

Modern Software for Data Science

Michael Reid

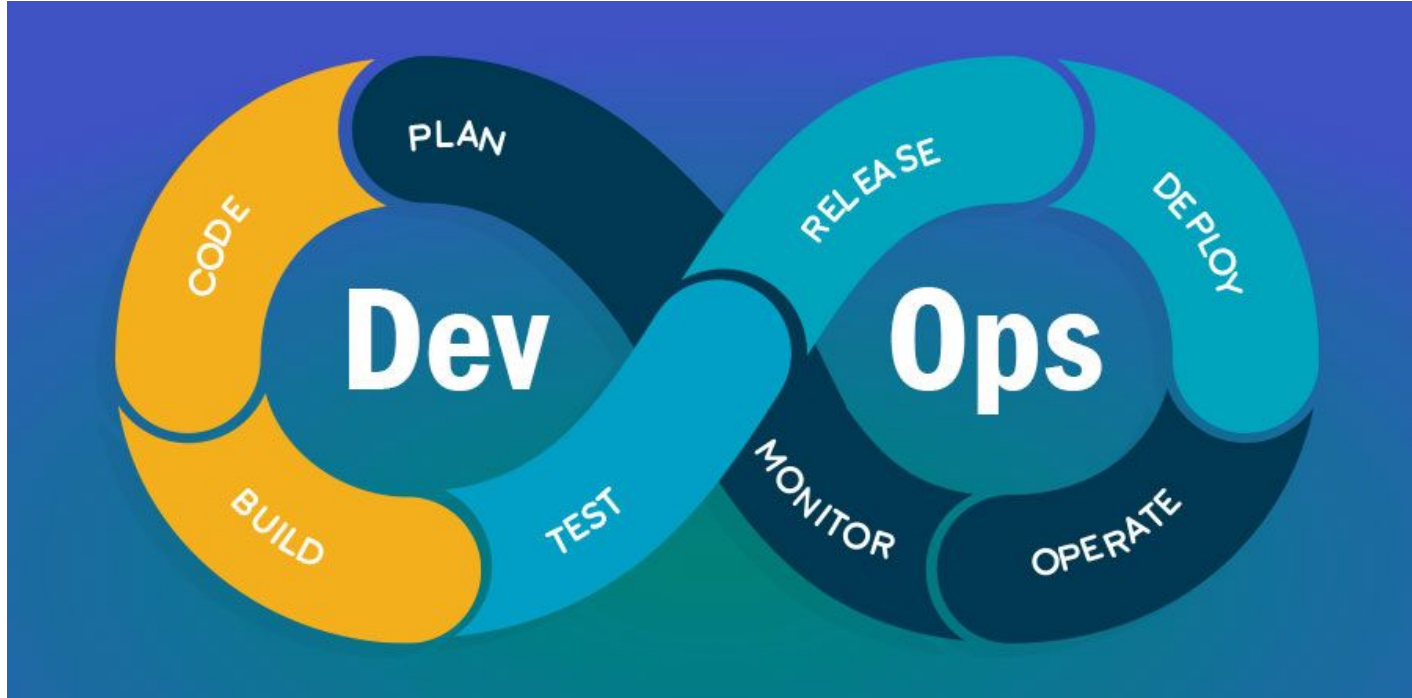
About Me - Mike Reid

- B.S. Mathematics from UMBC
- 10 years' software development experience
- Currently software development manager at AWS (RDS)
- Formerly software engineer for machine learning team at Splunk
- Software engineering experience at Hootsuite, Global Relay, USDA, FAA

Development and Ops, the Old Days



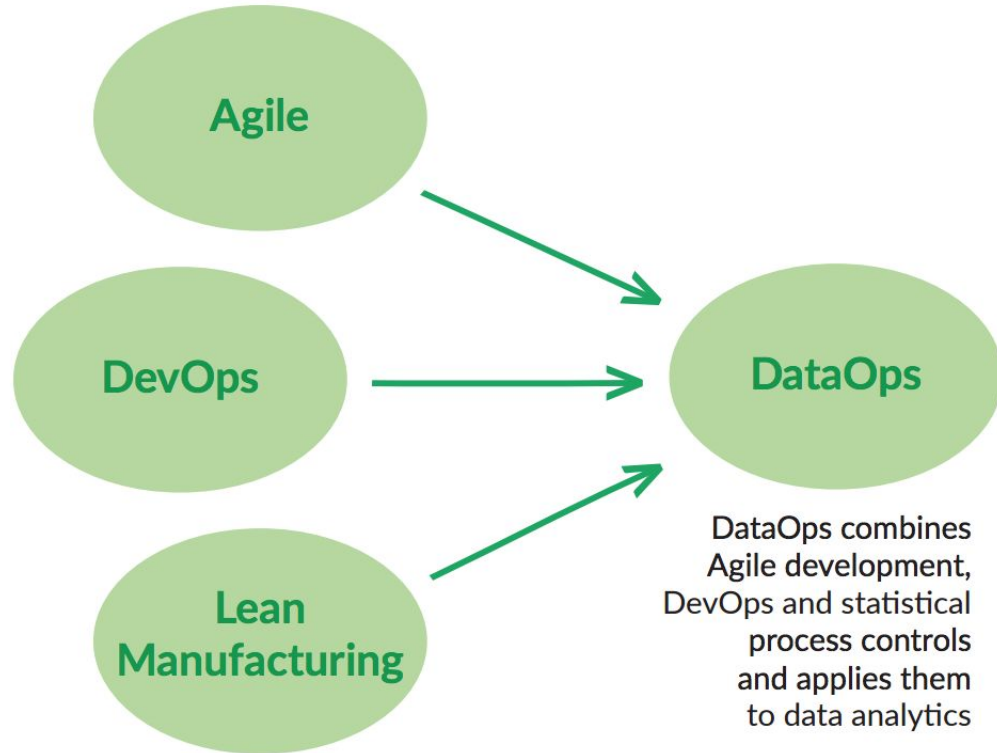
DevOps



Data Scientists and Ops, Present Day



DataOps?



Continuous Integration

- What testing do you do today before you push models and algorithms to production?
- Automate it

Continuous Integration - Testing Ideas

- Input data handling
 - Missing/incorrectly typed fields are handled correctly
 - Clearly invalid values are handled correctly
 - Abnormally large data is handled correctly
 - Out-of-order events are handled correctly
- Model performance changes
 - Test set accuracy
 - Edge case or adversarial data handling

Continuous Integration Tools

- Jenkins - de facto standard



- Bamboo - Atlassian stack



- TeamCity - JetBrains offering



- TravisCI/CircleCI - hosted solutions,
Github integration



Version Controlling Code

- git



Version Controlling Data?

- No great options
 - git (LFS)
 - Dropbox
 - Amazon S3
- Recommendation - store data externally and immutably, version control lists of data used in training/validation/test sets
 - This is what git LFS does.

Immutability

- Being able to consistently reproduce results has been a tenet of science for years, and now software development is catching up
- If the software artifacts you had running in production disappeared, could you create an *exact* copy?
 - Requires mature version control + build process + configuration management

Configuration Management

- Fundamental problem: The development data store is different than the production data store, but you're running the same artifact
- Typical solution: store configuration that changes per environment in a config file
- Follow-up problem: How do you manage the values in that configuration file?
- *Configuration Management* - use a tool which stores *configuration as code*, in version control, to control your per-environment configuration

Configuration Management Tools

- Ansible - most popular despite being newest
- Puppet, Chef - require DSL knowledge and setup
- Salt (aka Saltstack) - simpler, but less powerful

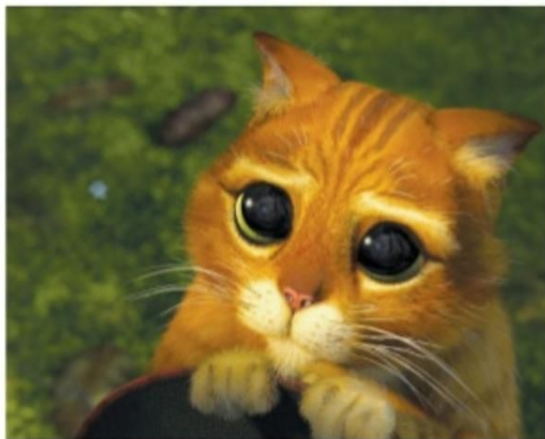


Infrastructure Management

- Thought experiment
 - *If you went into the office one day and found out your servers had been wiped clean, how difficult would it be to get everything back to the way it was?*

Cattle, Not Pets

- Pets have names, require special care, and need individual attention
- Cattle are numbered and replaceable (and delicious)



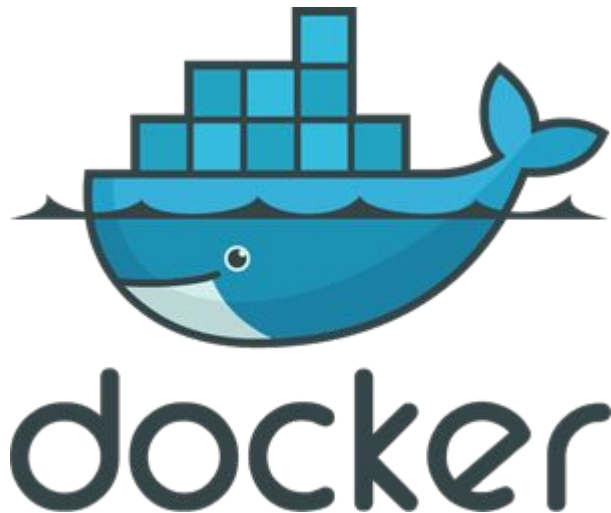
To The Cloud

- On the cloud, every server **must** be a cattle
 - Your servers can and will be replaced
- AWS, GCP and Azure all have APIs and automation tools for server management



Docker

- Infrastructure immutability
- Every package, library, etc is built into a single compact image that can be distributed to any system
- Configuration is managed through environment variables or external sources



Docker - Why?

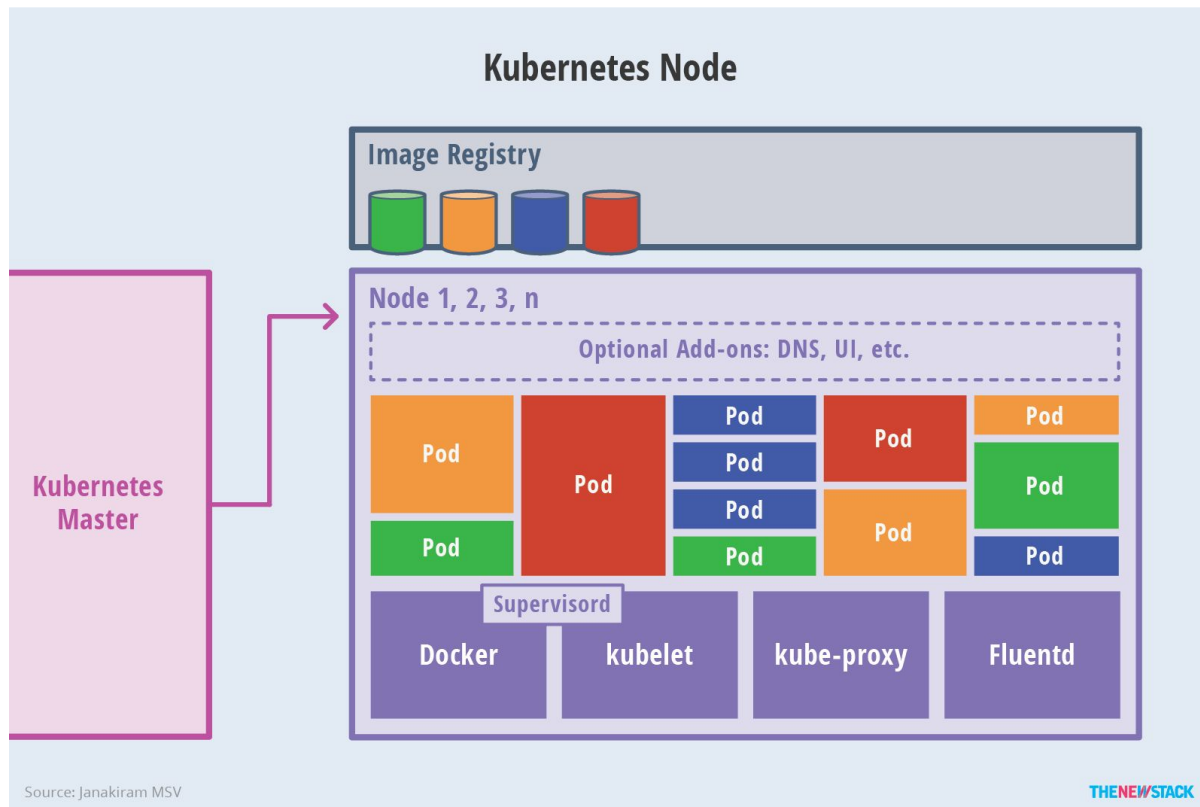
- No more version differences of system libraries in dev/staging/prod
- Simple packaging - one artifact that can be deployed and run anywhere
- Minimal time to boot; extremely low overhead compared to virtual machines

Kubernetes

- An orchestration layer that sits on top of containers (i.e. Docker)
- Provides mechanisms outside of your immutable infrastructure for maintaining your runtime: service discovery, service mesh, complex routing rules, etc.
- In a sense, a cloud without a cloud



Kubernetes - In Detail

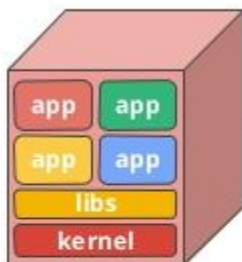


What's the point of it all?

- Provides a clear separation of ownership between data scientists and operations (IT)
 - Operations owns and operates the underlying Kubernetes infrastructure and physical hardware
 - Data Science organization owns the containers and software running therein
- Fewer touch points allows for higher agility for both data science teams and operations

To Summarize...

Why Containers?



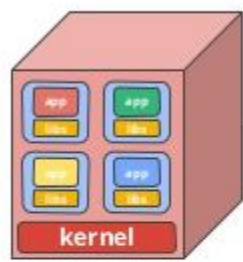
Shared Machines

- ✗ No isolation
- ✗ Shared Libraries



Virtual Machines

- ✓ Isolation
- ✓ No Shared Libraries
- ✗ Hard to manage
- ✗ Expensive and Inefficient



Containers

- ✓ Isolation
- ✓ No Shared Libraries
- ✓ Less overhead
- ✗ Less Dependency on Host OS



Monitoring and Operations

- If a server falls in the woods, who fixes it?
- With great power comes great responsibility
 - Developers and data scientists take ownership of the operation of their software



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pagerduty

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Warning - Data Platforms Can Lock You In

- Splunk - tough to spin up clusters in an automated fashion
- Spark - job submission and management is tricky to automate
- Amazon ML, Azure ML, Google ML, IBM Watson - all have tight vendor lock-in by default, need to devise workflows to be cloud-agnostic
- If your platform isn't built with DataOps in mind, it's hard to adjust

The Future - Stream Processing

- Spark Streaming - not really streaming
- Apache Flink and Apache Apex - next-generation native streaming platforms
- Streaming ML algorithms are not as common or frequently used



The Future - Secure Machine Learning

- Problem: You want to train a model, but you don't want to buy expensive GPUs
- Solution: Train on the cloud!
- Problem: Your data is sensitive. You can't put it on the cloud
- Solution: ???

Homomorphic Encryption

- *Fully Homomorphic Encryption* are cryptosystems that allow arbitrary computations on ciphertext
 - These cryptosystems exist, but are slow
- *Partially Homomorphic Encryption* supports certain operations on ciphertexts
 - Addition or multiplication, for example
- If you can perform encrypted multiplication and encrypted addition, you can do encrypted linear algebra

Thank You!

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