HOW NETFLIX HAS BEEN BENIFITTED BY AI/ML

Time, Context and Causality in Recommender Systems

1. 1. Time, Context and Causality in Recommender Systems Yves Raimond October 2018 France is AI
2. 2. ● A few seconds to find something great to watch… ● Can only show a few titles ● Enjoyment directly impacts customer satisfaction ● How? Personalize everything, for 130M members across 190+ countries
3. 3. Profile 1 Profile 2
4. 4. Correlational recommender systems

5. 5. p(Y|X) Outcome (e.g. play) Features (e.g. past plays)

6. 6. 0 1 0 1 0 0 0 1 1 0 1 0 0 1 1 0 1 0 0 0 0 0 0 0 1 UsersItems

7. 7. 1 0 0 1 0 0 1 0 0 1 0 0 0 1 0 0 0 1 0 0 K K

8. 8. V Softmax

9. 9. However… These models can serve you well, but ignore key aspects of the recommendation problem: Recommendations happen at a moment in time, in a given context

10. 10. Time ● Don't overfit the past, focus on predicting the future ● Explicitly model temporal drift and system dynamics

11. 11. Time + Context ● X: sequence of contextual user actions, plus current context ● Y: probability of next action ● E.g. "Given all the actions a user has taken so far, what's the most likely video they're going to play right now?"

12. 12. Offline ranking improvements

13. 13. Causal recommender systems

14. 14. However… … correlational recommender systems are missing something else: Recommendations are actions at a moment in time, in a given context

15. 15. Feedback loops User Researcher

16. 16. Offline/online mismatches Production Interaction data New model Offline evaluation Online evaluation (A/B)

17. 17. p(Y|X, do(R)) Recommendation

18. 18. Causal recommender systems ● p(Y|X) can be misleading ● Ignores the user in the loop ● Model the causal nature of a recommendation instead ● Two steps: ○ Model p(Y|X, do(R)) ○ Build policy, e.g. what R leads to max Y? (from http://www.tylervigen.com/spurious-correlations)

19. 19. Approach 1: Epsilon-Greedy Visit Explore policy Greedy policy N% 100-N%

20. 20. Epsilon Member Candidate Pool Selected Randomize

21. 21. Greedy Member Features Candidate Pool Model 1 Winner Probability Of Engagement Model 2 Model 3 Model 4

22. 22. Replay Replay play-rate = 2/3

23. 23. Approach 1 pros & cons ● Pros ○ Simple ○ Helps feedback loops & offline/online mismatches ● Cons ○ Exploration has a cost ○ Doesn't scale well with size of the candidate pool

24. 24. Approach 2: Propensities Policy p(R|X) + (X, R, Y) R Y Inverse propensity weighting X p(Y|X, R)

25. 25. Approach 2 pros & cons ● Pros: ○ Model-agnostic ○ Simple ○ Scale well to large candidate sets ● Cons: ○ Only unbiased if no unobserved confounders ■ Hard to validate in practice ○ Variance can blow up ■ Variance regularization or weights clipping can help

26. 26. Approach 3: Instrumental Variable Example: What's the causal impact of a recommendation? R YZ Noise OutcomeRec An instrumental variable Z can only influence the outcome Y through R Building causal models with instrumental variables: 2SLS (two-stage least-squares) or SGDIV (to be published)

27. 27. Approach 3 pros & cons ● Pros: ○ Robust to unobserved confounders ● Cons: ○ Bias/Variance depends on strength of the IV ○ Harder to scale?

28. 28. In summary… ● Epsilon-Greedy: simple, but expensive ● IPS: great and flexible, but doesn't deal with unobserved confounders ● IV: deals with unobserved confounders, harder to scale ● Many more approaches available…

29. 29. Conclusions

30. 30. Conclusions ● Recommendations are actions at a moment in time, in a given context ● Correlational algorithms are great, until they start driving most of the data ● Recommendation algorithms make decisions, which have consequences ● Causal models are required to reason about this impact

it is very much Interesting ways that Netflix uses data science (including machine learning and AI) to manage its business include using algorithms to provide video recommendations, using AI to ensure quality streaming even at lower bandwidths.

VIDEO RECOMMENDATION SYSTEM

Netflix uses various types of algorithms to recommend videos to its users. The company estimated that this system helped to save $1 billion a year in value from customer retention.

Users who watch movie A are likely to watch movie B. This is leading us to the most well-known feature of Netflix. Netflix uses the watching history of other users with similar tastes to recommend what you may be most interested in watching next *so that you stay engaged and continue your monthly subscription for more.*

so behind the stage, they feed this watching history to their ML models, and also with the help of AI, they recommend the movie to users and they are so powerful that their predictions are 90% correct.

the recommendations system estimates the probability of a user watching a particular title based on the following factors

- *Viewer interactions with Netflix services like viewer ratings, viewing history, etc.*
- *Information about the categories, year of release, title, genres, and more.*
- *Other viewers with similar watching preferences and tastes.*
- *The time duration of a viewer watching a show*
- *The device on which a viewer is watching.*

Personalized Artworks/ Thumbnails

without Artworks, it looks so boring

A Netflix homepage without artwork.

every user probably 90% comes to the particular title because of its catchiness. they will show some chasing seen or famous actors in thumbnails so the user thinks it is a good movie to see and sometimes they show some suspense part of the movie to attract even more users and they give these images or thumbnails a name called artworks.

A Netflix homepage with the artwork.

Netflix differs from a hundred other media companies by personalizing the so-called artworks. They say an image is worth a thousand words and Netflix is playing on to it with its new recommendation algorithm based on the artwork /thumbnails.

The artwork for a title is used to capture the attention of the viewer and gives them visual evidence on why it could be a perfect choice for them to watch it. The thumbnail or artwork might highlight an exciting scene from a movie like a car chase, a famous actor that the viewer recognizes, or a dramatic scene that depicts the essence of the TV show or a movie. For every new title, various images are created randomly for different subscribers based on the community interest and also ML models. Netflix then presents the image with the highest like on a user's homepage so that they will give it a try.

Netflix makes use of thousands of videos from existing TV shows and movies for thumbnail generation. The images are then annotated and ranked to predict the highest likelihood of *being clicked by a viewer. These calculations depend on what other viewers with similar interests and preferences have clicked on.*

For Ex, viewers who like a particular actor are most likely to click on images with the actor.

As we said earlier netfilex users also get some personalized thumbnails based on their interest and community interest as well you can see in the following image

Artwork for Stranger Things that each receives from the Netflix personalization algorithm. Different images cover a breadth of themes in the show to go beyond what any single image portrays.