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Research
Faculty Summit 2018

Systems | Fueling future disruptions

Microsoft

Machine Learning
Perspectives and Challenges

Michael I. Jordan
University of California, Berkeley

Machine Learning (aka, AI)

- First Generation ('90-'00): the backend
  - e.g., fraud detection, search, supply-chain management
- Second Generation ('00-'10): the human side
  - e.g., recommendation systems, commerce, social media
- Third Generation ('10-now): end-to-end
  - e.g., speech recognition, computer vision, translation
- Fourth Generation (emerging): markets
  - not just one agent making a decision or sequence of decisions
  - but a huge interconnected web of data, agents, decisions
  - many new challenges!

Perspectives on AI

- The classical “human-imitative” perspective
  - cf. AI in the movies, interactive home robotics
- The “intelligence augmentation” (IA) perspective
  - cf. search engines, recommendation systems, natural language translation
  - the system need not be intelligent itself, but it reveals patterns that humans can make use of
- The “intelligent infrastructure” (II) perspective
  - cf. transportation, intelligent dwellings, urban planning
  - large-scale, distributed collections of data flows and loosely-coupled decisions

Human-Imitative AI: Where Are We?

- Computer vision
  - *Possible*: labeling of objects in visual scenes
  - *Not Yet Possible*: common-sense understanding of visual scenes
- Speech recognition
  - *Possible*: speech-to-text and text-to-speech in a wide range of languages
  - *Not Yet Possible*: common-sense understanding of auditory scenes
- Natural language processing
  - *Possible*: minimally adequate translation and question-answering
  - *Not Yet Possible*: semantic understanding, dialog
- Robotics
  - *Possible*: industrial programmed robots
  - *Not Yet Possible*: robots that interact with humans and can operate autonomously over long time horizons

Human-Imitative AI Isn't the Right Goal

- Problems studied from the "human-imitative" perspective aren't necessarily the same as those that arise in the IA or II perspectives
  - unfortunately, the "AI solutions" being deployed for the latter are often those developed in service of the former

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- *To make an overall system behave intelligently, it is neither necessary or sufficient to make each component of the system be intelligent*

- *"Autonomy" shouldn't be our main goal; rather our goal should be the development of small intelligences that work well with each other and with humans*

Near-Term Challenges in II

- Error control for multiple decisions
- Systems that create markets
- Designing systems that can provide meaningful, calibrated notions of their uncertainty
- Managing cloud-edge interactions
- Designing systems that can find abstractions quickly
- Provenance in systems that learn and predict
- Designing systems that can explain their decisions
- Finding causes and performing causal reasoning
- Systems that pursue long-term goals, and actively collect data in service of those goals
- Achieving real-time performance goals
- Achieving fairness and diversity
- Robustness in the face of unexpected situations
- Robustness in the face of adversaries
- Sharing data among individuals and organizations
- Protecting privacy and data ownership

Multiple Decisions: The Load-Balancing Problem

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- There is an emerging need to build AI systems that create markets; i.e., blending statistics, economics and computer science

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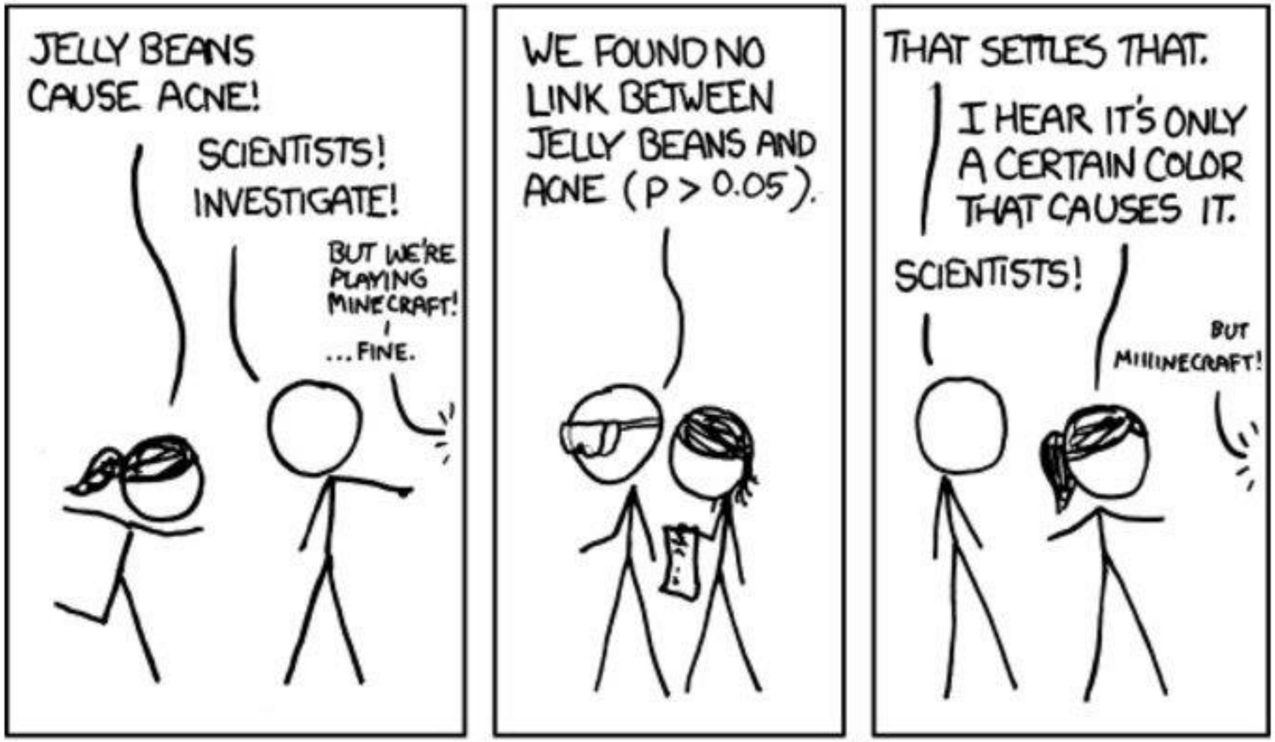
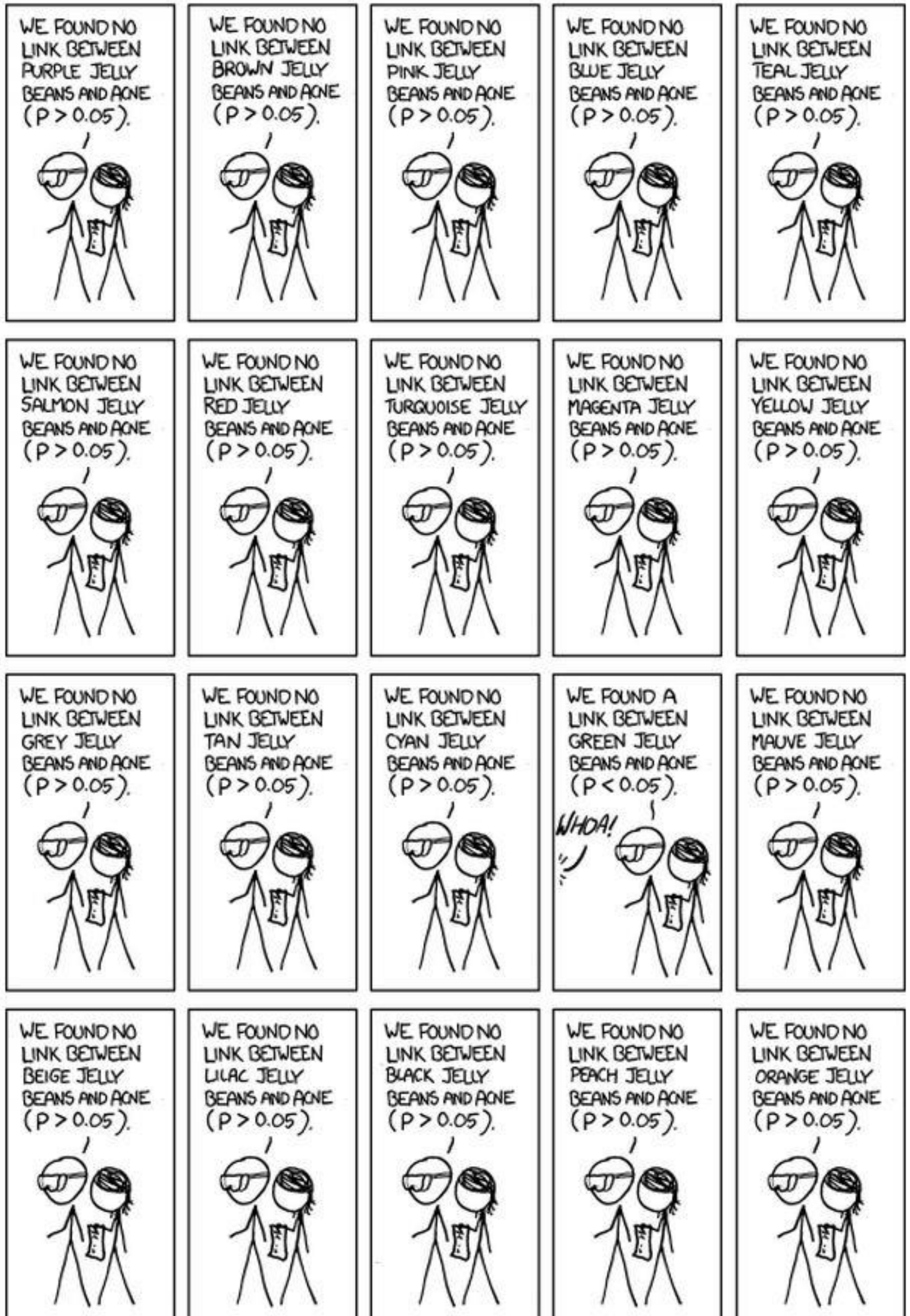
- Is it OK to recommend the same stock purchase to everyone?

Multiple Decisions: The Statistical Problem




WE FOUND NO LINK BETWEEN PURPLE JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN BROWN JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN PINK JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN BLUE JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN TEAL JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN SALMON JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN RED JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN TURQUOISE JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN MAGENTA JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN YELLOW JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN GREY JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN TAN JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN CYAN JELLY BEANS AND ACNE (P > 0.05).
WE FOUND A LINK BETWEEN GREEN JELLY BEANS AND ACNE (P < 0.05).
WHOA!
WE FOUND NO LINK BETWEEN MAUVE JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN BEIGE JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN LILAC JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN BLACK JELLY BEANS AND ACNE (P > 0.05).
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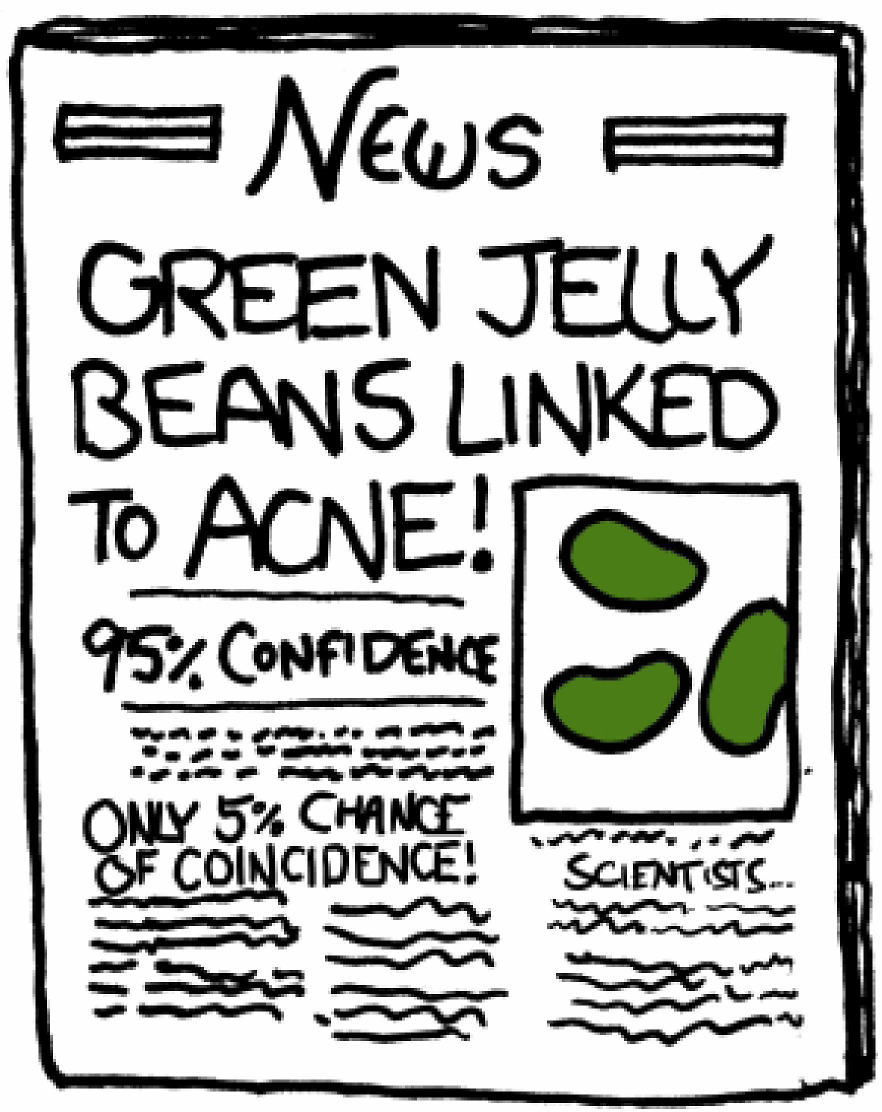
News
GREEN JELLY BEANS LINKED TO ACNE!
95% CONFIDENCE
ONLY 5% CHANCE OF COINCIDENCE!
SCIENTISTS...

DAGGER

(Ramdas, Chen, Wainwright & Jordan, 2018)

Inputs: DAG $\mathcal{G}$, p-values attached to each node, target FDR α.

Procedure:

Partition the DAG into $\mathcal{H}_1, \ldots, \mathcal{H}_D$.

for $d = 1, 2, \cdots, D$ **do**

Run a step-up procedure to test the hypotheses in $\mathcal{H}_d$ with threshold functions $\{\alpha_{d,i}(r)\}_{i=1}^{|\mathcal{H}_d|}$ defined by

$$\alpha_{d,i}(r) = \mathbf{1}\left\{\bigcap_{j \in \mathrm{Par}(i)} H_{d,j} \in \mathcal{R}_{1:d-1}\right\} \alpha \frac{\ell_i}{L} \frac{\beta_d(m_i + r + R_{1:d-1} - 1)}{m_i},$$

where $R_{1:d-1}$ is the number of rejected hypotheses in the first $d-1$ layers.

end for

Data and Markets

- Where data flows, economic value can flow
- Data allows prices to be formed, and offers and sales to be made
- The market can provide load-balancing, because the producers only make offers when they have a surplus

- Load balancing isn't the only consequence of creating a market
- It's also a way that AI can create jobs

Example: Music in the Data Age

- More people are making music than ever before
- More people are listening to music than ever before

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- More people are making music than ever before
- More people are listening to music than ever before
- But there is no economic value being exchanged
- And most people who make music cannot do it as their full-time job

An Example: United Masters

- *United Masters* partners with sites such as Spotify, Pandora and YouTube, using ML to figure out which people listen to which musicians
- They provide a dashboard to musicians, letting them learn where their audience is
- The musician can give concerts where they have an audience
- And they can make offers to their fans

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- I.e., consumers and producers become linked, and value flows: a market is created
- The company that creates this market profits

Learning with Long-Term Goals

- Current deep-learning technology is based mostly on supervised learning
  - this requires enormous numbers of labels
- It’s also based mostly on short-term temporal relationships (or snapshots)
- Moving beyond this requires the kinds of concepts that are found in optimal-control theory, specifically its sampled-based version known as reinforcement learning (RL)

Reinforcement Learning (RL)

- Reinforcement learning involves trying out sequences of actions and seeing what the outcome is
- A sequence of actions is referred to as a "roll-out"
  - actions from a successful roll-out are "backed-up" in time, so that the subsequences of that roll-out are more probable in the future

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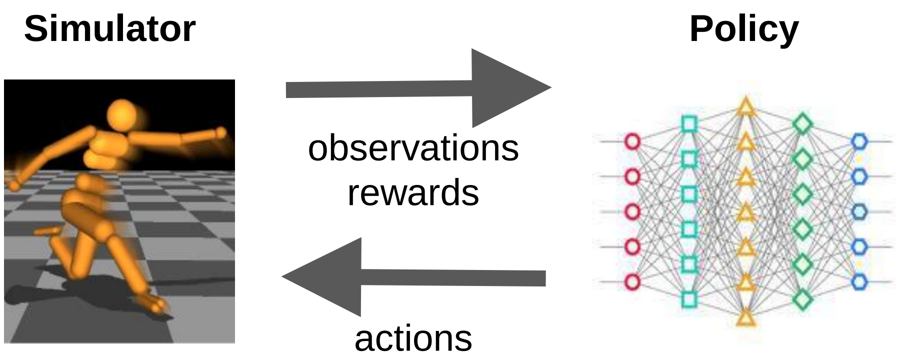
  - actions from a successful roll-out are "backed-up" in time, so that the subsequences of that roll-out are more probable in the future
- Most of the successes to date (e.g., AlphaGo) have been done using simulators
- When one has a simulator, one can do many many millions or billions of roll-outs
  - some roll-outs terminate quickly, others terminate much more slowly
- This setting yields major new requirements on distributed hardware and software platforms

Roll-Outs



Try lots of different policies and see which one works best…

Ray: A Distributed Execution Framework for Emerging RL Applications

Moritz, Nishihara, Wang, Tumanov, Liaw, Liang, Paul,
Jordan and Stoica

https://github.com/ray-project/ray

About Ray

Goal: Make it easy to write high-performance, real-time distributed applications, especially AI/ML applications.

Example use cases:

- Reinforcement learning
- Distributed stochastic gradient descent (training neural networks)
- Hyperparameter search
- General purpose parallel/distributed Python
- Streaming

About Ray

Goal: Make it easy to write high-performance distributed applications, especially AI/ML applications.

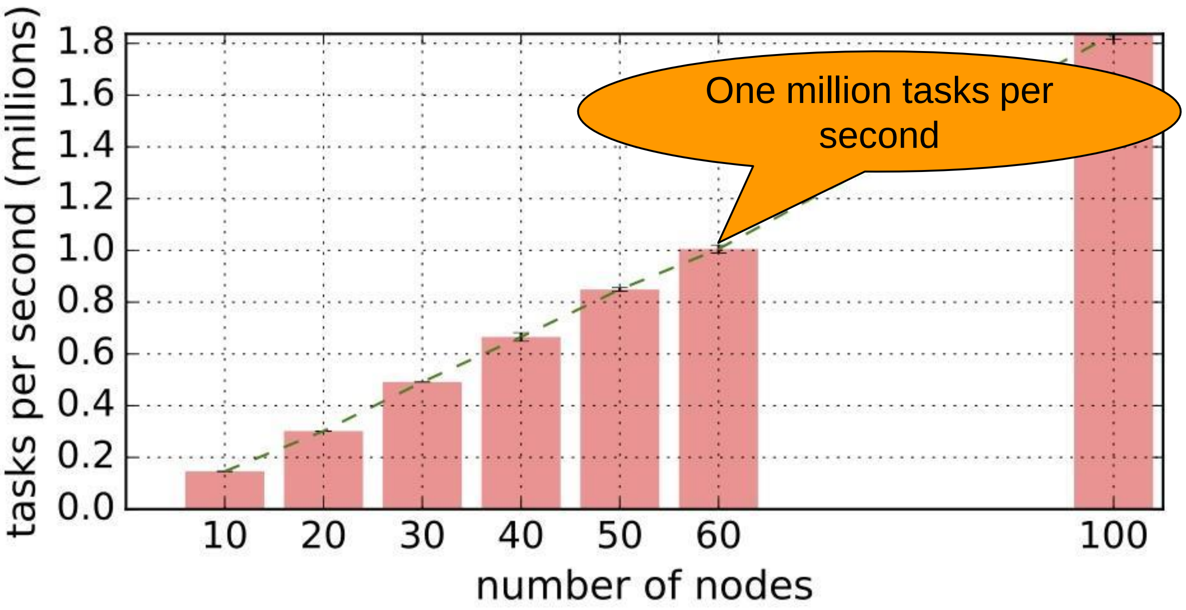
Problems with existing solutions:

- Spark
  - Not sufficiently expressive (limited to bulk synchronous parallel (BSP) model)
  - Insufficient performance (target sub-second as opposed to sub-millisecond latencies)
  - Doesn’t handle numerical data well
  - Difficulty to integrate with third-party libraries
- MPI
  - Not fault tolerant
  - Difficult to write correct code
  - User has to implement scheduling and communication logic

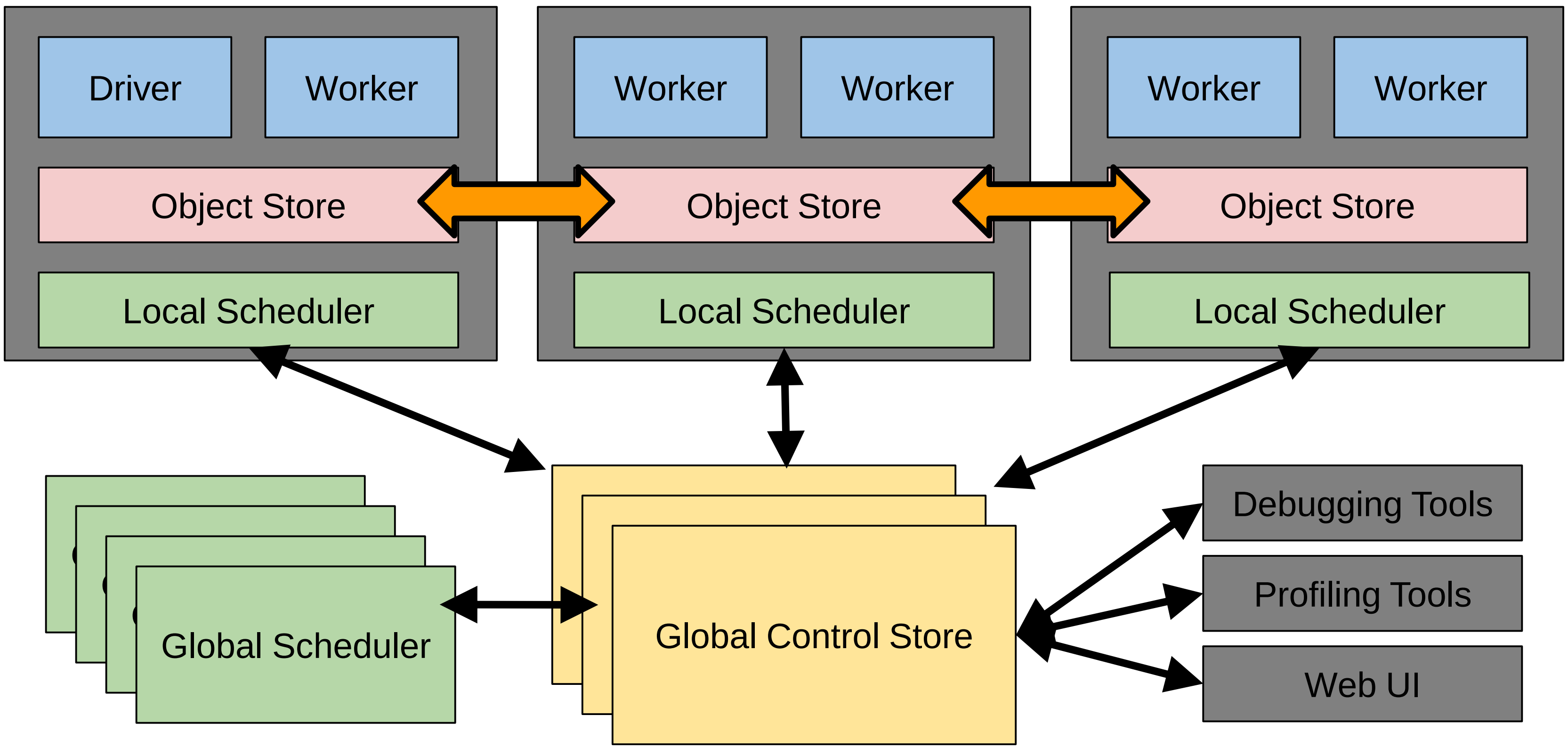
About Ray

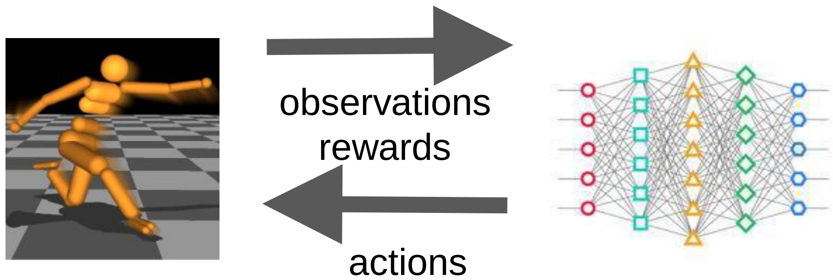
- Generality
  - Combines two key ingredients of a modern programming language: functions and objects
  - These are called tasks (stateless) and actors (stateful)
  - Cf. the Map-Reduce paradigm, which dispensed with objects
  - Can create tasks within tasks
- Ease of use
  - Integrates easily with arbitrary Python libraries (e.g., TensorFlow, PyTorch)
  - Easy to implement/customize new algorithms
  - Easy to parallelize existing Python code
  - Transparent fault tolerance

Ray performance



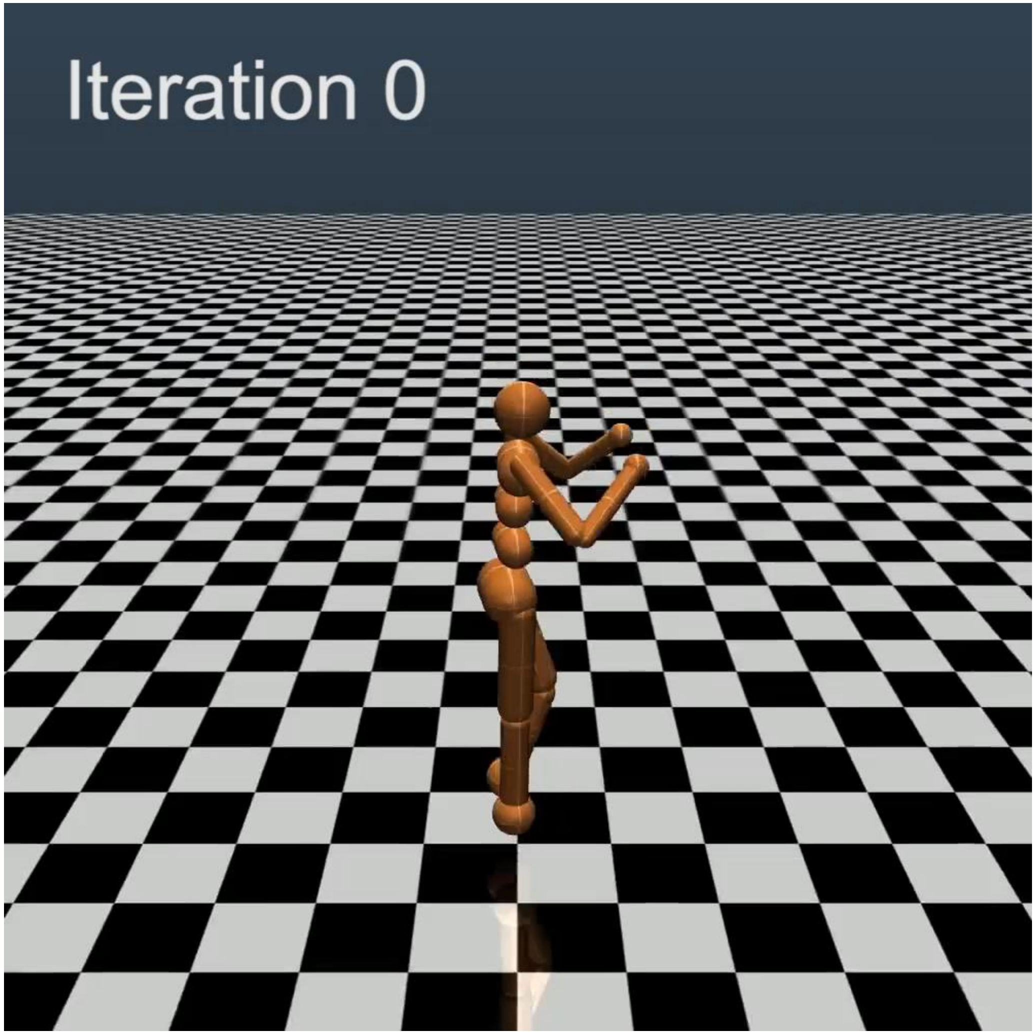
Ray architecture



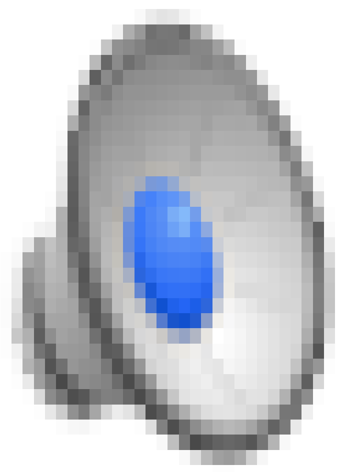



```
@ray.remote
class Worker(object):
  def do_simulation(policy, seed):
    # perform simulation and return reward

workers = [Worker.remote() for i in range(20)]
policy = initial_policy()

for i in range(200):
  seeds = generate_seeds(i)
  rewards = [workers[j].do_simulation.remote(policy, 
seeds[j])
             for j in range(20)]
  policy = compute_update(policy, ray.get(rewards), seeds)
```

Video 1



Video 2



Ray is Open Source

- https://github.com/ray-project/ray
- You can install Ray with

  pip install ray

Summary

- ML (AI) has come of age
- But it is far from being a solid engineering discipline that can yield robust, scalable solutions to modern data-analytic problems
- There are many hard problems involving uncertainty, inference, decision-making, robustness and scale that are far from being solved
  - not to mention economic, social and legal issues

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Thank you!

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