



**SIDDHARTH INSTITUTE OF ENGINEERING & TECHNOLOGY:: PUTTUR  
(AUTONOMOUS)**

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**QUESTION BANK (DESCRIPTIVE)**

**Subject with Code:** RECOMMENDATION SYSTEM (20CS1117)

**Course & Branch:** B.Tech – CAD

**Regulation:** R20

**Year & Sem:** IV - B.Tech & I-Sem

**UNIT –I**

**INTRODUCTION**

1	Analyse the Procedural control reasoning .	[L4][CO3]	[12M]
2	a Describe the Rule formation in KRR.	[L2][CO3]	[06M]
	b Analyse the types of Rules in KRR.	[L4][CO3]	[06M]
3	Illustrate searching strategies in KRR with examples	[L4][CO3]	[12M]
4	Analyse the Algorithm design in KRR	[L4][CO3]	[12M]
5	Identify key challenges in Algorithm design in KRR	[L3][CO3]	[12M]
6	a Explain the importance of Goal order in KRR	[L2][CO3]	[06M]
	b Explain the methods of specifying Goal Order	[L2][CO3]	[06M]
7	Analyze the committing to proof in KRR	[L4][CO3]	[12M]
8	Analyze the common challenges and limitations encountered by Recommender Systems and explain how they impact system performance.	[L4][CO3]	[12M]
9	a Discuss the Back Track controlling in KRR.	[L2][CO3]	[06M]
	b Discuss the concept Negation as Failure in KRR.	[L2][CO3]	[06M]
10	Create a production system of any real world problem	[L7][CO3]	[12M]
11	a Analyze working memory in KRR	[L4][CO3]	[06M]
	b Evolve Production rules in KRR	[L3][CO3]	[06M]
12	a Explain conflict Resolution in production systems	[L2][CO3]	[06M]
	b Describe applications and svantages of Peoduction system	[L2][CO3]	[06M]

**UNIT –II**  
**COLLABORATIVE FILTERING**

<b>1</b>	<b>a</b>	Describe the working principle of the User-Based Nearest Neighbour (UBNN) recommendation.	[L2][CO2]	[06M]
	<b>b</b>	Explain the application of the User-Based Nearest Neighbour (UBNN) recommendation in real-world systems.	[L2][CO2]	[06M]
<b>2</b>	<b>a</b>	Explain the steps involved in the Item-Based Nearest Neighbour (IBNN) recommendation.	[L2][CO2]	[06M]
	<b>b</b>	How does IBNN differ from UBNN? Provide a mathematical example to illustrate your explanation.	[L5][CO2]	[06M]
<b>3</b>	<b>a</b>	Describe model-based approaches in collaborative filtering and how they are applied in recommendation systems.	[L3][CO2]	[06M]
	<b>b</b>	Discuss one popular model-based approach in detail, including its mathematical foundation.	[L2][CO2]	[06M]
<b>4</b>		Analyze the pre-processing techniques commonly used in collaborative filtering to enhance recommendation accuracy and explain how each technique addresses specific challenges related to data sparsity, bias, and noise.	[L4][CO2]	[12M]
<b>5</b>		Evaluate different types of attacks on collaborative recommender systems, such as Sybil attacks and data poisoning, and assess the effectiveness of various mitigation strategies, including robust algorithms and detection mechanisms, in preventing these attacks.	[L5][CO2]	[12M]
<b>6</b>		Compare user-based and item-based collaborative filtering. Which scenarios favor one over the other?	[L5][CO2]	[12M]
<b>7</b>		Analyze the concept of sparsity in collaborative filtering and its impact on recommendation accuracy, explaining how sparse user-item interaction matrices lead to reduced system performance. Discuss different methods used to address this issue.	[L4][CO2]	[12M]
<b>8</b>	<b>a</b>	Explain the role of similarity measures in collaborative filtering.	[L2][CO2]	[06M]
	<b>b</b>	Distinguish different similarity measures such as Pearson correlation, cosine similarity, and Jaccard index.	[L4][CO2]	[06M]
<b>9</b>		Analyze the cold start problem in collaborative filtering, explaining how it affects both new users and new items. Discuss strategies such as hybrid models, content-based filtering, and active learning, and how they help mitigate the issue.	[L4][CO2]	[12M]
<b>10</b>		Analyze how latent factor models, like Matrix Factorization, are applied in collaborative filtering, and explain the mechanics of Singular Value Decomposition (SVD). Discuss how SVD helps to uncover latent relationships between users and items to improve recommendation accuracy.	[L3][CO2]	[12M]

**UNIT –III**  
**CONTENT-BASED RECOMMENDATION**

<b>1</b>	<b>a</b>	Explain the high-level architecture of a content-based recommendation system.	[L2][CO3]	[06M]
	<b>b</b>	How does content-based recommendation system differ from collaborative filtering systems?	[L2][CO3]	[06M]
<b>2</b>	<b>a</b>	Describe how item profiles are used in content-based recommendation systems to make recommendations.	[L3][CO3]	[06M]
	<b>b</b>	How are item profiles generated and used in making recommendations?	[L2][CO3]	[06M]
<b>3</b>		Analyze the pros and cons of content-based filtering, using examples to highlight its strengths and weaknesses.	[L4][CO3]	[12M]
<b>4</b>	<b>a</b>	Describe the process of discovering features of documents for content-based recommendations.	[L3][CO3]	[06M]
	<b>b</b>	Describe the role of document features in the recommendation process and how they influence recommendations.	[L3][CO3]	[06M]
<b>5</b>	<b>a</b>	How can item features be obtained from tags?	[L2][CO3]	[06M]
	<b>b</b>	Discuss the methodologies involved in leveraging tags for content-based recommendations.	[L5][CO3]	[06M]
<b>6</b>		Distinguish between contrast term frequency-inverse document frequency (TF-IDF) and word embeddings as feature extraction techniques in content-based systems.	[L5][CO3]	[12M]
<b>7</b>	<b>a</b>	Explain the challenges associated with content-based filtering when dealing with multimedia data, such as images and audio.	[L2f][CO3]	[06M]
	<b>b</b>	How can the challenges associated with content-based filtering be addressed?	[L2][CO3]	[06M]
<b>8</b>		Analyze how a content-based recommendation system adapts to changes in user preferences over time.	[L4][CO3]	[12M]
<b>9</b>		Evaluate the impact of over-specialization in content-based filtering and assess the effectiveness of diversification techniques.	[L5][CO3]	[12M]
<b>10</b>		Analyze how content-based recommender systems handle the 'long tail' problem and discuss strategies for recommending niche items.	[L2][CO3]	[12M]

**UNIT –IV****KNOWLEDGE-BASED RECOMMENDATION & HYBRID APPROACHES**

<b>1</b>	<b>a</b>	Describe knowledge representation in knowledge-based recommender systems and how it is used to enhance recommendations.	[L3][CO4]	<b>[06M]</b>
	<b>b</b>	Describe different methods used to represent knowledge.	[L2][CO4]	<b>[06M]</b>
<b>2</b>	<b>a</b>	Explain how constraint-based recommenders work.	[L2][CO4]	<b>[06M]</b>
	<b>b</b>	Provide an example of a system that uses constraint-based recommendations.	[L3][CO4]	<b>[06M]</b>
<b>3</b>	<b>a</b>	Discuss the role of case-based reasoning in knowledge-based recommender systems.	[L2][CO4]	<b>[06M]</b>
	<b>b</b>	Distinguish between rule-based systems and case-based reasoning approaches.	[L4][CO4]	<b>[06M]</b>
<b>4</b>	<b>a</b>	Explain the opportunities for hybridization in recommender systems and how they can improve recommendations.	[L2][CO5]	<b>[06M]</b>
	<b>b</b>	Discuss the benefits of combining different recommendation techniques.	[L5][CO5]	<b>[06M]</b>
<b>5</b>	<b>a</b>	Explain the concept of monolithic hybridization design.	[L2][CO5]	<b>[06M]</b>
	<b>b</b>	How do feature combination and feature augmentation techniques contribute to hybrid systems?	[L2][CO5]	<b>[06M]</b>
<b>6</b>	Distinguish between weighted and switching hybridization strategies in recommendation systems and provide examples of scenarios where each is most appropriate.		[L4][CO5]	<b>[12M]</b>
<b>7</b>	<b>a</b>	Describe how cascade hybridization works.	[L2][CO5]	<b>[06M]</b>
	<b>b</b>	Describe the potential advantages and drawbacks of using the cascade hybridization approach in recommender systems.	[L3][CO5]	<b>[06M]</b>
<b>8</b>	<b>a</b>	Discuss the challenges of implementing a hybrid recommender system.	[L5][CO5]	<b>[06M]</b>
	<b>b</b>	Explain some common pitfalls of hybrid recommender systems and how they can be avoided.	[L2][CO5]	<b>[06M]</b>
<b>9</b>	Analyze how a hybrid recommender system improves recommendation diversity and accuracy and provide examples to support your discussion.		[L4][CO5]	<b>[12M]</b>
<b>10</b>	<b>a</b>	Examine a real-world application of a hybrid recommender system.	[L4][CO5]	<b>[06M]</b>
	<b>b</b>	Discuss how the hybrid approach enhanced the system's performance.	[L2][CO5]	<b>[06M]</b>

**UNIT –V**  
**EVALUATING RECOMMENDER SYSTEMS**

<b>1</b>	<b>a</b>	Explain the general properties of evaluation research in recommender systems.	[L2][CO6]	<b>[06M]</b>
	<b>b</b>	Why is evaluation crucial for the development and deployment of recommender systems?	[L1][CO6]	<b>[06M]</b>
<b>2</b>	<b>a</b>	Discuss the various evaluation designs used in recommender systems.	[L2][CO6]	<b>[06M]</b>
	<b>b</b>	Provide examples of offline and online evaluation methods.	[L3][CO6]	<b>[06M]</b>
<b>3</b>	<b>a</b>	How is evaluation performed on historical datasets?	[L6][CO6]	<b>[06M]</b>
	<b>b</b>	Describe the advantages and limitations of using historical datasets for evaluating recommender systems.	[L3][CO6]	<b>[06M]</b>
<b>4</b>	<b>a</b>	Describe the different error metrics used to evaluate the accuracy of recommender systems.	[L2][CO6]	<b>[06M]</b>
	<b>b</b>	Explain metrics such as RMSE, MAE, and precision/recall.	[L2][CO6]	<b>[06M]</b>
<b>5</b>	Evaluate how decision-support metrics differ from accuracy metrics in recommender systems and their impact on recommendation effectiveness.		[L5][CO6]	<b>[12M]</b>
<b>6</b>	Analyze user-centered metrics in evaluating recommender systems and explain how they measure user satisfaction and engagement.		[L4][CO6]	<b>[12M]</b>
<b>7</b>	<b>a</b>	Distinguish the trade-offs between using accuracy and diversity as evaluation metrics.	[L4][CO6]	<b>[06M]</b>
	<b>b</b>	How can a balance between accuracy and diversity be achieved in a recommender system?	[L2][CO6]	<b>[06M]</b>
<b>8</b>	<b>a</b>	Discuss the importance of A/B testing in evaluating recommender systems.	[L2][CO6]	<b>[06M]</b>
	<b>b</b>	How is A/B testing typically conducted?	[L6][CO6]	<b>[06M]</b>
<b>9</b>	Analyze how cold-start users are considered in the evaluation of recommender systems and discuss the specific metrics or strategies used to address their unique challenges.		[L4][CO6]	<b>[12M]</b>
<b>10</b>	<b>a</b>	Discuss the challenges and best practices in cross-validation for recommender systems.	[L2][CO6]	<b>[06M]</b>
	<b>b</b>	How can cross-validation be leveraged to enhance the generalization capability of a predictive model?	[L6][CO6]	<b>[06M]</b>

