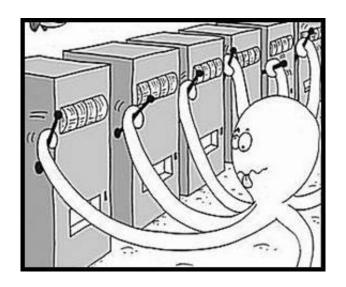
Multi-Armed Bandits

Michael Thomas

Multi-Armed Bandits (MAB)



Multi-Armed Bandits (MAB) Overview

- MABs get their name from a gambling scenario.
 - Note: A single slot machine is called a "one-armed bandit."
- Imagine a slot machine with 8 arms and each arm gives a different probability of winning.
- You don't know which arm is best, so you have to experiment.
- As you learn which is best, you'll want to experiment less and focus more on the arm with the best payout.
- Moving from the **experiment** phase to the **exploit** phase is difficult.
 - Spend too much time experimenting and you miss out on the chance to profit from the winning arm.
 - Start exploiting too soon and you might be focused on an arm that is not the best.
- Many algorithms exist to handle this, all of which are "multi-armed bandits."

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Multi-Armed Bandits (MAB) Key Characteristics of Problem

- Sequential decisions.
- Choosing from two or more different options (e.g, two or more arms).
- Uncertain about the payout from different options.
- Will have to chose many more times than there are options (arms).

Marketing Application – Selecting Ad Copy



- Which ad copy should we use?
- The one with the highest click through rate (CTR)?
- When are we certain that one of them has the highest CTR?
 - ▶ 1 click? 100 clicks? 10,000 clicks?



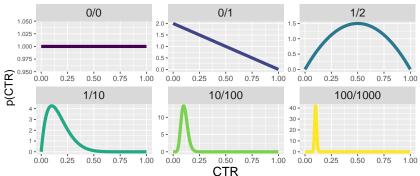
Quantifying our Beliefs about the CTR

- To answer the questions on the previous slide we need to quantify how much we know about the CTR of the different ads based on our experiments.
- Bayesian statistics offers a helpful and intuitive approach to this problem.
 - Specifies our "beliefs" about the CTR for each ad type.
 - ▶ Allows us to update our beliefs each time a new ad is shown.
 - ▶ Allows our beliefs to become more precise as more data is acquired.

Quantifying Our Beliefs on CTR

- For CTR the value must lie somewhere on [0,1].
- The beta distribution is convenient.
 - **ightharpoonup** Beta has two shape parameters: lpha and eta.
 - ▶ Set $\alpha = N_{\text{clicked impressions}} + 1$ and $\beta = N_{\text{not clicked impressions}} + 1$
 - ▶ This describes beliefs on the value of the true CTR.

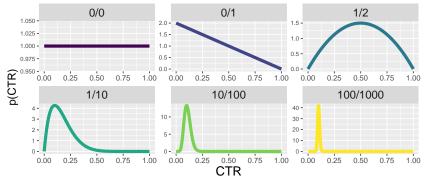
Beliefs on CTR for different (N clicks) / (N impressions)



Quantifying Our Beliefs on CTR

- At 0/0 beliefs are "flat." We have no data and therefore no idea what the CTR is. We give the same weight to every value on [0,1].
- \bullet At 0/1 we have just one impression delivered but no clicks. This gives a higher likelihood of lower CTRs, but without much nuance.
- \bullet At 1/2 we have one click out of two impressions. Our best guess for CTR is 0.5, but it could be many values around there.

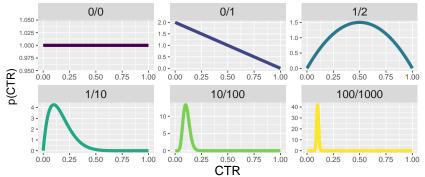
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Quantifying Our Beliefs on CTR

- At 1/10 we have one click out of ten impressions. We are much more confident that the CTR is less than 0.5, with most of the mass around 0.1.
- \bullet At 10/100 and 100/1000 we are increasingly confident that the CTR is close to 0.1.

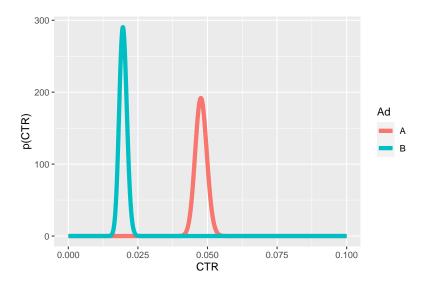
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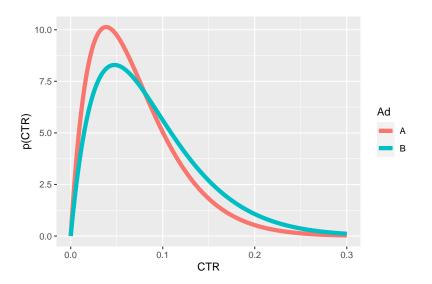
Poll Questions

Go to www.PollEv.com/mthomas

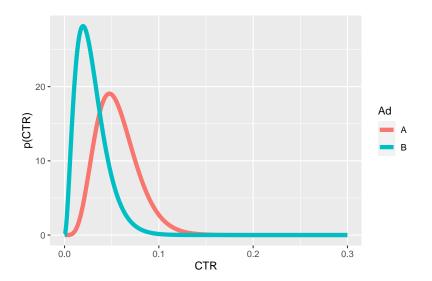
Compare Results from Ads



Compare Results from Ads

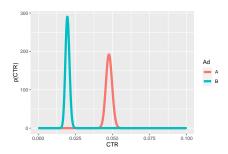


Compare Results from Ads



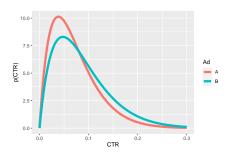
Thompson Sampling

- Simple method for balancing explore and exploit:
 - 1 Randomly draw a sample from each distribution.
 - Whichever sample is larger, show that ad next.
- Intuition:
 - When the distributions are similar then each ad has similar probability of being show next. This allows us to collect more information.
 - When the distributions are different, the one with the more favorable distribution is more likely to be chosen.



Given these beliefs about the CTR of two ads, should the firm

- Ans: Mostly explore
- Mostly exploit
- Neither
- About equal amounts of explore and exploit



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- Mostly explore
- Ans: Mostly exploit
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- About equal amounts of explore and exploit



Multi-armed Bandit problems have each of the following characteristics, except:

- It requires a sequence of decisions.
- It requires many options to chose from at each decision point.
- Ans: It requires that we are certain about the outcome associated with each decision.
- It involves an experimental phase.

Which of the following is *not* true about Thompson Sampling?

- It relies on beliefs about the CTR of different ads
- Ans: It runs faster when there are more ads to compare
- It is framed using Bayesian statistics
- It tends to find the optimal ad if given enough time.