

# Mastering ML-Powered Product Development at Scale

Challenges and strategies

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# Overview

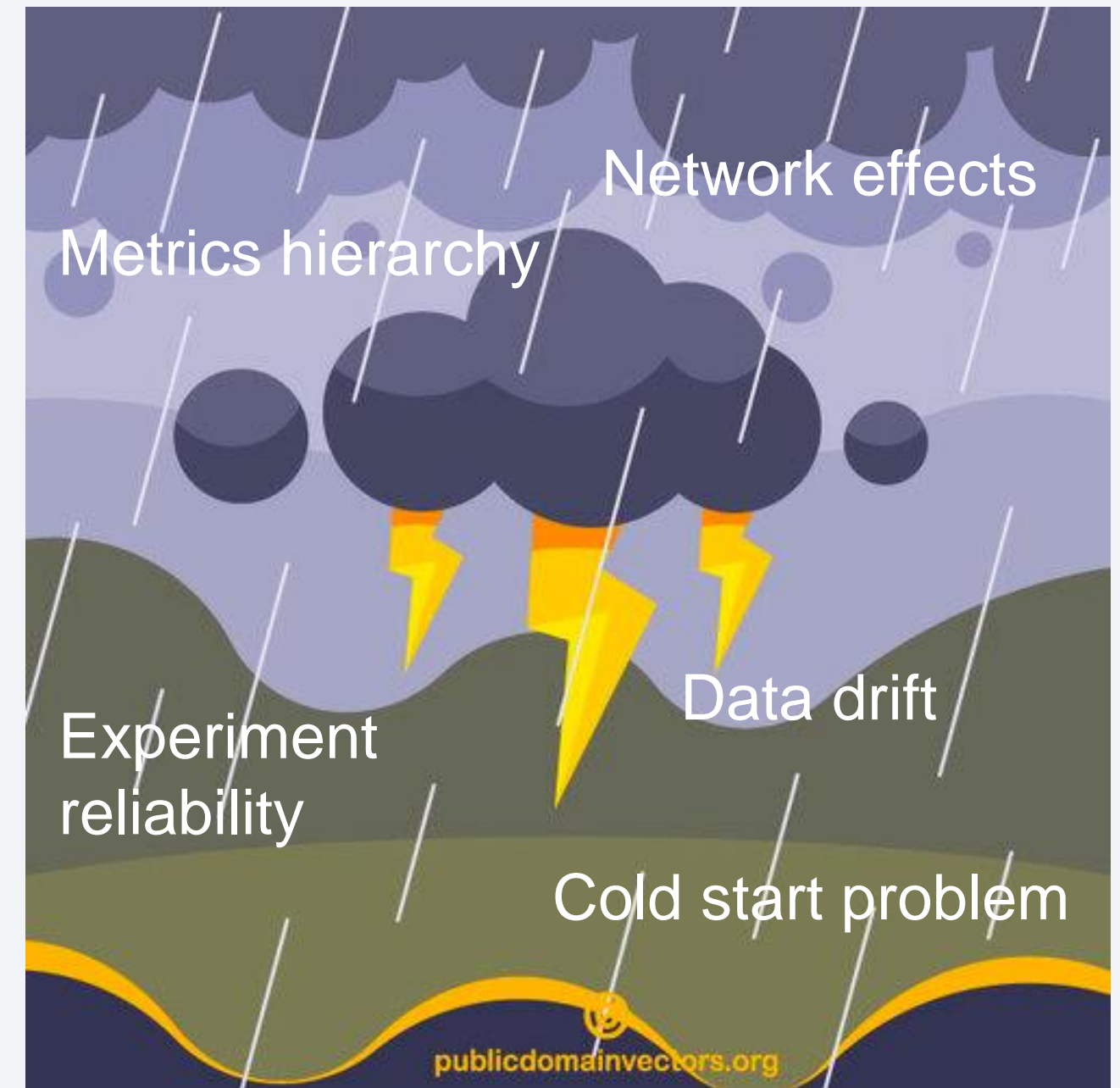
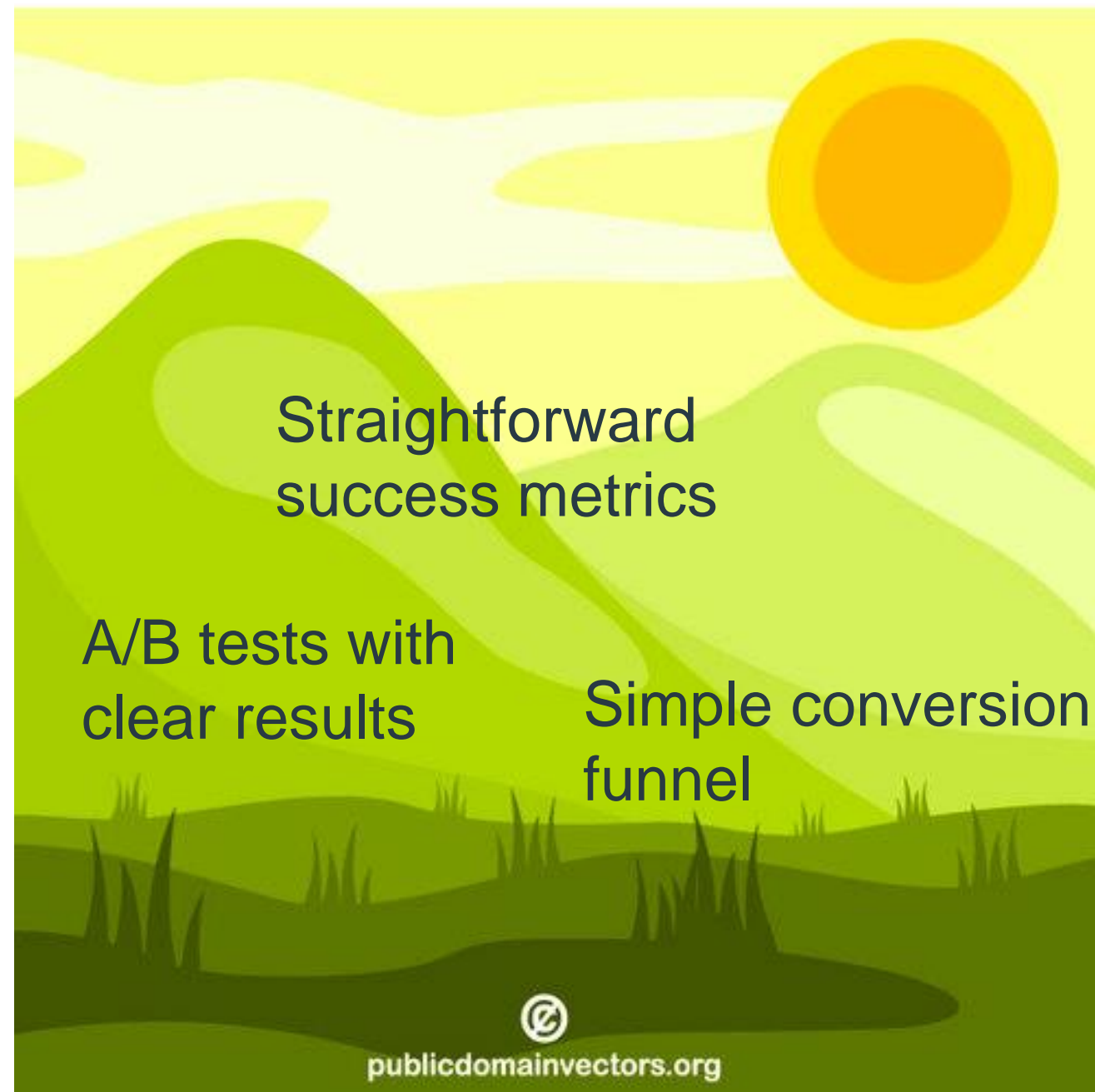
01 Challenges of ML-powered product development at a large scale

02 Pitfalls and things to consider at various stages

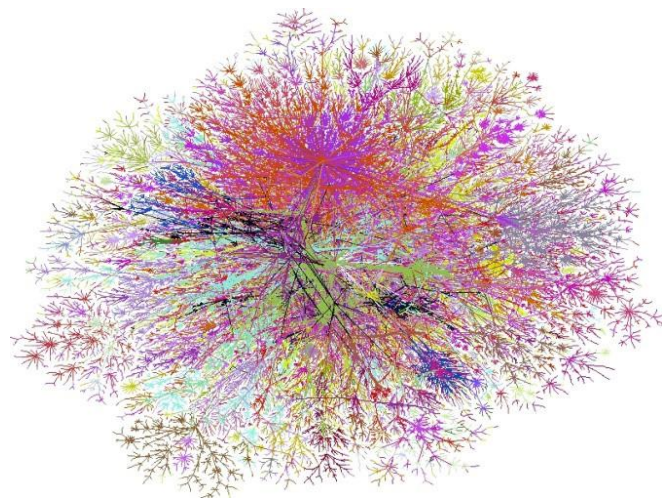
03 Strategies for experimenting in a complicated system

04 Illustrative cases from various companies across the industry

# Expectations vs reality



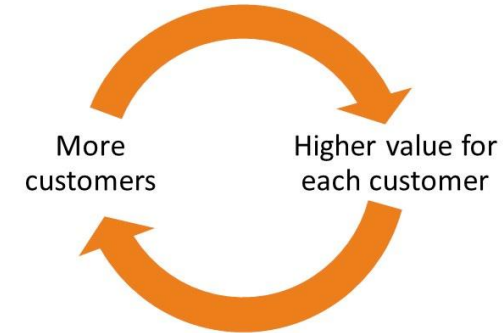
# (Some of the) sources of complexity



Complex systems



Data network effects



Regular network effects

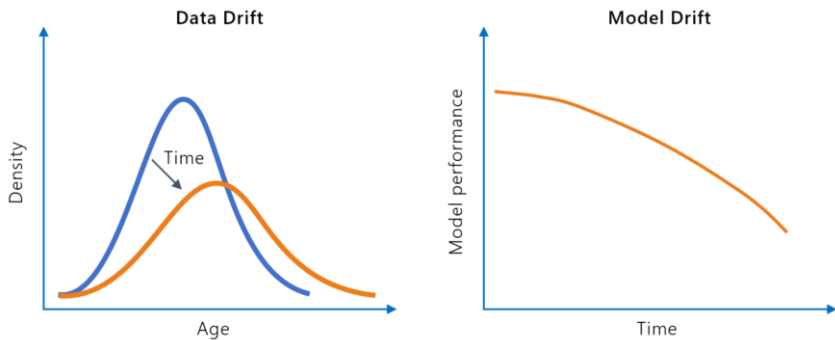
Network effects



Definitions of success



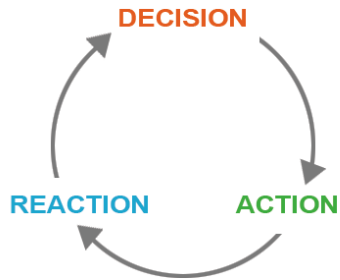
Designing metrics hierarchy



Monitoring for data drift

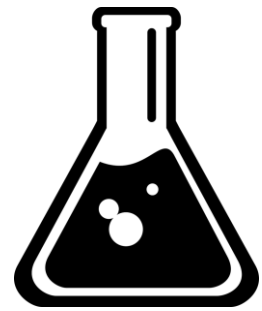


Identifying the main levers



Monitoring feedback loops





Investing in  
experiment design



Measuring progress  
reliably



Double-checking the  
impact



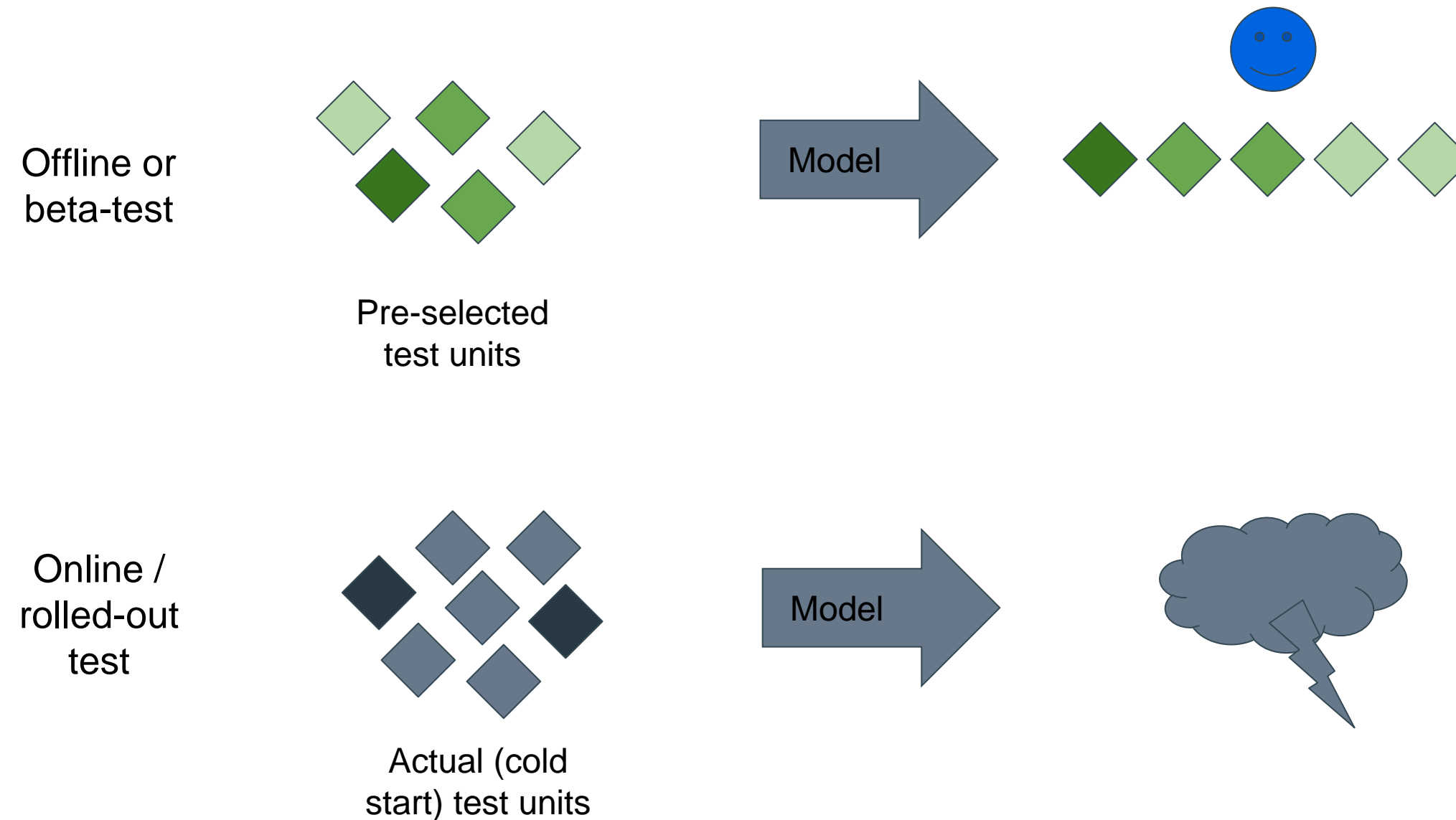
Accounting for  
granular impact

# Case study 1: Comparing two product ranking models

	Treatment	Effect	Intuitive explanation	Actual explanation
Test Cell 1	Neural net based ranking	No statistically significant difference	Models are performing equally good	Data sharing between test cells allows Cell 2 to quickly boost “good” products
Test Cell 2	Multi-armed bandits ranking			

Make sure the experiment design accounts for potential feedback loops and is not biasing the experiment results

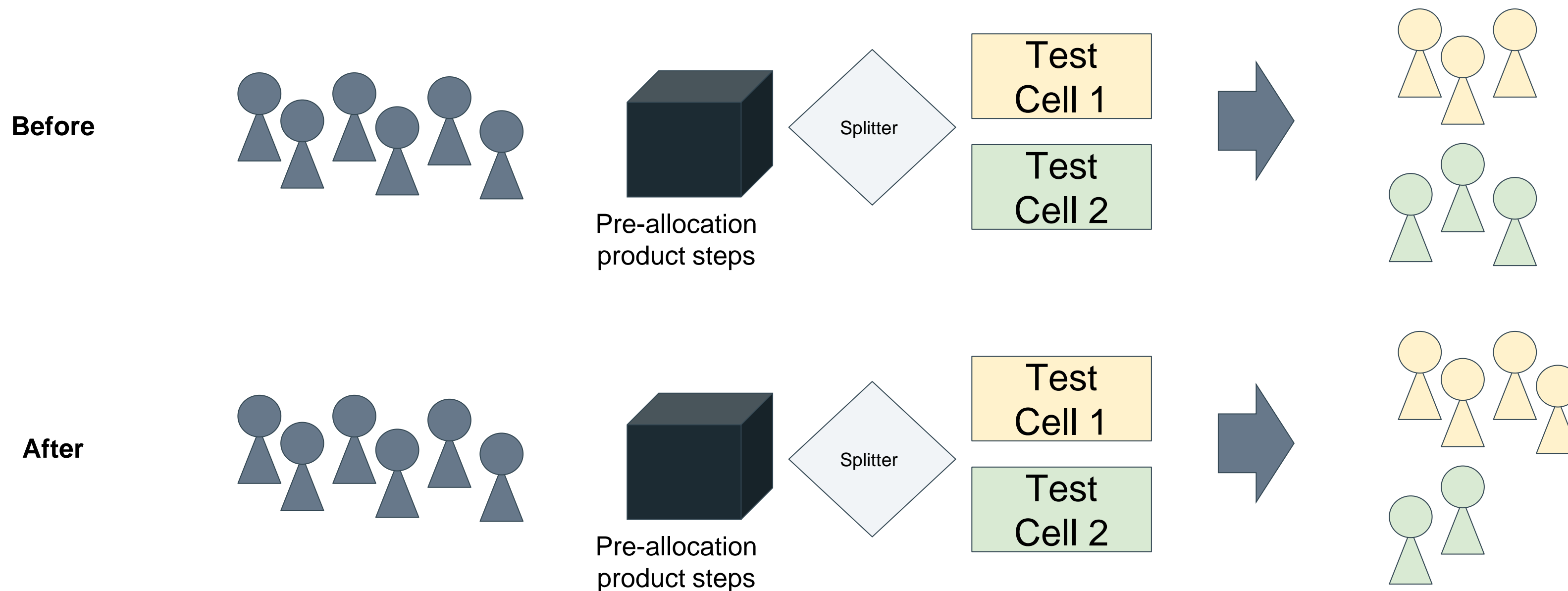
## Case study 2: Cold start after offline testing



Make sure the testing isn't happening in conditions too far from actual production environment to account for novelty effects



## Case study 3: Sample ratio mismatch



Try to account for the impact of the test results on the allocation as potentially it may lead to exposure imbalance

# Summary

- There are many things that can be neglected on a small scale but become important as scale and complexity of your products increase -> think about them in advance and design the systems accordingly;
- Invest into designing the easy but comprehensive hierarchy of metrics that would cover the major goals of product development and unblock both strategic and operational improvements;
- Think about potential issues with the data and invest into monitoring them to proactively address the potential issues;
- Make sure the experimentation techniques address for the specifics of the product developed and have the ways of dealing with potential issues, such as novelty and network effects;
- Plan for some backtests and other experiments that would double-check that the initial results hold and that the cumulative effects are as expected.

**Thank you!**