

Reinforcement Learning for Supply Chains

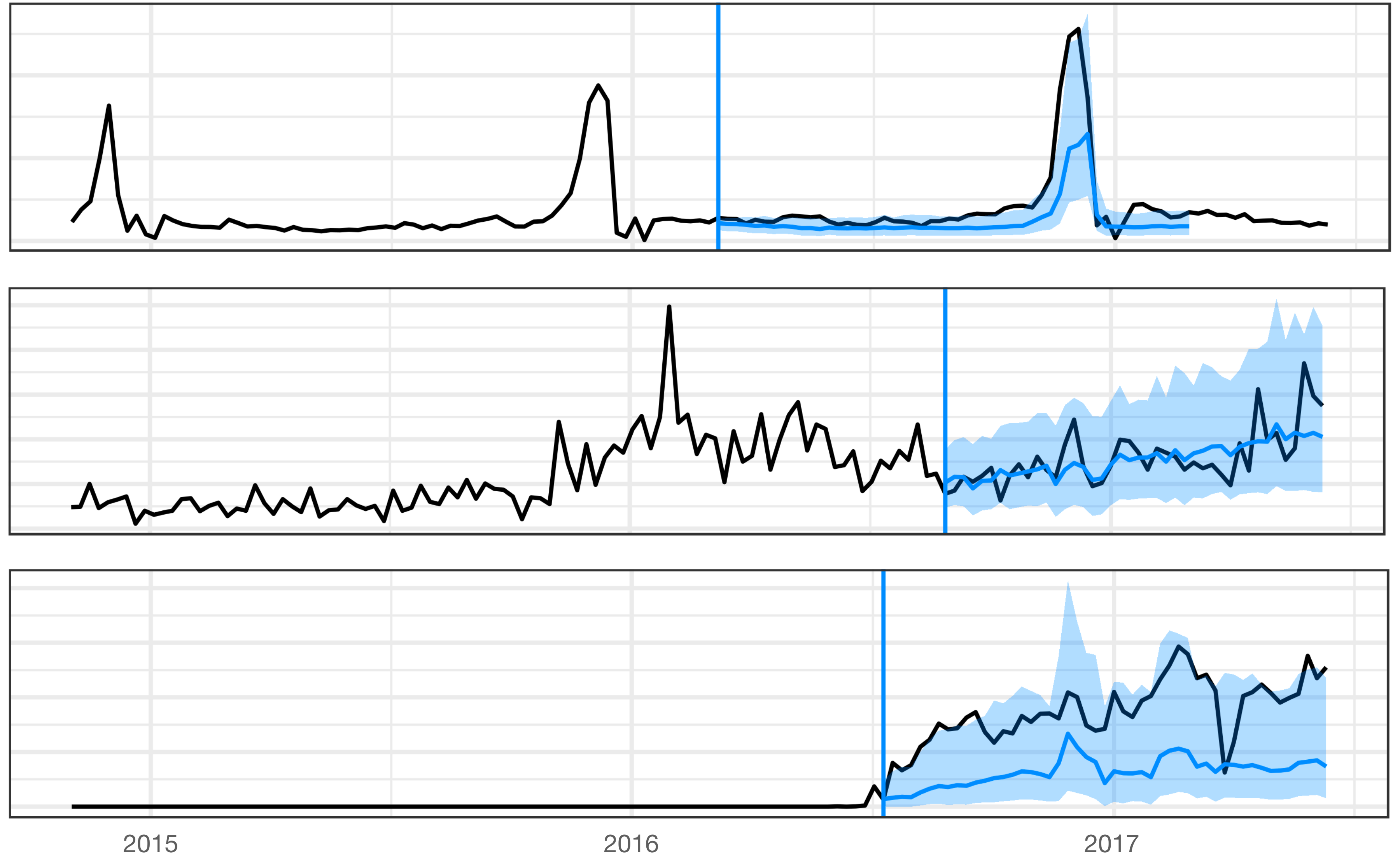
Dean Foster

Amazon

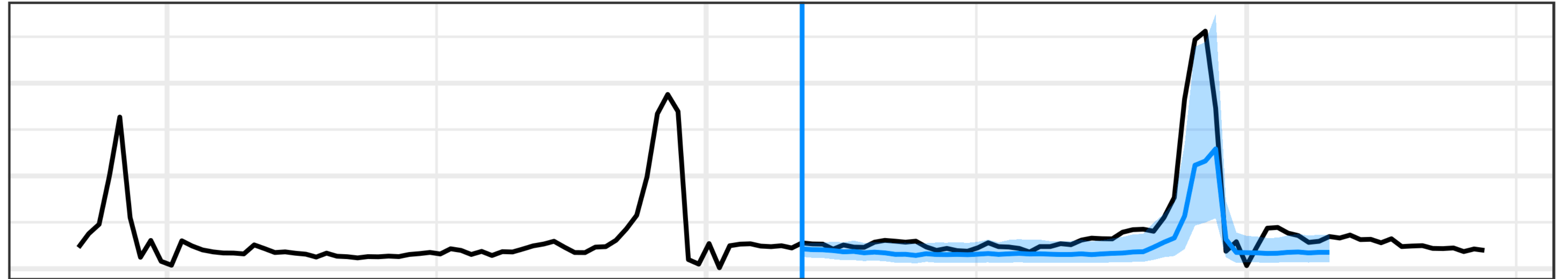
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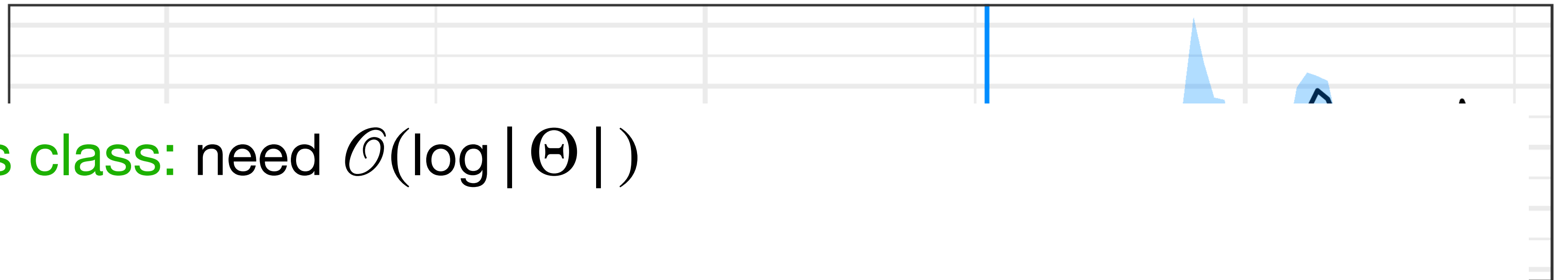
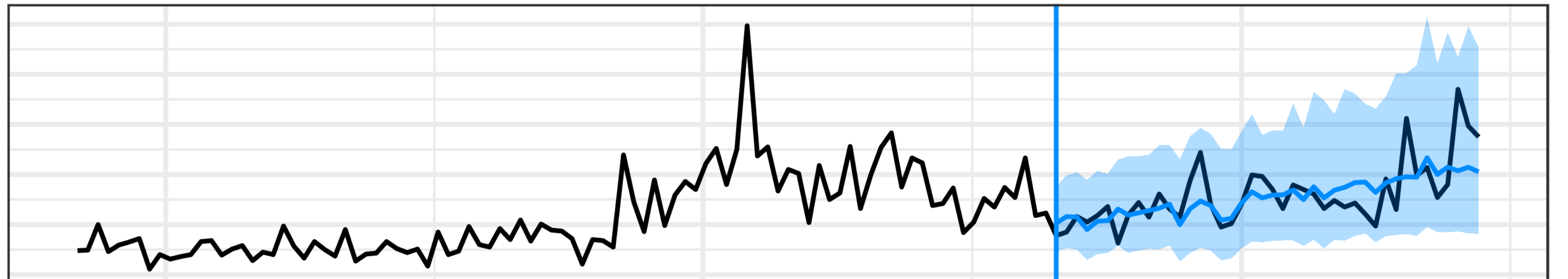
See Wen, Torkkola,
Narayanaswamy,
Madeka (2017)
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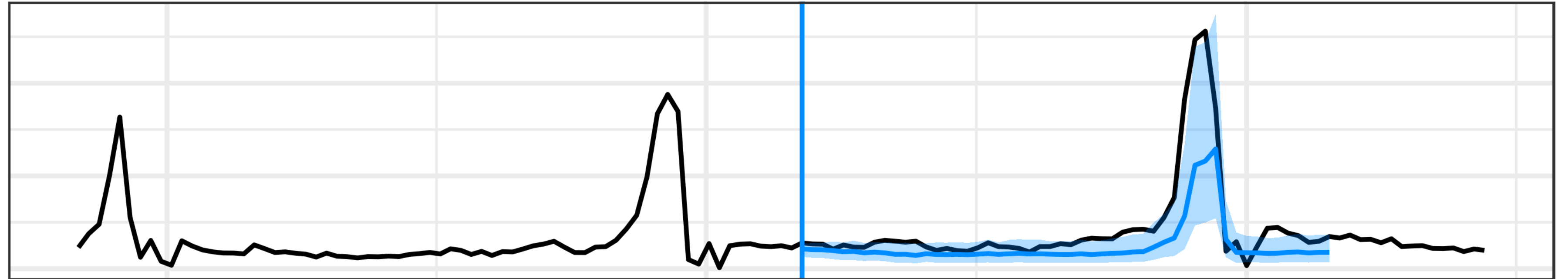


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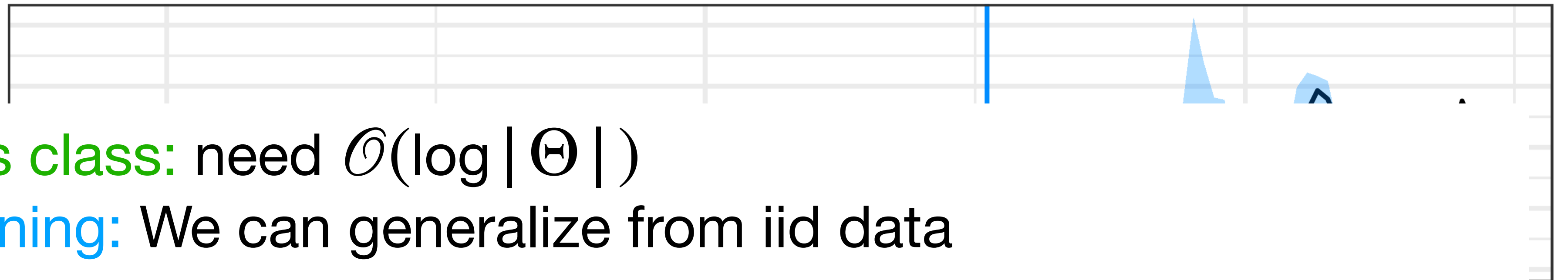
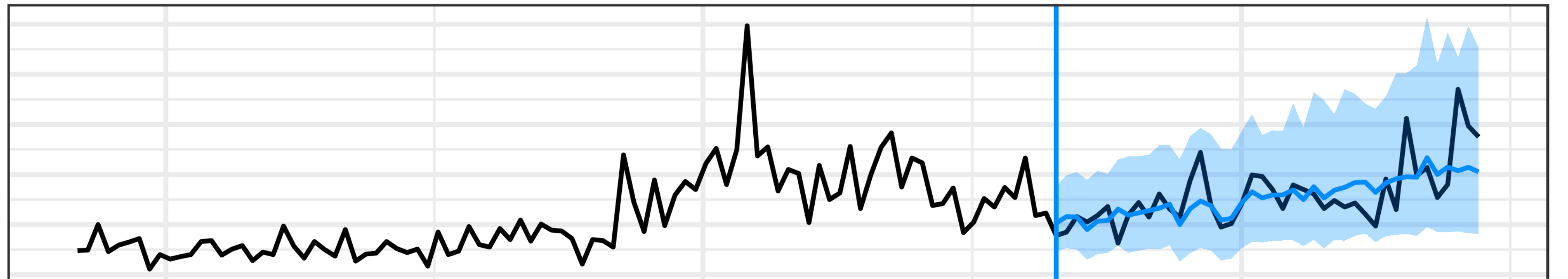


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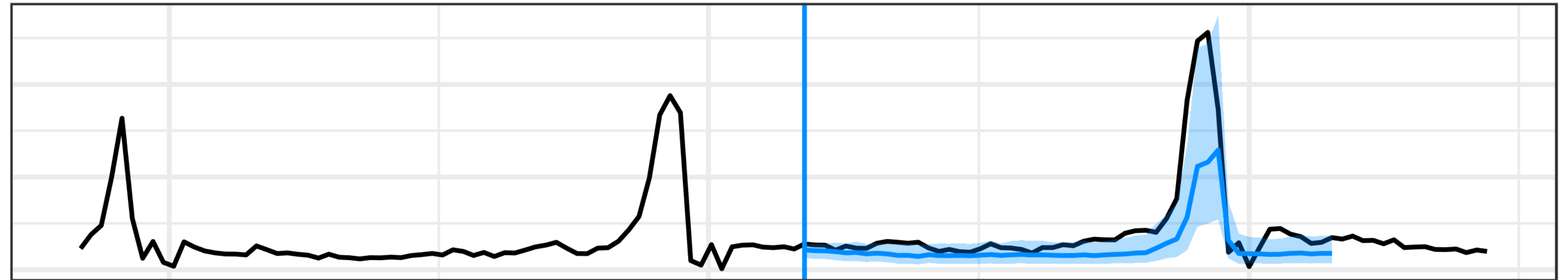


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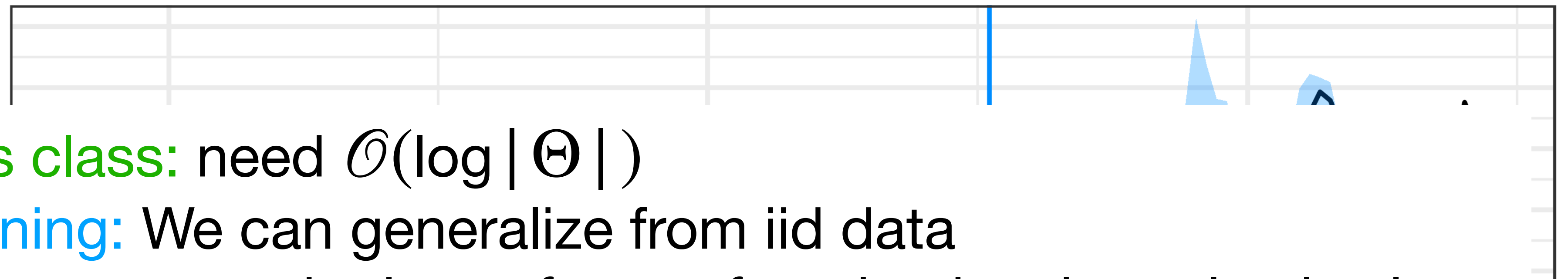
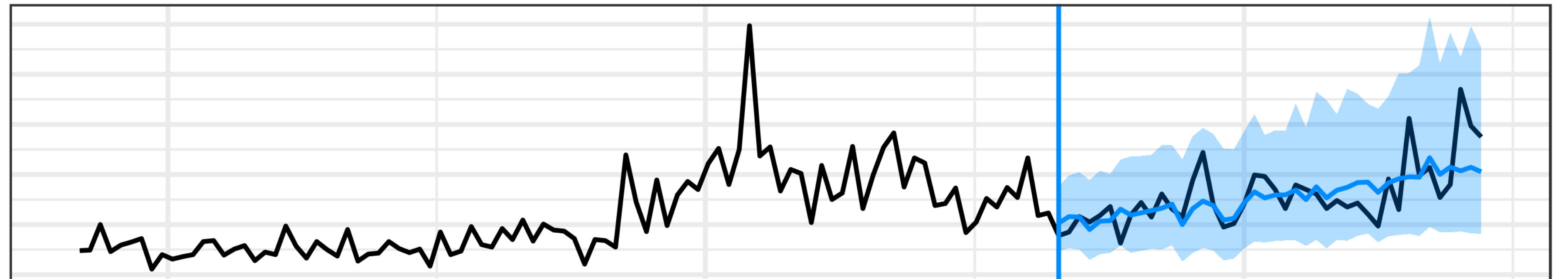


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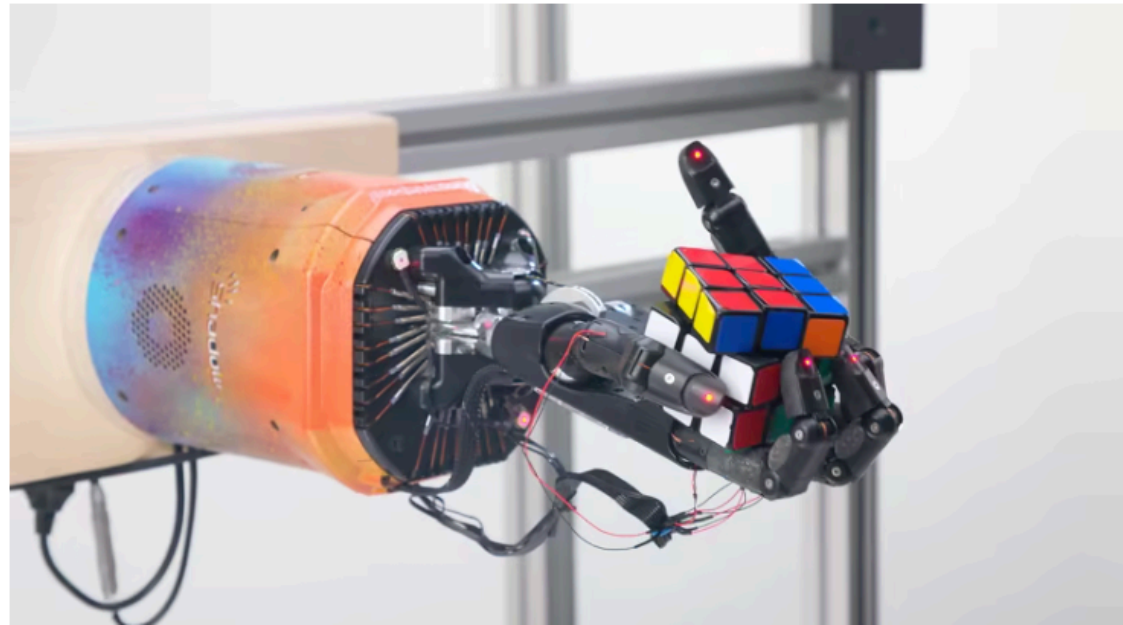
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 - **Supervised Learning:** We can generalize from iid data
- Data reuse:** We can compute the loss of every function in a hypothesis class



Real-world RL is hard.

The core challenges Amazon faces are sequential decision making problems.

Can RL help in this space?



amazon prime Deliver to Sham Boston 02118 Electronics

EN Hello, Sham Account & Lists Returns & Orders Cart

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LG OLED evo

Roll over image to zoom in

Product Energy Guide

LG C2 Series 77-Inch Class OLED evo Gallery Edition Smart TV OLED77C2PUA, 2022 - AI-Powered 4K TV, Alexa Built-in

Visit the LG Store 663 ratings | 268 answered questions

Amazon's Choice in OLED TVs by LG

Deal -5% \$2,496⁹⁹

Was: \$2,627.05

prime Scheduled Delivery

or 12 monthly payments of \$208.09

Get 10% back on amount charged to an Amazon Prime credit card. Learn more

Size: 77 inch

42 inch 48 inch 55 inch 65 inch 77 inch 83 inch

Style: TV Only

TV + \$65Q TV + \$75Q TV + \$80QY TV Only TV + \$90QY

TV wall mounting options: Get expert TV wall mounting Details

Without expert wall mounting Expert wall mounting +\$200.00 per unit

What's included

12 monthly payments: \$208.09/mo. (\$2,496.99 / 12 mo.)

One-time payment: \$2,496⁹⁹ prime Scheduled Delivery

FREE Inside Entryway delivery as soon as Saturday, November 26, 9 AM - 12 PM

Ships from nearby Learn more

Deliver to Sham - Boston 02118

In Stock

Qty: 1

Add to Cart

Buy Now

Secure transaction

Ships from Amazon.com Sold by Amazon.com Packaging Shows what's insi...

RL is hard!

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Dexterous Robotic Hand Manipulation
OpenAI, '19



RL is hard!

- Sample complexity **can be as large** as $\min(|\Theta|, 2^T)$

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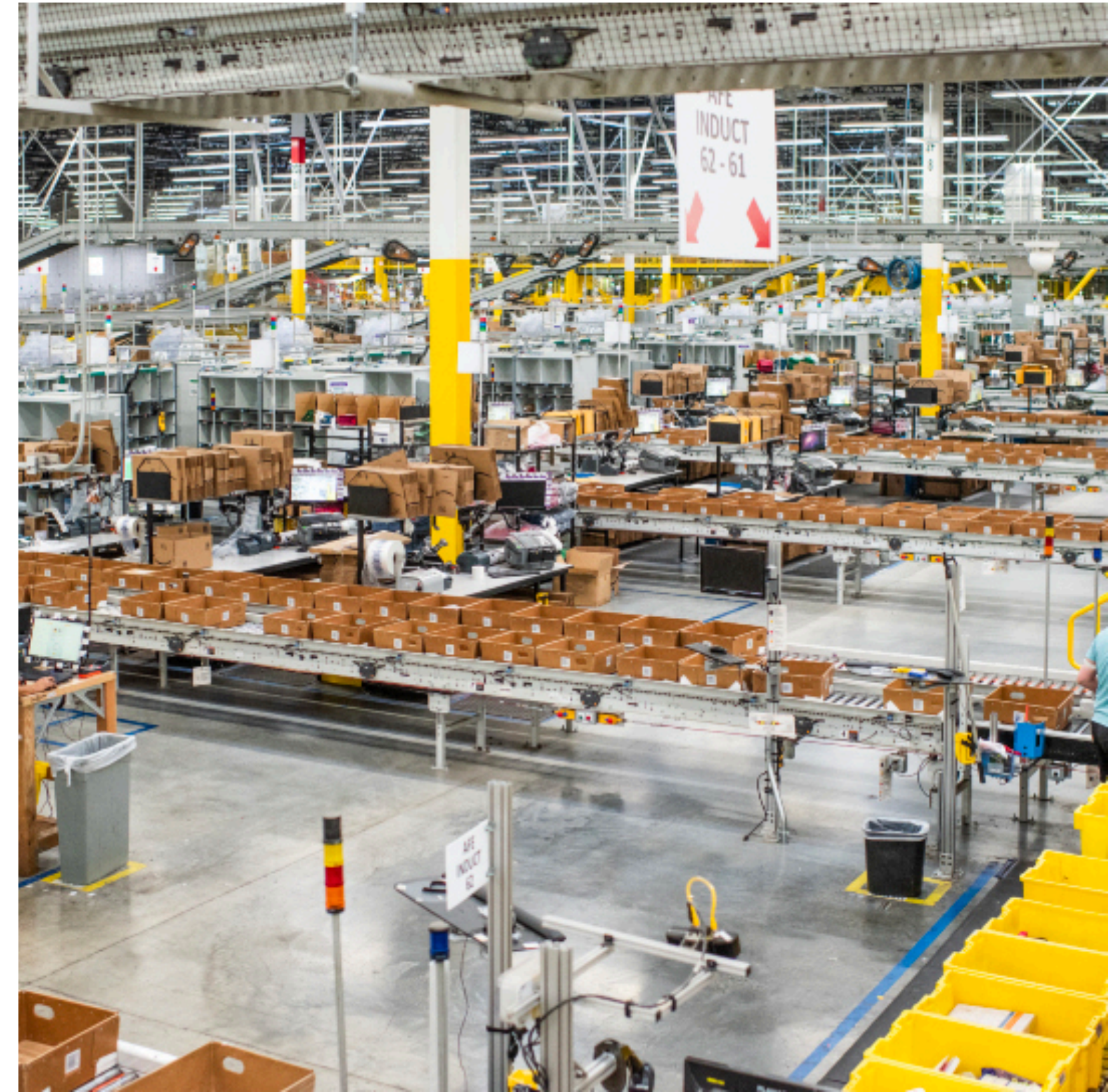
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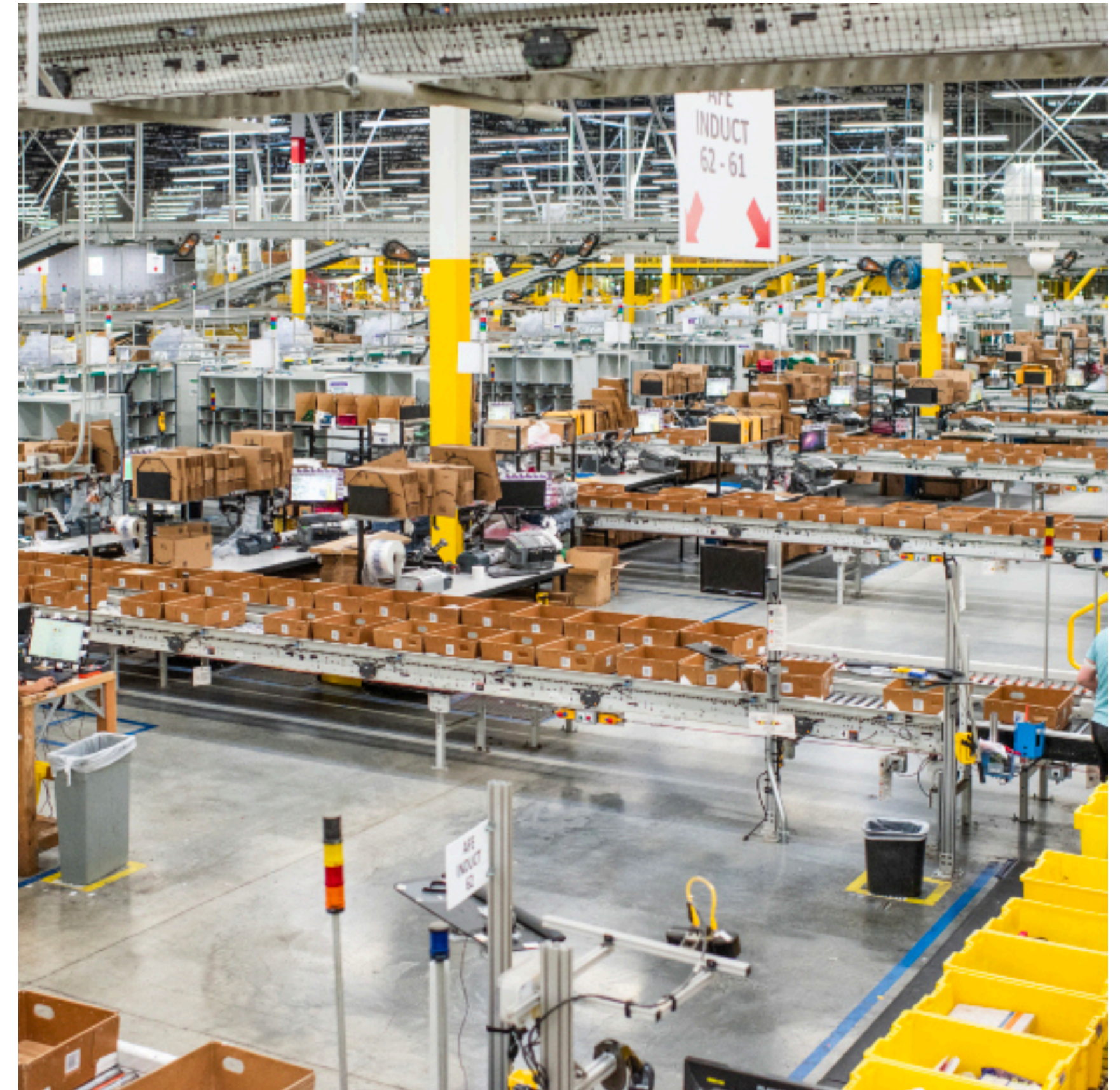
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 - There is a lot of historical “off-policy” data
 - How do we use it?
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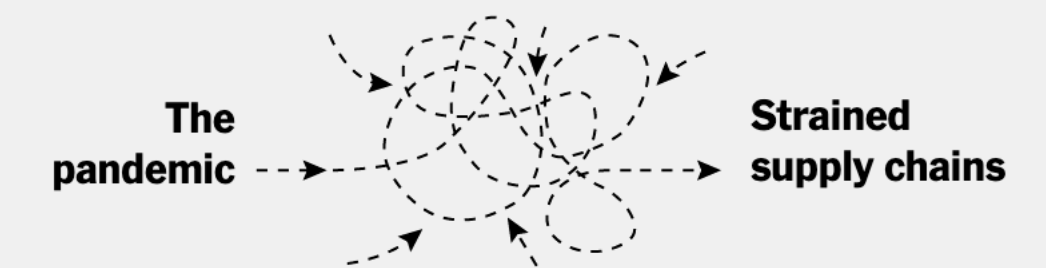


Supply Chain Hurdles Will Outlast Pandemic, White House Says

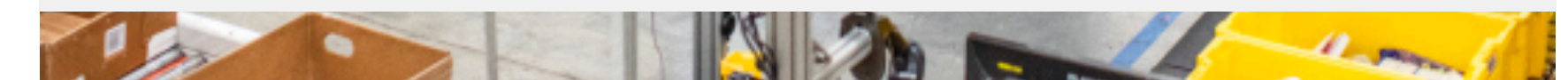
The administration's economic advisers see climate change and other factors complicating global trade patterns for years to come.



The New York Times



How the Supply Chain Crisis Unfolded



Outline

Can we use historical data to solve inventory management problems in supply chain?

- Part I: Utilizing Historical Data
- Part II: Moving to real-world inventory management problems
- Part III: Real World Results

Deep Inventory Management

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Carson Eisenach

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Anna Luo

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Dean P. Foster

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Sham M. Kakade

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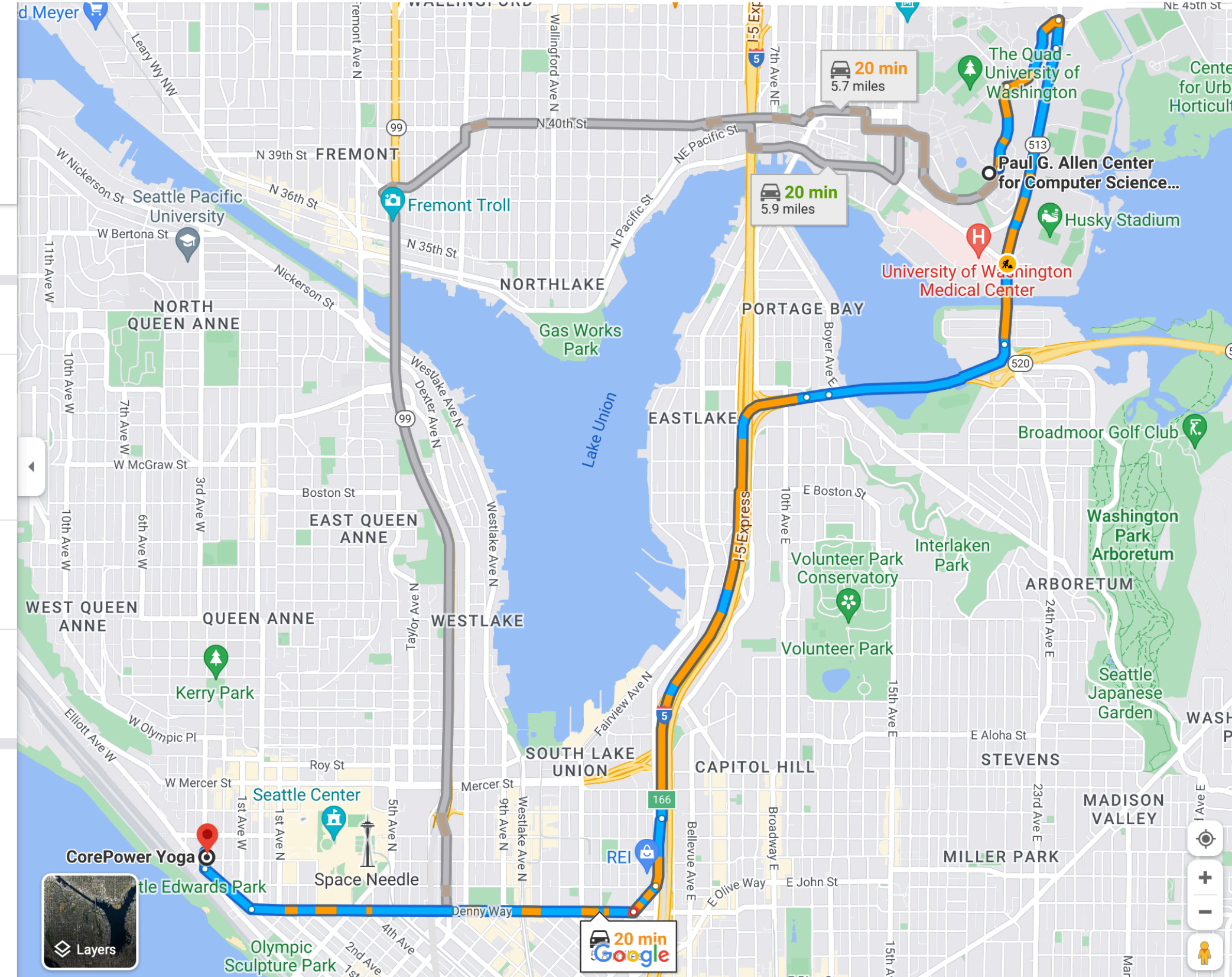
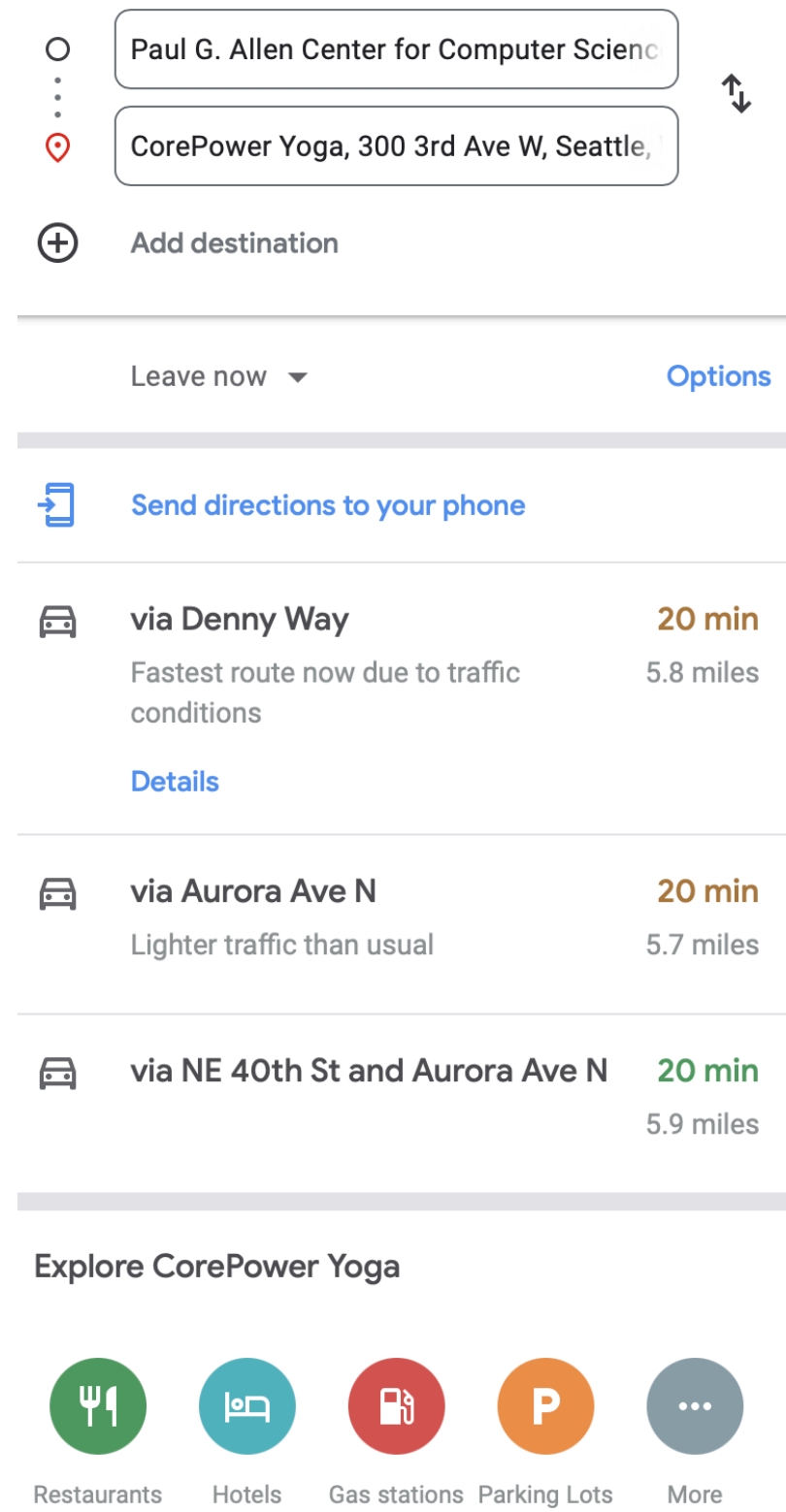
Largely based on this paper: [arxiv/2210.03137](https://arxiv.org/abs/2210.03137)

I: Utilizing historical data

Warm up: Vehicle Routing

(when using historical data might be ok)

- We want a good policy for routing a single car.
- **Policy π : features \rightarrow directions features:**
time of day, holiday indicators, current traffic, sports games, accidents, location, weather,
- **Historical Data:**
suppose we have logged historical data of features
- **Backtesting policies:**
 - Key idea: a single route minimally affects traffic
 - Counterfactual: with the historical data, we can see what would have happened with another policy.



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 - Key idea: a small fleet route may have small affects on traffic.
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Price= \$2

Cost= \$1

[illegible]

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Time	Inventory	Demand	Order	Revenue
0	100	20	-	40

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 - Empirically, backlog due to unmet demand does not look significant.¹

1. See Verhoef et al (2006)

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$$V_T(\pi) = E_{\pi} \left[\sum_{t=1}^T \gamma^t r(s_t, I_t, a_t) \right]$$

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 - Tons of correlation across time (Demand, Price, Cost)
- We can explore (linear risk in every product)

Theorem: Backtesting in ExoMDPs

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Theorem [Madeka, Torkkola, Eisenach, Luo, F., Kakade '22]:

Suppose we have a set of K policies $\Pi = \{\pi_1, \dots, \pi_K\}$, and we have N sampled exogenous paths. Then we can accurately backtest up to nearly $K \approx 2^N$ policies.

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Formally, for any $\delta \in (0,1)$, with probability greater than $1 - \delta$ - we have that for all $\pi \in \Pi$:

$$|V_T(\pi) - \hat{V}_T(\pi)| \leq T \sqrt{\frac{\log(K/\delta)}{N}}$$

(assuming the reward r_t is bounded by 1).

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- **Implications:**
 - We can optimize a **neural policy** on the past data.
 - In the usual RL setting (not exogenous), we would have an **amplification factor of (at least) $\min\{2^T, K\}$** , using historical data due to the counterfactual issue.

II: Real World Inventory Management Problems

Real-world Issue: **Censored** Demand

- When $\text{demand} \geq \text{inventory}$, what customers see:


\$19.99
& **FREE Shipping**
Get it Tue, Jan 29 - Thu, Jan 31,
or
Get it Fri, Jan 25 - Fri, Jan 25 if
you choose paid Local Express
Shipping at checkout

**In stock on January 23,
2019.**

Order it now.
Ships from and sold by Vertellis.

Qty: 1 ▼

\$19.99 + Free Shipping


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Buy New **\$18.96**
Qty: 1 ▴ ▾ List Price:
\$29.99
Save: \$11.03 (37%)

FREE Shipping on orders over \$35.

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We only observe **sales** not the **demand**:
 $\text{Sales} := \min(\text{Demand}, \text{Inventory})$

Can we still backtest?

Our historical data is then censored....

Sales := min(Demand, Inventory)

Price= \$2

Cost= \$1

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Time	Inventory	True Demand	Sales	Order	Revenue
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⋮	⋮				
⋮	⋮				
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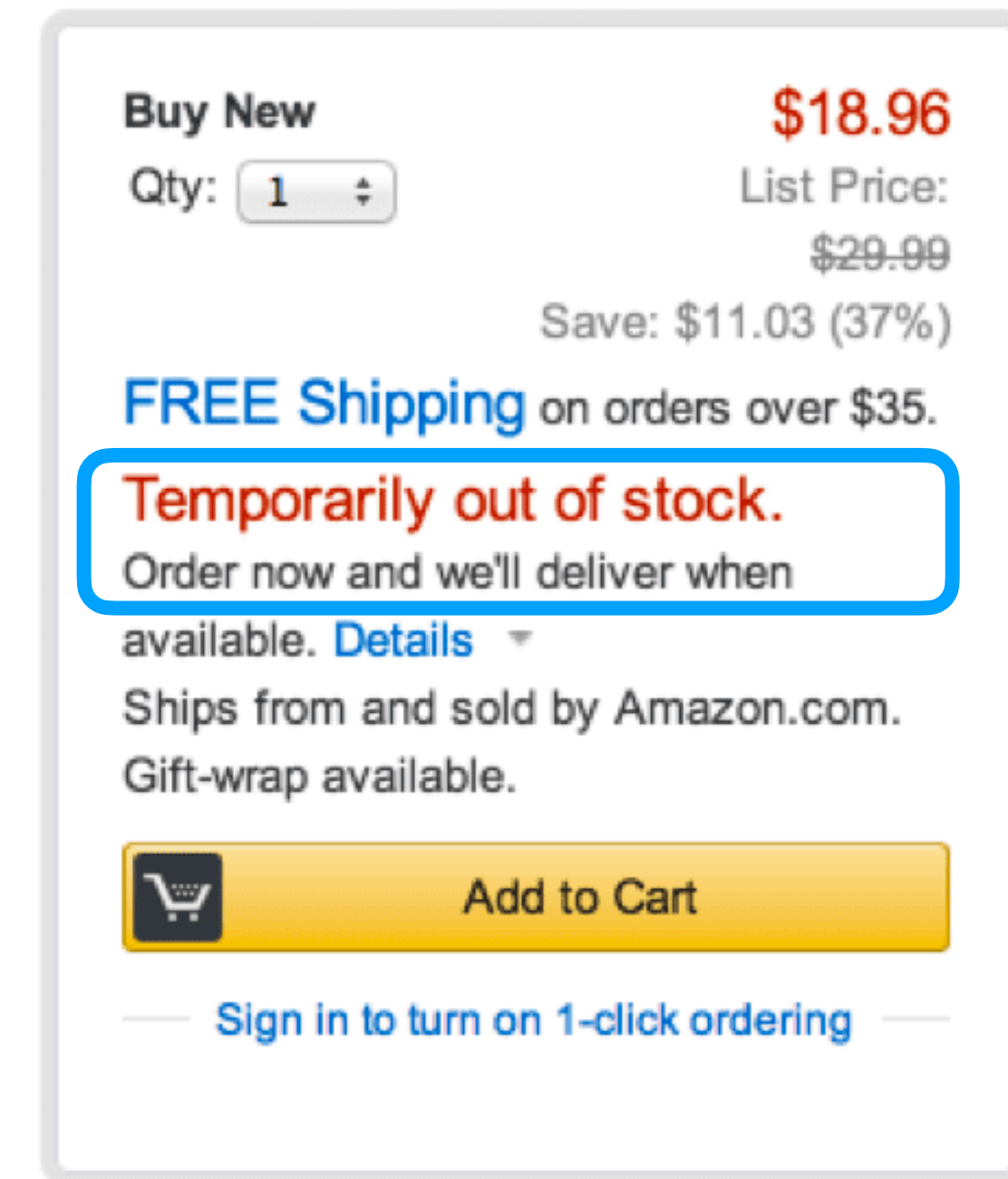
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If we could fill in the missing demand, then we could still backtest!

We have many observed historical covariates

- **Covariates:**
Sales, Web Site, **Glance Views**, Product Text, Reviews
- **Example:** the #times customers look at an item gives us info about the unobserved demand.
- **Let's forecast the missing variables** from the observed covariates!
 $\hat{P}(\text{Missing Data} \mid \text{Observed Data})$

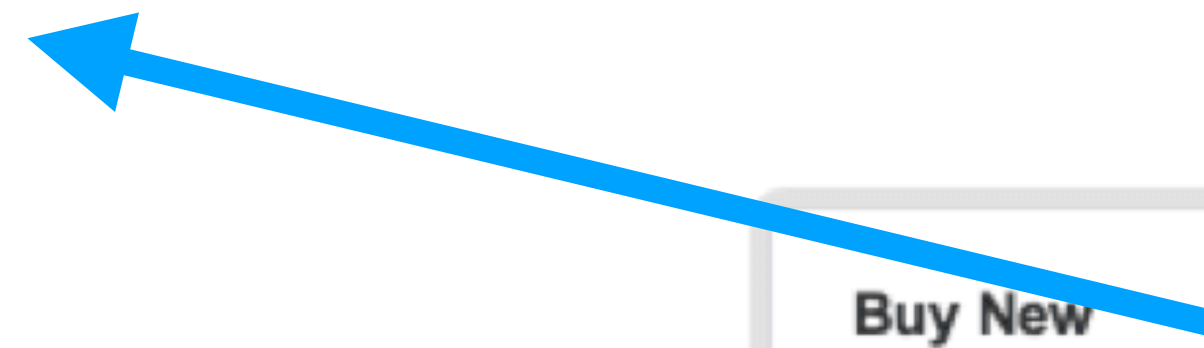


Uncensoring the data....

Sales := min(Demand, Inventory)

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⋮	⋮	⋮	⋮		
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⋮	⋮	⋮	⋮		

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Key idea:
Use covariates
(e.g. glance
views) to forecast
missing demand,
vendor lead
times, etc

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Theorem: Backtesting in Uncensored ExoMDPs

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Setting: we have N sampled sequences $\{s_1^i, s_2^i, \dots, s_T^i\}_{i=1}^N$,

where M_i and O_i are the missing and observed exogenous variables in sequence i .

Forecast: $\widehat{\mathbb{P}}^i = \widehat{\Pr}(M_i | O_i)$ is our forecast of $\mathbb{P}^i = \Pr(M_i | O_i)$.

Assume: With pr. 1, forecasting has low error:
$$\frac{1}{N} \sum_{i=1}^N \text{TotalVar}(\mathbb{P}^i, \widehat{\mathbb{P}}^i) \leq \epsilon_{\text{sup}}.$$

Guarantee: For any $\delta \in (0,1)$, with pr. greater than $1 - \delta$, for all $\pi \in \Pi$:

$$|V_T(\pi) - \hat{V}_T(\pi)| \leq T \left(\epsilon_{\text{sup}} + \sqrt{\frac{\log(K/\delta)}{N}} \right)$$

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- **Key idea:** We can backtest even in the **censored** setting!

III: Training Policies & Empirical Results

The Simulator

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- Collection of historical trajectories:
 - 1 million products
 - 104 weeks of data per product



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 - Demand
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- Policy gradient methods in a “gym”:
 - “gym” \leftrightarrow backtesting \leftrightarrow simulator
(note the “simulator” isn’t a good world model).
 - The policy can depend on many features.
(seasonality, holiday indicators, demand history, ASIN, text features)



Data



Corrections



Simulator

Differentiable Control Problem

- Note that each term of our state evolution is a **differentiable function** of previous actions

$$I_t = \max(I_{t-1} + a_{t-1} - D_t, 0)$$

- So, we can take gradients directly from our Reward through our policy

$$r(s_t, I_t, a_t) := \text{Price}_t \times \min(\text{Demand}_t, I_t) - \text{Cost}_t \times a_t$$

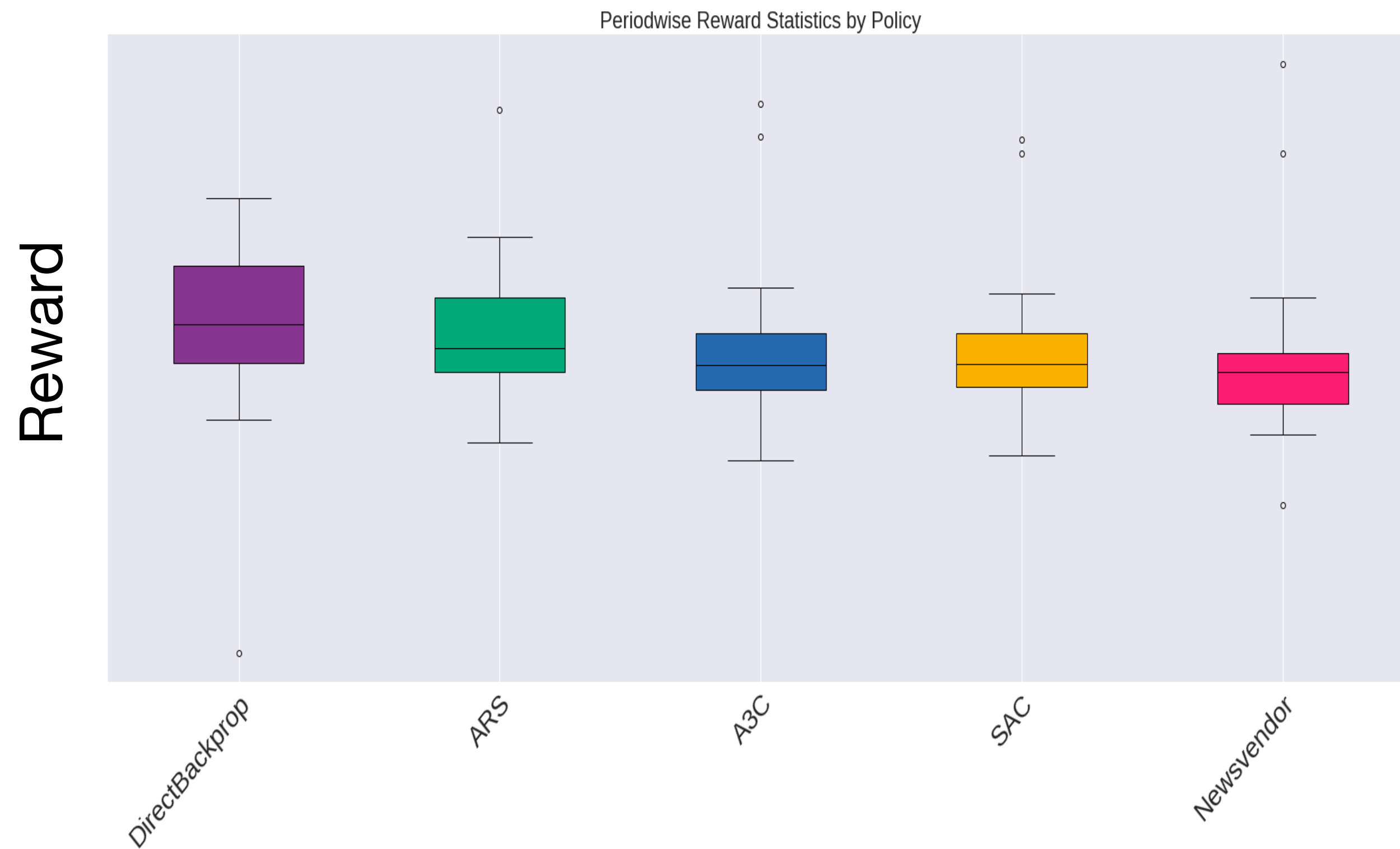
- This is our current production policy, called *DirectBackprop*
- Similar in spirit to Perturbation Analysis (Glasserman et al 1995), except it uses a **neural policy**

Sim to Real Transfer

Sim to Real Transfer

- Sim: the backtest of [DirectBackprop](#) improves on Newsvendor.

Simulation

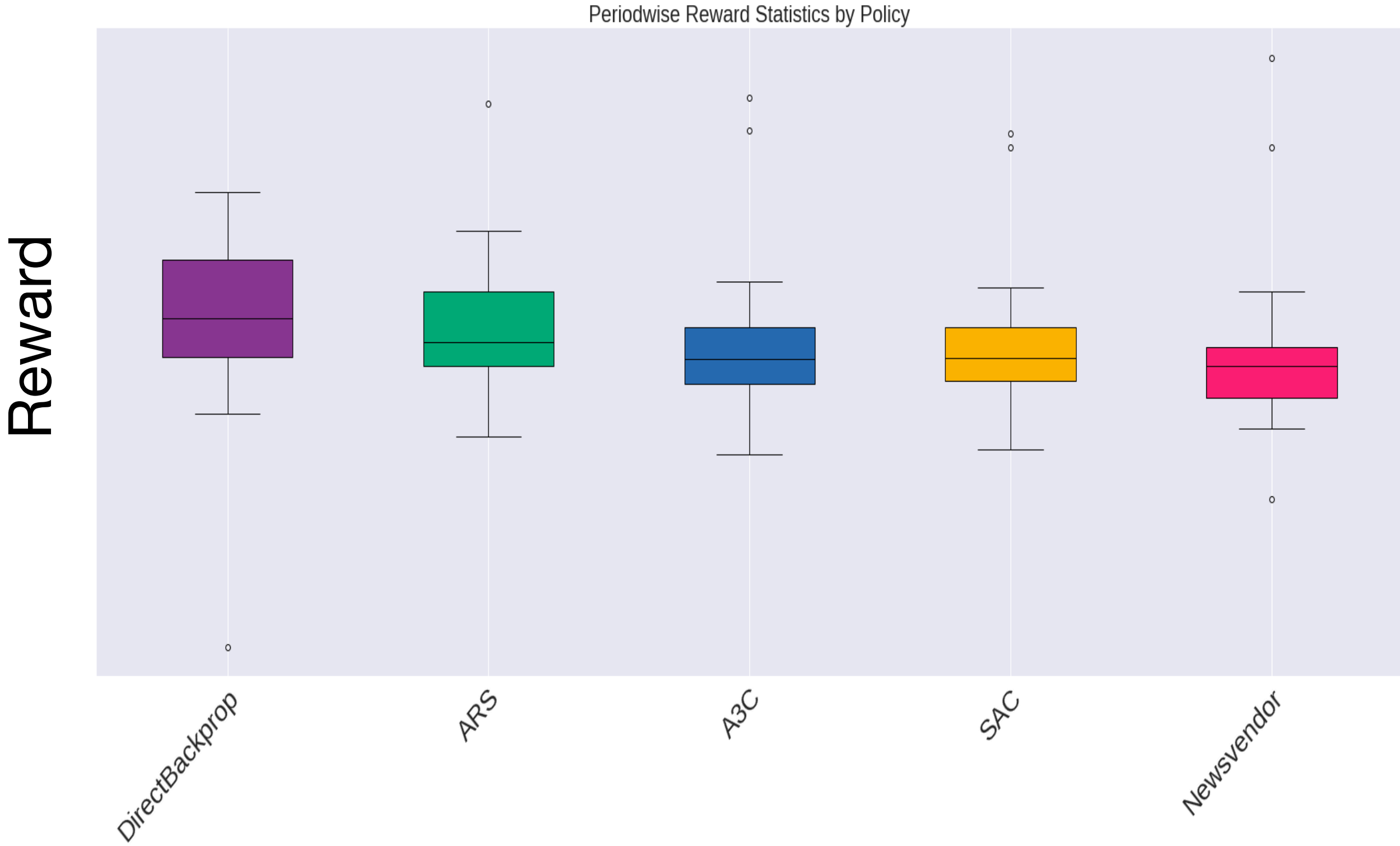


Sim to Real Transfer

- Sim: the backtest of **DirectBackprop** improves on Newsvendor.
- Real: **DirectBackprop** significantly reduces inventory without significantly reducing total revenue.

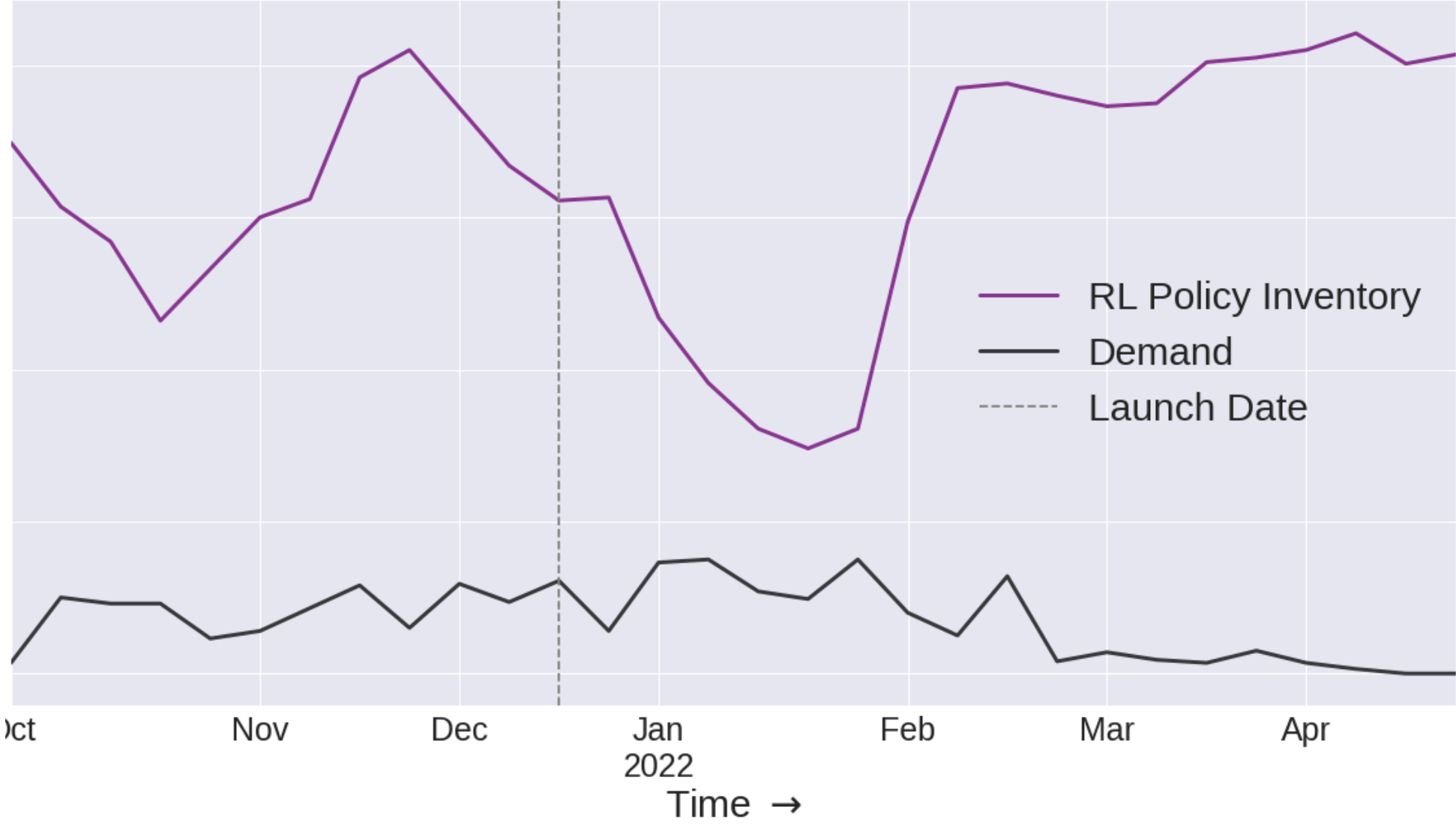
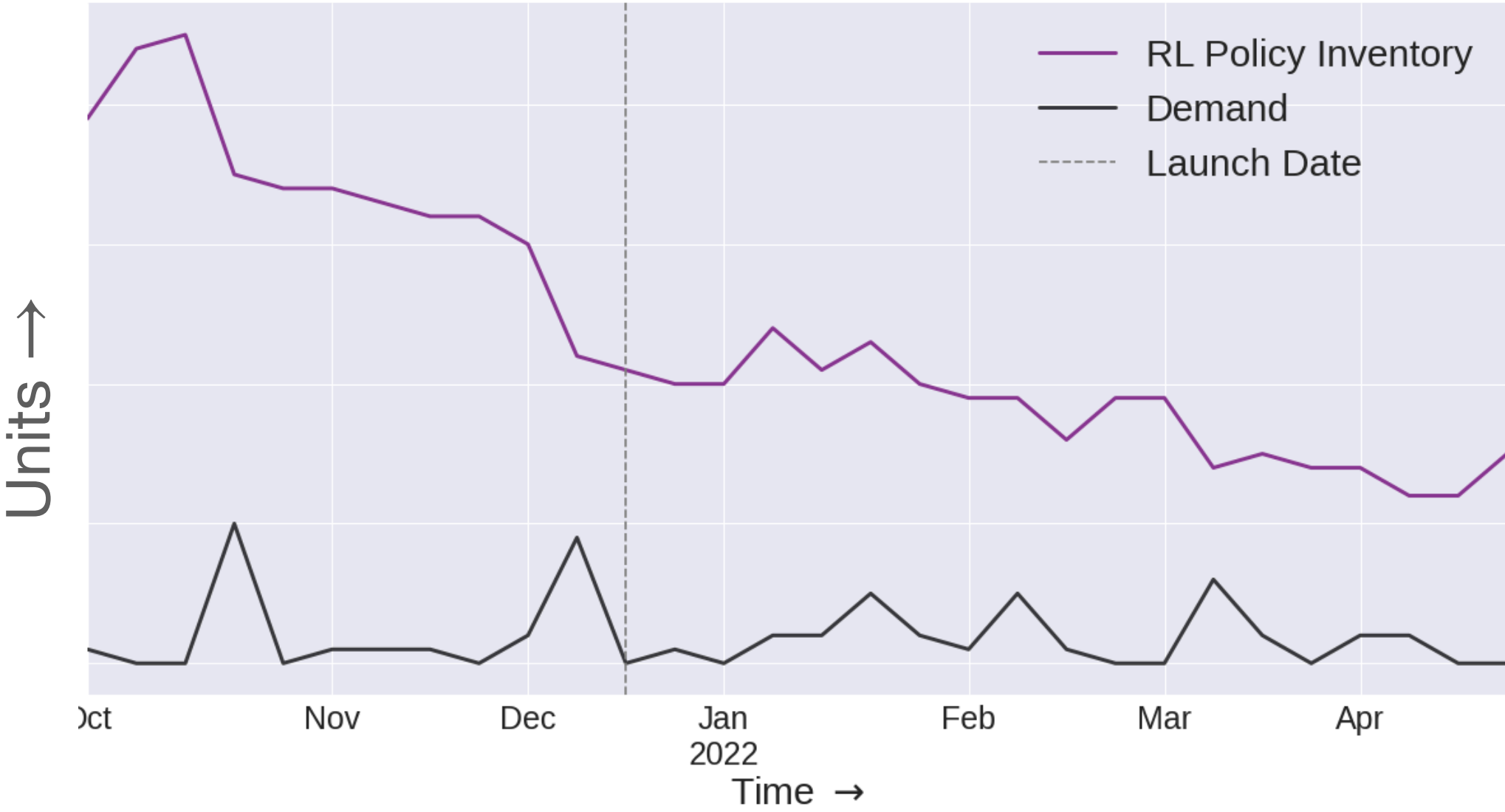
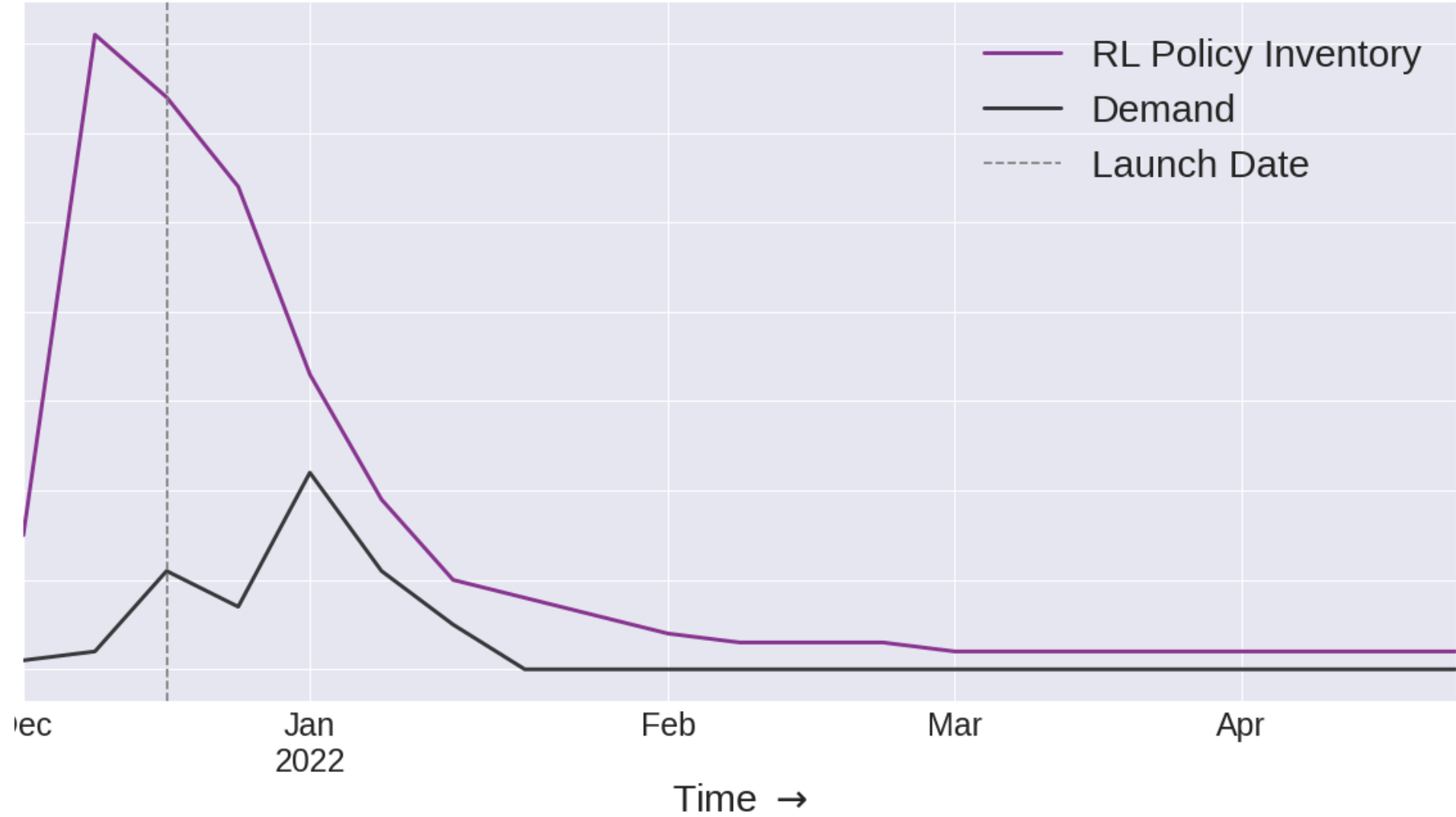
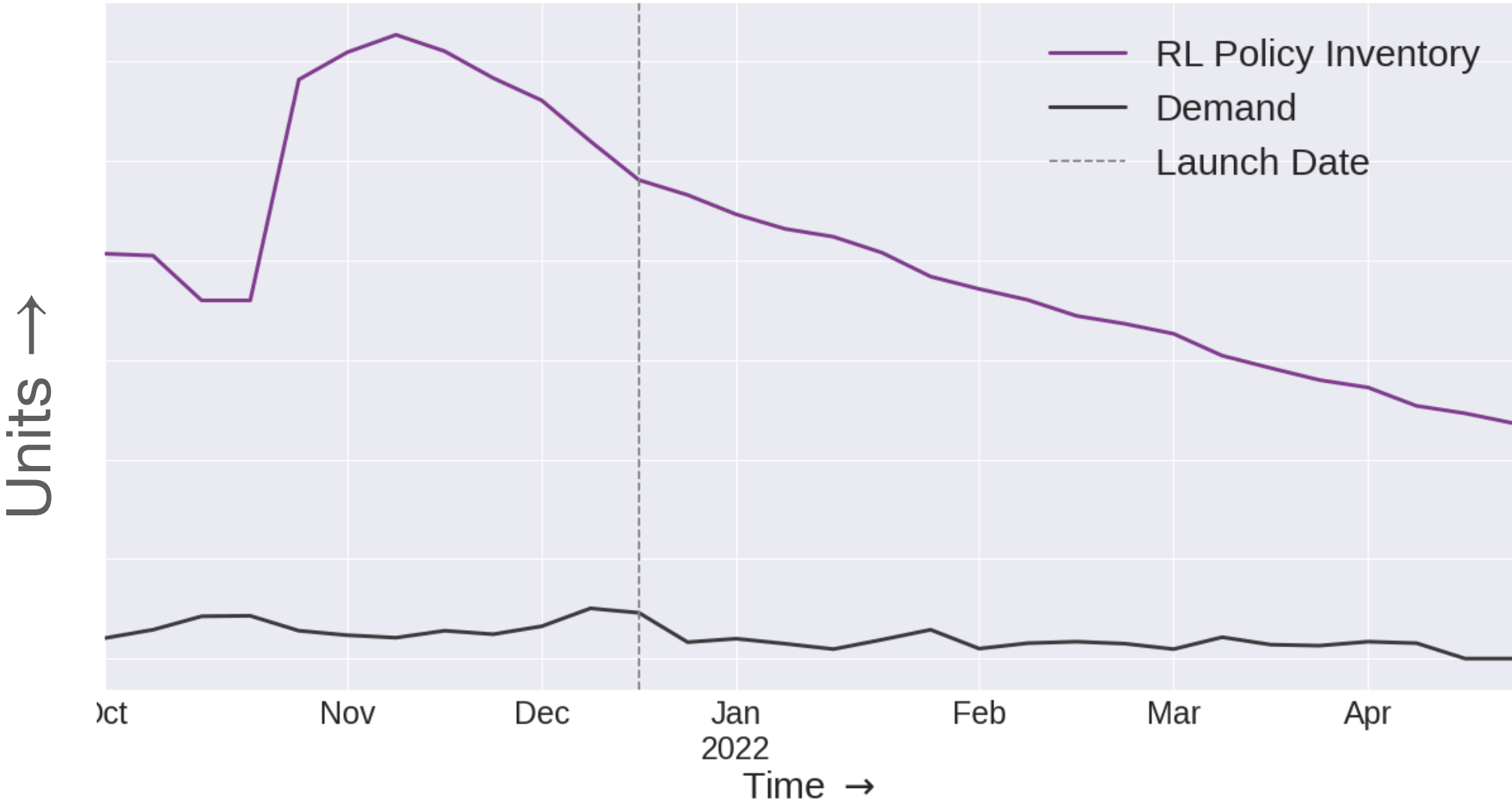
Simulation

Real World



Metrics	% change
Inventory Level	-12 ± 6
Revenue	~

Anecdotaly, RL has reasonable strategies in the real world...



Real World RL Challenges

- World is **not perfectly** exogenous (some terms may depend on our actions)
- Cross product constraints are **computationally intensive**
- Not **every Supply Chain** problem can be written in this framework

Conclusion

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- There are a class of RL Problems that work in the real world!

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Carson



Kari



Anna



Dhruv



Sham