Machine Learning in Production

Testing in Production

Changelog
@changelog · Follow

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

2:03 PM · Jun 8, 2019

2K Reply Copy link

Read 11 replies

Back to QA...

Fundamentals of Engineering AI-Enabled Systems

Holistic system view: AI and non-AI components, pipelines, stakeholders, environment interactions, feedback loops

Requirements:
System and model goals
User requirements
Environment assumptions
Quality beyond accuracy
Measurement
Risk analysis
Planning for mistakes

Architecture + design:
Modeling tradeoffs
Deployment architecture
Data science pipelines
Telemetry, monitoring
Anticipating evolution
Big data processing
Human-AI design

Quality assurance:
Model testing
Data quality
QA automation
Testing in production
Infrastructure quality
Debugging

Operations:
Continuous deployment
Contin. experimentation
Configuration mgmt.
Monitoring
Versioning
Big data
DevOps, MLOps

Teams and process: Data science vs software eng. workflows, interdisciplinary teams, collaboration points, technical debt

Responsible AI Engineering

Provenance, versioning, reproducibility

Safety

Security and privacy

Fairness

Interpretability and explainability

Transparency and trust

Ethics, governance, regulation, compliance, organizational culture

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

Readings

Required Reading:

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

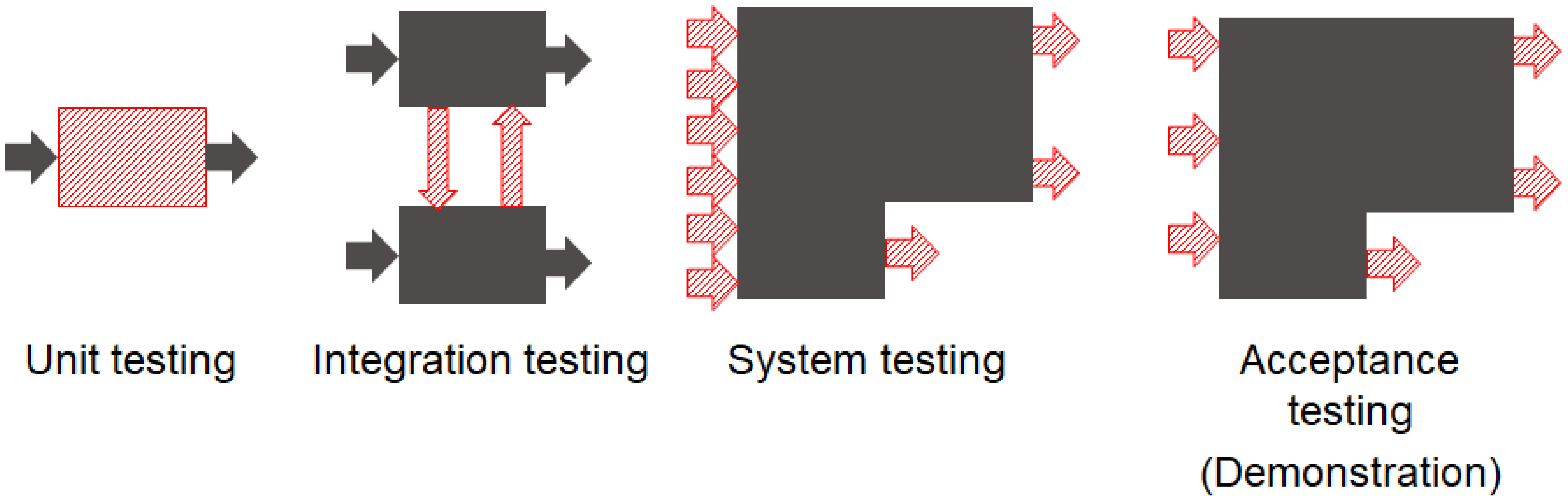
Suggested Readings:

- Alec Warner and Štěpán Davidovič. "Canary Releases." in The Site Reliability Workbook, O'Reilly 2018
- Kohavi, Ron, Diane Tang, and Ya Xu. "Trustworthy Online Controlled Experiments: A Practical Guide to A/B Testing." Cambridge University Press, 2020.

From Unit Tests to Testing in Production

(in traditional software systems)

Unit Test, Integration Tests, System Tests



Speaker notes

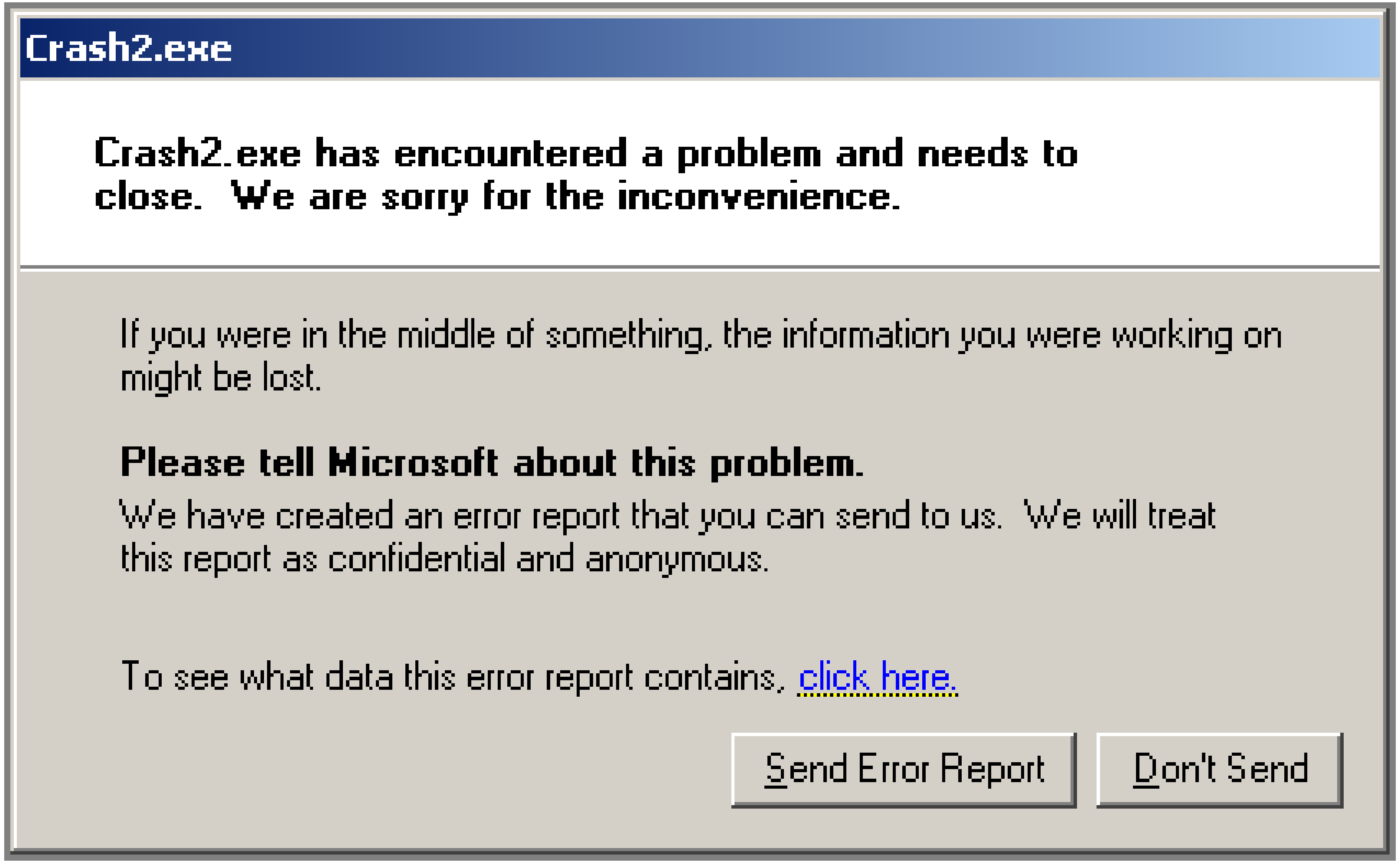
Testing before release. Manual or automated.

Beta Testing

Speaker notes

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

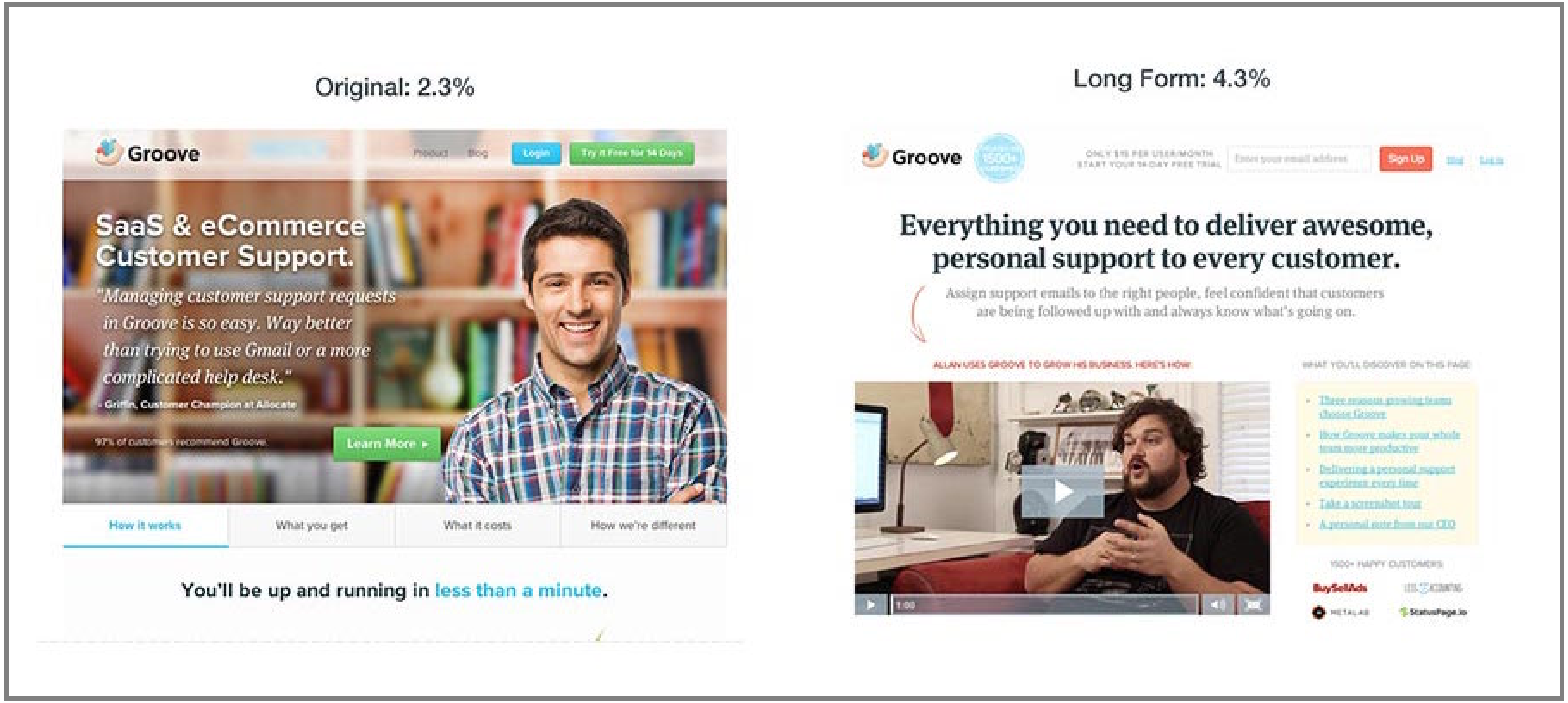
Crash Telemetry



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.

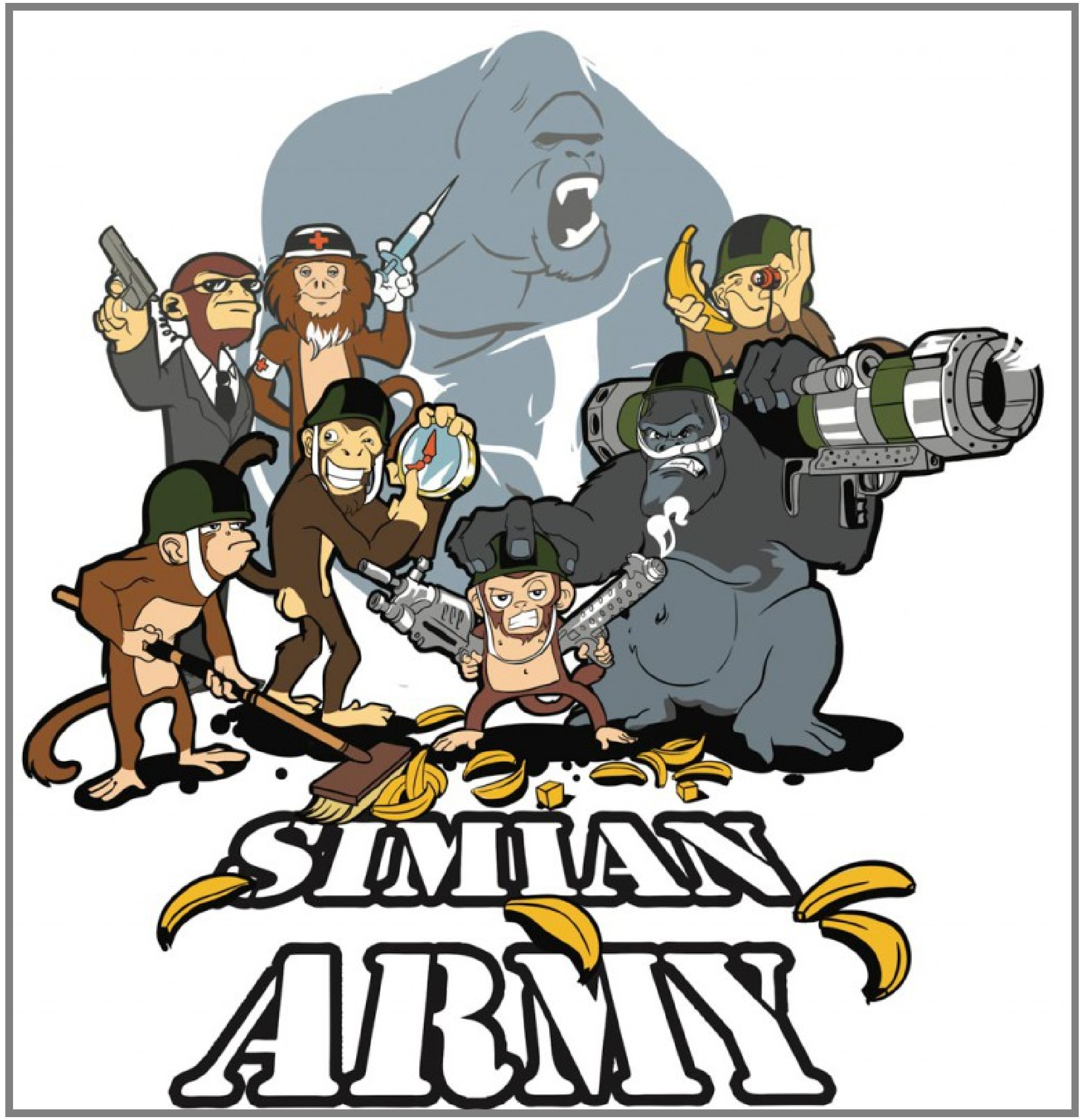
A/B Testing


Original: 2.3%
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.
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.

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**
- leakage and overfitting problems quite common

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:

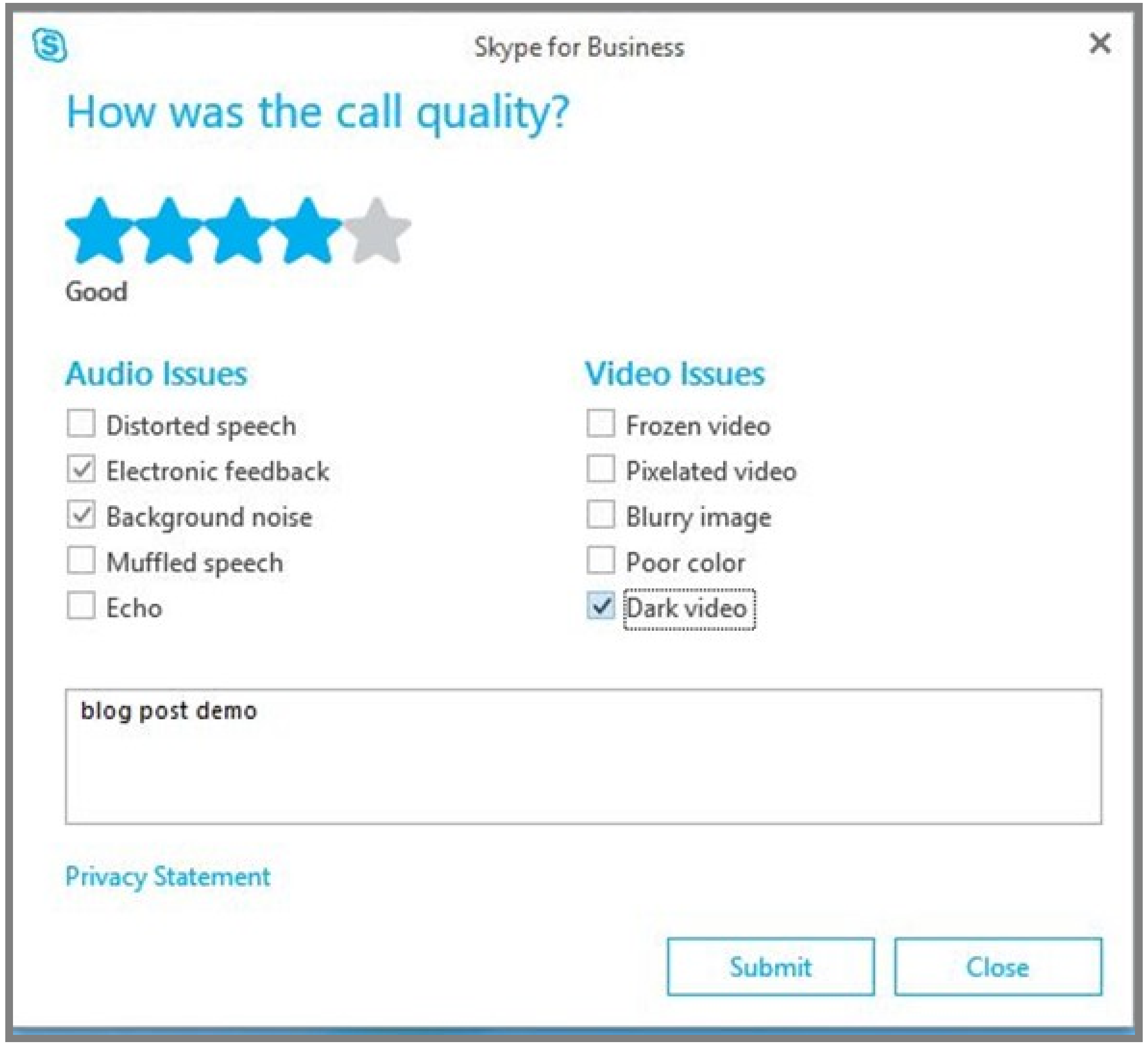
- Gather feedback without being intrusive (i.e., labeling outcomes), without harming user experience
- Manage amount of data
- Isolating feedback for specific ML component + version

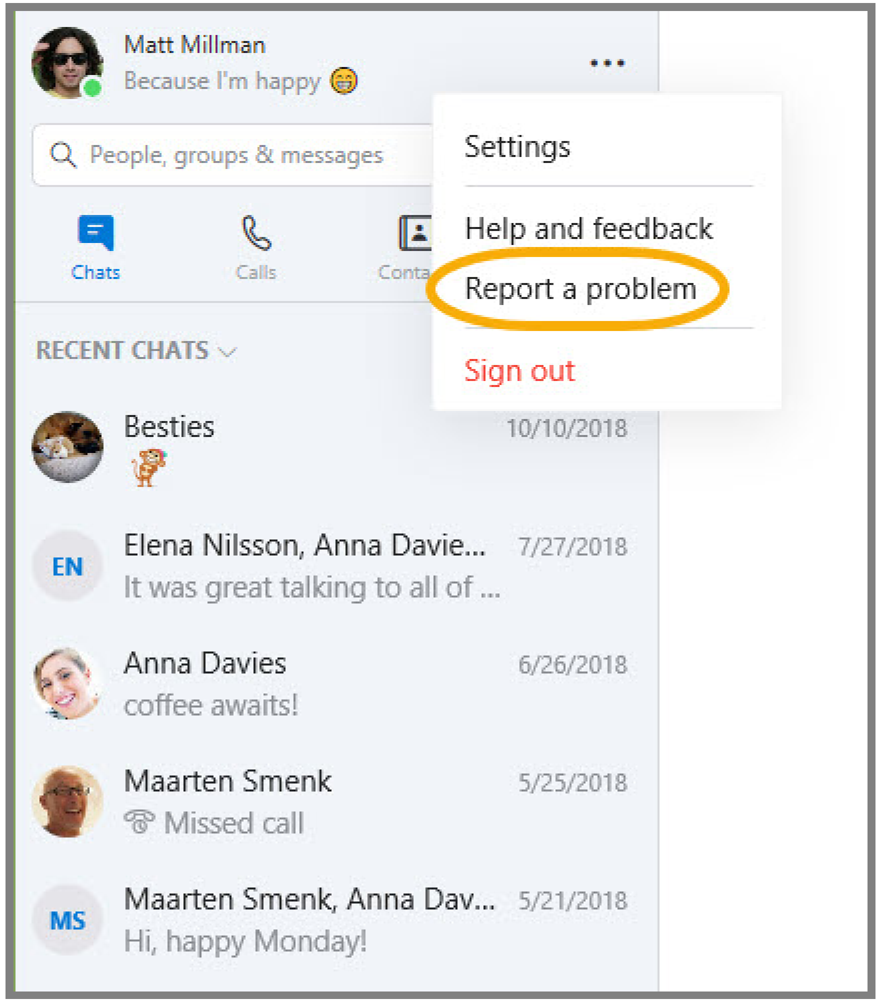
Discuss how to collect feedback

Speaker notes

More:

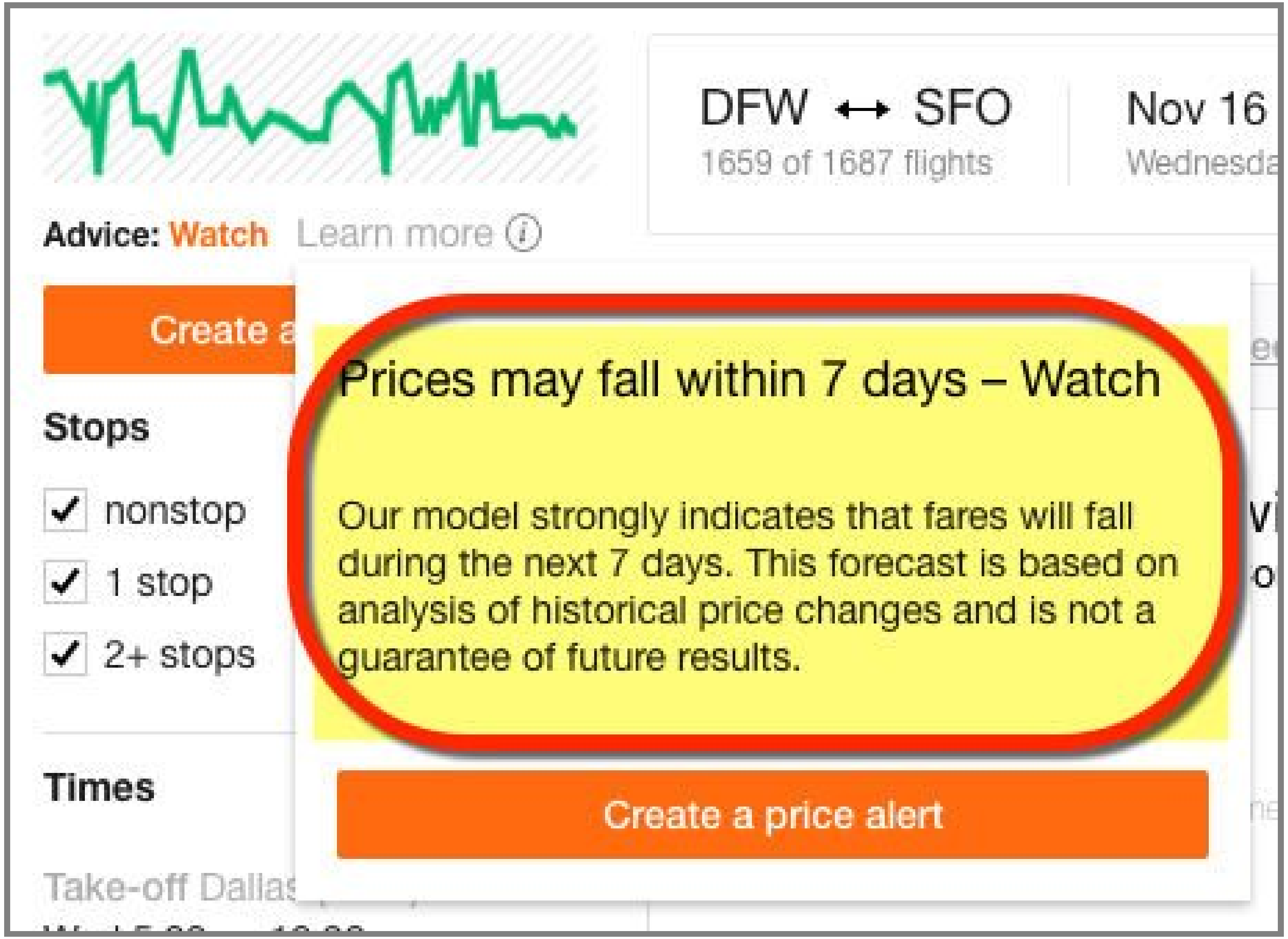
- SmartHome: Does it automatically turn of the lights/lock the doors/close the window at the right time?
- Profanity filter: Does it block the right blog comments?
- News website: Does it pick the headline alternative that attracts a user’s attention most?
- Autonomous vehicles: Does it detect pedestrians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

Breakout: 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:

- Front-left: Amazon: Shopping app feature that detects the shoe brand from photos
- Front-right: Google: Tagging uploaded photos with friends' names
- Back-left: Spotify: Recommended personalized playlists
- Back-right: Wordpress: Profanity filter to moderate blog posts

(no need to post in slack yet)

Measuring Model Quality with Telemetry

- Usual 3 steps: (1) Metric, (2) data collection (telemetry), (3) operationalization
- 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

Breakout: Design Telemetry in Production

Discuss how to collect telemetry, the metric to monitor, and how to operationalize

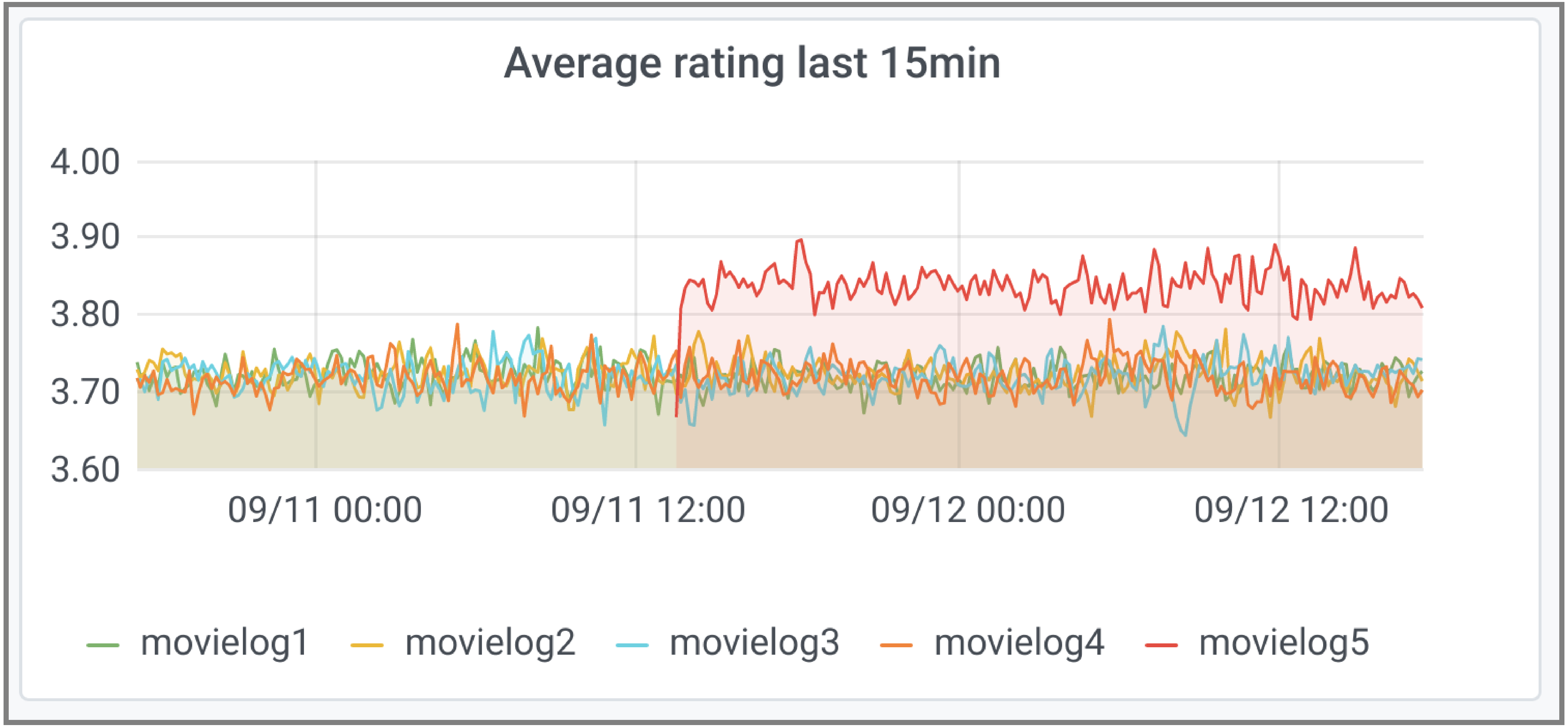
Scenarios:

- Front-left: Amazon: Shopping app detects the shoe brand from photos
- Front-right: Google: Tagging uploaded photos with friends' names
- Back-left: Spotify: Recommended personalized playlists
- Back-right: Wordpress: Profanity filter to moderate blog posts

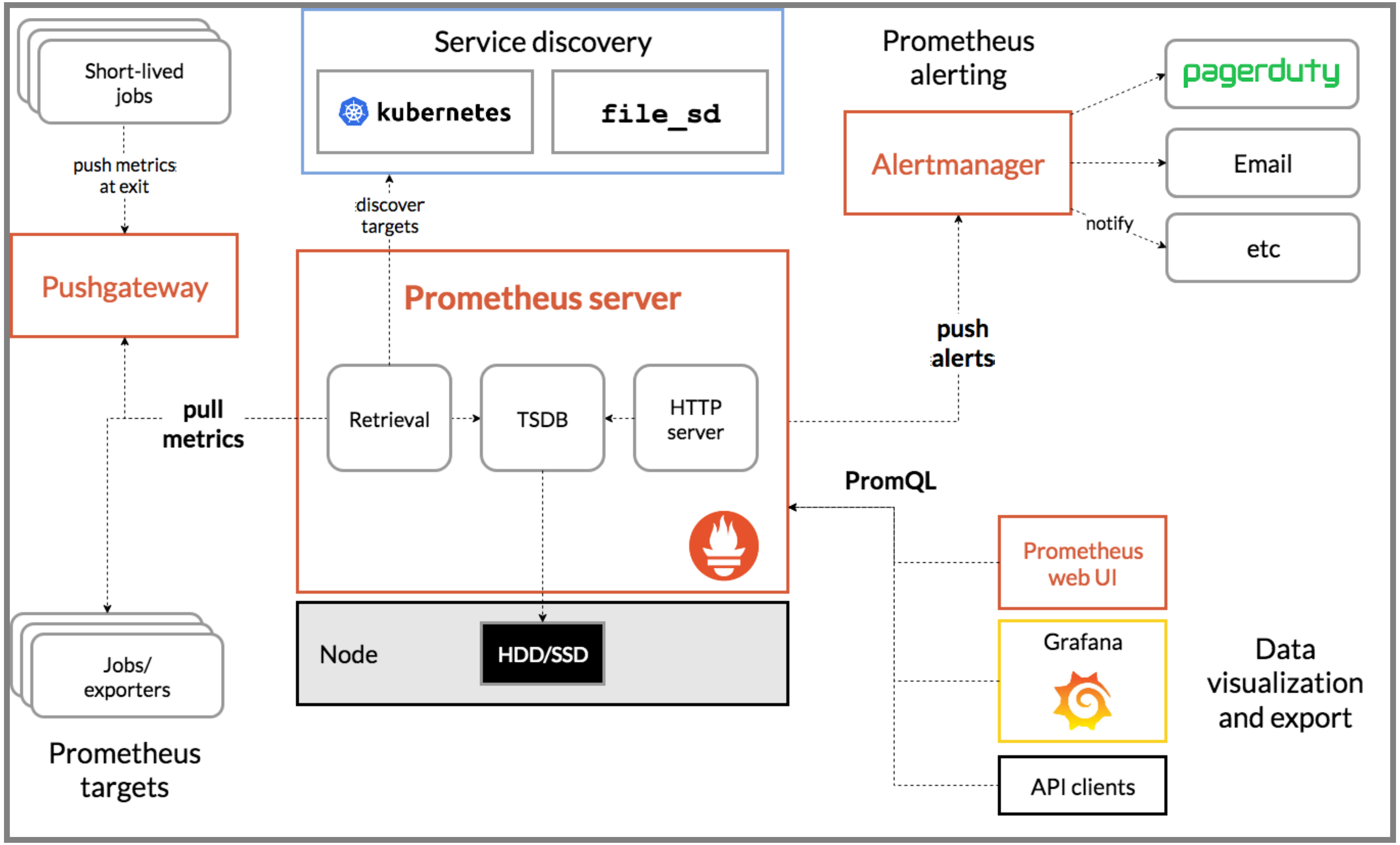
As a group post to `#lecture` and tag team members:

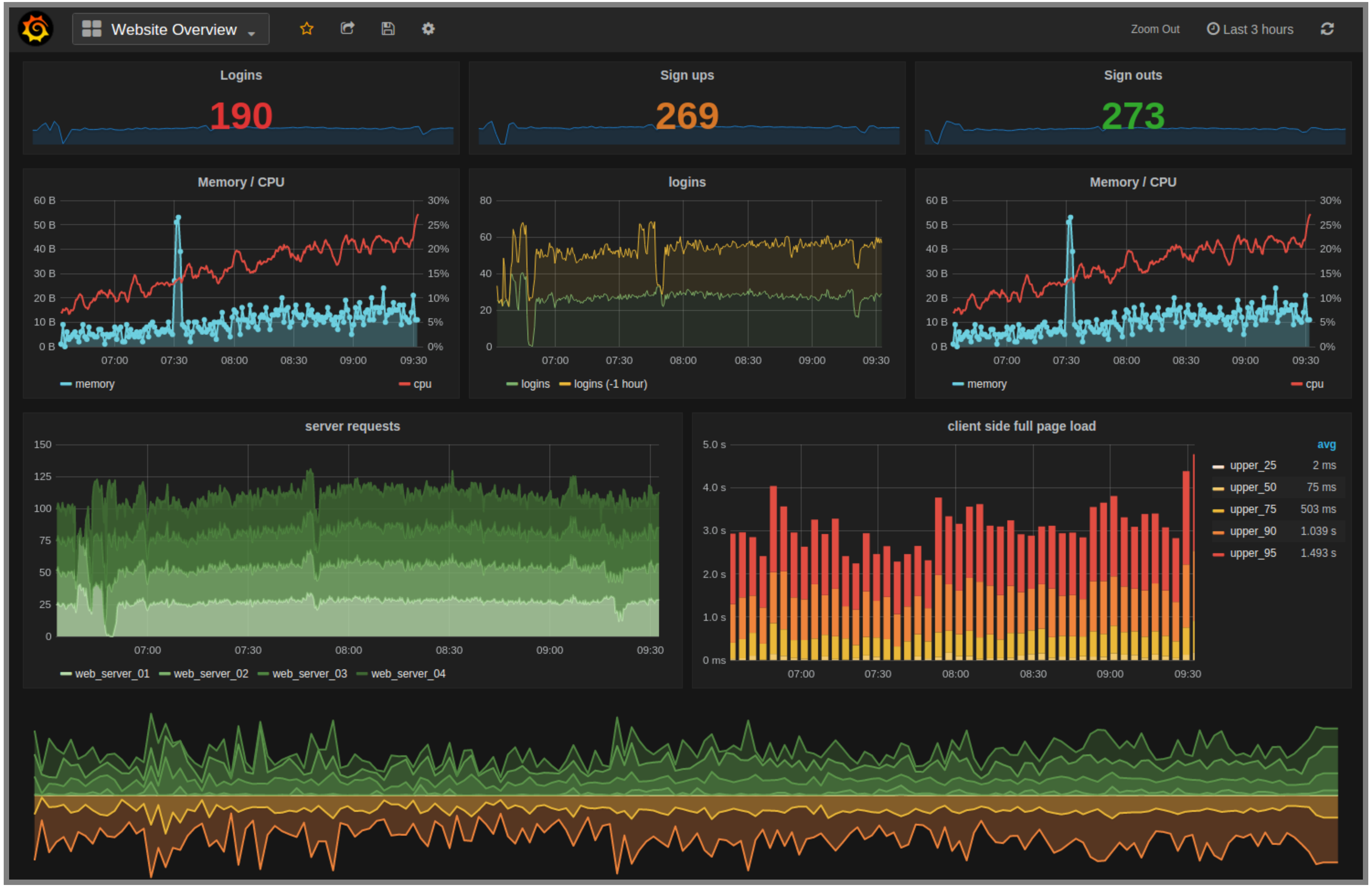
Monitoring Model Quality in Production

- 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

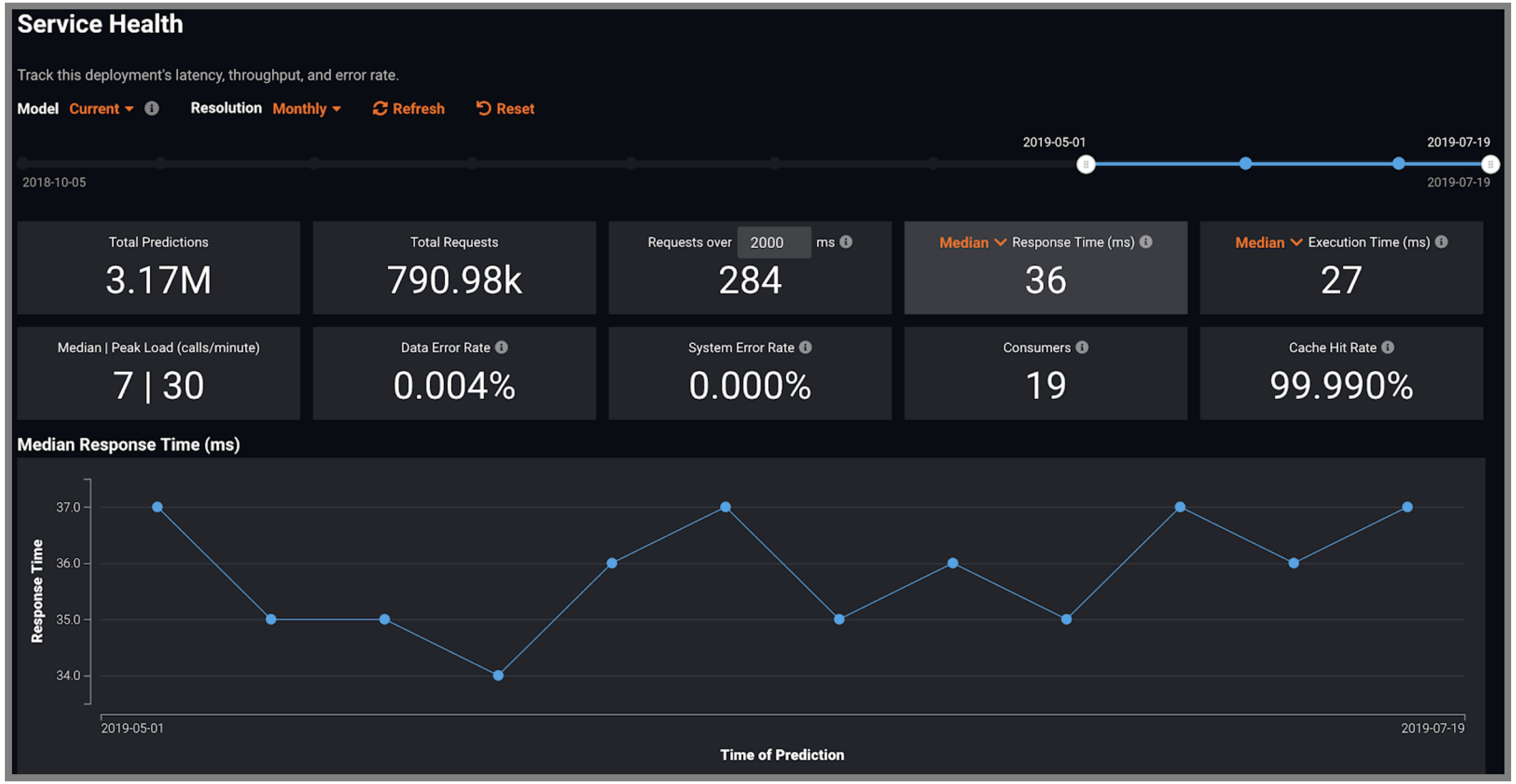

Average rating last 15min
4.00
3.90
3.80
3.70
3.60
09/11 00:00
09/11 12:00
09/12 00:00
09/12 12:00
movielog1
movielog2
movielog3
movielog4
movielog5

Prometheus and Grafana




Website Overview
Zoom Out
Last 3 hours
Logins
190
Sign ups
269
Sign outs
273
Memory / CPU
60 B
50 B
40 B
30 B
20 B
10 B
0 B
30%
25%
20%
15%
10%
5%
0%
07:00
07:30
08:00
08:30
09:00
09:30
memory
cpu
logins
80
60
40
20
0
logins
logins (-1 hour)
Memory / CPU
memory
cpu
server requests
150
125
100
75
50
25
0
web_server_01
web_server_02
web_server_03
web_server_04
client side full page load
5.0 s
4.0 s
3.0 s
2.0 s
1.0 s
0 ms
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

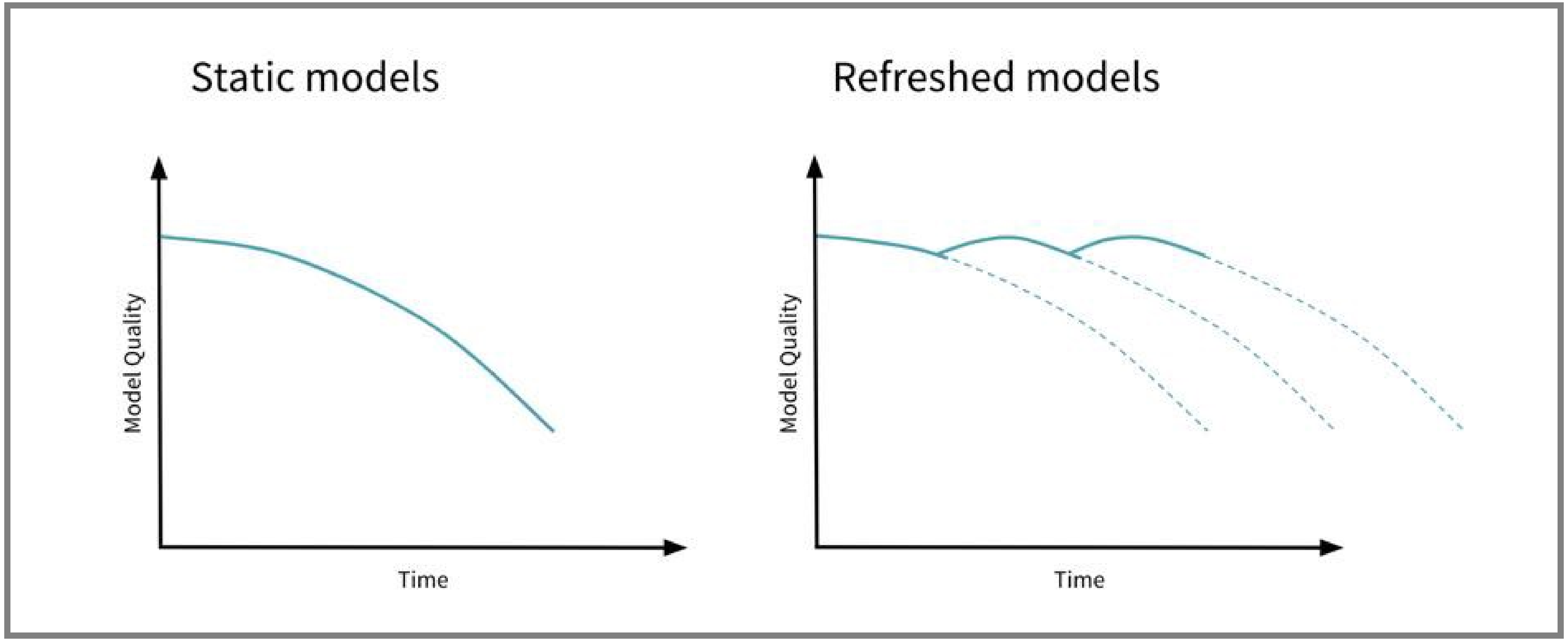


Image source: Joel Thomas and Clemens Mewald. Productionizing Machine Learning: From Deployment to Drift Detection. Databricks Blog, 2019

Engineering Challenges for Telemetry

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?

Breakout: Engineering Challenges in Telemetry

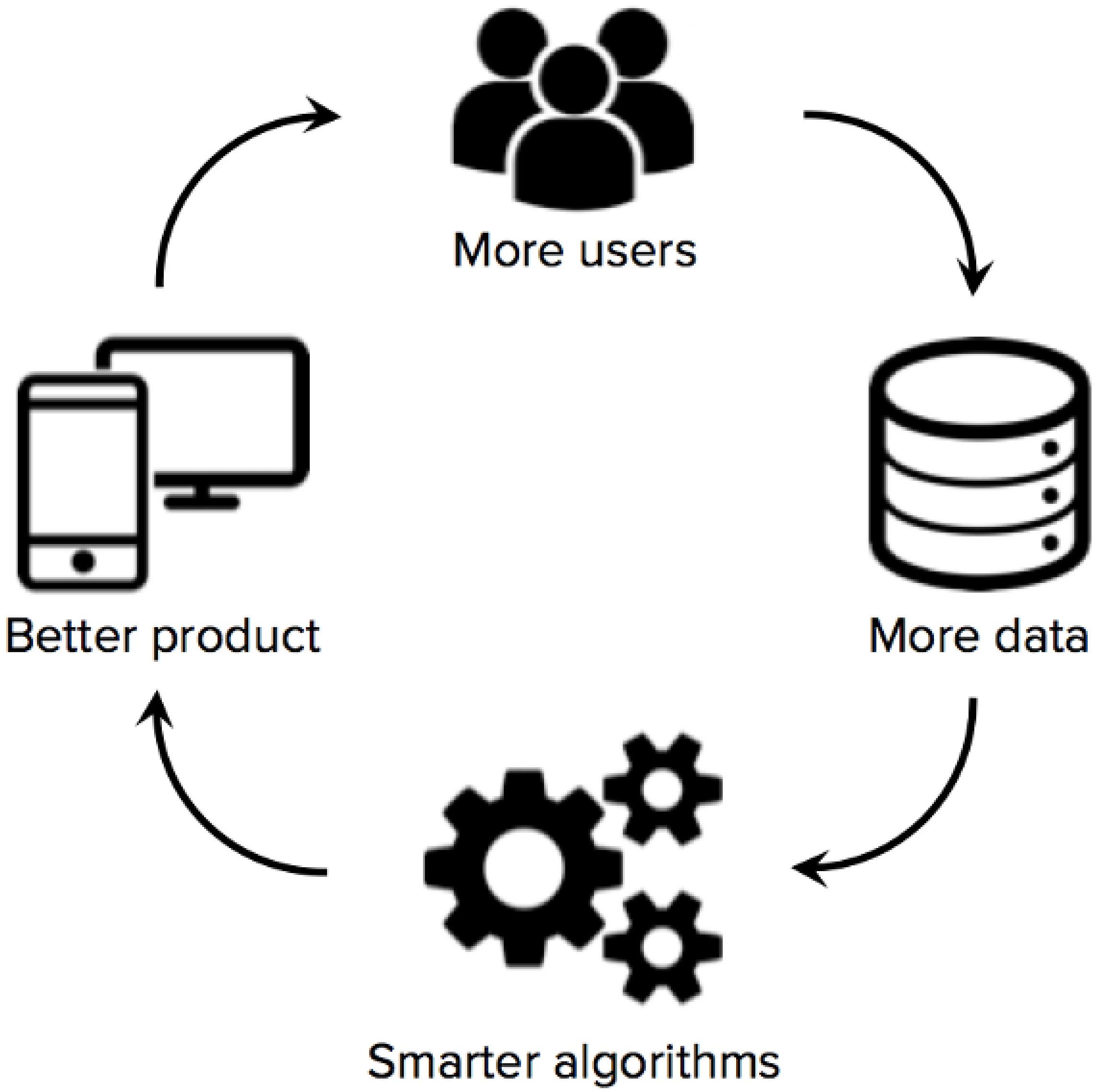
Discuss: Cost, privacy, rare events, bias

Scenarios:

- Front-left: Amazon: Shopping app feature that detects the shoe brand from photos
- Front-right: Google: Tagging uploaded photos with friends' names
- Back-left: Spotify: Recommended personalized playlists
- Back-right: Wordpress: Profanity filter to moderate blog posts

(can update slack, but not needed)

Telemetry for Training: The ML Flywheel



graphic by CBInsights

Revisiting Model Quality vs System Goals

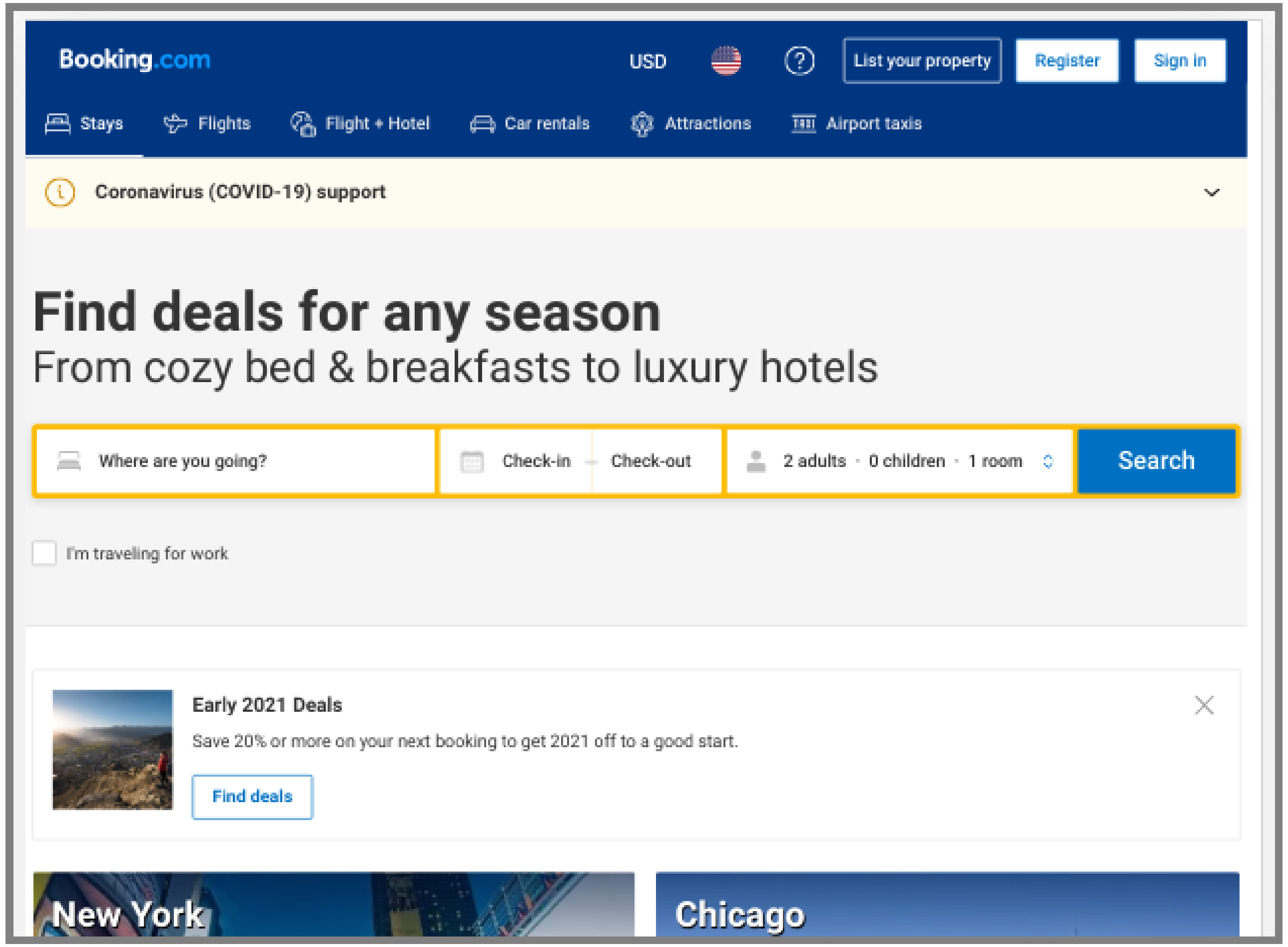
Model Quality vs System Goals

Telemetry can approximate model accuracy

Telemetry can directly measure system qualities, leading indicators, user outcomes

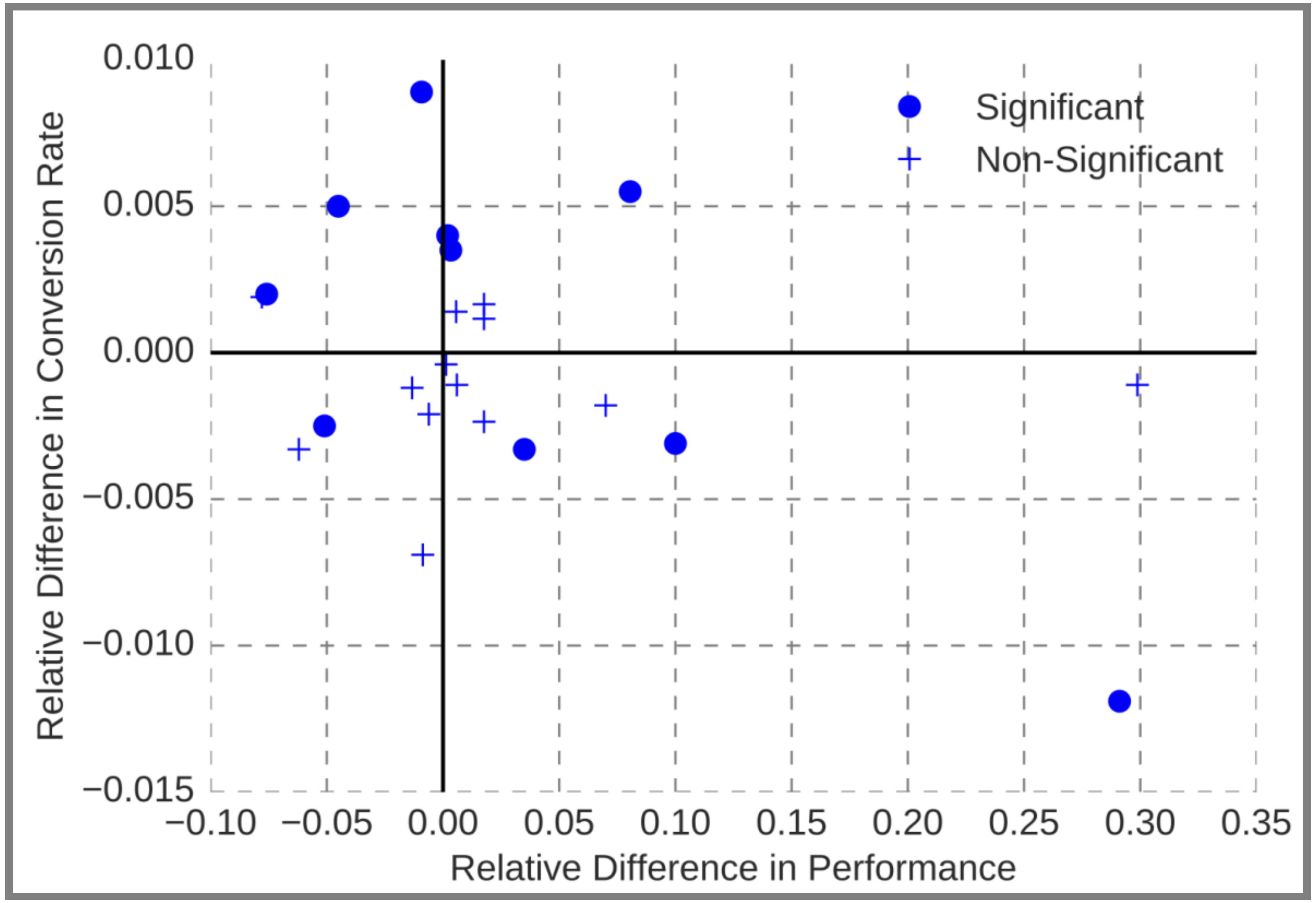
- define measures for "key performance indicators"
- clicks, buys, signups, engagement time, ratings
- operationalize with telemetry

Model Quality vs System Quality



Bernardi, Lucas, et al. "150 successful machine learning models: 6 lessons learned at Booking.com." In Proc. Int'l Conf. Knowledge Discovery & Data Mining, 2019.

Possible causes of model vs system conflict?



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"

Breakout: Design Telemetry in Production

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

Scenarios:

- Front-left: Amazon: Shopping app feature that detects the shoe brand from photos
- Front-right: Google: Tagging uploaded photos with friends' names
- Back-left: Spotify: Recommended personalized playlists
- Back-right: Wordpress: Profanity filter to moderate blog posts

(can update slack, but not needed)

Experimenting in Production

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

Grady Booch
@Grady_Booch · Follow

Testing in production.

> **Elon Musk**
> @elonmusk
>
> Made my account private until tomorrow morning to test whether you see my private tweets more than my public ones
>
> 1:06 AM · 2/1/23 · **633K** Views
>
> **27.2K** Likes **21** Quotes

9:47 AM · Feb 1, 2023

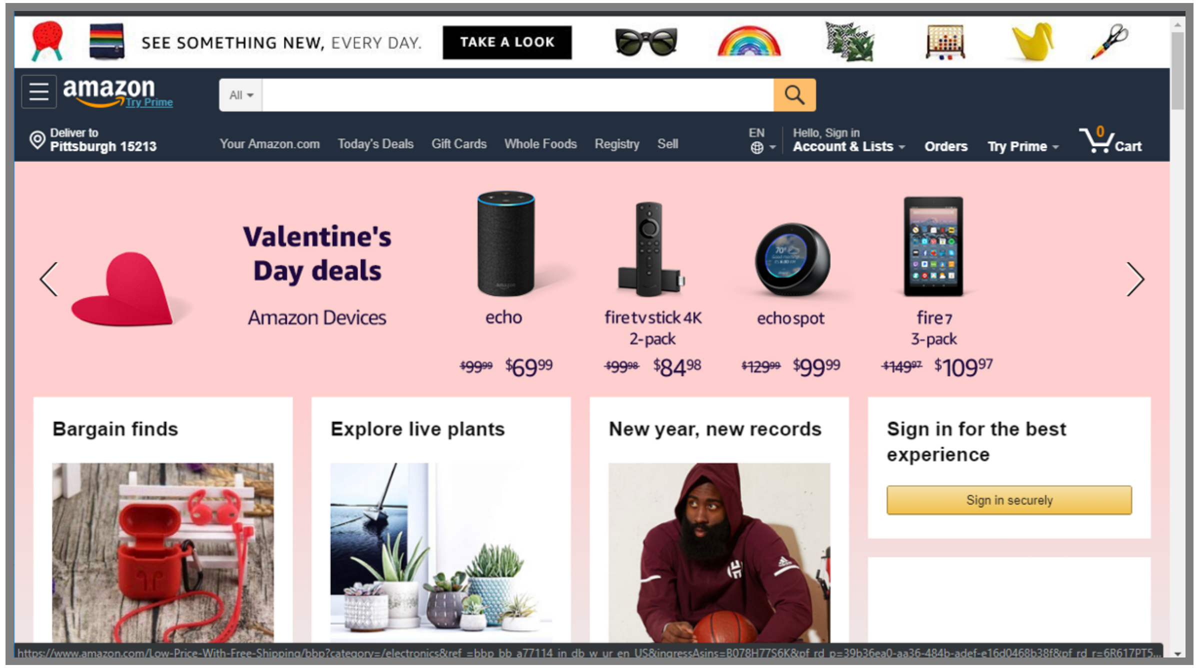
2.7K Reply Copy link

Read 157 replies

A/B Experiments

What if…?

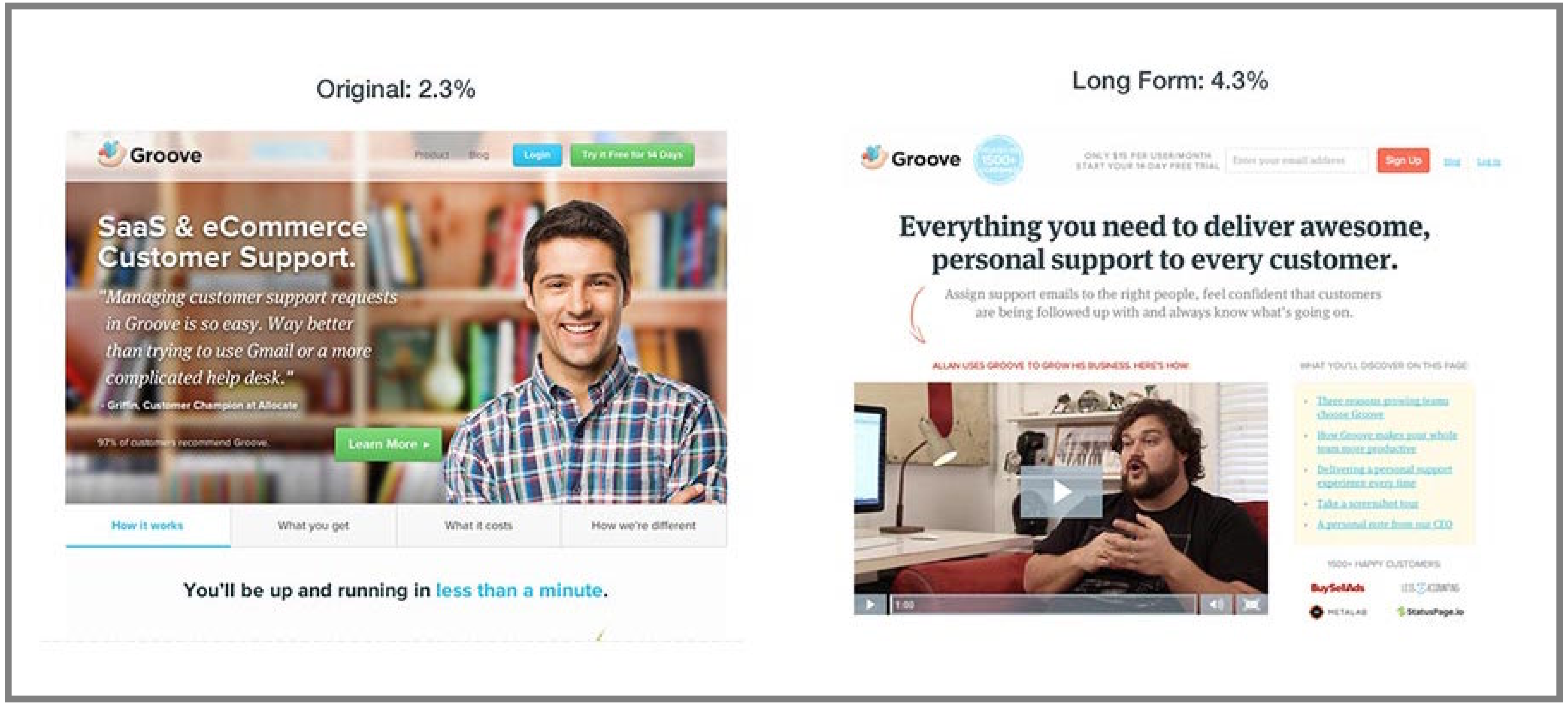
- … we hand plenty of subjects for experiments
- … we could randomly assign to treatment and control group without them knowing
- … we could analyze small individual changes and keep everything else constant



▶ Ideal conditions for controlled experiments

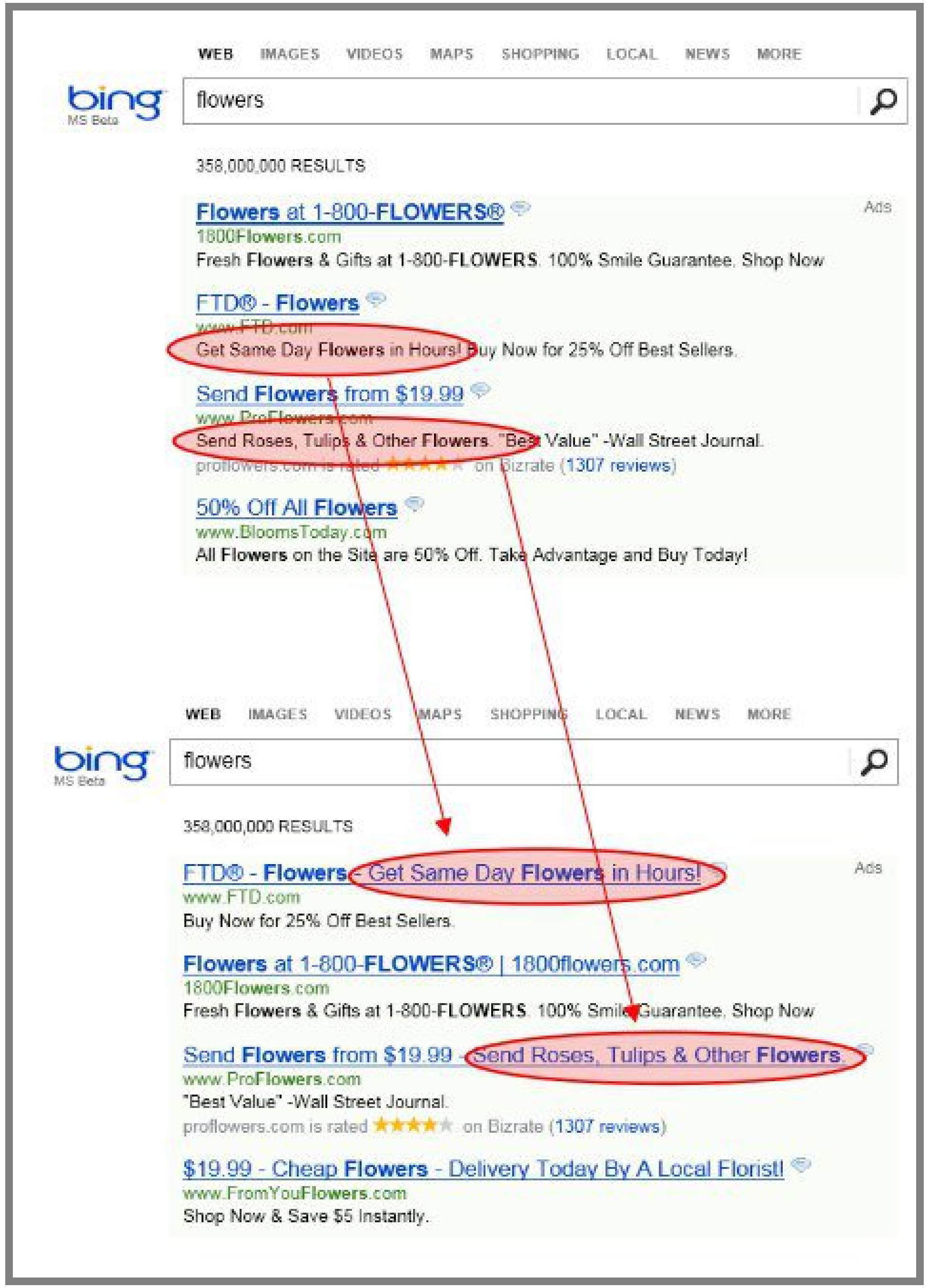
A/B Testing for Usability

- In running system, random 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/



Bing Experiment

- Experiment: Ad Display at Bing
- Suggestion prioritzed low
- Not implemented for 6 month
- Ran A/B test in production
- Within 2h *revenue-too-high* alarm triggered suggesting serious bug (e.g., double billing)
- Revenue increase by 12% - $100M anually in US
- Did not hurt user-experience metrics

From: Kohavi, Ron, Diane Tang, and Ya Xu. "Trustworthy Online Controlled Experiments: A Practical Guide to A/B Testing." 2020.

A/B Experiment for ML 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*

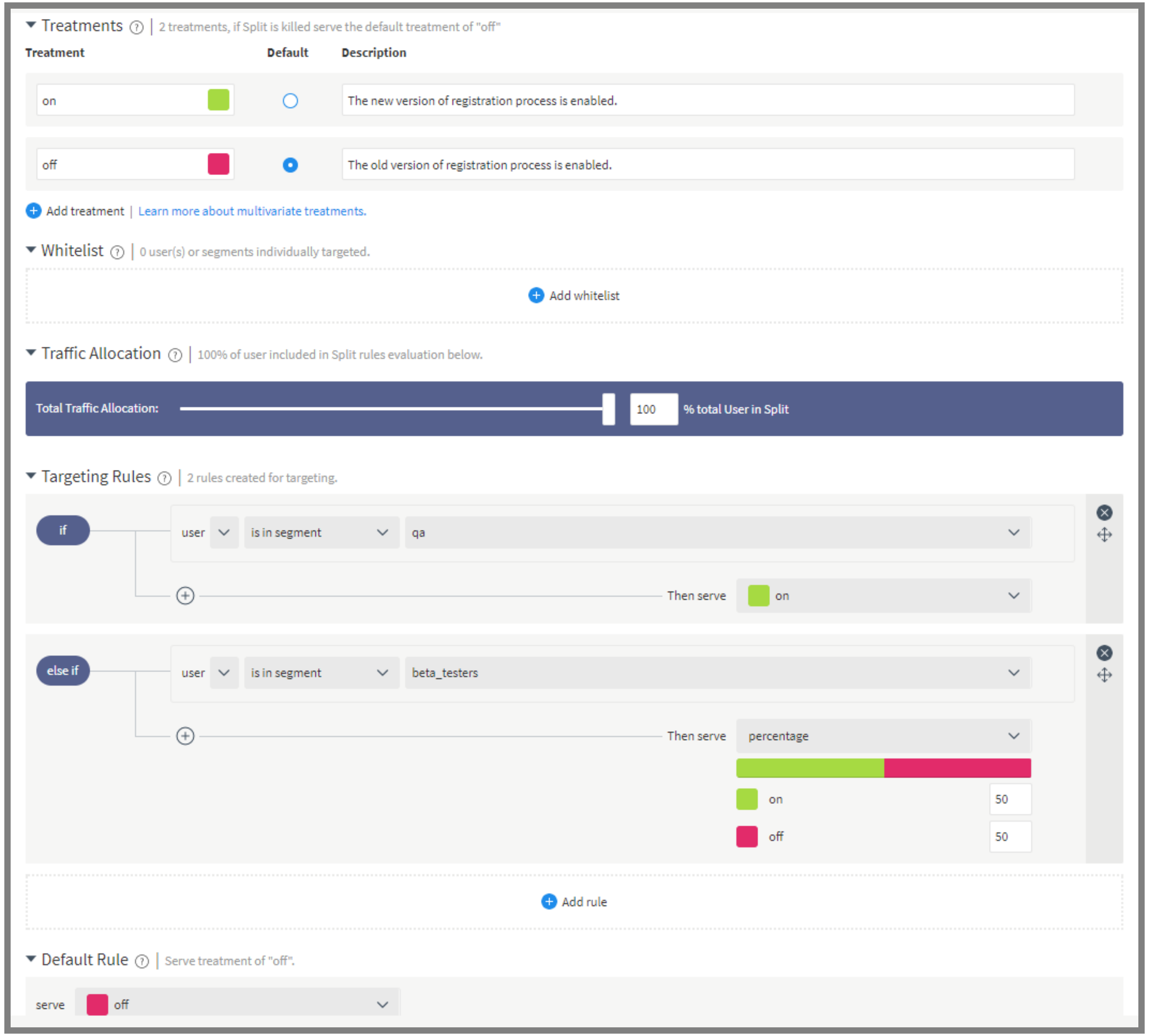
- Telemetry, sales, time on site, server load, crash rate

Feature Flags (Boolean flags)

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

- 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

classic personalized content recommendation model

2158 Users

average 3:13 min time on site

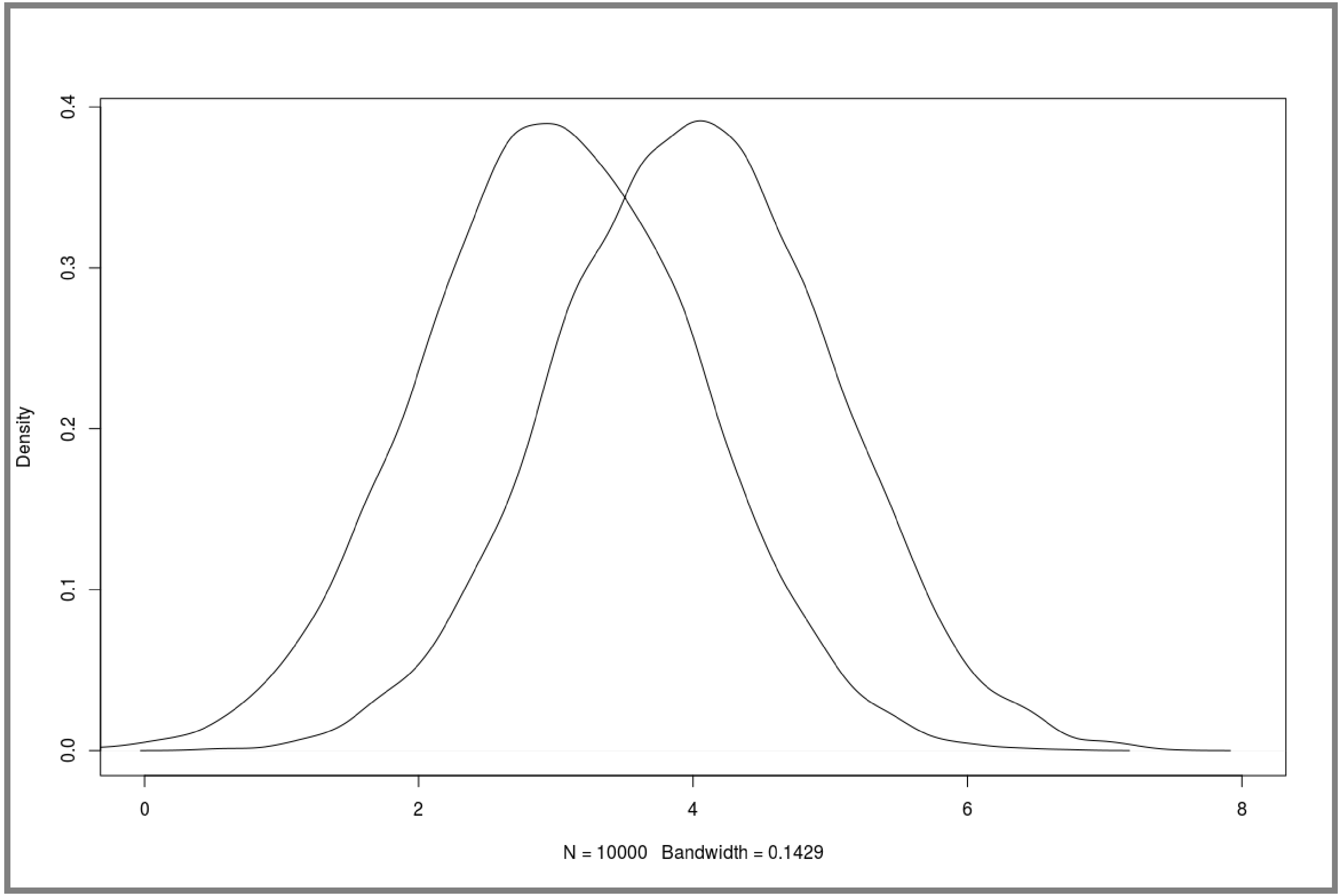
Group B

updated personalized content recommendation model

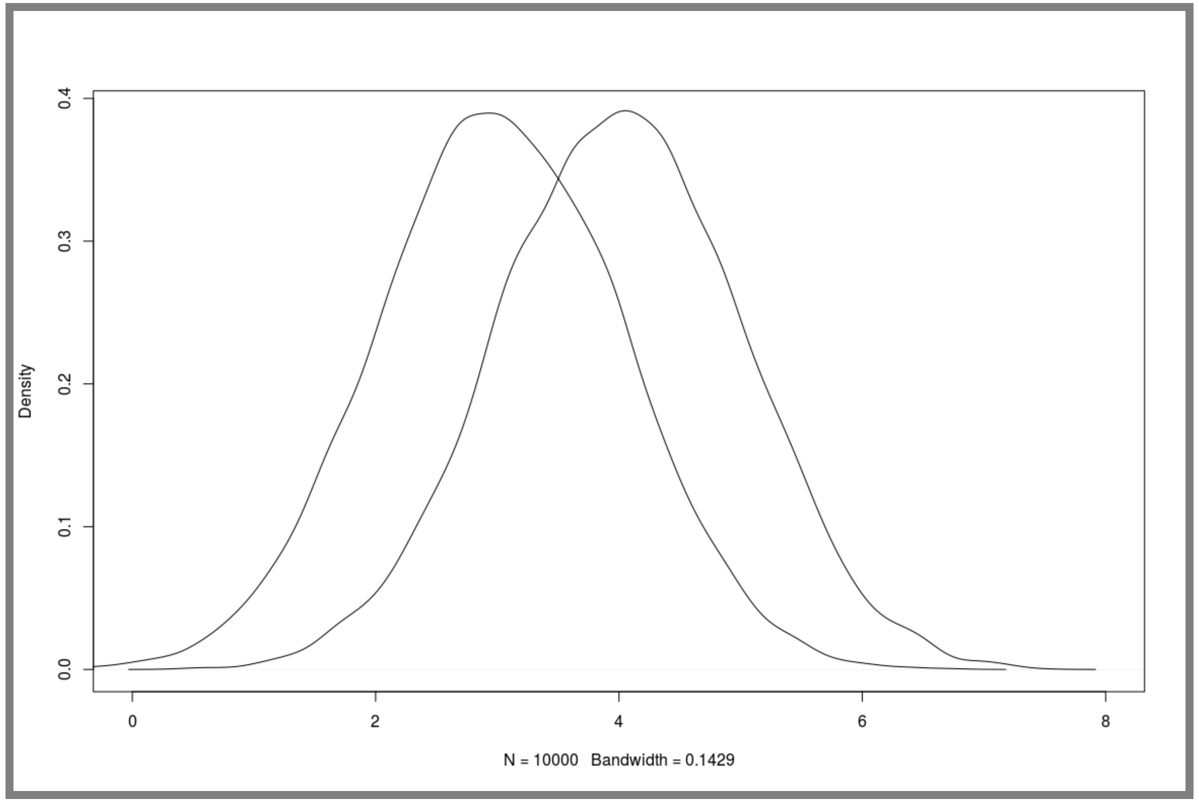
10 Users

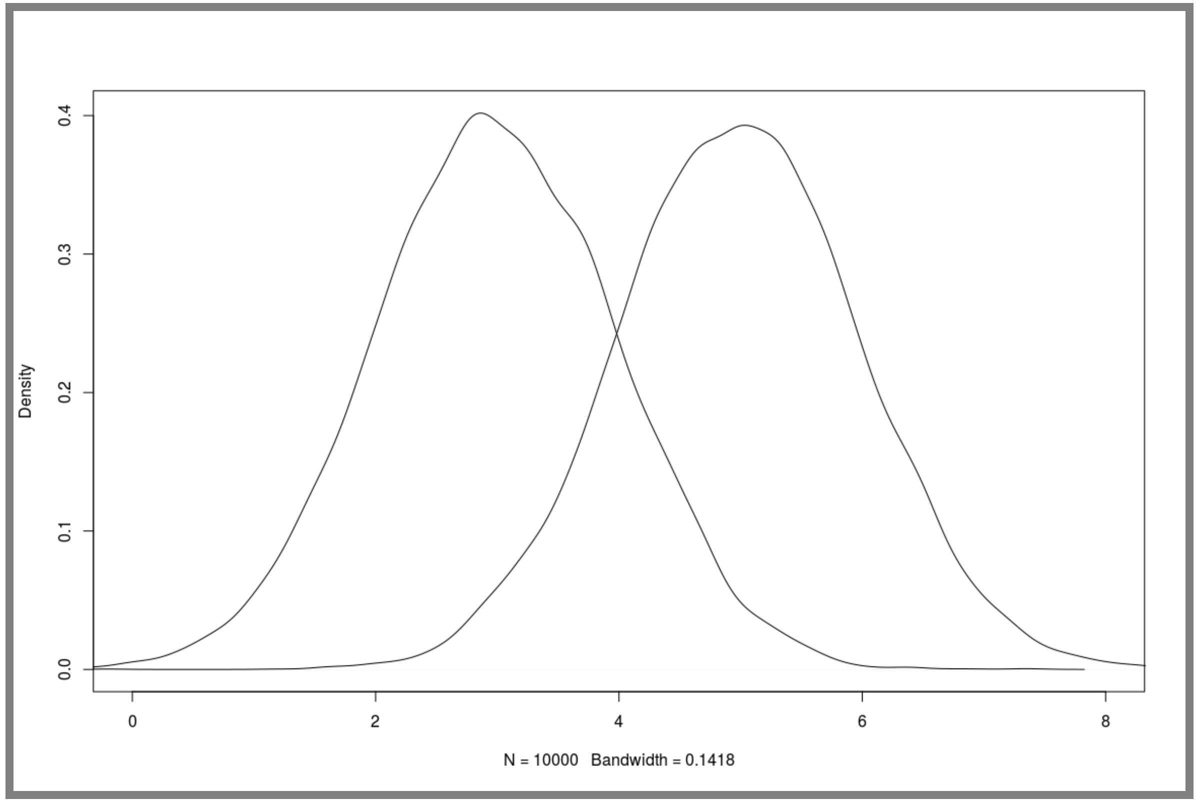
average 3:24 min time on site

Comparing Distributions

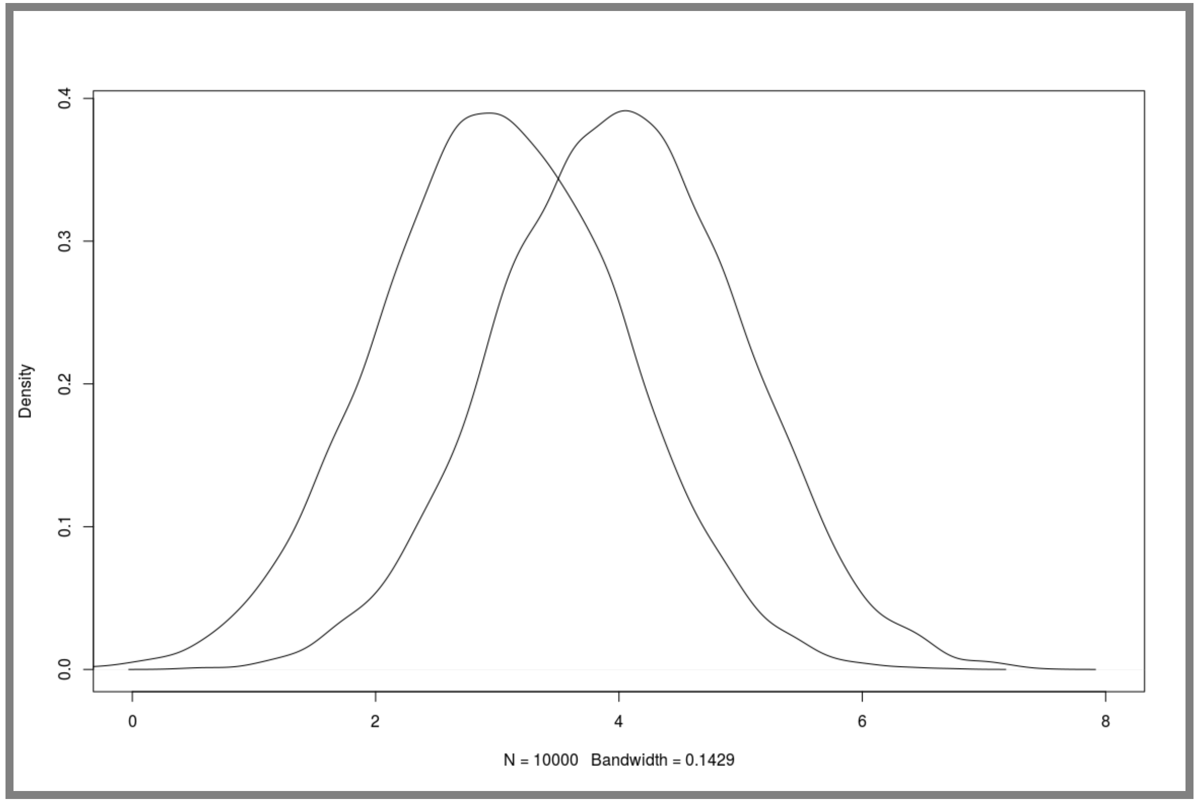


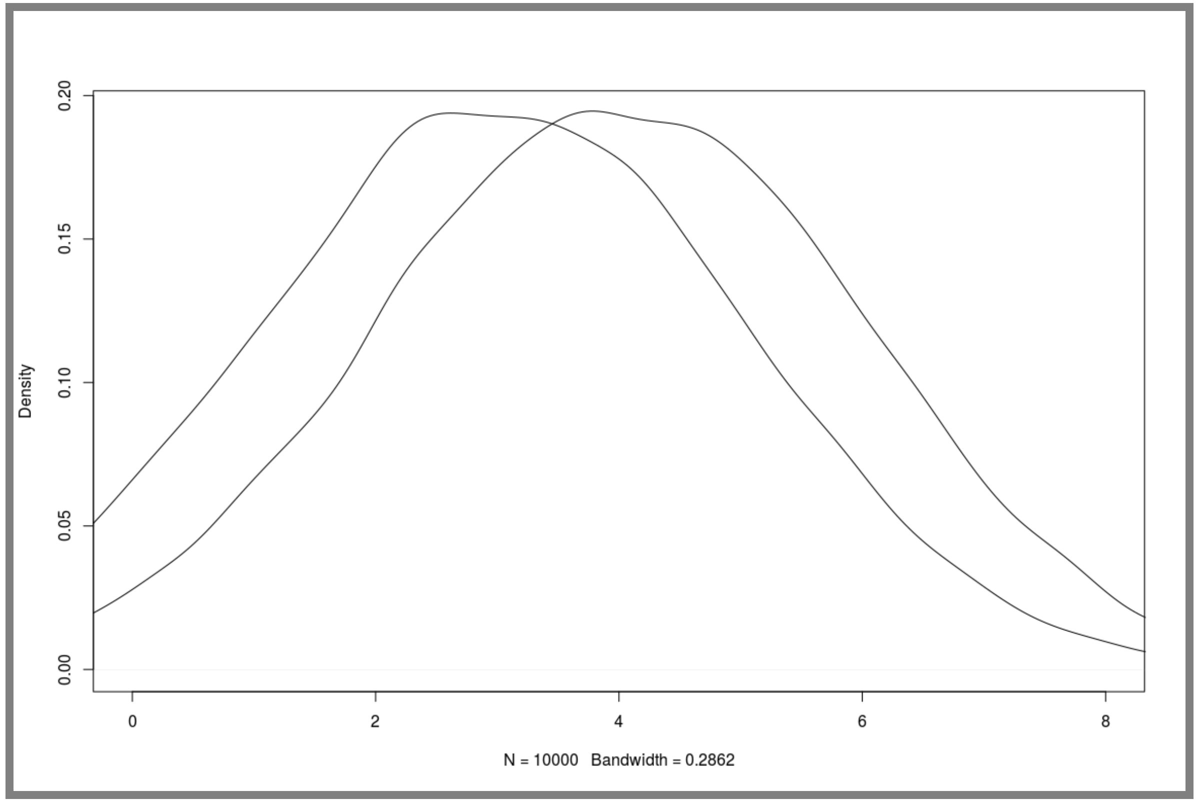
Different effect size, same deviations





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 $\nRightarrow$ proof
- Statistically significant result $\nRightarrow$ 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%)

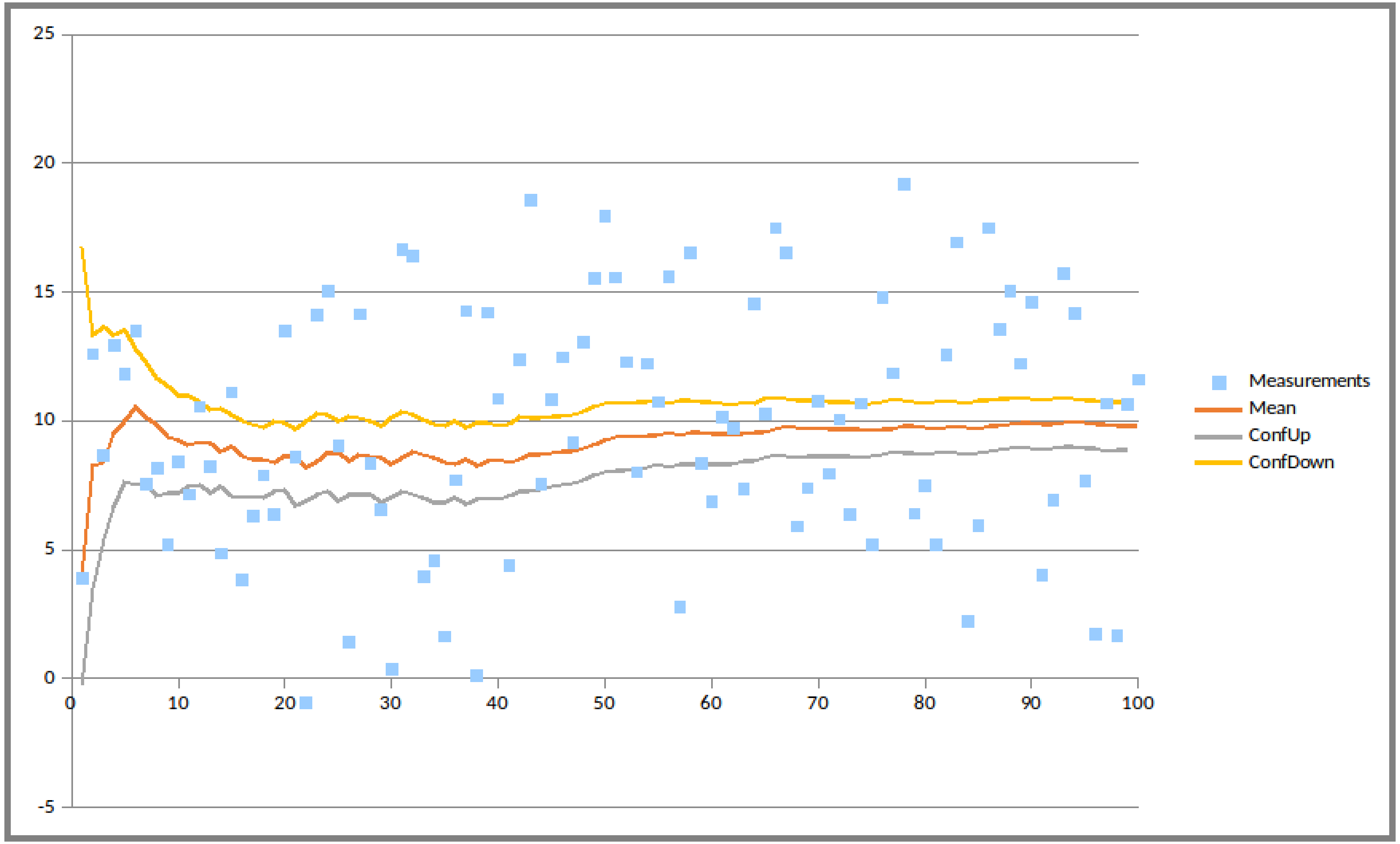
- 2 random errors, each +/- 1
- Measurements: 8 (25%), 10 (50%) und 12 (25%)

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

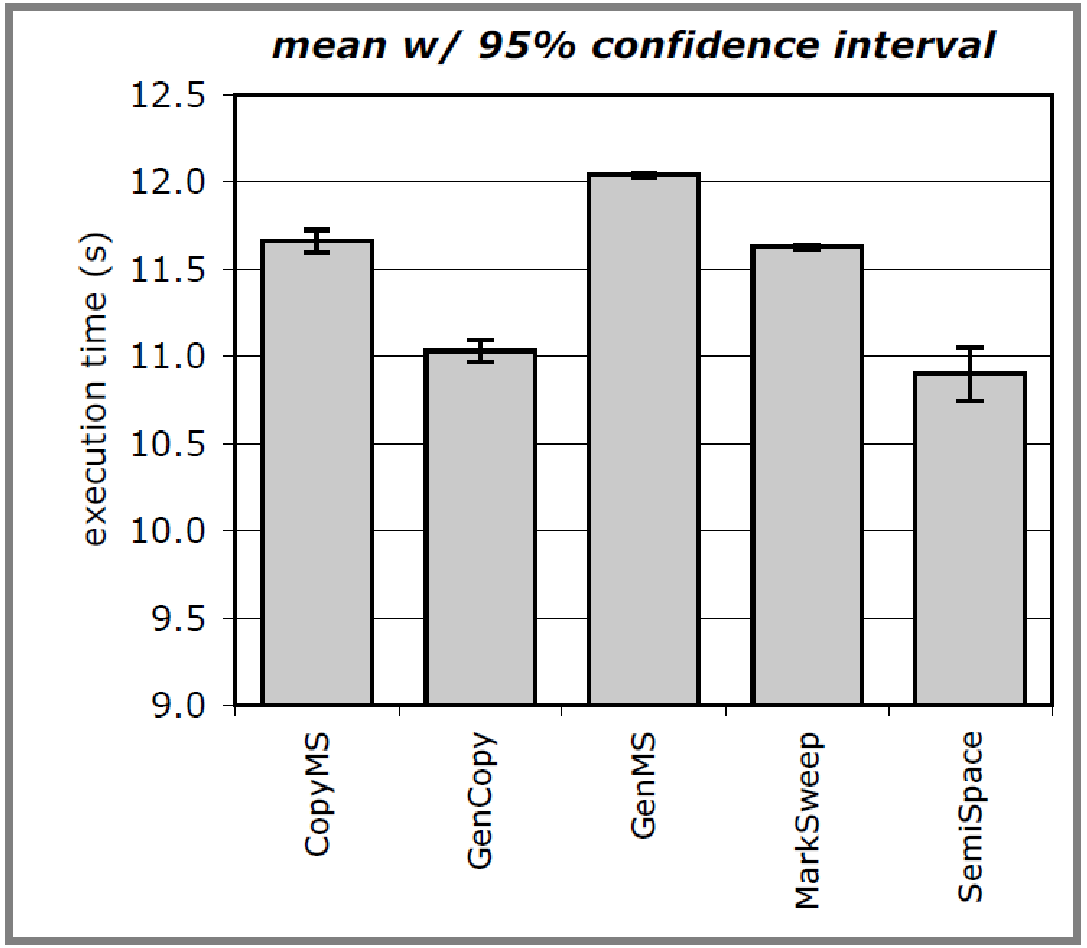
Normal Distribution

Normal distribution

Confidence Intervals



Comparison with Confidence Intervals



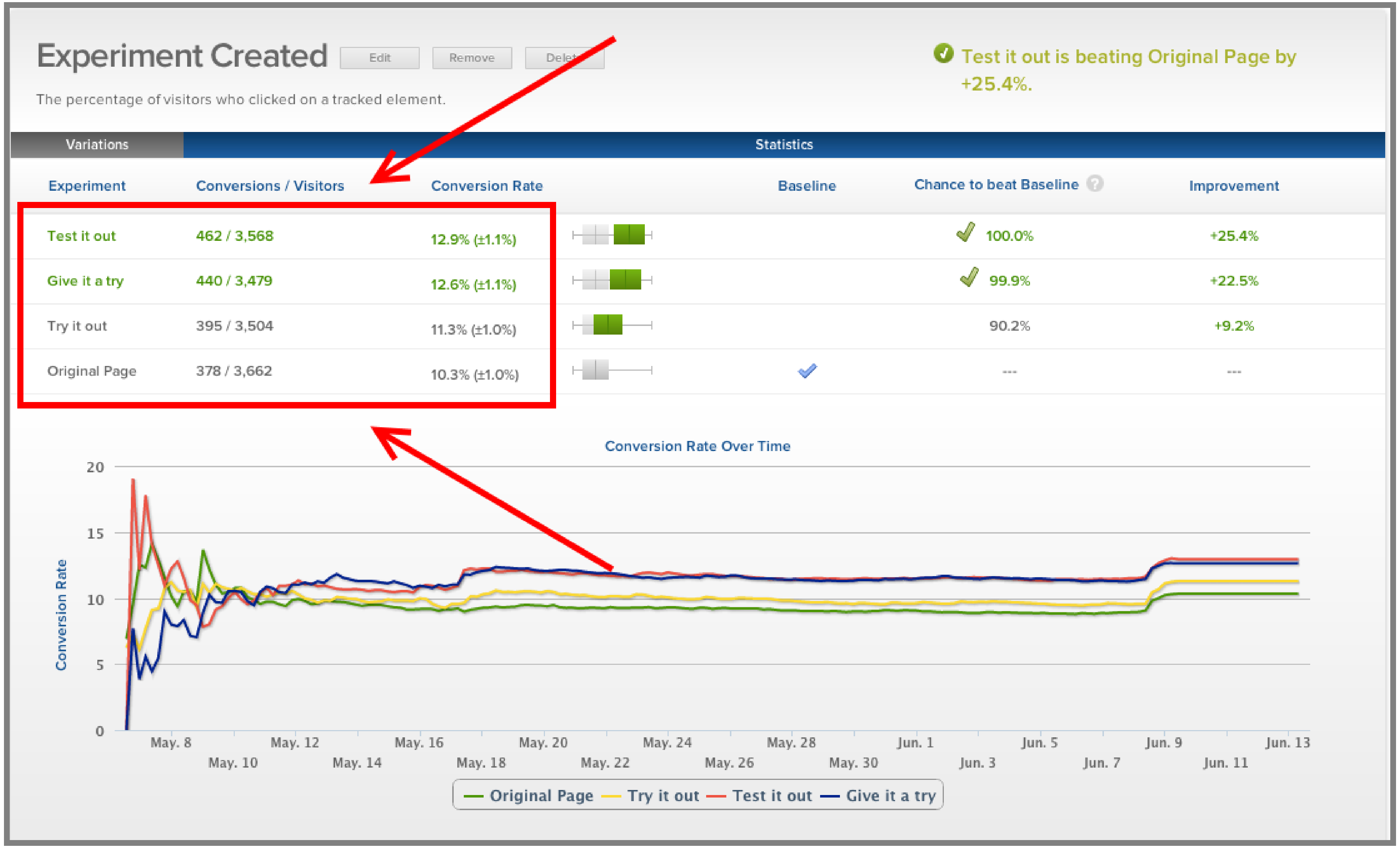
Source: Andy Georges, et al. 2007. Statistically rigorous java performance evaluation. In Proc. Conference on Object-Oriented Programming Systems and Applications.

t-test

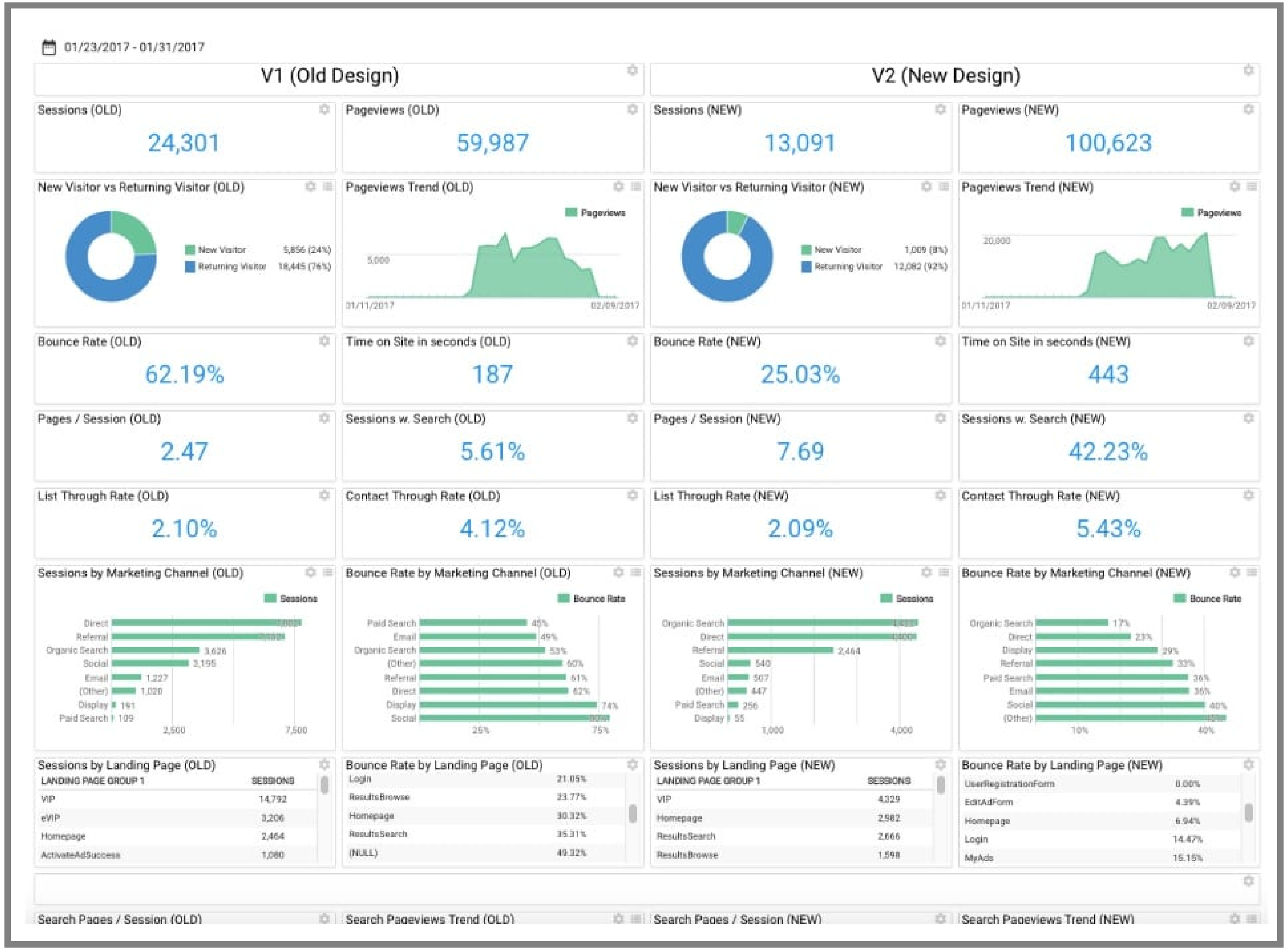
```
> t.test(x, y, conf.level=0.9)

        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
```



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



Source: https://cognetik.com/why-you-should-build-an-ab-test-dashboard/

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:

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);
```

Further readings: Bakshy, Eytan et al. Designing and deploying online field experiments. Proc. WWW, 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 (layers)

Further readings:

Other Experiments in Production

Shadow releases / traffic teeing

Blue/green deployment

Canary releases

Chaos experiments

Shadow releases / traffic teeing

Run both models in parallel

Use predictions of old model in production

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?

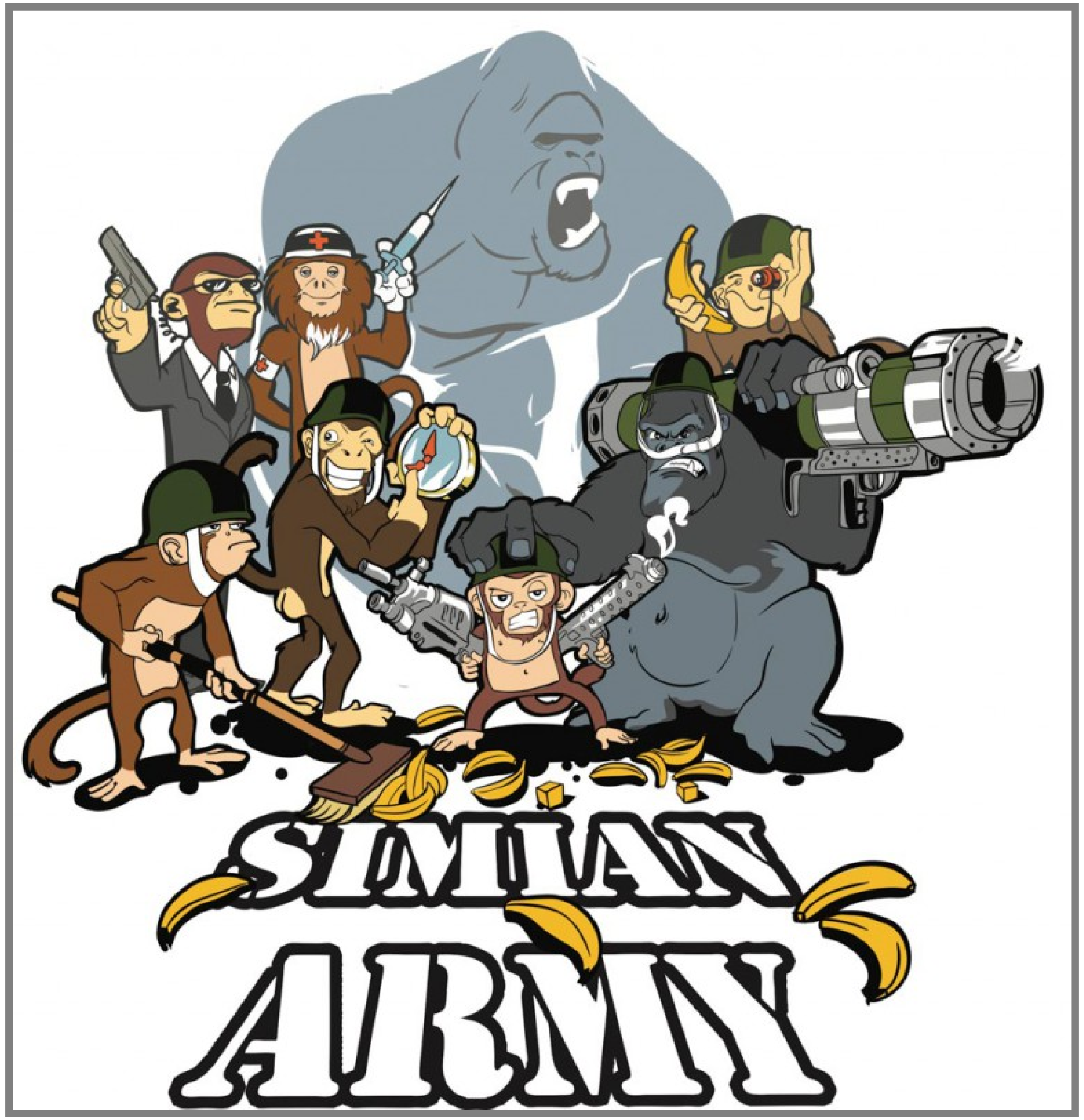
Canary Releases

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 ML 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

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

Summary

Production data is ultimate unseen validation data

Both for model quality and system quality

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

Further Readings

- On canary releases: Alec Warner and Štěpán Davidovič. "Canary Releases." in The Site Reliability Workbook, O'Reilly 2018
- Everything on A/B testing: Kohavi, Ron. *Trustworthy Online Controlled Experiments: A Practical Guide to A/B Testing*. Cambridge University Press, 2020.
- A/B testing critiques: Josh Constine. The Morality Of A/B Testing. Blog 2014; the Center of Humane Technology; and the Netflix documentary The Social Dilemma
- Ori Cohen "Monitor! Stop Being A Blind Data-Scientist." Blog 2019
- Jens Meinicke, Chu-Pan Wong, Bogdan Vasilescu, and Christian Kästner. Exploring Differences and Commonalities between Feature Flags and Configuration Options. In Proceedings of the Proc. International Conference on Software EngineeringICSE-SEIP, pages 233–242, May 2020.