Multitask Rank System: Evaluation methods and application

Timothy Cheung

University of Illinois at Urbana-Champaign

tcheung5@illinois.edu

Introduction

Zhao et al. has introduced a multi-objective ranking system for video recommendation (Zhao et al., 2019). In the paper, it is used to recommend videos on online video and sharing platforms. By using implicit feedback, they train a complicated neural network based model. In this paper, I will explore other potential methods to train and evaluate models, as well as applications that may be outside the realm of online video and sharing platforms.

Add-ons for training model

In this section, I will explore the possible add-ons to the ranking system. The first add-on is a gaze tracker to measure the users' patterns when viewing the recommendations made by the system. Using such system will require explicit agreement from the user, so it will need to take place in a controlled experiment. Gaze prediction has been used in many environments to predict human behavior. For example, one paper explores how gaze can be used in Atari games to predict the next action made by the player (Thammineni et al., 2021). The same can be done for online video and sharing platforms. For example, if the user gazes at a particular recommendation longer than others, it can be inferred that the recommendation may be more interesting to them. This is a form of implicit feedback, as the user does not need to do anything extra to produce the results. They merely need to act normally, and we can determine their gaze and use it for predictions.

Another possible add-on is normalizer based on user settings, preferences, geographical location, or any other characteristic in which we can classify users. This is an add-on that will weigh some categories of videos higher than others, based on other users in the same group. For example, if

we are classifying by geographical location, those in Chicago may be recommended more videos on Chicago pro sports teams.

Allowing the user to flag is also another add-on that may improve user experience. In this add-on, we place a flag next to each recommendation, such that users may explicitly state whether each video appeals to them or not. Then, we can use clustering to find similar videos. This will allow the model to produce more personalized results.

These add-ons can provide an extra layer of feedback, to better fit the user. In addition to add-ons, we can apply this model to other environments outside of online video streaming.

Other applications

One application of the model is online food delivery services, such as UberEats and DoorDash. There are many similarities that can be drawn between online video streaming and sharing platforms, and online food delivery services. The video recommendation, or a list of names, is like a list of restaurant recommendations. The content of the video is similar to the menu of the restaurant. The model can be tweaked to be able to recommend restaurants on an online food delivery service platform.

Another application of the model is educational platforms such as Coursera. By using the same logic, instead of recommending videos, we can group videos. This can produce series. For example, we could create a series about natural language processing, and have videos from different institutions grouped together.

Conclusion

A few add-ons have been suggested, and while they may produce more personalized results, some may require explicit agreement from the user. The model may also be applied to a few different fields, such as online food delivery services.

Thammineni, C., Manjunatha, H., & Esfahani, E. T. (2021). Selective Eye-gaze augmentation to enhance imitation learning in Atari Games. *Neural Computing and Applications*. https://doi.org/10.1007/s00521-021-06367-y

Zhao, Z., Hong, L., Wei, L., Chen, J., Nath, A., Andrews, S., Kumthekar, A., Sathiamoorthy, M., Yi, X., & Chi, E. (2019). Recommending what video to watch next. *Proceedings of the 13th ACM Conference on Recommender Systems*. https://doi.org/10.1145/3298689.3346997