# Microsoft® Research Faculty Summit

NIVERS



# Some Vignettes from Learning Theory

Robert Kleinberg Cornell University

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#### Prelude: Tennis or Boxing?

You're designing a sporting event with *n* players of unknown quality

- Spectators want to see matches between the highest-quality players
  - No preference for variety or for seeing upsets

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- Tennis solution: single-elimination tournament
- Boxing solution: players challenge the current champion until he/she is defeated
- Which is optimal? Or is a third alternative better?

# **Online Learning**



#### Algorithms that make decisions with uncertain consequences, guided by past experience



rdk:~\$ dig nicrosoft.com

; <<>> DiG 9.3.6-P1 <<>> nicrosoft.com ;; global options: printend :: Got answer:

;; ->>HEADER<<- opcode: QUERY, status: NOERROR, id: 65839

;; flags: ar rd ra; QUERY: 1, ANSWER: 2, AUTHORITY: 5, ADDITIONAL: 5

;; QUESTION SECTION:

microsoft.com.		IN	A .	
; ANSWER SECTION:				
icrosoft.com.	3583	IN	A .	207.46.232.182
icrosoft.com.	3583	IN	A	207.46.197.32
; AUTHORITY SECTION:				
icrosoft.con.	3153	IN	NS	ns2.msft.net.
icrosoft.com.	3153	IN	NS	ns5.msft.net.
icrosoft.com.	3153	IN	NS	nsi.nsft.net.
icrosoft.com.	3153	IN	NS	ns3.msft.net.
icrosoft.com.	3153	IN	NS	ns4.maft.net.
; ADDITIONAL SECTION:				
s1.nsft.net.	148615	IN	A	65.55.37.62
s2.nsft.net.	148615	IN	A	64.4.59.173
	445445			DAD 400 444 DB

148615	IN	A	213.199.161.77
148615	IN	A	207.46.66.126
148615	IN	A	65.55.226.140

;; Query time: 5 msec

;; SERVER: 171.64.7.99#53(171.64.7.99)

;; WHEN: Fri Jul 10 12:49:82 2809

MSG SIZE revd: 241

## **Multi-armed Bandits**



- Decision maker picks one of k actions (slot machines) in each step, observes random payoff
- Try to minimize "regret"
  - Opportunity cost of not knowing the best action a priori

0.3	0.7	0.4
0.5	0.1	0.6
0.2	0.2	0.7
0.3	0.8	0.5
0.6	0.1	0.4
2.2	VS.	2.6

## **Multi-armed Bandits**









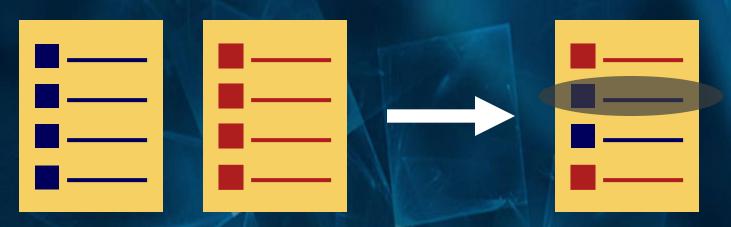
Studied for more than 50 years, but the theory is experiencing a renaissance influenced by the Web

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#### Example: Learning to Rank



- You have many different ranking functions for constructing a list of search results
- Interactively learn which is best for a user or population of users
- Elicit quality judgments using "interleaving experiments." (Radlinski, Korup, Joachims, CIKM'08)



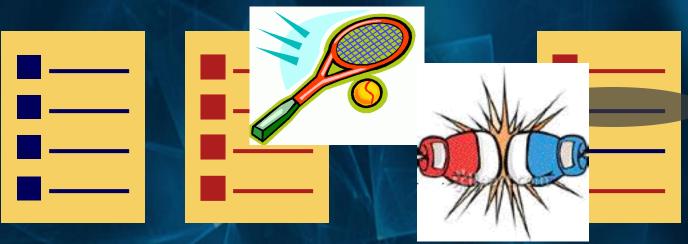
#### **Example: Learning to Rank**



Much more reliable than other ways of detecting retrieval quality from "implicit feedback"

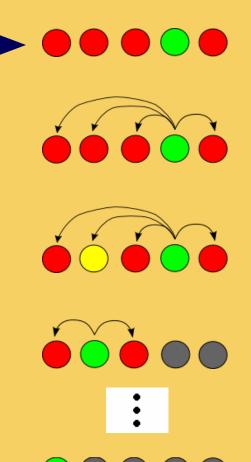
E.g. abandonment rate, query reformulation rate, position of the clicked links

This is like multi-armed bandits, but with a twist: you can compare two slot machines, but you can't just pick one and observe its payoff



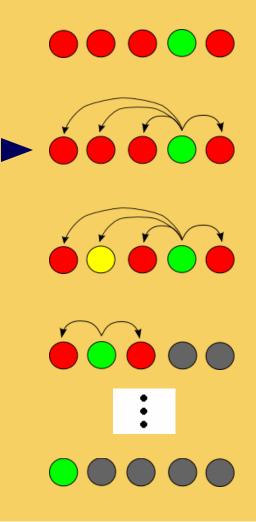


#### Choose arbitrary "incumbent"



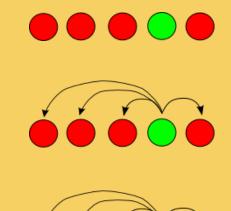


Choose arbitrary "incumbent"
Play matches against all other players in round-robin fashion... (noting mean, confidence interval)





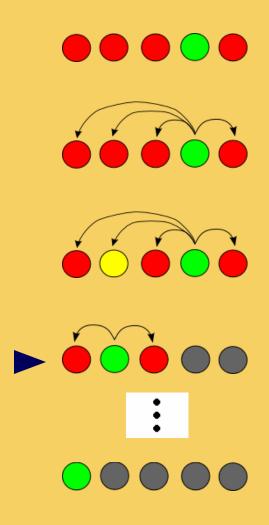
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... until a challenger is better with high confidence





Choose arbitrary "incumbent"

- Play matches against all other players in round-robin fashion... (noting mean, confidence interval)
- until a challenger is better with high confidence
- Eliminate old incumbent and all empirically worse players
- Repeat process with new incumbent...

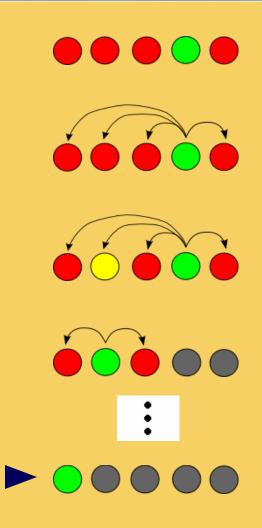




Choose arbitrary "incumbent"

- Play matches against all other players in round-robin fashion... (noting mean, confidence interval)
- until a challenger is better with high confidence
- Eliminate old incumbent and all empirically worse players
- Repeat process with new incumbent...

... until only one player is left

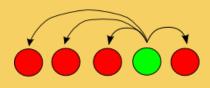


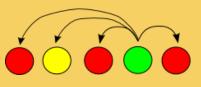


 This algorithm is information theoretically optimal

Boxing is better than tennis!





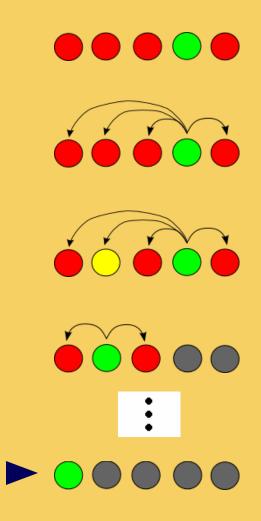




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Thank you, Microsoft! Yisong Yue, the lead student on the project, is supported by a Microsoft Graduate Research Fellowship



#### Vignette #2: Research Learning with Similarity Information

- Recall the multi-armed bandit problem
- Can we use this for web advertising?
- Slot machines are banner ads, which one should I display on my site?



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- Recall the multi-armed bandit problem
- Can we use this for web advertising?
- Slot machines are banner ads, which one should I display on my site?
- Scalability issue: there are 10<sup>5</sup> bandits, not 3!
- On the other hand, some ads are similar to others, and this should help



#### Solution: The Zooming Algorithm

 The set of alternatives (ads) are a metric space

 We designed a bandit algorithm for metric spaces, that starts out exploring a "coarse" action set and "zooms in" on regions that are performing well



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## Thank you, Microsoft!!





Alex Slivkins

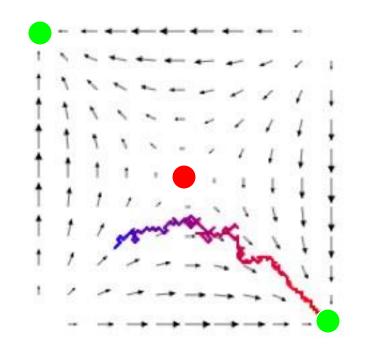
One of many collaborations with MSR over six years ... a major influence on my development as a computer scientist

# What Next?



 Often, the systems we want to analyze are composed of many interacting learners

- How does this influence the system behavior?
- Answering these questions requires combining:
  - Game theory
  - Learning theory
  - Analysis of algorithms



# Thank you, Microsoft!!!



Joining our team next year...

- Katrina Ligett (Ph.D. CMU, 2009)
- Shahar Dobzinski (Ph.D. Hebrew U., 2009)
- ...the top graduates this year in online learning theory and algorithmic game theory
- An unprecedented postdoc recruiting success for myself and Cornell
- Brought to you by the Microsoft Research New Faculty Fellowship!