A/B Testing, Statistical Experimentation and Reinforced Learning Are the Future of Product Development

Vamsi Sistla

April 1st 2021

Vamsi Sistla

About Me

- **Currently –**
  - **Head of Data Science and Machine Learning @ Unify**
- **Past –**
  - **15+ years of IT experience**
  - **7+ Years of Data Science/Machine Learning leadership experience**
  - **Founded & operated 2 venture backed startups as CTO**
  - **Advisor/Mentor to Women In Voice (WiV) and Watson Institute**

Agenda

- Module #1 - Basics of AB Testing
- Module #2 - AB Testing Quick Test Run
- Module #3 - Multi Arm Bandit & Reinforced Learning
- Module #4 - Summary and Closing Comments

Module #1
Intro AB Testing

What is AB Testing?

What is AB Testing?

Why AB Test?

What is AB Testing?

- What you know vs what you want to know
  - Incremental Improvements
- Compare the two versions of a variable to find out which performs better in a controlled environment
  - Established method of experimentation

Popular AB Testing Tools for Online

- Optimizely
- VWO
- Convert Experiences
- SiteSpect
- AB Tasty
- Evolv
- Google Experiments
- Qubit
- Adobe Target
- Marketing Tools With Built-In Testing

Source: conversionsciences.com

AB Testing Applications

- Web and mobile product development
- Life sciences – drug development
- Behavioral sciences and Economics
- Anywhere Causality should be assessed

Some definitions & terms

Hypothesis

"IF ____________ [Variable], THEN ____________ [Result] DUE TO ____________ [Rationale]."

The Variable:
A website element that can be modified, added, or taken away to produce a desired outcome.

Result:
The predicted outcome. (More email sign-ups, clicks on a call to action, or another type of behavior.)

Rationale:
Demonstrate that you have informed your hypothesis with research: what do you know about your visitors from your qualitative and quantitative research that indicates your hypothesis is correct?

Source: optimizely.com

- A **hypothesis** is a prediction that states what is being changed, what you believe the outcome will be, and why. Running the experiment will either prove or disprove your **hypothesis**
- Null Hypothesis
  - The null hypothesis is a baseline assumption that no real effect behind the data your test has produced
- Alternate Hypothesis
  - This challenges the status quo (the null hypothesis) and is basically a hypothesis that the researcher believes to be true.

Some definitions & terms

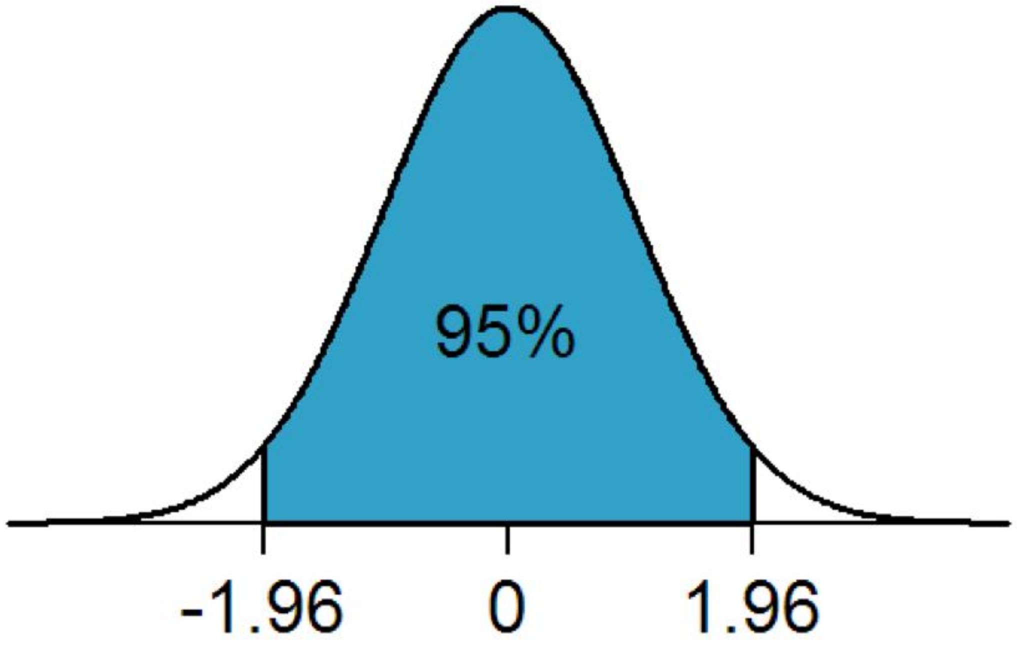
Control and Treatment

Source: Towards data science

- The **control** is simply the "Version A" of your test -- it's what you normally use as your landing page, email, call-to-action, headline, etc.
- The **treatment** is the "Version B" of your test -- it's the version that has the changes you're trying to test.
- A/B **Testing** is a way of conducting an experiment where you compare a **control** group to the performance of one or more **test** groups by randomly assigning each group a specific single-variable **treatment**.

Some definitions & terms

Statistical Significance

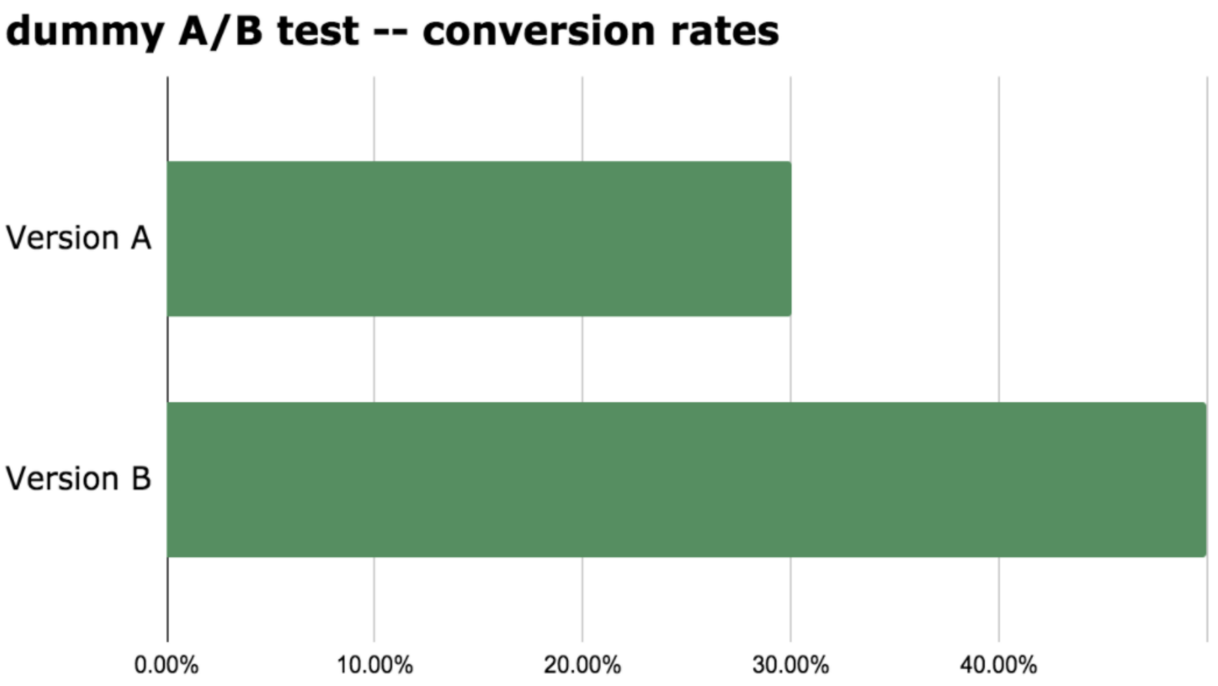


Source: Wikipedia

- Statistical significance is useful in quantifying uncertainty
- In AB testing experiments, **statistical significance** is how likely it is that the difference between your experiment's **control version** and **test version** isn't due to error or random chance.
- For example, if you run a test with a 95% significance level, you can be 95% confident that the differences are *not occurring by chance*.

Some definitions & terms

Statistical Significance



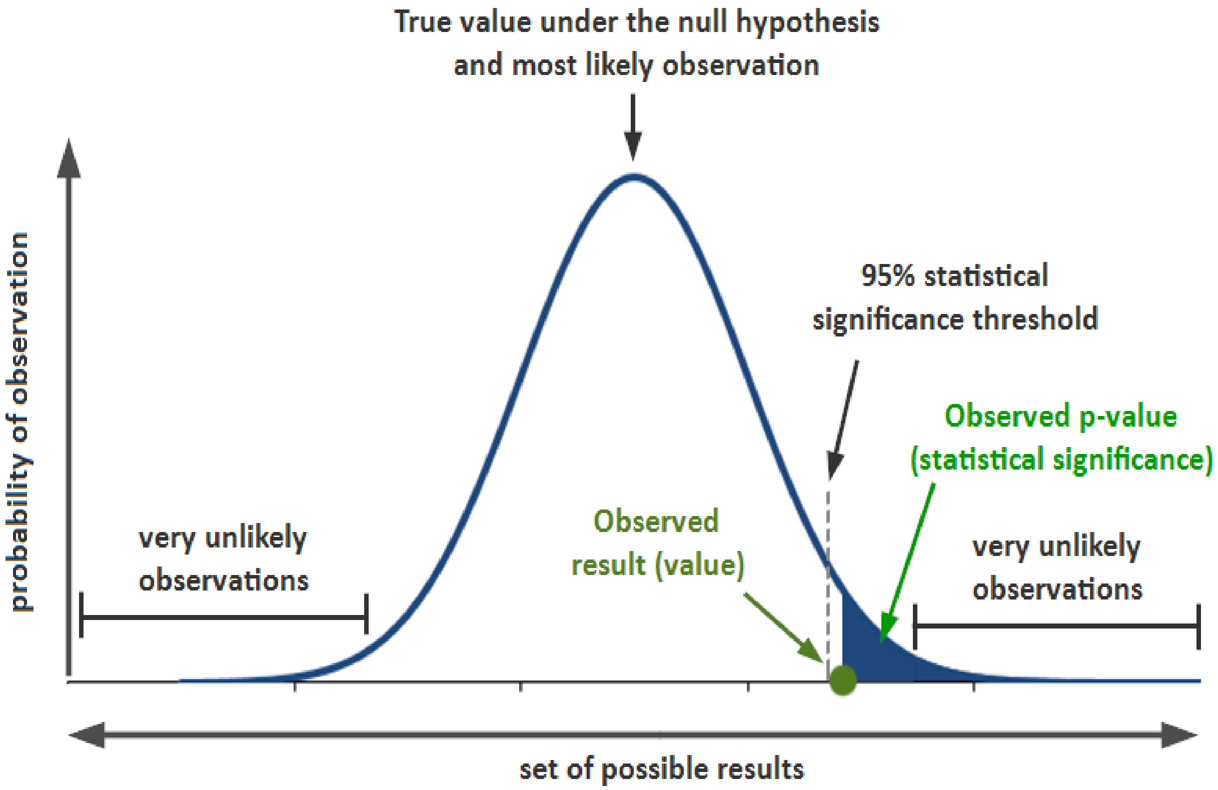
Version A: 10 users – 3 conversions – 30% conversion rate

Version B: 10 users – 5 conversions – 50% conversion rate

Source: Data36.com

Some definitions & terms

P-Value

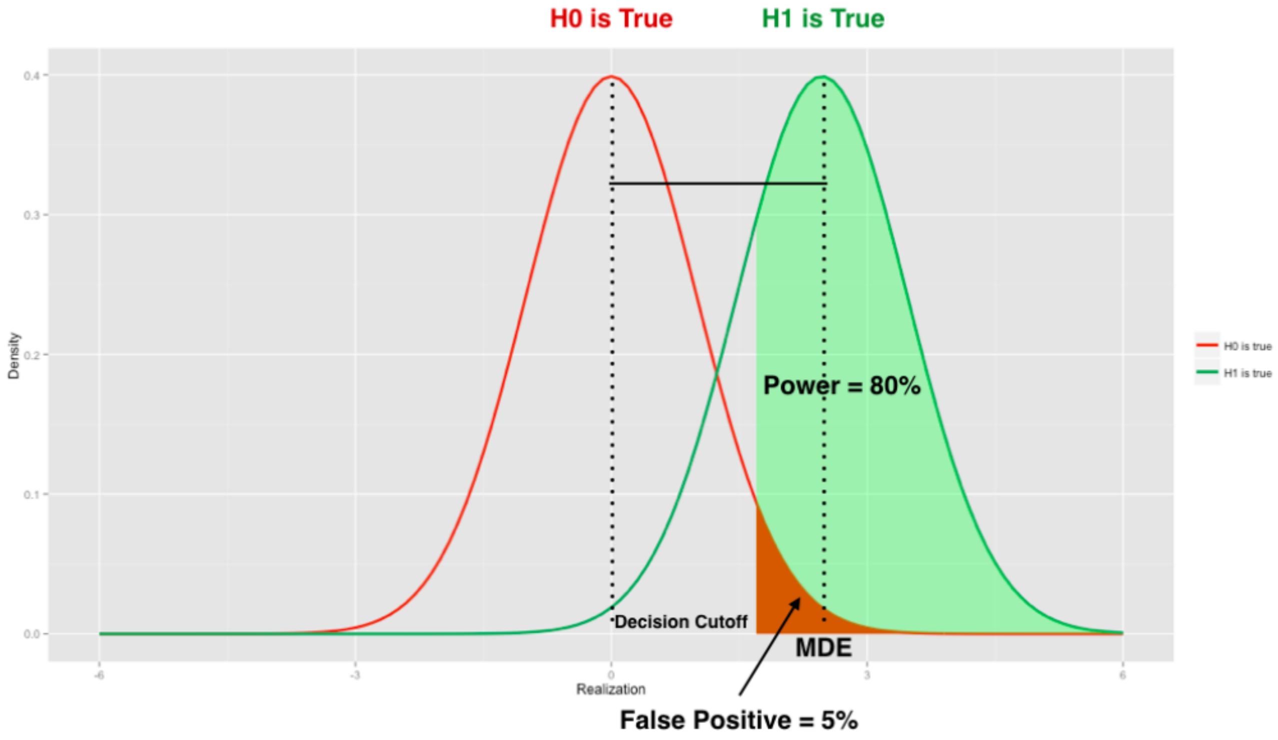


Source: SimplyPsychology

- **P-value** – a measure of evidence against the null hypothesis.
- **P-value** is created to show you the exact probability that the outcome of your ***A/B test*** is a result of chance.
- The level of **statistical significance** is often expressed as a **p-value between** 0 and 1. The smaller the **p-value**, the stronger the evidence that you should reject the null hypothesis. A **p-value** less than 0.05 (typically ≤ 0.05) is **statistically significant**.

Some definitions & terms

Minimal Detectable Effect

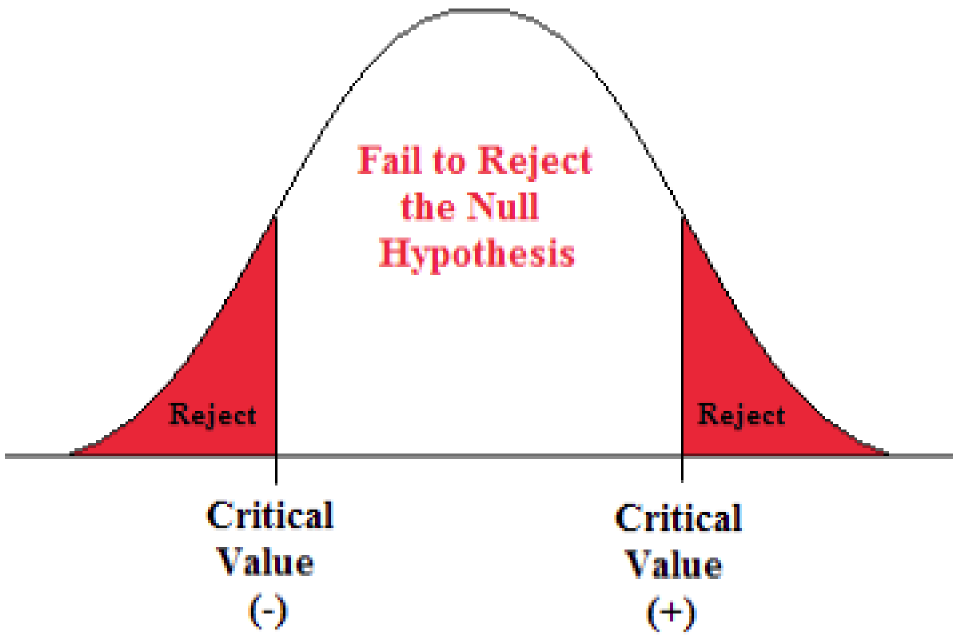


Source: Twitter blog

- **Minimal Detectable Effect (MDE)** refers to the minimal amount of change outside of error that reflects true change
- The MDE is defined as a valid change in data/outcome/result that is not due to chance.

Some definitions & terms

Rejecting the Null Hypothesis



Source: lumenlearning

- Rejecting Null Hypothesis means
  - No difference between A & B variants
  - The difference is too small to be relevant
  - There is enough difference but the **sample size** is too small to detect it.
  -

Some definitions & terms

Sampling Size

Source: Convertize

- **Sample size** calculation is based on your conversion rate, MDE, Statistical Significance and Statistical Power.
- *A sample too small* will not permit you to detect a statistically significant effect, while a *sample too large* may be a waste of limited resources.
- Sample size depends on many factors - such as what's your definition of a winner? Which depends on your baseline When choosing sample size, consider the marginal value of added observations or, in other words, the trade-offs between accuracy and cost.

Some definitions & terms

Relationship With Sampling Size

	Relationship with Sample Size
Effect Size / Minimum Detectable Effect Size	**Inverse:** smaller the effect size, the larger the required sample size
Significance Threshold	**Inverse:** the lower the threshold, the larger the required sample size
Power / Sensitivity	**Direct:** larger the Power, the higher the required sample size

Source: Paulynn Yu blog

Some definitions & terms

Type 1 Error

	Reality	
	H_0 is True	H_1 is True
Do Not Reject H_0	Correct Conclusion	Type II Error
Reject H_0	Type I Error	Correct Conclusion

Source: Lumenlearning

- A type 1 error, or **alpha**, is made when H_0 is rejected, when in fact H_0 is true.
- Alpha is the probability of saying on the outcome of a test there is an effect for the manipulation, while on population level there actually is none. This is called **reliability.**

Some definitions & terms

Type 2 Error

	Reality	
	H_0 is True	H_1 is True
Do Not Reject H_0	Correct Conclusion	Type II Error
Reject H_0	Type I Error	Correct Conclusion

Source: LumenLearning

- A type 2 error, or **beta**, is made when H_0 is *not* rejected, when in fact H_0 is *not* true.
- Beta is the probability of saying on the outcome of a test there is no effect for the manipulation, while on population level there actually is. This is called **power**.
- Power is a function of alpha, sample size and effect.
- The smaller alpha, sample size or effect the smaller power is.

Some definitions & terms

Type 1 Error , Type 2 Error & Sample Size

As (Type 1 error) α increases, (Type 2 error) β decreases

As α decreases, β increases

As sample size increases (n), both **α and β** decrease

Module #2
Test Drive AB Testing

AB Testing Test Drive

Post Test Drive Comments

- With the power of Statistics and Data Sciences in general, product managers can use more tools to build superior products than ever before
- Historically, logs, data and analysis comes at the tail end of product development.

Module #3
Multi Arm Bandits & Reinforced Learning

Drawbacks with Traditional AB Testing

In case of traditional AB testing

- We have to select random samples. You don't know what should be size of your sample.
- Most of AB testing is online – it is offline – meaning you learn about which is better after the fact.
- AB testing is time consuming – and you don't know when to stop.
- While you are at it, you might also alienate some segment of your customer who got suboptimal offering.
- Often, traditional AB testing is limited to simple decisions – not complex systems – especially when they are sequential decisions with long term goals.

Traditional AB Testings vs Reinforced Learning

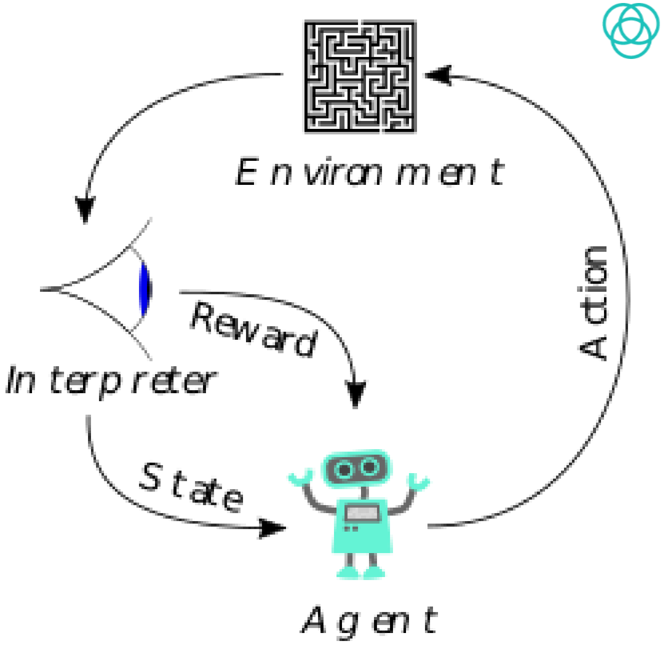
Pros and Cons between Traditional AB Testing vs AB Using Reinforced Learning

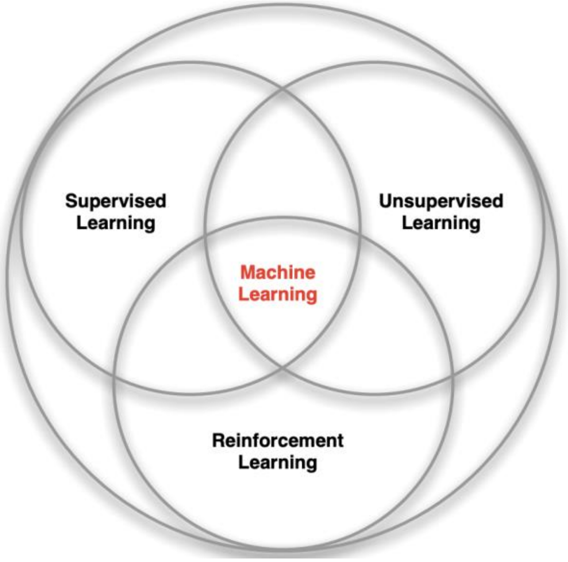
Traditional AB Testing	Reinforced Learning AB Testing
AB testing is a manual selection of what to try to improve products	Reinforced Learning is an automated selection process where the algorithm will search and select features that may improve the product
Often is best to uncover improvements in user experience without simple attribution (outcomes that may be too difficult to quantify or engineer as a goal-seek exercise)	Far more efficient and comprehensive. Ideal for complex and sequential decisions. Ideal for outcomes with long incubation period.
Comparing only a few versions at a time	Ideal for many versions and complex use cases. Better for specific outcomes with more direct attribution
Trial run for something ahead of production	Can Iterate while in production and quality will improve in real time. Far less resource and time intensive than AB testing (*depending on quality of data)

Reinforcement Learning

Overview

- Reinforcement learning (RL) is an area of ML with intelligent agents that take actions in an environment in order to maximize cumulative reward
- Reinforcement learning is one of three basic ML methods, alongside supervised and unsupervised learning.
- The focus is on finding a balance between **exploration** (of uncharted territory) and **exploitation** (of current knowledge)



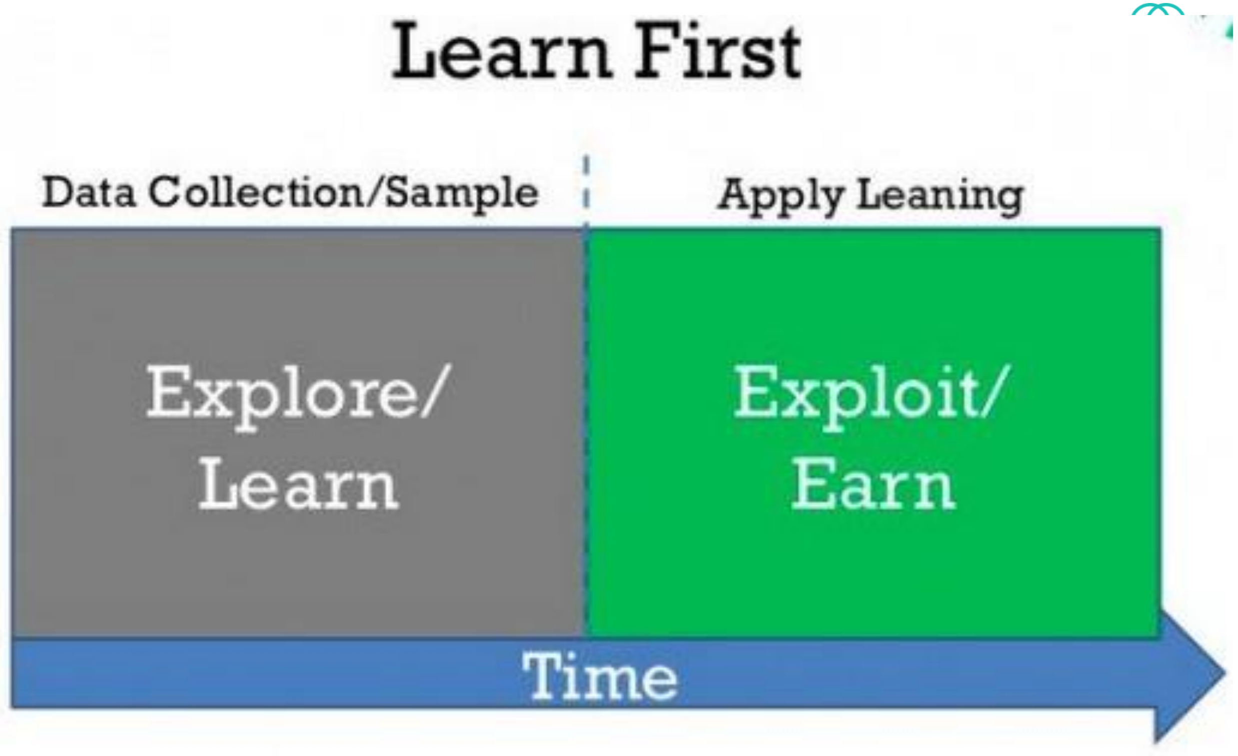


Source: Wikipedia

Reinforcement Learning

Exploration and Exploitation

- Reinforcement learning is like trial-and-error learning
- The agent should discover a good policy from its experiences of the environment without losing too much reward along the way
  - **Exploration** finds more information about the environment
  - **Exploitation** exploits known information to maximize reward
- It is usually important to explore as well as exploit



Source: Prakhar Mishra blog

Reinforcement Learning

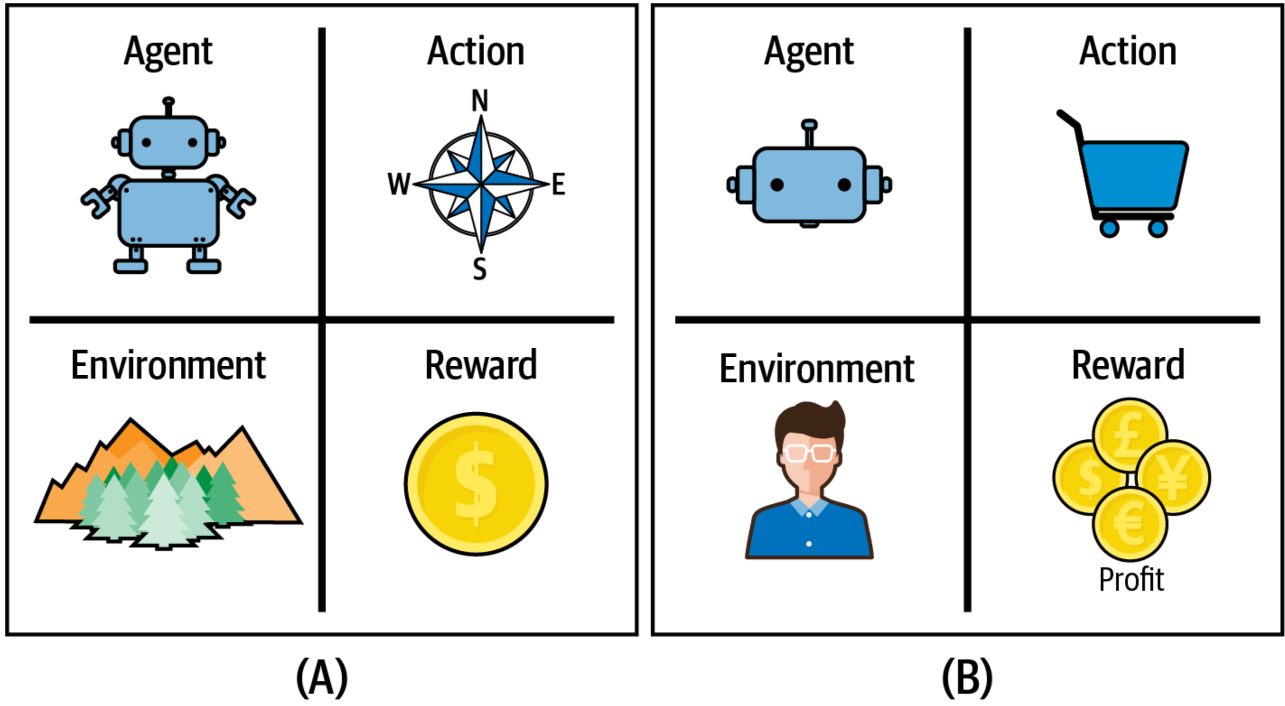
Exploration and Exploitation Examples

- Restaurant Selection
  - Exploitation - Go to your favorite restaurant
  - Exploration - Try a new restaurant Online Banner
- Advertisements
  - Exploitation - Show the most successful advert
  - Exploration - Show a different advert
- Game Playing
  - Exploitation - Play the move you believe is best
  - Exploration - Play an experimental move

Reinforcement Learning

Three Core Aspects

- Markov Decision Process (MDP)
  - An ***agent*** influences the observed behavior of a stochastic system (the ***environment***) by choosing *actions*. The goal is to choose the set of **actions** that allow the system to behave in an optimal way, as defined by some success criterion (the ***reward***).
- Dynamic Programming
  - is a collection of algorithms that can solve a problem with *perfect model of the environment and where an agent can only take discrete actions.*
- Monte Carlo
  - Monte Carlo Simulations Are Like Unit Tests for Bandit Algorithms



Example (A) shows a robot that intends to move through a maze to collect a coin.
Example (B) shows an ecommerce application that automatically adds products to users' baskets, to maximize profit.

Source: [Reinforcement Learning]() by Phil Winder

RL – Some Examples

Few RL examples as related to AB Testing

- Comparing Model Performance Using RL techniques.
- RL for Personalization at Gaming Companies
- Machine Translation At Scale
- Question & Answer Use Cases In Large Document Repos
- Cathy WU – UC Berkeley/MIT – Built a traffic management scenario (Deep RL) -
  - https://sites.google.com/view/ieee-tro-flow/home

RL – Multi Arm Bandit Algorithms

What is MAB?

Multi-armed bandits (MAB) is a type of RL.

Multi-armed bandits extend RL by ignoring the state and try to balance between exploration and exploitation.

Applications

- Website design
- Clinical trials
- Marketing & Recommender Systems

A multi-armed bandit solution is a ‘smarter’ or more complex version of A/B testing that uses machine learning algorithms

- Optimizely

Bandits vs ML

How are Bandits different from typical ML algorithms?

Unlike standard machine learning tools, bandit algorithms aren’t simply black-box functions you can call to process the data you.

Bandit algorithms have to actively select which data you should acquire and analyze that data in real-time.

Indeed, bandit algorithms support two types of learning that are not present in standard ML examples:

- ***active learning***, which refers to algorithms that actively select which data they should receive; and
- ***online learning***, which refers to algorithms that analyze data in real-time and provide results on the fly.

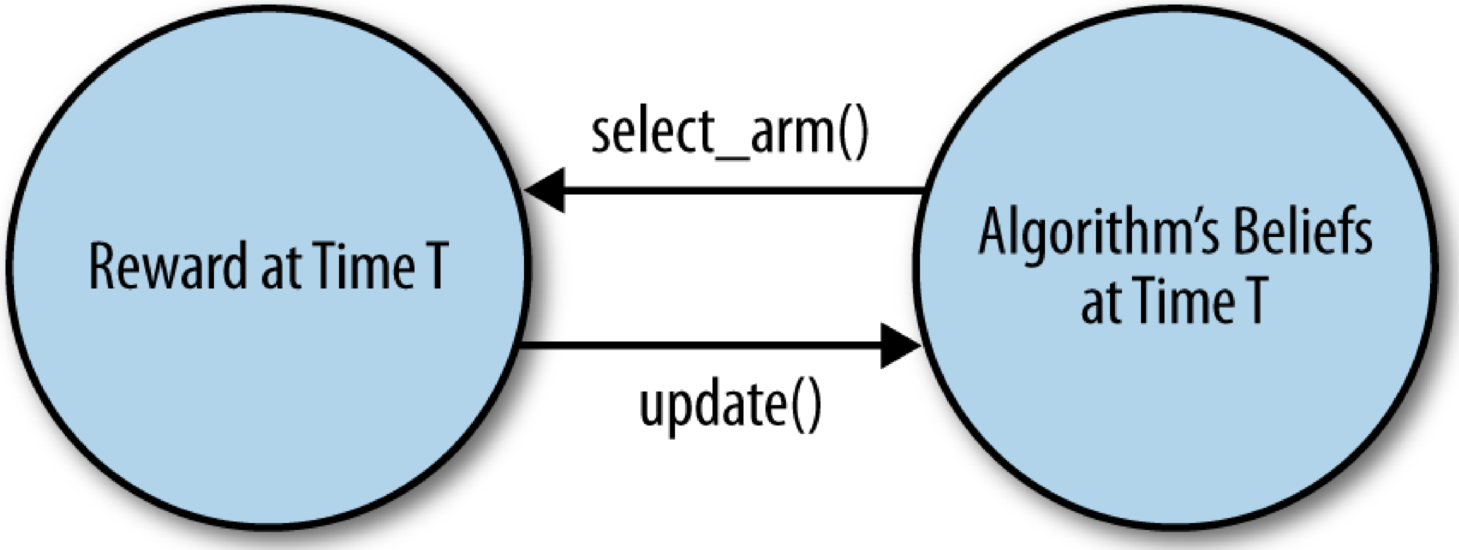
RL – Multi Arm Bandit Algorithms

So, how to use MAB to do AB Testing?

- Reward Engineering
  - To quantify performance, the result of an action must be measurable. In RL, this is the purpose of the reward.
  - There are many ways to quantify the performance.
- The Actions
  - Bandit approach to optimize your returns.
  - Compromise between exploitation and exploration
- The environment
  - If you have prior data - A simulated environment that can mimic a real world scenario?
  - If you don't have prior data – then explore the possibility of using a segment of the real world environment

RL – Multi Arm Bandit Algorithms

Rewards



- Behavior of Algorithm depends on the data
- What data the algorithm sees depends on its behavior

RL – Multi Arm Bandit Algorithms

Actions

input: a exploration probability $0 \leq \epsilon \leq 1$,

Initialize $r^{avg}(a) \leftarrow 0, N(a) \leftarrow 0$, for each $a \in \mathscr{A}$

loop for ever:

$$a \leftarrow \begin{cases} \underset{a_s \in \mathscr{A}(s)}{\text{argmax}}\; r^{avg}(a_s) & \text{with probability } 1 - \epsilon \text{, breaking ties randomly} \\ \text{random } a & \text{with probability } \epsilon \end{cases}$$

Present action a in the environment and receive reward r

$N(a) \leftarrow N(a) + 1$

$$r^{avg}(a) \leftarrow r^{avg}(a) + \frac{1}{N(A)}\left[r - r^{avg}(a)\right]$$

- Average of all the rewards
- Iterative Online Approach
- The environment

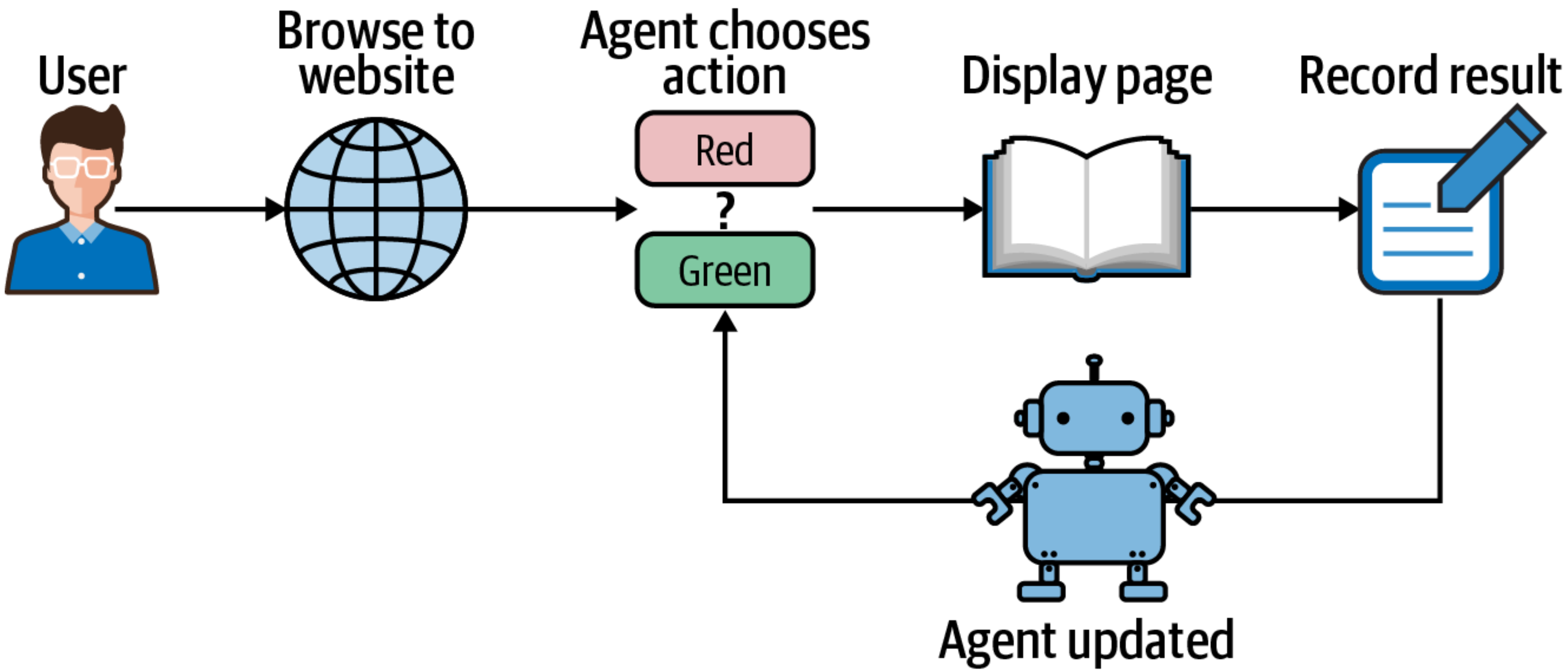
RL – Multi Arm Bandit Algorithms

Environment & running the experiment

function ENVIRONMENT$(a, p(a))$

input: The action, a, and its probability, $p(a)$

output: $r \leftarrow 1$ with probability $p(a)$, else 0.



Bandit Algorithms

Types of Bandit Algorithms

- Stochastic Bandits
  - Ex – Epsilon Greedy, Uniform Exploration, Adaptive Exploration
- Bayesian Bandits
  - Ex – Thompson Sampling
- Lipschitz Bandits
  - Ex – Continuum Armed
- Adversarial Bandits
- Linear Bandits
- Contextual Bandits

Bandit Algorithms

Epsilon Greedy - Definition

- The epsilon-Greedy algorithm is one of the easiest bandit algorithms tries to be fair to the two opposite goals of exploration and exploitation by using a mechanism of randomly choosing one of the options.
- That randomness is set by epsilon - ϵ
- It works by oscillating between (A) exploiting the best option that it currently knows about and (B) exploring at random among all of the options available to it

Arm

- Arm is this algorithm is option. So, in case of A/B testing, it would be 2 options or arms.

Bandit Algorithms

Epsilon Greedy

With probability $1 - \epsilon$, the algorithm ***exploits*** the best known option.

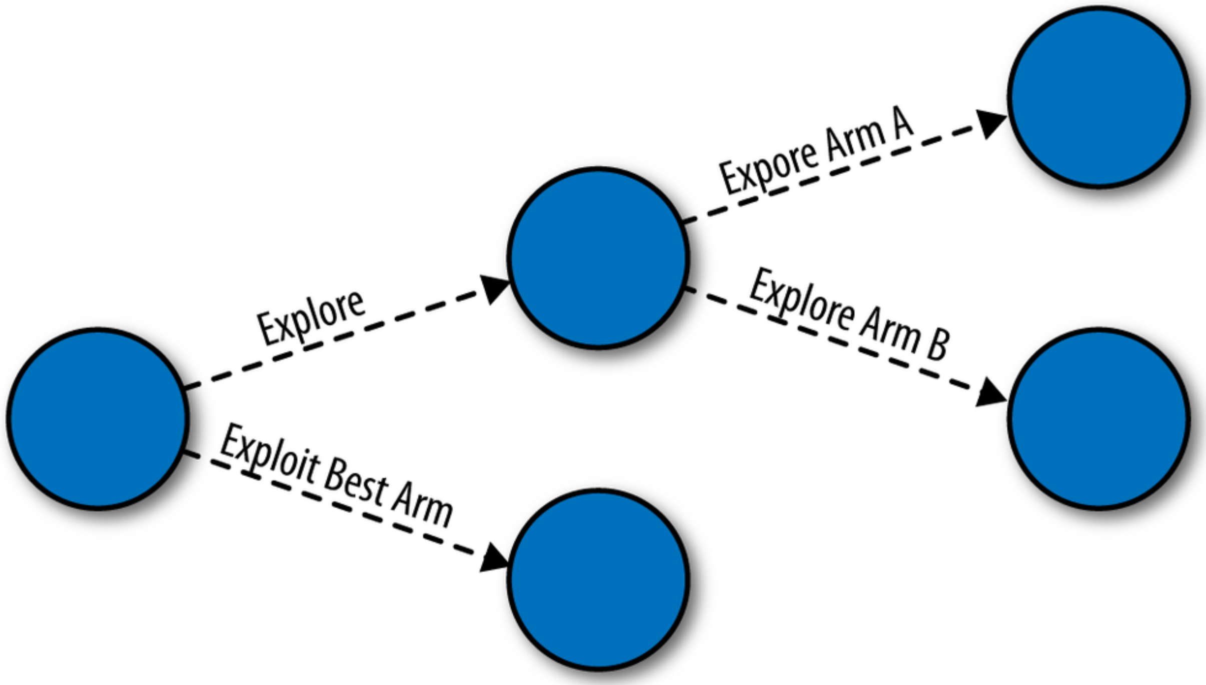
With probability $\epsilon / 2$, the algorithm ***explores*** the best known option.

With probability $\epsilon / 3$, the algorithm ***explores*** the worst known option.

Bandit Algorithm Test Drive

Epsilon Greedy Algorithm

- Greedy Algorithm that adds some randomness when deciding: Instead of picking always the best available option, randomly explore options with a probability $= \epsilon$ or pick the best option with a probability $= 1 - \epsilon$.
- ϵ is a hyper-parameter that needs to be tuned based on the experiment, i.e. there is no value that works best on all experiments

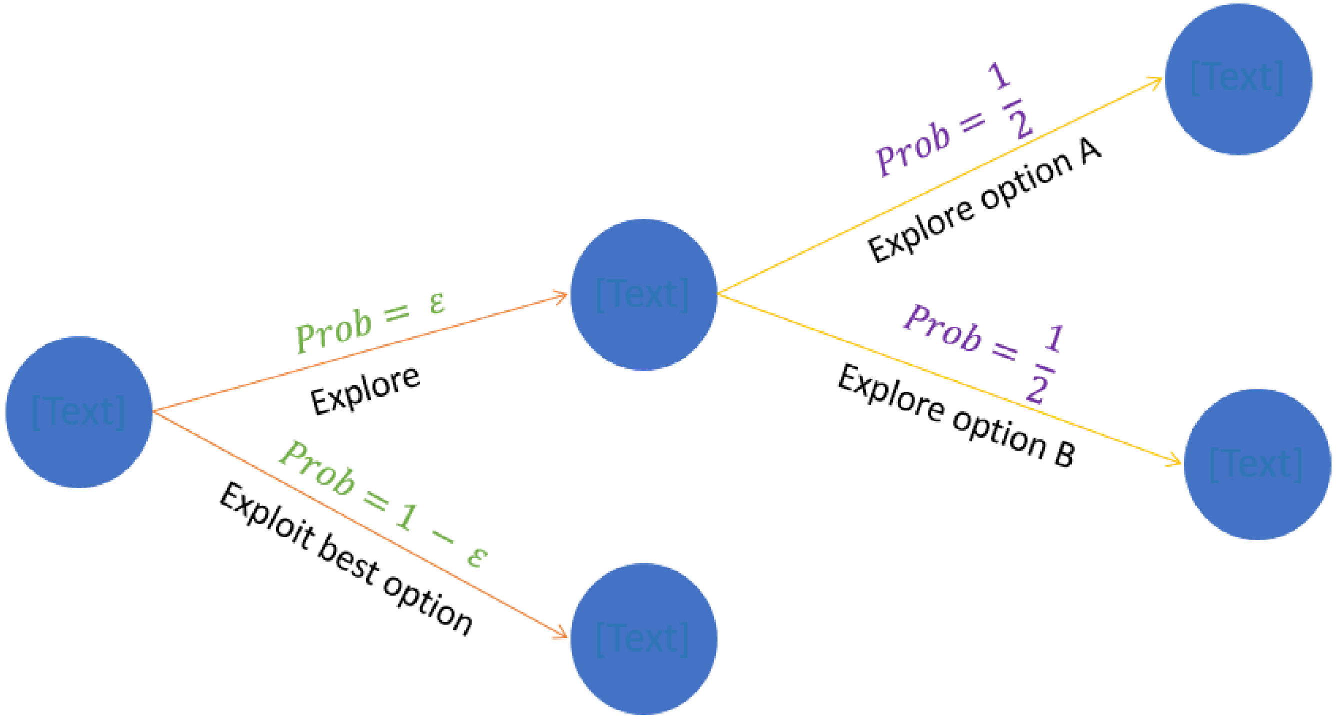


The epsilon-Greedy Algorithm

Bandit Algorithm Test Drive

Multi Arm Bandits - Demo 1

- In this demo, author used coin toss as the task.



Source: imaddabbura.github.io

Bandit Algorithm Test Drive

Notes before we do the test drive

- Some of the code from This repository was forked from John Myles White's "BanditsBook" repository.
    - https://pypi.org/project/banditsbook/
    -

- Some from Dr. Phil Winder's work in RL Book
    - https://rl-book.com/
- Other comments

Module #4
Wrap up and Summary

Epsilon Greedy Takeaways

Some Takeways after the test drive

- The epsilon-Greedy algorithm does eventually figure out which arm is best no matter how epsilon is set. But the length of time required to figure our which arm is best depends a lot on the value of epsilon.
- What’s appropriate for you depends on how long you intend to run your algorithm and how different the arms you’re testing will be

Key Takeaways

Final Take aways of the tutorial

- When AB testing is not practical, is it fair to say MAB algorithms can help simulate users and experiment through variations quickly and efficiently? (if not generating valuable data for other analysis)
- Traditional AB testing worked wonders for websites and mobile apps but comes with many challenges.
  - Especially ideal non sequential and binary decisions.
  - Risk of alienating your users and prospective customers
- Product development should start using RL algorithms to learn and iterate
  - Multi Arm Bandit Algorithms are super powerful

Blogs & Articles

- Power, minimal detectable effect, and bucket size estimation in A/B tests - **https://blog.twitter.com/engineering/en_us/a/2016/power-minimal-detectable-effect-and-bucket-size-estimation-in-ab-tests.html**
- Understanding Power Analysis in AB Testing - **https://towardsdatascience.com/understanding-power-analysis-in-ab-testing-14808e8a1554**
- Imad Dabbur Blog on Epsilon Greedy Algorithm -**https://imaddabbura.github.io/**
  - He implemented based on the book - Bandit Algorithms for Website Optimization
- Google Colab - ### For those of you want a refresher for Google Colab, here's a source for you to get started - https://towardsdatascience.com/getting-started-with-google-colab-f2fff97f594c

- Another blog - https://github.com/raffg/multi_armed_bandit
- Code & Files
  - I have ran the demos using Google Collab. So, you don't need to do any special setup on your laptop. If you have Gmail a/c, you are off to races.
  - Location of these files –