成都理工大學 中英合作办学
CDUT Sino-British Collaborative Education

OXFORD BROOKES UNIVERSITY

UNDERGRADUATE PROJECT PROPOSAL

Project Title:	**Book Recommendation using variational autoencoders**
Surname:	**Wang**
First Name:	**Yutong (Ryan)**
Student Number:	**202018010315**
Supervisor Name:	**Joojo Walker**
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1 Introduction

1.1 Background

The development of e-commerce has facilitated shopping by providing a new way to shop. Over the past decade, there has been a dramatic increase in the use of e-commerce websites because of rapidly advancing technology. The contribution of e-commerce to total retail sales increased from 5.1% in 2007 to 16.0% in 2019. Books are also one of the commodity categories in shopping platforms, and the modern book industry is characterized by an extremely rich variety, which gives readers numerous choices when purchasing books on online platforms while also making it increasingly challenging to identify and select books that match their preferences and interests [1]. Therefore, an effective personalized book recommendation system (RS) is very important. At the same time, the act of reading is beneficial to both individuals and society, but studies have shown a decline in reading among young people. Recommender systems can also help stop this decline [2].

1.2 Aim

The goal of this project is to establish a user-centric recommendation platform utilizing Variational Autoencoders (VAEs) as the foundation. By implementing various models based on VAE, their strengths and weaknesses are thoroughly evaluated, and the most effective model is finally identified and integrated into the platform. Optimize the recommendation process using VAE's latent representation capabilities to improve the platform's ability to provide tailored and diverse book recommendations that are closely aligned with users' personal preferences and reading habits.

1.3 Objectives

- Collect a diverse dataset of books and perform thorough data cleansing and preprocessing to ensure uniformity and suitability for model training.
- Evaluate and compare the performance of various models based on VAE by implementing them, assessing metrics including recommendation accuracy, diversity, and coverage, and conducting a comprehensive analysis to identify the strengths and weaknesses of each model.
- Integrate the selected VAE model into the recommendation platform.
- Conduct performance testing to validate the efficiency and effectiveness of the system in generating personalized book recommendations tailored to individual user preferences.

- Optimize and fine-tune the model parameters and architecture, iteratively refining the selected VAE model to enhance recommendation accuracy and ensure an enriched overall user experience.
- Compile a comprehensive report detailing the project's methodology, implementation, and findings, summarizing key insights, challenges, and recommendations for future enhancements to the recommendation system.

1.4 Project Overview

1.4.1 Scope

This research aims to explore the efficacy of variational autoencoders (VAEs) in enhancing book recommendation systems with a focus on providing highly personalized and diverse book recommendations to users. By testing and evaluating a variety of models based on VAE, this project seeks to identify the most effective model and integrate it into a recommendation platform that can provide customized book recommendations according to readers' unique reading preferences and habits. This can contribute to improving the reading experience of users.

The significance of this research is that it develops a new book recommendation system utilizing cutting-edge deep learning techniques. Using VAE facilitates a closer connection between individuals and a wide range of literary domains. Furthermore, the findings and insights from this study are expected to contribute to broader research on personalized recommender systems.

1.4.2 Audience

The outcomes of this project will benefit several key stakeholders. These stakeholders include:

- Readers (users): Enhance their book exploration experience by exploring a wider range of literature to suit their individual preferences.
- Publishing professionals: Authors, editors, and publishers can use recommender systems to gain a deep understanding of reader preferences and trends. Adjust content creation and marketing strategies based on user preferences to increase book sales and readers' feeling of engagement.
- E-commerce platform: The platform can utilize the recommendation algorithms developed in this project to increase user engagement and conversion rates (the ratio of user purchases to views).

- Academics and Research: The findings of this project can contribute to existing research on personalized recommender systems and promote the understanding of the application of VAE.

2 Background Review

A recommender system (RS) predicts the likelihood that users will be interested in items that they may not yet know about. To make recommendations, RS typically require user data and user commentary on these elements. User's feedback on items can be obtained either explicitly or implicitly following a proposal is put forward. The system preserves the feedback in a database and utilizes it for future suggestions [2]. Deploying recommendations in e-commerce has many benefits for both sellers and consumers. The former's goal is to get more orders. On the other hand, consumers receive a list of products they are most likely to find useful. They also save time, energy, and money that they would have spent on discovering items they appreciate [2]. However, RS still faces challenges. The most well-known issue is rating scarcity, which can lead to cold starts for users or items.

Collaborative filtering is a prevalent approach employed within recommender systems. It facilitates prediction of user preferences by identifying and utilizing similarities between users and items [2]. The variational autoencoder (VAE) extends to collaborative filtering with implicit feedback. VAE generalizes the linear latent factor model, allowing us to explore nonlinear probabilistic latent variable models supported by neural networks on large-scale recommendation datasets. The article presented a polynomial conditional likelihood model of neurodegeneration [3]. Recommender systems are often evaluated using ranking-based metrics. Previous research has shown that direct optimization of Top-N ranking loss is challenging, and previous work on this subject has resorted to employing relaxations and approximations [4, 5]. Here, it is evident that the multinomial likelihoods are well-equipped to simulate implicit feedback data and are a superior substitute to more traditional likelihood functions such as Gaussian and logistic in terms of their correspondence with ranking loss [3].

Kingma and Welling [6] showed how the reparameterization of variational lower bounds produces simple differentiable unbiased estimators of the lower bounds; such SGVB (Stochastic Gradient Variational Bayesian) estimators can be used for efficient approximate a posteriori inference in virtually any model with continuous latent variables and/or parameters and can be optimized directly using standard stochastic gradient ascent techniques. For the case of continuous latent variables in the dataset and at each data point, they propose the auto-encoding VB (AEVB) algorithm. In the AEVB algorithm, optimize the recognition model to make inference and learning particularly efficient by using an SGVB estimator that allows us to perform very efficient approximate a posteriori inference using simple ancestor sampling, which in turn allows us to efficiently learn the model parameters without the need for costly iterative inference schemes (e.g., MCMC) for each data point. The approximate a posteriori inference model, which has been learned, can be applied to a multitude of tasks, such as image recognition, noise reduction, data representation, and visualization [6]. When using neural networks for recognition models, we obtain variational autoencoders (VAEs).

3 Methodology

3.1 Approach

Variational Auto-Encoder [6]:

There are multiple advantages of applying VAE for collaborative filtering in recommender systems. VAE can map users and items into a continuous latent space, which helps to discover potential user interests and item characteristics. In addition, using VAE can fill in the gaps in the data by learning the representations in the latent space, which improves the system's ability to handle the missing data. VAE can alleviate the cold-start problem in recommender systems by learning the latent space and combining it with information about other relevant features to provide them with meaningful recommendations.

(High dimensional) variable: X – generated from conditional distribution $P_{\theta*}(x|z)$

Unobserved continuous random variable: Z – generated from prior distribution $P_{\theta*}(z)$

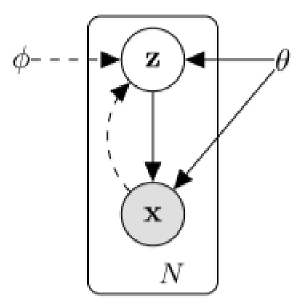

Figure 1 Directed graphical model [6]

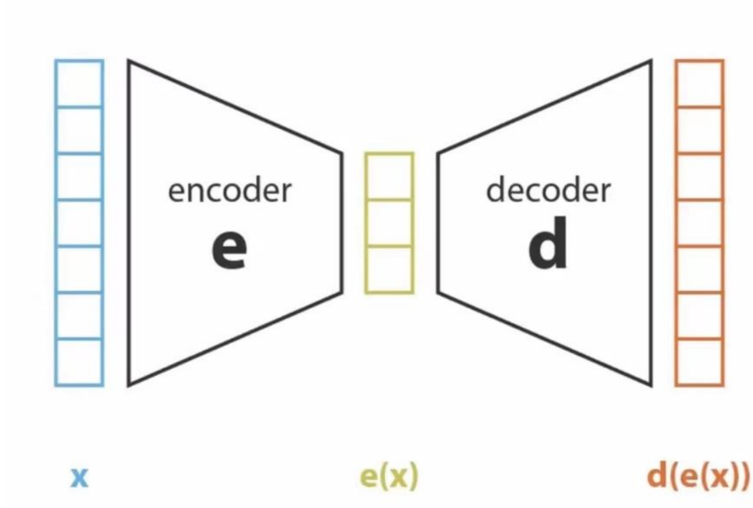

Figure 2 Abstract figure of VAE

VAE is a network architecture belonging to the probabilistic graphical and variational Bayesian models.

Two neural networks of VAE:

- Encoder: Encoding and compression of data.
- Decoder: Data generation.

However, there is still a prerequisite before decoding: e(x) is a regularized latent space. In order to make latent space regularized, the way to do this is to add some randomness. That means input the same x, output different z every time. The specific mathematical representation of increased randomness is the application of Bayesian Rules.

$$P(z|x) = \frac{P(x|z)P(z)}{P(x)} = \frac{P(x|z)P(z)}{\int P(x|u)P(u)du}$$

Next, calculate loss function to ensure P(z) and P(z|x) are regularized.

$$q_\theta(z)(encoder) \approx p(z|x)$$

$$D(q_\theta(z)||p(z|x))(KL\ Divergence) = E_{z\sim q}\left[\log\frac{q_\theta(z)}{p(z|x)}\right] = E_{z\sim q}[\log q_\theta(z) - \log p(z|x)]$$

$$= E_{z\sim q}[\log q_\theta(z) - \log p(z,x)] + \log p(x)\ \ (evidence\ lower\ bound)$$

$$\log p(x) = E_{z\sim q}[\log p(z,x) - \log q_\theta(z)] + D(q_\theta(z)||p(z|x))$$

$$\log p(x) \geq E_{z\sim q}[\log p(z,x) - \log q_\theta(z)] \equiv \varsigma_q$$

The objective: minimizing KL divergence leads maximizing evidence lower bound (ELBO).

Recommender VAE (RecVAE) [7]:

The RecVAE model is an improved model based on the Mult-VAE model, which uses multinomial distributions as the likelihood function instead of Gaussian and Bernoulli distributions, which are commonly used in VAE models.

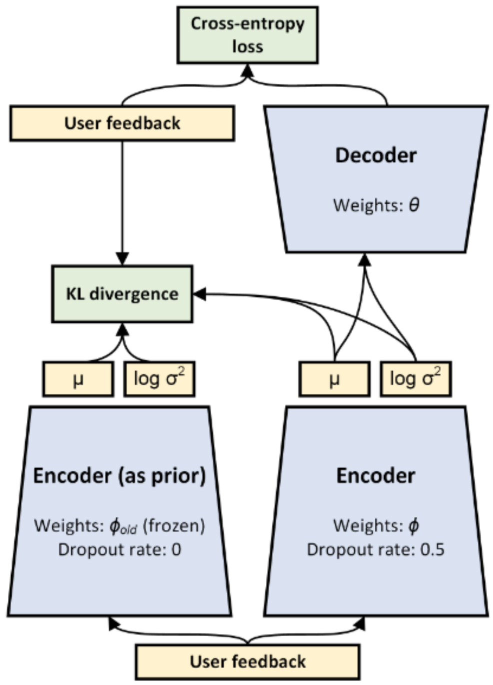

Figure 3 RecVAE structure [7]

RecVAE is denoising variational autoencoder, it changes evidence lower bound (ELBO) to:

$$E_{q_\phi}(z_u|x'_u)E_q(x'|x)[\log p_\theta(x|z) - \beta'(x)KL(q_\varphi(z|x')||p(z|\varphi_{old}, x))]$$

Next, a method like Alternating Least Squares (ALS) (a common matrix factorization technique) is utilized to train the model, alternating before user and item embeddings. User embeddings are apportioned by the inference network, while each item embedding is trained separately.

ALGORITHM 1: Proposed training procedure

Data: $\mathcal{D} = \{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_{|U|}\}$
Result: $\boldsymbol{\phi}, \boldsymbol{\theta}$
for $n := 1, \ldots, N$ **do**
    for $m := 1, \ldots, M_{\text{enc}}$ **do**
        Sample batch $\{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_b\} \sim \mathcal{D}$;
        Update $\boldsymbol{\phi}$ based on $\widetilde{\mathcal{L}}$;
    end
    $\boldsymbol{\phi}_{old} := \boldsymbol{\phi}$;
    for $m := 1, \ldots, M_{\text{dec}}$ **do**
        Sample batch $\{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_b\} \sim \mathcal{D}$;
        Update $\boldsymbol{\theta}$ based on $\widetilde{\mathcal{L}}_{\text{dec}}$;
    end
end

Figure 4 Training Method [7]

Dataset:

In the project, datasets about books from different e-commerce platforms will be used like Amazon, which has very comprehensive data.

3.2 Technology

- **CPU:** Intel(R) Core(TM) i7-10750H CPU @ 2.60GHz
- **GPU:** NVIDIA GeForce GTX 1660 Ti
- **Memory:** 16G (Samsung 8G 2933 MHz, Micron 8G 2933 MHz)
- **Operating system:** Windows 11
- **Database:** MySQL 8.0.29, DBeaver 22.1.2
- **Coding language:** Python 3.9
- **Coding environment:** Microsoft VS Code, PyCharm 2022.3
- **Writing environment:** Microsoft Office

3.3 Version Management Plan

Using GitHub to manage the several versions of project code. And the Git repository link is https://github.com/FOMOKN/Project.git.

4 Project Management

4.1 Activities

To complete each objective, some details will be given in the table.

Objectives	Activities
Learning the Variational Autoencoders (VAE) model	Research articles and codes about the model like VAE, Mult-VAE, and RecVAE
Dataset	Download suitable datasets about books and data processing
Book Recommendation	Decide which features of the book will be used by the recommender system
Comparative Study	Evaluate the performance of different models and list their strengths and weaknesses
Implementing the model	Based on VAE, develop an efficient model and use the dataset to perform multiple tests to demonstrate its performance
Report	● Weekly log ● Record test results and improvement measures ● Final report

4.2 Schedule

Using Gantt charts to show the activities and their deadlines.

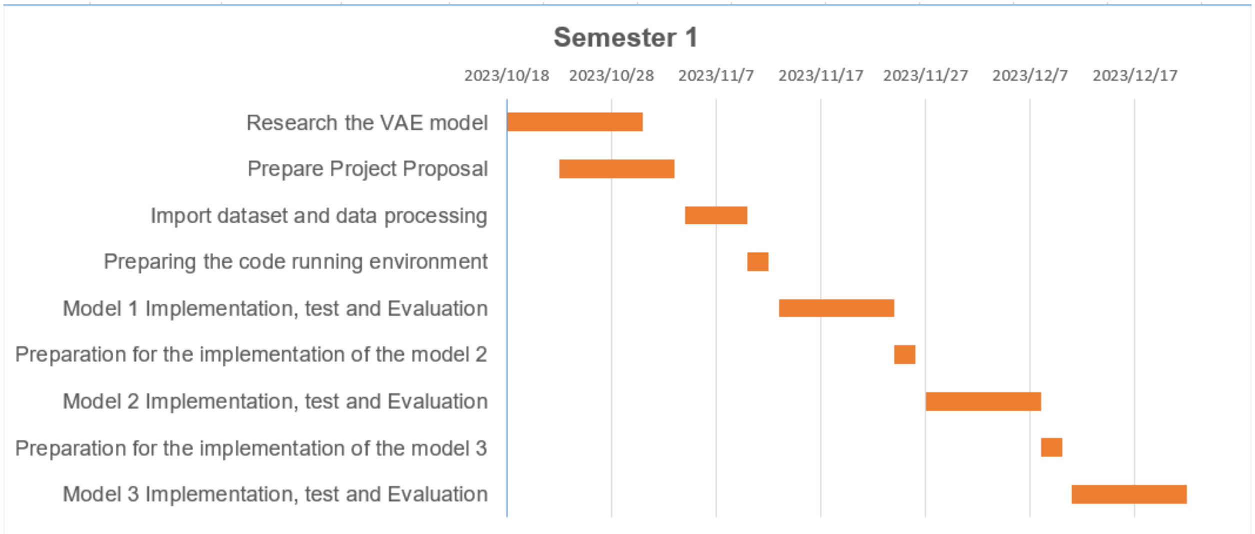

Figure 5

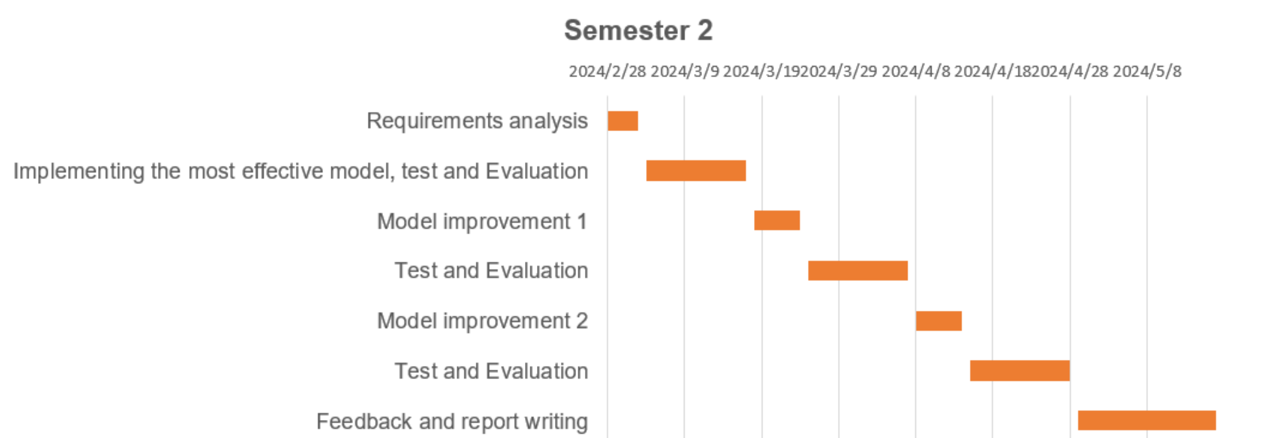

Figure 6

4.3 Data Management Plan

To have a better grasp of the project's progress, both local and cloud-based storage management will be used. Use the Feishu cloud document folder to store documents including bibliographies, project proposal, weekly reports, final report, etc. Feishu link is https://y1jgvfzywn.feishu.cn/drive/folder/QYKhfak5OlAv5Hdz8UycoHu8neh.

4.4 Project Deliverables

- Project Proposal
- Ethic Forms
- Weekly Report
- Progress Report
- Slides

- Finial Report
- Project Code

5 References

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