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AI Performance Benchmarking & A/B Testing Playbook

Comparing AI model versions with the same statistical rigor any other experiment deserves

- Practitioner
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- Administrator
- 08 December 2018
- 3 minute(s)

Overview

A framework for AI performance benchmarking and A/B testing — rigorous comparison methodology for evaluating model versions or AI approaches against each other, applying genuine experimental design discipline rather than informal or biased comparison that produces misleading conclusions about which AI approach genuinely performs better.

Isn't comparing two AI model versions on a held-out test set

sufficient for determining which performs better? A single held-out test comparison is a reasonable starting point, but genuine rigor requires the same experimental design discipline as any other A/B test — adequate sample size, avoiding cherry-picked test conditions, and testing against production-representative data, not just a single convenient benchmark.

What's the most common AI benchmarking mistake?

Comparing model versions on a benchmark dataset that doesn't genuinely represent production conditions, or reporting results from favorable test conditions selected after seeing multiple results — both of which produce benchmarking conclusions that don't hold up in actual production deployment.

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