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## MIDTERM REPORT

**Topic: SMART TOURISM SYSTEM - TRAVEL TOGETHER**

**Course: Computational Thinking**

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# 1 Abstract

This article presents an overview of recommendation systems, focusing on their components, classification, main techniques, applications, and a comparison of different approaches. Recommendation systems are essential tools in various domains, including e-commerce, entertainment, and social media, as they help users discover relevant content based on their preferences and behaviors.

# 2 Introduction

## 2.1 About recommendation system

What is it?

Recommendation systems address the issue of information overload. The systems personalize user experiences by suggesting items such as products, services, or content that align with individual preferences. Therefore, enhance user experiences and increase engagement and satisfaction. Recommendation systems are divided into three types: Content-based filtering, Collaborative filtering, and Hybrid methods. Recommendation systems are now have the knowledge-based

# 3 Analysis of Personalized Recommender Systems

## 3.1 Collaborative Filtering (CF)

Driven by user profiles or historical interactions

### 3.1.1 Memory-Based CF

is simple and popular but it faces challenges such as sparsity in the interaction matrix and computational complexity in extensive user or item domains.

Solution is to transform high-dimensional sparse vectors into low-dimensional dense ones, e.g prefs2vec by Valcarece et al.

### 3.1.2 Model-Based CF

Use mathematical model to predict the user-item relationships. For example: Neural Network Matrix Factorization (NNMF) and Neural Collaborative Filtering (NCF) demonstrating the power of multilayer perceptrons (MLPs) for latent feature learning. Able to capture complex relationships.

### 3.1.3 Context-Aware-Based CF

enhances recommendation quality by incorporating contextual information. provide more relevant and timely suggestions by using dynamic information like time, location, weather.

## 3.2 Content-Based Systems

Content-Based recommender systems treat recommendation as a user-specific classification problem. The system learns a classifier for a user based on the features of items they have previously rated positively. The model then uses this classifier to recommend other items with similar features.

## 3.3 Knowledge-Based Systems

Knowledge-Based recommender systems are uniquely suited for high-consideration, infrequent purchase domains (e.g., automobiles, real estate) where traditional methods falter. This category employs two main methodologies:

- Knowledge Graph Embedding (KGE): This method encodes external knowledge from sources like knowledge graphs into higher-level, dense vector representations.
- Path-Based RS: This method leverages connectivity patterns, known as meta-paths, within a knowledge graph. By analyzing these paths, the system can evaluate the semantic similarity between entities

### 3.4 LLM-Based Systems

### 3.5 Hybrid Systems

## 4 Challenges in Recommender System Design

### 4.1 System Robustness

### 4.2 Scalability

### 4.3 Data Bias

## 5 Similarity Measures

Similarity measures are fundamental to certain recommendation approaches, particularly memory-based collaborative filtering, where they are used to identify neighboring users or items. The most fundamental of these are the Pearson Correlation Coefficient and Cosine Similarity. Pearson Correlation Coefficient (PCC): This measures the linear correlation between the ratings of two users ( $u$  and  $v$ ) on their co-rated items ( $I_{u,v}$ ), defined as: Cosine Similarity (COS): This measures the cosine of the angle between two user rating vectors in the item space, defined

## 6 Conclusion