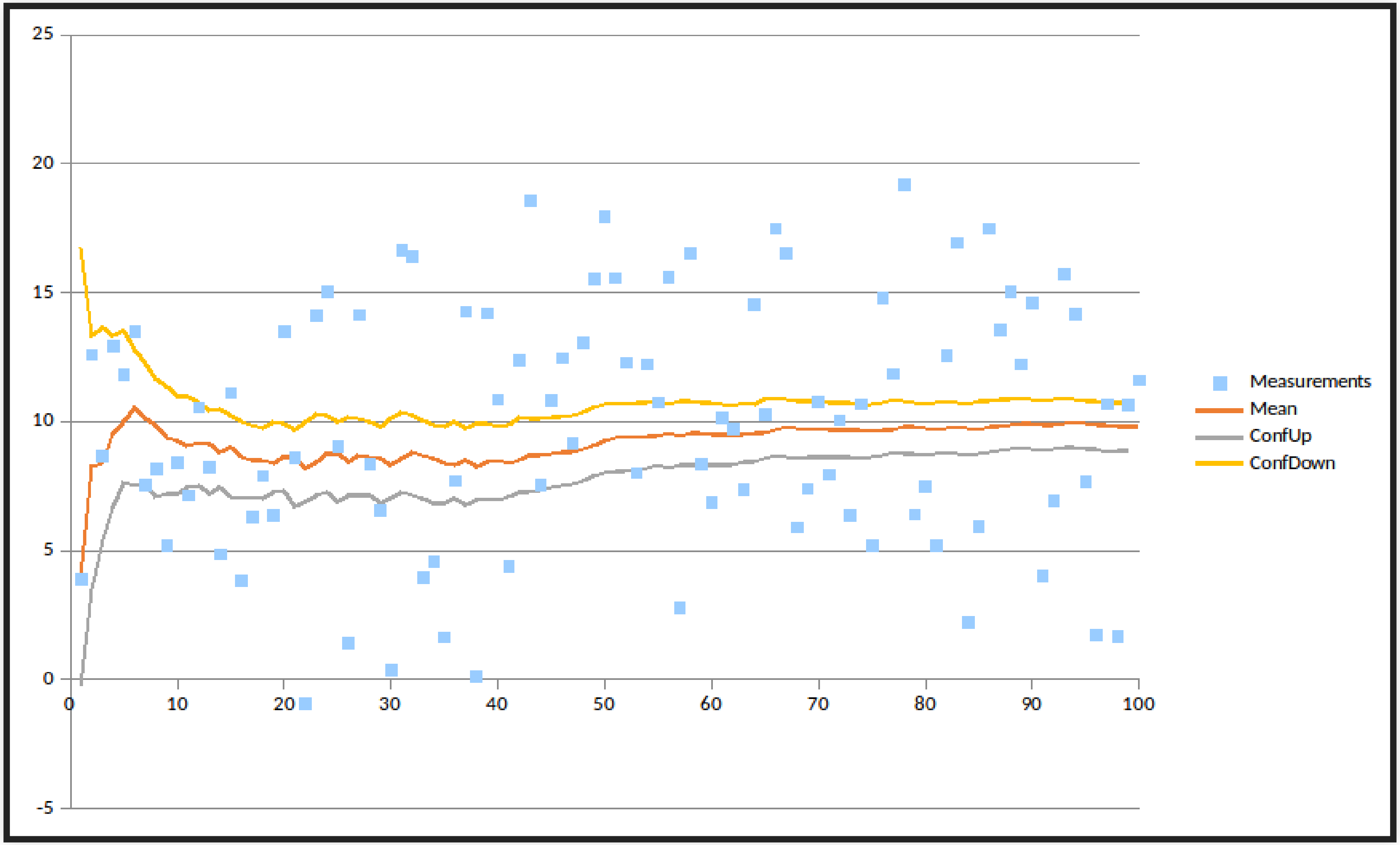
- 3 random errors, each +/- 1
- Measurements : 7 (12.5%), 9 (37.5), 11 (37.5), 12 (12.5)


@callister
0.00 s
SD

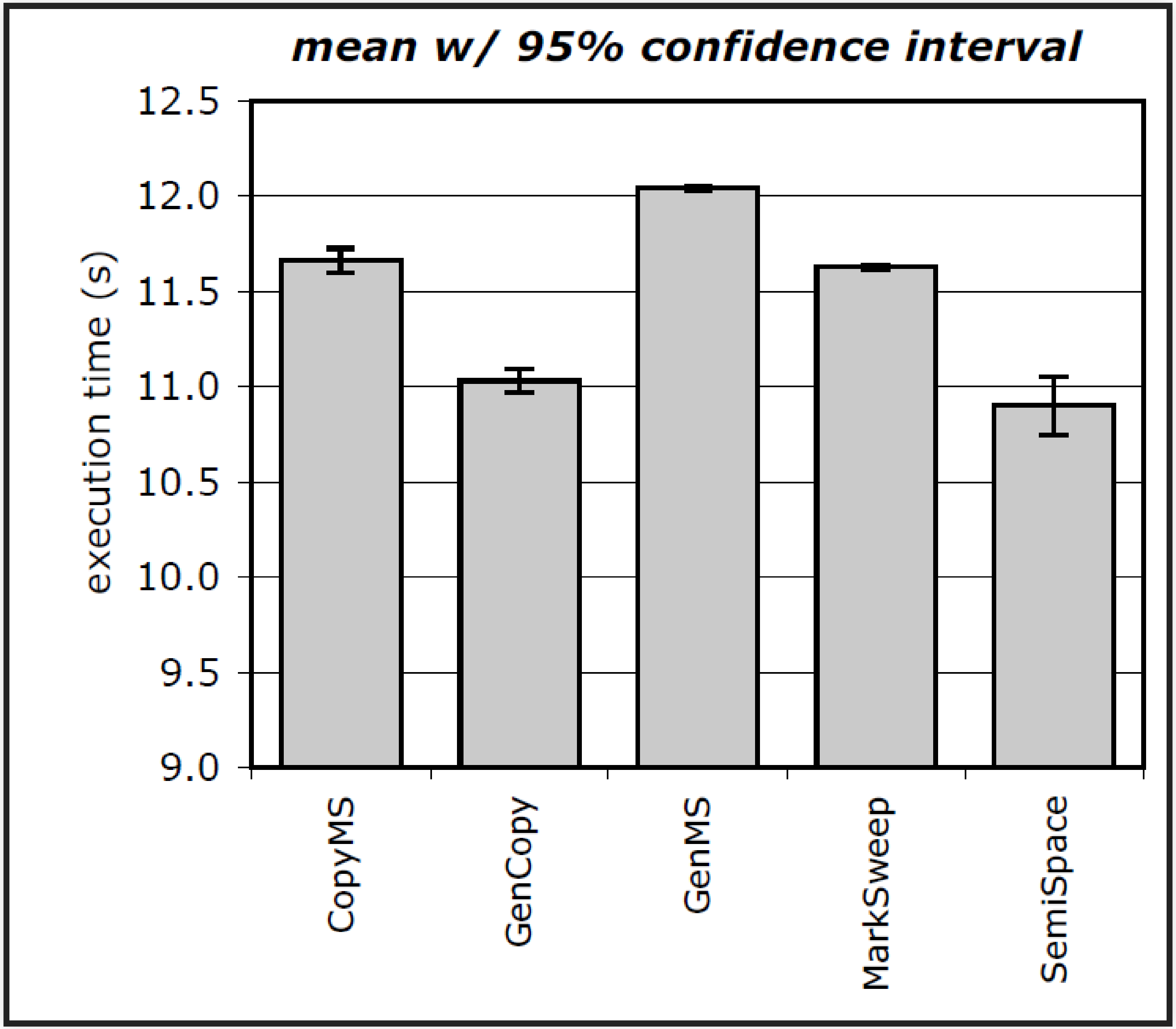
# NORMAL DISTRIBUTION



# CONFIDENCE INTERVALS

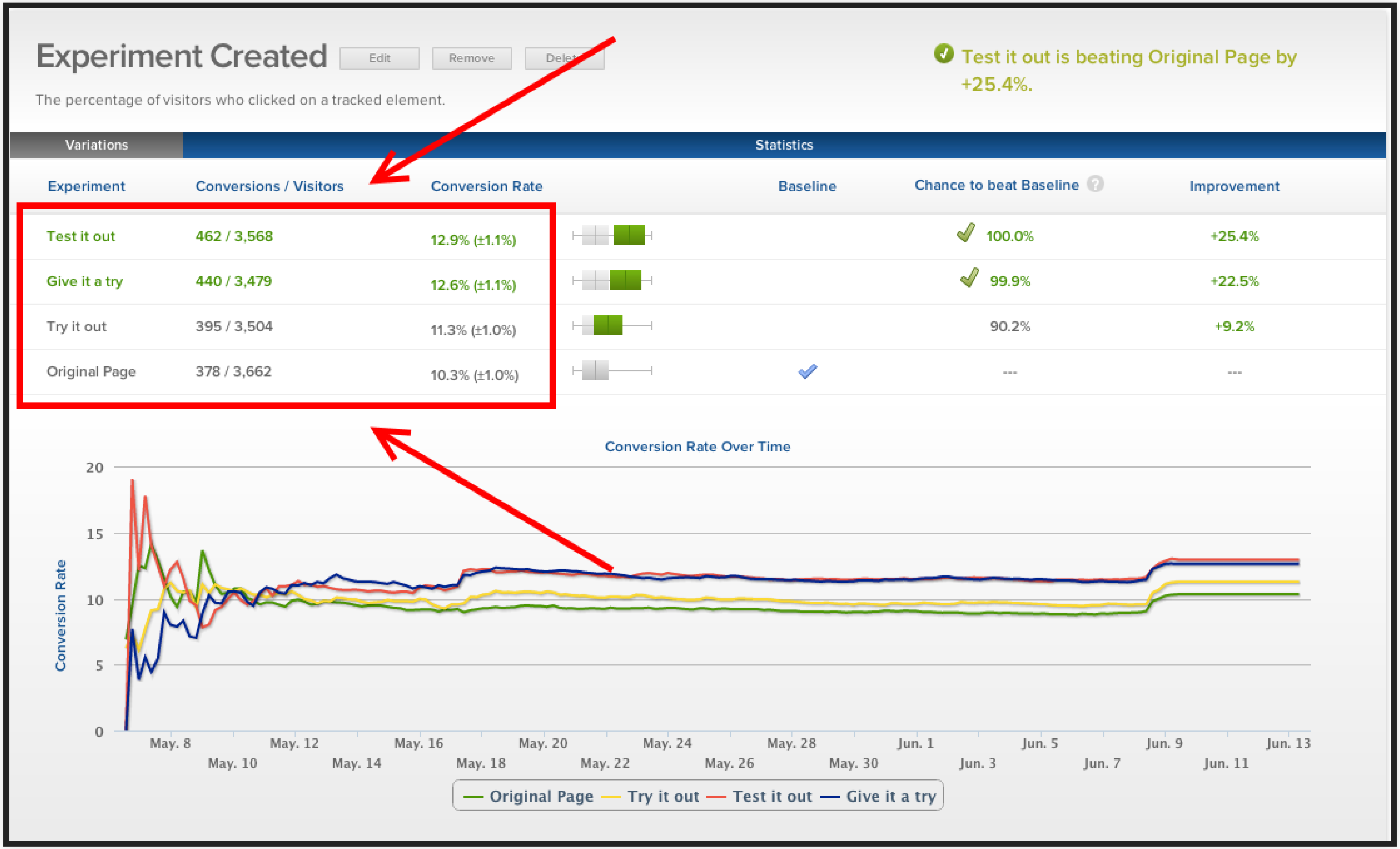


# COMPARISON WITH CONFIDENCE INTERVALS

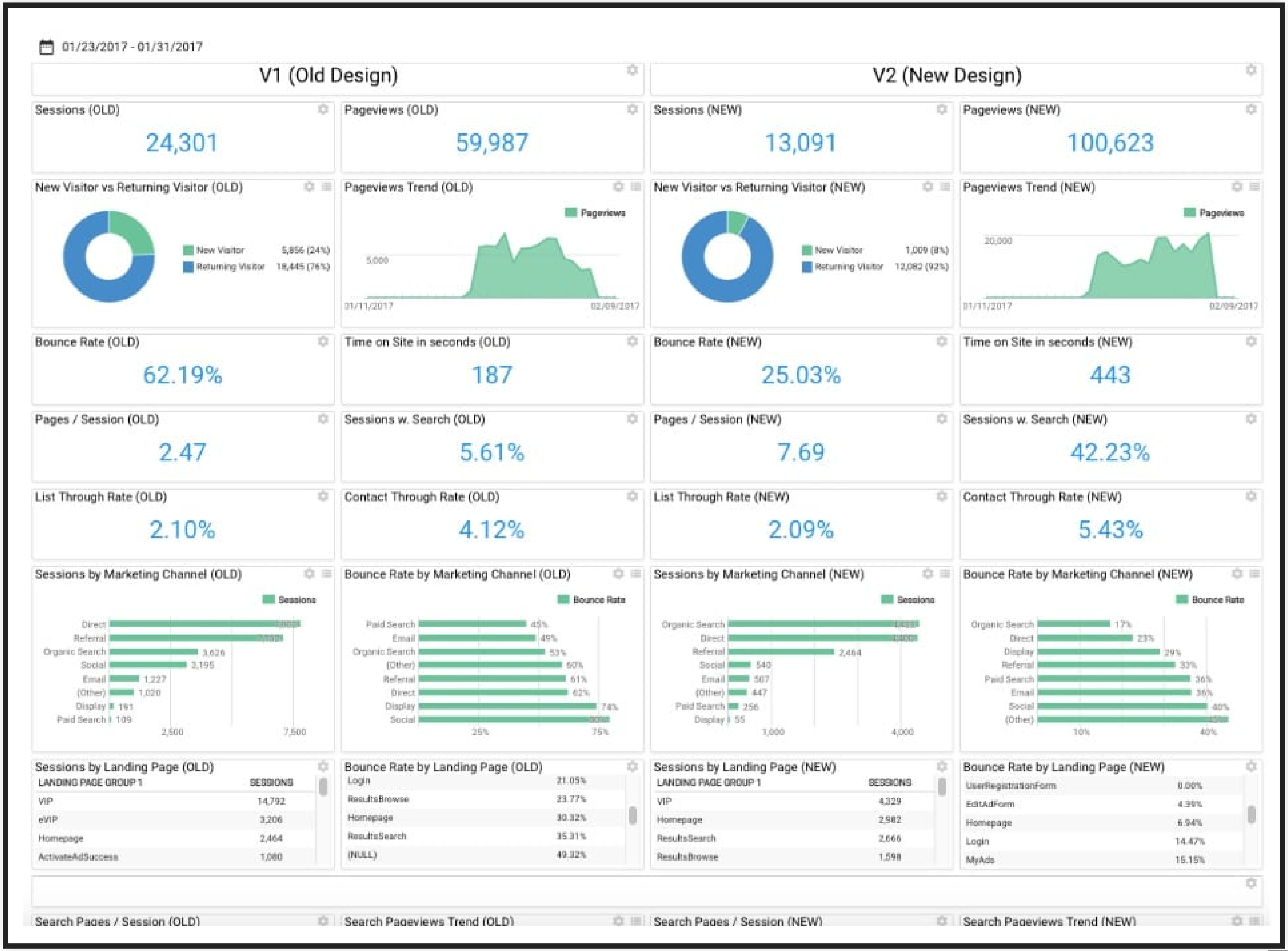

mean w/ 95% confidence interval
execution time (s)
12.5
12.0
11.5
11.0
10.5
10.0
9.5
9.0
CopyMS
GenCopy
GenMS
MarkSweep
SemiSpace

# 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)
```




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)
New Visitor 5,856 (24%)
Returning Visitor 18,445 (76%)
Pageviews Trend (OLD)
Pageviews
5,000
01/11/2017
02/09/2017
New Visitor vs Returning Visitor (NEW)
New Visitor 1,009 (8%)
Returning Visitor 12,082 (92%)
Pageviews Trend (NEW)
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)
Sessions
Direct
Referral
Organic Search 3,626
Social 3,195
Email 1,227
(Other) 1,020
Display 191
Paid Search 109
2,500
7,500
Bounce Rate by Marketing Channel (OLD)
Bounce Rate
Paid Search 45%
Email 49%
Organic Search 53%
(Other) 60%
Referral 61%
Direct 62%
Display 74%
Social
25%
75%
Sessions by Marketing Channel (NEW)
Sessions
Organic Search
Direct
Referral 2,464
Social 540
Email 507
(Other) 447
Paid Search 256
Display 55
1,000
4,000
Bounce Rate by Marketing Channel (NEW)
Bounce Rate
Organic Search 17%
Direct 23%
Display 29%
Referral 33%
Paid Search 36%
Email 36%
Social 40%
(Other)
10%
40%
Sessions by Landing Page (OLD)
LANDING PAGE GROUP 1 SESSIONS
VIP 14,792
eVIP 3,206
Homepage 2,464
ActivateAdSuccess 1,080
Bounce Rate by Landing Page (OLD)
Login 21.05%
ResultsBrowse 23.77%
Homepage 30.32%
ResultsSearch 35.31%
(NULL) 49.32%
Sessions by Landing Page (NEW)
LANDING PAGE GROUP 1 SESSIONS
VIP 4,329
Homepage 2,982
ResultsSearch 2,666
ResultsBrowse 1,598
Bounce Rate by Landing Page (NEW)
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. Proceedings of the 23rd International Conference on World Wide Web. ACM, 2014. (Facebook)

# 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

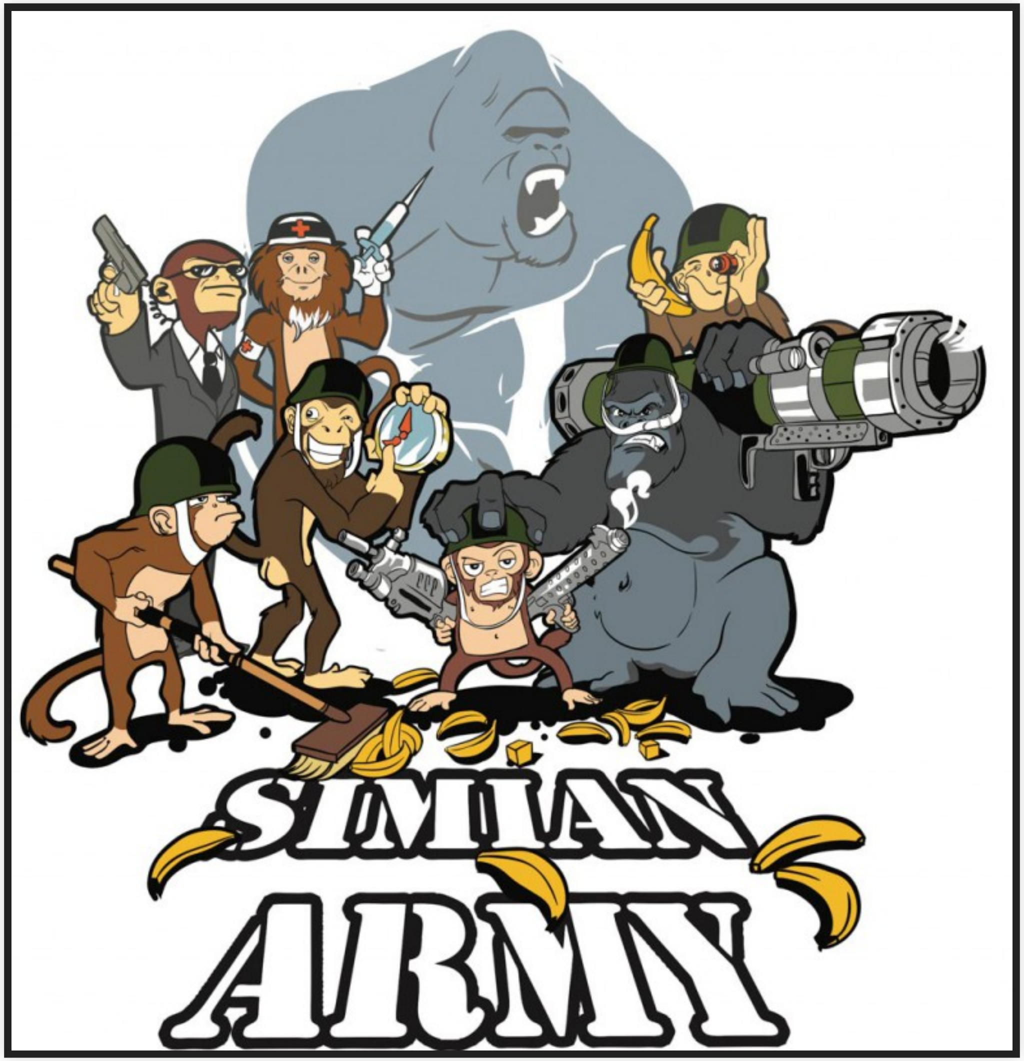
- Provision service both with old and new model (e.g., services)
- Support immediate switch with load-balancer
- Allows to undo release rapidly

**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



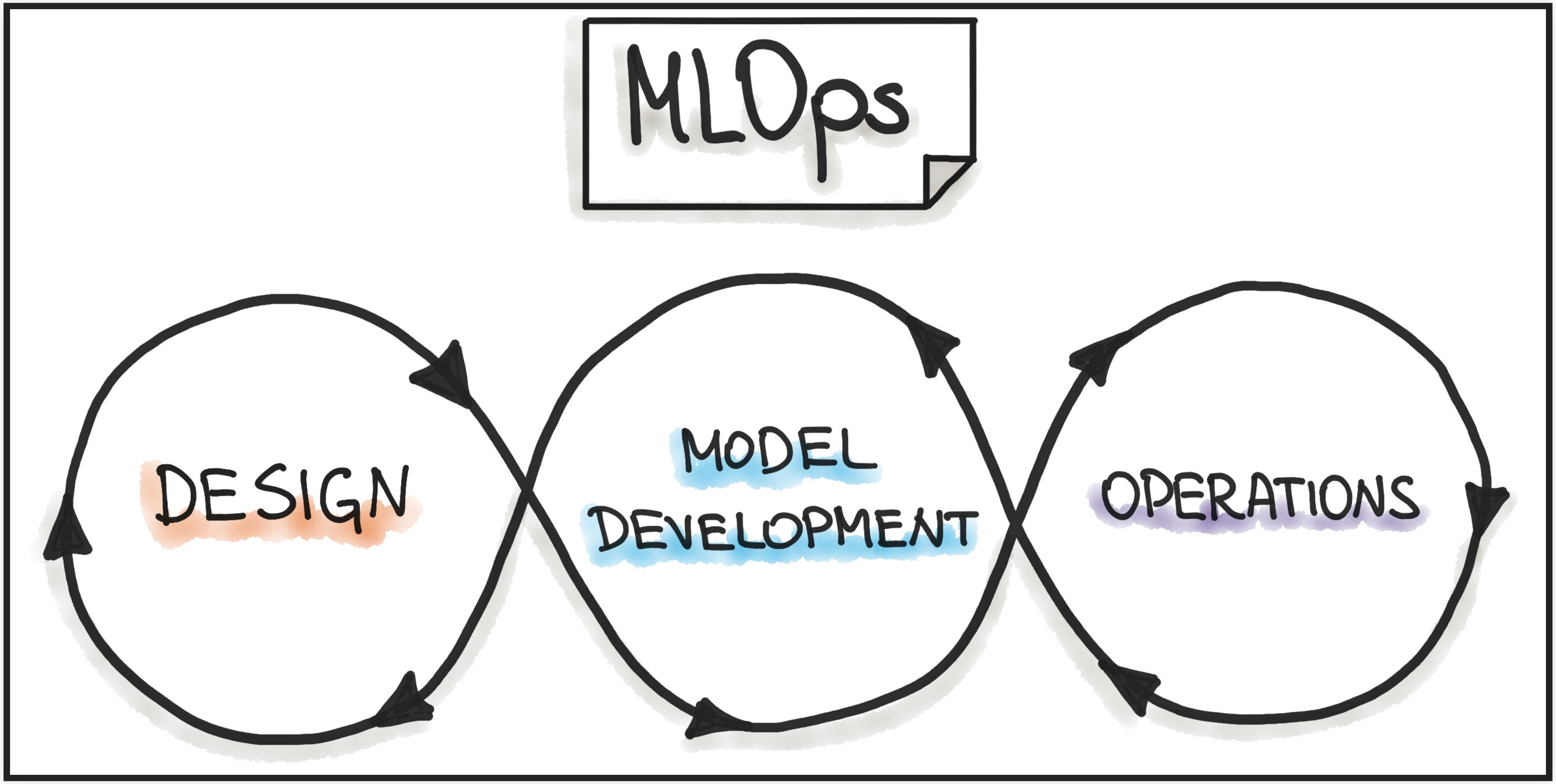
# CHAOS EXPERIMENTS FOR AI COMPONENTS?

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




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