From Hypothesis to Member Satisfaction: A Scientific Approach to Product ML Innovation

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ABSTRACT

Recommendation algorithms are pivotal to Netflix's services. They provide our members around the world with personalized entertainment suggestions that align with their preferences at any given moment. Delivering truly satisfying member experiences requires highly cross-functional collaboration between product managers, data scientists, and engineers. Our goal is to maximize subscription value by helping members find entertainment they truly love so that they keep coming back to the service.

In recommendations - a product Machine Learning (ML) space - we personalize the discovery process for members, guiding them to engaging & well-matched titles. Product innovation in this domain presents a unique challenge. As our business needs rapidly grow and change, the research space of possible member experiences grows exponentially. It becomes critical to identify which of our hypotheses will lead to higher member satisfaction. This process relies on collecting quantifiable evidence that supports investing in a particular experience. The difficulty of this process is compounded further by Netflix's *scale* — our recommender system generates very large amounts of data, often influenced by presentation & selection biases among many confounding factors. Biased evidence can further lead to incorrect conclusions on initial hypotheses and potentially end in sub-optimal product experiences that do not satisfy members.

In this talk, we share a scientific approach to continuous ML product innovation. Our approach:

1. Produces trustworthy metric analyses for given hypotheses that are anchored in member satisfaction using observational causal inference methods and AB test meta-analysis,
2. Delivers a prioritized roadmap of impactful product experiences,
3. Enables large scale ML experiences through state-of-the-art personalization algorithms enabled by efficient engineering infrastructure and,
4. Proves high member satisfaction as evidenced by our online A/B tests

We also talk about an example case study that shows how this approach helps in decisions & turning hypotheses into real product experiences. We conclude with possible enhancements to this approach.

1 Potential Discussion Points

1.1 Challenges in large scale ML product innovation

- As the systems scale and business grows, many hypotheses and ideas become possible, but prioritization becomes increasingly difficult.
- ML technology, member tastes, and product offering continuously evolve, necessitating nimble innovation strategy.

1.2 Answering prioritization through evidence analysis

- We describe a set of tools such as correlational analysis, observational causal inference, A/B test meta-analysis etc. for finding answers to which ideas have more promise in improving member satisfaction.
- We explain what presentation and selection biases are in ML products and how our approach can help mitigate these biases affecting our evidence.

1.3 ML engineering for innovation

- We build personalization algorithms that align recommendations to member satisfaction. Our previous work [1] describes the engineering approach.
- We provide ideas on creating efficient ML infrastructure to try a hypothesis once prioritized.

1.4 Generate new learnings through A/B tests

- For brand new product experiences which have little or no observational analysis, this iterative approach generates reliable learnings for what members value by setting up online A/B tests, feeding these learnings into this virtuous cycle.

1.5 Case study & opportunities

- We talk about some examples of this approach and how practitioners can further maximize their cross functional collaboration with these methods.

2 Relevance to the Workshop

We believe that our approach is highly transferable to any industrial application of ML product management and engineering. It offers a solution to best utilize cross functional collaboration resources, to approach prioritization dilemmas and to improve innovation velocity.

The talk will be a mixture of technical depth and cross functional learnings - very much in congruence with the workshop's theme. Our insights will contribute to the development of best practices in the field, helping participants in choosing the right things to work on and creating successful ML products within their industries.

3 Bios

3.1 A short bio of the main presenter

Swanand is an applied machine learning researcher at Netflix, focusing on developing personalization algorithms and machine learning models to improve member satisfaction. Before joining Netflix, he worked at Facebook, where he specialized in feed ranking by removing objectionable content such as hate speech and misinformation, and at Amazon, where he focused on natural language processing for Amazon Alexa.

3.2 Company Portrait

At Netflix, we want to entertain the world. We give you personalized access to best-in-class TV series, documentaries, feature films and games. Our members control what they want to watch, when they want it, in one simple subscription. We're streaming in more than 30 languages and 190 countries, because great stories can come from anywhere and be loved everywhere.

REFERENCES

[1] Gary Tang, Jiangwei Pan, Henry Wang, and Justin Basilico. 2023. Reward innovation for long-term member satisfaction. In Proceedings of the 17th ACM Conference on Recommender Systems (RecSys '23). Association for Computing Machinery, New York, NY, USA, 396–399. https://doi.org/10.1145/3604915.3608873