Carnegie Mellon University

Data Analytics in Software Engineering

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Learning Goals

- Understand importance of data-driven decision making also during software engineering
- Collect and analyze measurements
- Design evaluation strategies to evaluate the effectiveness of interventions
- Understand the potential of data analytics at scale for QA data

Once Upon a Time...

Seven Years' War (1754-63)

Britain loses 1,512 sailors to enemy action...

...and almost 100,000 to scurvy

Oh, the Irony

James Lind (1716-94)

1747: (possibly) the first-ever controlled medical experiment

× cider
× sulfuric acid
× vinegar
× sea water
√oranges
×barley water

No-one paid attention until a proper Englishman repeated the experiment in 1794...

Like Water on Stone

1992: Sackett coins the term "evidence-based medicine"

Randomized double-blind trials are accepted as the gold standard for medical research

The Cochrane Collaboration (http://www.cochrane.org/) now archives results from hundreds of medical studies

What about Software Engineering?

What metrics are the **best predictors of failures**?

If I increase **test coverage**, will that actually increase software quality?

What is the **data quality** level used in empirical studies and how much does it actually matter?

Are there any **metrics that are indicators of failures** in both Open Source and Commercial domains?

I just submitted a **bug report**. Will it be fixed?

Should I be writing **unit tests** in my software project?

How can I tell if a piece of software will have **vulnerabilities**?

Do **cross-cutting concerns** cause defects?

Is strong **code ownership** good or bad for software quality?

Does **Distributed/Global software development** affect quality?

Does **Test Driven Development** (TDD) produce better code in shorter time?

How would you approach these questions with data?

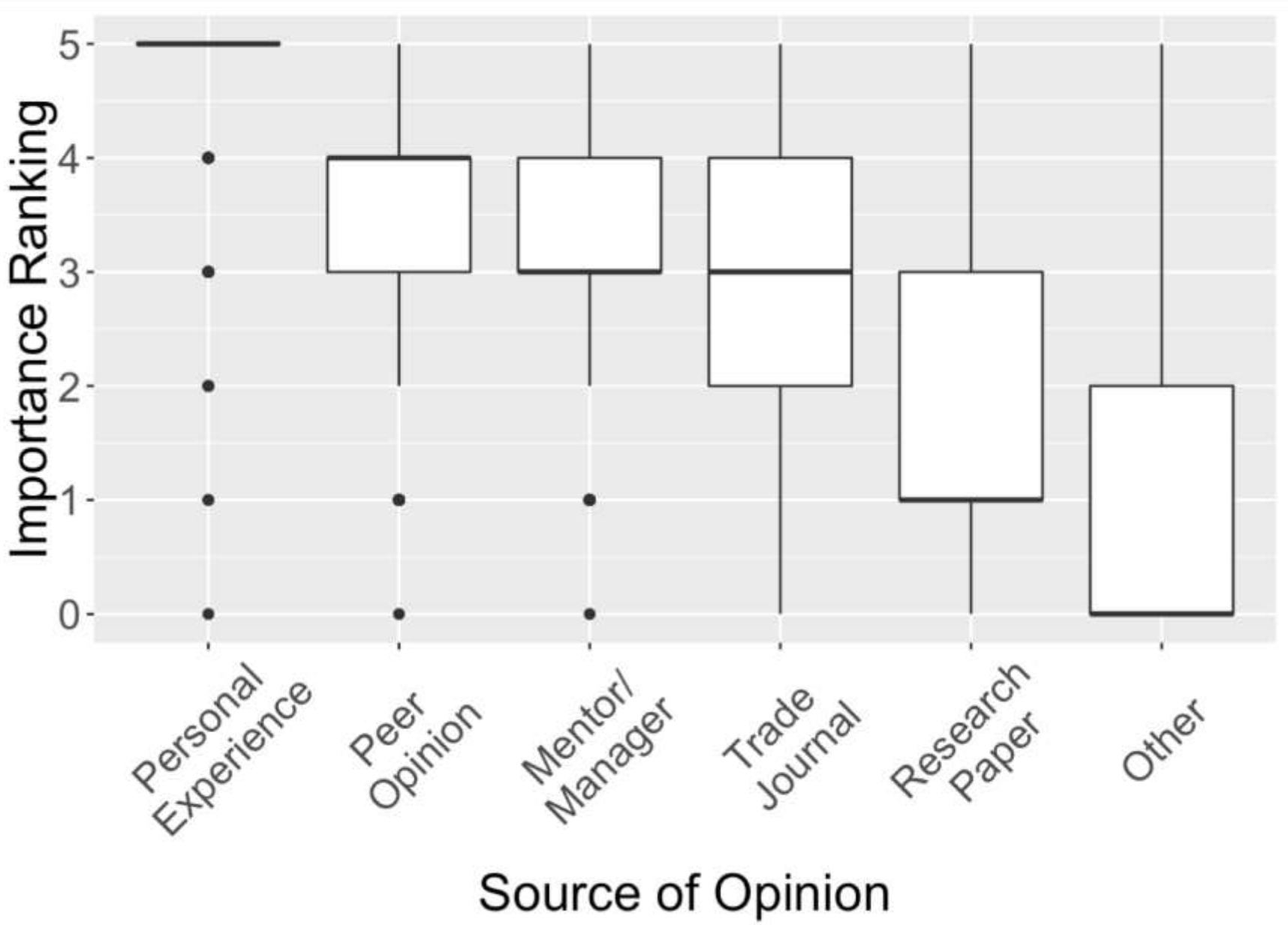
- Where to focus testing effort?
- Is our review practice effective?
- Is the expensive static analysis tool paying off?
- Should we invest in security training?

Believes vs Evidence?

- "40% of major decisions are based not on facts, but on the manager's gut" [Accenture survey among 254 US managers in industry]
- E.g., strong believes in survey among 564 Microsoft engineers
  - Code Reviews improve code quality
  - Coding Standards improve code quality
  - Static Analysis tools improve code quality
- Controversial believes from same survey
  - Code Quality depends on programming language
  - Fixing Defects is riskier than adding new features
  - Geographically distributed teams produce code of as good quality as non-distributed teams.

Devanbu, P., Zimmermann, T., & Bird, C. (2016, May). Belief & evidence in empirical software engineering. In *Proceedings of the 38th international conference on software engineering* (pp. 108-119). ACM.

Source of Believes



Software Engineering is becoming more like modern medicine?

Measurement and Metrics

- Discussed throughout the semester
- Everything is measurable
- Define measures, be critical (precision, accuracy, …)
- Be systematic in data collection (prefer automation)

How would you approach these questions with data?

- Where to focus testing effort?
- Is our review practice effective?
- Is the expensive static analysis tool paying off?
- Should we invest in security training?

Evaluate Effectiveness of an Intervention

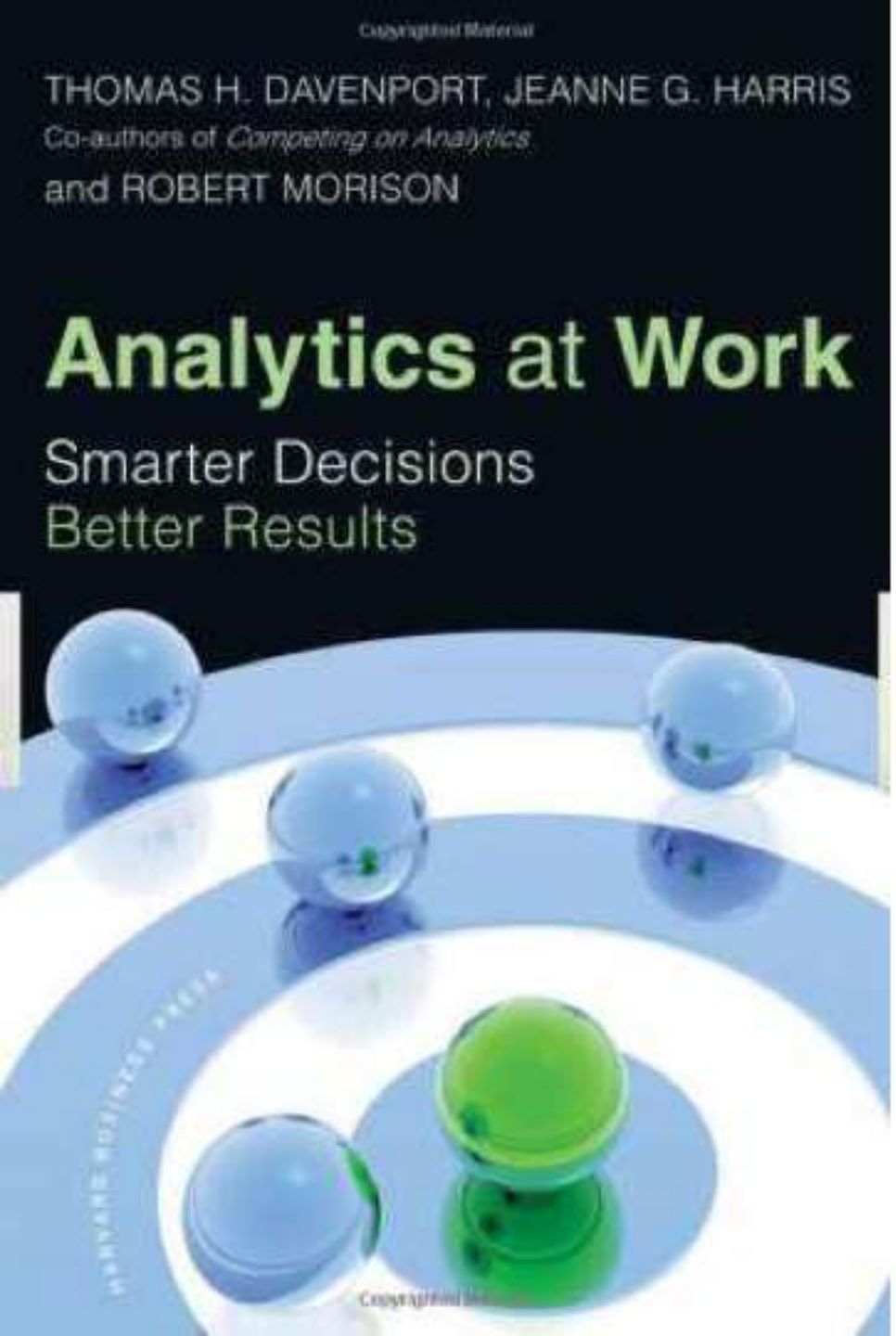
- Controlled experiments
  - Compare group with intervention against control group without,
  - Randomized controlled trials, AB testing, …
  - Ideally blinded
- Natural experiments, Quasi experiments
  - Compare similar groups that naturally only differ in the intervention
  - No randomized assignment of treatment condition
- Time series analyses
  - Compare measures before and after intervention, preferably across groups with the intervention at different times

On Experiments

- Understand experimental methods and limitations
  - Chose appropriate design (e.g., quasi experiment, vs timeseries, vs controlled)
  - Appropriate to research question and available subjects
- Design carefully, control confounds, avoid biases
- Use appropriate statistics to draw conclusions

- This requires sound understanding of quantitative research methods
- Many pitfalls

data science / analytics 101



Use of data, analysis, and systematic reasoning to [inform and] make decisions

the many names

software intelligence
software analytics
software development analytics
analytics for software development
empirical software engineering
mining software repositories

Microsoft Research

DATA

Data Scientist: The Sexiest Job of the 21st Century

by Thomas H. Davenport and D.J. Patil

FROM THE OCTOBER 2012 ISSUE

SUMMARY | SAVE | SHARE | COMMENT | TEXT SIZE | PRINT | BUY COPIES

When Jonathan Goldman arrived for work in June 2006 at LinkedIn, the business networking site, the place still felt like a start-up. The company had just under 8 million accounts, and the number was growing quickly as existing members invited their friends and colleagues to join. But users weren't seeking out connections with the people who were already on the site at the rate executives had expected. Something was apparently missing in the social experience. As one LinkedIn manager put it, "It was like arriving at a conference reception and

WHAT TO READ NEXT

Big Data: The Management Revolution

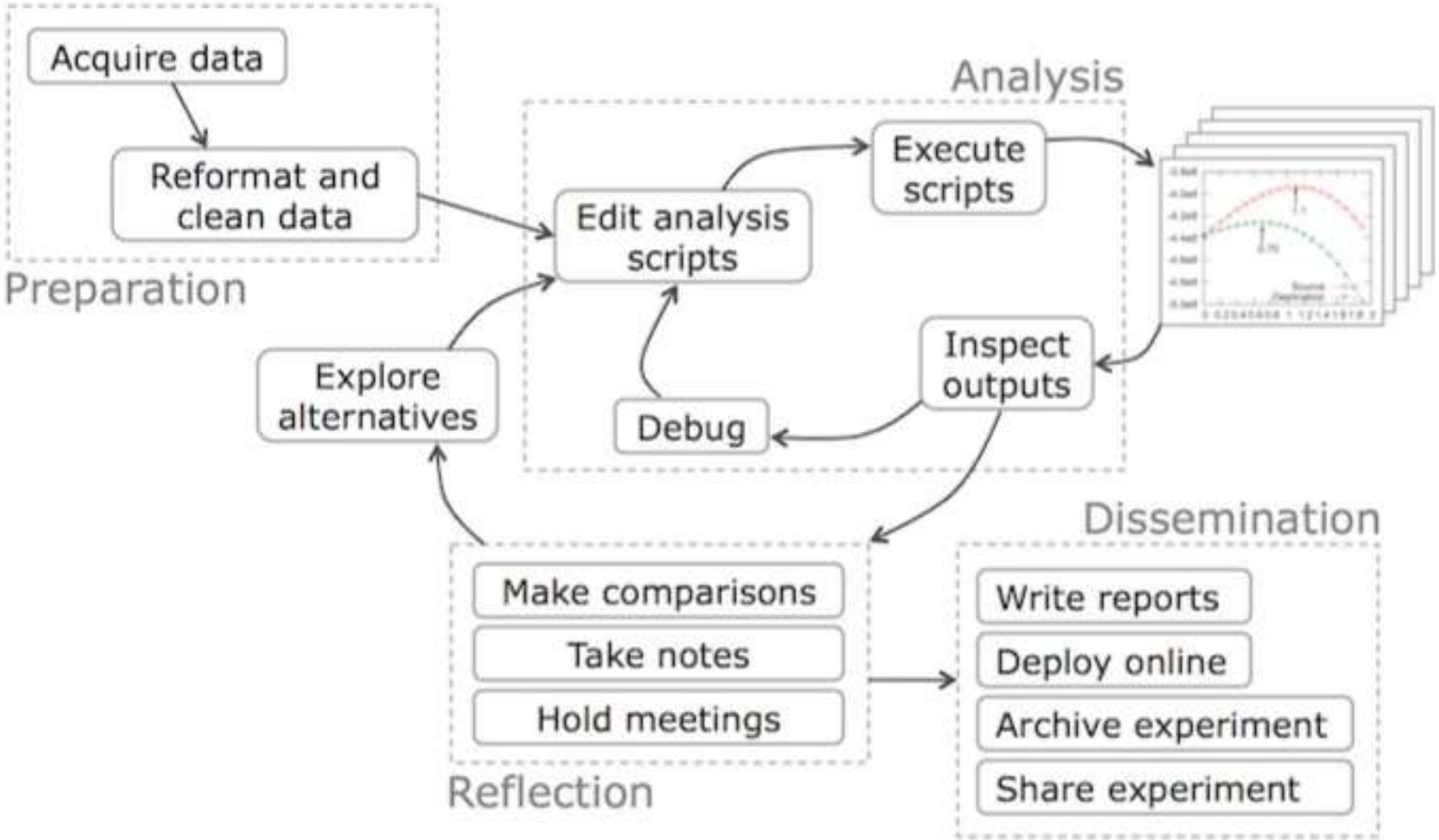
Making Advanced Analytics Work for You

Google Flu Trends' Failure Shows Good Data > Big Data

VIEW MORE FROM THE

October 2012 Issue

Typical data science workflow



https://cacm.acm.org/blogs/blog-cacm/169199-data-science-workflow-overview-and-challenges/

Background of Data Scientists

Most CS, many interdisciplinary backgrounds

Many have higher education degrees

Strong passion for data

> *I love data, looking and making sense of the data. [P2]*
>
> *I've always been a data kind of guy. I love playing with data. I'm very focused on how you can organize and make sense of data and being able to find patterns. I love patterns. [P14]*

"Machine learning hackers". Need to know stats

> *My people have to know statistics. They need to be able to answer sample size questions, design experiment questions, know standard deviations, p-value, confidence intervals, etc.*

Abundance of Data

Abundance of Data

- Code history
- Developer activities
- Bug trackers
- Sprint backlog, milestones
- Continuous integration logs
- Static analysis and technical debt dashboards
- Test traces; dynamic analyses
- Runtime traces
- Crash reports from customers
- Server load, stats
- Customer data, interactions
- Support requests, customer reviews
- Working hours
- Team interactions in Slack/issue tracker/email/…
- …

Measurement is Hard Example: Performance

Twitter Case Study

Timer Overhead

- Measurement itself consumes time

Request time

Even starts

Event ends,
request time

Time reported

Saved end time

Memory access and interaction with operating system

Measured event should be 100-1000x longer than measurement overhead

Confounding variables

Confounding variables

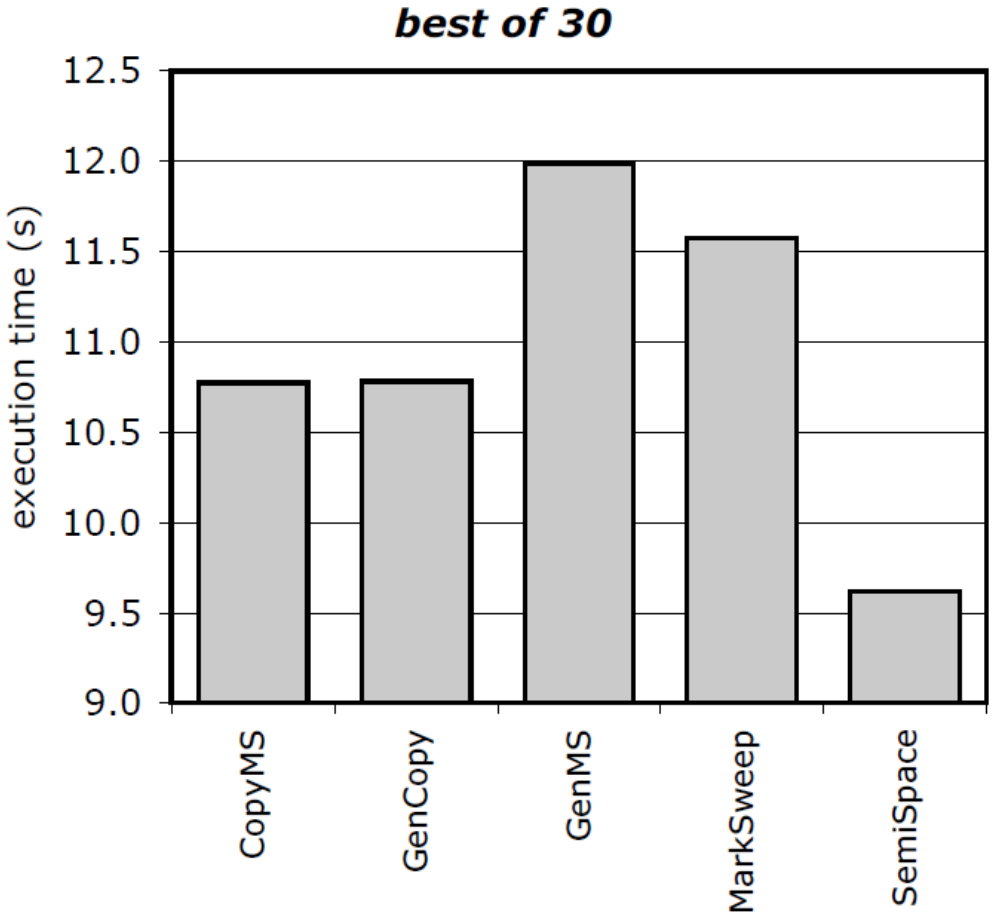
- Background processes
- Hardware differences
- Temperature differences
- Input data; random?
- Heap size
- System interrupts
- Single vs multi core systems
- Garbage collection
- Memory layout
- …

Handling confounding variables

- Keep constant
- Randomize
  - -> Repeated measurements
  - -> Large, diverse benchmarks
- Measure and compute influence ex-post

Common approach: best result

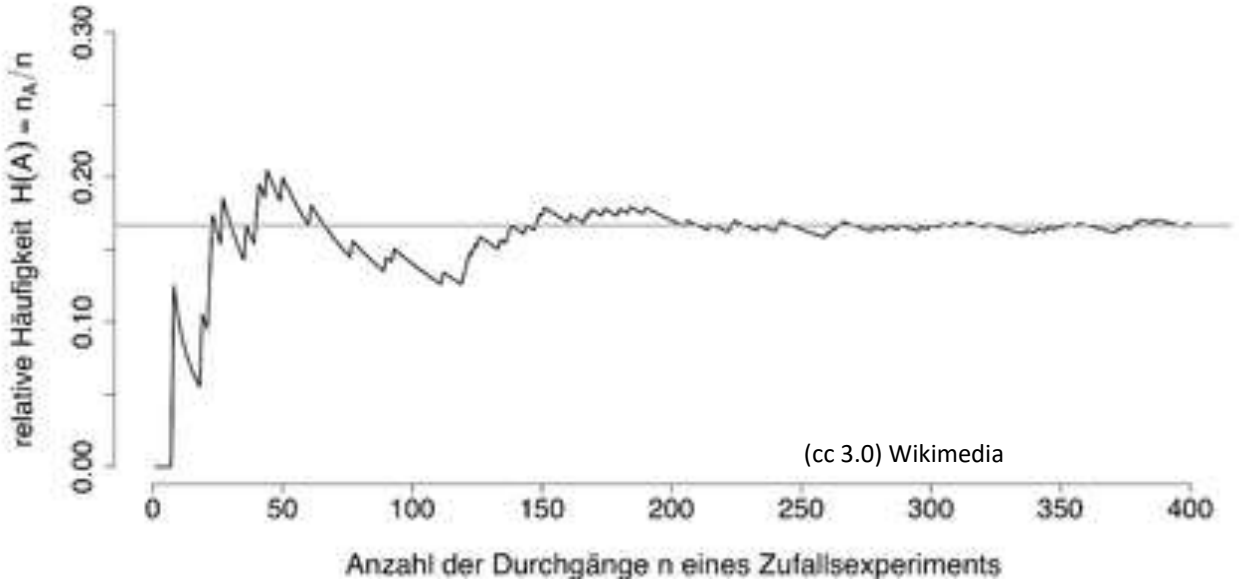
- Repeat measurement
- Report best result (or second best, or worst)



Common approach: Mean values

- Repeat measurement (how often?)
- Report average

- Basic assumptions: Law of large numbers and central limit theorem



Means

- Arithmetic mean

$$\bar{x}_{arithm} = \frac{1}{n}\sum_{i=1}^{n} x_i = \frac{x_1 + x_2 + \ldots + x_n}{n}$$

mean(c(1,4,6,10)) = 5.25
mean(c(-5,3,4,6,50)) = 11.6

- Median: The value in the middle
  - On even data sets, the arithmetic mean between the two values in the middle
  - Robust against outliers
- Truncated mean
  - Remove 10% outliers (on both ends), then arithm. mean
- Geometric mean
- …

median(c(1,4,6,10)) = 5
median(c(-5,3,4,6,50)) = 4

Median

- Median instead of arithmetic mean, if
  - ordinal data ("distance" has no meaning)
  - only few measurements
  - asymmetric distributions
  - expecting outliers

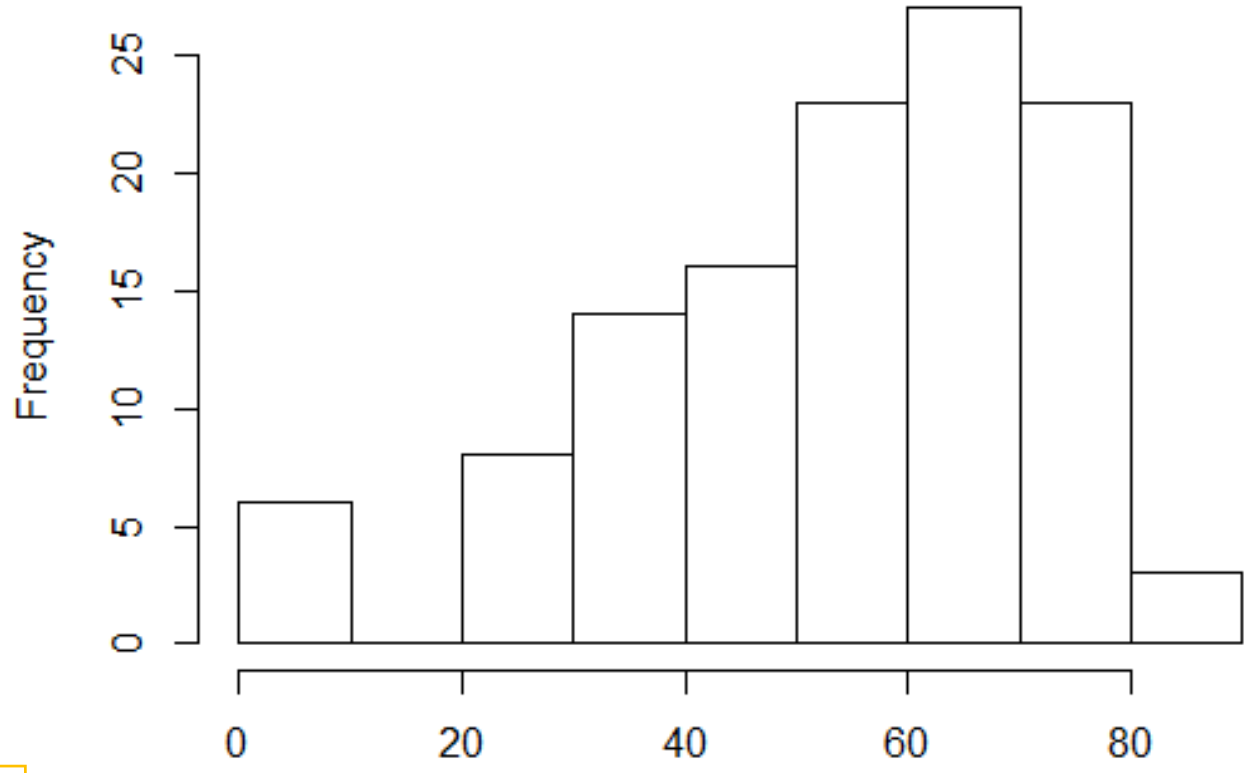
But

- How many measurements?
  - Are 3, 10, or 50 sufficient? Or 100 or 10000?
  - (to find the higgs boson, several million measurements were necessary)
- Measuring order?
  - AAABBB or ABABAB
- Iterate in a single batch or multiple batches?
- Are measurements independent?
- Is the average good enough?

Visualize data

- Get an overview
- Visually inspect distribution and outliers

Histograms



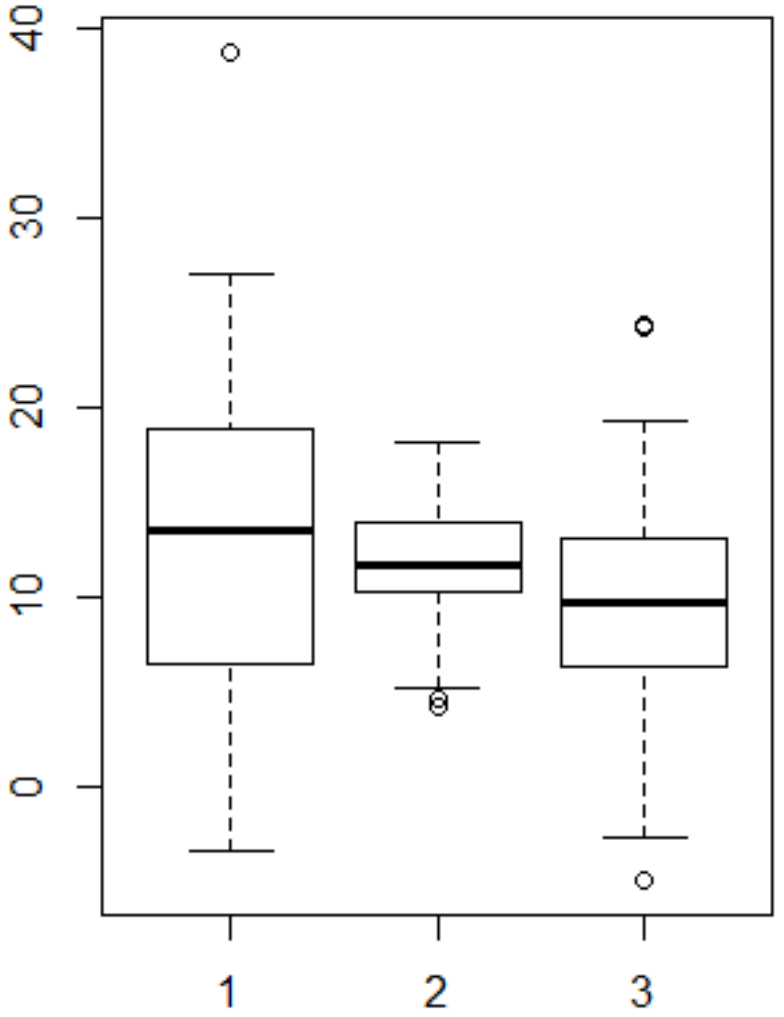
hist(c)

Reporting distributions

- Boxplot show
  - Median as thick line
  - Quartiles as box (50% of all values are ir
  - Whiskers
  - Outliers as dots
- Cumulative probability distributions
- Visual representation of distributions

boxplot(c)

plot(ecdf(c))



Error Models and Probability Distributions

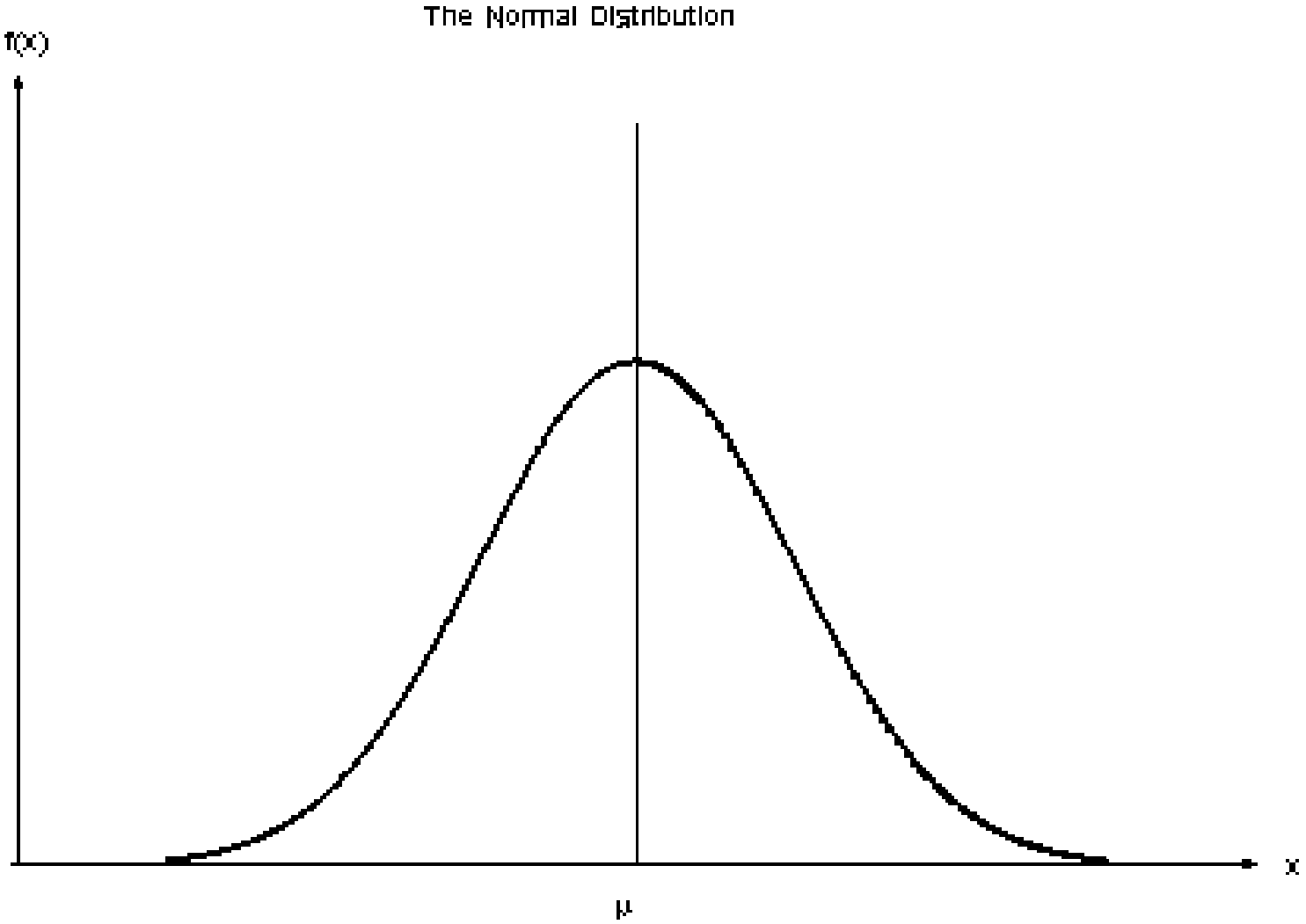
Intuition: Error Model

- 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%)

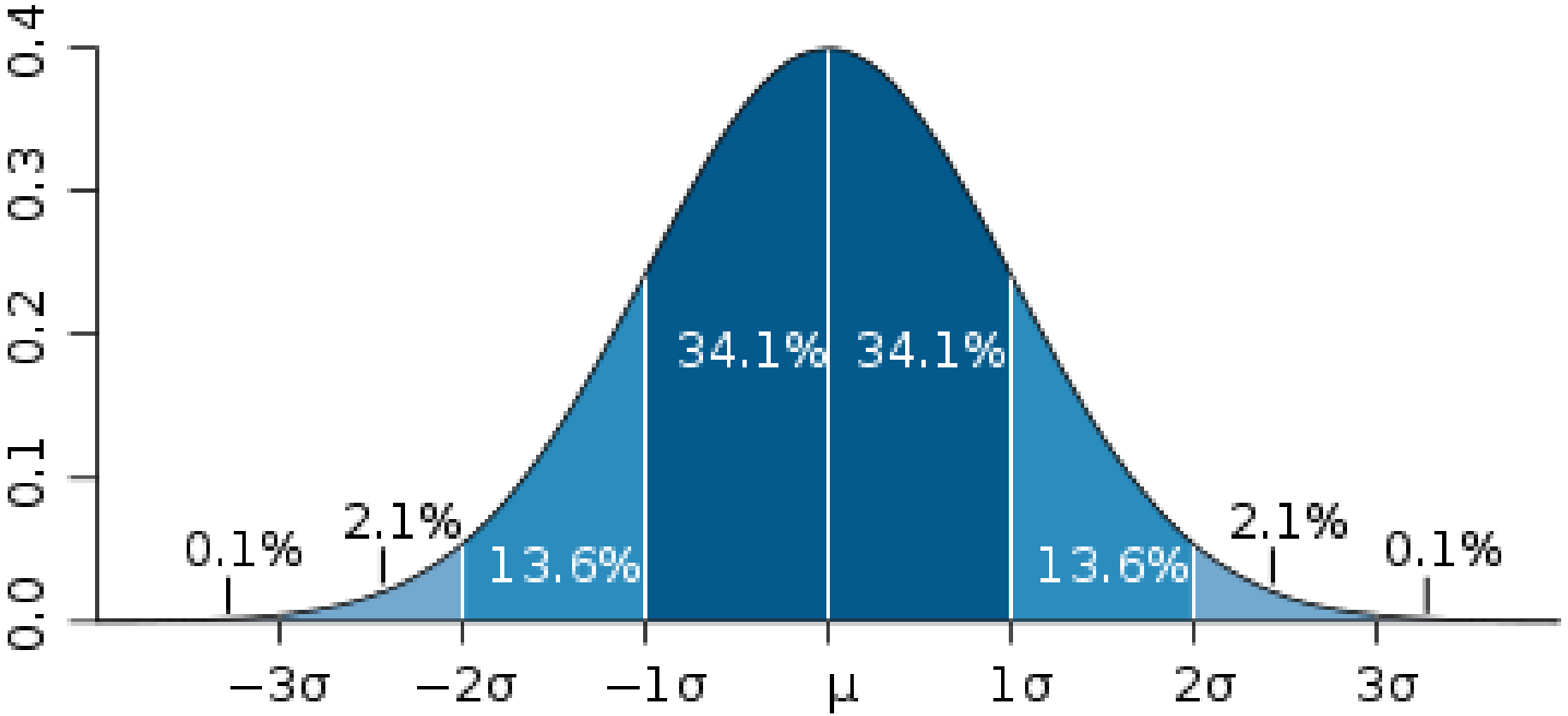
- 3 random errors, each +/- 1
- Measurements : 7 (12.5%), 9 (37.5), 11 (37.5), 12 (12.5)

Normal distributions



Standard deviation

$$s = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2} = \sqrt{\frac{(x_1 - \bar{x})^2 + (x_2 - \bar{x})^2 + \ldots + (x_n - \bar{x})^2}{n}}$$



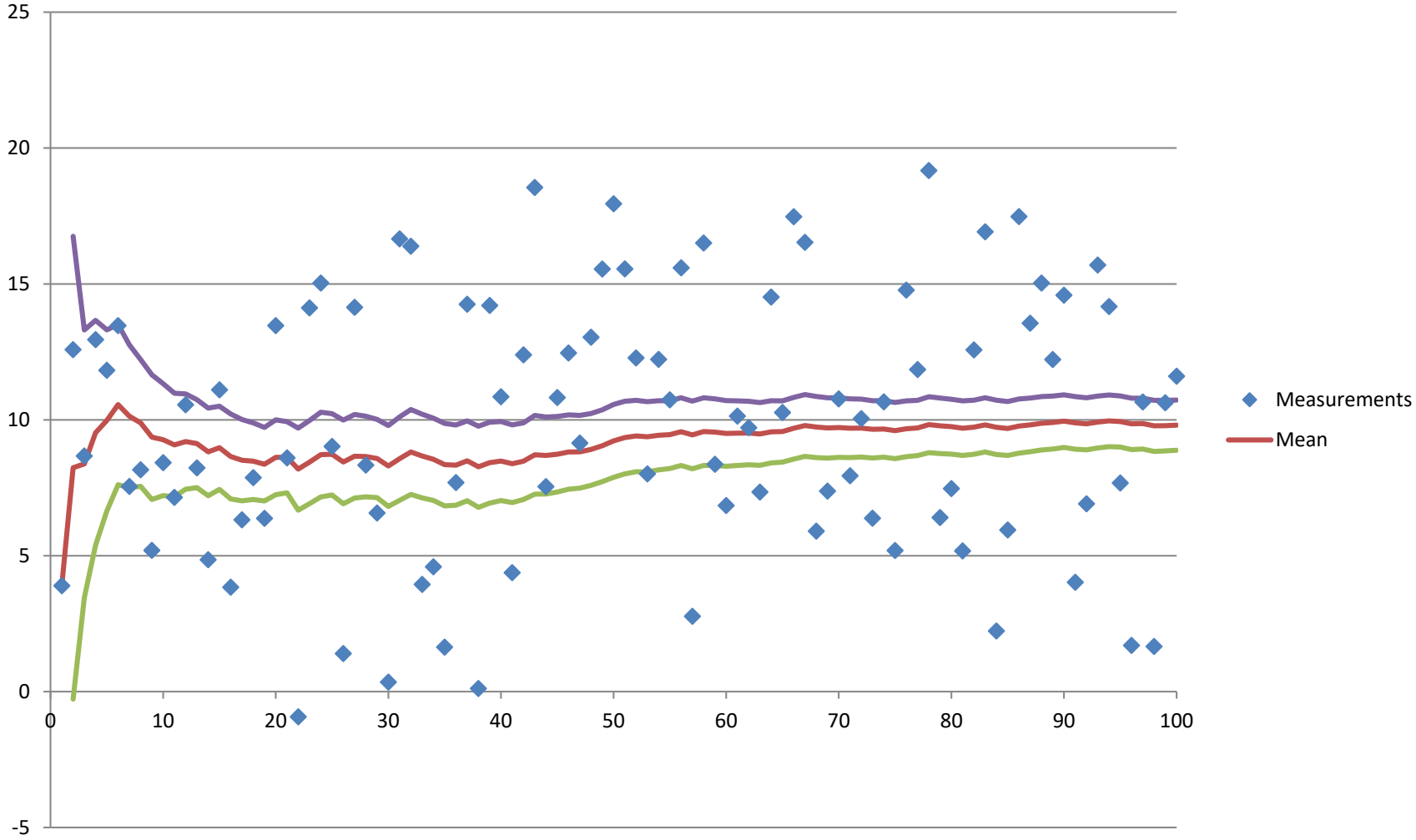
Confidence intervals (formal)

$$\left[\bar{x} - z_{(1-\frac{\alpha}{2})}\frac{\sigma}{\sqrt{n}} \; ; \; \bar{x} + z_{(1-\frac{\alpha}{2})}\frac{\sigma}{\sqrt{n}}\right]$$

$$\left[\bar{x} - t_{(1-\frac{\alpha}{2};n-1)}\frac{s}{\sqrt{n}} \; ; \; \bar{x} + t_{(1-\frac{\alpha}{2};n-1)}\frac{s}{\sqrt{n}}\right]$$

Confidence intervals

Collect data until confidence interval at an expected size, e.g, +/- 10%



Confidence intervals

- Results of independent measurements are normally distributed (central limit theorem)

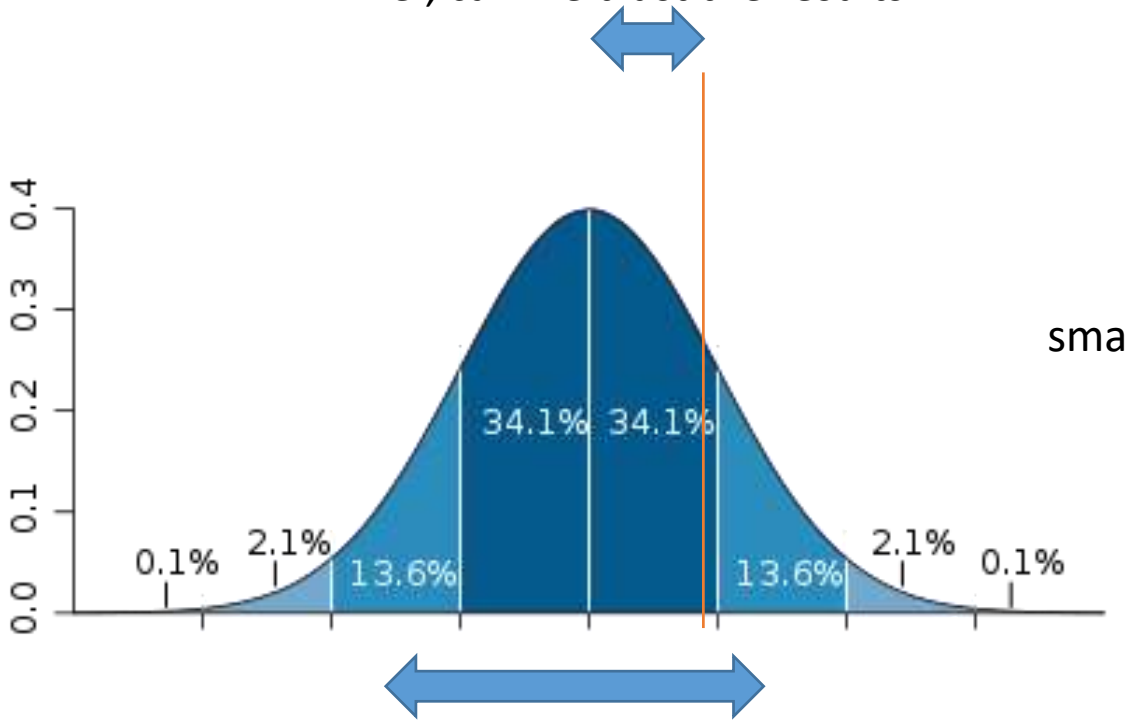
```
> t.test(data, conf.level=.95)
…
95 percent confidence interval:
 8.870949 10.739207
```

- Confidence level 95% =>
  with 95% probability, the real mean is within the interval*
  - Mean of the measurements vs real mean of the statistical population

*Technically more correct: When repeating the experiment very often, in 95% of the repetitions the real mean will be within the confidence interval of that measurement

Accuracy vs Precision

Accuracy:
Deviations of the measured mean from the real mean
i.e., can we trust the results



Resolution:
smallest measureable difference

Precision:
Distribution around the mean (repeatability)
Source of measurement error, usually not attributable

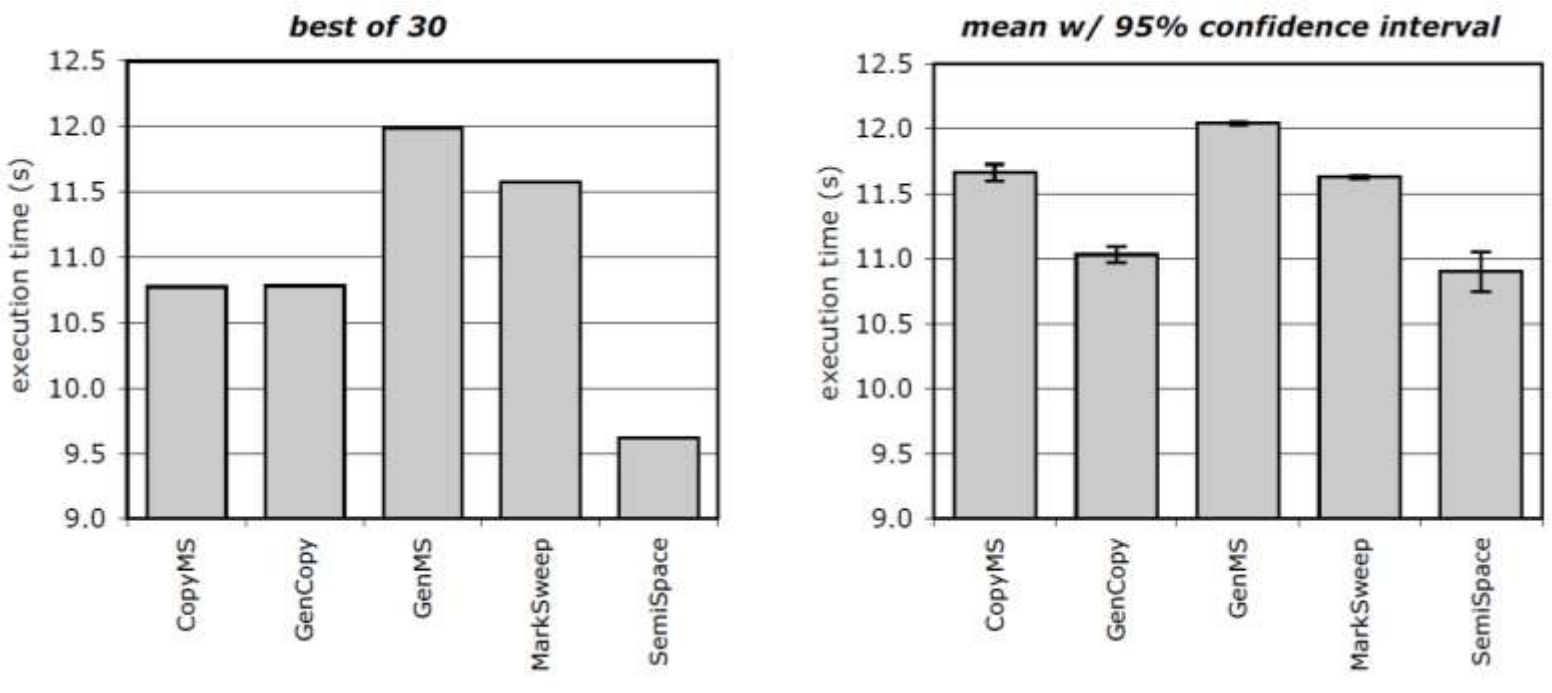
Random vs. Systematic Errors

- Systematic errors: Error of experimental design or measurement technique
  - CPU Speed: Measuring at different temperatures
  - Forgot to reset counter for repeated measurement
  - -> Small variance over repeated measurements
  - -> Experience to exclude them during design
  - -> Accuracy
- Random errors
  - Cannot be controlled
  - Stochastic methods
  - -> Precision

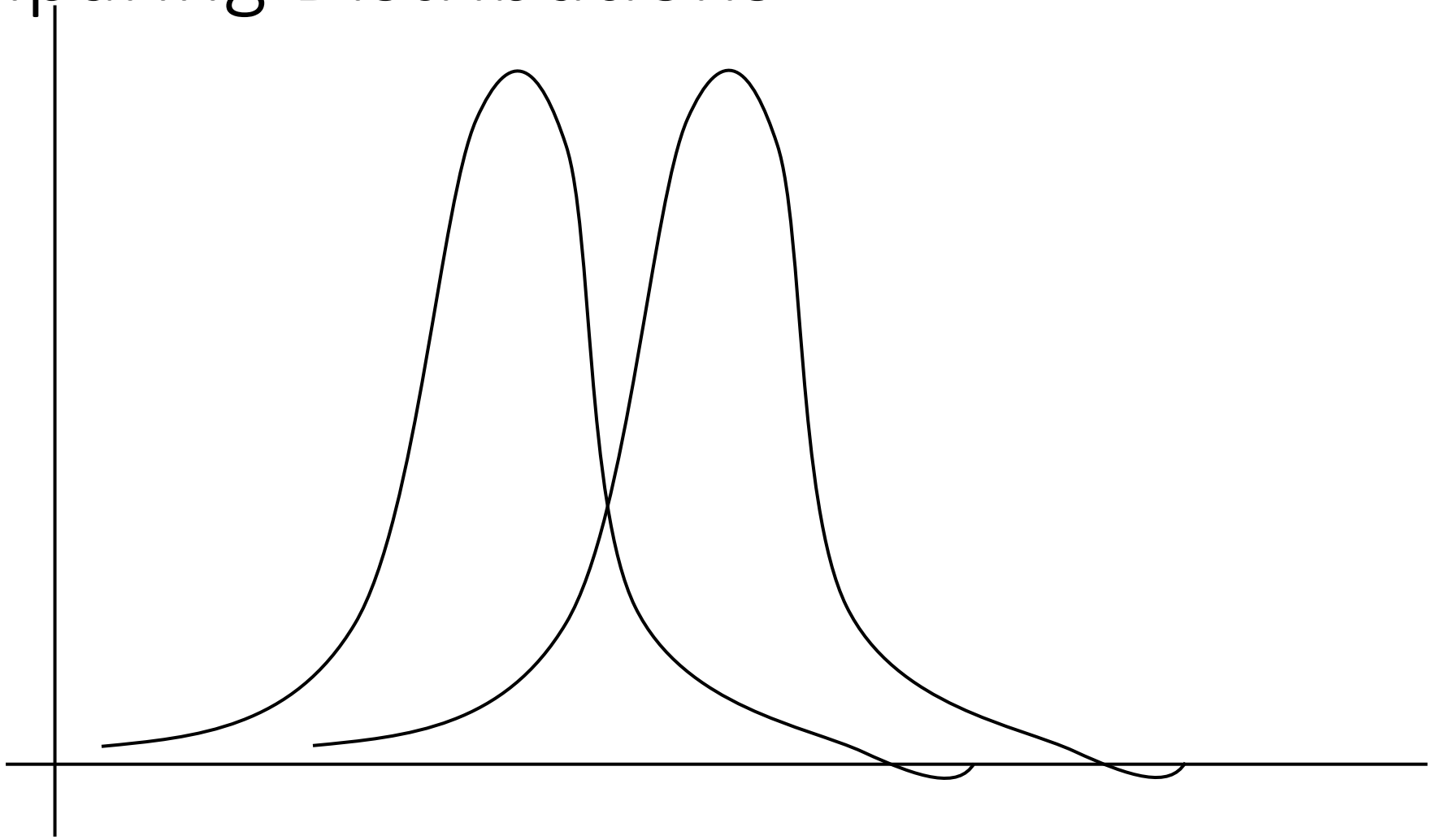
Comparing Measurements

Comparing measurement results

- GenCopy faster than GenMS?
- GenCopy faster than SemiSpace?

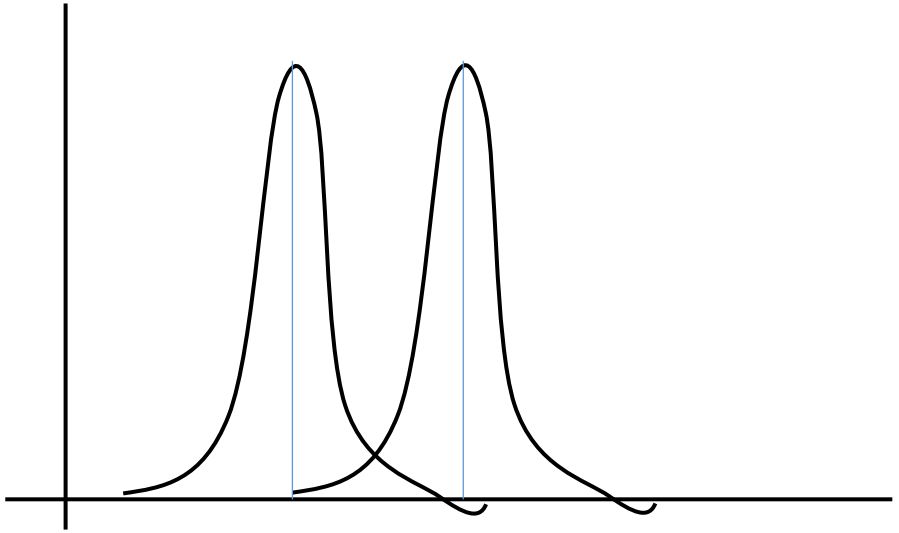


Comparing Distributions

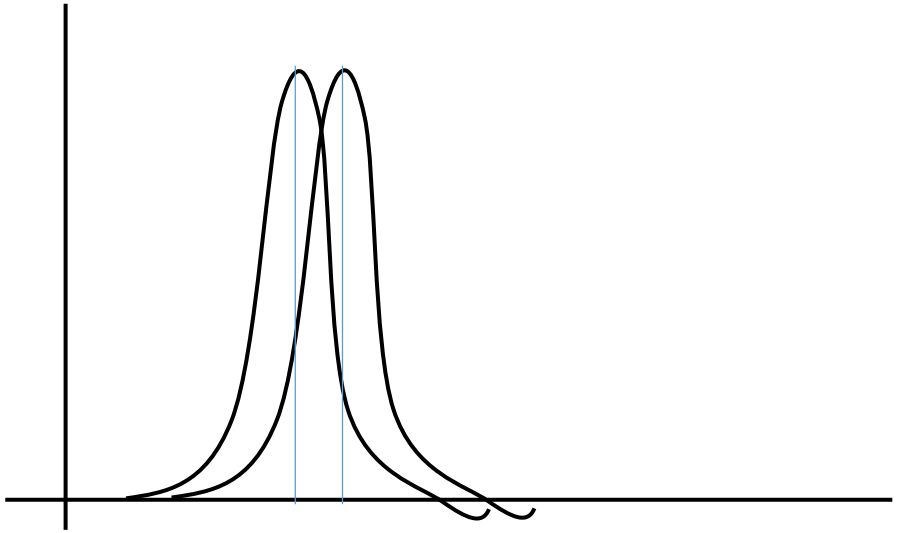


Different effect size, same deviations

small overlap
=> significant difference

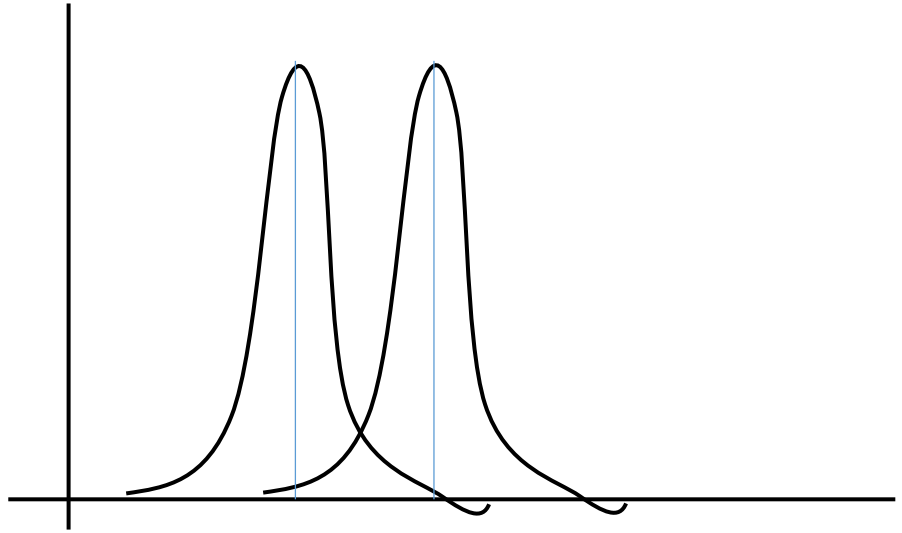


large overlap
=> no significant difference

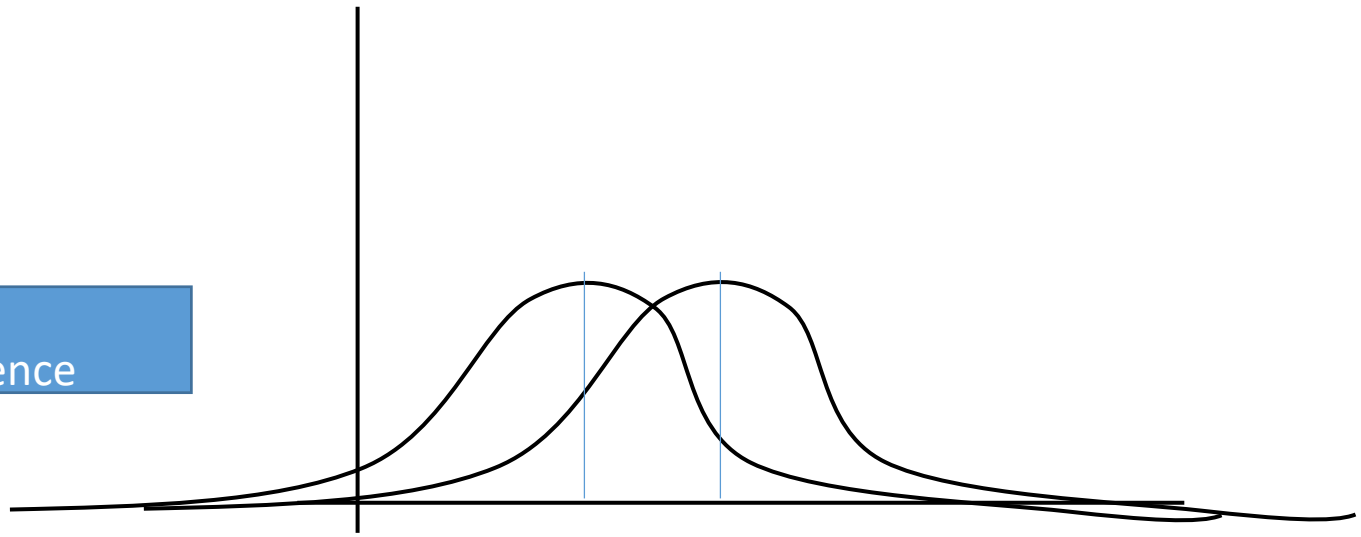


Same effect size, different deviations

small overlap
=> significant difference



large overlap
=> no significant difference



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

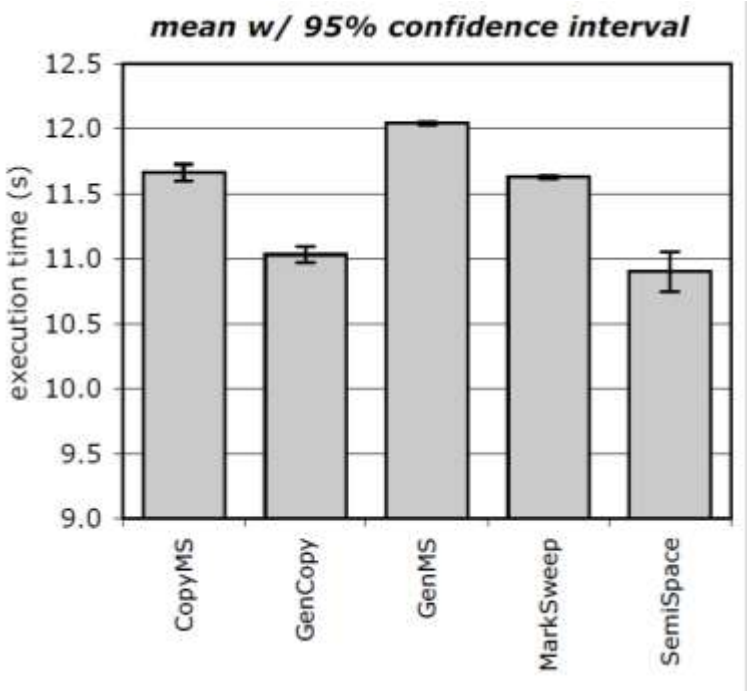
Significance level

- 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)

Compare confidence interval

- Rule of thumb: If the confidence intervals do not overlap, the difference is significant



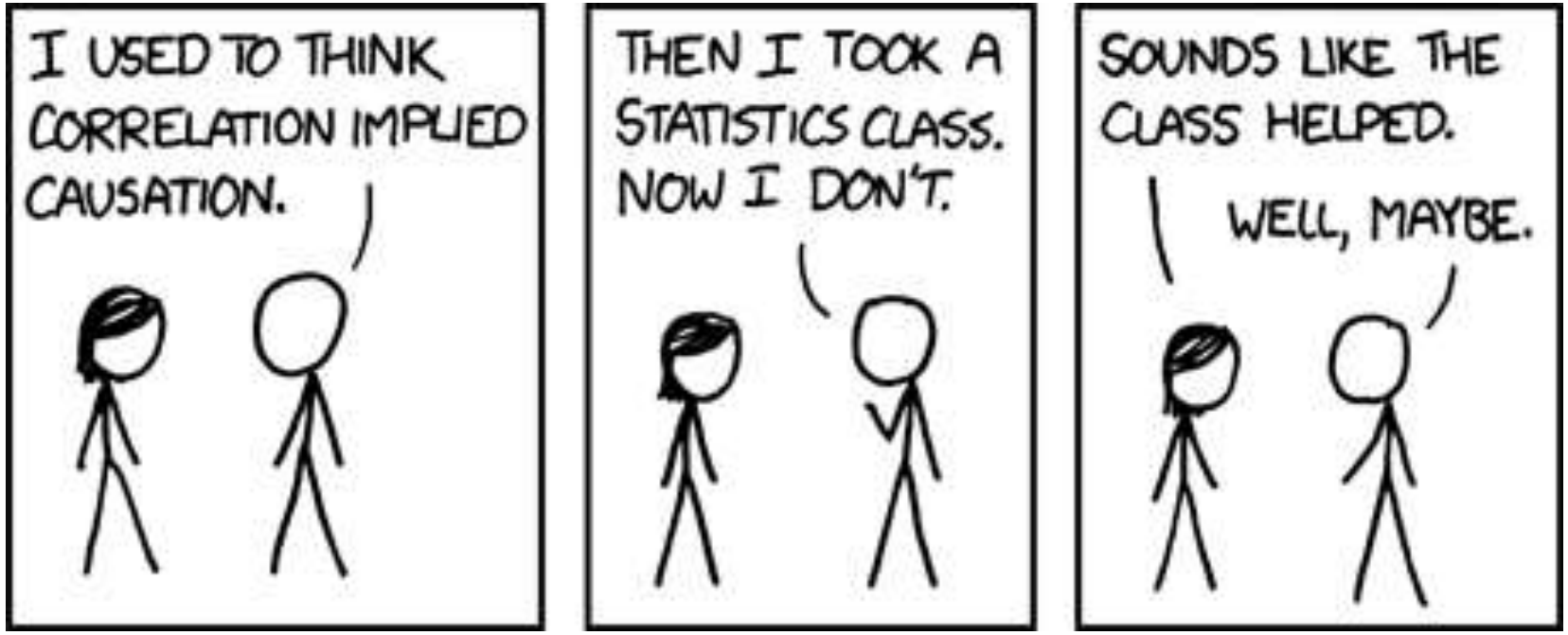
t test

- Requires: normally distributed metric data
  - very large data sets almost always follow a normal distribution
- Compares to measurement
- Basic idea:
  - Assume that both measurements are from the same basis population (follow the same distribution)
  - t test computes the chance that both samples are from the same distribution
  - If probability is smaller than 5% (for significance level 0.05) the assumption is considered refuted

t test with R

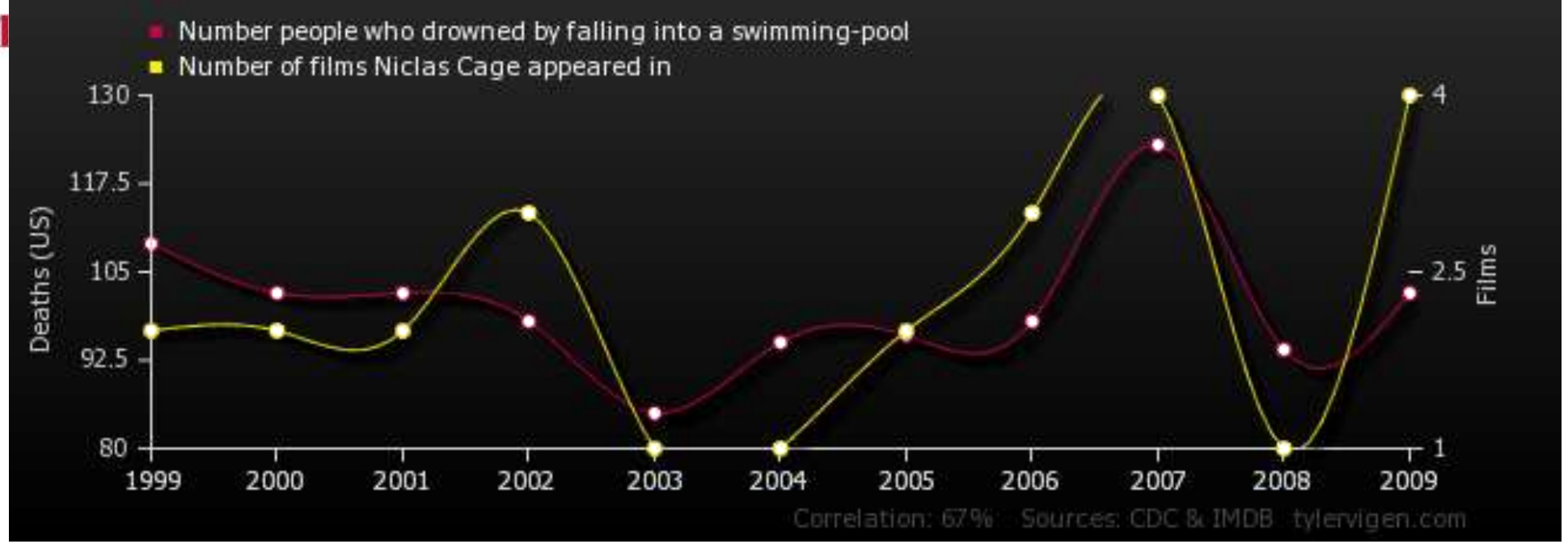
```
> t.test(x, y, conf.level=0.9)

        Welch Two Sample t-test

data:  x and y
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
```

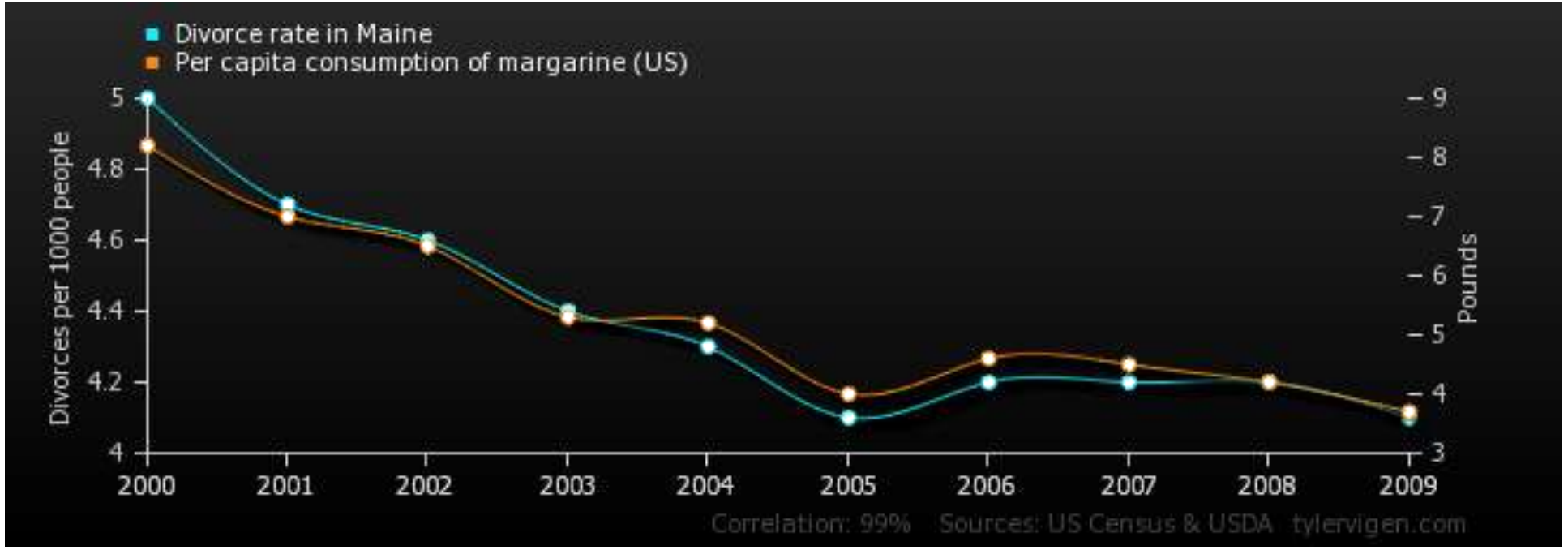
`> t.test(x-y, conf.level=0.9)` (paired)



- For causation
  - Provide a theory (from domain knowledge, independent of data)
  - Show correlation
  - Demonstrate ability to predict new cases (replicate/validate)

http://xkcd.com/552/


Number people who drowned by falling into a swimming-pool
Number of films Niclas Cage appeared in
Deaths (US)
130
117.5
105
92.5
80
Films
4
2.5
1
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
Correlation: 67%
Sources: CDC & IMDB
tylervigen.com


Divorce rate in Maine
Per capita consumption of margarine (US)
Divorces per 1000 people
5
4.8
4.6
4.4
4.2
4
Pounds
9
8
7
6
5
4
3
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
Correlation: 99%
Sources: US Census & USDA
tylervigen.com

Big Code Data Science

Abundance of Data

- Code history
- Developer activities
- Bug trackers
- Sprint backlog, milestones
- Continuous integration logs
- Static analysis and technical debt dashboards
- Test traces; dynamic analyses
- Runtime traces
- Crash reports from customers
- Server load, stats
- Customer data, interactions
- Support requests, customer reviews
- Working hours
- Team interactions in Slack/issue tracker/email/…
- …

Large Datasets now accessible

- Huge codebases in Google, Facebook, Microsoft, …
- Public activates of open source projects, including hobby projects and industrial systems (e.g., GitHub
  - 27M contributors, 80M projects, 1B traces, 10 years
- Lots of data: Code, commits, commit messages, issues, bug-fixing patches, discussions, reviews, pull requests, teams, build logs, static analysis logs, coverage history, performance history
- Lots of noise: Multitasking, interruptions, offline communication, project and team cultures, …

Data Science on Big Code

- Answer large, more general questions:
  - What team size is most productive or produces highest quality?
  - Is multitasking causing buggy code?
  - Do co-located teams perform better?
  - Does code review improve quality?
- Find trends in big noisy data sets using advanced statistics
- Find even small relationships with natural experiments: Compare similar projects that differ only in one aspect (given the size, there will be many pairs for most questions)

Example Results

- "Geographically distributed teams produce code whose quality (defect occurrence) is just as good as teams that are not geographically distributed"
  - No statistical difference detected at Microsoft
- "Defect probability increases if teams consist of members with large organizational distance"
  - Key predictor for defect density found at Microsoft
- "Multitaskers are more productive in open source projects, but not beyond 5 projects"
  - Confirmed on GitHub data by CMU Faculty Vasilescu

Example: Badges

	Basic Model response: *freshness = 0* 17.3% deviance explained		Full Model response: *freshness = 0* 17.4% deviance explained		RDD response: log(*freshness*) $R^2_m = 0.04$, $R^2_c = 0.35$	
	Coeffs (Err.)	LR Chisq	Coeffs (Err.)	LR Chisq	Coeffs (Err.)	Sum sq.
(Interc.)	3.54 (0.03)***		3.50 (0.03)***		1.45 (0.09)***	
Dep.	−1.78 (0.01)***	32077.8***	−1.79 (0.01)***	32292.8***	−0.04 (0.02)	3.01
RDep.	0.22 (0.01)***	610.3***	0.21 (0.01)***	560.6***	−0.01 (0.02)	0.11
Stars	−0.08 (0.00)***	301.4***	−0.09 (0.00)***	311.2***	0.00 (0.01)	0.00
Contr.	−0.24 (0.01)***	500.5***	−0.25 (0.01)***	548.7***	−0.04 (0.02)*	4.39*
lastU	−0.65 (0.01)***	12080.9***	−0.64 (0.01)***	11537.9***	0.01 (0.02)	0.37
hasDM			0.24 (0.03)***	116.1***	0.45 (0.08)***	2.43
hasInf			0.11 (0.02)***	48.3***	0.04 (0.05)	0.45
hasDM:hasInf			−0.05 (0.04)	1.9	−0.32 (0.10)**	
hasOther			0.01 (0.01)			
time					0.03 (0.00)***	82.99***
intervention					−0.93 (0.03)***	1373.22***
time_after_intervention					0.11 (0.00)***	455.56***
time_after_intervention:hasDM					−0.10 (0.01)***	230.36***
time_after_intervention:hasInf					−0.00 (0.01)	1.14
time_after_intervention:hasDM:hasInf					0.03 (0.01)**	10.62**

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$;
Dep: dependencies; RDep: dependents; Contr.: contributors; lastU: time since last update;
hasDM: has dependency-manager badge; hasInf: has information badge; hasOther: adopts

Quality Assurance

Travis CI
Coveralls
CodeClimate
CodeCov
Circle CI
AppVeyor
BitHound
SauceLabs
Inch CI

Dependency Management

David DM
Gemnasium
Greenkeeper
Snyk
VersionEye

A. Trockman, S. Zhou, C. Kästner, and B. Vasilescu. Adding Sparkle to Social Coding: An Empirical Study of Repository Badges in the npm Ecosystem. In Proceedings of the 40th International Conference on Software Engineering (ICSE), New York, NY: ACM Press, May 2018.

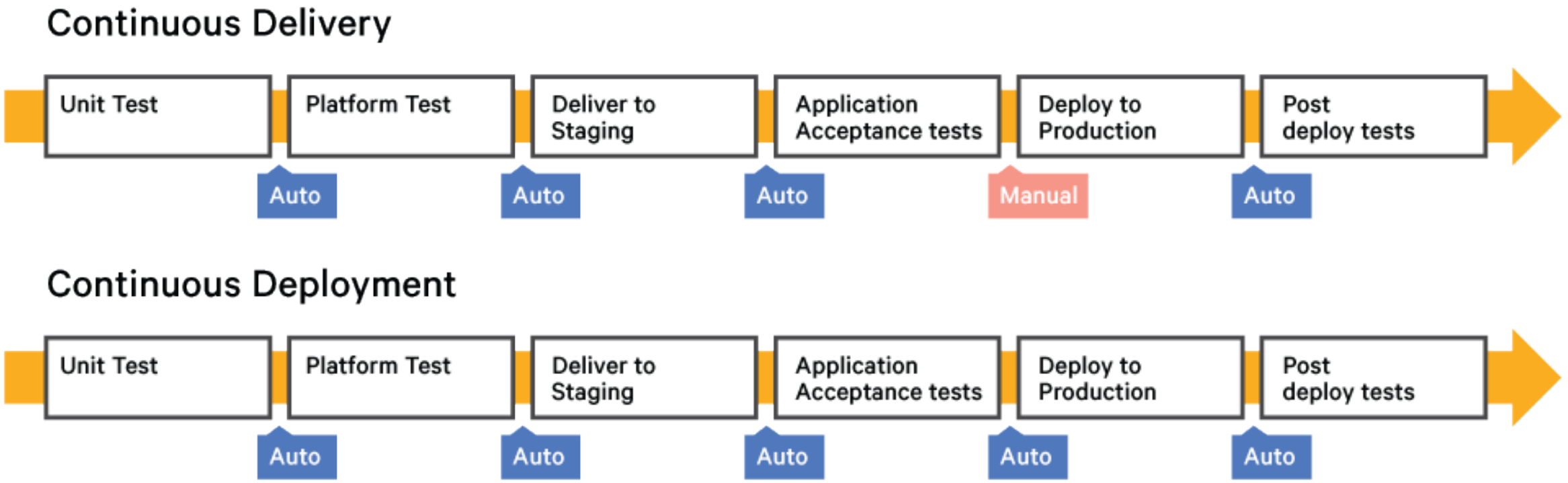
Experimenting in Production

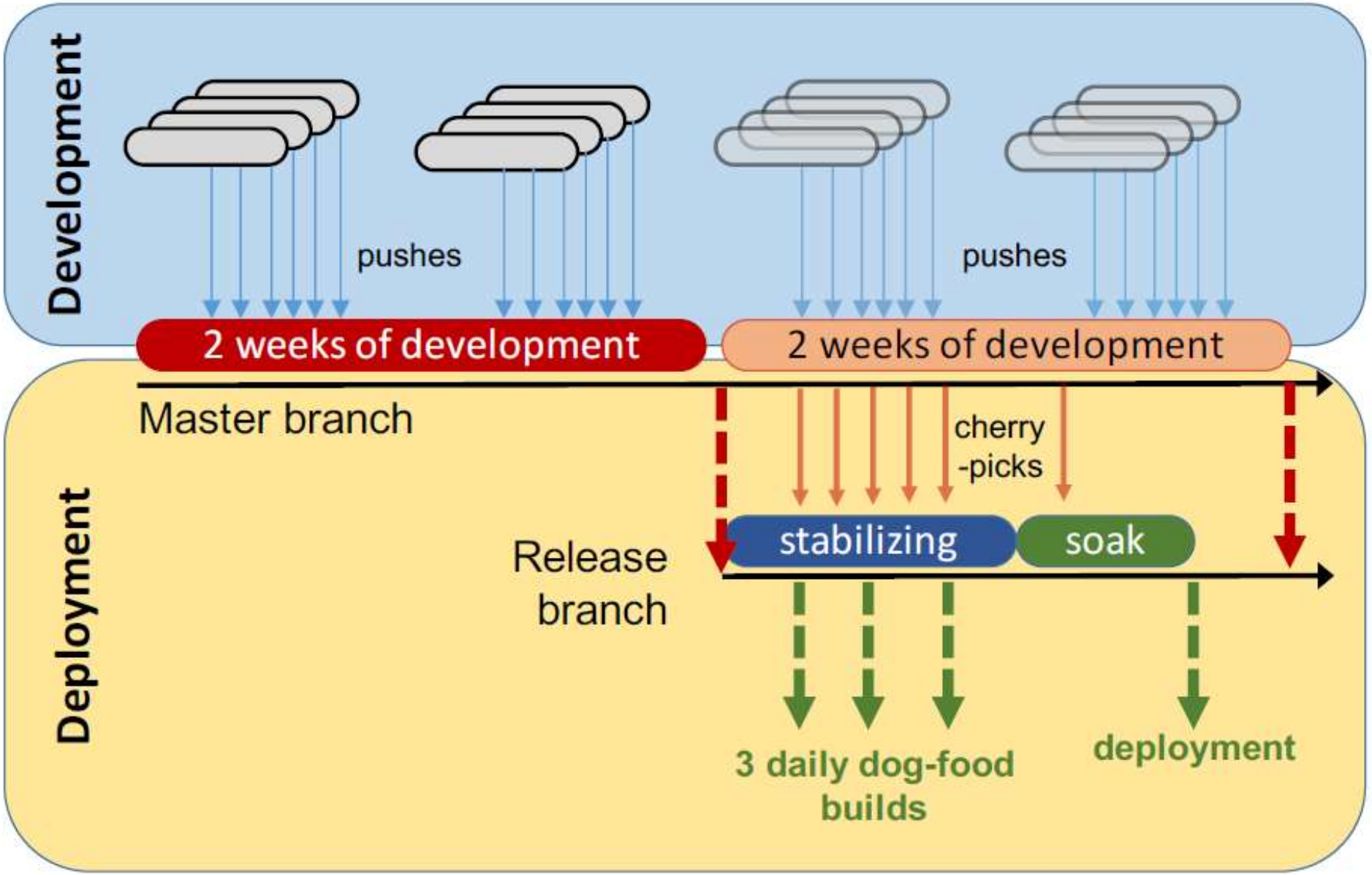
Canary Testing and AB Testing

Testing in Production

- Beta tests
- AB tests
- Tests across hardware/software diversity (e.g., Android)
- “Most updates are unproblematic”
- “Testing under real conditions, with real workloads”
- Avoid expensive redundant test infrastructure

Pipelines

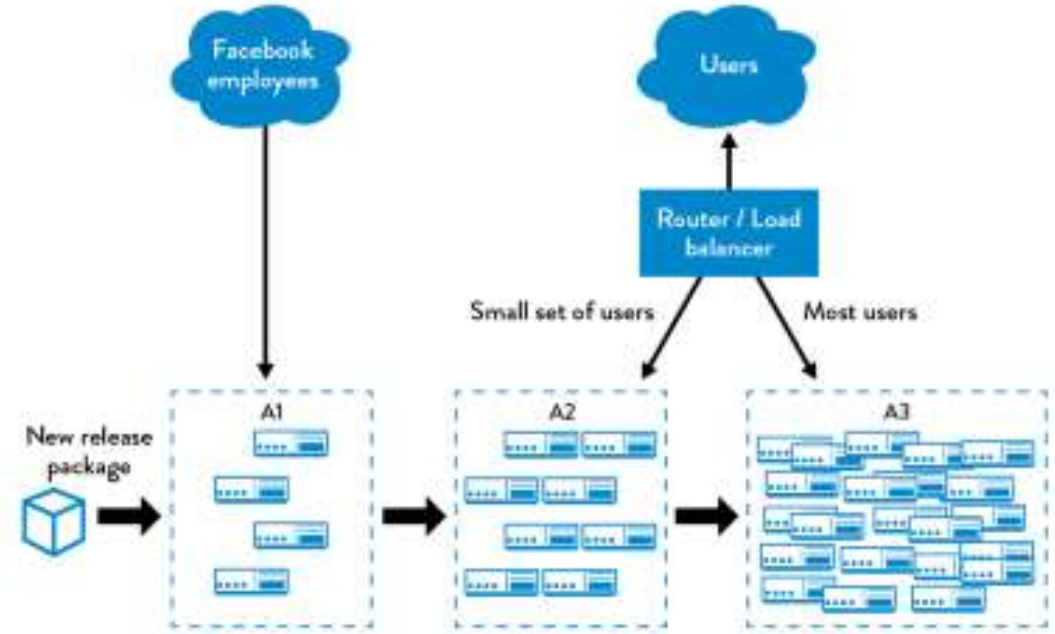

Continuous Delivery
Unit Test
Platform Test
Deliver to Staging
Application Acceptance tests
Deploy to Production
Post deploy tests
Auto
Auto
Auto
Manual
Auto
Continuous Deployment
Unit Test
Platform Test
Deliver to Staging
Application Acceptance tests
Deploy to Production
Post deploy tests
Auto
Auto
Auto
Auto
Auto

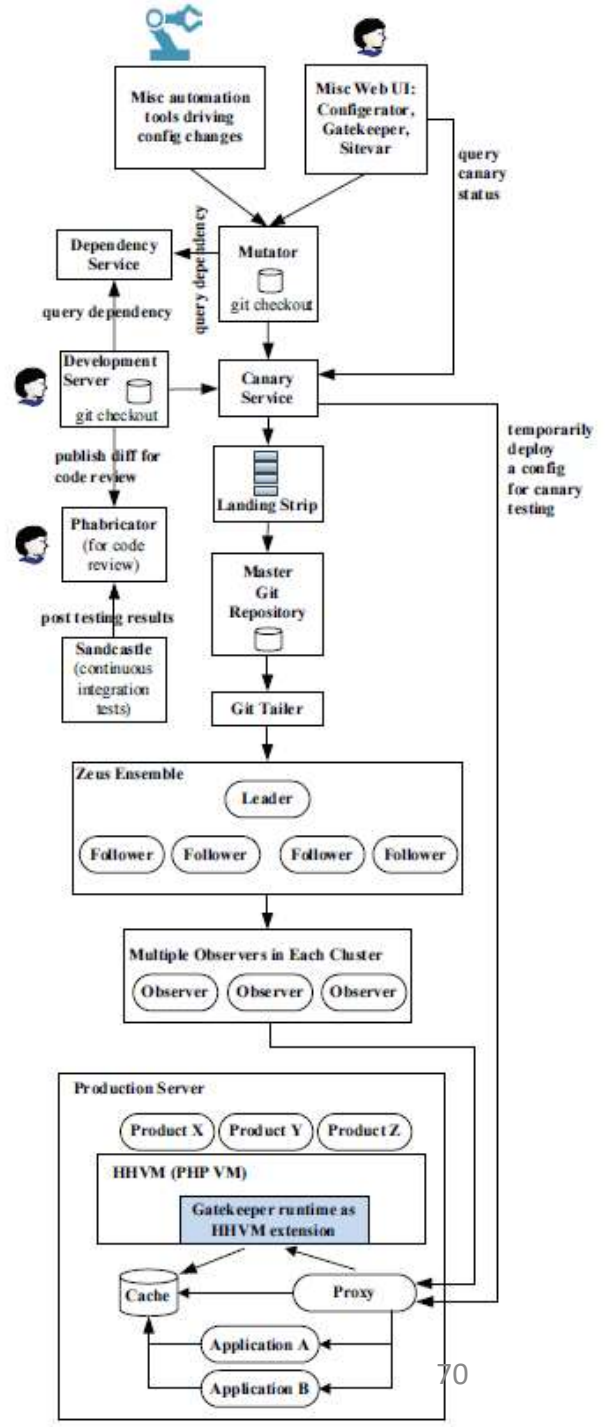


Release cycle of Facebook's apps

Real DevOps Pipelines are Complex

- Incremental rollout, reconfiguring routers
- Canary testing
- Automatic rolling back changes





Chunqiang Tang, Thawan Kooburat, Pradeep Venkatachalam, Akshay Chander, Zhe Wen, Aravind Narayanan, Patrick Dowell, and Robert Karl. Holistic Configuration Management at Facebook. Proc. of SOSP: 328--343 (2015).

Configuration management, Infrastructure as Code

- Scripts to change system configurations (configuration files, install packages, versions, …); declarative vs imperative
- Usually put under version control

(ansible)

```
- hosts: all
  sudo: yes
  tasks:
  - apt: name={{ item }}
    with_items:
      - ldap-auth-client
      - nscd
  - shell: auth-client-config -t nss -p lac_ldap
  - copy: src=ldap/my_mkhomedir dest=/…
  - copy: src=ldap/ldap.conf dest=/etc/ldap.conf
  - shell: pam-auth-update --package
  - shell: /etc/init.d/nscd restart
```

(Puppet)

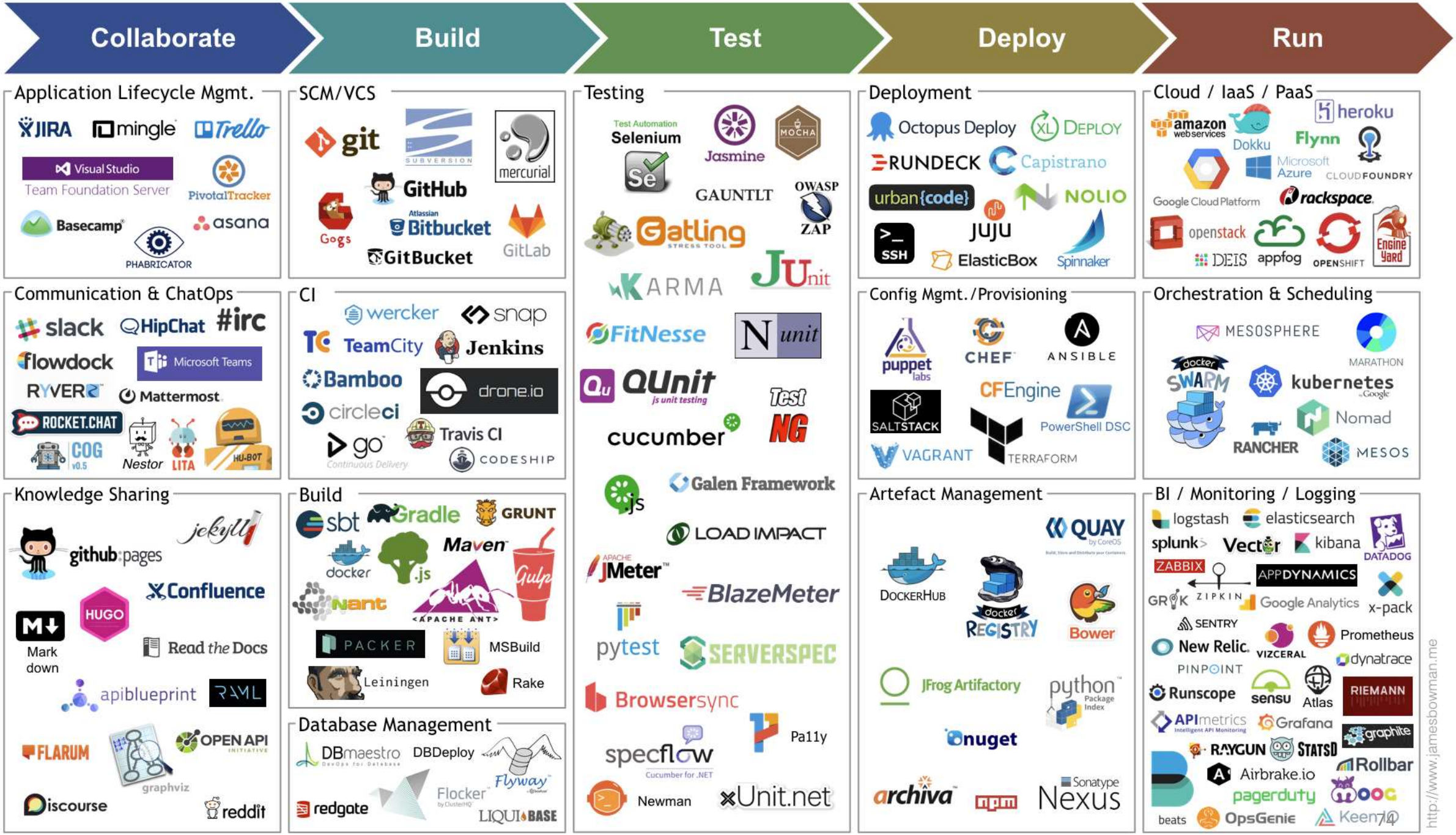
```
$nameservers = ['10.0.2.3']
file { '/etc/resolv.conf':
        ensure => file,
        owner => 'root',
        group => 'root',
        mode => '0644',
        content => template('resolver/resolv.conf.erb'),
}
```

Monitoring

- Many standard and custom tools for monitoring, aggregation and reporting
- Logging infrastructure at scale
- Open source examples
  - collectd/collect for gathering and storing statistics
  - Monit checks whether process is running
  - Nagios monitoring infrastructure, highly extensible

(Netflix)

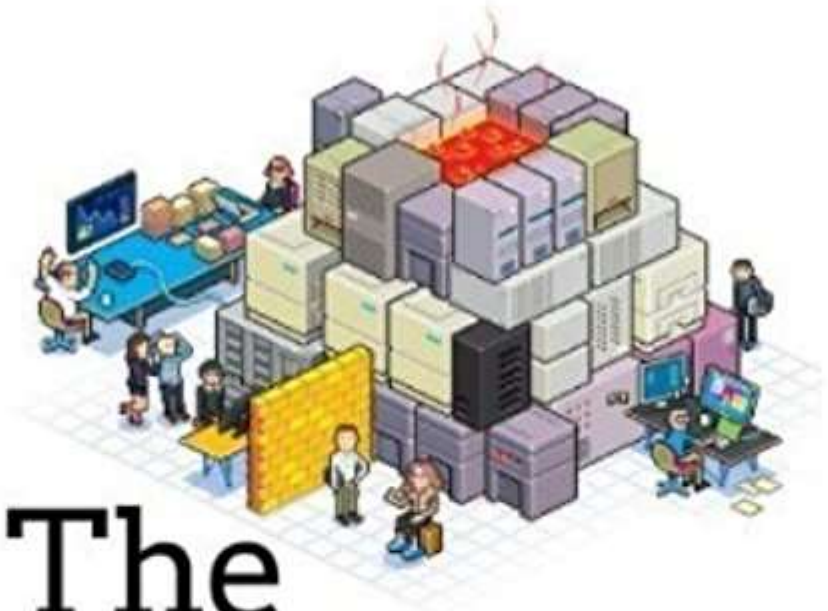
https://www.slideshare.net/jmcgarr/continuous-delivery-at-netflix-and-beyond


Collaborate
Build
Test
Deploy
Run
Application Lifecycle Mgmt.
JIRA
mingle
Trello
Visual Studio
Team Foundation Server
PivotalTracker
Basecamp
asana
PHABRICATOR
SCM/VCS
git
SUBVERSION
mercurial
GitHub
Gogs
Atlassian Bitbucket
GitBucket
GitLab
Testing
Test Automation
Selenium
Jasmine
MOCHA
GAUNTLT
OWASP ZAP
Gatling STRESS TOOL
KARMA
JUnit
FitNesse
N unit
QUnit js unit testing
Test NG
cucumber
js
Galen Framework
LOAD IMPACT
JMeter
BlazeMeter
pytest
SERVERSPEC
Browsersync
specflow Cucumber for .NET
Pa11y
Newman
xUnit.net
Deployment
Octopus Deploy
DEPLOY
RUNDECK
Capistrano
urban{code}
NOLIO
SSH
juju
ElasticBox
Spinnaker
Cloud / IaaS / PaaS
amazon web services
Dokku
heroku
Flynn
Google Cloud Platform
Microsoft Azure
CLOUDFOUNDRY
rackspace
openstack
DEIS
appfog
OPENSHIFT
Engine Yard
Communication & ChatOps
slack
HipChat
#irc
flowdock
Microsoft Teams
RYVER
Mattermost
ROCKET.CHAT
COG v0.5
Nestor
LITA
HU-BOT
CI
wercker
snap
TeamCity
Jenkins
Bamboo
drone.io
circleci
Travis CI
go Continuous Delivery
CODESHIP
Config Mgmt./Provisioning
puppet labs
CHEF
ANSIBLE
SALTSTACK
CFEngine
PowerShell DSC
VAGRANT
TERRAFORM
Orchestration & Scheduling
MESOSPHERE
MARATHON
docker SWARM
kubernetes Google
Nomad
RANCHER
MESOS
Knowledge Sharing
github pages
jekyll
Confluence
HUGO
Mark down
Read the Docs
apiblueprint
RAML
FLARUM
OPEN API INITIATIVE
graphviz
Discourse
reddit
Build
sbt
Gradle
GRUNT
docker
.js
Maven
Gulp
Nant
APACHE ANT
PACKER
MSBuild
Leiningen
Rake
Artefact Management
DockerHub
QUAY by CoreOS
docker REGISTRY
Bower
JFrog Artifactory
python Package Index
nuget
archiva
npm
Sonatype Nexus
Database Management
DBmaestro
DBDeploy
Flyway
Flocker
redgate
LIQUIBASE
BI / Monitoring / Logging
logstash
elasticsearch
splunk
Vector
kibana
DATADOG
ZABBIX
APPDYNAMICS
GROK
ZIPKIN
Google Analytics
x-pack
SENTRY
New Relic
VIZCERAL
Prometheus
dynatrace
PINPOINT
Runscope
sensu
Atlas
RIEMANN
APImetrics
Grafana
graphite
RAYGUN
STATSD
Rollbar
Airbrake.io
pagerduty
beats
OpsGenie
Keen IO
http://www.jamesbowman.me

Why DevOps when testing in production

- Ability to quickly change configurations for different users
- Track configuration changes
- Track metrics at runtime in production system
- Track results per configuration; analysis dashboard to test effects
- Induce realistic fault scenarios (ChaosMonkey…)
- **Ability to roll back bad changes quickly**

From the authors of *The Visible Ops Handbook*



The Phoenix Project

A Novel About IT, DevOps, and Helping Your Business Win

Gene Kim, Kevin Behr, and George Spafford

Summary

- Pursue data-supported decisions, rather than relying on “belief”
- Learn from scientific methods, experiments, statistics
  - Experimental designs
  - Biases, confounding variables
  - Measurements, systematic vs random errors
- Big code provides new opportunities
- Measurement in production with DevOps
- Measurement is essential for software engineering professionals

Some slides with input from

- Bogdan Vasilescu, ISR/CMU
- Thomas Zimmermann, Microsoft Research:
    - https://speakerdeck.com/tomzimmermann
- Greg Wilson, Mozilla
    - https://www.slideshare.net/gvwilson/presentations