The Decision-Making Side of Data Science

Computational, Inferential and Economic Perspectives

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A Personal View on “Data Science”: It is the Emergence of a New Engineering Field

- Cf. chemical engineering in the 40s and 50s
  - built on chemistry, fluid mechanics, etc
  - driven by the possibility of building chemical factories
  - new concepts and mathematical principles were needed
- Cf. electrical engineering at the turn of the last century
  - built on electromagnetism, optics, etc
  - new concepts and mathematical principles were needed
- The new field builds on inferential ideas and algorithmic ideas from the past three centuries
  - what’s fundamentally new is the idea of building large-scale systems based on these ideas, using data flows at planetary scale

The Two Sides of Machine Learning

- The current era of machine learning has focused on pattern recognition
  - platforms such as TensorFlow and PyTorch have arisen to help turn pattern recognition into a commodity
- The decision-making side of machine learning will be a focus in the future
  - individual high-stake decisions
  - explanations for decisions, and dialog about decisions
  - sequences of decisions
  - multiple simultaneous decisions
  - decisions in the context of multiple decision-makers
  - market mechanisms

Data Science: The Emergence of a New Field of Engineering

- First Generation (‘90-’00): the backend
  - e.g., fraud detection, supply-chain management, fourth paradigm
- Second Generation (‘00-’10): the human side
  - e.g., recommendation systems, commerce, social science
- Third Generation (‘10-now): pattern recognition
  - 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!

Decisions

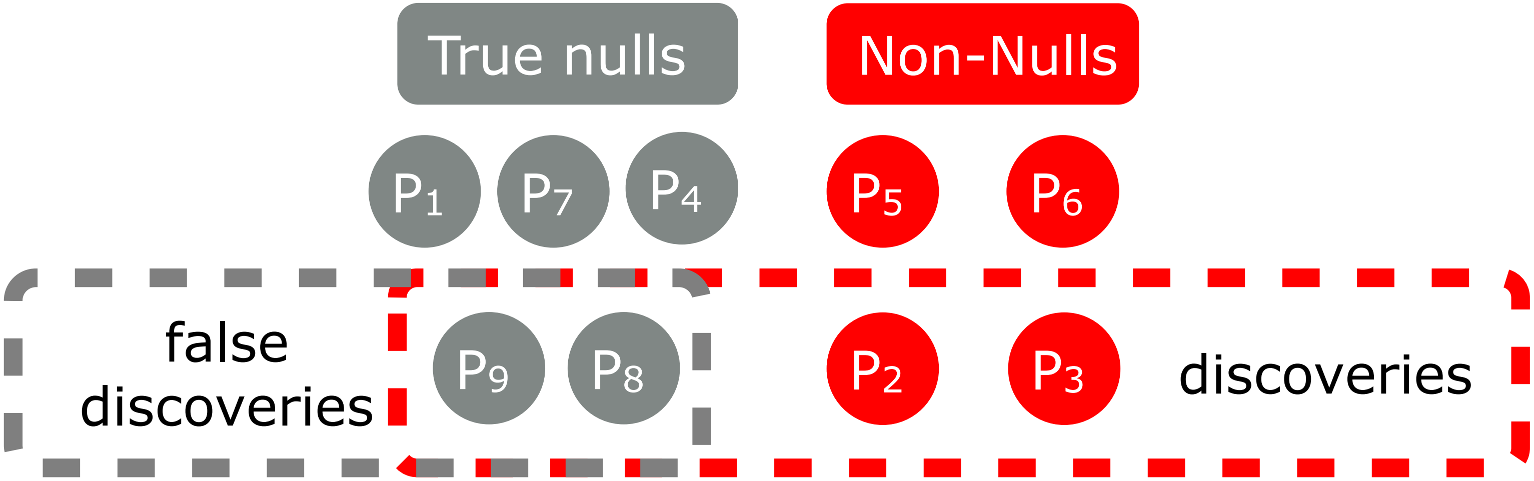
- It's not just a matter of a threshold
- Real-world decisions with consequences
  - counterfactuals, provenance, relevance, dialog
- Sets of decisions across a network
  - false-discovery rate (instead of precision/recall/accuracy)
- Sets of decisions across a network over time
  - streaming, asynchronous decisions
- Decisions when there is scarcity and competition
  - need for an economic perspective
  - what counts as a "good decision" depends on what other decision-makers are doing, which is something that a good decision-maker will model

Anytime Control of the False-Discovery Rate

Aaditya
Ramdas

Tijana
Zrnic

Foster-Stine ’08
Aharoni-Rosset ‘14
Javanmard-Montanari ’16

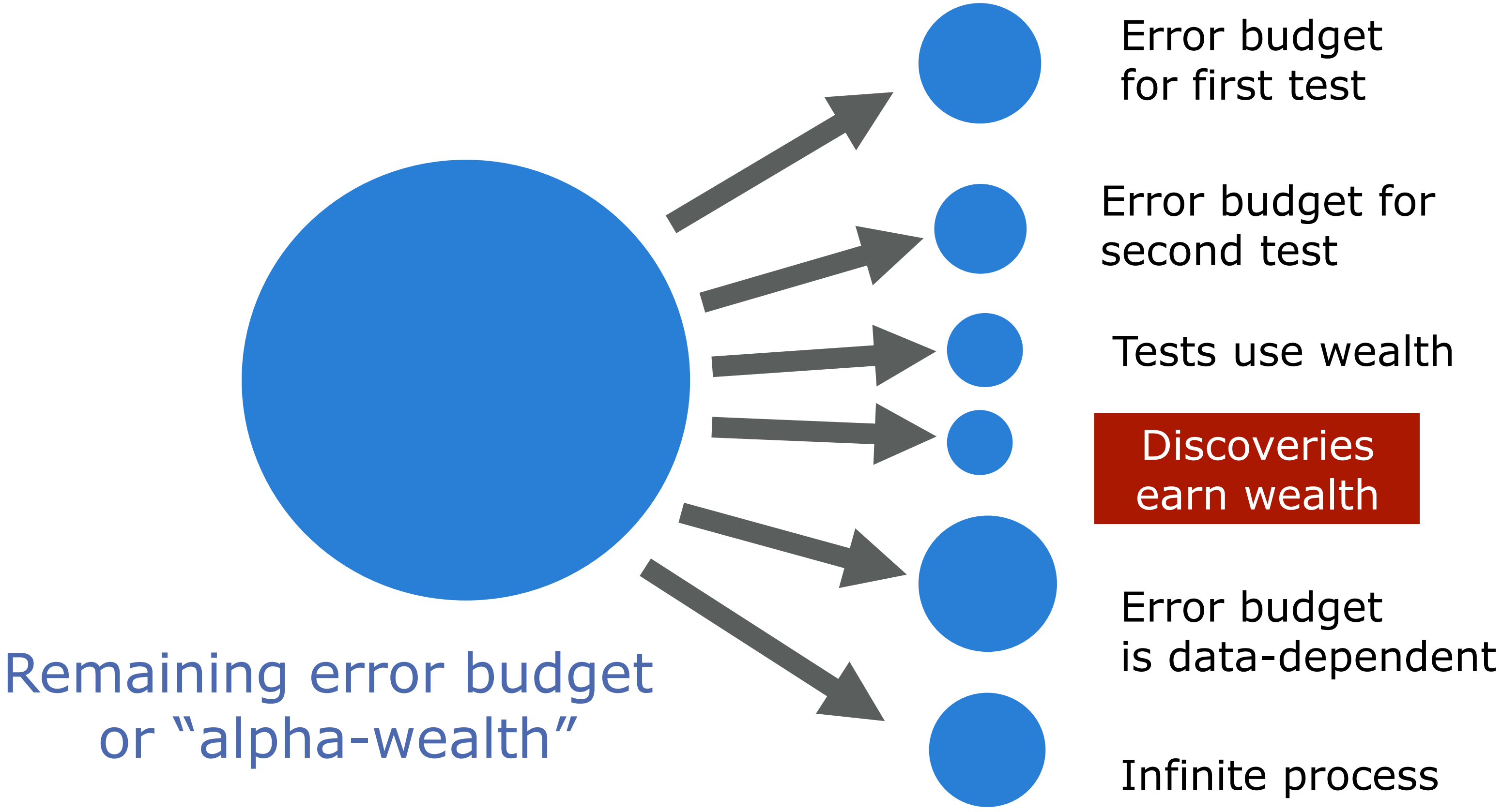


- False discovery proportion $\mathrm{FDP} = \frac{\#\text{ false discoveries}}{\#\text{ discoveries}}$
- Want low false discovery rate $\mathrm{FDR} = \mathbb{E}[\mathrm{FDP}]$
- Want high $\mathrm{Power} = \mathbb{E}\left[\frac{\#\text{ true discoveries}}{\#\text{ non-nulls}}\right]$

Anytime Control of FDR

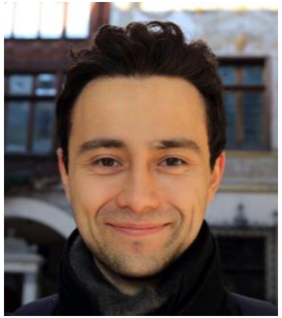
- The decision-maker engages in an infinite sequence of tests
- We want to probe the decision-maker at an arbitrary time, asking for control of the FDR relative to the tests conducted thus far
  - this is possible because the FDP is a ratio, and it can be made small by making the numerator small and/or the denominator large
- Economic metaphor: the decision-maker starts with a fixed amount of “alpha wealth”, which is decremented each time the null is accepted, and incremented (in a particular way) whenever a discovery is made

Online FDR control : high-level picture



Competing Bandits in Matching Markets

Lydia Liu



Horia Mania

Consider Classical Recommendation Systems

- A record is kept of each customer’s purchases
- Customers are “similar” if they buy similar sets of items
- Items are “similar” are they are bought together by multiple customers

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- A record is kept of each customer’s purchases
- Customers are “similar” if they buy similar sets of items
- Items are “similar” are they are bought together by multiple customers
- Recommendations are made on the basis of these similarities
- These systems have become a commodity
- They are on the prediction side of ML

Multiple Decisions with Competition

- Suppose that recommending a certain movie is a good business decision (e.g., because it’s very popular)
- Is it OK to recommend the same movie to everyone?
- Is it OK to recommend the same book to everyone?
- Is it OK to recommend the same restaurant to everyone?
- Is it OK to recommend the same street to every driver?
- Is it OK to recommend the same stock purchase to everyone?

The Alternative: Create a Market

- A two-way market between consumers and producers
  - based on recommendation systems on both sides
- E.g., diners are one side of the market, and restaurants on the other side
- E.g., drivers are one side of the market, and street segments on the other side

- This isn't just classical microeconomics; the use of recommendation systems, and thus statistics, is key

In the Footsteps of David Blackwell

- Blackwell's work was decision-focused
- It often blended statistics, economics, and algorithms
- The concept of approachability has had enduring relevance in multiple fields
  - in particular, it has provided foundations for exciting recent work on bandit algorithms

- Unfortunately, Blackwell was rare, and the links between statistics and microeconomics have been limited
  - in particular, game theory and mechanism design have had little statistical flavor
  - and statistics has had little microeconomic flavor

Examples at the Interface of ML and Econ

- Multi-way markets in which the individual agents need to explore to learn their preferences
- Large-scale multi-way markets in which agents view other sides of the market via recommendation systems
- Inferential methods for mitigating information asymmetries
- Latent variable inference in game theory
- Data collection in strategic settings
- Information sharing, free riding

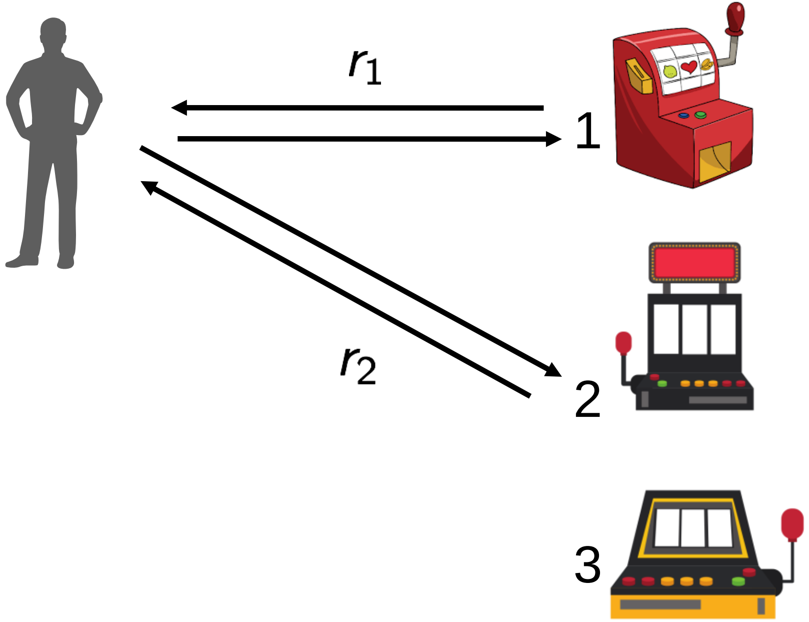
- The goal is to discover new principles to build healthy (e.g., fair) learning-based markets that are stabilized over long stretches of time

Markets as Algorithms

- Markets can be viewed as decentralized algorithms
- They accomplish complex tasks like bringing the necessary goods into a city day in and day out
- They are adaptive (accommodating change in physical or social structure), robust (working rain or shine), scalable (working in small villages and big cities), and they can have a very long lifetime
  - indeed, they can work for decades or centuries
  - if we're looking for principles for lifelong adaptation, we should be considering markets as intelligent systems!
- Of course, markets aren't perfect, which simply means that there are research opportunities

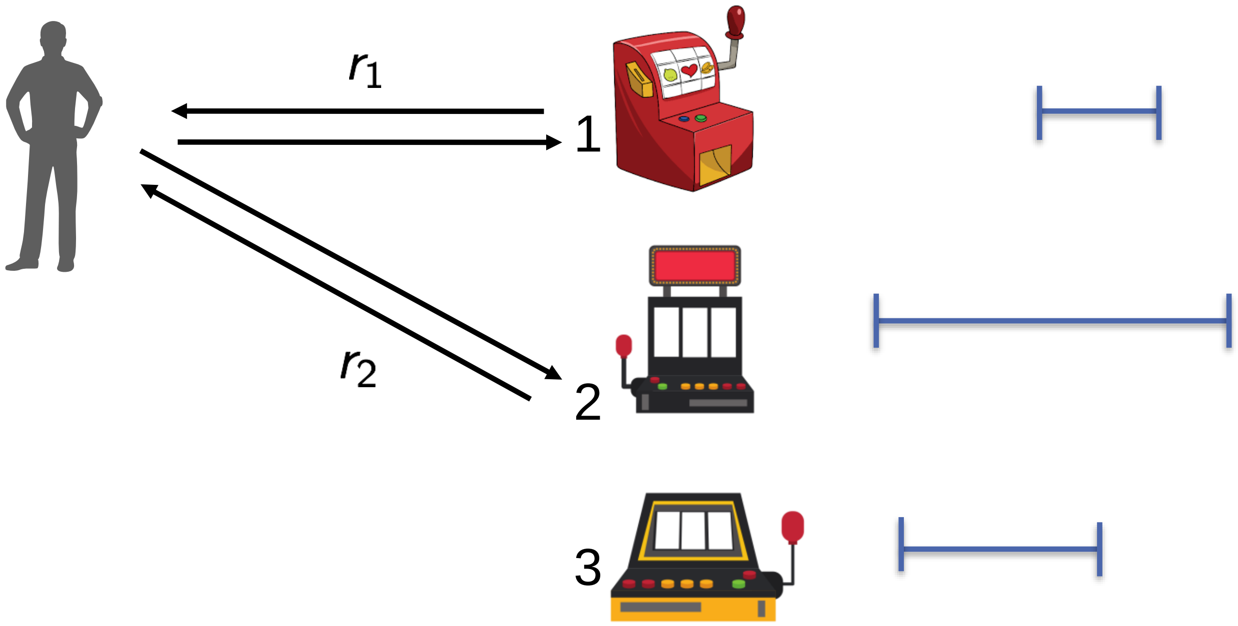
Multi-Armed Bandits

- MABs offer a natural platform to understand exploration / exploitation trade-offs



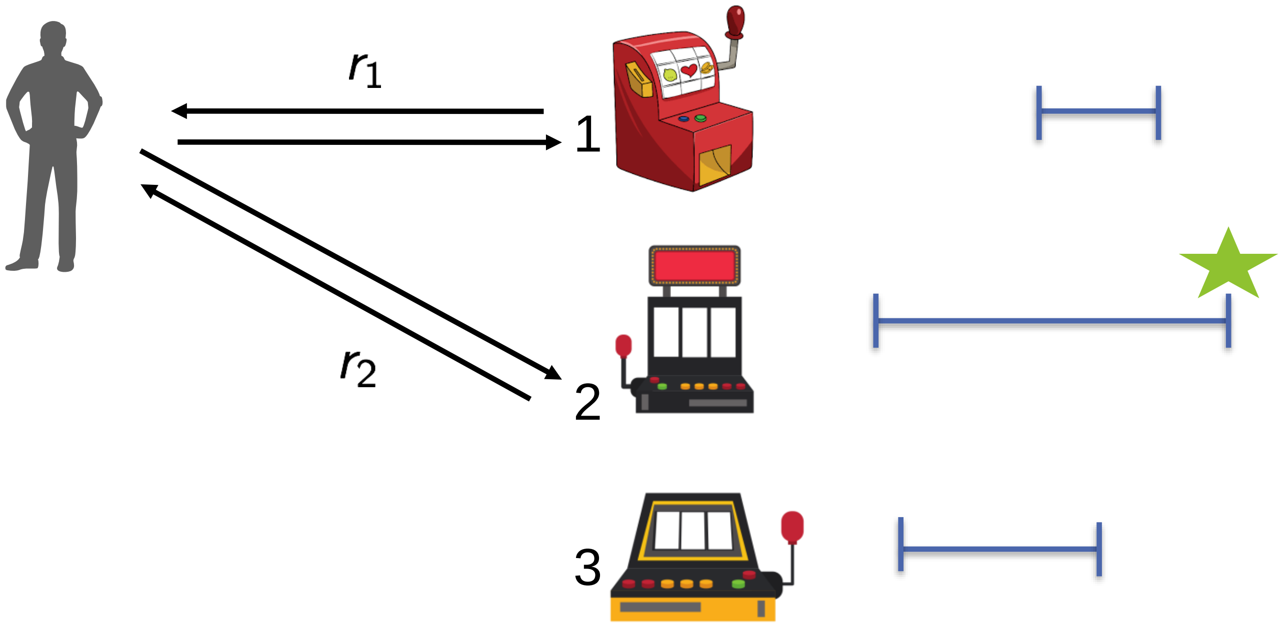
Upper Confidence Bound (UCB) Algorithm

- Maintain an upper confidence bound on reward values



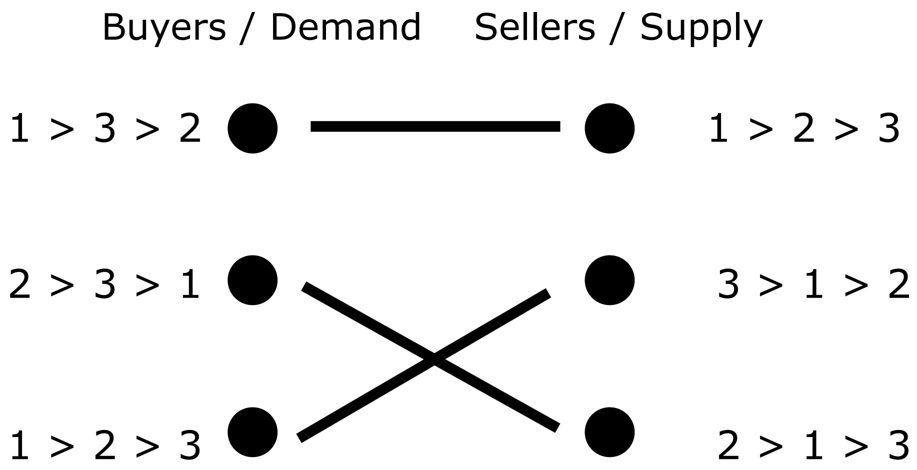
Upper Confidence Bound (UCB) Algorithm

- Maintain an upper confidence bound on reward values
- Pick the arm with the largest upper confidence bound



Matching Markets

Suppose we have a market in which the participants have preferences:



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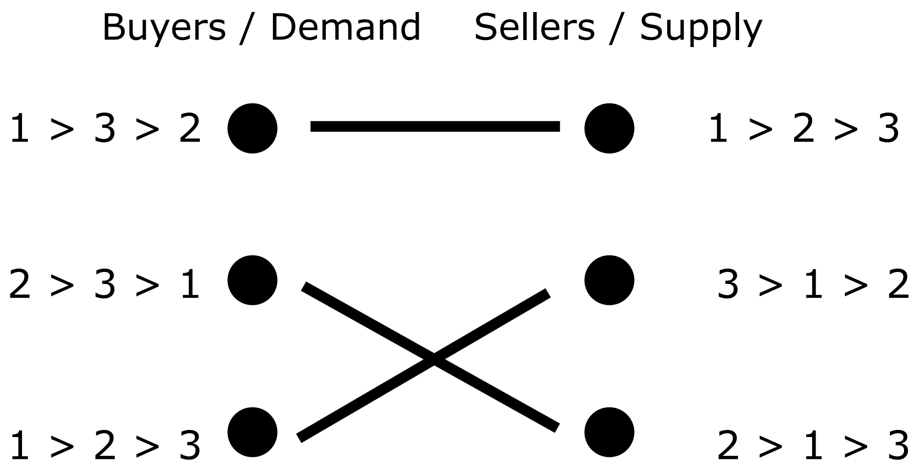

Gale and Shapley introduced this problem in 1962 and proposed a celebrated algorithm that always finds a stable match

Matching Markets

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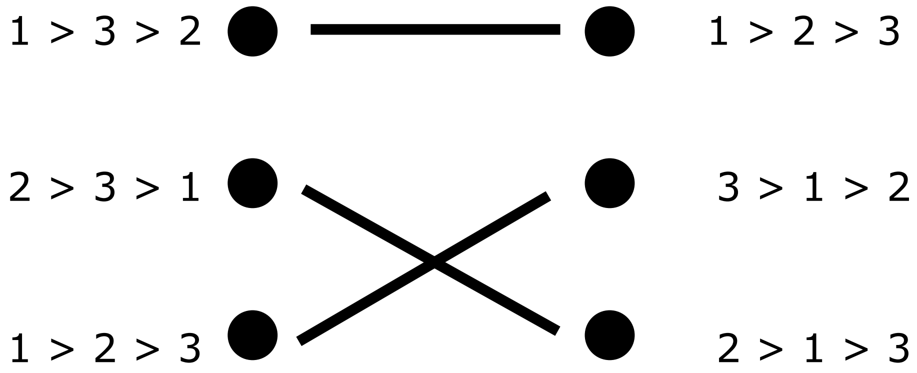
Buyers / Demand   Sellers / Supply



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In this algorithm one side of the market iteratively makes proposals to the other side

Matching Markets Meet Bandit Learning

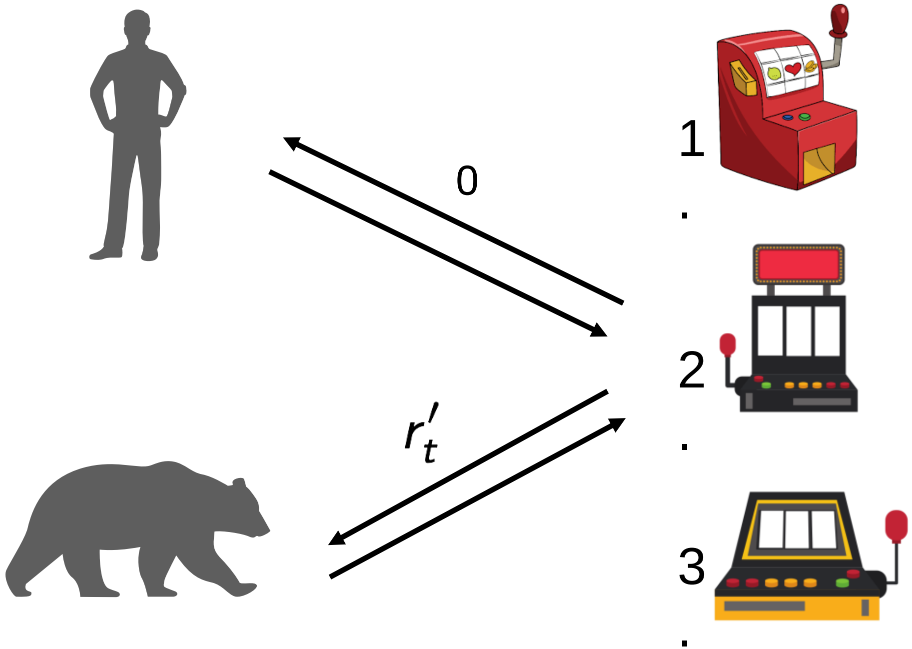
What if the participants in the market do not know their preferences a priori, but observe noisy utilities through repeated interactions?

Matching Markets Meet Bandit Learning

What if the participants in the market do not know their preferences a priori, but observe noisy utilities through repeated interactions?

Now the participants have an exploration/exploitation problem, in the context of other participants

Competing Agents



Bandit Markets

- We conceive of a bandit market: agents on one side, arms on the other side.

Agents get noisy rewards when they pull arms.

Arms have preferences over agents (these preferences can also express agents’ skill levels)

When multiple agents pull the same arm only the most preferred agent gets a reward.

Regret in Bandit Markets

Then it is natural to define the regret of agent i up to time n as:

$$R_i(n) = \underbrace{n\mu_i(m(i))}_{\text{Mean reward of stable match}} - \sum_{t=1}^{n} \mathbb{E}\underbrace{X_{i,m_t}(t)}_{\text{Reward at time t}}$$

Minimizing this regret is natural. It says that agents should expect rewards as good as their stable match in hindsight.

Regret-Minimizing Algorithm

Gale-Shapley upper confidence bounds (GS-UCB):

- Agents rank arms according to upper confidence bounds for the mean rewards.
- Agents submit rankings to a matching platform.
- The platform uses these rankings to run the Gale-Shapley algorithm to match agents and arms.
- Agents receive rewards and update upper confidence bounds.
- Repeat.

Theorem

Theorem (informal): If there are N agents and K arms and GS-UCB is run, the regret of agent i satisfies

$$R_i(n) = \mathcal{O}\left(\frac{NK\log(n)}{\boxed{\Delta^2}}\right)$$

Reward gap of possibly other agents.

- In other words, if the bear decides to explore more, the human might have higher regret.

- See paper for refinements of this bound and further discussion of exploration-exploitation trade-offs in this setting.

- Finally, we note that GS-UCB is incentive compatible. No single agent has an incentive to deviate from the method.

Parting Comments

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