Attractiveness Learning: A General Solution for the Cold-Start Problem

Yajuan Gu
Extreme Advanced Technology Department
A Super, Super, Super Tiny Start-up Company
Somewhere, Southern Part, China
heng6534605@163.com

Yuxun Lu*
National Institute of Informatics
University for Advanced Studies
Chiyoda, Tokyo, Japan
lu-yuxun@nii.ac.jp

Abstract

The cold-start problem is an essential issue in the recommender system. Recommender systems based on Collaborative Filtering or Deep Neural Network need sufficient user-item interactions to optimize the parameters. It is difficult to provide recommendations related to new users and new items because of the insufficient records. We proposed an attractiveness Learning approach as a general solution for the cold-start problem. Our approach does not need any data, GPUs, hard-working researchers, graduate school students (especially Ph. D. students). Experiments show that our method has achieved the state-of-the-art performance on zero-shot recommendation for items and users.

1 Introduction

Recommender system has become an core component in wide categories of online services. It encourages users to keep surfing so that the online platform can take the money out from pockets of the users, bigly and silently. Recommender systems suffer from the cold-start problem, i.e. they cannot provide satisfying recommendation to new items and new users because of the insufficient interactions (Lee et al., 2019).

Current methods alleviate the cold-start problem by interaction data from existing users and items to help the fast adaption of the parameters in the recommender system in a meta-learning framework (Lee et al., 2019; Finn et al., 2017; Wang et al., 2021; Snell et al., 2017; Sankar et al., 2021). These solutions are with a common flaw: all of them require hard efforts from diligent researchers and Ph. D. students. The inner loop in MAML (Finn et al., 2017) training procedure results in unbearably slow optimization, and the usage of GPU servers accelerates the carbon emission indirectly (Strubell et al., 2019).

We proposed a novel solution for the cold-start problem in zero-shot learning. Our approach employs attractive persons to recommend items to consumers. Our contributions are summarized as follows.

1. Our approach does not need any electric computation resources and outperform all methods that need them in the zero-shot scenario for cold-start problem.
2. The carbon emission of our method is significantly reduced compared to methods that need computational resources.

2 Methodology

The key point in our method is "how to find attractive persons and persuade them to do the sale". Both authors realized such research must satisfy the standard of experiments that related to human. However, the regulations and rules, although absolutely vital, are long and tedious for laymen. Both authors (Gu and Lu) have read the regulations and rules about, you know, about, ugh, 5 minutes-ish and found out that the management is less strict if the human involved in the experiments are limited to the authors *per-se*, so the persons involved in our methods are the authors of this paper, Yajuan Gu and Yuxun Lu.

According to their common friends, Gu "is charming and outgoing.", and the comment for the same question in regard to personality about Lu is "I'd rather not to say for the sake of our friendship". We use Lu as the control group and Gu as the experimental group. Our method is described in Algorithm 3.

3 Experiments

We conduct the experiments in (1) a restaurant use a red hair person in cartoon style as its logo; (2) a

Algorithm 1: the Attractiveness Learning Framework

Data: A group of consumers $\mathcal{C}$. A set of all items in store $\mathcal{G}$. The seller s.

Sort $g \in \mathcal{G}$ by the profit as ordered set $\mathcal{G}^*$.

Estimate the gullibility of all $c \in \mathcal{C}$ by the s.

while $\mathcal{C}$ *is not empty* **do**

  Greeting c^* with the highest gullibility.

  while c^* *is not leaving* **do**

    Try to sell $g^* \in \mathcal{G}^*$ to c^*.

luxury shop whose design is famous for being similar to checkerboard; (3) A membership mall being known for its "suspicious" low price. We take binary Normalized Discounted Cumulative Gain and Ratio in Total Sales as performance measures. The Ratio in Total Sales is

$$r = p(s)/p^*. \tag{1}$$

$p(s)$ is the sale amount from s in Algorithm , and p^* is the total sale amount of the day. The equation for binary NDCG is (relatively) too complicated for the lazy authors to type here. Please use the search engine Google [1] for the formula. The results for 6 days sale in 3 domains are shown in Figure 1 and Figure 2, respectively.

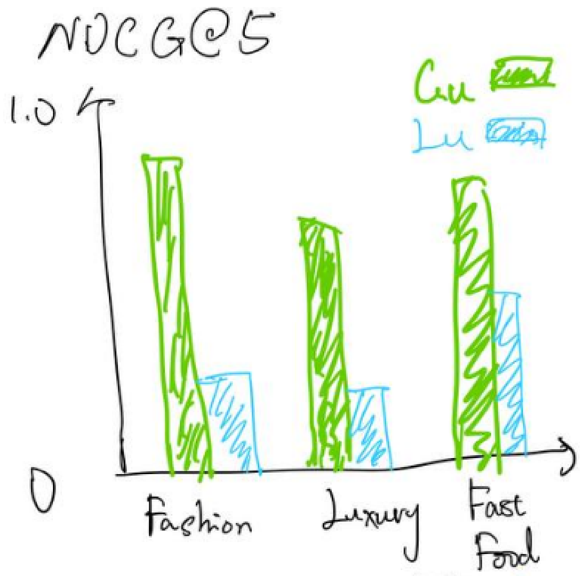


Figure 1: The averaged NDCG@5 for Gu and Lu in 3 domains. Drawn by Yajuan Gu (the first author).

[1]https://www.google.com

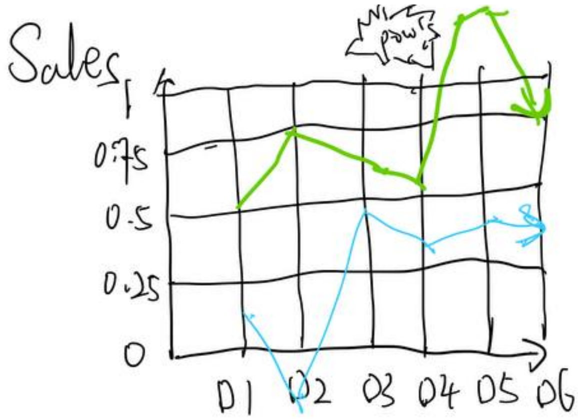


Figure 2: The Ratio in Total Sale for Gu and Lu in the "Fast Food" domain for 6 days. Drawn by Yajuan Gu (the first author).

3.1 Discussion

The results in Figure 1 and Figure 2, show that the attractiveness is a critical property for the saler s in Algorithm 3. Especially, the total sale ratio for the "Fast Good" domain on Day 5 is over 1.0 for Gu because a generous customer paid a big tip after ordering [2] while Lu arrived negative ratio in Day 2 because he was caught by the cantine manager when sneaking burger and fries in the kitchen and has to pay the fine.

It worth note that the saler s has no information about the demographic information of the consumers in $\mathcal{C}$. Hence, every consumer is treated as a new consumer in the system. Beside, in Algorithm 3, the saler s does not care about the attributes of the goods in $\mathcal{G}$ at all. Therefore, it is unimportant if the item is new or not.

4 Related Work

Attractiveness based recommender system has been known in many popular cultures. For example, the character "Penny" in "the Big Bang Theory" and "Max" in the "2 Broke Girls". But it seems that no rigorous research has been done yet for investigating the impact of attractiveness in the recommender system domain. We wish this letter will encourage more researchers to extend the future investigation about this topic.

5 Conclusion

We proposed a attractiveness learning framework in this letter. The system does not rely on any

[2]Both nations in which the authors resident do not have tipping tradition.

data to solve the cold-start problem in user side and item side. The experiment result shows that attractiveness learning can significantly improve the profit resulted from recommendation.

Acknowledgement

We appreciate the suggestions from all reviwers, if any, about the spelling and grammartic issues in this paper. Especially the opinion that suggested an extremely expensive service on editing. Our answer, as always, is “hack know. VR nut going two yuzit.”

References

Chelsea Finn, Pieter Abbeel, and Sergey Levine. 2017. Model-agnostic meta-learning for fast adaptation of deep networks. In *Proceedings of the 34th International Conference on Machine Learning*, pages 1126–1135.

Hoyeop Lee, Jinbae Im, Seongwon Jang, Hyunsouk Cho, and Sehee Chung. 2019. Melu: Meta-learned user preference estimator for cold-start recommendation. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 1073–1082.

Aravind Sankar, Junting Wang, Adit Krishnan, and Hari Sundaram. 2021. Protocf: Prototypical collaborative filtering for few-shot recommendation. In *Fifteenth ACM Conference on Recommender Systems*, pages 166–175.

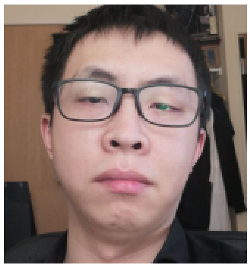
Jake Snell, Kevin Swersky, and Richard Zemel. 2017. Prototypical networks for few-shot learning. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, page 4080–4090.

Emma Strubell, Ananya Ganesh, and Andrew McCallum. 2019. Energy and policy considerations for deep learning in nlp. *arXiv preprint arXiv:1906.02243*.

Li Wang, Binbin Jin, Zhenya Huang, Hongke Zhao, Defu Lian, Qi Liu, and Enhong Chen. 2021. Preference-adaptive meta-learning for cold-start recommendation. In *Proceedings of the 30th International Joint Conference on Artificial Intelligence*, pages 1607–1614.

A Author Biography

Gu Yajuan is a senior researcher in a super start up company. Gu is also the saler, door keeper, cook, cheif, account, treasory, general affair manager, human resource manager, stakeholder, general manager of the company. The research interest Gu is about all aspects in fashion and food.



Lu Yuxun is a slob in the National Institute of Informatics in Japan. Lu focus on the research of rushing paper draft before submission deadline.