Name: Phani Valasa
UNI – PKV2103
Subject – Personalization: Homework 1 (Part I)

This case study discusses competitive analysis of Video-On-Demand streaming service with Prime Video as a reference. Amazon Prime Video: https://www.primevideo.com

User Experience:

Video on Demand is about choice – what to watch, where to watch and when to watch. I typically spend up to 20 minutes searching a video that I would like and if I can't find any interesting choice, I end up doing something else and not watch anything. Humans are generally bad at choosing between many options, quickly getting overwhelmed and making poor choices.

We need a Video-on-demand service, such as Prime Video, that would help viewers find just those videos that they would like to watch and should be easy to use. As more and more videos (TV shows, Movies, Games etc.,) are available online, it's crucial for this service to dig deeper into customer's interests and preferences and present them with only relevant videos.

The recommender system consists of a variety of algorithms that collectively define the user experience, most of which come together on the homepage. This is the first page that a member sees upon logging onto one's profile on any device (TV, tablet, phone, or browser). It is the main presentation of recommendations.

Prime Video:

There are typically about 25 rows on each homepage and approx. 25 videos per row. This is on my mobile. These numbers vary across devices (TV, Mobile, Tablet and Browser) because of hardware and user experience considerations. Each row is generated from Personalization and/or Recommendation algorithms that are categorized with an intuitive explanation such as 'Because you watched', 'Recommended for you', 'Watch next', 'Trending Now', 'Original Series', 'Prime Video Channels', 'Recently Added', 'Genres' etc.,

Personalization only:

User Profile: Information such as name, address etc.

Recommendation only:

Prime Video has sections for *'Trending Now', 'Recently Added', 'Genres' etc.,* which are pure recommendation based.

Personalization and Recommendation:

Watch next: This sorts the subset of recently viewed titles based on best estimate of whether the member intends to resume watching or re-watch, or whether the member has abandoned something not as interesting as anticipated. The signals used include the time elapsed since viewing, the point of abandonment (mid-program vs. beginning or end), whether different titles have been viewed since, and the devices used.

Because you watched: This row anchors its recommendations to a single video watched by the member. The video-video similarity algorithm drives the recommendations in these rows. This algorithm is an un-personalized algorithm that computes a ranked list of videos.

Recommend for you: Personalized video ranking algorithm orders the entire catalog of videos (or subsets selected by genre or other filtering) for each member profile in a personalized way. The resulting ordering is used to select the order of the videos in genre and other rows, and is the reason why the same genre row shown to different members often has completely different videos. This works better when we blend personalized signals with a pretty healthy dose of (un-personalized) popularity, which is used to drive the recommendations in the popular row.

There are several other kinds of rules/algorithms implemented combined with evidence matching to determine if the video is relevant for the user.

Considerations in Prime Video and Suggested Changes:

Accuracy: Using our own intuition, to choose the best variant of a recommendation algorithm often yields the wrong answer. Few processes that could be measured has an effect on accuracy: the acquisition rate of new members, member cancellation rates, hours watched, and the rate at which former members rejoin. In practice this evaluation is employed by conducting randomized controlled experiments, which are called AB tests. And this test will be run for several months to measure the impact.

Interpretability: The engine provides a high level explanation on the kind of recommendation. Example: Because you watched XYZ.

The Rich Get Richer/ Filter Bubble: An item centric feedback loop and user centric feedback loop. When I open prime video, I am bombarded with suggested videos based on my past views. A possible solution to this would be a setting that allows me to explore things outside my comfort zone. Categories such as current events, history, social awareness, TED Talks etc., should be an option for me to explore if I wanted instead of being filtered out without my knowledge.

Serendipity: I would like to be surprised with recommendations outside my comfort zone. I would prefer to explore new content recommendations based on my profile settings.

Diversity: Prime has a right mix of Diversity added to recommendations.

Time-Variance: I've seen the recommendation on my profile changing overtime as my daughter was growing up. I wouldn't change anything here.

Aspirations Vs Actual: Add more features to capture the sentiment of like/dislike.

Cold Start: When I was a new user on Prime Video, the recommendations were not very relevant. This is a generic issue with all recommendation engines. The service could capture additional information during sign-up process to classify users taste.

The Other engineering aspects such *Scalability, Real-time Vs Batch, and New Features* are very important as well to have the competitive advantage over a Tech giant like Amazon who can host the services in their data centers at scale.

Most Innovative Aspects:

The ease of use combined with the ability of satisfying personalization and recommendation requirements along with an infrastructure that could scale up and address potential engineering concerns.

Summary:

The goal of this study is to create a feasibility plan for a new Regional Video streaming product that could have competitive advantage over competitors such as Amazon prime. Based on the study, it's determined that it is absolutely necessary to satisfy the personalization and recommendation requirements along with an infrastructure that could scale up and address potential engineering concerns. In addition, I would also prefer to change few aspects of the recommendation engine, as highlighted above, to address user-facing concerns in an ever growing internet age that is creating bubbles. The resulting product could potentially have a competitive advantage.