



# Methods for Effective Online Testing in Real-Time Bidding

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Data scientist



# Intro

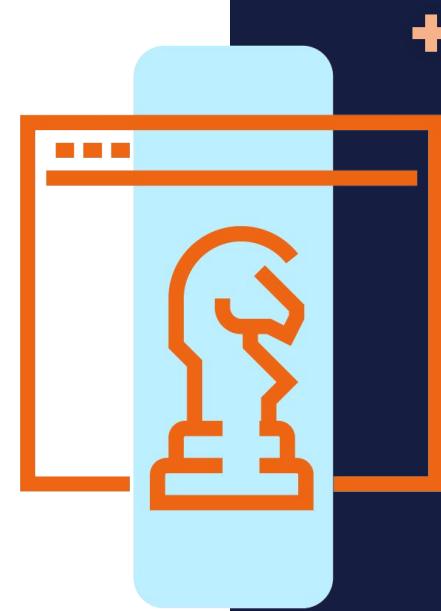
- ❑ Zemanta, an Outbrain Company
- ❑ Real-Time Bidding (RTB)
- ❑ We are one of the bidders

**Zemanta™**  
an  Outbrain Company



# Online Advertising

- ❑ The past:
  - ❑ direct publisher and advertiser deals
  - ❑ paid upfront for rental like billboards
  - ❑ more expensive upfront
  - ❑ only big advertisers
  - ❑ no guarantees about users



# Online Advertising

- ❑ The present:
  - ❑ use of middlemen
  - ❑ programmatic buying of ad space
  - ❑ real-time auctions
  - ❑ single placements
  - ❑ more accessible

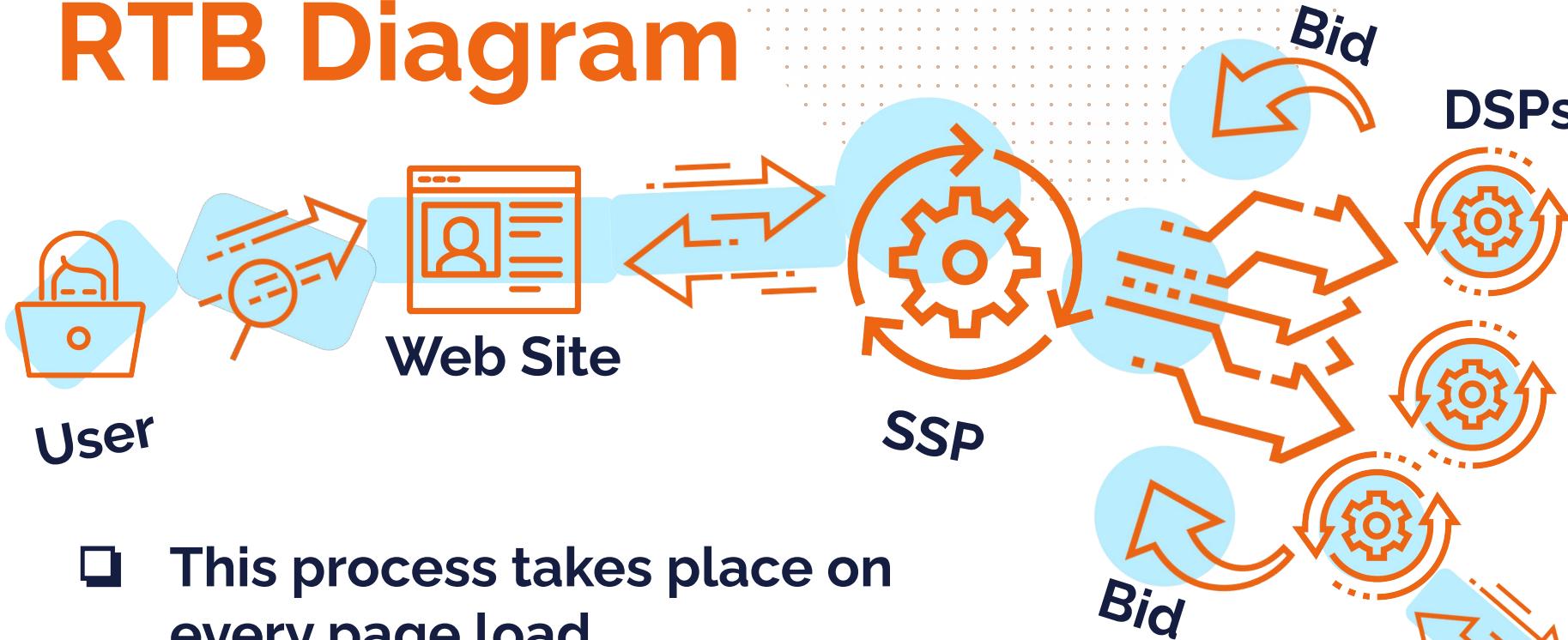


# RTB

- ❑ More auctions than stock exchanges
- ❑ Allows for targeted buying
- ❑ Basic participants:
  - ❑ Advertiser
  - ❑ Demand-side platforms (DSP)
  - ❑ Ad exchange
  - ❑ Supply-side platforms (SSP)
  - ❑ Publisher



# RTB Diagram



- This process takes place on every page load
- Takes less than 100ms
- most people don't even know it exists

Processes data and returns the bid

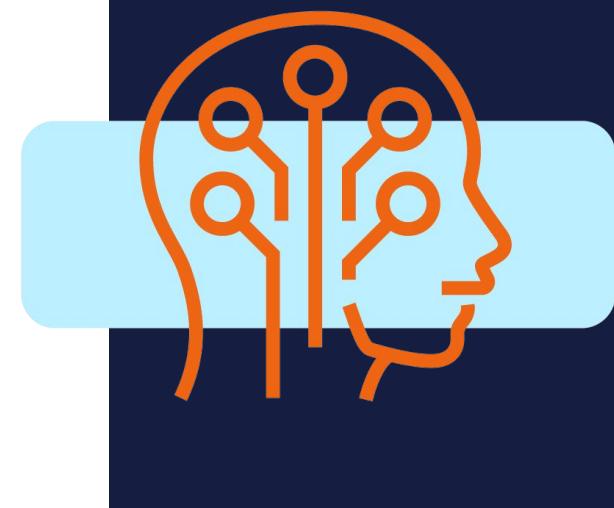
# Image Cropping Optimization

- ❑ Provided images don't always fit
- ❑ Solution: Cropping
- ❑ Crops alter the image
- ❑ We have millions of images
- ❑ Picking the best option is subjective



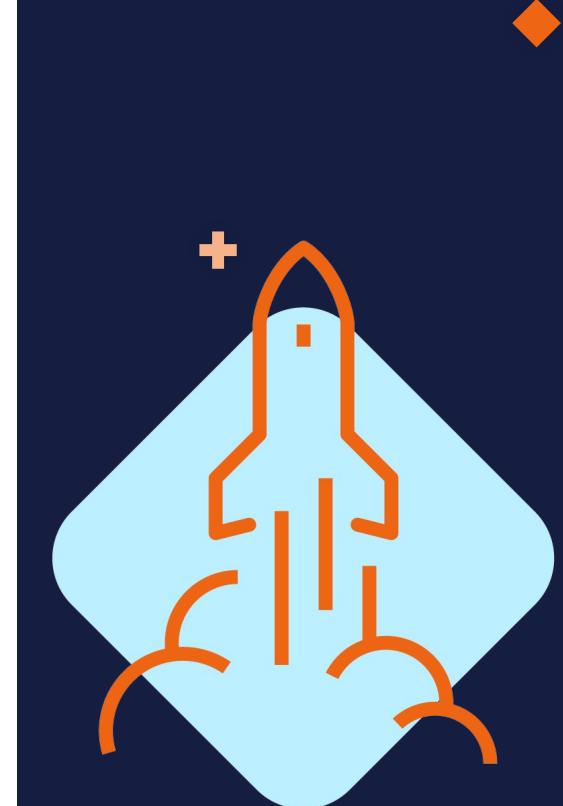
# Statistics to the Rescue

- ❑ Can we make it objective?
- ❑ Find the combinations that work best on average
- ❑ Leverage statistics
- ❑ Online tests come to mind



# Testing

- ❑ Code testing <> online tests
  - ❑ making sure your implementations work
  - ❑ making sure your ideas work
- ❑ Code testing is important but limited
- ❑ Online tests provide a framework for gauging the performance of your features
- ❑ Test as you fly.
- ❑ Test as close to the production as possible



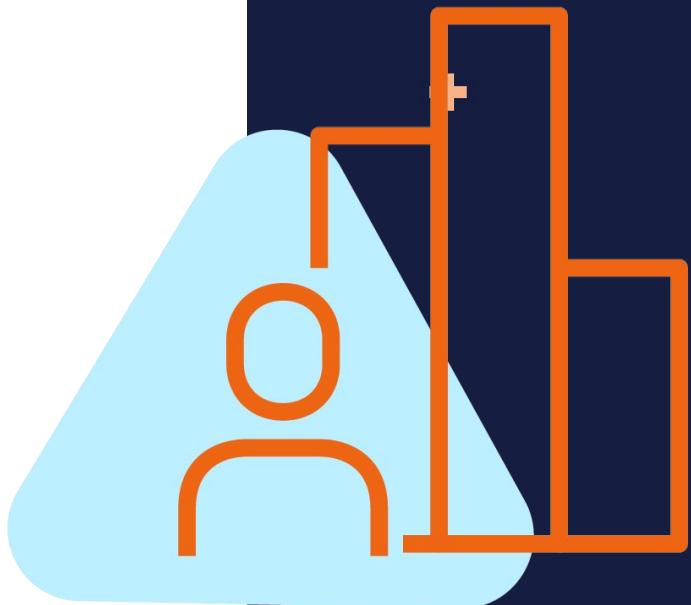
# Leveraging Online Tests

- ❑ Outside factors impact performance
- ❑ Testing online in production
- ❑ Truly actionable results
- ❑ There is some due diligence before going online



# Online tests

- ❑ Data hungry
- ❑ Zemanta processes 1.5+ mil requests per second
- ❑ Online tests can be cheaper than developing an elaborate simulation environment
- ❑ Data-driven decision and development
- ❑ Gaining traction in the industry



# A/B Tests

- ❑ Probably the most common
- ❑ Start with a hypothesis
- ❑ Pick a KPI as statistical variable
- ❑ Calculate needed examples
- ❑ Split traffic between groups uniformly
- ❑ Analyse results with a statistical test



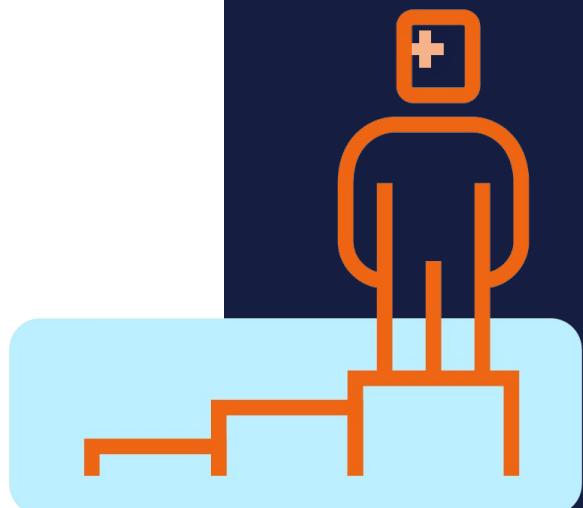
# Can We A/B Test?

- ❑ Comparing similar distributions => large pool of examples
- ❑ 1.5+ Million opportunities per second
- ❑ Trying to optimize millions of images
- ❑ Hard deadlines
- ❑ Average overall business results



# Multi-Armed Bandits

- ❑ Define the test as a MAB problem
- ❑ Allocation of limited resources between competing choice to maximize expected gain
- ❑ Exploit-explore tradeoff
- ❑ Different strategies



# Epsilon Greedy MAB

- ❑ Frequentist approach
- ❑ Separate traffic into explore and exploit
- ❑ Explore traffic uniformly distributed across bandits and measure their performance
- ❑ Apply best bandit on exploit traffic
- ❑ Reap rewards sooner
- ❑ Has some downsides



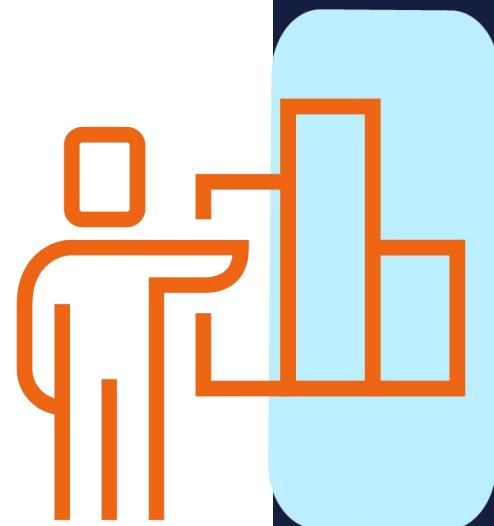
# Thompson Sampling

- ❑ Bayesian approach
- ❑ Set priors for bandits and sample them
- ❑ Pick best bandit based on sampled results
- ❑ Update priors and repeat
- ❑ Can start uniformly and converge to the best bandit
- ❑ Has some downsides as well



# MAB not the solution you were looking for

- ❑ We have to trust our code
- ❑ Hard to report exact lifts
- ❑ Changes in user experience
- ❑ Workarounds



# Hard Constraints

- ❑ 100 ms per request
- ❑ Sharded net of bidder nodes spread worldwide
- ❑ Central data store
- ❑ Sampling is an expensive operation



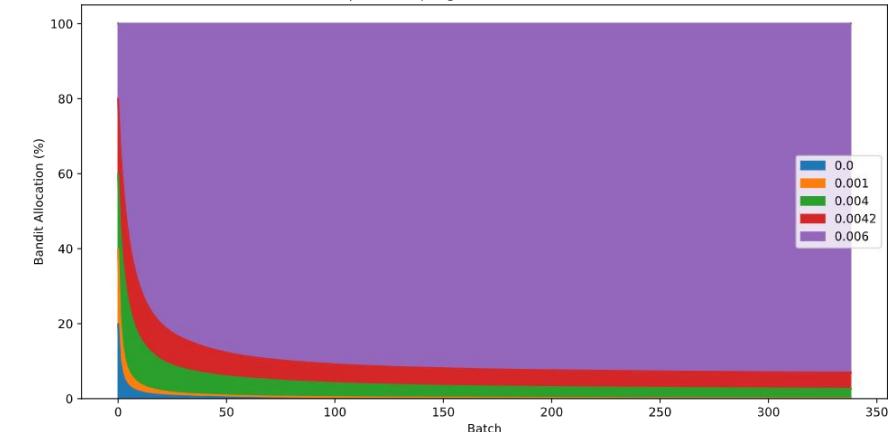
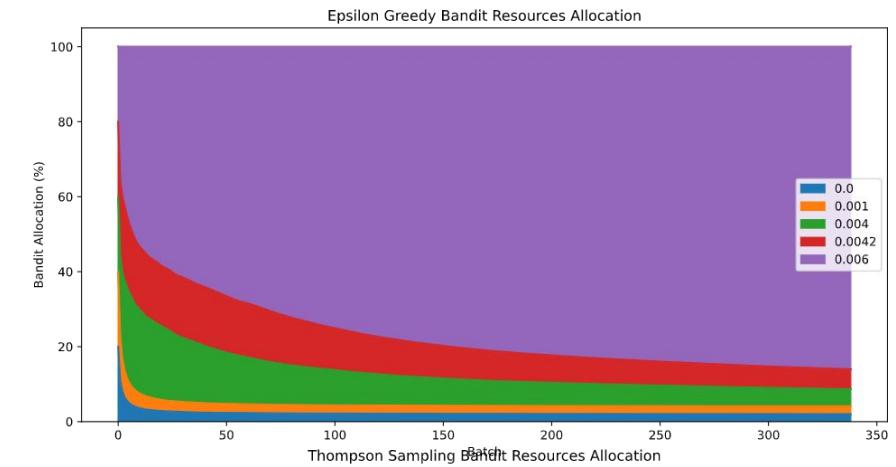
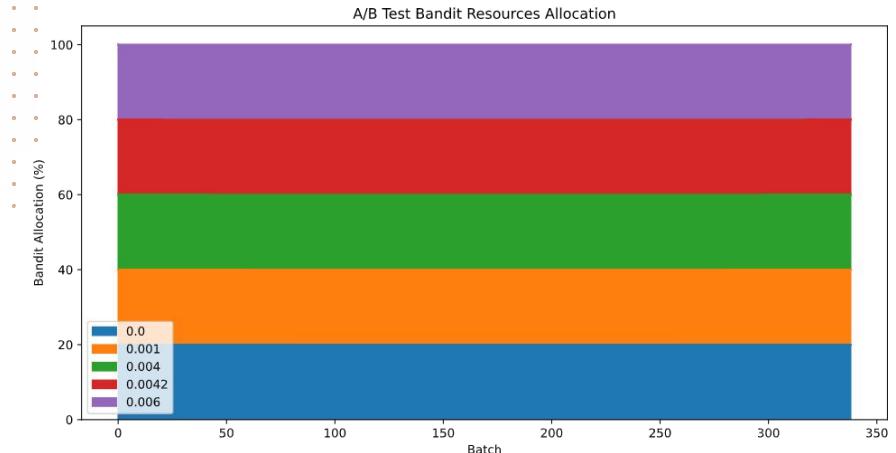
# MAB Going Online

- ❑ Workaround: batching
- ❑ Periodically
  - ❑ get data and update priors
  - ❑ sample prior distributions
  - ❑ create weights for bandits
  - ❑ pull weights into bidders
- ❑ Weighted lottery while bidding



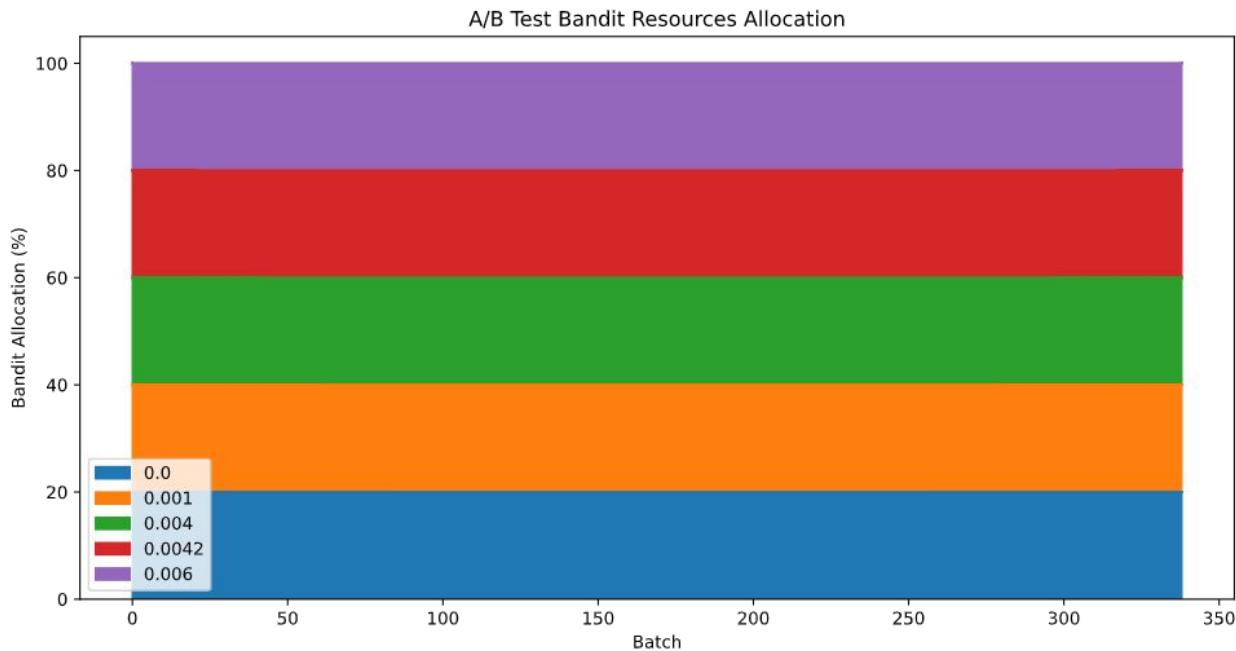
# Simulations

- ❑ Simple simulation environment
- ❑ Results are based on plugged in numbers
- ❑ Code available on [GitHub](#)



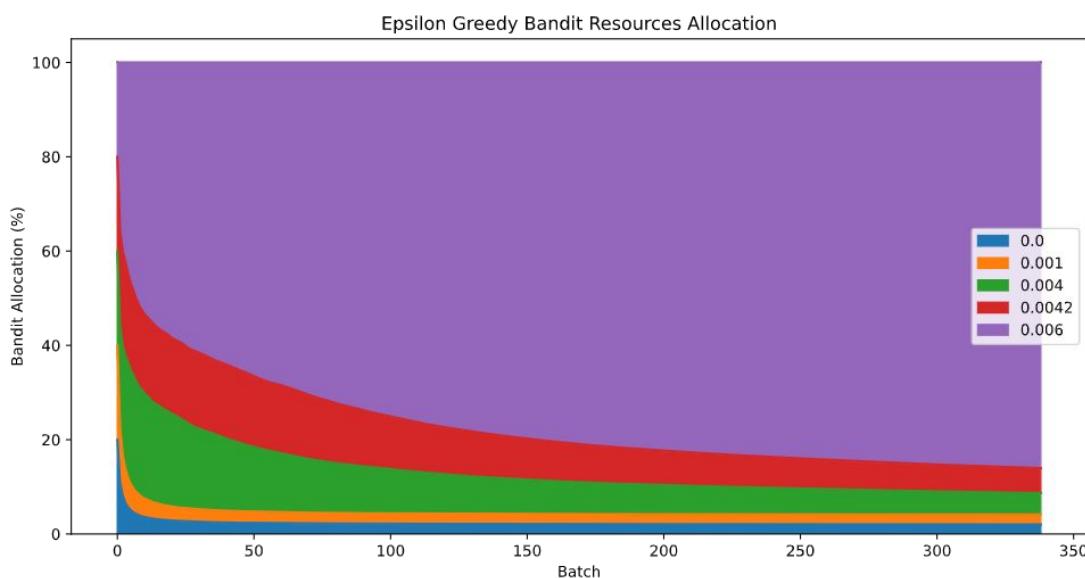
# A/B Test Allocation

- ❑ Uniform allocation between bandits
- ❑ This is expected behaviour
- ❑ The plots are cumulative



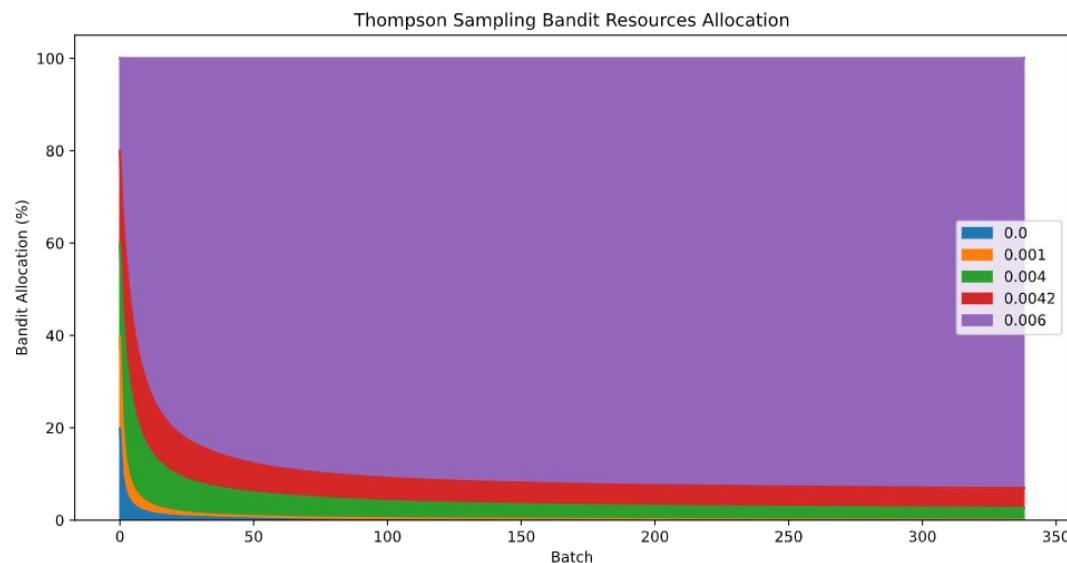
# Epsilon Greedy Allocation

- ❑ The best bandit is a lot more prevalent
- ❑ Hard to decide which is best at the start
- ❑ Exploration continues till we stop the test
- ❑ There are some add-ons to the base strategy



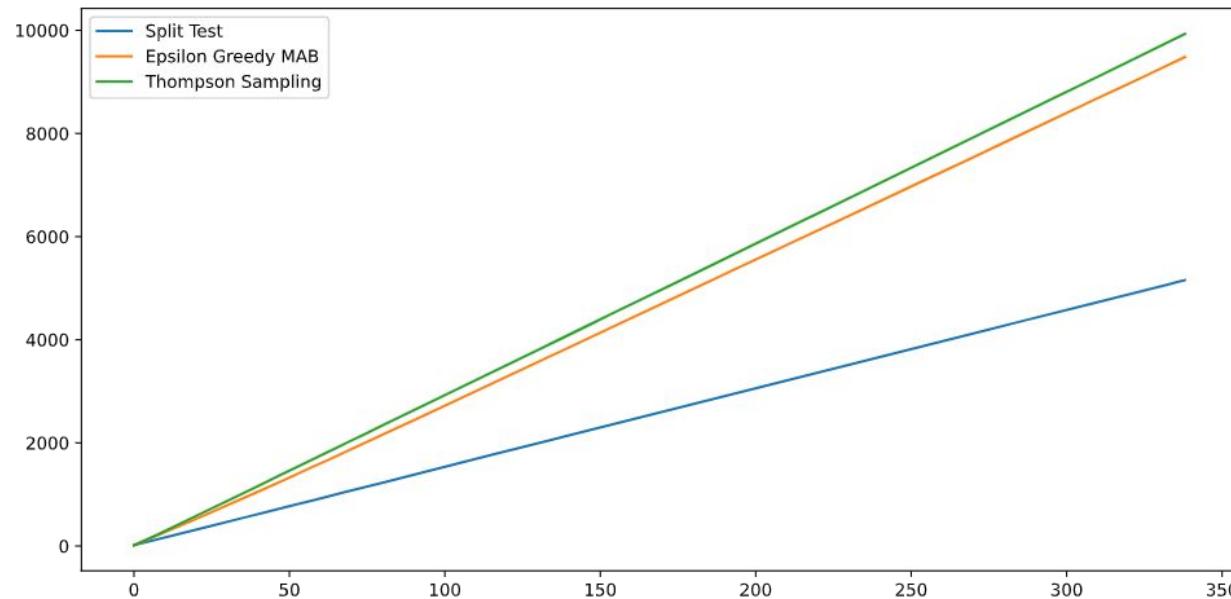
# Thompson Sampling Allocation

- ❑ Best bandit is preferred again
- ❑ Bandits that aren't performing get omitted
- ❑ Somewhat better than Epsilon-greedy
- ❑ Also has some add-ons



# Final Results

- ❑ Thompson sampling did perform best
- ❑ The margin between MAB methods is small
- ❑ MAB clearly outperformed A/B tests
- ❑ There are pros and cons to all methods
- ❑ You have to  
figure out  
which will  
work best



# Final Optimization and Test

- ❑ Exploration and exploitation of crops is done by Thompson sampling
- ❑ The whole system gets tested in an A/B test
- ❑ We get both
  - ❑ the benefits of fast exploitation
  - ❑ knowing how well the new system works



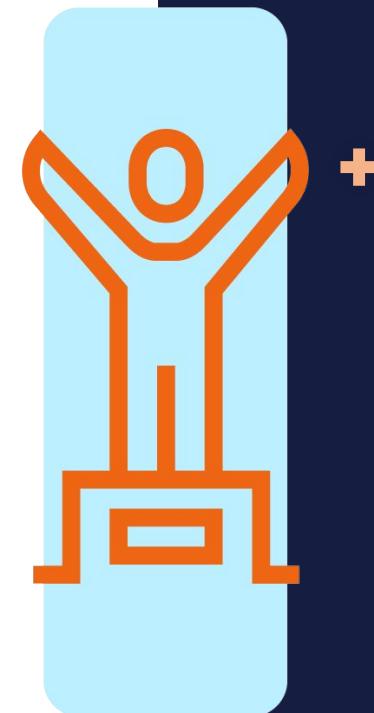
# Takeaways

- ❑ Online tests are great
- ❑ Small risks if done correctly
- ❑ There are different approaches to online testing, pick the one that suits your problem
- ❑ Scientific approach to development



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# Thank You.

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