

# Haiku Presentation

## An Introduction to my Research Agenda



Carlos Gonzalez, Econometrics Lunch

November 26, 2024

- ▶ Interested in **Learning**, Dynamic Games, and its Policy Implications
- ▶ Looking at the intersection of ML Theory, Micro Theory and Applied Economics. Different approaches to similar problems
- ▶ **ML**: Result oriented. Heuristic approach to learning. Refined theory developed ex-post. Algorithms are very powerful, but usually a black box

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- ▶ **ML**: Result oriented. Heuristic approach to learning. Refined theory developed ex-post. Algorithms are very powerful, but usually a black box
- ▶ **MT**: Economically founded learning rules (positive and normative). Predom of Bayesian learning. Deliberately simple and analytically limited
- ▶ **Applications**: Adverse Selection, IC Recommendation systems, Monopsony markets, Labor markets, data rationalizability, recovery of utility functions ...

- ▶ Establish connections between Machine Learning and Econ Theory
  - ▶ Hannan Consistency and Convergence to Best Reply [Gonzalez, 2023]
  - ▶ An Epistemological Approach to Causality in ML [Gonzalez and Mazlish, 2024]
- ▶ Expand Economic Theory leveraging ML heuristics and Algorithms
  - ▶ A Prior-Free Theory of Adverse Selection [Gonzalez, 2023]
  - ▶ The Econometrics of Behavioral Parameters [Auer et al., 2024]
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  - ▶ **Optimal Ordering Provisions in Sequential Search Problems**
- ▶ The Economics of Machine Learning
  - ▶ Rationalizing Upper Confidence Bound Algorithms [Gonzalez, 2024]
  - ▶ Using Neural Networks to Recover Utility Functions [Gonzalez and Wu, 2024]

- ▶ There exists a long-lived welfare-maximizer **principal** who optimally trades-off exploration and exploitation across different options  $j, h, \dots$
- ▶ And a short-lived **agent** who (i) conducts the actual exploration, but (ii) who just cares about exploitation. **Delegated Exploration Problem**
- ▶ P is the **platform owner**, but she can't force A to pick a particular option. Instead, she provides an **ordering of all options**  $\{j h k, h j k, k j h, \dots\}$

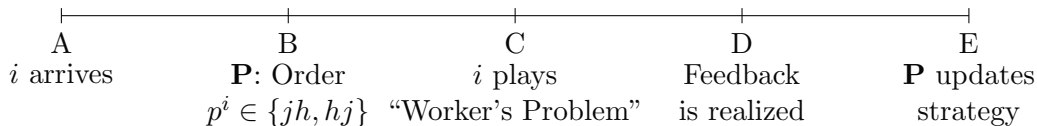
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- ▶ P is the **platform owner**, but she can't force A to pick a particular option. Instead, she provides an **ordering of all options**  $\{j h k, h j k, k j h, \dots\}$
- ▶ Agent will query such options sequentially and select one
- ▶ Can we characterize a **(near)-optimal ordering policy** when only observing the actions of the agent and not the rewards?

- ▶ **Methodologically relevant:**
  - ▶ **Blurred trade-off** between exploration and exploitation (as every element can be observed in any sequence)
  - ▶ **Cross-exploration.** Need to query different arms to recover relevant statistics of desired arms
  - ▶ **New information structures**



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- ▶ **Economically relevant:**
  - ▶ Agent's exploration is mediated by a **dynamic search problem**
  - ▶ Important economic applications like **job listings**

- **Public Officer** wants to match **workers**  $i = 1, \dots, N$  and **firms**  $J \in \{j, h\}$ , where the quality of the worker-firm match is unknown



- ▶ When  $i$  visits firm  $J$ , he observes  $m_J^i = \mu^J + \gamma_i + \varepsilon_i^J$ ,  $\varepsilon_i^J \sim M^J$
- ▶ Outside option  $\phi_i$
- ▶ Expected value of exploration after observing first firm is
$$m_{0i}^{J'} = \mathbb{P}_{0i}(M_i^J \geq 0) \cdot \mathbb{E}_{0i}[M_i^J \mid M_i^J \geq \phi_i] + \mathbb{P}_{0i}(M_i^J < 0) \cdot \phi_i.$$

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- ▶ Under two “small” **simplifying conditions** we may assume that
$$m_{0i}^J = m_0^J, m_i^J = \mu^J + \varepsilon_i^J, \phi_i = 0$$

$$a_i^{jh} = \begin{cases} T & \text{if } m_i^j \geq m_0^h \\ \{C, T\} & \text{if } m_i^j < m_0^h \text{ \& } m_i^h \geq 0 \\ \{C, C\} & \text{if } m_i^j < m_0^h \text{ \& } m_i^h < 0 \end{cases} \quad (1)$$

- Rewards given by

$$r_i^{jh} = \mathbb{1}(m_i^j \geq m_0^h) \cdot m_i^j + \mathbb{1}(m_i^j < m_0^h, m_i^h \geq 0) \cdot m_i^h \quad (2)$$

- **Other assumptions:** No participation cost (no IR), no discounting, risk neutrality, **agents can't go back**, they only get to play once, present bias if indifferent

- Maximize expected welfare = Minimize Stochastic Regret

$$\begin{aligned}\arg \max_{\pi} \mathbb{E} \left[ \sum_i^N r_i^{\pi(i)} \right] &= \arg \min_{\pi} N \cdot v^{p^*} - \mathbb{E} \left[ \sum_i^N r_i^{\pi(i)} \right] \\ &= \arg \min_{\pi} \mathcal{R}_N(\pi)\end{aligned}\tag{3}$$

- ▶ In a nutshell,  $P$  needs to learn  $V = \{\mu^j, \mu^h, m_0^j, m_0^h\}$  from agents decisions
- ▶ Parametric assumptions st  $V$  is identified from these decisions

$$q^1 = \mathbb{P}(a_{1i}^{jh} = T), \quad \hat{q}^1 = \frac{\sum_i \mathbb{1}(a_{1i}^{jh} = T, p^i = jh)}{\sum_i \mathbb{1}(p^i = jh)} \quad (4)$$

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- ▶ Assuming  $\varepsilon^J \sim \text{Log}(0, 1) \implies$

$$\mu^J = \ln\left(\frac{q^k}{1 - q^k}\right), \quad m_0^J = \mu^{J'} - \ln\left(\frac{q^l}{1 - q^l}\right) \quad (5)$$

- ▶ This allows us to rewrite  $\mathbb{E}[r^p] = f(q^1, q^2, q^3, q^4)$



- ▶ If  $\mathbb{E}[r^p] = f(q^1, q^2, q^3, q^4)$  this means that we need to sample  $p'$  to recover consistent estimates of  $\hat{r}^p \implies$  **Cross-exploration**
- ▶ “ $Q$ -space” is non-monotonic (as opposed to the reward space). Adjust classic algorithms in non-trivial ways
- ▶  $f(Q)$  is very much not well-behaved (non-Lipschitz)






### Proposition 1: Near Optimality under Partial Feedback

Let  $k = |Q|$ , then a version of UCB yields  $\mathcal{R}_N = \mathcal{O}(2^k \cdot \ln(N))$

- **Same regret as under full-feedback (!?)** with worse constant ( $2^k, k = 3$ ) and at the expense of parametric assumptions. Still not bad



- ▶ Exploit internal searching structure. Some initial results
- ▶ Extend analysis to  $J > 2$  arms
- ▶ Refine bounds
- ▶ Data Application
- ▶ Interplay between Information and Sequencing strategies

-  Auer, J., Ballester, M., and Gonzalez, C. (2024).  
The econometrics of behavioral parameters.
-  Gonzalez, C. (2023).  
Adaptive wage setting: A prior-free theory of adverse selection and monopsony markets.
-  Gonzalez, C. (2024).  
Rationalizing upper confidence bound algorithms.
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An epistemological approach to causality in machine learning.
-  Gonzalez, C. and Wu, H. (2024).  
Using neural networks to recover utility functions.