Machine Learning in Production

Infrastructure Quality & MLOps

Infrastructure and Operations...

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

Readings

Required reading: Eric Breck, Shanqing Cai, Eric Nielsen, Michael Salib, D. Sculley. The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction. Proceedings of IEEE Big Data (2017)

Recommended readings:

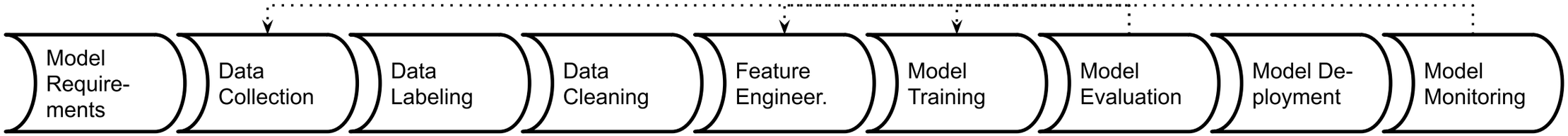
- O'Leary, Katie, and Makoto Uchida. "Common problems with Creating Machine Learning Pipelines from Existing Code." Proc. Conference on Machine Learning and Systems (MLSys) (2020).
- Larysa Visengeriyeva. Machine Learning Operations - A Reading List, InnoQ 2020

Learning Goals

- Implement and automate tests for all parts of the ML pipeline
- Understand testing opportunities beyond functional correctness
- Automate test execution with continuous integration
- Deploy a service for models using container infrastructure
- Automate common configuration management tasks
- Devise a monitoring strategy and suggest suitable components for implementing it
- Diagnose common operations problems
- Understand the typical concerns and concepts of MLOps

Beyond Model and Data Quality

Possible Mistakes in ML Pipelines



Danger of "silent" mistakes in many phases

Examples?

Possible Mistakes in ML Pipelines

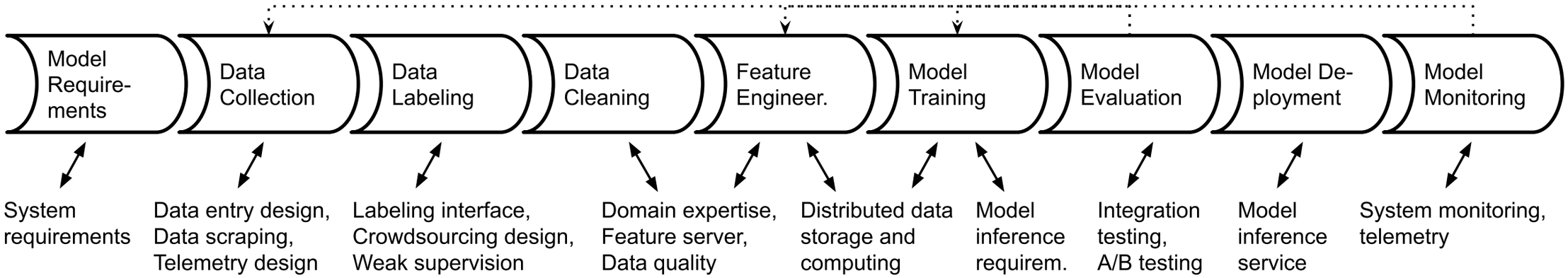
Danger of "silent" mistakes in many phases:

- Dropped data after format changes
- Failure to push updated model into production
- Incorrect feature extraction
- Use of stale dataset, wrong data source
- Data source no longer available (e.g web API)
- Telemetry server overloaded
- Negative feedback (telemtr.) no longer sent from app
- Use of old model learning code, stale hyperparameter
- Data format changes between ML pipeline steps

Building Robust Pipeline Automation

- Support experimentation and evolution
  - Automate
  - Design for change
  - Design for observability
  - Testing the pipeline for robustness
- Thinking in pipelines, not models
- Integrating the Pipeline with other Components

Integrating the Pipeline with other Components



Pipelines are Code

From experimental notebook code to production code

Each stage as a function or module

Well tested in isolation and together

Robust to changes in inputs (automatically adapt or crash, no silent mistakes)

Use good engineering practices (version control, documentation, testing, naming, code review)

Everything can be tested?

Speaker notes

Many qualities can be tested beyond just functional correctness (for a specification). Examples: Performance, model quality, data quality, usability, robustness, ... not all tests are equality easy to automate

Testing Strategies

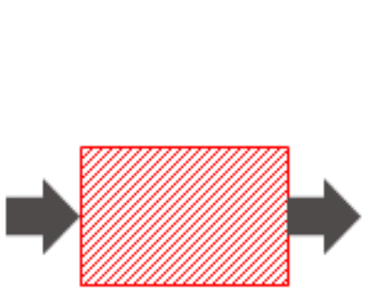
- Performance
- Scalability
- Robustness
- Safety
- Security
- Extensibility
- Maintainability
- Usability

How to test for these? How automatable?

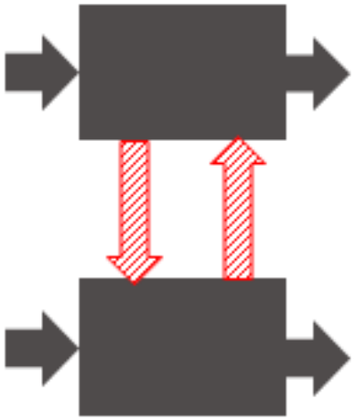
Test Automation

From Manual Testing to Continuous Integration

Unit Test, Integration Tests, System Tests



Unit testing



Integration testing

System testing

Acceptance testing

(Demonstration)

Speaker notes

Software is developed in units that are later assembled. Accordingly we can distinguish different levels of testing.

Unit Testing - A unit is the "smallest" piece of software that a developer creates. It is typically the work of one programmer and is stored in a single file. Different programming languages have different units: In C++ and Java the unit is the class; in C the unit is the function; in less structured languages like Basic and COBOL the unit may be the entire program.

Integration Testing - In integration we assemble units together into subsystems and finally into systems. It is possible for units to function perfectly in isolation but to fail when integrated. For example because they share an area of the computer memory or because the order of invocation of the different methods is not the one anticipated by the different programmers or because there is a mismatch in the data types. Etc.

System Testing - A system consists of all of the software (and possibly hardware, user manuals, training materials, etc.) that make up the product delivered to the customer. System testing focuses on defects that arise at this highest level of integration. Typically system testing includes many types of testing: functionality, usability, security, internationalization and localization, reliability and availability, capacity, performance, backup and recovery, portability, and many more.

Acceptance Testing - Acceptance testing is defined as that testing, which when completed successfully, will result in the customer accepting the software and giving us their money. From the customer's point of view, they would generally like the most exhaustive acceptance testing possible (equivalent to the level of system testing). From the vendor's point of view, we would generally like the minimum level of testing possible that would result in money changing hands. Typical strategic questions that should be addressed before acceptance testing are: Who defines the level of the acceptance testing? Who creates the test scripts? Who executes the tests? What is the pass/fail criteria for the acceptance test? When and how do we get paid?

Anatomy of a Unit Test

```
import org.junit.Test;
import static org.junit.Assert.assertEquals;

public class AdjacencyListTest {
    @Test
    public void testSanityTest(){
        // set up
        Graph g1 = new AdjacencyListGraph(10);
        Vertex s1 = new Vertex("A");
        Vertex s2 = new Vertex("B");
        // check expected results (oracle)
```

Ingredients to a Test

Specification

Controlled environment

Test inputs (calls and parameters)

Expected outputs/behavior (oracle)

Unit Testing Pitfalls

Working code, failing tests

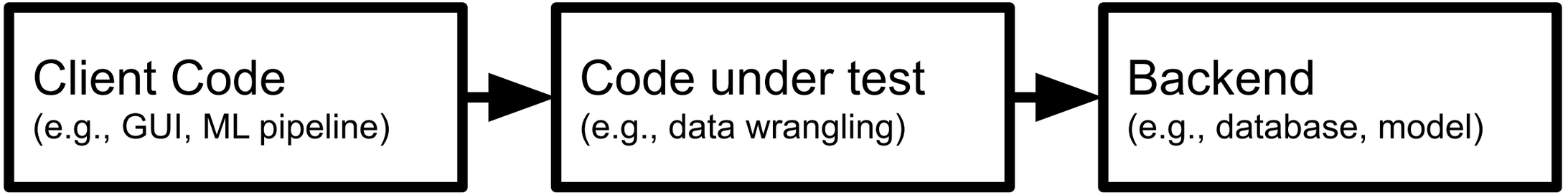
"Works on my machine"

Tests break frequently

How to avoid?

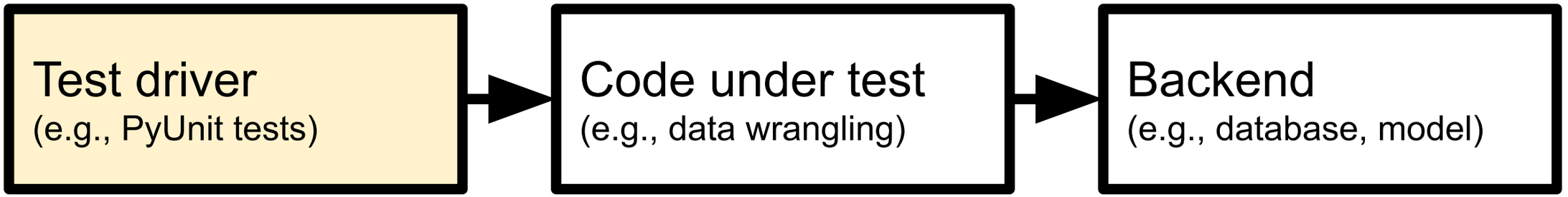
How to unit test component with dependency on other code?

How to Test Parts of a System?



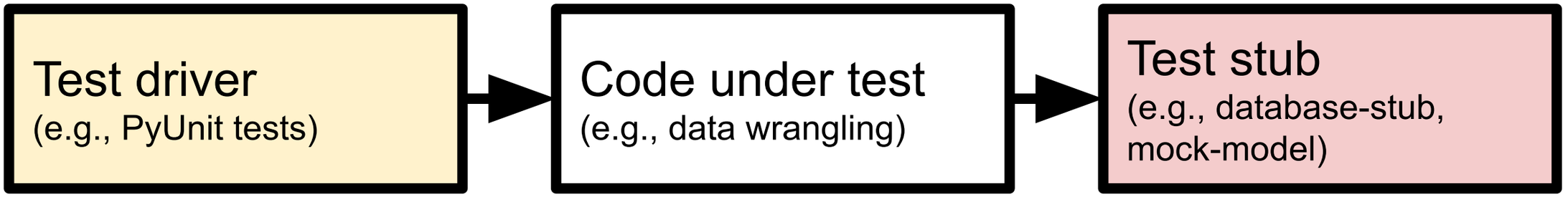

```
Model learn() {
    Stream stream = openKafkaStream(...)
    DataTable output = getData(testStream,
                               new DefaultCleaner());
    return Model.learn(output);
}
```

Automating Test Execution



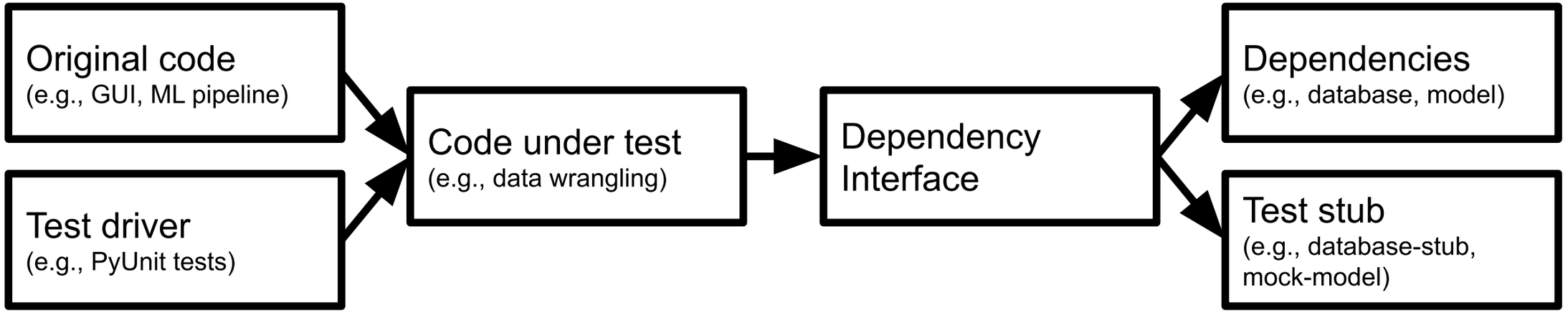

```
DataTable getData(Stream stream, DataCleaner cleaner) { ... }

@Test void test() {
    Stream stream = openKafkaStream(...)
    DataTable output = getData(stream,
                               new DefaultCleaner());
    assert(output.length==10)
}
```

Decoupling from Dependencies




```
DataTable getData(Stream stream, DataCleaner cleaner) { ... }
Stream testStream = new Stream() {
        int idx = 0;
        // hardcoded or read from test file
        String[] data = [ ... ]
        public void connect() { }
        public String getNext() {
            return data[++idx];
```

General Testing Strategy: Decoupling Code Under Test



Example: Mocking a DataCleaner Object

```
DataTable getData(KafkaStream stream, DataCleaner cleaner){...

@Test void test() {
    DataCleaner dummyCleaner = new DataCleaner() {
        boolean isValid(String row) { return true; }
        ...
    }
    DataTable output = getData(testStream, dummyCleaner);
    assert(output.length==10)
}
```

Example: Mocking a DataCleaner Object

```
DataTable getData(KafkaStream stream, DataCleaner cleaner){...

@Test void test() {
    DataCleaner dummyCleaner = new DataCleaner() {
        int counter = 0;
        boolean isValid(String row) {
            counter++;
            return counter!=3;
        }
        ...
    }
```

Mocking frameworks provide infrastructure for expressing such tests compactly.

Subtle Bugs in Data Wrangling Code

```
df['Join_year'] = df.Joined.dropna().map(
    lambda x: x.split(',')[1].split(' ')[1])
```

```
df.loc[idx_nan_age,'Age'].loc[idx_nan_age] =
    df['Title'].loc[idx_nan_age].map(map_means)
```

```
df["Weight"].astype(str).astype(int)
```

Subtle Bugs in Data Wrangling Code (continued)

```
df['Reviws'] = df['Reviews'].apply(int)
```

```
df["Release Clause"] =
    df["Release Clause"].replace(regex=['k'], value='000')
```

```
df["Release Clause"] =
    df["Release Clause"].astype(str).astype(float)
```

Speaker notes

1 attempting to remove na values from column, not table

2 loc[] called twice, resulting in assignment to temporary column only

3 astype() is not an in-place operation

4 typo in column name

5&6 modeling problem (k vs K)

Tests for Data Wranging Code?

(data quality checks, data cleaning, feature engineering, ...)

Modularizing and Testing Data Cleaning

```
def is_valid_row(row):
    try:
        datetime.strptime(row['date'], '%b %d %Y')
        return true
    except ValueError:
        return false
```

```
@test
def test_dates(self):
    self.assertTrue(is_valid_row(...))
    self.assertTrue(is_valid_row(...))
    self.assertFalse(is_valid_row(...))
```

Modularize and Test Feature Encoding

```
def encode_date(df):
    df.date_time = pd.to_datetime(df.date_time)
def encode_day_part(df):
    def daypart(hour):
        if hour in [2,3,4,5]:
            return "dawn"
        elif hour in [6,7,8,9]:
            return "morning"
        elif hour in [10,11,12,13]:
            return "noon"
        elif ...
```

```
@test
def test_day_part(self): ...
```

Test Error Handling

```
@Test void missingDataErrorTest() {
    DataTable missingData = new DataTable();
    try {
        Model m = learn(missingData);
        Assert.fail();
    } catch (NoDataException e) { /* correctly thrown */ }
}
```

(This tests expects the learn function to throw an exception. Test fails if no exception thrown.)

Speaker notes

Code to test that the right exception is thrown

Testing for Robustness

```
Stream faultyTestStream = new Stream() {
    ...
    public String getNext() {
        if (++idx == 3) throw new IOException();
        return data[++idx];
    }}
@Test void retryOnStreamProblemTest() {
    DataTable output = retry(getData(faultyTestStream, ...));
    assert(output.length==10)
}
```

(manipulating the (controlled) environment: injecting errors into backend to test error handling)

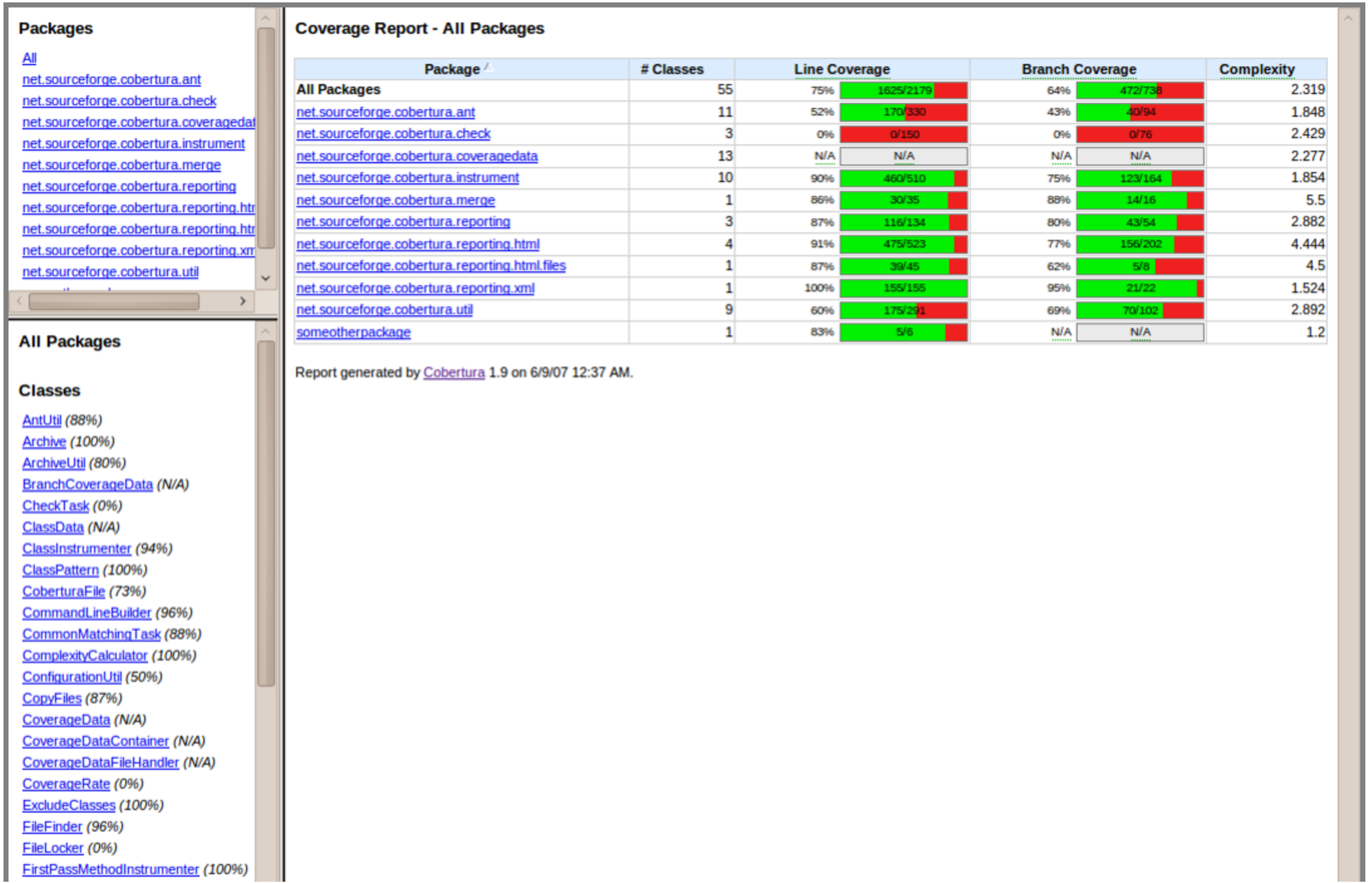
Test *Modular* Error Handling

```
Stream faultyTestStream = new Stream() {
    int idx = 0;
    public void connect() {
        if (++idx < 3) throw new IOException(
                "cannot establish connection")
    }
    public String getNext() { ... }
}
@Test void integrationTest() {
    DataLoader loader = new DataLoader(faultyTestStream,
                                       new DefaultCleaner());
```

(Modular protection/isolation: Ensure error is handled locally and does not propagate to other modules.)

Speaker notes

Test that errors are correctly handled within a module and do not leak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All Packages
Classes
AntUtil (88%)
Archive (100%)
ArchiveUtil (80%)
BranchCoverageData (N/A)
CheckTask (0%)
ClassData (N/A)
ClassInstrumenter (94%)
ClassPattern (100%)
CoberturaFile (73%)
CommandLineBuilder (96%)
CommonMatchingTask (88%)
ComplexityCalculator (100%)
ConfigurationUtil (50%)
CopyFiles (87%)
CoverageData (N/A)
CoverageDataContainer (N/A)
CoverageDataFileHandler (N/A)
CoverageRate (0%)
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FileFinder (96%)
FileLocker (0%)
FirstPassMethodInstrumenter (100%)
Coverage Report - All Packages
Package
Classes
Line Coverage
Branch Coverage
Complexity
All Packages 55 75% 1625/2179 64% 472/738 2.319
net.sourceforge.cobertura.ant 11 52% 170/330 43% 40/94 1.848
net.sourceforge.cobertura.check 3 0% 0/150 0% 0/76 2.429
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net.sourceforge.cobertura.instrument 10 90% 460/510 75% 123/164 1.854
net.sourceforge.cobertura.merge 1 86% 30/35 88% 14/16 5.5
net.sourceforge.cobertura.reporting 3 87% 116/134 80% 43/54 2.882
net.sourceforge.cobertura.reporting.html 4 91% 475/523 77% 156/202 4.444
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net.sourceforge.cobertura.reporting.xml 1 100% 155/155 95% 21/22 1.524
net.sourceforge.cobertura.util 9 60% 175/291 69% 70/102 2.892
someotherpackage 1 83% 5/6 N/A N/A 1.2
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Testable Code

Think about testing when writing code

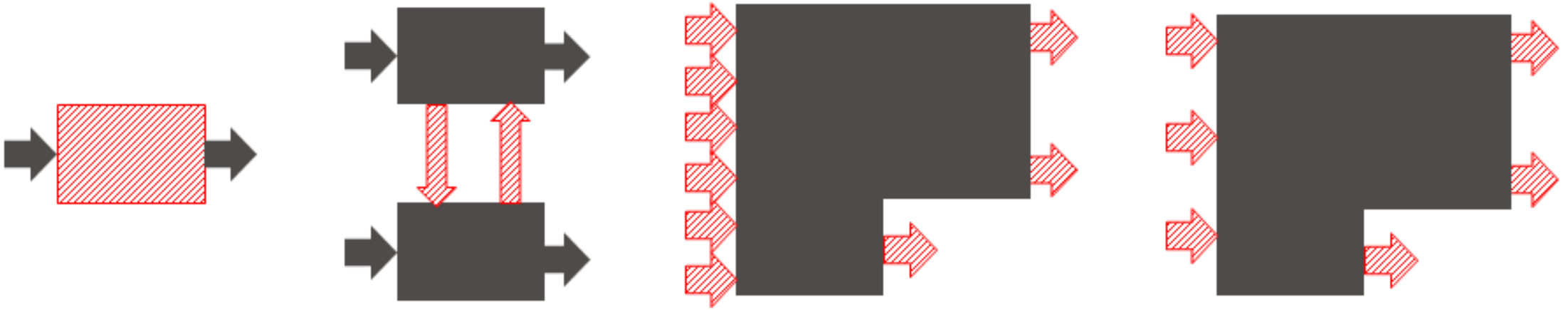
Unit testing encourages you to write testable code

Separate parts of the code to make them independently testable

Abstract functionality behind interface, make it replaceable

Bonus: Test-Driven Development is a design and development method in which you *always* write tests *before* writing code

Integration and system tests



Unit testing

Integration testing

System testing

Acceptance testing

(Demonstration)

Integration and system tests

Test larger units of behavior

Often based on use cases or user stories -- customer perspective

```
@Test void gameTest() {
    Poker game = new Poker();
    Player p = new Player();
    Player q = new Player();
    game.shuffle(seed)
    game.add(p);
    game.add(q);
    game.deal();
    p.bet(100);
    q.bet(100);
```

Integration and system tests

Test larger units of behavior

Often based on use cases or user stories -- customer perspective

```
@Test void testCleaningWithFeatureEng() {
    DataFrame d = loadTestData();
    DataFrame cd = clean(d);
    DataFrame f = feature3.encode(cd);
    assert(noMissingValues(f.getColumn("m")));
    assert(max(f.getColumn("m"))<=1.0);
}
```

Data Pipeline Integration Test

```
@Test void integrationTest() {
    DataLoader loader = new DataLoader(testStream,
                                       new DefaultCleaner());
    ModelBuilder model = new ModelBuilder(loader, ...);
    // assume all exceptions are handled correctly internally
    assert(model.accuracy > .91)
}
```

Build systems & Continuous Integration

Automate all build, analysis, test, and deployment steps from a command line call

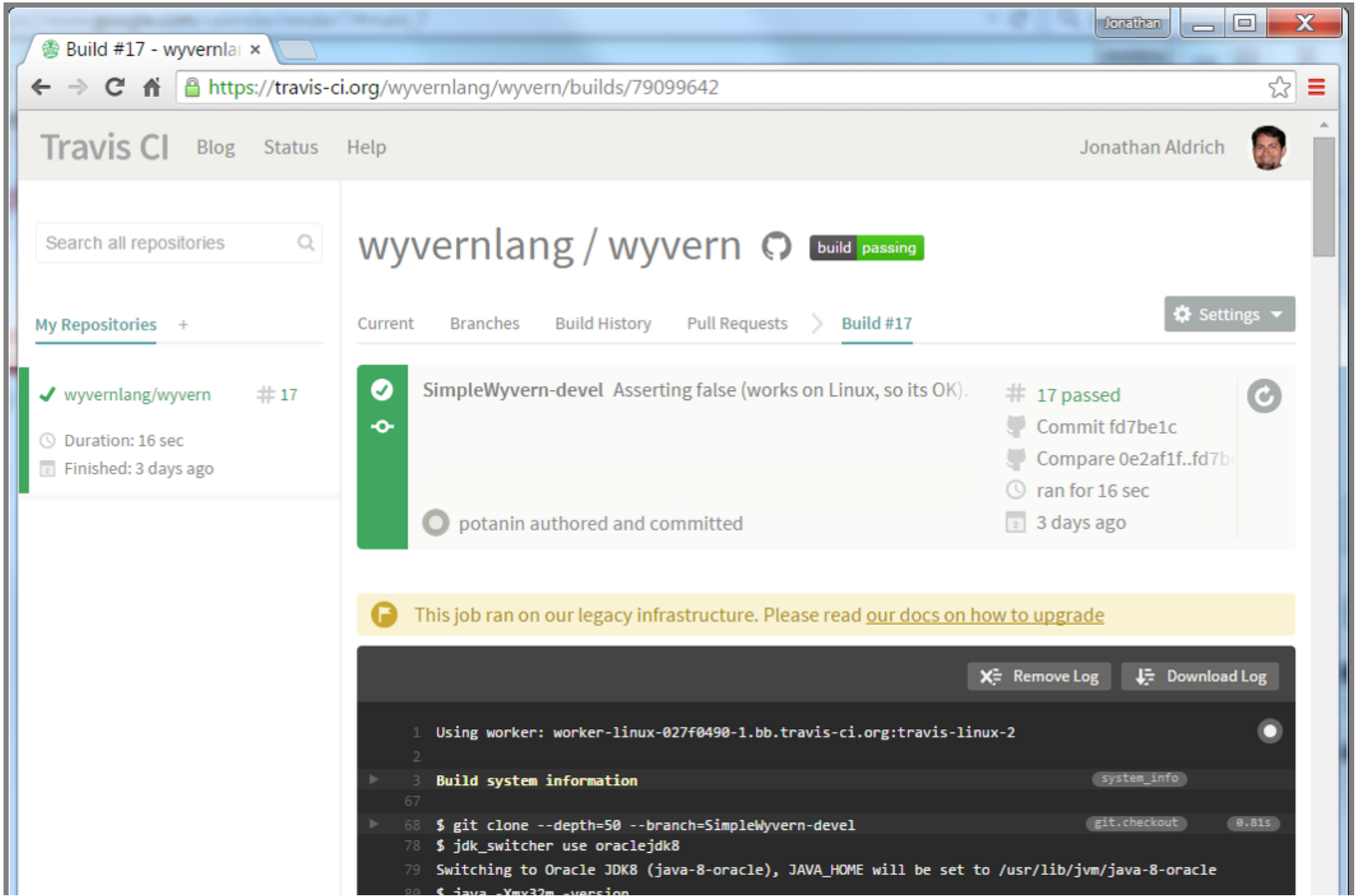
Ensure all dependencies and configurations are defined

Ideally reproducible and incremental

Distribute work for large jobs

Track results

Key CI benefit: Tests are regularly executed, part of process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Branches
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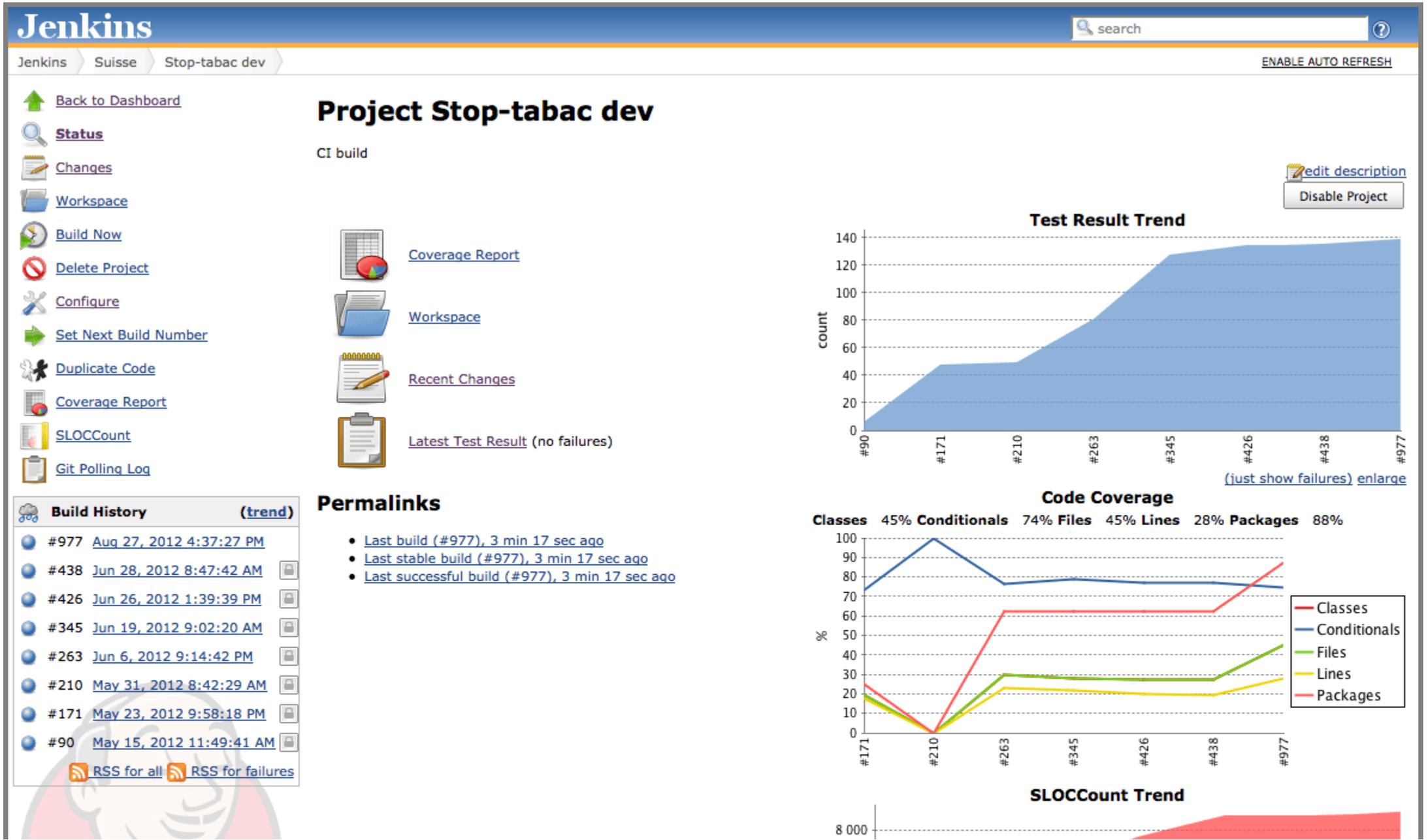
Pull Requests
Build #17
Settings
wyvernlang/wyvern
17
Duration: 16 sec
Finished: 3 days ago
SimpleWyvern-devel Asserting false (works on Linux, so its OK).
potanin authored and committed
17 passed
Commit fd7be1c
Compare 0e2af1f..fd7b
ran for 16 sec
3 days ago
This job ran on our legacy infrastructure. Please read our docs on how to upgrade
Remove Log
Download Log
1 Using worker: worker-linux-027f0490-1.bb.travis-ci.org:travis-linux-2
2
3 Build system information
system_info
67
68 $ git clone --depth=50 --branch=SimpleWyvern-devel
git.checkout
0.81s
78 $ jdk_switcher use oraclejdk8
79 Switching to Oracle JDK8 (java-8-oracle), JAVA_HOME will be set to /usr/lib/jvm/java-8-oracle

Tracking Build Quality

Track quality indicators over time, e.g.,

- Build time
- Test coverage
- Static analysis warnings
- Performance results
- Model quality measures
- Number of TODOs in source code


Jenkins
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ENABLE AUTO REFRESH
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#977 Aug 27, 2012 4:37:27 PM
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#426 Jun 26, 2012 1:39:39 PM
#345 Jun 19, 2012 9:02:20 AM
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#210 May 31, 2012 8:42:29 AM
#171 May 23, 2012 9:58:18 PM
#90 May 15, 2012 11:49:41 AM
RSS for all
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Project Stop-tabac dev
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Coverage Report
Workspace
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Latest Test Result (no failures)
Permalinks
Last build (#977), 3 min 17 sec ago
Last stable build (#977), 3 min 17 sec ago
Last successful build (#977), 3 min 17 sec ago
Test Result Trend
count
(just show failures) enlarge
Code Coverage
Classes 45% Conditionals 74% Files 45% Lines 28% Packages 88%
%
Classes
Conditionals
Files
Lines
Packages
SLOCCount Trend

Tracking Model Qualities

Many tools: MLFlow, ModelDB, Neptune, TensorBoard, Weights & Biases, Comet.ml, ...

ModelDB Example

```
from verta import Client
client = Client("http://localhost:3000")

proj = client.set_project("My first ModelDB project")
expt = client.set_experiment("Default Experiment")

# log a training run
run = client.set_experiment_run("First Run")
run.log_hyperparameters({"regularization" : 0.5})
model1 = # ... model training code goes here
run.log_metric('accuracy', accuracy(model1, validationData))
```

Test Monitoring

- Inject/simulate faulty behavior
- Mock out notification service used by monitoring
- Assert notification

```
class MyNotificationService extends NotificationService {
    public boolean receivedNotification = false;
    public void sendNotification(String msg) {
        receivedNotification = true; }
}
@Test void test() {
    Server s = getServer();
    MyNotificationService n = new MyNotificationService();
    Monitor m = new Monitor(s, n);
    s.stop();
```

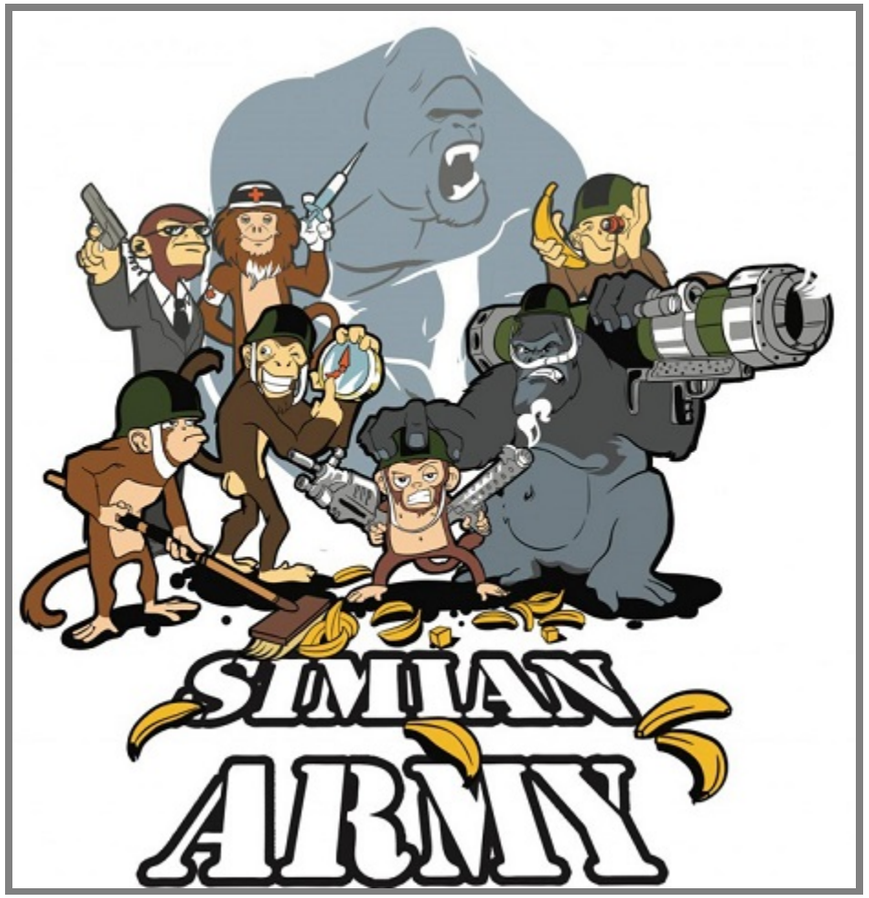
Test Monitoring in Production

Like fire drills (manual tests may be okay!)

Manual tests in production, repeat regularly

Actually take down service or trigger wrong signal to monitor

Chaos Testing



- http://principlesofchaos.org

Speaker notes

Chaos Engineering is the discipline of experimenting on a distributed system in order to build confidence in the system’s capability to withstand turbulent conditions in production. Pioneered at Netflix

Chaos Testing Argument

- Distributed systems are simply too complex to comprehensively predict
  - experiment to learn how it behaves in the presence of faults
- Base corrective actions on experimental results because they reflect real risks and actual events

- Experimentation != testing -- Observe behavior rather then expect specific results
- Simulate real-world problem in production (e.g., take down server, inject latency)
- *Minimize blast radius:* Contain experiment scope

Netflix's Simian Army

- Chaos Monkey: randomly disable production instances
- Latency Monkey: induces artificial delays in our RESTful client-server communication layer
- Conformity Monkey: finds instances that don’t adhere to best-practices and shuts them down
- Doctor Monkey: monitors external signs of health to detect unhealthy instances
- Janitor Monkey: ensures cloud environment is running free of clutter and waste
- Security Monkey: finds security violations or vulnerabilities, and terminates the offending instances
- 10–18 Monkey: detects problems in instances serving customers in multiple geographic regions
- Chaos Gorilla is similar to Chaos Monkey, but simulates an outage of an entire Amazon availability zone.

Chaos Toolkit

- Infrastructure for chaos experiments
- Driver for various infrastructure and failure cases
- Domain specific language for experiment definitions

```
{
    "version": "1.0.0",
    "title": "What is the impact of an expired certificate on
    "description": "If a certificate expires, we should gracef
    "tags": ["tls"],
    "steady-state-hypothesis": {
        "title": "Application responds",
        "probes": [
            {
                "type": "probe",
```

Chaos Experiments for ML Infrastructure?

Speaker notes

Fault injection in production for testing in production. Requires monitoring and explicit experiments.

Code Review and Static Analysis

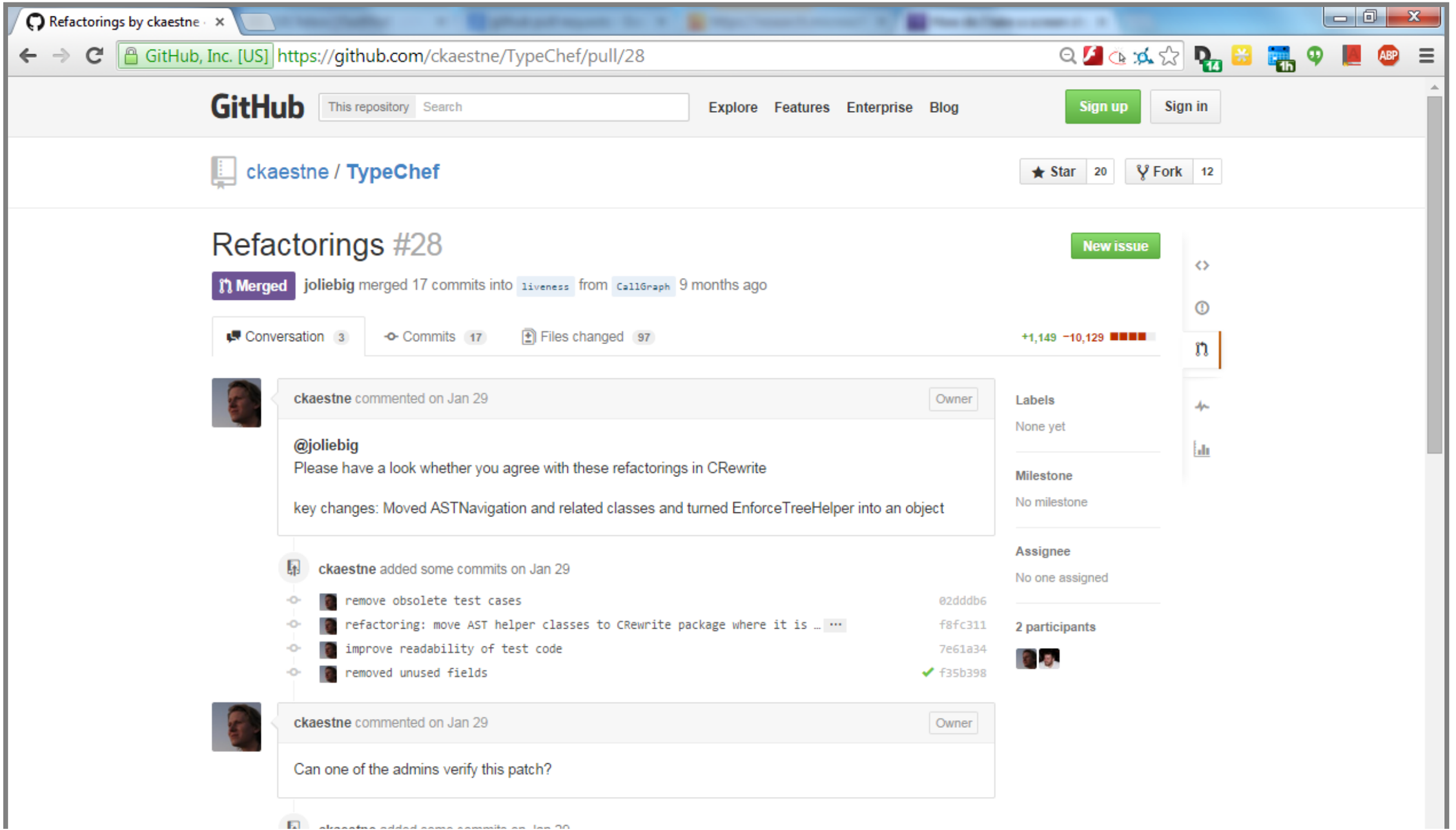
Code Review

Manual inspection of code

- Looking for problems and possible improvements
- Possibly following checklists
- Individually or as group

Modern code review: Incremental review at checking

- Review individual changes before merging
- Pull requests on GitHub
- Not very effective at finding bugs, but many other benefits: knowledge transfer, code imporvement, shared code ownership, improving testing


Refactorings by ckaestne
GitHub, Inc. [US] https://github.com/ckaestne/TypeChef/pull/28
GitHub
This repository Search
Explore Features Enterprise Blog
Sign up Sign in
ckaestne / TypeChef
Star 20 Fork 12
Refactorings #28
New issue
Merged joliebig merged 17 commits into liveness from CallGraph 9 months ago
Conversation 3 Commits 17 Files changed 97 +1,149 −10,129
ckaestne commented on Jan 29 Owner
@joliebig
Please have a look whether you agree with these refactorings in CRewrite
key changes: Moved ASTNavigation and related classes and turned EnforceTreeHelper into an object
ckaestne added some commits on Jan 29
remove obsolete test cases 02dddb6
refactoring: move AST helper classes to CRewrite package where it is … f8fc311
improve readability of test code 7e61a34
removed unused fields f35b398
ckaestne commented on Jan 29 Owner
Can one of the admins verify this patch?
Labels
None yet
Milestone
No milestone
Assignee
No one assigned
2 participants

Subtle Bugs in Data Wrangling Code

```
df['Join_year'] = df.Joined.dropna().map(
    lambda x: x.split(',')[1].split(' ')[1])
```

```
df.loc[idx_nan_age,'Age'].loc[idx_nan_age] =
    df['Title'].loc[idx_nan_age].map(map_means)
```

```
df["Weight"].astype(str).astype(int)
```

```
df['Reviws'] = df['Reviews'].apply(int)
```

Speaker notes

We did code review earlier together

Static Analysis, Code Linting

Automatic detection of problematic patterns based on code structure

```
if (user.jobTitle = "manager") {
    ...
}
```

```
function fn() {
    x = 1;
    return x;
    x = 3;
}
```

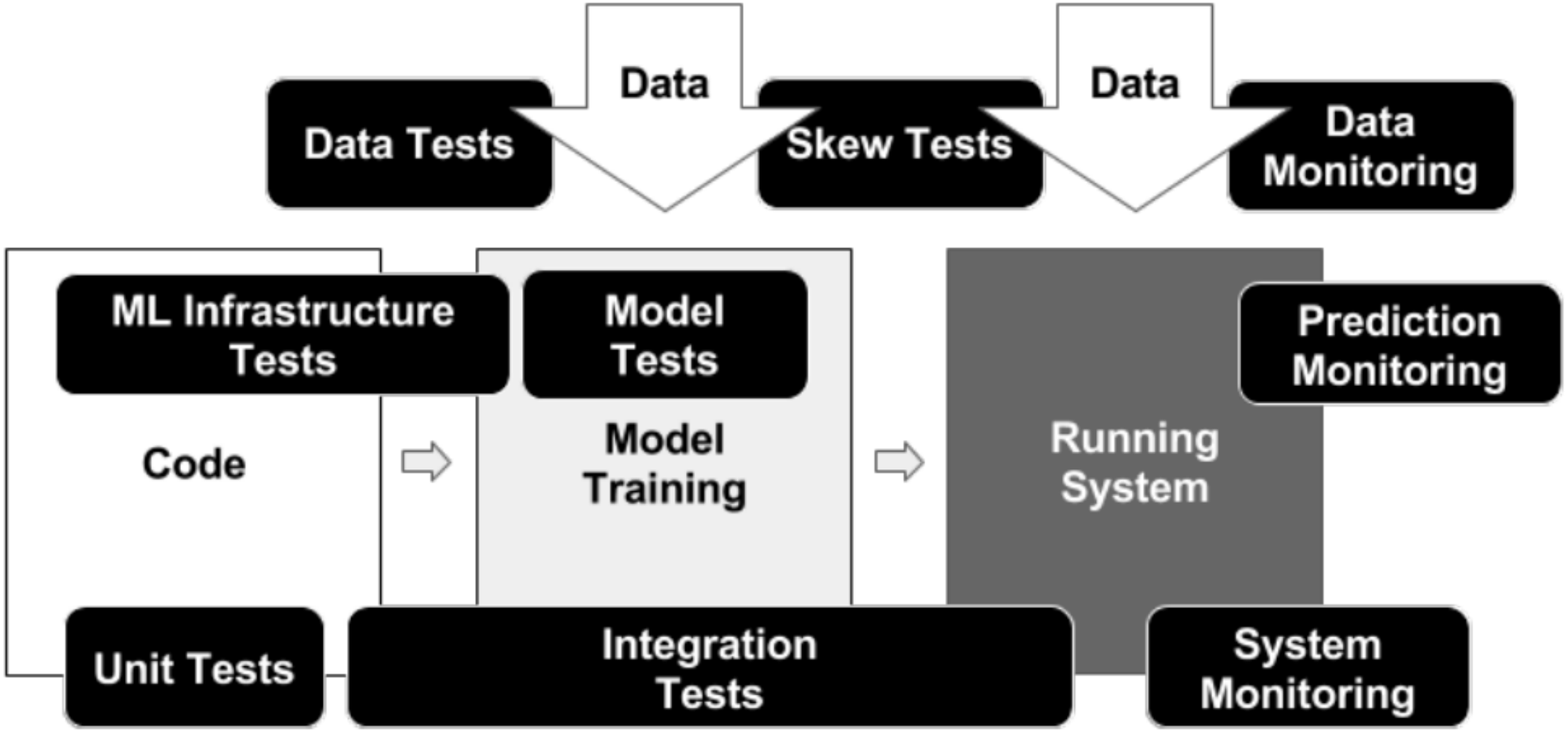
Process Integration: Static Analysis Warnings during Code Review

Speaker notes

Social engineering to force developers to pay attention. Also possible with integration in pull requests on GitHub.

Infrastructure Testing

Eric Breck, Shanqing Cai, Eric Nielsen, Michael Salib, D. Sculley. The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction. Proceedings of IEEE Big Data (2017)



Source: Eric Breck, Shanqing Cai, Eric Nielsen, Michael Salib, D. Sculley. The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction. Proceedings of IEEE Big Data

Data Tests

1. Feature expectations are captured in a schema.
2. All features are beneficial.
3. No feature's cost is too much.
4. Features adhere to meta-level requirements.
5. The data pipeline has appropriate privacy controls.
6. New features can be added quickly.
7. All input feature code is tested.

Eric Breck, Shanqing Cai, Eric Nielsen, Michael Salib, D. Sculley. The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction. Proceedings of IEEE Big Data (2017)

Tests for Model Development

1. Model specs are reviewed and submitted.
2. Offline and online metrics correlate.
3. All hyperparameters have been tuned.
4. The impact of model staleness is known.
5. A simpler model is not better.
6. Model quality is sufficient on important data slices.
7. The model is tested for considerations of inclusion.

Eric Breck, Shanqing Cai, Eric Nielsen, Michael Salib, D. Sculley. The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction. Proceedings of IEEE Big Data (2017)

ML Infrastructure Tests

1. Training is reproducible.
2. Model specs are unit tested.
3. The ML pipeline is Integration tested.
4. Model quality is validated before serving.
5. The model is debuggable.
6. Models are canaried before serving.
7. Serving models can be rolled back.

Eric Breck, Shanqing Cai, Eric Nielsen, Michael Salib, D. Sculley. The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction. Proceedings of IEEE Big Data (2017)

Monitoring Tests

1. Dependency changes result in notification.
2. Data invariants hold for inputs.
3. Training and serving are not skewed.
4. Models are not too stale.
5. Models are numerically stable.
6. Computing performance has not regressed.
7. Prediction quality has not regressed.

Eric Breck, Shanqing Cai, Eric Nielsen, Michael Salib, D. Sculley. The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction. Proceedings of IEEE Big Data (2017)

Case Study: Covid-19 Detection

(from S20 midterm; assume cloud or hybrid deployment)

Breakout Groups

- In the Smartphone Covid Detection scenario
- Discuss in groups:
  - Back left: data tests
  - Back right: model dev. tests
  - Front right: infrastructure tests
  - Front left: monitoring tests
- For 8 min, discuss some of the listed point in the context of the Covid-detection scenario: what would you do?
- In `#lecture`, tagging group members, suggest what tests to implement

Dev vs. Ops

Common Release Problems?

Common Release Problems (Examples)

- Missing dependencies
- Different compiler versions or library versions
- Different local utilities (e.g. unix grep vs mac grep)
- Database problems
- OS differences
- Too slow in real settings
- Difficult to roll back changes
- Source from many different repositories
- Obscure hardware? Cloud? Enough memory?

Developers

- Coding
- Testing, static analysis, reviews
- Continuous integration
- Bug tracking
- Running local tests and scalability experiments
- ...

Operations

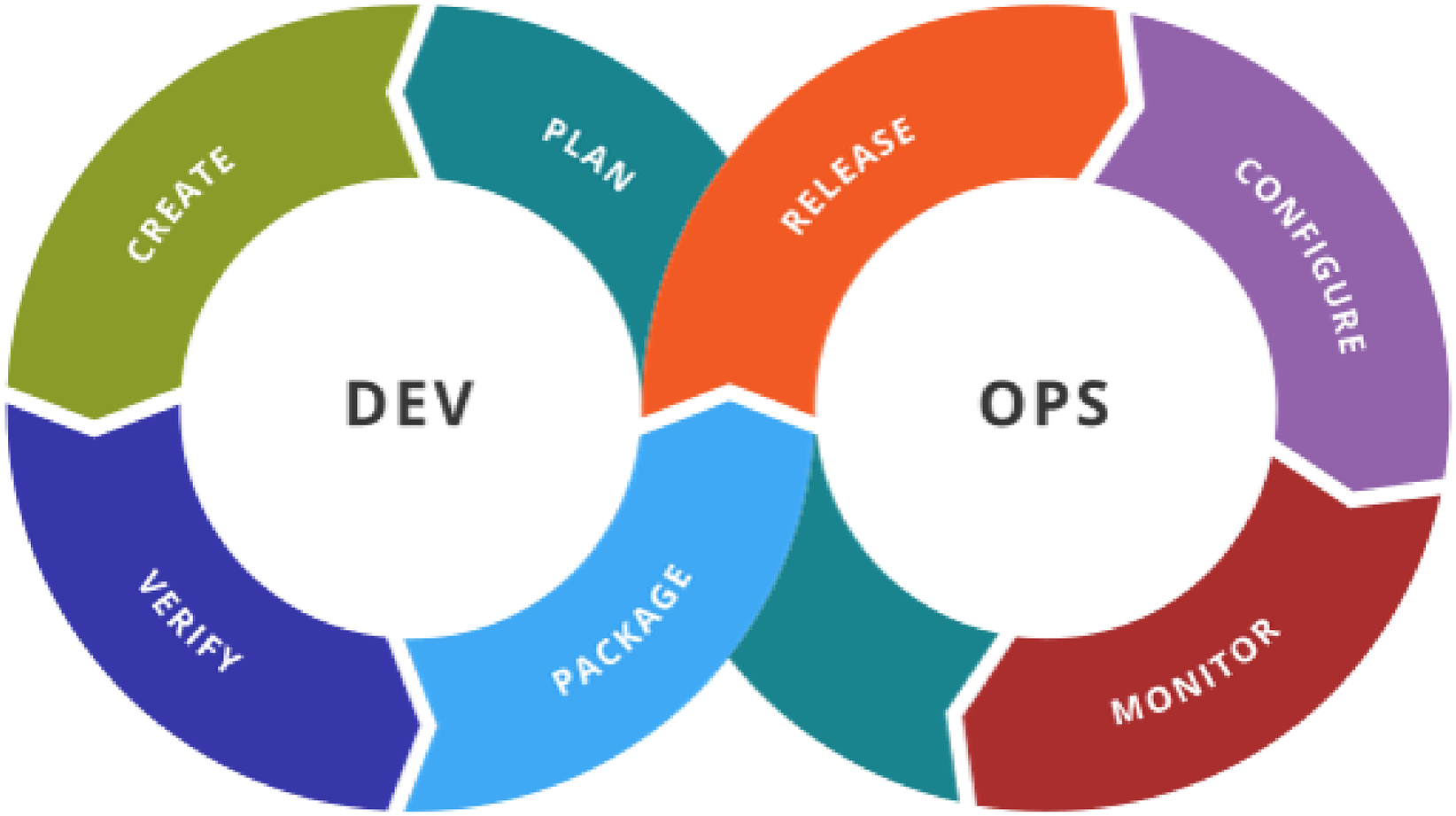
- Allocating hardware resources
- Managing OS updates
- Monitoring performance
- Monitoring crashes
- Managing load spikes, ...
- Tuning database performance
- Running distributed at scale
- Rolling back releases
- ...

QA responsibilities in both roles

Quality Assurance does not stop in Dev

- Ensuring product builds correctly (e.g., reproducible builds)
- Ensuring scalability under real-world loads
- Supporting environment constraints from real systems (hardware, software, OS)
- Efficiency with given infrastructure
- Monitoring (server, database, Dr. Watson, etc)
- Bottlenecks, crash-prone components, … (possibly thousands of crash reports per day/minute)

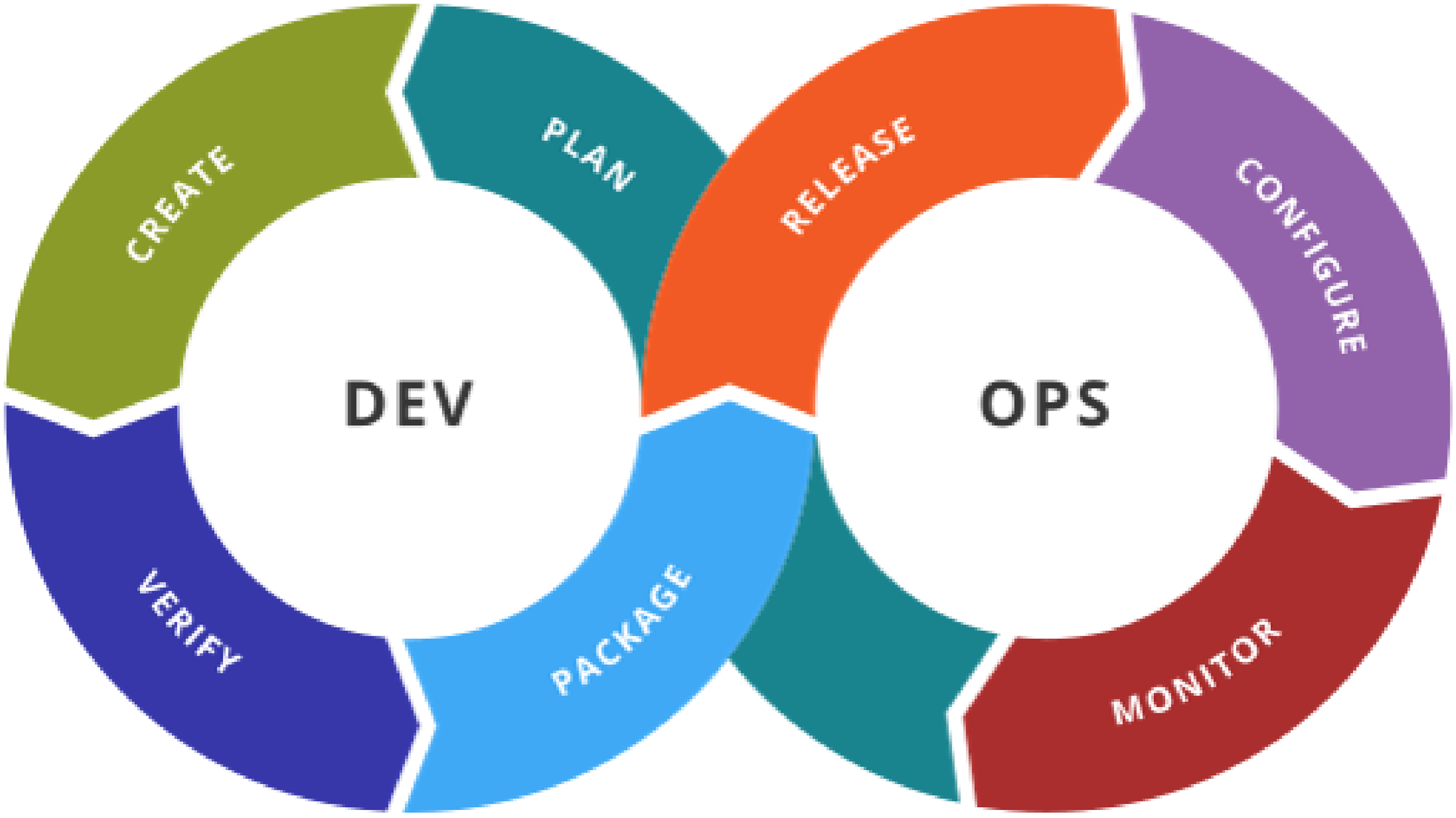
DevOps


CREATE
PLAN
RELEASE
CONFIGURE
DEV
OPS
VERIFY
PACKAGE
MONITOR

Key ideas and principles

- Better coordinate between developers and operations (collaborative)
- Key goal: Reduce friction bringing changes from development into production
- Considering the *entire tool chain* into production (holistic)
- Documentation and versioning of all dependencies and configurations ("configuration as code")
- Heavy automation, e.g., continuous delivery, monitoring
- Small iterations, incremental and continuous releases

- Buzz word!


CREATE
PLAN
RELEASE
CONFIGURE
DEV
OPS
VERIFY
PACKAGE
MONITOR

Common Practices

All configurations in version control

Test and deploy in containers

Automated testing, testing, testing, ...

Monitoring, orchestration, and automated actions in practice

Microservice architectures

Release frequently

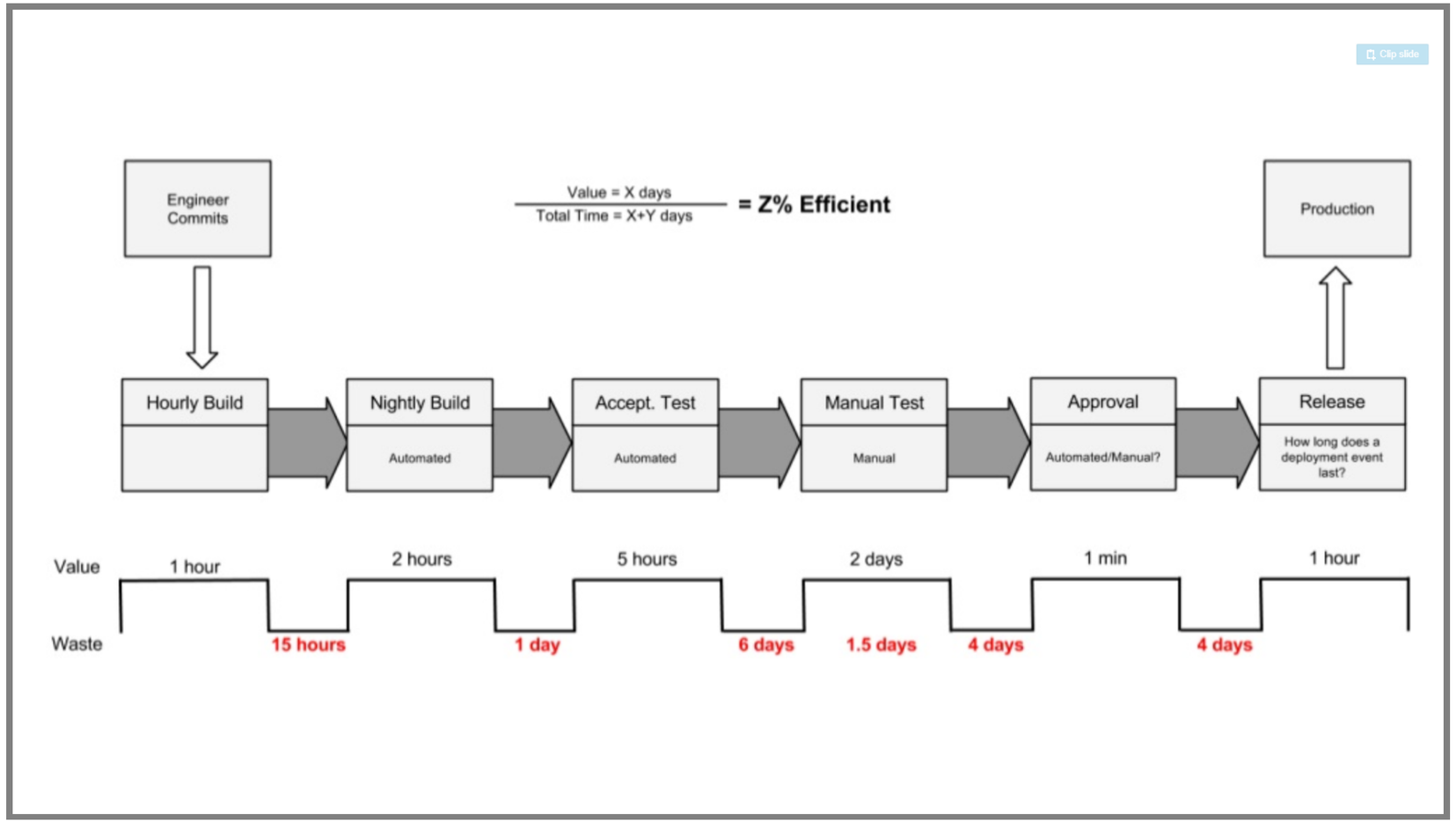
Heavy tooling and automation

Heavy tooling and automation -- Examples

- Infrastructure as code — Ansible, Terraform, Puppet, Chef
- CI/CD — Jenkins, TeamCity, GitLab, Shippable, Bamboo, Azure DevOps
- Test automation — Selenium, Cucumber, Apache JMeter
- Containerization — Docker, Rocket, Unik
- Orchestration — Kubernetes, Swarm, Mesos
- Software deployment — Elastic Beanstalk, Octopus, Vamp
- Measurement — Datadog, DynaTrace, Kibana, NewRelic, ServiceNow

Continuous Delivery

Manual Release Pipelines



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

Continuous Integr.

- Automate tests after commit
- Independent test infrastructure

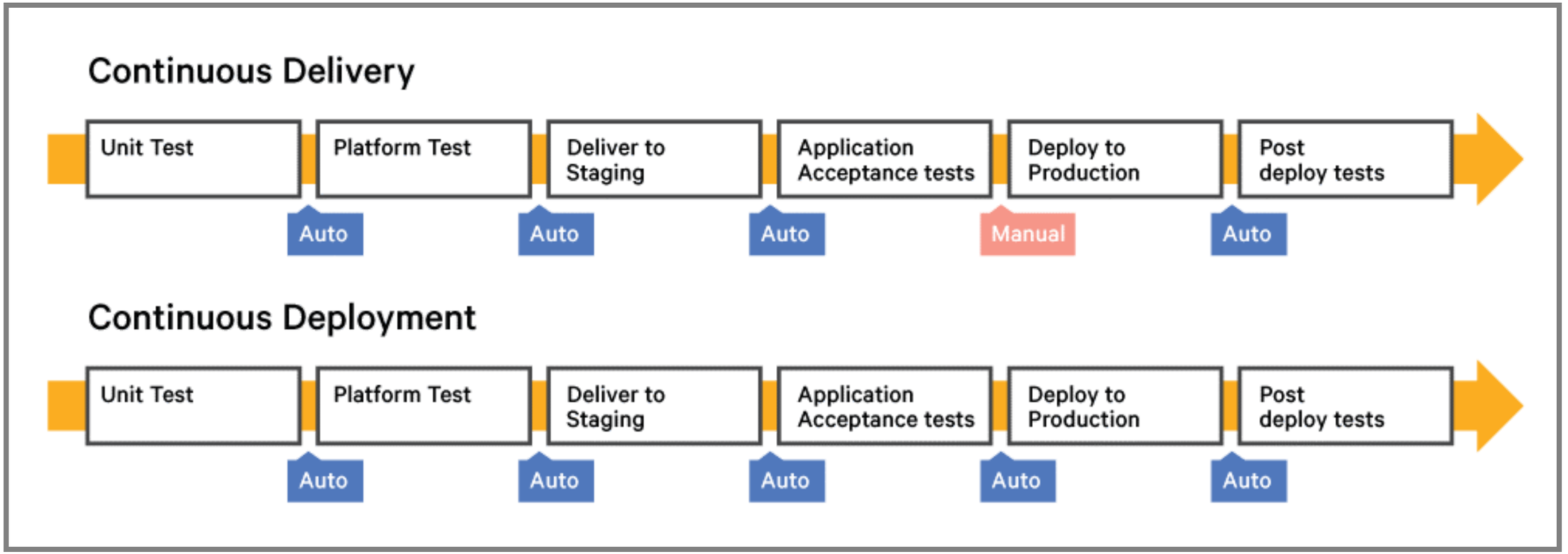
Continuous Delivery

- Full automation from commit to deployable container
- Heavy focus on testing, reproducibility and rapid feedback, creates transparency

Continuous Deployment

- Full automation from commit to deployment
- Empower developers, quick to production
- Encourage experimentation and fast incremental changes
- Commonly integrated with monitoring and canary releases

Automate Everything



Example: Facebook Tests for Mobile Apps

- Unit tests (white box)
- Static analysis (null pointer warnings, memory leaks, ...)
- Build tests (compilation succeeds)
- Snapshot tests (screenshot comparison, pixel by pixel)
- Integration tests (black box, in simulators)
- Performance tests (resource usage)
- Capacity and conformance tests (custom)

Further readings: Rossi, Chuck, Elisa Shibley, Shi Su, Kent Beck, Tony Savor, and Michael Stumm. Continuous deployment of mobile software at facebook (showcase). In Proceedings of the 2016 24th ACM SIGSOFT International Symposium on Foundations of Software Engineering, pp. 12-23. ACM, 2016.

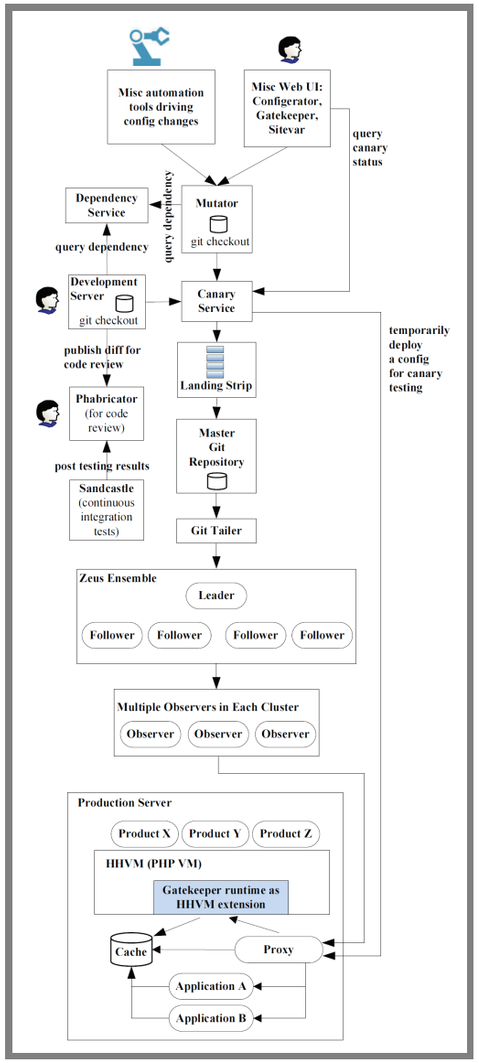
Release Challenges for Mobile Apps

- Large downloads
- Download time at user discretion
- Different versions in production
- Pull support for old releases?

- Server side releases silent and quick, consistent

- -> App as container, most content + layout from server

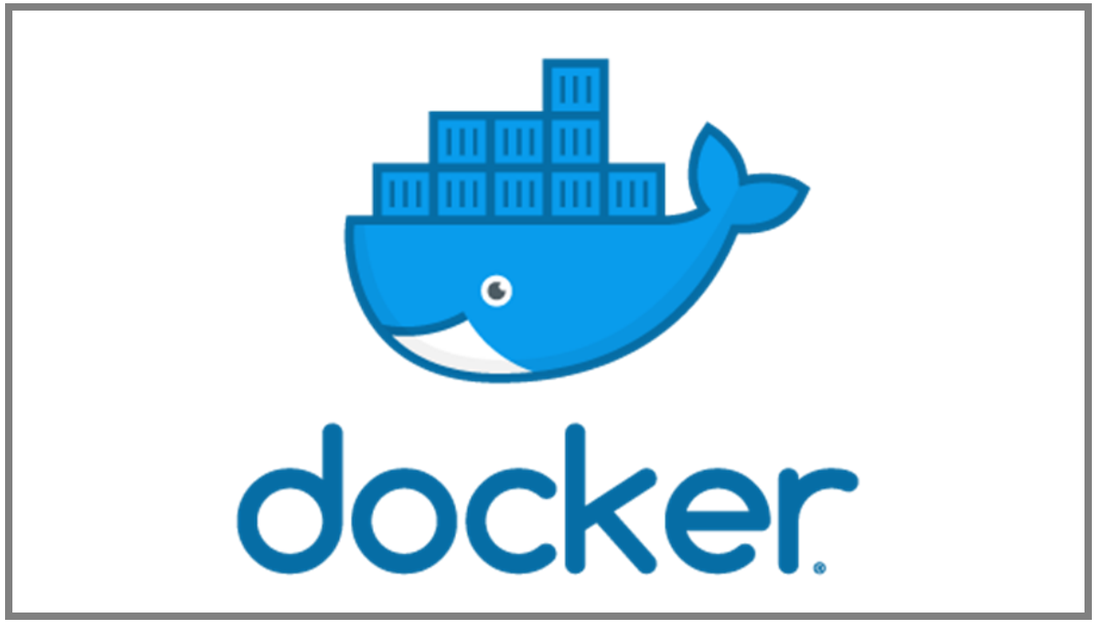
Real-world pipelines are complex



Containers and Configuration Management

Containers

- Lightweight virtual machine
- Contains entire runnable software, incl. all dependencies and configurations
- Used in development and production
- Sub-second launch time
- Explicit control over shared disks and network connections



Docker Example

```
FROM ubuntu:latest
MAINTAINER ...
RUN apt-get update -y
RUN apt-get install -y python-pip python-dev build-essential
COPY . /app
WORKDIR /app
RUN pip install -r requirements.txt
ENTRYPOINT ["python"]
CMD ["app.py"]
```

- Source: http://containertutorials.com/docker-compose/flask-simple-app.html

Common configuration management questions

What runs where?

How are machines connected?

What (environment) parameters does software X require?

How to update dependency X everywhere?

How to scale service X?

Ansible Examples

- Software provisioning, configuration mgmt., and deployment tool
- Apply scripts to many servers

```
[webservers]
web1.company.org
web2.company.org
web3.company.org

[dbservers]
db1.company.org
db2.company.org

[replication_servers]
...
```

```
# This role deploys the mongod processe
- name: create data directory for mongo
  file: path={{ mongodb_datadir_prefix
  delegate_to: '{{ item }}'
  with_items: groups.replication_server

- name: create log directory for mongod
  file: path=/var/log/mongo state=direc

- name: Create the mongodb startup file
  template: src=mongod.j2 dest=/etc/ini
```

Puppet Example

Declarative specification, can be applied to many machines

```
$doc_root = "/var/www/example"

exec { 'apt-get update':
 command => '/usr/bin/apt-get update'
}

package { 'apache2':
 ensure  => "installed",
 require => Exec['apt-get update']
}
```

Speaker notes

source: https://www.digitalocean.com/community/tutorials/configuration-management-101-writing-puppet-manifests

Container Orchestration with Kubernetes

Manages which container to deploy to which machine

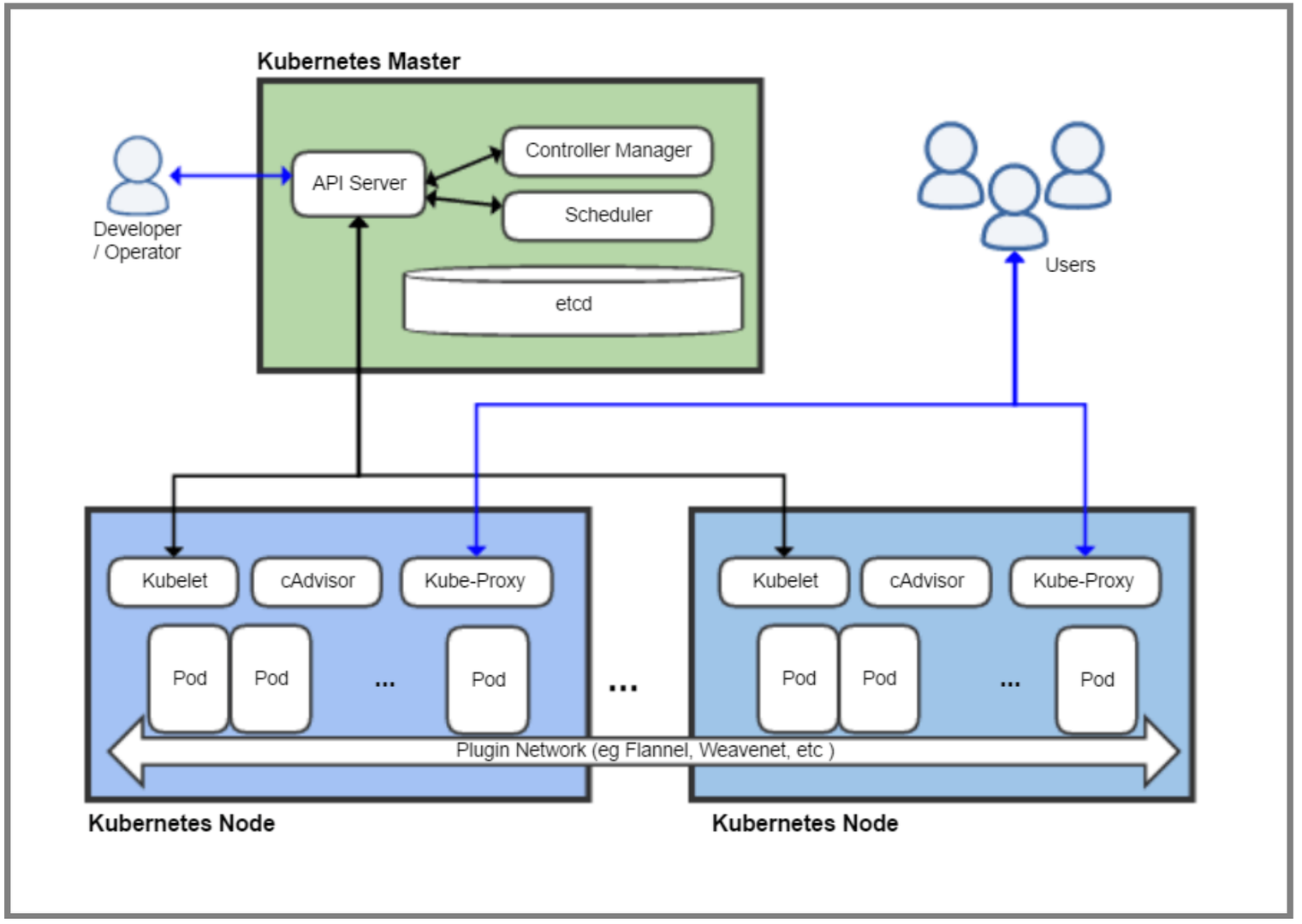
Launches and kills containers depending on load

Manage updates and routing

Automated restart, replacement, replication, scaling

Kubernetis master controls many nodes

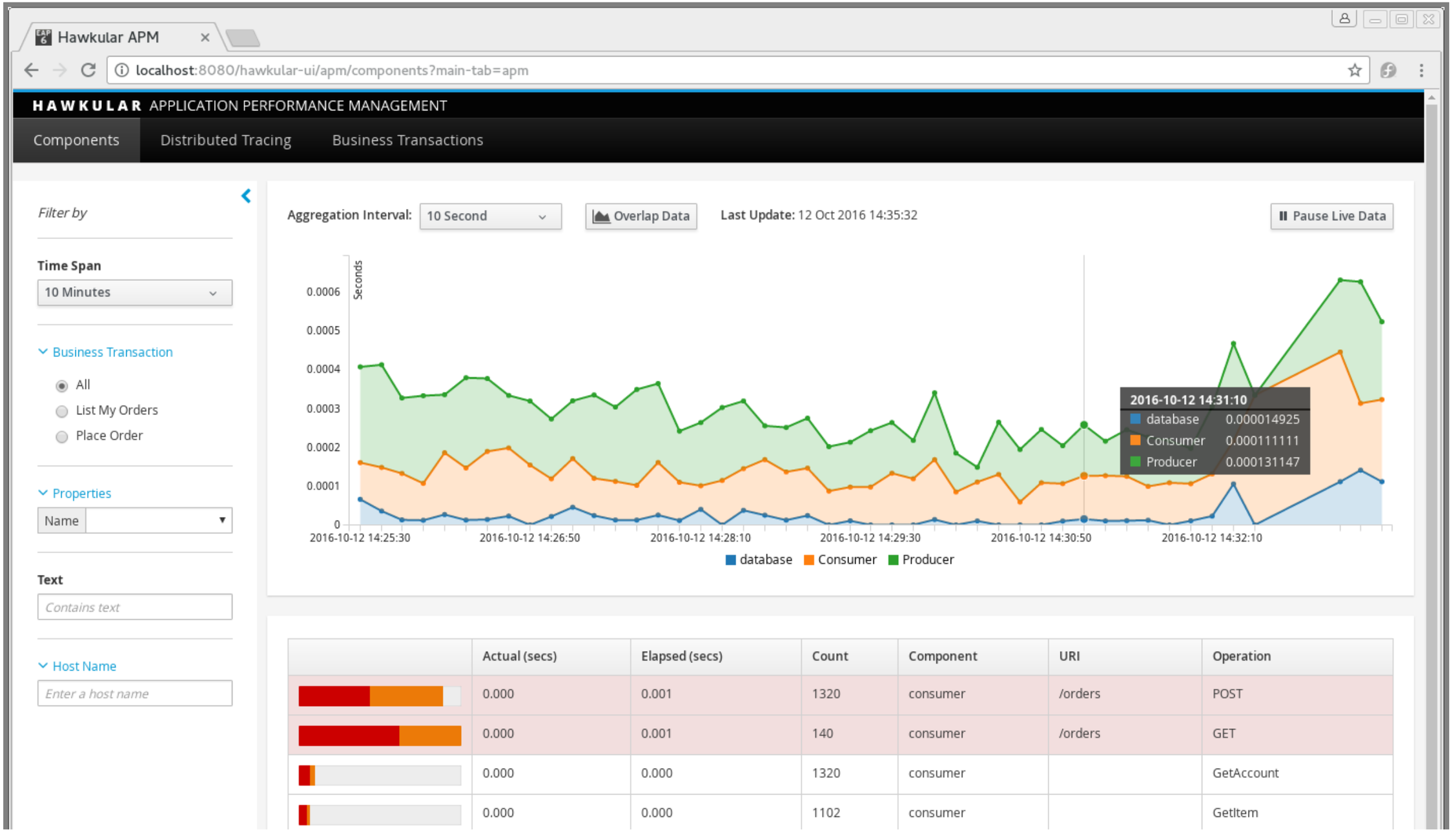
Substantial complexity and learning curve

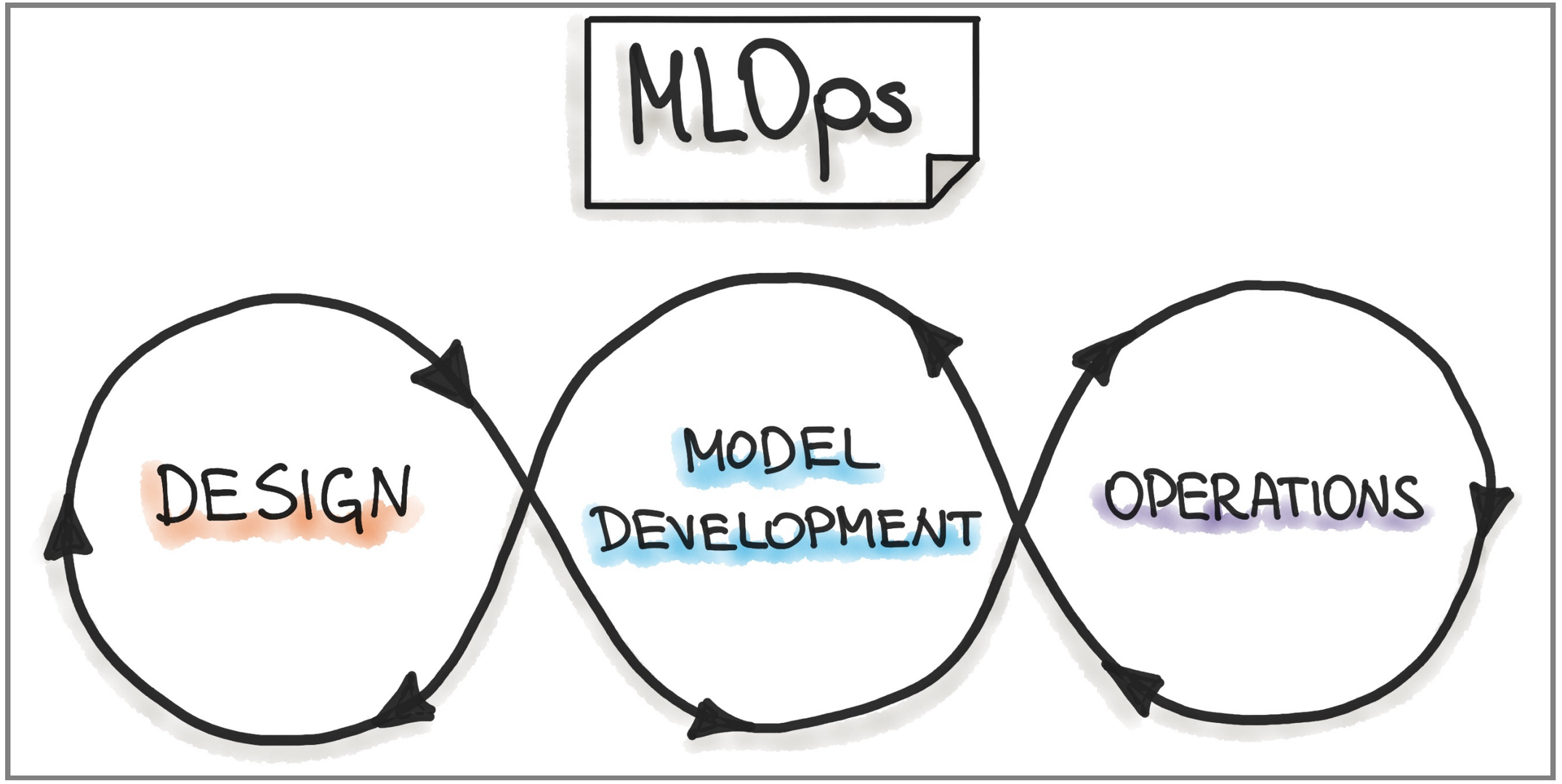


Monitoring

- Monitor server health
- Monitor service health
- Monitor telemetry (see past lecture)
- Collect and analyze measures or log files
- Dashboards and triggering automated decisions

- Many tools, e.g., Grafana as dashboard, Prometheus for metrics, Loki + ElasticSearch for logs
- Push and pull models


Hawkular APM
localhost:8080/hawkular-ui/apm/components?main-tab=apm
HAWKULAR APPLICATION PERFORMANCE MANAGEMENT
Components
Distributed Tracing
Business Transactions
Filter by
Time Span
10 Minutes
Business Transaction
All
List My Orders
Place Order
Properties
Name
Text
Contains text
Host Name
Enter a host name
Aggregation Interval:
10 Second
Overlap Data
Last Update: 12 Oct 2016 14:35:32
Pause Live Data
Seconds
0.0006
0.0005
0.0004
0.0003
0.0002
0.0001
0
2016-10-12 14:25:30
2016-10-12 14:26:50
2016-10-12 14:28:10
2016-10-12 14:29:30
2016-10-12 14:30:50
2016-10-12 14:32:10
2016-10-12 14:31:10
database 0.000014925
Consumer 0.000111111
Producer 0.000131147
database
Consumer
Producer
Actual (secs)
Elapsed (secs)
Count
Component
URI
Operation
0.000
0.001
1320
consumer
/orders
POST
0.000
0.001
140
consumer
/orders
GET
0.000
0.000
1320
consumer
GetAccount
0.000
0.000
1102
consumer
GetItem



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
  - Combines agile, DevOps, Lean Manufacturing ideas

MLOps Overview

Integrate ML artifacts into software release process, unify process (i.e., DevOps extension)

Automated data and model validation (continuous deployment)

Continuous deployment for ML models: from experimenting in notebooks to quick feedback in production

Versioning of models and datasets (more later)

Monitoring in production (discussed earlier)

Further reading: MLOps principles

Tooling Landscape LF AI

MLOps Tools -- Examples

- Model versioning and metadata: MLFlow, Neptune, ModelDB, WandB, ...
- Model monitoring: Fiddler, Hydrosphere
- Data pipeline automation and workflows: DVC, Kubeflow, Airflow
- Model packaging and deployment: BentoML, Cortex
- Distributed learning and deployment: Dask, Ray, ...
- Feature store: Feast, Tecton
- Integrated platforms: Sagemaker, Valohai, ...
- Data validation: Cerberus, Great Expectations, ...

Long list: https://github.com/kelvins/awesome-mlops

Summary

- Beyond model and data quality: Quality of the infrastructure matters, danger of silent mistakes
- Automate pipelines to foster evolution and experimentation
- Many SE techniques for test automation, testing robustness, test adequacy, testing in production useful for infrastructure quality
- DevOps: Development vs Operations challenges
  - Automate everything: deployment, configuration, testing
  - Telemetry and monitoring are key
- MLOps: Automation around ML pipelines, incl. training, evaluation, versioning, and deployment

Further Readings

- O'Leary, Katie, and Makoto Uchida. "Common problems with Creating Machine Learning Pipelines from Existing Code." Proc. Third Conference on Machine Learning and Systems (MLSys) (2020).
- Eric Breck, Shanqing Cai, Eric Nielsen, Michael Salib, D. Sculley. The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction. Proceedings of IEEE Big Data (2017)
- 📰 Zinkevich, Martin. Rules of Machine Learning: Best Practices for ML Engineering. Google Blog Post, 2017
- Serban, Alex, Koen van der Blom, Holger Hoos, and Joost Visser. "Adoption and Effects of Software Engineering Best Practices in Machine Learning." In Proc. ACM/IEEE International Symposium on Empirical Software Engineering and Measurement (2020).
- 📰 Larysa Visengeriyeva. Machine Learning Operations - A Reading List, InnoQ 2020