Recommendation Systems

BI, metrics, AB-tests, bandits

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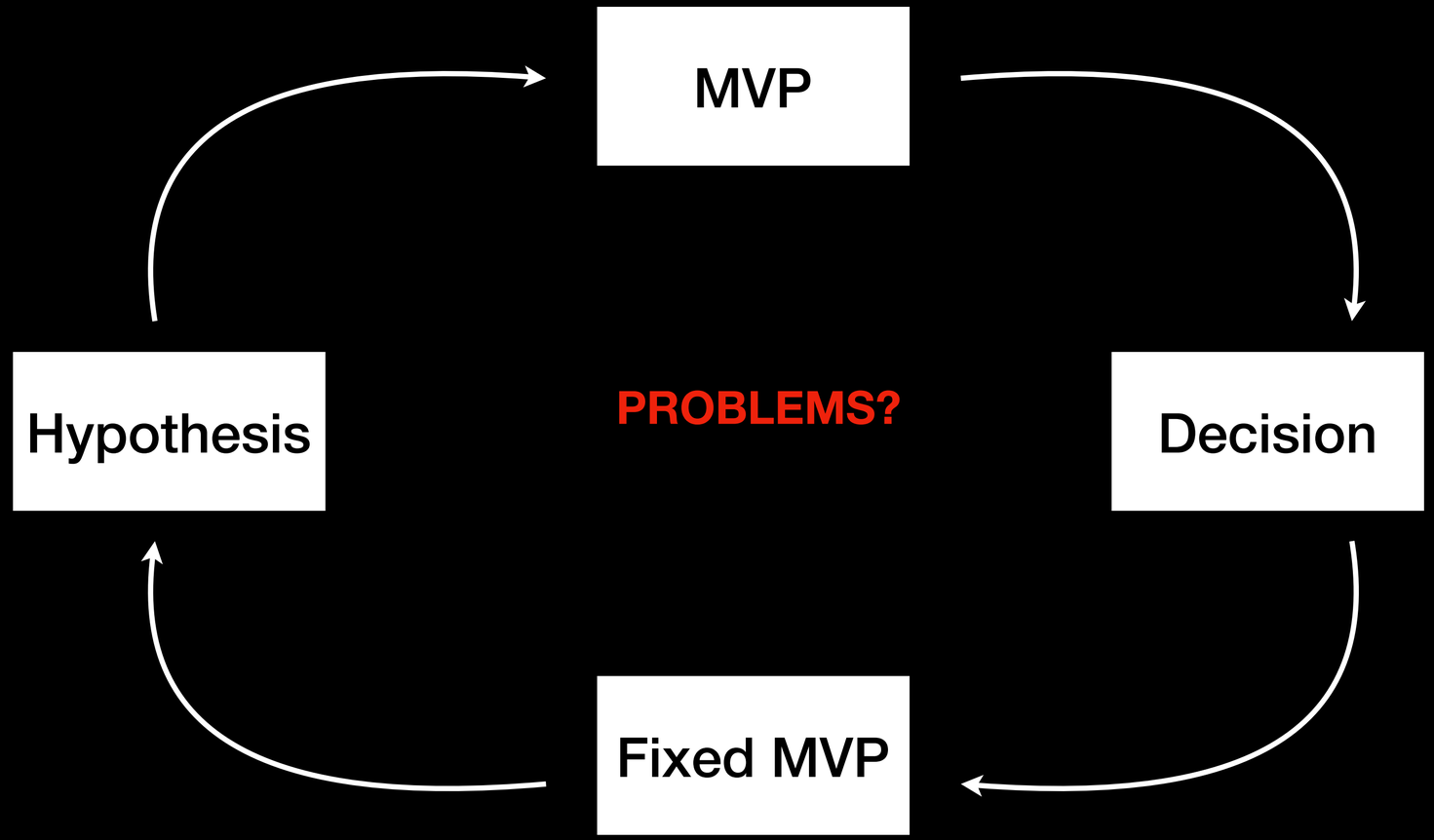
To discuss:

- A good startup is a **data-driven** «startup»
- Data-driven «startup» - is not **isn’t always good** startup
- Data **fatigue**
- **No** direction

«Startup» progress:



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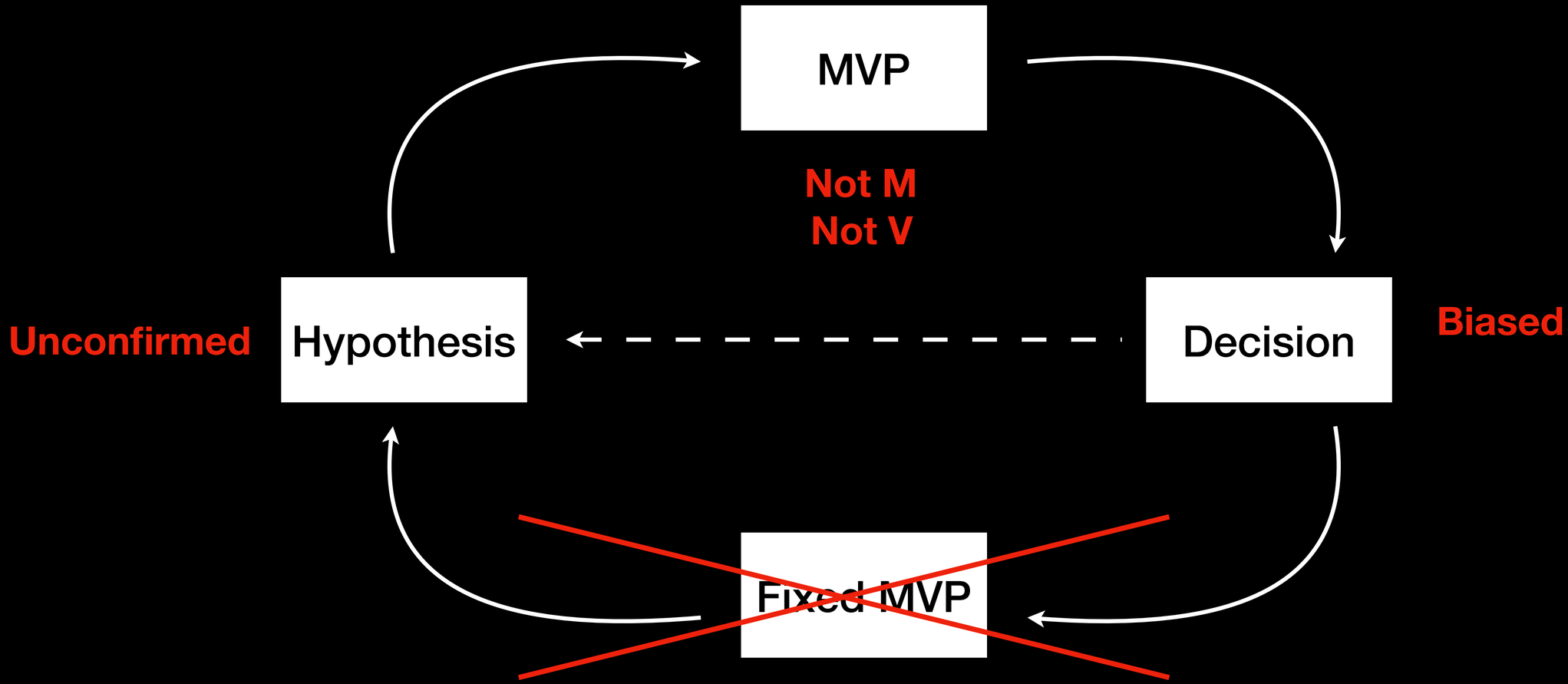
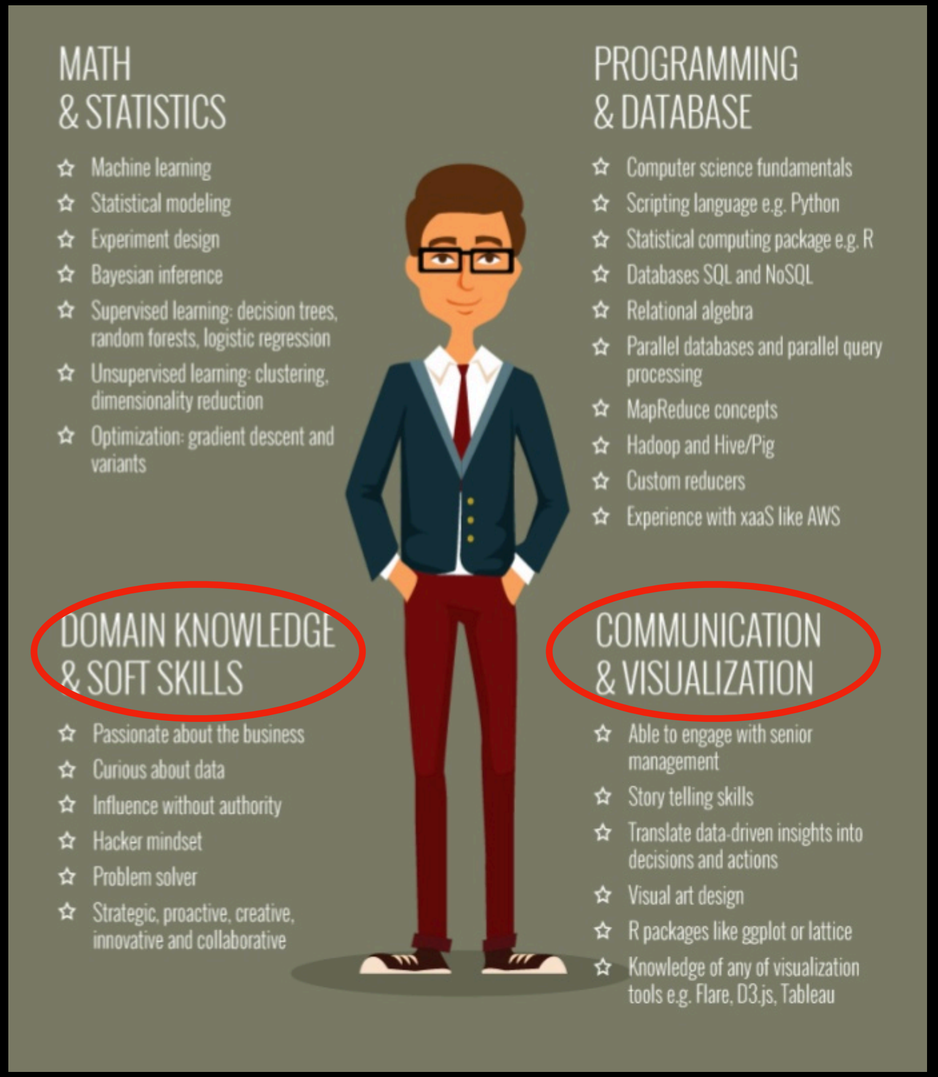


Metrics canvas discussion:

- Why should you care about it?
  - Most time you are not just an «ML-engineer», but self-sufficient product maker
  - Your product = your bonuses
- Canvas = schema = table
- Answers question:
  - What’s going on? Why is the audience not growing?
  - Where to go next?
  - We got AB result sheet with 100+ metrics, what’s next?

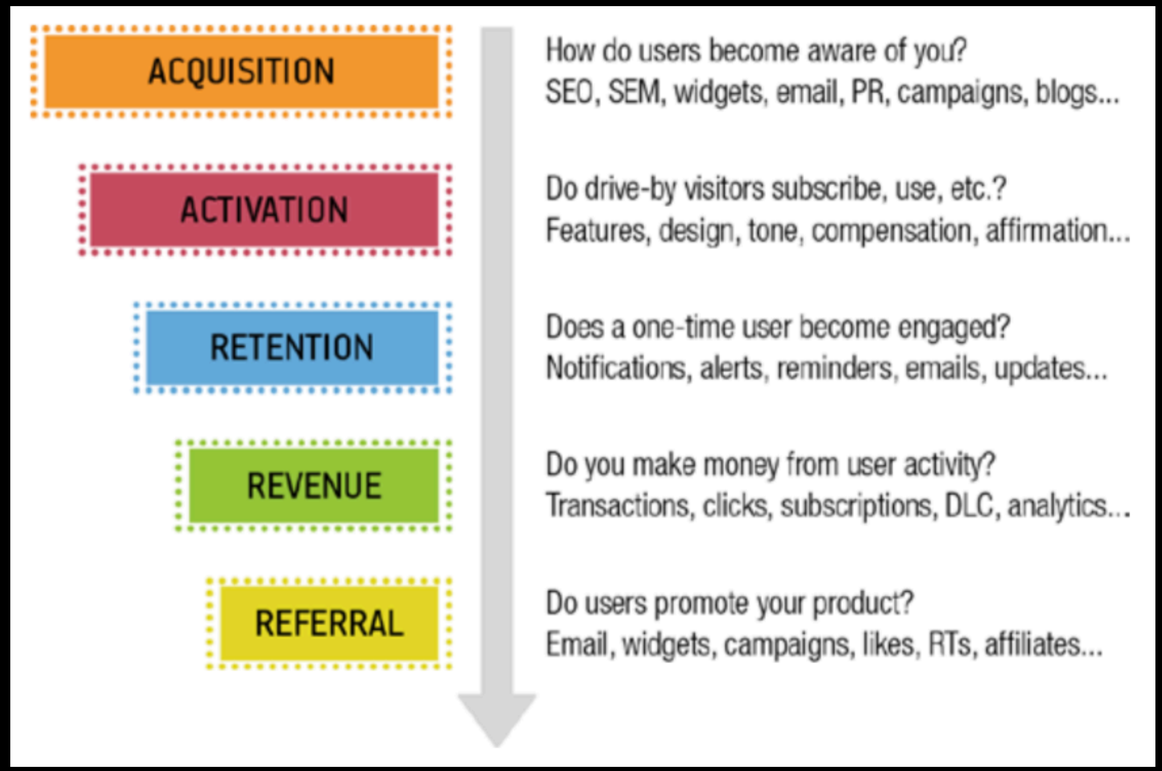


«AARRR» framework:

- **A**cquisition
- **A**ctivation
- **R**etention
- **R**evenue
- **R**eferral

Good at question: where to go next?
Whats to look in AB-sheet?

Bad at question: How concretely move further?
A bit b2c-centered.



AARRR

- **What:** Acquisition
- **About-what:** How do users become aware of you?
- **Instruments:** SEO / SEM / widgets / email / PR / campaigns / blogs
- **Utility:** Generate attention and traffic (either organic or not)
- **Metrics:** traffic / mentions / cost-per-click / search results / cost of acquisition / open rate

AARRR

- **What:** Activation
- **About-what:** Are new users subscribing?
- **Instruments:** Features / design / tone / confirmations
- **Utility:** Turn attracted users into engaged
- **Metrics:** Engagement / registrations / onboarding finished / used service at least once

AARRR

- **What:** Retention
- **About-what:** Are users returns?
- **Instruments:** notifications / alerts / reminders / updates / emails / game mechanics
- **Utility:** Encourages users to come back
- **Metrics:** engagement / time since last visit / DAU/MAU / «retention rate»: 1d, 7d, 30d
  …

AARRR

- **What:** Revenue
- **About-what:** Are we earn moneys?
- **Instruments:** transactions / dlc / pricing / subscriptions …
- **Utility:** Money-money-money
- **Metrics:** ARPU (avg revenue per user) / conversion rate / shopping cart / click-through-revenue

AARRR

- **What:** Refferal
- **About-what:** Are our users promote our product?
- **Instruments:** promo / referral system / affiliates …
- **Utility:** Virality
- **Metrics:** invites / viral coefficient / viral cycle lifetime

OMTM:

One metric that matters:

- It answers the most important question you have
- It focuses the entire company
- It inspire a culture of experimentation

OMTM:

One metric that matters:

- Easy
- Every-day measured
- Easy to move
- Easy to compare
- Fundamental

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PROBLEMS?

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PROBLEMS?

YEP, it does not exists!

OMTM:

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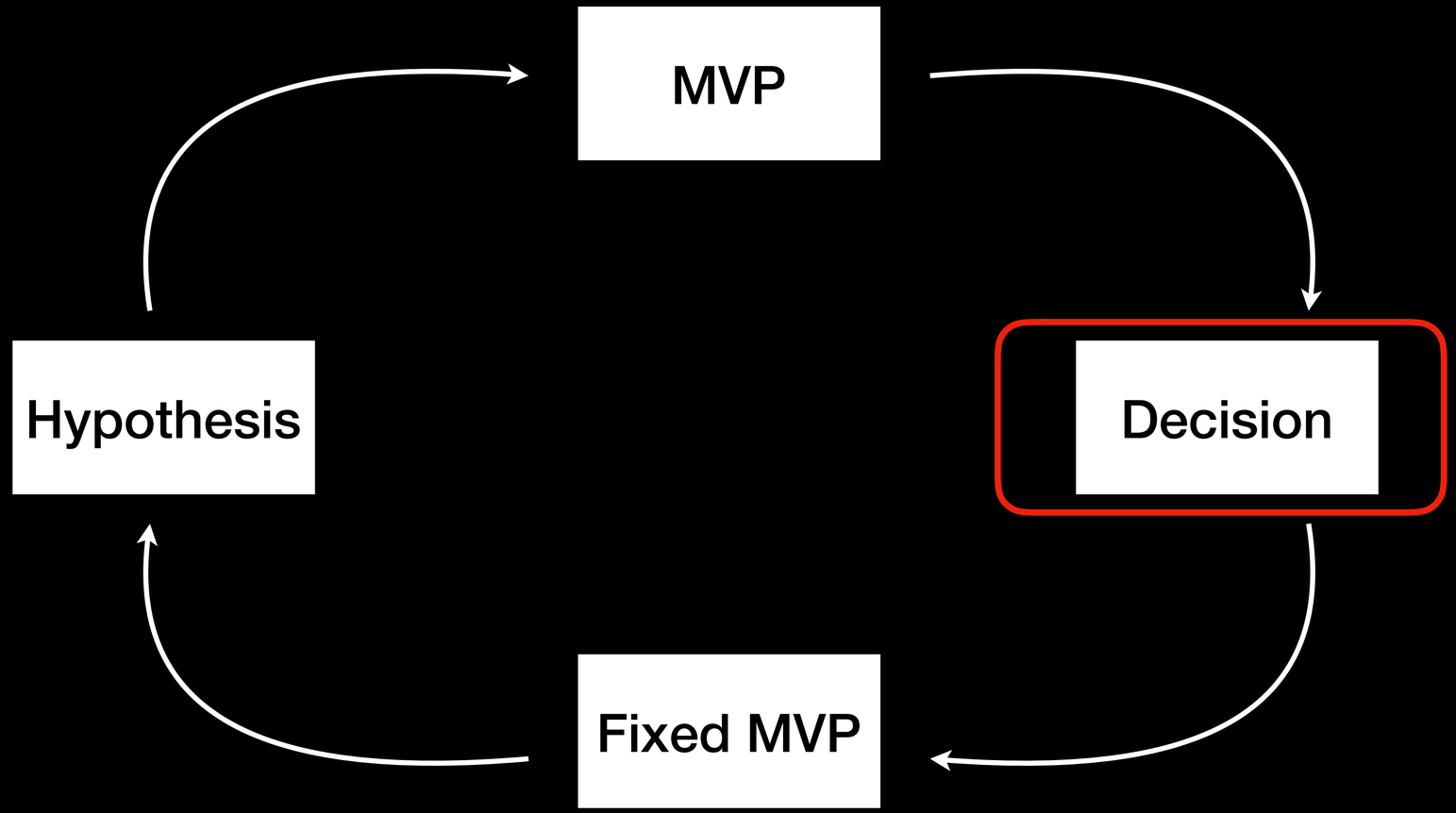
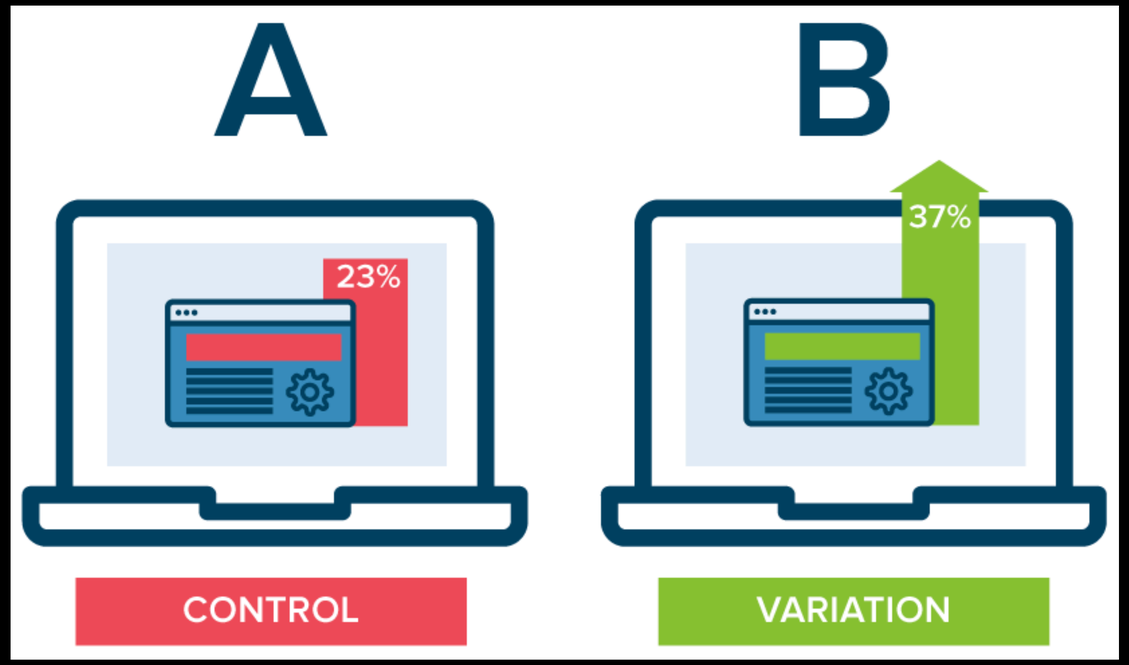
Don’t worry, we will fix it further!

«Startup» progress:



A/B tests:

- Two options of banner. Which one is better?
- Split user into two groups,
  show default banner for control group,
  new one — for test group.
- Wait a bit
- Measure performance.
- Compare
- Choose best



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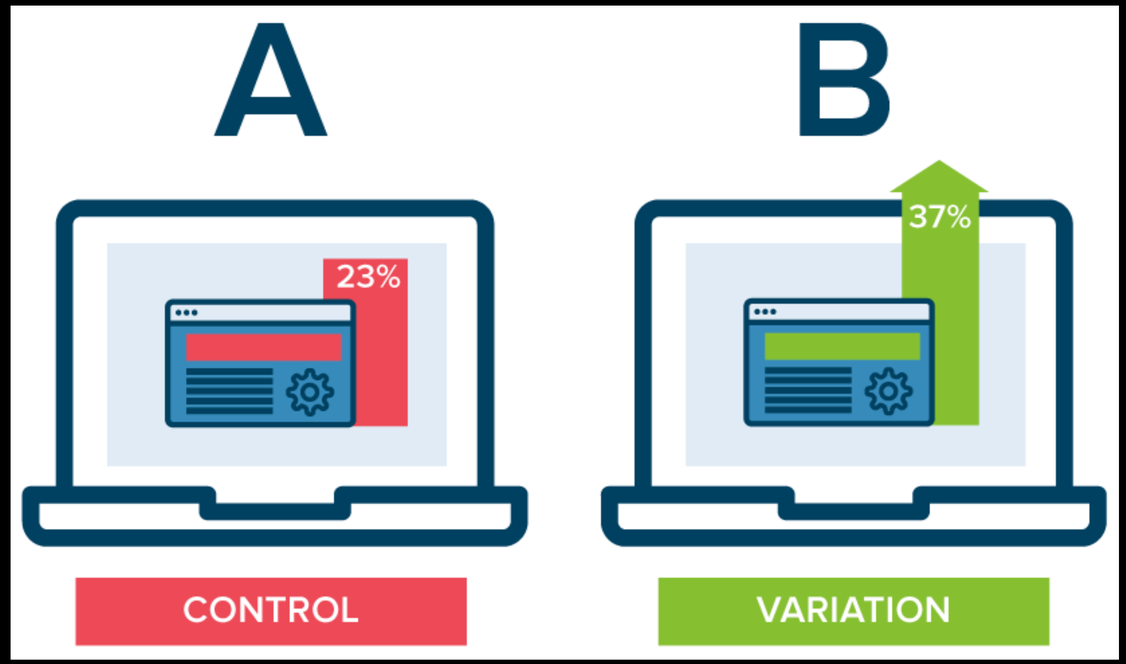


How to compare?

- $k \sim Bernoulli(\theta)$, k — binary click or not
  θ — Bern. parameter, probability of a click, mean…

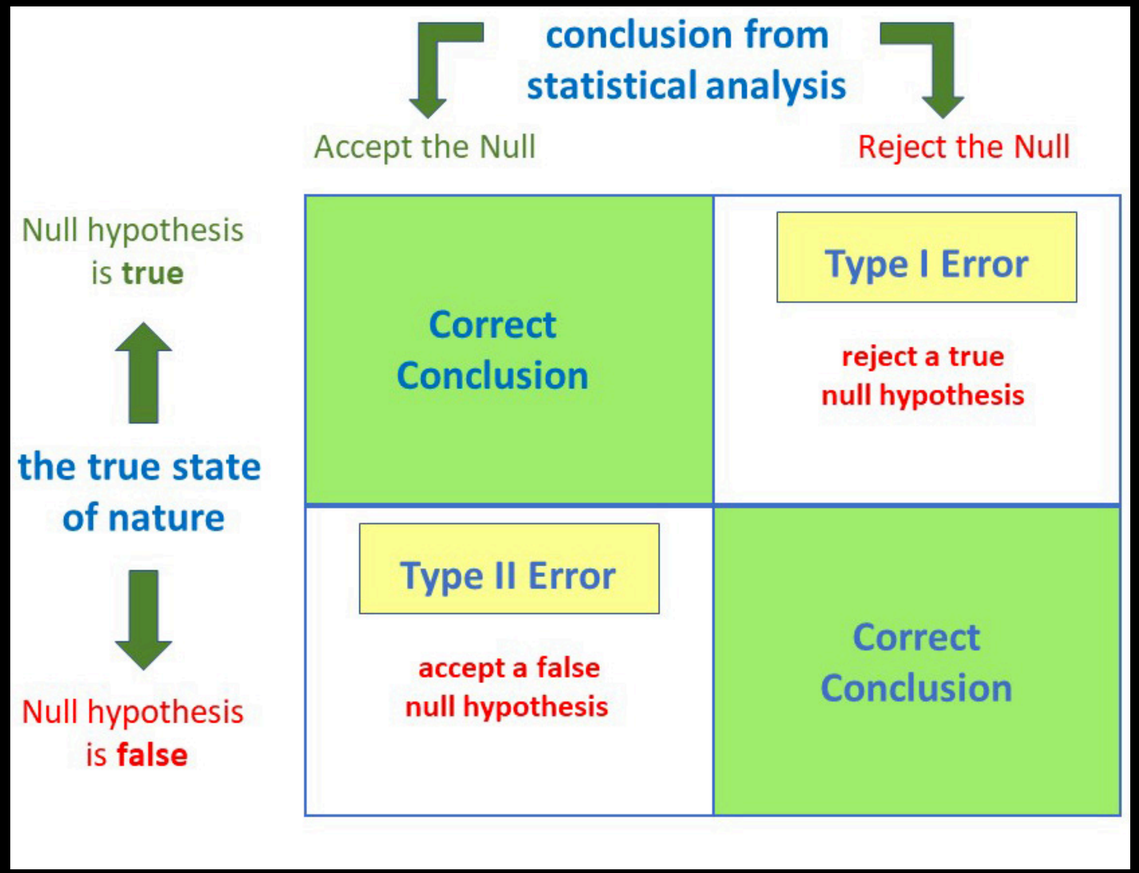
  $p(k) = \theta^k(1-\theta)^{1-k}$, $\sigma^2 = \theta(1-\theta)$ — dispersion

- $H_0 : \theta_c = \theta_t$
  $H_1 : \theta_c < \theta_t$
  $\theta_c \sim clicks/views$

- $\bar{\theta} = N(\mu, \frac{\sigma^2}{n})$ —> **T**-test for comparing

How to compare?

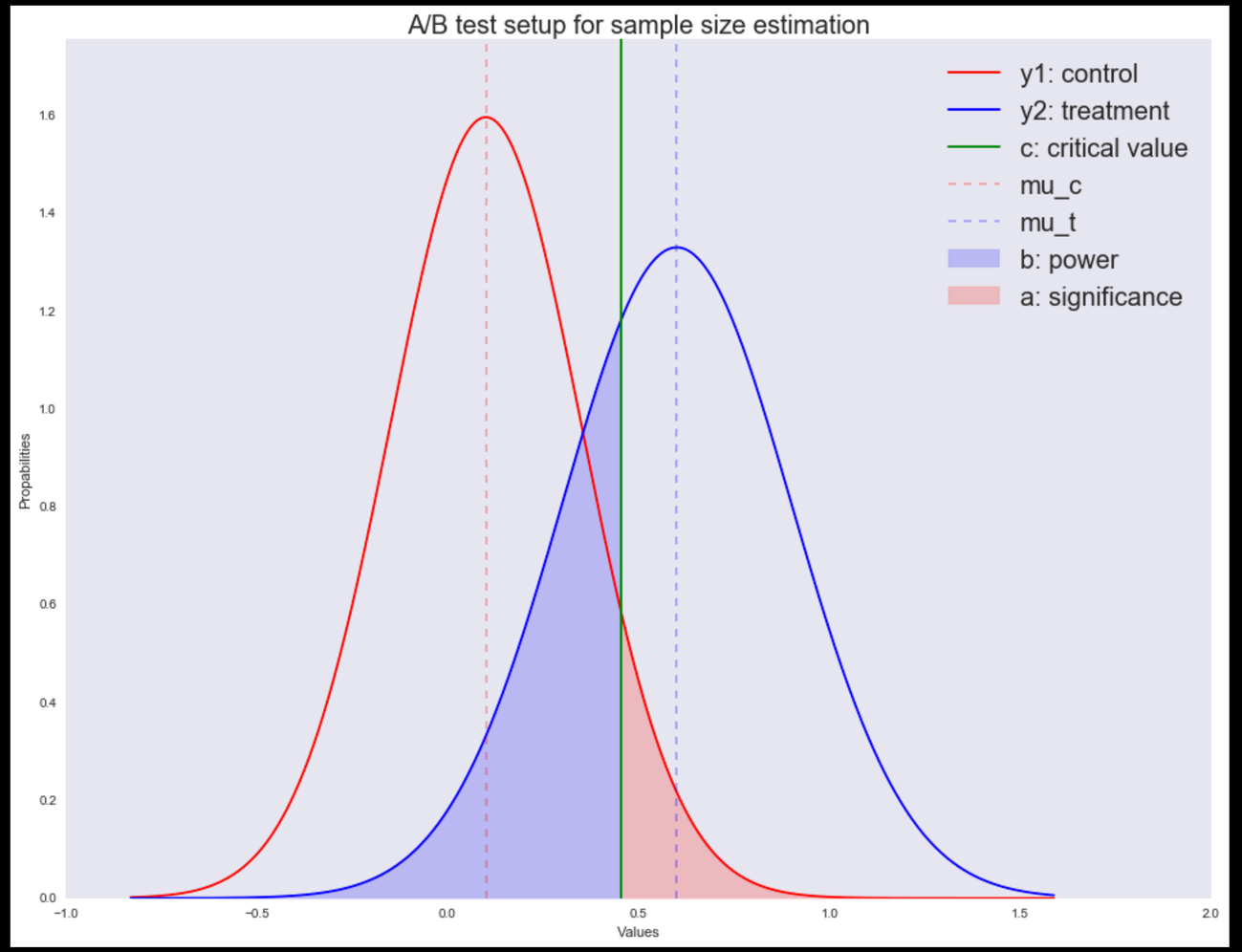
- $\alpha = P(H_1 \mid H_0)$ (0.05)
  $\beta = P(H_0 \mid H_1)$ (0.2),
  $(1 - \beta)$ – statistical power)
- Stat test concept:
  $T(X) = t$
  $P(T(x) > t) = p_{value}$
  $p_{value} < \alpha$ – H_0 rejected



How long to hold?

- $c = \mu + t\frac{\sigma}{\sqrt{n}}$, t – quantile N(0,1)
- $c = \theta_c + t_\alpha\sqrt{\frac{\theta_c(1-\theta_c)}{n}}$

  $c = \theta_t + t_\beta\sqrt{\frac{\theta_t(1-\theta_t)}{n}}$
- ^^ with known θ_c, α, β and expected θ_t solvable for n



Dead salmon case

- Happens on multiple tests
- Take dead salmon, put them into MRI
- Conduct low-quality research
- Salmon is alive
- Holm–Bonferroni method $\alpha := \alpha/n$

$$
\begin{aligned}
P\left(\text{хотя бы один результат значимый}\right) &= 1 - P\left(\text{все результаты незначимы}\right) \\
&= 1 - (1 - 0.05)^5 \\
&= 1 - 0.95^5 \\
&\approx 0.2262
\end{aligned}
$$

AB tests IRL:

- Tons of metrics:
  - No one knows what amount of change to care
  - How to make a decision?
  - How long should we hold for 100 metrics on radar
  - Have you heard about novelty effect?

Действие	Метрика	Эффект (%)	Увереность в отличии (%)	Увереность в новизне (%)
[redacted]	users	-62.16%	99.00%	97.38%
[redacted]	counts	-57.08%	99.00%	97.38%
[redacted]	users	36.40%	99.00%	97.38%
[redacted]	counts	35.66%	99.00%	97.38%
[redacted]	counts	28.75%	99.00%	97.38%
[redacted]	counts	28.53%	99.00%	97.38%
[redacted]	users	24.04%	99.00%	97.38%
[redacted]	avgs	14.60%	99.00%	97.38%
[redacted]	avgs	8.10%	99.00%	97.38%
[redacted]	users	7.48%	99.00%	97.38%
e_click:Content	avgs	-6.60%	99.00%	97.38%
e_click:Content	users	5.83%	99.00%	96.10%

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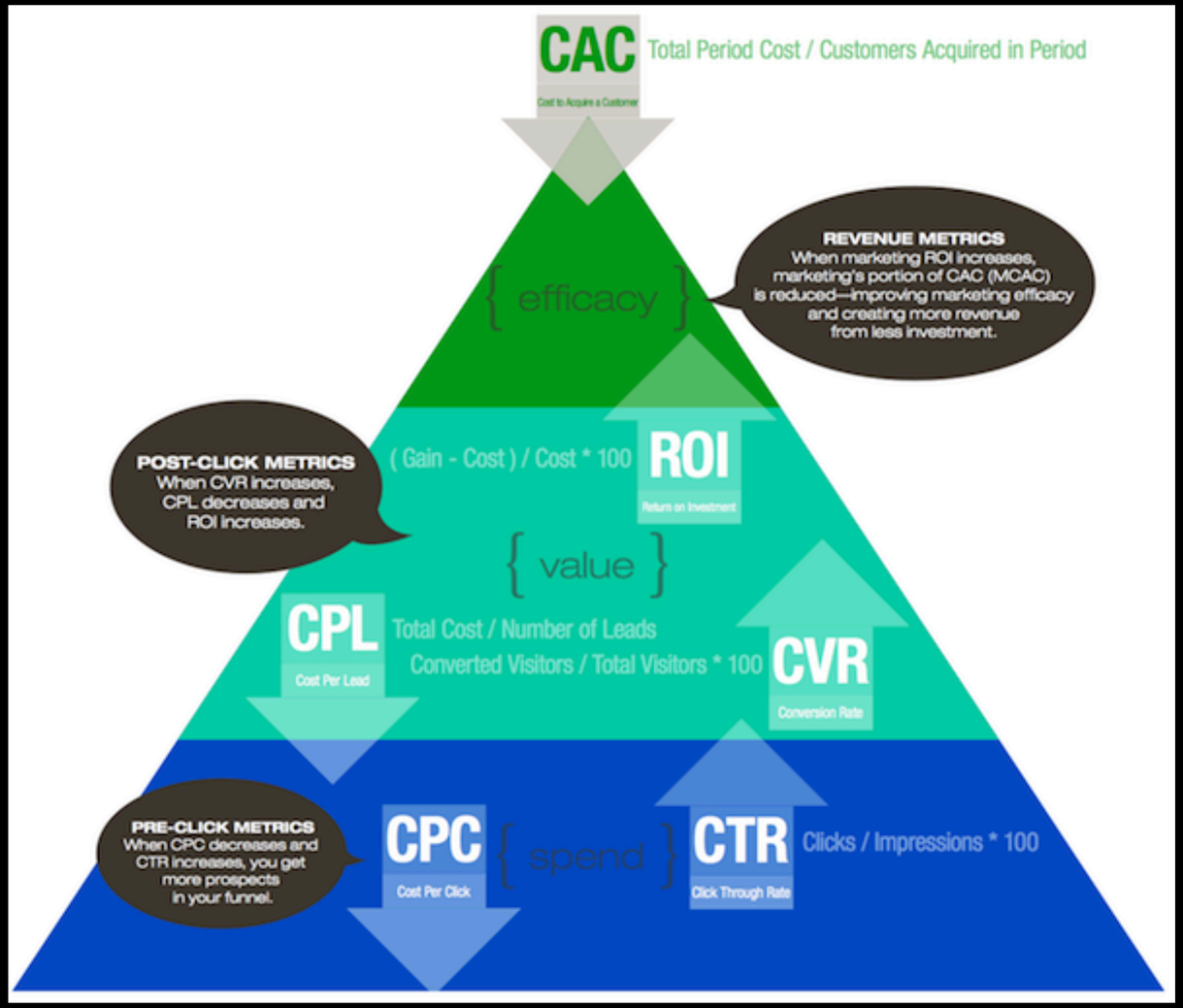


Good AB tests IRL:

- Automatised
- Based on metrics. Plug-in plug-out
- Based on separation unit. Flexible separation
- A/A test auto and stable
- Easy for everyone
- Based on world-wide experience:
  https://exp-platform.com/

AB tests nature:

- Origins from medicine and agriculture:
  - High cost of one **experiment**
  - High cost of an single **error**
- Classical AB/tests allows you to estimate budget beforehand, set different α, β and estimate result

Bayesian multi-armed bandits:

Unformally:

- You ended up in casino with fixed amount money and time.
- You want to find the best one and maximise your gain.
- Let’s look at Thompson sampling schema.
- Yahoo use it to optimise banners. Microsoft too. Netflix and artwork optimisation.

Bayesian multi-armed bandits:

Formally:

- Let us observe the sequence $y_t = (y_1, y_2 \dots y_t)$ at time t
- Let us denote action a_t taken at moment t
- $y_t \sim f_{a_t}(y \mid \vec{\theta})$, where $\vec{\theta}$ some unknown parameters vector
- We don't know the actual distribution and/or $\vec{\theta}$ thats why we can't optimise mean directly

Bayesian multi-armed bandits:

- $f_a(y \mid \theta_a) = \theta_a^y (1-\theta_a)^{1-y}$ and expected reward $\mu_a = \theta_a$. So let we **assume** that $\theta \sim Beta(\alpha, \beta)$
- Beta is conjugate prior to Bernoulli

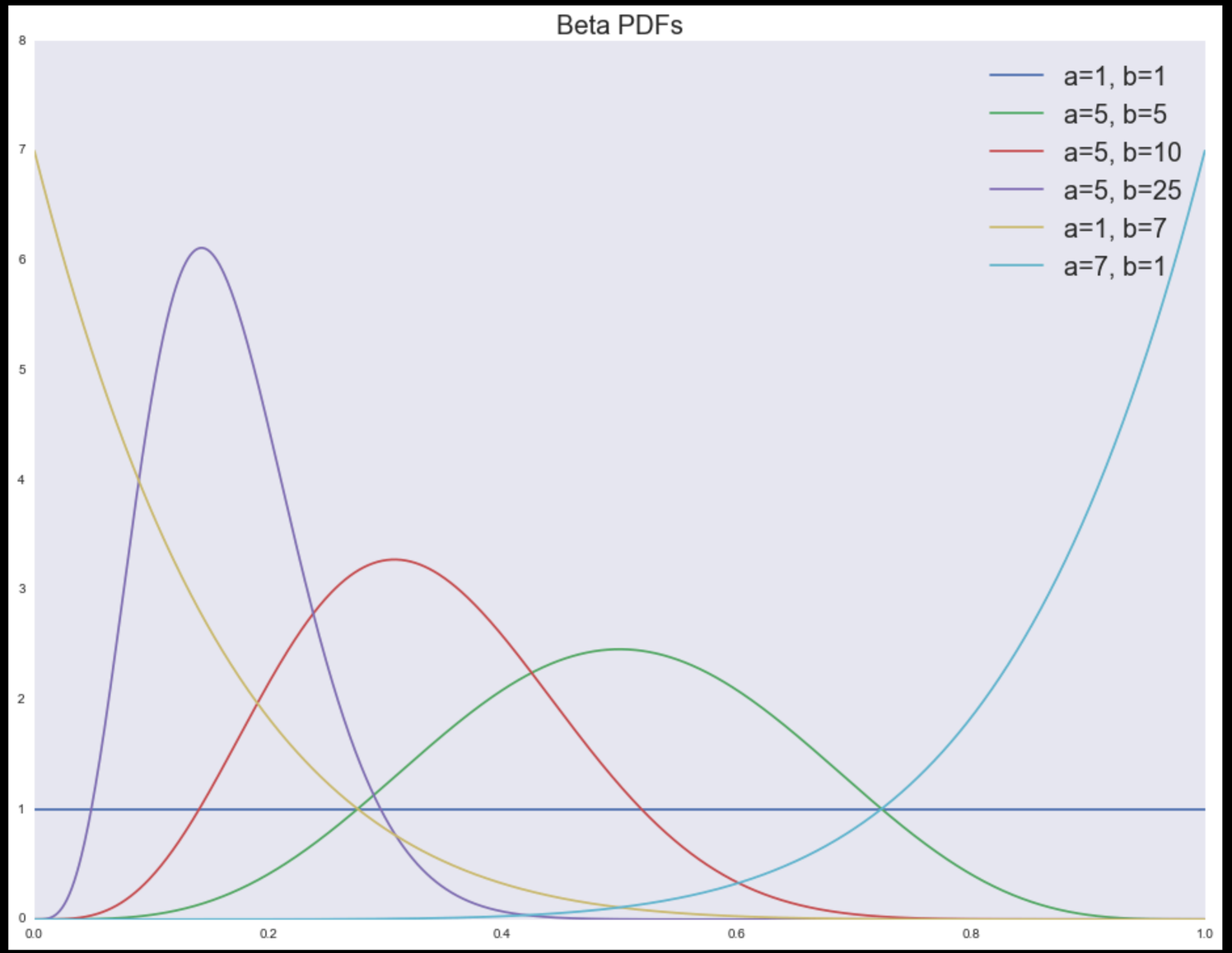
$$
\begin{aligned}
p(\theta \mid y) &\propto p(\theta) \cdot p(y \mid \theta) \\
&\propto \tfrac{1}{\mathrm{B}(\alpha,\beta)} \theta^{\alpha-1}(1-\theta)^{\beta-1} \cdot \theta^{y}(1-\theta)^{1-y} \\
&\propto \theta^{\alpha-1+y}(1-\theta)^{\beta-1+1-y}
\end{aligned}
$$

$$
\mathrm{Beta}(\alpha+y, \beta+1-y) = \mathrm{Beta}(\theta \mid \alpha, \beta) \cdot \mathrm{Bernoulli}(y \mid \theta)
$$

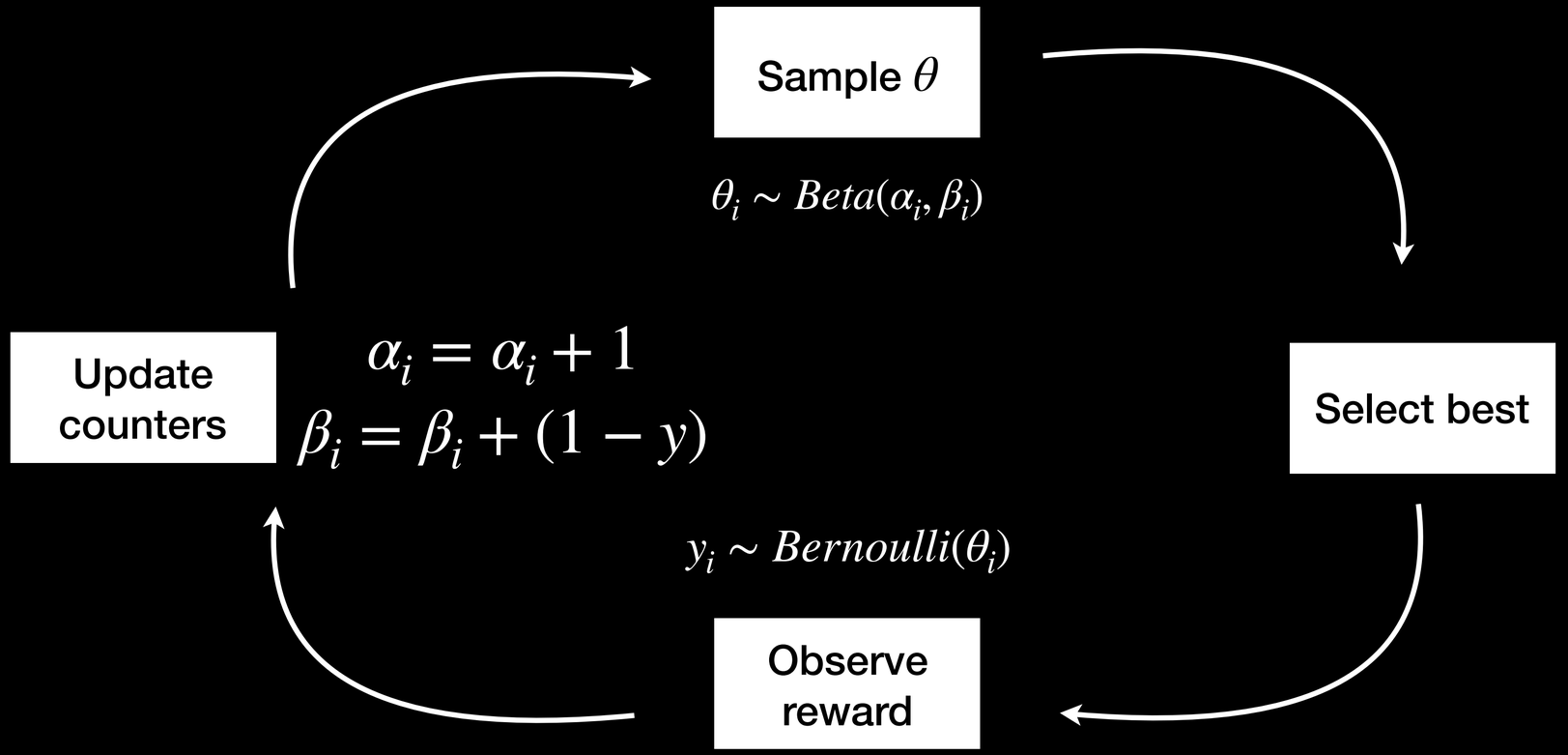
- Beta becomes uniform when $\alpha = \beta = 1$
- α as num of successes, β as num of failures

Beta-distribution:

$$f(\theta, \alpha, \beta) = \frac{1}{\mathbf{B}(\alpha, \beta)} \theta^{\alpha-1} \cdot (1-\theta)^{\beta-1}$$

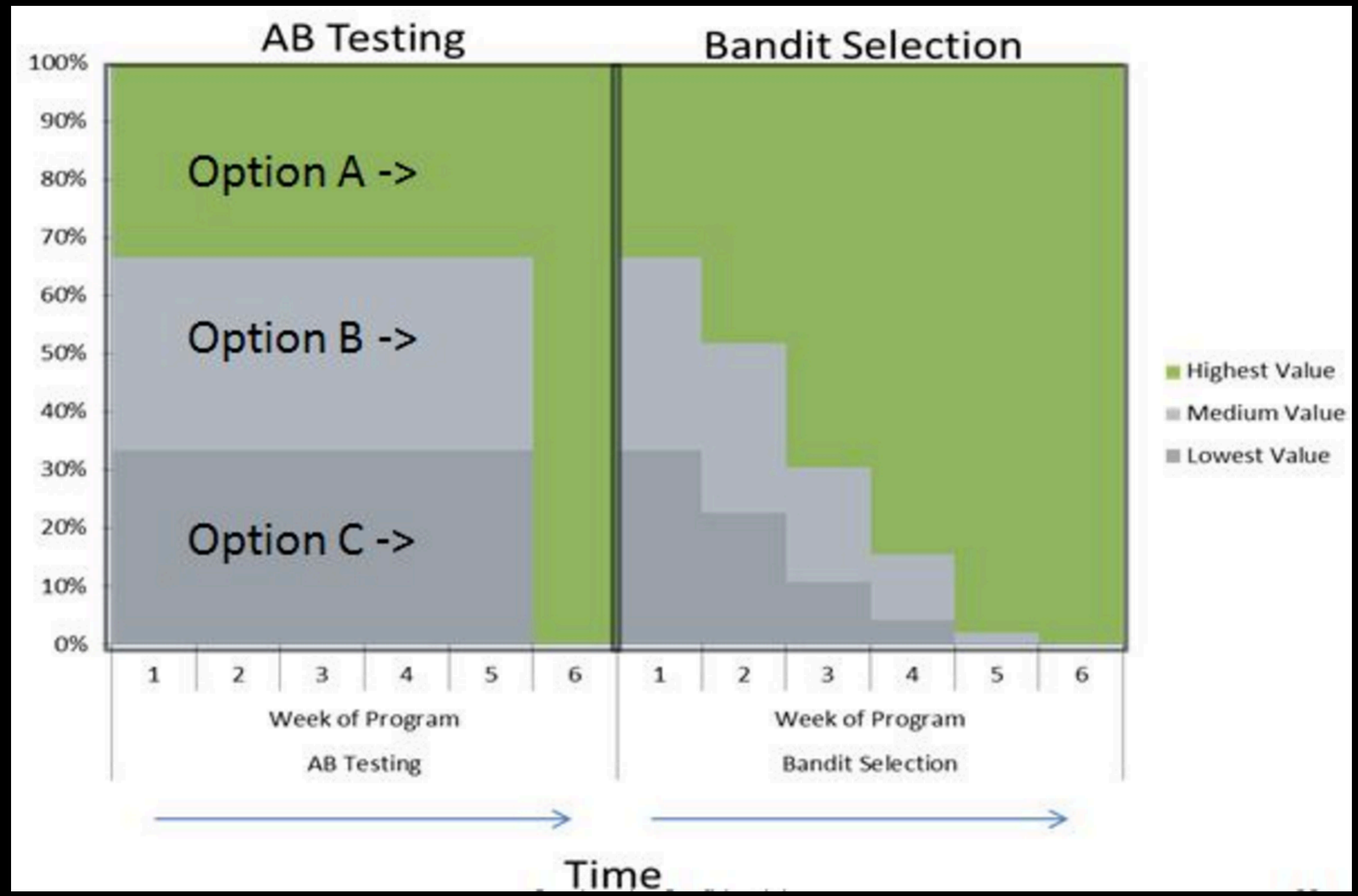


Beta-distribution sampling



Beta-distribution sampling

- Traffic proportion ~ probability of the best bandit θ^*
- Have all needed counters to perform AB-test calculation on runtime
- Maximises CTR directly



Bandits as recommender:

- Allows to add new options during experiments
- Allows to take account of a-priori by setting non-default α, β
- Greediness problem -> $ewma_i = (1-\alpha) \bullet ewma_{i-1} + \alpha \bullet freq_i$
- Relatively easy to code. Especially if you have no historic data and need to implement something on launch.

Sources

- Metrics: Lean Analytics: How to build startup faster
- Bandits https://habr.com/ru/company/ods/blog/325416/