Overview of Amazon's Product Recommendation Systems

Introduction

Amazon is arguably the most influential eCommerce company on the planet. Being founded in 1994, it began by selling books. Within a few years, however, Amazon soon began expanding their catalogue to cassette tapes, CDs, DVDs, to what finally is now a catalogue of millions of products. Amazon also accumulated more than just available products: customers. As a company that prides itself in being the most customer-centric company in the world, Amazon prioritizes a personalized shopping experience. Hence, it has become a leader in the development of cutting edge recommendation systems. I will give an overview of the history, improvements, and modern challenges of Amazon's product recommendation systems.

2003: Item-to-item Collaborative Filtering

In their early days of using recommendation systems to suggest products to customers, Amazon first relied purely on item-based filtering. One of their strategies was to recommend products that are commonly bought together with the products in the customer's shopping cart. Linden, Smith, and York provide the following pseudo-code for this algorithm in the award winning paper *Amazon.com Recommendations - Item-to-Item Collaborative Filtering*:

```
For each item in product catalog, I1
  For each customer C who purchased I1
    For each item I2 purchased by
       customer C
      Record that a customer purchased I1
       and I2
  For each item I2
    Compute the similarity between I1 and I2
```

The authors note it is not time or resource efficient to compute over every item-to-item pair, but rather only those that have both been bought by a single customer. Additionally, the authors note that its main advantage is that its computations can be performed offline, which is essential due to their extremely large item and user base. Lastly, it proved to give excellent results. Some of the most significant challenges they faced during this time were due to scalability challenges, which included:

- Traditional collaborative filtering does most computation online, which is impractical unless certain measures are taken to reduce data dimensionality which would reduce recommendation quality
- Cluster models can perform computations offline, however they have reduced recommendation quality
- Search-based models can perform computations offline, however results are often uninteresting and poorly targeted at the user

These challenges lead Amazon to turn to their unique item-based collaborative filtering algorithm. And, what is most surprising, this simple algorithm proved to outperform many of the future state-of-the-art approaches even a decade later (Linden, Smith, & York, 2003).

Discounting Heavy Buyers

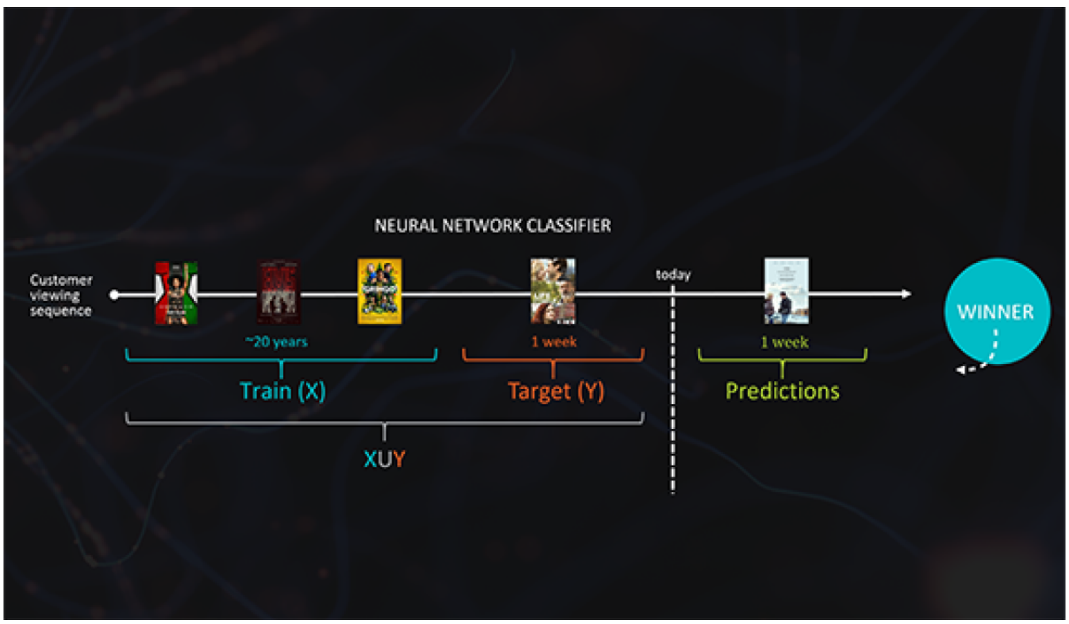
A key problem that Amazon faced was that the algorithm was systematically underestimating the baseline likelihood that someone who bought A would also buy B. The authors of the original 2003 paper realized that users being randomly selected were also more likely to be heavy buyers. Heavy buyers are more likely to buy *any* product. Hence, it was necessary to discount the heavy buyers' increased likelihood of buying another product B given A. Smith and his colleagues used Fubini's theorem and a binomial expansion to predict the expected number of customers who bought both X and Y.

$$
\begin{aligned}
E_{XY} &= \sum_{c \in X}\left[1-(1-P_Y)^{|c|}\right] = \sum_{c \in X}\left[1-\sum_{k=0}^{|c|}\binom{|c|}{k}(-P_Y)^k\right] \\
&= \sum_{c \in X}\left[1-\left[1+\sum_{k=1}^{|c|}\binom{|c|}{k}(-P_Y)^k\right]\right] = \sum_{c \in X}\sum_{k=1}^{|c|}(-1)^{k+1}\binom{|c|}{k}P_Y^k \\
&= \sum_{c \in X}\sum_{k=1}^{\infty}(-1)^{k+1}\binom{|c|}{k}P_Y^k && \left(\text{since } \binom{|c|}{k}=0 \text{ for } k>|c|\right) \\
&= \sum_{k=1}^{\infty}\sum_{c \in X}(-1)^{k+1}\binom{|c|}{k}P_Y^k && (\text{Fubini's theorem}) \\
&= \sum_{k=1}^{\infty}\alpha_k(X)P_Y^k && \text{where } \alpha_k(X)=\sum_{c \in X}(-1)^{k+1}\binom{|c|}{k}.
\end{aligned}
$$

This adjustment in the item-based collaborative filtering algorithm improved results significantly (Smith & Linden, 2017).

The Importance of Time

The next biggest advancement in the effectiveness of Amazon's recommendation algorithm came in the use of a very important factor: time. If a user buys a book 5 months after buying a different book, these purchases are unlikely to be related. Certain items are commonly bought in a certain order. As people age, their tastes may change and they may go through new stages in life. Taking these ideas into account proved to take Amazon's recommendation systems to the next level, improving results 2-fold as stated by Jeff Wilke, Amazon's CEO of World-Wide Consumer, in 2019 at Amazon's re:MARS conference. Jeff Wilke discusses how time is used for recommending movies in Prime Video, explaining that the algorithm predicts what the user might want to watch *in the next week* given their history from the last week, as well as before then. This approach is demonstrated in the graphic below:



Although this approach is used for movie and TV-series recommendations in Prime Video, this approach is used all across Amazon in their product recommendations to customers.

Some Modern Challenges and Areas for Future Research

As the domain of data that can be used for recommendation rapidly increases, more and more areas for research arise that could potentially lead to the next breakthrough. One area of research is analyzing customer intents. Customers can be shopping for a multitude of reasons, with a goal that can be both simple and complex. For example, to fix a hole in their wall, or to buy a coffee machine. A potential area of research is identifying customer intents through their queries and interactions with the website and dynamically using this information to make new, relevant recommendations. Limited research has been done in this area. Until now, it has mostly concluded that intent approaches are highly domain specific to the type of products being sold.

Another interesting area for future research is the concept of the user-journey, whether within the site or globally in other sites and applications as well. The on-site experience can be thought of in different stages. First, the user begins with a wide lens, beginning with a general search like *jeans*. Then, through exploration and search, the user gains confidence in the product they would like to buy. How can the state of the customer's journey be used to make relevant recommendations? What strategies can be used to determine the state of the journey? These are all important questions to answer in this area of research. As for the global journey, a primary challenge lies in abiding by privacy policies in collecting information about internet browsing history. If this information can be gathered, looking at previous sites visited can significantly improve the quality of product recommendations.

Lastly, the Learning to Rank has been an increasingly popular algorithm for optimizing the ranking function across the entire spectrum of queries, customer intents, and business goals. However, there are many areas for improvement. Firstly, product representation can be expanded for a more robust LtR algorithm, such as incorporating the number of times the products have been purchased, the view-to-buy ratio, and number of clicks. Secondly, it is an ongoing research area in how to define the objective function to prioritize both the goals of the business and those of the customer. A linear interpolation of signals can be written to optimize each of these given a series of signals, however combining them remains a prominent challenge. Lastly, there are practical limitations of LtR, such as the reliance on individual rankers for every aspect of queries such as type, brand, color, price, etc. and discontinuity in search results usefulness, where a returned list of recommendations may be organized in a way such that users stop browsing results before they can find a relevant product.

Conclusion

Beginning with the simple yet highly effective item-based collaborative filtering in 2003, to using time and thousands of other features in deep neural networks for making relevant recommendations, Amazon has held an important role in the advancement of recommendation systems in the modern era. It is fascinating to see the concepts of text retrieval systems used in practice and how far the simple intuition behind the core algorithms can take even modern cutting edge algorithms. As we venture further into a world where terabytes and terabytes of data are available for use, the potential areas for improvement and research accumulate exponentially.

References

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