**Yoga Recommender System using RoBERTa Model**

**Madhav Parmar**

**madhav.parmar@hotmail.com**

**Introduction**

Recommender systems have become a cornerstone of modern technology, enabling personalized user experiences across various domains, such as e-commerce, entertainment, healthcare, and education. These systems leverage vast data to provide tailored suggestions, enhancing user engagement and satisfaction. However, traditional single-domain recommender systems often face challenges such as data sparsity, cold-start problems, and limited understanding of user preferences across diverse domains.

To address these limitations, Cross-Domain Recommender Systems (CDRS) have emerged as an advanced approach, enabling the transfer of knowledge between related or unrelated domains. By integrating data and features from multiple domains, CDRS enhances the accuracy and diversity of recommendations, thereby offering more comprehensive solutions. For instance, a system recommending yoga based on a user’s search for specific medications exemplifies the power of CDRS in connecting seemingly disparate domains to improve user outcomes.

Recommender systems estimate users’ preference on items and recommend items that users might like to them proactively [6, 10]. Recommendation models are usually classified into three categories [6, 11]: collaborative filtering, content based and hybrid recommender system. Collaborative filtering makes recommendations by learning from user-item historical interactions, either explicit (e.g. user’s previous ratings) or implicit feedback (e.g. browsing history). Content-based recommendation is based primarily on comparisons across items’ and users’ auxiliary information.

This explores the foundational aspects of recommender systems, the evolution of cross-domain methodologies, and their application in scenarios like healthcare and wellness. The study aims to identify key challenges, analyze existing approaches, and propose innovative strategies to overcome limitations, particularly in addressing the cold-start problem and data sparsity. By delving into metrics like Label Ranking Average Precision (LRAP) and techniques like Cosine Similarity, this work underscores the importance of accurate and effective evaluation measures for developing robust recommender systems.

Through this exploration, the research aspires to contribute to the growing field of cross-domain recommendations, paving the way for more intelligent and user-centric systems that can adapt to complex and dynamic user needs.

**Method**

**RoBERTa Model Overview**

RoBERTa is an advanced language representation model that builds on the foundation of BERT. It enhances BERT. By utilizing more data, larger batch sizes, and longer training sequences, leading to improved performance.

The RoBERTa training process enhances the published BERT results on both GLUE and SQuAD during training data. RoBERTa matches the 88.4 on the public GLUE leaderboard with a score of 88.5 after being trained for a longer period of time over more data. [12, 9] On 4/9 of the GLUE tasks—MNLI, QNLI, RTE, and STSB—it sets a new state-of-the-art.

3. Cross-Domain Recommendation

Cross Domain Recommendation transfers knowledge across domains based on similarity of user and item. It combines information (for e.g., review and rating) from multiple source domains and transfers it to target domain, primarily to overcome the drawback of single domain recommendation system (SDRS). SDRS is unable to capture the full spectrum of user's interest and evolving preferences. Generally, domains are defined at four levels: Attribute level, Type level, Hem level, and System level. In each level, different information sets are available, and CDRS often utilizes information from different levels of a domain to handle Cold-Start problems in recommendation. Few existing works highlight the needs of CDRS to alleviate data sparsity issues as well.

In recent years, Multilayer Perceptron (MLP), a Neural Network ecosystem, is used to learn non-linear mapping functions across domains. In these, MLP takes the user latent factor in source domain as input and user latent factor in target domain as output. Different approaches, such as Knowledge transfer, Feature Engineering, Hybrid model, Meta and Transfer learning have also been implemented to develop the Cross-domain recommendation system for different application domains.

For example: Imagine an online platform that recommends both medicine and yoga. A user who frequently searched medicine for pneumonia may have their preferences transferred to the yoga domain. The system might use the user's medicine requirements to recommend relevant yoga poses or use shared features like the medicine specification and yoga posture characteristics to suggest yoga that match their need.

**Example Process**

(i) **Collect Data** Gather user requirements and medication details.

(ii) **Analyze Preferences** Identify the user's disease.

(iii) **Transfer Knowledge** Use this preference to recommend relevant yoga.

(iv) **Refine Recommendations** Continuously adjust recommendations based on new data from both medicine and yoga.

3.1 Current approaches of Cross-domain Recommendation System

Cross-domain recommendation aims to provide personalized recommendations across multiple domains. There are several approaches used in developing such a system.

(i) Hybrid Approaches

(ii) Shared Nearest Neighbor

(iii) Cross-domain Collaborative Filtering

(iv) Joint Factorization Model

3.2 Working Steps of Cross-domain Recommendation System (CDRS)

(i) Cross-domain recommendation system collects data on user-item interaction from multiple domains. Data may be selected according to the match of user profile, and item attribute information.

(ii) Common techniques like collaborative filtering, content-based methods, and matrix factorization are used to extract latent features from data

(iii) Transfer learning technique is used for latent features mapping across multiple domains

(iv) Finally, the recommendation model is used to generate recommendation from multiple domains.

**3.2.1 Key Concepts**

**(i) Enhanced Data Utilization** By integrating data from various domains (e.g., medicine and yoga), cross-domain systems can make more informed recommendations. For example, if a user is diagnosed with insomnia; the system might suggest yoga therapy based on this related information.

**(ii) Cold-Start Problem Mitigation** New users or items with insufficient data can benefit from existing data in related domains. For instance, a new user's medicine prescription might be used to recommend yoga even before they have searched yoga.

**(iii) Domain Definitions** Domains can be defined in various ways, such as broad categories (e.g., medicine vs. yoga) or more specific subcategories (e.g., allopathy vs. homeopathy). Understanding the context and nature of these domains is crucial for effective recommendations.

**Related Work**

**Evaluation**

**Result**

**Future Scope**

**Conclusion**

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Appendix