

## Final Report

Raj Bunsha — IMT2021010 Pannaga Bhat — IMT2021080 Kadaru Jashwanth Reddy— IMT2021095

Instructor: Prof. Raghuram Bharadwaj Date: May 1st, 2024

#### 1 Overview

We have chosen "Blog Recommendation System" as our topic. For implementation purposes, we have specifically limited ourselves to particular types of blogs, so that analysis and evaluation of models becomes easier. We have chosen blogs related/relevant to users who are part of online competitive programming communities. For scraping of data we have specifically chosen 'Codeforces Blog Recommendation System'. The rest of the report contains the description of the dataset that we have constructed, the novel methods/models that we have formulated to recommend blogs to users, and the evaluation metrics that we added later upon feedback.

#### 2 Introduction

Recommendation systems play a vital role in various online platforms, aiding users in discovering relevant content based on their preferences and behaviors. In this project, we focus on developing a recommendation system tailored for users involved in online competitive programming communities. Specifically, we aim to recommend blogs from platforms such as Codeforces, which provide valuable insights, tutorials, and discussions related to competitive programming.

## 3 Dataset Description

#### 3.1 Dataset Construction

To construct our dataset, we utilized a combination of the Codeforces API and web scraping techniques with Selenium. We collected over 40,000 blogs from Codeforces, focusing on diverse topics within the competitive programming domain.

#### 3.2 Data Overview

The dataset comprises various attributes for each blog entry, including the user, title, tags, and net upvotes/downvotes. This information forms the basis for our recommendation system.

#### 3.3 Preprocessing & EDA

Prior to analysis, we performed preprocessing steps such as data cleaning and exploratory data analysis (EDA) to gain insights into the distribution and characteristics of the dataset.



## 4 Methodology & Approaches

#### 4.1 Methodology 1

Our methodology involves leveraging natural language processing (NLP) techniques and machine learning algorithms to develop effective recommendation models.

## 4.2 Representing blogs as vector

The different ways to get vector from text is as follows:

- 1. Spacy
- 2. Gensim model of Doc2Vec
- 3. BERT model

Once this is done we can move for cosine similarity and find the most similar blogs with the user representation

#### 4.3 PCA for better representation and clustering

As the vector representing the blog can be of very high dimensions or represented in such a way that it cannot be easily clustered we get the PCA of the blog vectors this also helps us in getting the latent features that shape the blogs.

#### 4.4 User representation

We start with trying to get user representation of to do so we started out with making user representation as average of all the blogs that user has liked. However this has a huge problem that average of the blogs just might not accurately represent the user. So we Use KMeans to get centroids of clusters formed from the blogs. They represent the likes of user. Thus the user representation is not a vector but a set of vectors, formed by clustering the blogs.

Now since we don't have a single vector as user representation we can instead get the similarity through all the all the centers and take the maximum which gives us the maximum correlation with all the topics that the user likes.

## 5 Sample results

#### 5.1 Input:

This are the sample blogs that have been liked

#### 5.2 Bert Image:

We can see blogs with similar tags

#### 5.3 Gensim Image:

We can see blogs with similar tags

#### 5.4 Spacy:

We can see blogs with similar tags



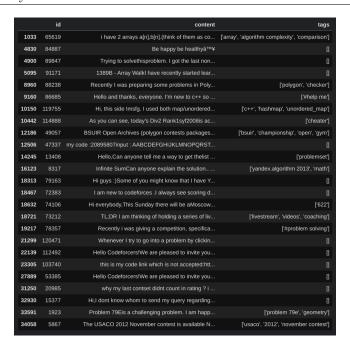


Figure 1: Liked blogs



Figure 2: Top results using bert

## 6 Methodology 2

Here, we try to group or categorize blogs into several bags, where each bag represents a topic. After we do this, we use MAB to explore and exploit user interests. This is a good strategy to learn the interests of a new user with no representation, in a manner where we simultaneously exploit the information we acquired from the user via implicit/explicit feedback, and also explore further, those topics where the user has a chance of finding reward.





Figure 3: Top results using gensim



Figure 4: Top results using spacy

#### 6.1 Topic Modelling of Blogs using N-grams + LDA

Documents (in this case blogs) are represented as a bag of words. In this case, for better representation and better results, we try to represent the documents as a bag of n-grams (a bag of words/n-grams, is basically a collection of tokens/strings) & then pass the processed blogs to LDA model which then fits and labels the blogs with respective topic numbers.

Each topic is modelled as a distribution over tokens or words. We have tried bi, tri, quad, and pentagrams, and obtained results. Tri-grams gave better probabilities for most weighted word in each topic.

#### 6.2 MAB - Upper Confidence Bound for Recommendations

We then used multi-arm bandit to make batch recommendations to users and simulated user interaction programmatically by programming predefined stochastic user behaviour. The MAB model uses the Upper Confidence Bound (UCB) method to calculate the reward associated with each arm. This method takes into account the number of trials made per arm, and follows the principle of "optimism in the face of uncertainty". If a particular topic is not tried or recommended as many times as other topics, then the MAB chooses that topic with a high probability initially, to compose the next batch of recommendations. The topics that have a high average reward, are also picked with a high probability later in the recommendation process.



#### 6.3 Sample Results:

Below are pics of Topic modelling output, dataset after topic labelling, and changing probabilities over topics. (Topics cannot be described in well-defined english terms, as they are generated and are represented as distribution over tokens.)



Figure 5: Topic Modelling using n-grams + LDA

### 6.4 Topic labelled dataset:

Dataset after topic labelling

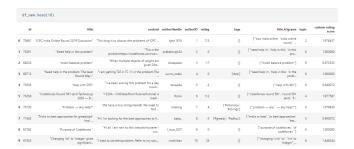


Figure 6: dataset df.head

# 6.5 MAB changing probabilities of rewards associated with Blogs for particular user:

We can see randomly assigned probabilities moving towards actual probability scores.



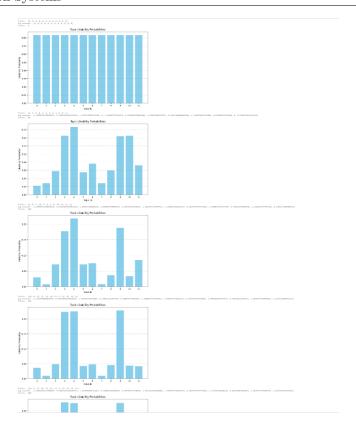


Figure 7: MAB-UCB results

#### 7 Evaluation of Models

#### 7.1 Evaluation Metrics

We evaluated the performance of our models using metrics such as precision, recall, and mean average precision (MAP), considering both overall performance and user-specific recommendations.

#### 7.2 Results

Our results indicate promising performance of the recommendation models, with high precision and recall scores. Additionally, user feedback and interaction data further refine the recommendations over time.

#### 8 Conclusion

In conclusion, our project demonstrates the feasibility and effectiveness of developing a blog recommendation system tailored for competitive programming communities. By leveraging advanced NLP techniques and machine learning algorithms, we have successfully provided users with personalized and relevant blog suggestions, thereby enhancing their overall experience on platforms like Codeforces.