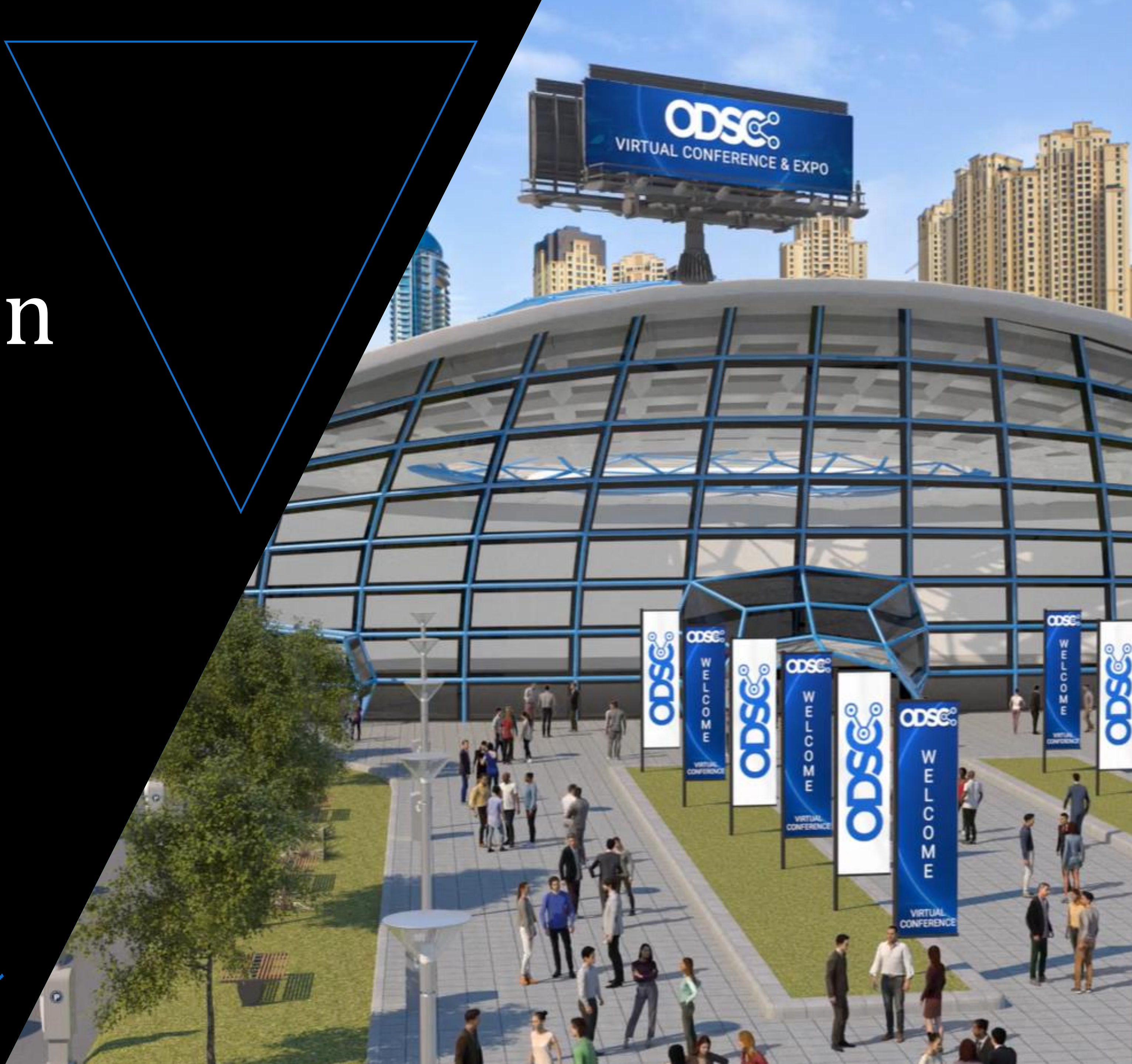
2020 East Open Data Science Conference Presentation

NICK MORRIS

APRIL 29, 2020



- MLOps: The Assembly Line of Machine Learning
- The Future of MLOps and How Did We Get Here?
- AI/ML Operationalization Anti-Patterns
- Challenges and Best Practices in Industrial AI Applications
- How Google Uses AI and Machine Learning in the Enterprise
- Reinforcement Learning and Inverse Reinforcement Learning in Finance
- Workshops – Python, R, Kubernetes

MLOps: The Assembly Line of Machine Learning

Jordan Birdsell
Chief Machine Learning Architect
phData

We we're thinking through MLOps and its impact and value to the broader machine learning space; And it reminded me of the assembly line and how Henry Ford didn't invent the automobile, but he did innovate that assembly line process.

It wasn't until we were able to mass produce and distribute vehicles that they went mainstream. So, in my mind MLOps serves that same role to machine learning.

Jordan Birdsell

Machine Learning

Research

Academia
Algorithms are first coming out. Very few companies are engaged.

Presentations

Corporate R&D
Teams are creating initiatives and ideas. Largely talking about the business value.

Proof of Concepts

Data Science
Data science teams are building out PoC's and production models.

Industrialized Machine Learning

MLOps & ML Engineering
This is connecting the models to the business process to directly affect decisions.

Why MLOps?

ONE
Organizations need to deploy a system of models, not just one-off solutions.

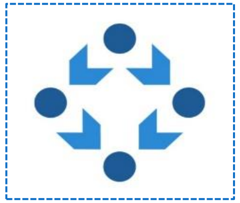
TWO
Organizations need to monitor models for scientific, production, and auditing purposes.

THREE
Organizations need to have a standard development process to reproduce projects.

The Future of MLOps and How Did We Get Here?

Chris Sterry
Vice President of Operations
Dotscience

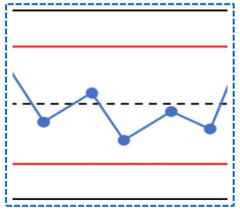
Requirements of MLOps



Reproducible
You can re-train a model built months ago and reproduce it within tolerance.

Accountable
You can recover the raw data, training data, and build procedure of every model in production.

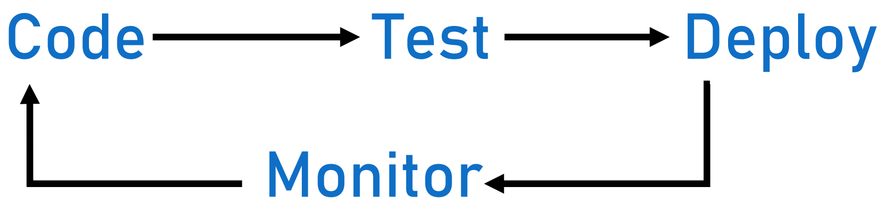
Collaborative
You can prove someone else's model works correctly without talking to them.



Continuous
You can statistically monitor your models to correct abnormal behavior in production.

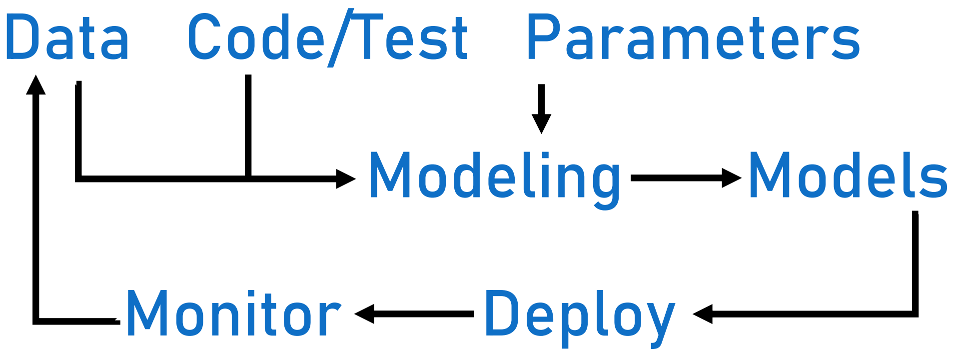
Comparing DevOps to MLOps

DevOps



Code	source code, unit tests
Test	behavior test, performance test
Deploy	package build, software release
Monitor	statistical quality control

MLOps



Data	raw/new data
Parameters	hyperparameter settings
Modeling	improving goodness of fit

Observations

In the deployment what I’ve typically found in talking to ML teams is right now it seems like a data scientist is expected to be a software engineer and, in some organizations, to be a master of DevOps as well. And often the gap between data scientist and DevOps and software engineering is pretty broad; And when you have to wear all those hats it’s: how do you simplify that?

From a monitoring standpoint, I always say that if you knew the right answer then you wouldn't need machine learning. Models can go wonky quickly in production without normal monitoring techniques, and so you need to do statistical monitoring.

Chris Sterry

AI/ML Operationalization Anti-Patterns

Matt Maccaux
Field CTO
Hewlett Packard

Big Data Systems

Duplication
A silo for each group. This duplicates data and blocks enterprise-wide analytics.

Unavailable
Too much governance. This centralizes the data without providing access.

Unregulated
Too little governance. This neglects quality control, rendering analytics untrustworthy.

Pet Projects
Rolling out projects that never engaged end-users during development. This risks irrelevance.

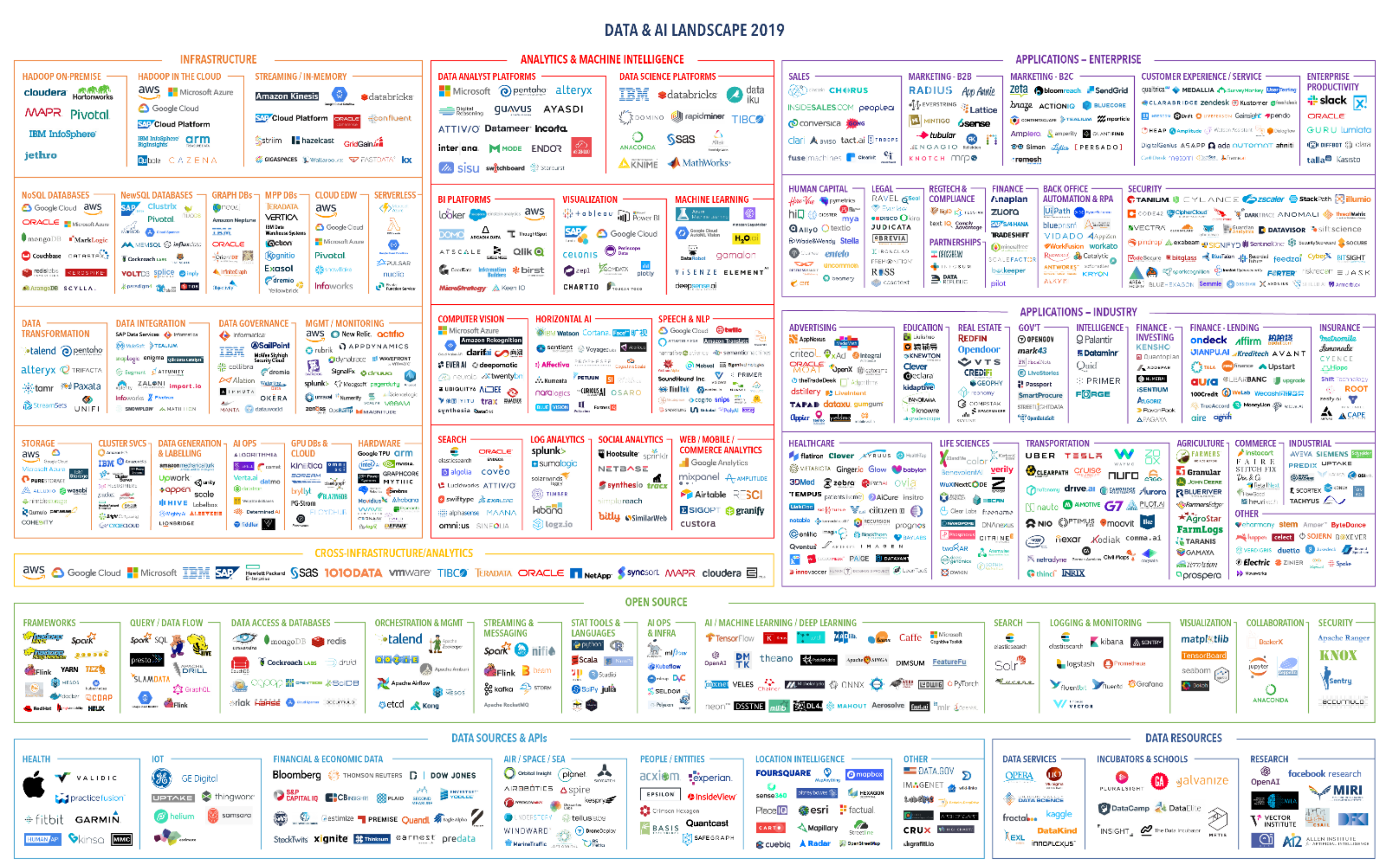
Rush to the Cloud

The cloud should be used as infrastructure. Abstract your business logic away from it as much as possible, so you have portability in choice.

When business logic became so embedded in the propitiatory capabilities of mainframes, it became difficult to unwind them.

The Monolith

- Data science teams need environments, notebook tools, and infrastructure for data (like Hadoop).
- It's common to replicate this *monolith* for each data science team, but that is not sustainable.
- Put data into a separate repository and give read-only access to the team's applications.

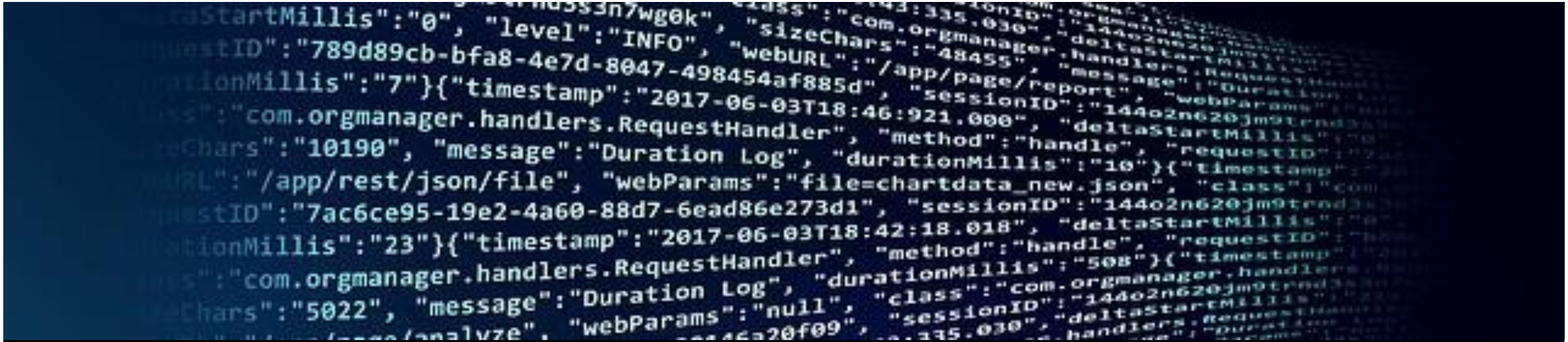


Challenges and Best Practices in Industrial AI Applications

Xiaohui Hu, PhD
Principal Data Scientist
GE Digital

Comparing AI Applications

Netflix Recommendation	Factory Recommendation
Fidelity: It doesn't hurt the user if there is a bad recommendation.	**Fidelity:** A bad recommendation could injure a worker or stop work unnecessarily.
Transparency: The user doesn't need to know how the match ratings are scored.	**Transparency:** The user needs to know how the model recommends, given the consequences.
Restrictions: There are no regulations on the value of match ratings.	**Restrictions:** The are natural laws of physics that define feasible operations.



Industrial Data Challenge

- Owning the data is more valuable than owning the algorithm. The algorithm is becoming an open-source commodity.
- Data Quality: *Missing* – empty entries, no domain knowledge
  Redundant
  Noisy – bad sensor, harsh conditions
  Class Imbalance – not all production modes are observed

Knowledge Driven AI

Systematically incorporate tacit knowledge to influence any part of the AI engine. This is not hybrid AI because the tacit knowledge is not embedded in the data or model. For example, a rule-based expert system that interprets a data-driven AI for actionable insights. This rule-based expert system may do failure mode analysis.

Tacit Knowledge:

The inherent understanding of actions and consequences that are not captured in the model. This information may come from documentation, textbooks, and experience.

How Google Uses AI and Machine Learning in the Enterprise

Rich Dutton
Head of Corporate Engineering
Google

Business Challenges

Human Resources
Binary classifier to suggest co-workers you may pair well with. Cluster schedules to determine natural teams.

IS Tickets
Multiclass estimator to route tickets to queues. Cluster tickets to find major issues.

Building Temperature
Built a model to detect anomalies in real-time for HVAC maintenance.

Cafeteria Demand
Built a regression model to determine how much food to buy each day.

Document Similarity
Comparing patents and design documents to prevent duplicate work and find references.

Enterprise AI Team

Implementation
Building production models and pushing other teams to build their own models.

Empower
Running AI workshops. Educating other teams and leadership. New teams ask us to start projects.

Research
Brainstorming project initiatives to determine if the problem is tractable. Re-purposing any known-good platforms.

AI Considerations

Privacy

Differential Privacy

- Add noise to queries to protect anonymity.

Federated Learning

- Use multiple devices to process raw data in chunks, never sharing the full set.

Secure Computation

- Compute data while it's encrypted.

Remote Execution

Fairness

Papers

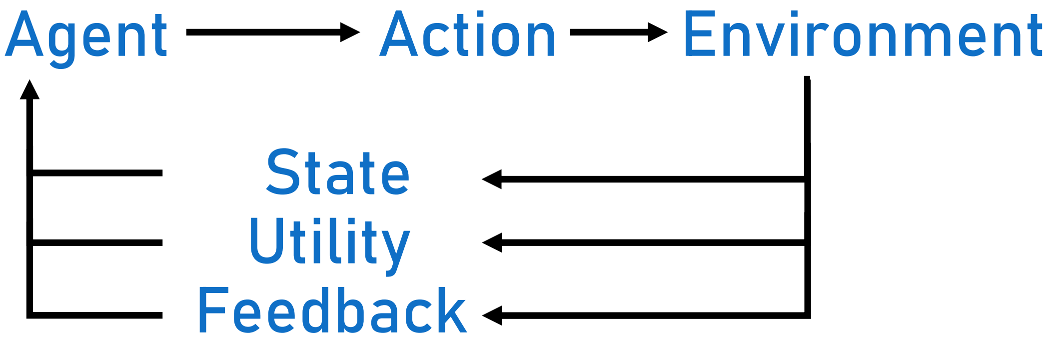
- *Satisfying Real-world Goals with Dataset Constraints*
- *The Reel Truth: Women Aren't Seen or Heard*
- *Equality of Opportunity in Supervised Learning*
- *Fair Resource Allocation in a Volatile Marketplace*

Reinforcement Learning and Inverse Reinforcement Learning in Finance

Igor Halperin, PhD
Research Professor of Financial Machine Learning
NYU |
AI Asset Management
Fidelity Investments

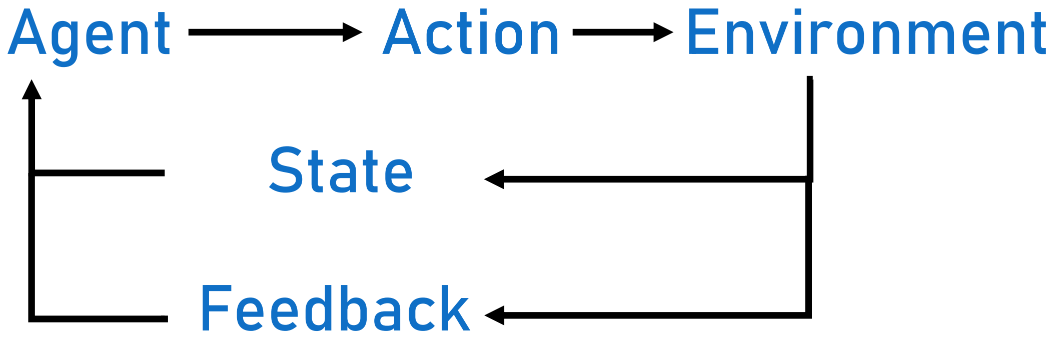
Comparing RL to IRL

Reinforcement Learning



Utility is the agent's perception of reward for one's actions. Feedback can be implicit, such as data drift. State is a direct reading of the environment using any representative descriptor.

Inverse Reinforcement Learning



The agent must infer a strategy without knowing the value of one's actions. This assumes that the actions are influencing the environment, which can be observed from the action-state relationship.

Starting Reinforcement Learning

Temptation
Avoid starting with off-the-shelf libraries. Avoid deep learning. Black boxes won't be as meaningful.

Simplicity
Model the agent and their utility function using classical, interpretable, or semi-analytical methods.

Boundaries
Find links between your simple RL and practical operating conditions. Create control boundaries.

High Resolution
Deep learning requires clean big data to outperform other approaches.

Architect
Move onto more complex model architectures to discover further improvements.

Workshops

Scikit-Learn
https://github.com/amueller/ml-workshop-1-of-4

API Service
https://github.com/wahalulu/odsc-east-2020

Monitoring AI
https://github.com/CognitiveScale/cortex-certifai-workshop/tree/master/odsc-boston-15-april-2020

Thank You