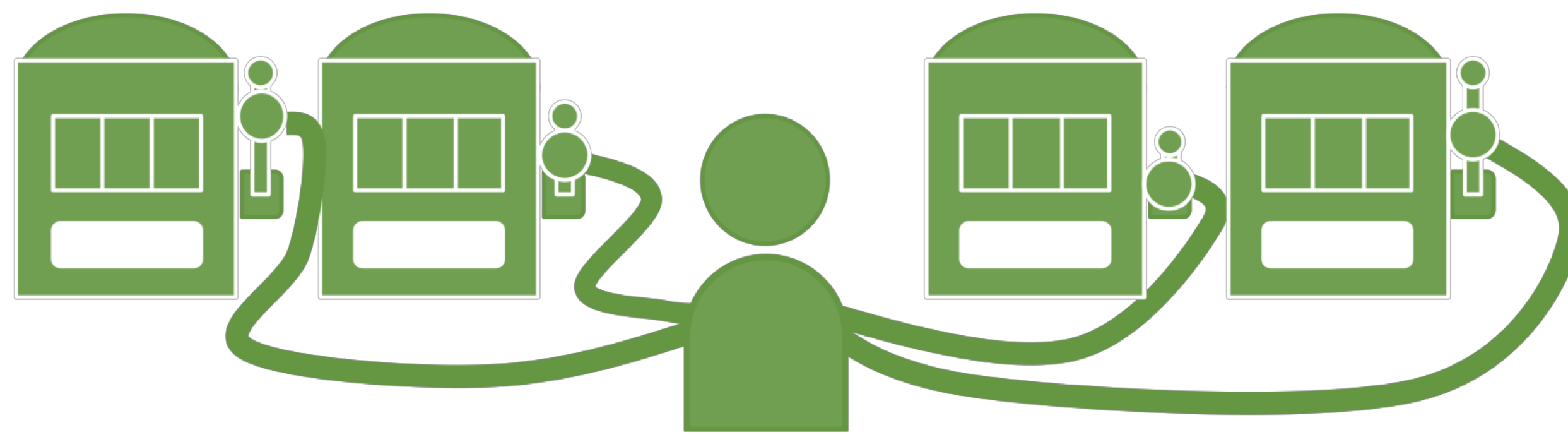
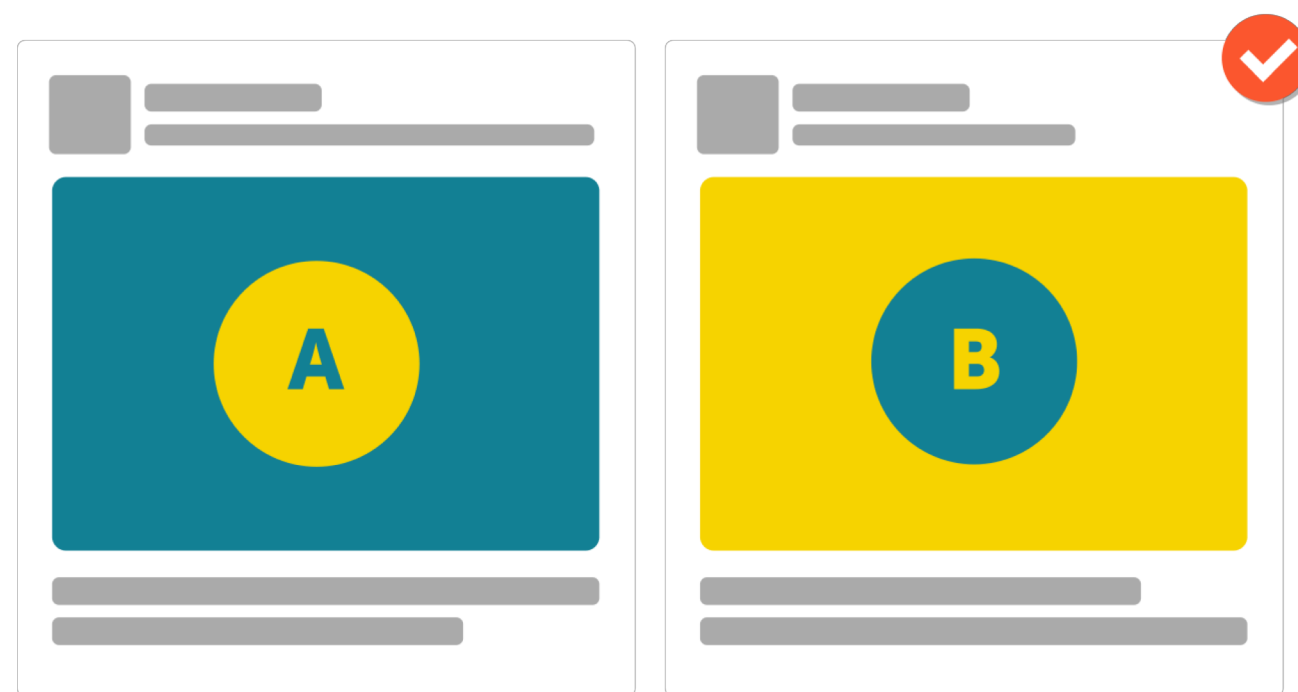


The Bandit Problem: Are You Winning Enough?

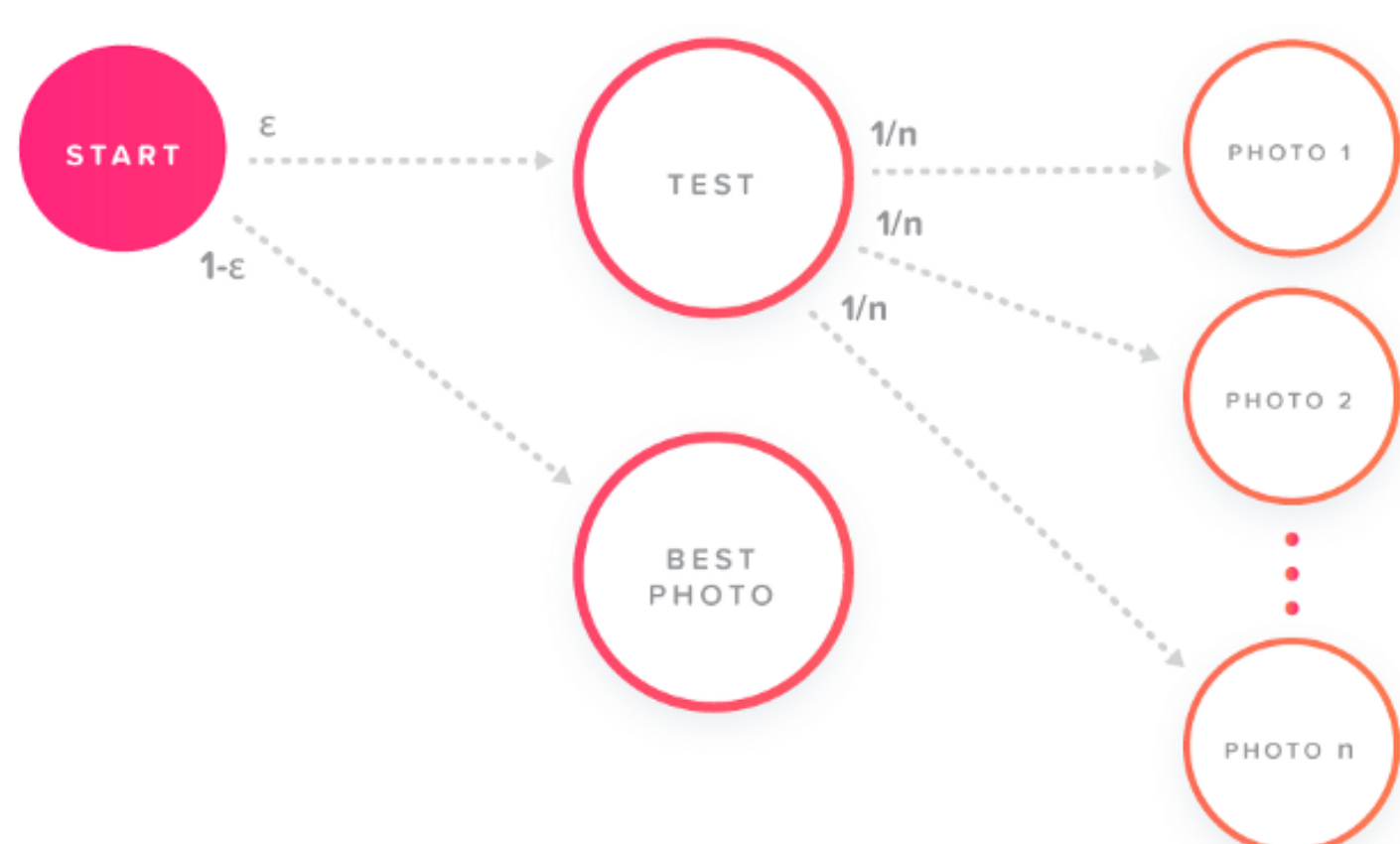


A/B Testing: Problem?



- ❑ Decide the level of statistical significance
- ❑ Send visitors to all the landing pages simultaneously, randomly
- ❑ All the pages get equal share of visitors
- ❑ Run the experiment for a long enough time
- ❑ Don't interrupt it; don't change anything while it runs
- ❑ Wait patiently, where it's advisable not to look at the intermediate results
- ❑ Throws away money on ineffective pages throughout the experiment

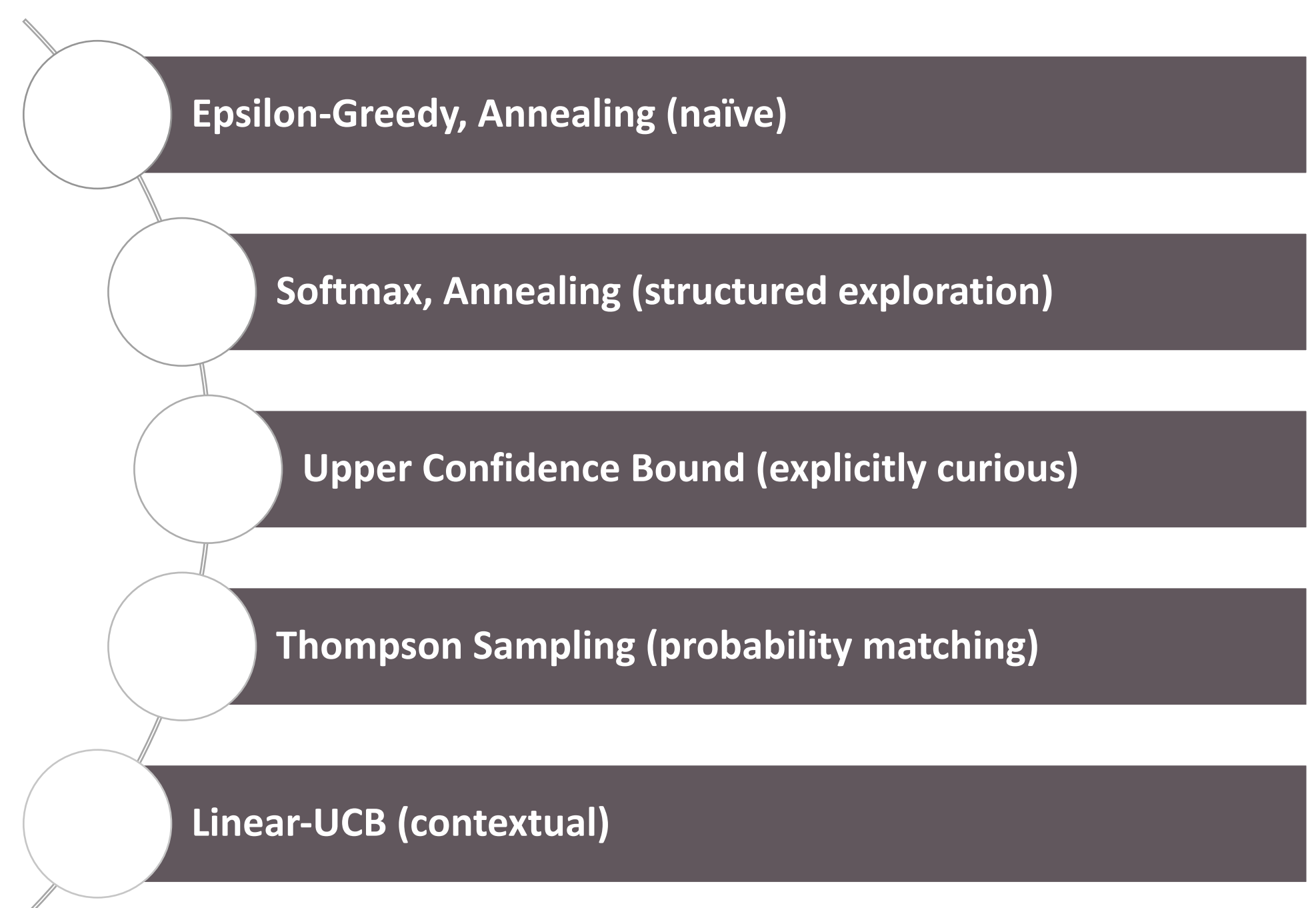
Proposed Solution: Multi-armed Bandits



- ❑ Let's imagine a bandit machine where humans could choose to pull either the left or the right arm
- ❑ Each given a random payoff with the distribution of payoffs for each arm unknown
- ❑ Will you keep pulling the left arm and ignore the right or would you pull the right arm a few more times hoping that it might get better?
- ❑ Balance between exploration and exploitation
- ❑ Multi-armed bandit algorithms are more flexible and generally more efficient than A/B testing

Research & Simulations

- ❑ Multiple experiments conducted and documented to estimate performance, cumulative rewards, and probability of selecting the best arm, under various circumstances
- ❑ Monte-Carlo simulations performed to estimate the behavior in hypothetical worlds



Rewards Maximized!

- ❑ For instance, if we have two arms (variants) with 20% and 10% reward (conversion) probabilities, and 10,000 trials
- ❑ Then A/B testing would generate a reward for 1,500 trials
- ❑ While multi-armed bandits would generate a reward for ~ 1900 trials with epsilon-greedy strategy ($\epsilon = 0.2$)
- ❑ Where the maximum achievable reward would be 2,000, if only we knew the best variant before the experiment

