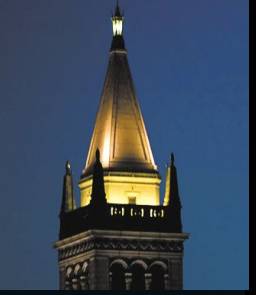

DS 102: Data, Inference, and Decisions

Lecture 18

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Decisions and Learning

- In our lectures on FDR, we talked about making sets of decisions
  - and in our lectures on online FDR, we talked about making sets of decisions over time
  - the sets of decisions can be unrelated
- We now wish to consider problems in which we make the same decision over and over again, and we want to get better at making that decision
  - let's call this a learning problem
  - learning involves both exploration and exploitation

Exploration and Exploitation

- Let's suppose that we obtain rewards based on our decisions
  - good decisions mean high rewards, and bad decisions mean low rewards
  - sometimes we refer to losses instead of rewards, converting between the two with negation
- We want to obtain a high rate of reward over time
  - in doing so we aim to exploit our knowledge as it accrues
- But no one is telling us which choice yields highest reward
  - we have to explore to figure that out

Exploration and Exploitation

- Too little exploration means that the learner may not discover which choice yields the highest reward
  - they stick with a suboptimal choice, and they will not be as happy or successful as they could be over the long run
  - but too much exploration means forgoing the opportunity to reap immediate rewards in the possibly vain hope of future rewards
- So, at any given moment there is a tradeoff--should I exploit what knowledge I currently have, or explore further to improve my knowledge?
- Can we devise a formal theory that makes that tradeoff explicit, and actionable?

The Multi-Armed Bandit

- We consider a decision-maker who is given K options to choose from
  - we refer to those options as “arms”
  - please Google “multi-armed bandit” to see a picture of a casino, from whence the language comes
- Associated with each arm is a probability distribution over rewards
- The decision-maker chooses an arm, and receives a reward sampled from the corresponding reward distribution
- This repeats

The Goal

- Generally the goal is to maximize the sum of the rewards over all time steps
- Sometimes the rewards are discounted, when rewards in the future are viewed as less valuable than more immediate rewards
- A key idea is regret, which is the difference between our total reward and the reward of some kind of oracle who knows more than we do
  - for example, an oracle who knows in advance which is the optimal arm

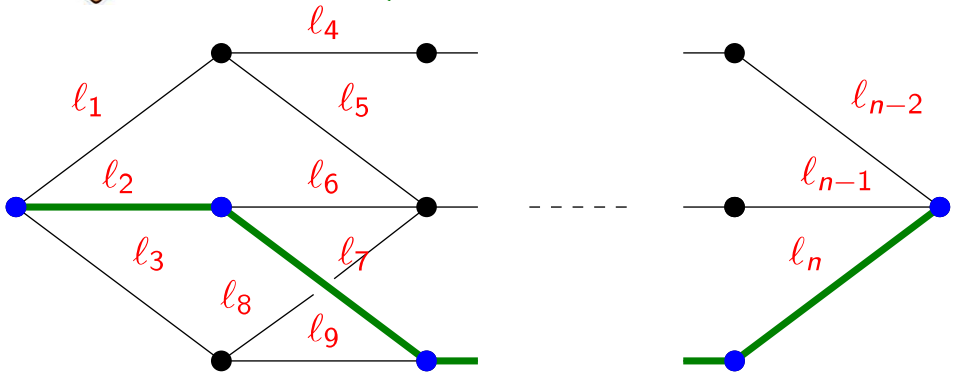
Variations on the basic multi-armed bandit

- The environment can be stochastic or adversarial
- Contextual bandits blend bandits with regression
- There are structured bandits, in which the actions and the rewards have mathematical structure that can be exploited
  - see the example of path planning on the following page
  - in such settings, the feedback can be more detailed than simply the reward associated with the selected arm

Example: path planning

Adversary $\longrightarrow$  Feedback:

Full Info:	$\ell_1, \ell_2, \ldots, \ell_n$
Semi-Bandit:	$\ell_2, \ell_7, \ldots, \ell_n$
Bandit:	$\ell_2 + \ell_7 + \ldots + \ell_n$



Player $\longrightarrow$ 

loss suffered: $\ell_2 + \ell_7 + \ldots + \ell_n$

Real-World Problems

- Drug discovery
- A/B testing
- Routing in networks
- Robot skills
- Human-computer interaction

To the Whiteboard and to Jupyter…

Comparing UCB to Explore-then-Commit