Reinforcement Learning in Public Policy

Peter Henderson Stanford Computer Science & Stanford Law School



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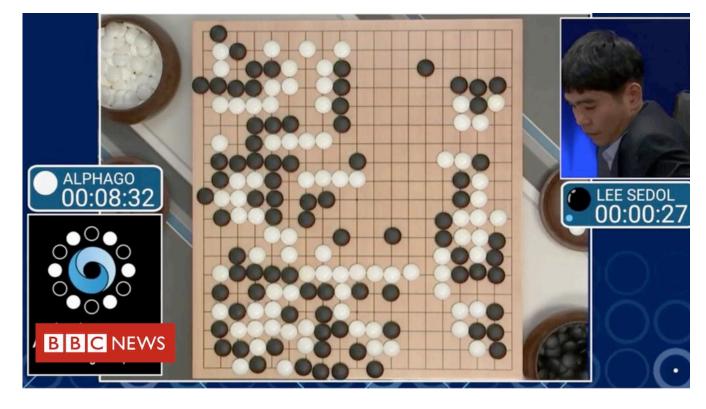
Presentation based loosely on work with a number of wonderful collaborators:

Henderson*, Chugg*, Anderson, and Ho. "Beyond Ads: Sequential Decision-Making Algorithms in Public Policy." arXiv preprint arXiv:2112.06833 (2021).

And also forthcoming work with Chugg, Anderson, Altenburger, Turk, Guyton, Goldin, and Ho.

All views and opinions expressed in this presentation are my own and not of any of my co-authors, nor of the Internal Revenue Service or any other company or government entity.

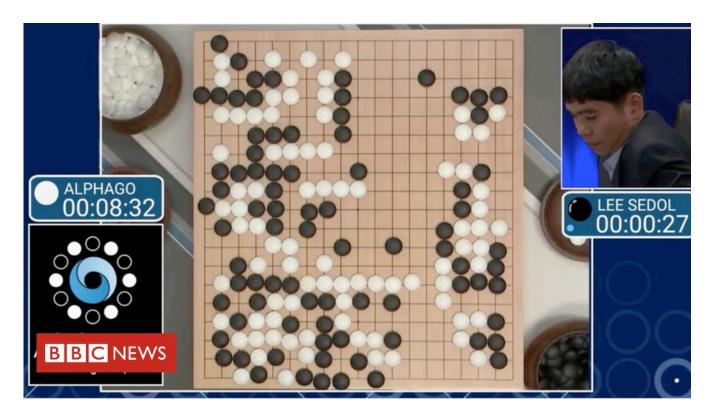




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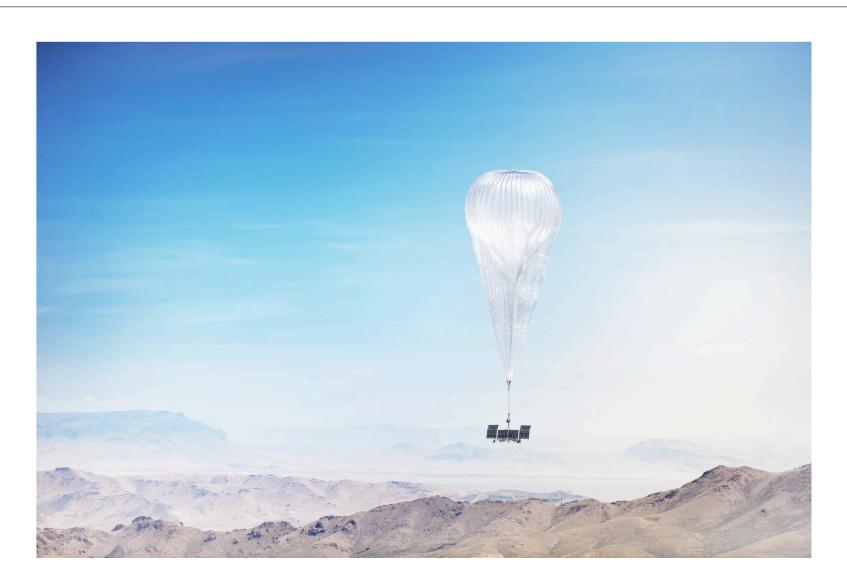
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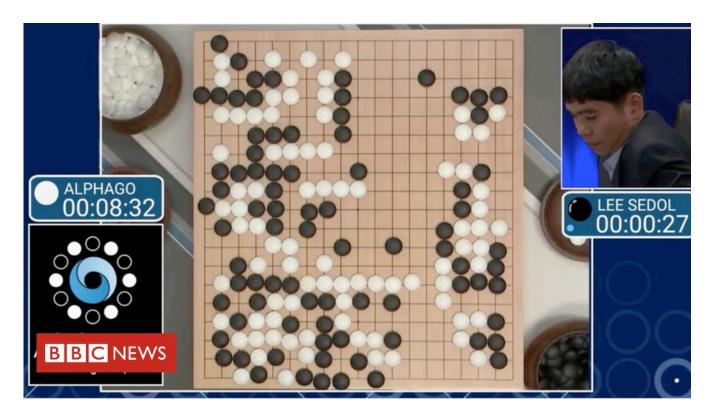
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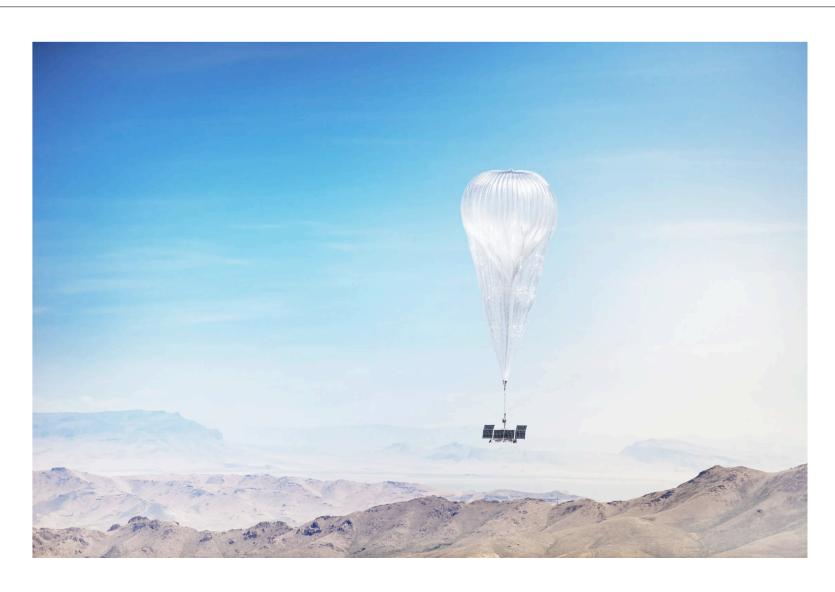
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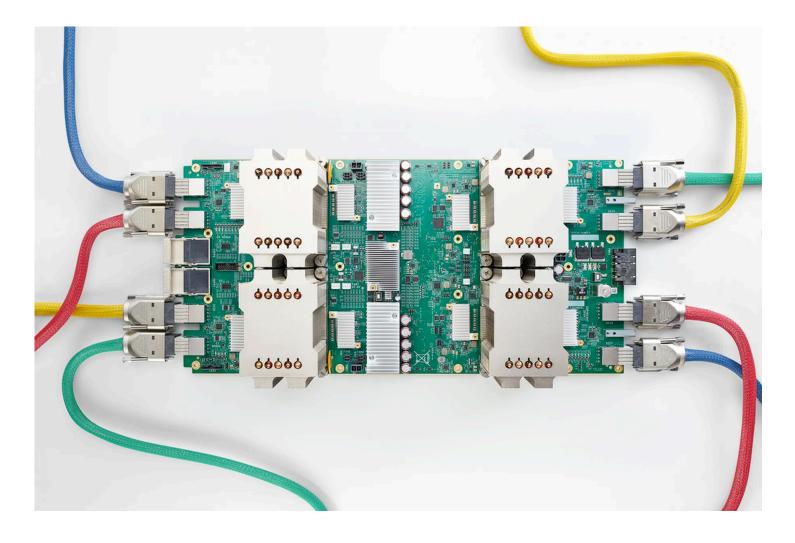
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Mirhoseini, A., Goldie, A., Yazgan, M. et al. A graph placement methodology for fast chip design. Nature 594, 207–212 (2021). https:// doi.org/10.1038/s41586-021-03544-w



Military AI vanquishes human fighter pilot in F-16 simulation. How scared should we be?

Artificial intelligence can master difficult combat skills at warp speed, but the Pentagon's futurists must remain mindful of its limitations and risks.

All the more remarkable, Heron's AI pilot was self-taught using deep reinforcement learning, a method in which an AI runs a combat simulation over and over again and is "rewarded" for rapidly successful behaviors and "punished" for failure. Initially, the AI agent is simply learning not to fly its aircraft into the ground. But after 4 billion iterations, Heron seems to have mastered the art of executing energy-efficient air combat maneuvers.

https://www.nbcnews.com/think/opinion/military-ai-vanquishes-human-fighter-pilot-f-16-simulation-how-ncna1238773



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How do neural networks work?

In its most basic form, a neural network has two layers: an input layer and an output layer^[3]. The output layer is the component of the neural network that makes predictions^[3]. In a feedforward network, information flows through the network in the following way: patterns of information are fed into the network via the input units, which trigger the layers of hidden units, and these in turn arrive at the output units^[1]. The network learns by a feedback process called backpropagation, which involves comparing the output a network produces with the output it was meant to produce, and using the difference between them to modify the weights of the connections between the units in the network, working from the output units through the hidden units to the input units, going backward^{[2][4]}. Over time, backpropagation causes the network to learn, reducing the difference between actual and intended output to the point where the two exactly coincide, so the network figures things out exactly as it should^[2].

- 1. How neural networks work A simple introduction (www.explainthatstuff.com)
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- 3. How Do Neural Networks Really Work? | Nick McCullum (nickmccullum.com) 🗹
- 4. How Do Neural Networks Really Work? | Nick McCullum (nickmccullum.com)

www.explainthatstuff.com

between the input and the output. A richer structure like this is called a deep neural network (DNN), and it's typically used for tackling much more complex problems. In theory, a DNN can map any kind of input to any kind of output, but the drawback is that it needs considerably more training: it need to "see" millions or billions of examples compared to perhaps the hundreds or thousands that a simpler network might need. Deep or "shallow," however it's structured and however we choose to illustrate it on the page, it's worth reminding ourselves, once again, that a neural network is not actually a brain or anything brain like. Ultimately, it's a bunch of clever math... a load of equations... an algorithm, if you prefer. [4]

How does a neural network learn things?

Information flows through a neural network in two ways. When it's learning (being trained) or operating normally (after being trained), patterns of information are fed into the network via the input units, which trigger the layers of hidden units, and these in turn arrive at the output units. This common design is called a feedforward network. Not all units "fire" all the time. Each unit receives inputs from the units to its left, and the inputs are multiplied by the weights of the connections they travel along. Every unit adds up all the inputs it receives in this way and (in the simplest type of network) if the sum is more than a certain threshold value, the unit "fires" and triggers the units it's connected to (those on its right).

[Image: A man launches a red ball down a ten-pin bowling alley toward skittles.]

Photo: Bowling: You learn how to do skillful things like

Reinforcement learning on 175B parameter models https://openai.com/blog/webgpt/

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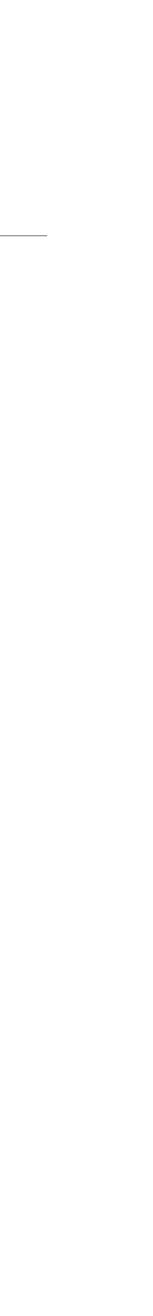


Government has launched many AI investment projects

The Biden Administration Launches AI.gov Aimed at Broadening Access to Federal Artificial Intelligence Innovation Efforts, Encouraging Innovators of Tomorrow

BRIEFING ROOM

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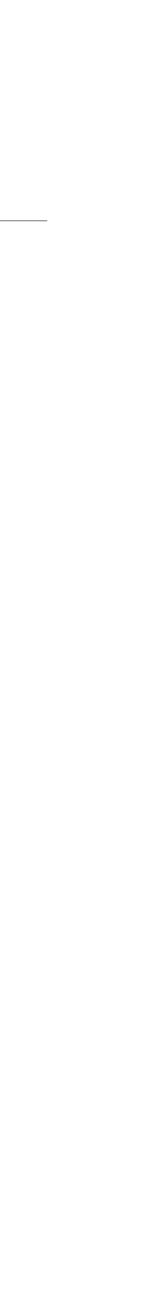
Artificial Intelligence: An Accountability Framework for Federal Agencies and Other Entities

"So if you don't have an integration layer like that, then you have to go find all of the data sources yourself... This is something we don't have yet in the department," Lt. Gen. Michael Groen told Breaking Defense.

By JASPREET GILL on February 09, 2022 at 11:13 AM

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Artificial Intelligence: An Accountability Framework for Federal Agencies and Other Entities

How The Federal Government's AI **Center Of Excellence Is Impacting Government-Wide Adoption Of AI**



Kathleen Walch Contributor **COGNITIVE WORLD** Contributor Group ① NETWORKS/CYBER

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Where does RL fall into government or public policy deployments?

What makes for a good RL and Public Policy problem? What are the areas of public policy & government services that can be improved by RL? What are the unique research challenges encountered in RL for public policy? Can we verify RL well enough to feel confident in deployments? Is deployment of RL in these settings a net social good?



What makes for a good RL and Public Policy problem?

Recall that RL maximizes future reward as part of a Markov Decision Process.

- 1. Your environment changes over time.
- 2. You need to both explore and exploit.
- 3. You (maybe) need to plan ahead.*

* For the purposes of this talk, we will consider contextual bandits as in-scope as they can be formulated as an RL problem with discount 0.

nanges over time. plore and exploit. plan ahead.*



What are the areas of public policy & government services that can be improved by RL?



Environmental Protection Agency audits Concentrated Animal Feeding Operations for compliance [Chugg, Anderson, Eicher, Lee, & Ho 2021]

> Internal Revenue Service audits taxpayers for compliance [Henderson et al., 2022]

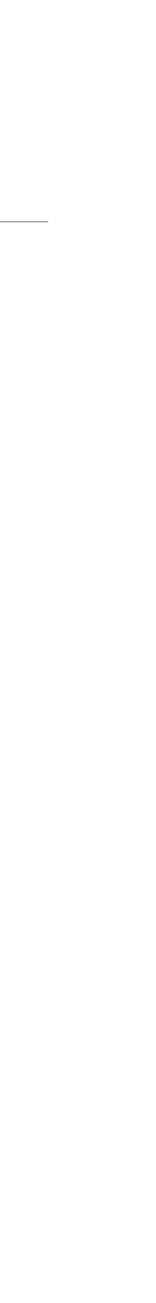
Brazilian government audits regional governments for corruption [Ash, Galletta, & Giommoni, 2021] Optimal Policymaking

Optimal Tax Policy [Zheng & Trott et al., 2020]

Resource Allocation

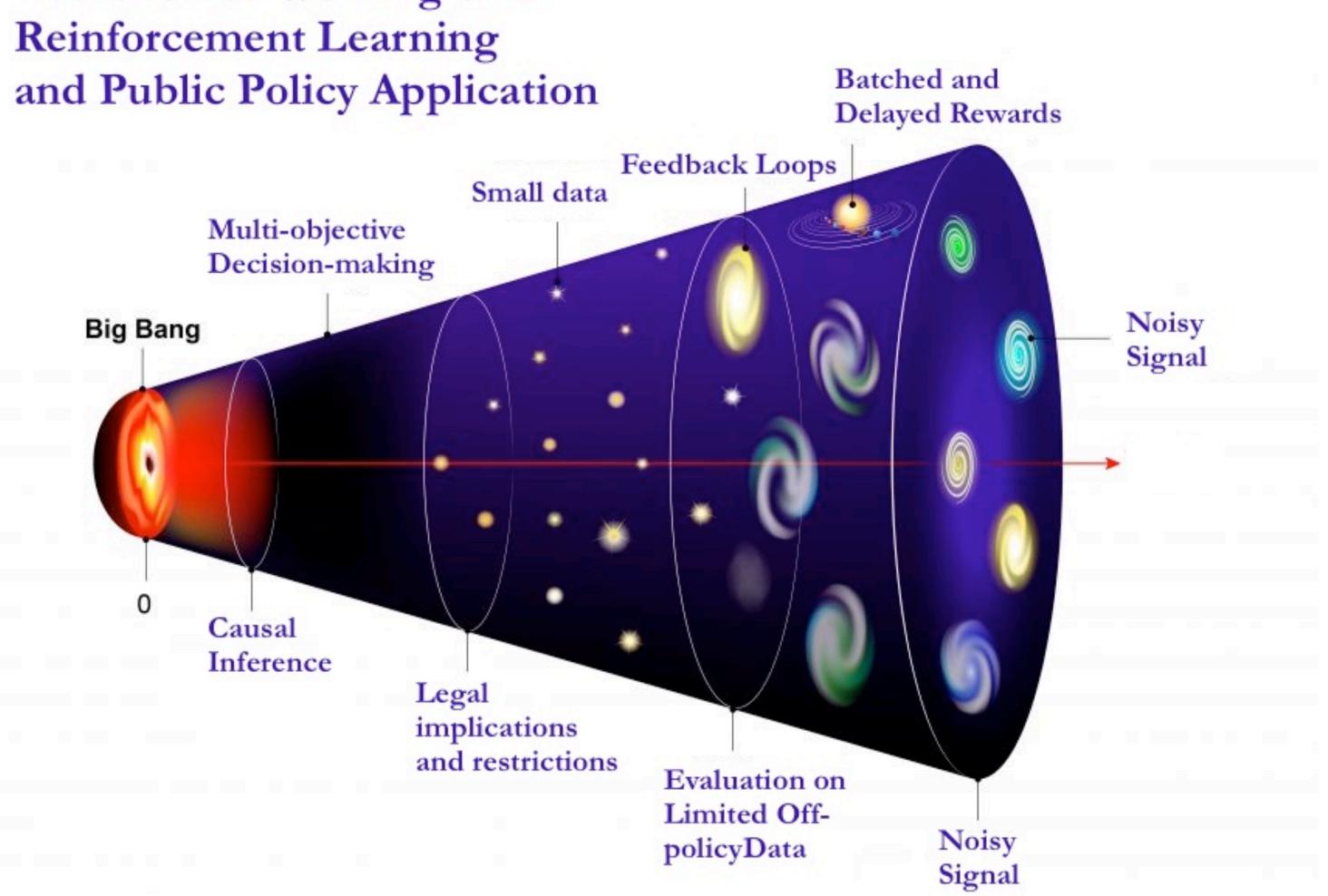
Covid-19 test allocation [Chugg et al., 2021; Bastani et al., 2021]

Delaware Department of Transportation plans to test RL for traffic control [Gettman, 2019]



What are the difficult research challenges encountered in RL for public policy?

Evolution of Working on a





What are the difficult research challenges encountered in RL for public policy?

Multi-objective decision-making

In enforcement, many agencies must both prioritize where to target enforcement to maximize misreporting (reward) and they are required by law to give statistically valid estimates of overall misreporting (estimation).

> The Improper Payments Information Act of 2002 (IPIA) Improper Payments Elimination and Recovery Act of 2010 (IPERA) Improper Payments Elimination and Recovery Improvement Act of 2012 (IPERIA)





The presenter is a detailed IRS employee working with the IRS under a student volunteer agreement. All data work for this project involving confidential taxpayer information was done on IRS computers by IRS employees. At no time was confidential taxpayer data ever outside of the IRS computing environment. The views and opinions presented in this presentation reflect those of the author and do not necessarily reflect the views or the official position of the Internal Revenue Service.



Tax gap estimate (difference between paid and true owed taxes) is **\$441 billion per** year.

https://www.irs.gov/newsroom/the-tax-gap Sarin, Natasha, and Lawrence H. Summers. Shrinking the tax gap: approaches and revenue potential. No. w26475. National Bureau of Economic Research, 2019.

Some estimate that investment into information technology for identifying misreporting could yield **10:1 returns on investment**. See Sarin and Summers (2019).

<u>Sources</u>





National Research Program

Stratified Random Sample ~15k audits per year

Risk Model & other selection methods

Estimates to meet reporting requirements.

Current Process (simplified)

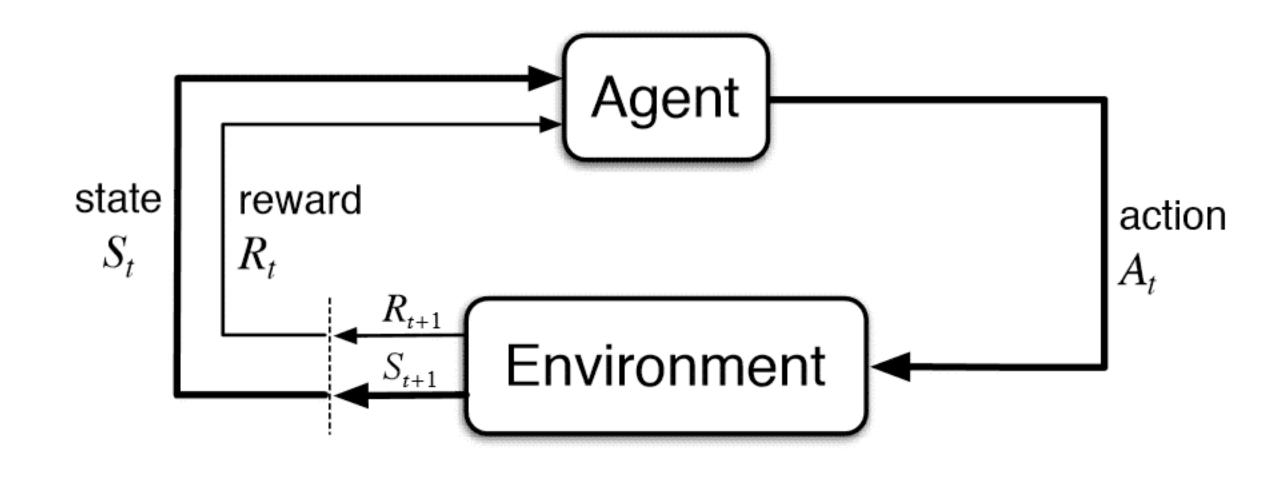
Op Audit Selection

Risk-selected + Other Selection Mechanisms

>>100k audits per year

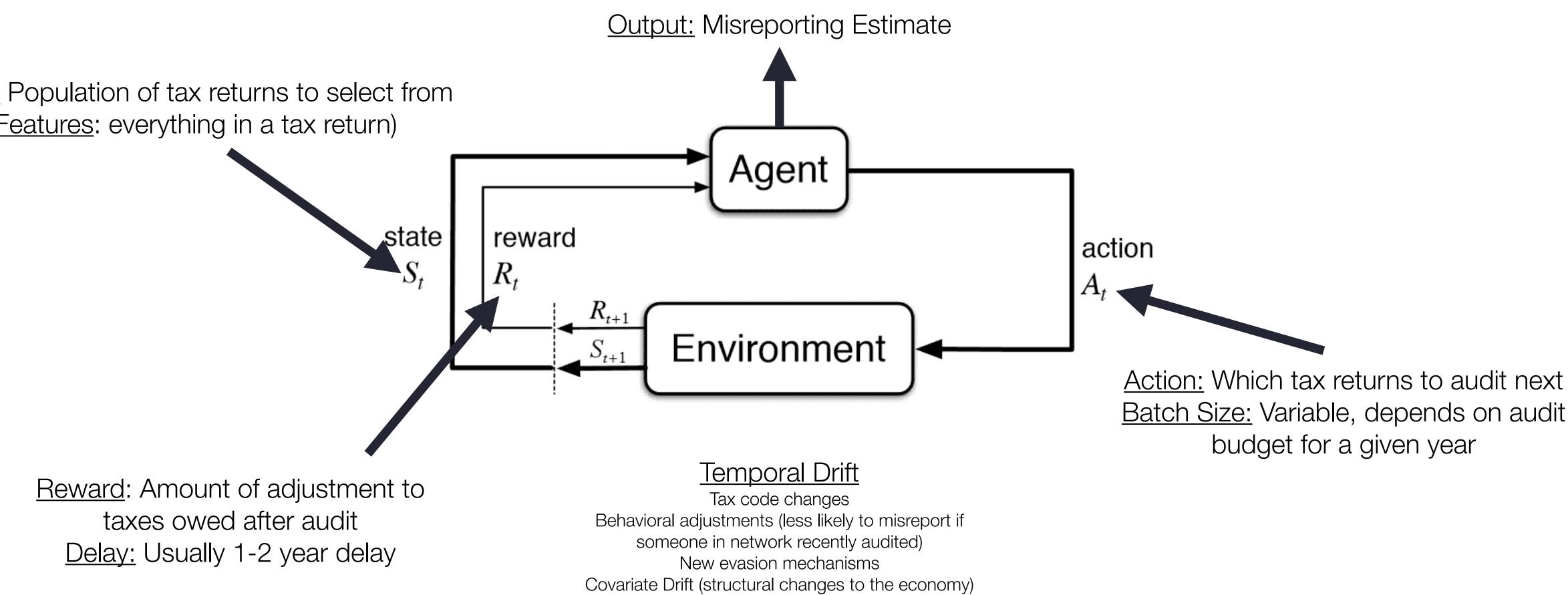
* Note there are a number of other methods that go into current Op Audit selection and tax gap estimation.

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State: Population of tax returns to select from (Features: everything in a tax return)



A case study of unique challenges: Internal Revenue Service Audit Selection

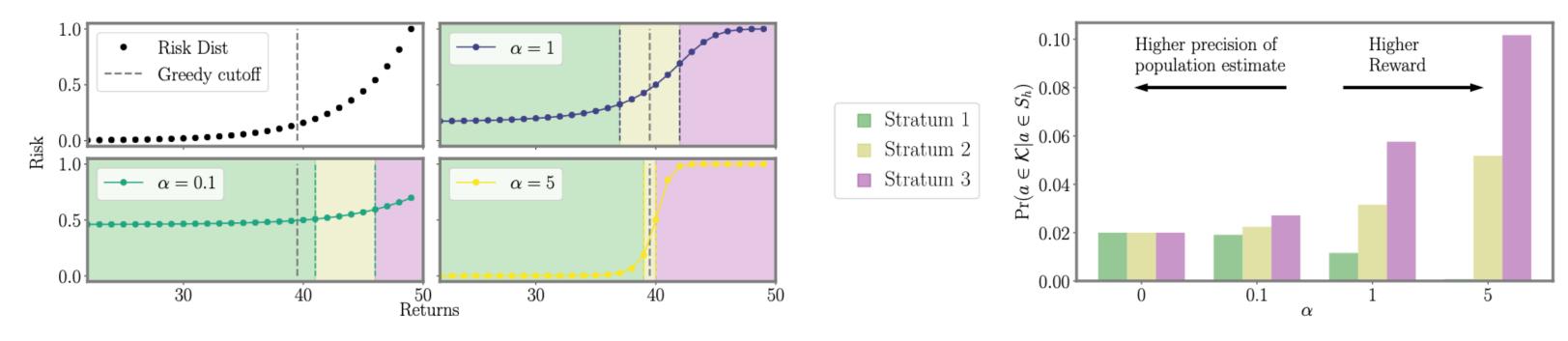
Batch Size: Variable, depends on audit budget for a given year





Problem: Population estimation requires reward-sub-optimal exploration. Exacerbates the explore-exploit trade-off problem.

Solution: Planning required to optimally re-use information to achieve robust population estimates.



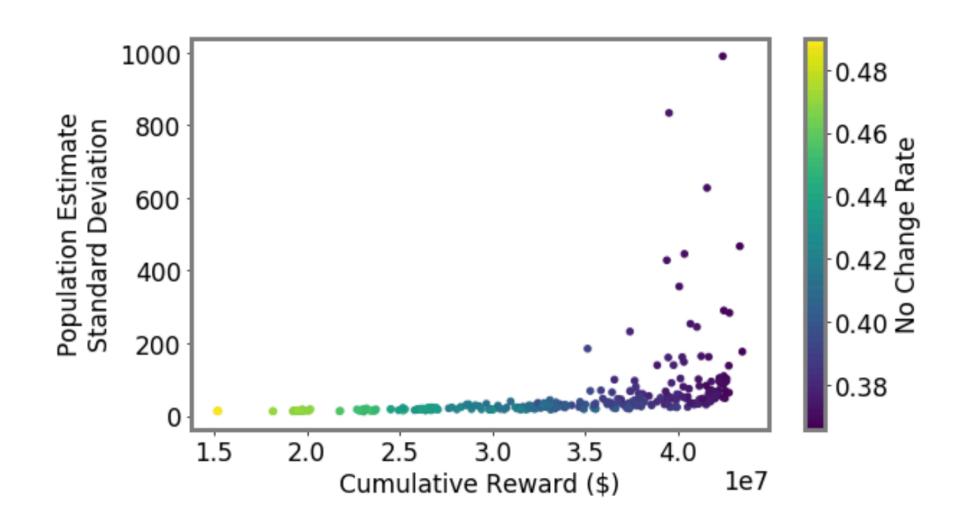
(a) Risk distribution and parameterizations

A case study of unique challenges: Internal Revenue Service Audit Selection

(b) Probability of sampling an individual





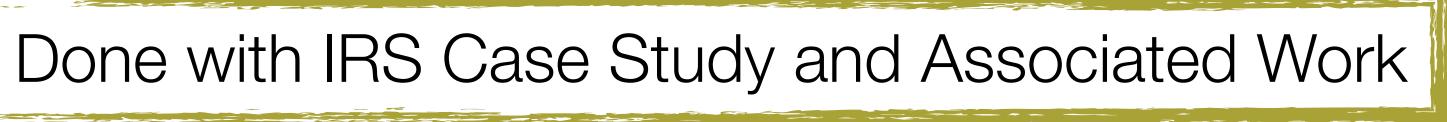


We find some **bias-variance-reward trade-off** between estimation and reward maximization objectives.

Future research: reduce the impact of this trade-off.









What are the difficult research challenges encountered in RL for public policy?

Public Policy & Government Applications

Interesting Reinforcement Learning Research Challenges



Can we verify RL well enough to feel confident in deployments?

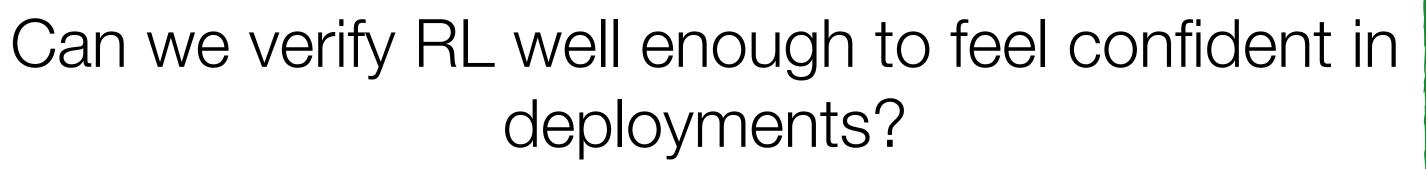
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Formalization is better than status quo in many cases. Can identify biases/problems and can adjust in iterative fashion. **But** not if evaluation is bad and gives false sense of security or if there are dramatic failure modes.



Famous example is the use of 7 positive labels with leave-oneout validation to train/evaluate a random forest for detecting "couriers" as part of the SKYNET program at the NSA.

https://arstechnica.com/information-technology/2016/02/the-nsas-skynet-program-may-be-killing-thousands-of-innocent-people/







Safety fallbacks when not functioning within acceptable parameters [Gramble & Gao, 2018]

Policy performance certificates [Dann et al., 2018]

Bias/Fairness Audits

Often not thought about in the context of RL, but important for real-world deployment.

[EEOC, https://www.eeoc.gov/newsroom/ eeoc-launches-initiative-artificial-intelligenceand-algorithmic-fairness]

Can we verify RL well enough to feel confident in deployments?



Across distributions of data simulating different populations/conditions [Henderson & Islam et al., 2017; Bouthillier et al., 2021; Agarwal et al., 2021]

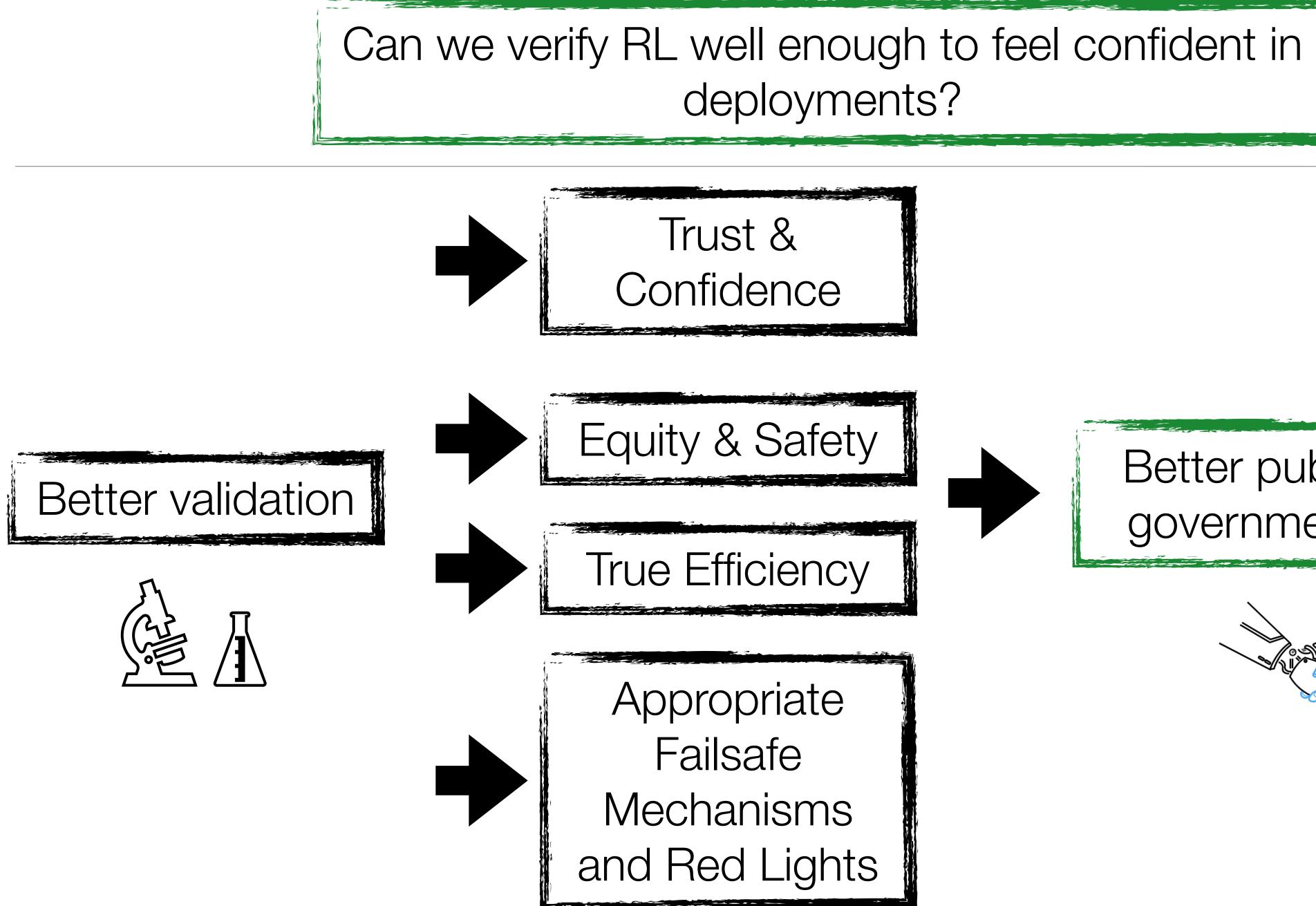
Statistically well-powered evaluation [Colas et al., 2018; Card et al., 2021]

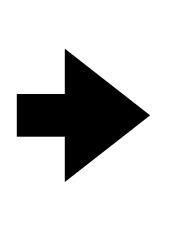


Is the agent making rational decisions?

* Robust evaluation already a common requirement across some, but not agencies/applications. See, e.g., NIST Facial Recognition Test framework.

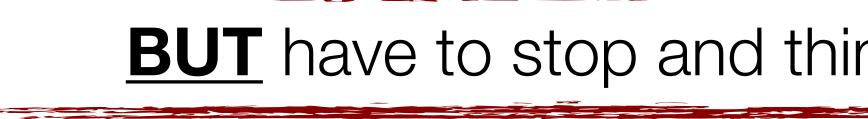






Better public policy & government services





BUT have to stop and think about what you're working on.



How can the RL system fail in a way that makes things socially worse than the existing human system?

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Need to think hard about some deployments where mistakes cost lives.



Thank you! Feel free to reach out with questions and comments.

