جامعة جدة
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CCAI422 Recommender System Course Project

Variational Autoencoders for Collaborative Filtering

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TITLE:
Variational Autoencoders for Collaborative Filtering by Dawen Liang, Rahul G. Krishnan, Matthew D. Hoffman,Tony Jebara Netflix [1].

ABSTRACT:
The paper proposes the use of Variational Autoencoders (VAEs) for collaborative filtering in recommender systems. The paper adjusts the standard VAE objective to improve performance. The proposed approach outperforms state-of-the-art baselines on real-world datasets. This non-linear probabilistic model enables us to go beyond the limited modeling capacity of linear factor models which still largely dominate collaborative filtering research. we have implemented the code on a new dataset with multinomial likelihood. Finally, we identify the pros and cons of employing Variational Autoencoders (VAEs) for collaborative filtering approach and characterize settings where it provides the most significant improvements.

INTRODUCTION:
In our journey through a recommendation system course project, we embarked on an exciting exploration of recommendation system and dive deep into its concepts, implement its findings, and push the boundaries of its capabilities to improve and innovate in the field of personalized recommendations. The major challenging "small-data" problem where most users only interact with a tiny proportion of the items and our goal is to collectively make informed inference about each user's preference . we find that to make use of the sparse signals from users and avoid overfitting, we build a probabilistic latent-variable model that shares statistical strength among users and items. Empirically, we show that employing a principled Bayesian approach is more robust regardless of the scarcity of the data. However, we did not stop at mere replication. We fine-tuned parameters of the Variational Autoencoders (VAEs) , explored alternative dataset to create a functional system that could generate personalized recommendations.

AIM:
Our goal is to explore a research paper, implement its findings, and further improve upon the proposed methodology. Through our implementation and enhancements, we strive to contribute to the advancement of personalized recommendations and push the boundaries of existing techniques. By conducting thorough evaluations, we aim to gain valuable insights and draw meaningful conclusions that can guide future developments in the field of recommendation systems.

BACKGROUND:

here are some background readers need to know in order to understand this project.

1. Recommendation System:

A recommendation system is a software algorithm that analyzes user data and provides personalized suggestions on items or content that the user may find interesting or relevant. These systems are commonly used in e-commerce, streaming platforms, social media, and other online services to enhance the user experience, increase engagement, and drive sales. Recommendation systems can employ various techniques, such as collaborative filtering, content-based filtering, deep learning, or hybrid approaches, to generate recommendations based on user preferences, item characteristics, or both.

2. Collaborative Filtering:

Collaborative filtering is a popular technique used in recommendation systems. It leverages the collective behavior and preferences of a group of users to make predictions or recommendations for individual users. This approach assumes that users who have similar tastes or preferences in the past are likely to have similar preferences in the future. Collaborative filtering can be divided into two main types: user-based and item-based. User-based collaborative filtering recommends items to a user based on the preferences of similar users, while item-based collaborative filtering recommends items based on the similarities between items themselves.

3. Deep Learning:

Deep learning is a subfield of machine learning that focuses on training artificial neural networks with multiple layers to learn and extract complex patterns from data. In the context of recommendation systems, deep learning techniques can be applied to process large amounts of user and item data, including textual, visual, or sequential data, to generate personalized recommendations. Deep learning models, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers, can capture intricate relationships and patterns in user-item interactions, leading to more accurate and relevant recommendations.

4. Variational Autoencoders (VAEs):

Variational autoencoders (VAEs) are generative models that combine the concepts of autoencoders and probabilistic modeling. In recommendation systems, VAEs are used to learn low-dimensional representations of user preferences or item features. By mapping high-dimensional data to a lower-dimensional latent space, VAEs can capture the underlying structure and generate new data samples. VAE-based recommendation systems can learn meaningful representations of users and items, enabling personalized recommendations. Additionally, by modeling the probabilistic nature of user-item interactions, VAEs can generate diverse and novel recommendations, enhancing the user experience.

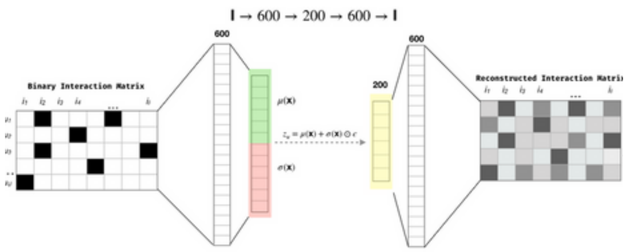
APPROCHE:

Recommendation systems utilize algorithms to analyze user data and provide personalized suggestions, enhancing user experience and engagement across various online platforms. Collaborative filtering, a prevalent technique, derives recommendations based on user behavior patterns. Deep learning methods, such as convolutional and recurrent neural networks, enable the processing of diverse data types for more accurate suggestions. Variational Autoencoders (VAEs) are generative models used in recommendation systems to learn representations of user preferences and item features, facilitating personalized and diverse recommendations. The paper "Variational Autoencoders for Collaborative Filtering" by Dawen Liang et al. proposes using Variational Autoencoders (VAEs) to improve collaborative filtering in recommendation systems. This method combines probabilistic graphical models and deep learning to tackle challenges in collaborative filtering, such as implicit feedback and scalability.

Variational Autoencoder :

1. Model Architecture: The VAE consists of an encoder and a decoder. The encoder maps the input (user-item interaction data) into a latent probabilistic space, and the decoder reconstructs the input from this latent space as shown in the figure.

- The encoder is defined by a probability distribution $q\phi(z|x)$, where x is the input and z is the latent variable.
- The decoder is modeled by $p\phi(x|z)$ aiming to reconstruct x from z.



Hyperparameters and Metrics:
we determined the hyperparameters through a combination of experimentation, domain knowledge, and sometimes grid/random search.

- as for the learning rate value of 1e-3 is common and often works well for many tasks small enough for stable convergence but not too small to slow down learning.
- as for 200 epochs is a common starting point, and it's likely that this value was chosen through experimentation to find a balance between training for long enough to capture patterns and avoiding overfitting.
- the chosen values for annealing steps and cap is task-specific and have been fine-tuned through experimentation.
- Evaluation Metrics: we used metrics like Recall, and Normalized Discounted Cumulative Gain (NDCG) are used to evaluate the model's performance in recommending relevant items to users.

Implementation and Optimization:

- AdamOptimizer: The model is trained using Adam, a scalable approach to optimizing the ELBO.
- Mini-batch Training: The model is trained on mini-batches of user-item interaction data, making it scalable to large datasets.

Experement

NETFLIX DATASET:

The Netflix dataset contains two main files: Movie and Rating. The Movie file holds essential details such as Movie_ID (unique identifier), Name (movie title), and Year (release year). In contrast, the Rating file includes Movie_ID (movie being rated), User_ID (unique user identifier), and Rating (user-generated movie ratings on a scale from 1 to 5 stars). This dataset combines movie specifics, user IDs, and associated ratings, offering insights into user preferences and movie popularity, enabling the creation of recommendation systems and predictive models for streaming platforms like Netflix

Run Experement

We experimented on two types of autoencoders Multi DAE & Multi VAE , setting the same parameters for both, and compared their performance to understand the differences between them. We determined the learning rate through research and experimentation. We found that using values such as 0.1, 0.3, and 0.001 significantly affected the performance. If the learning rate is very small, it might take a long time to make progress in the training process. In some cases, this could lead to getting stuck in local minima or the learning process struggling to make significant performance improvements. On the other hand, if the learning rate is too large, it could lead to instability and large fluctuations during the training process. This might cause rapid transitions towards local minima and could also result in overshooting optimal points. we found that the 1e-3 is the best to use as reasercher suggest. Regarding annealing, we experimented with multiple values from 0.1 to 1. It turned out that the value that suited us best was 0.9 for thae annel cap . Regarding the runtime, when it was 10 epochs, it didn't take much time, but when we increased it to 200 epochs, it took more runing time, so we used a GPU100 to speed up the process.

Evaluation metric

We used Discounted Cumulative Gain (DCG) is a metric commonly used to evaluate the ranking quality of a model. NDCG@k specifically refers to the NDCG calculated at a particular position, typically at position k, and Recall@k It provides insight into how effective the system is at suggesting items that users find relevant within the top 'k' recommendations.

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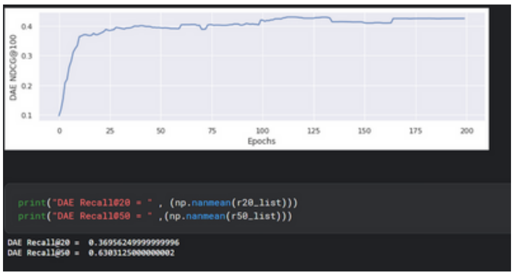
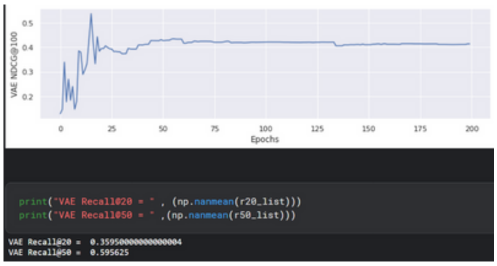


RESULTS

compared to the paper results we have slight enhancment sinice we have got 0.431 NDCG at Multi -DAE while we have got 0.52 at Multi - VAE. Even using Recall@50 we have gain an improvment compared to the paper results. But when it comes to the Recall@20 metrics the paper results are clearly better with a small difference. Intuitively, Mult-vaepr and Mult-dae have roughly similar performance. but Mult-vae imposes stronger modeling assumptions and therefore could be more robust when user-item interaction data is scarce.



PAPER RESULTS	Recall@20	Recall@50	NDCG@100
Mult-VAE^{PR}	**0.395**	**0.537**	**0.426**
Mult-DAE	0.387	0.524	0.419

FUTURE WORK

To prevent Bias we used an undersampling technique that handles imbalanced data to prevent Variance we used Regularization L2 and to prevent overfitting but we still gained low NDCG so in the **future,** we want to Increase the size of the dataset or use simpler models that are less prone to overfitting, especially when the amount of data is limited.

DISCUSSION & CONCLUSION:

In the end, our journey through this recommendation system course project has been an enriching experience. We have not only explored a research paper and implemented its findings but have also gone above and beyond, striving to improve and innovate within the field. Through our collective efforts, dedication, and unwavering commitment, we hope to contribute to the advancement of recommendation systems and leave a lasting impact on the field as aspiring researchers and engineers.

REFERENCE:

[1] - Liang, D., Krishnan, R. G., Hoffman, M. D., & Jebara, T. (2018). Variational Autoencoders for Collaborative Filtering. arXiv preprint arXiv:1802.05814.

TEAM CONTRIBUTIONS:

Name	ID	Work Tasks
Bedoor Ayad	2005961	Report writing, Coding, Approch
Raneem Alomari	2006352	Paper Selection, Report writing, Coding
Deema Al-sayegh	2006085	Data Selection, Presentaion design, Experiments, Documentation