Examples of Exam Questions

Research Topics in Recommender Systems (INFO345)

Autumn 2024 - *version 1.0*

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1. Briefly explain the recommendation approach known as Content-based Filtering (CBF).

Answer: Content-based Filtering (CBF) is a popular recommendation approach that primarily focuses on using the content features of items, such as genre or keywords, to suggest items with content features similar to those items previously liked by a user. For instance, in the book recommendation domain, a CBF might analyze the words within books to find content-based similarities and generate recommendations of books for users.

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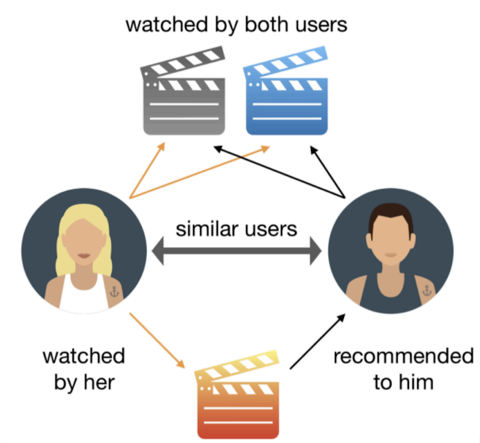
2. What type of recommender systems is displayed in the following figure:



- (a) Content-Based Filtering (CBF)
- (b) Collaborative Filtering (CF)
- (c) Pipelined hybridization
- (d) None of the given options.

Answer: (b) Collaborative Filtering (CF)

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3. Which of the following options represents the result of *lemmatization* applied to “am”, “are”, and “is”?

(a) am, are, is → was
(b) am, are, is → been

(c) am, are, is → being
(d) am, are, is → be

Answer: (d) am, are, is → be
Lemmatization aims to obtain real, grammatically correct words by reducing variant forms to their base form. Consequently, “am”, “are”, and “is” are *lemmatized* to “be”.

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4. What is the name of the evaluation metric represented by the following formula?

$$? = \sqrt{\frac{1}{|\hat{R}|} \sum_{\hat{r}_{ui} \in \hat{R}} (r_{ui} - \hat{r}_{ui})^2}$$

Answer: RMSE (Root Mean Squared Error)

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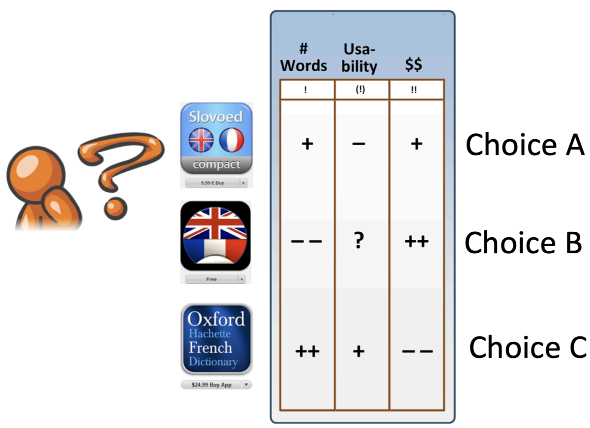
5. Consider the provided figure, which displays three dictionary choices for a customer.



Which of the following methods does the customer use in making a choice?

(a) Social model.
(b) Policy-based.
(c) Attribute-based.
(d) None of the given options.

Answer: (c) Attribute-based. The figure displays that the customer compares dictionary apps and makes choices by checking their specific “attributes”: number of words, usability, and cost.

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6. What is the challenge addressed by “regularization” when training a recommender model?

Answer: Addressing the overfitting challenge.

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7. What is the primary objective of ‘rating prediction’ algorithms in recommender systems?

(a) To group items based on their profile image.
(b) To create visual descriptions for items.
(c) To find the number of items in the dataset.
(d) To count the total number of ratings in the dataset.
(e) None of the given options.

Answer: (e) None of the given options. The primary objective of ‘rating prediction’ algorithms is to achieve *accurate* predictions of user ratings. This is typically accomplished by minimizing the prediction error, i.e., the difference between the known (true) ratings and predicted ratings.

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8. Consider the following dataset with ratings provided by users for some items:

Items

	A	B	C	D	E	F	G	H	I	J
User 1	10	4	3	6	10	9	6	8	10	8
User 2	1	9	8	9	7	9	6	9	3	8
User 3	10	5	2	7	9	9	5	6	7	8

Suppose User 1, User 2, and User 3 are members of a group. A group recommender system is requested to generate a recommendation list with the Top 5 items for this group. Based on the ‘Average’ strategy in group recommender systems, which items will be recommended to this group?

Answer: Top 5 items recommended to the group: F, E, J, H, D
This is determined by calculating the average rating (mean rating) for each item across the three group members and selecting items with the highest average ratings as the group's preferences:

- Item F with an average rating of $(9 + 9 + 9) / 3 = 9.0$
- Item E with an average rating of $(10 + 7 + 9) / 3 = 8.6$
- Item J with an average rating of $(8 + 8 + 8) / 3 = 8.0$

- Item H with an average rating of (8 + 9 + 6) / 3 = 7.6
- Item D with an average rating of (6 + 9 + 7) / 3 = 7.3

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9. If the primary task of a recommender system is to predict the 'exact' ratings of users, which metrics are most suitable for evaluation?

(a) Precision and Recall
(b) MAE and RMSE
(c) F1-Score
(d) MAP
(e) None of the given options.

Answer: (b) MAE and RMSE

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10. Which of the following options is NOT an example of an Active Learning strategy for selecting items to show to users and asking them to provide ratings?

(a) Lemmatization
(b) Random
(c) Highest-predicted
(d) Popularity-based
(e) Entropy-based

Answer: (a) Lemmatization

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11. What is a potential disadvantage of A/B testing when evaluating recommender systems?

Answer: There is a risk of losing customers if the recommendation quality is not good. If one of the models in A/B testing provides poor recommendations, users might be dissatisfied, leading to the potential loss of customers.

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12. Suppose this information is provided for a set of movie items:

	Popularity	Entropy
Item 1	100000	1.2
Item 2	10000	2.0
Item 3	1000	1.5
Item 4	100	2.5
Item 5	10	2.0

If each of the following Active Learning strategies selects one item to present to a user for rating, identify the item that is selected by each strategy:

- (a) Popularity strategy
- (b) Entropy strategy
- (c) Log_{10}(Popularity)*Entropy strategy

Answer: According to the above information:

	Popularity	log(Popularity)	Entropy	log(Popularity)* Entropy
Item 1	100000	5	1.2	6
Item 2	10000	4	2.0	8
Item 3	1000	3	1.5	4.5
Item 4	100	2	2.5	5
Item 5	10	1	2.0	2

- (a) Popularity strategy: selects item 1 (highest popularity score)
- (b) Entropy strategy: selects item 4 (highest entropy score)
- (c) Log_{10}(Popularity)*Entropy: selects item 2 (highest Log_{10}(Popularity)*Entropy)

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13. Briefly explain the cold start problem in recommender systems

Answer: The cold start problem in recommender systems refers to the challenge faced when a recommender system needs a certain number of ratings before it can produce accurate recommendations. However, not all users may have rated enough items to meet this threshold, leading to the “cold start” problem.

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14. In the user-centric evaluation framework, what does SSA stand for?
    (a) Subjective System Aspects
    (b) Systematic Study App
    (c) Subjective Structural Assessment
    (d) Cyclic Assessment of Explanation
    (e) None of the given options.

Answer: (a) Subjective System Aspects (SSA)

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15. Below is the formula for RMSE (Root Mean Squared Error):

$$\text{RMSE} = \sqrt{\frac{1}{|\hat{R}|} \sum_{\hat{r}_{ui} \in \hat{R}} (r_{ui} - \hat{r}_{ui})^2}$$

Given the dataset below, which includes true ratings and their corresponding predictions computed by a recommender system, calculate the RMSE value:

Nr.	UserID	MovieID	Rating (r_{ui})	Prediction ($\hat{r}_{ui}$)
1	1	134	5	4.5
2	1	238	4	5
3	1	312	5	5
4	2	134	3	5
5	2	767	5	4.5

Answer:

sum = $(5 - 4.5)^2 + (4 - 5)^2 + (5 - 5)^2 + (3 - 5)^2 + (5 - 4.5)^2$

sum = 0.25 + 1 + 0 + 4 + 0.25 = 5.5

RMSE = $\sqrt{(5.5/5)} = \sqrt{1.1} = 1.04$

See also the following illustration:

Nr.	UserID	MovieID	Rating (r_{ui})	Prediction ($\hat{r}_{ui}$)	$(r_{ui}-\hat{r}_{ui})^2$
1	1	134	5	4.5	0.25
2	1	238	4	5	1
3	1	312	5	5	0
4	2	134	3	5	4
5	2	767	5	4.5	0.25
sum					**5.5**

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16. Which of the following is NOT a goal for providing explanations in a recommendation?

(a) Transparency.
(b) Efficiency.
(c) Cold starting.

Answer: (c) Cold starting. Explanations in recommender systems aim for goals such as transparency, efficiency, trustworthiness, etc., but not cold starting.

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17. Determine the type of explanation provided by the following statement:

"*You have to do your homework because your dad said so.*"

(a) Functional explanation.
(b) Causal explanation.
(c) Intentional explanation.
(d) Scientific explanation.
(e) None of the given options.

Answer: (c) Intentional explanation. This type of explanation gives reasons for human behavior.

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18. Consider the formula for calculating the sparsity of a dataset:

$$sparsity = 1 - \frac{|R|}{|I| \cdot |U|}$$

If a dataset comprises 100000 ratings provided by 943 users to 1682 items, what is the sparsity of this dataset?

Answer:

Number of Ratings = $|R|$ = 100000

Total Possible Ratings = $|I| \times |U|$ = 943 × 1682

Sparsity = 1 - 100000 / (943*1682) ≈ 0.936

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19. Which of the following approaches would be most suitable for a house recommender system?

- (a) Content-based
- (b) Knowledge-based
- (c) Collaborative Filtering

Answer: (b) Knowledge-based. In such a scenario, a pure Collaborative Filtering (CF) system will not perform well because of the low number of available ratings. Moreover, in the complex product domains (e.g., housing), customers often want to define their requirements explicitly, which is not typical for Collaborative and Content-based recommendation frameworks.

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20. Consider the following product set and features:

ID	**f1**	**f2**	**f3**	**f4**	**f5**
P1	100	199	21	15	20
P2	15	15	1	80	30
P3	72	30	30	14	40
P4	33	9000	40	5	50

Which product is the best for each filter condition C_F:

- (a) **C_F1 :** (f2 < 150)
- (b) **C_F2 :** (f4 < 15)

Answer: To find the solution for this type of question, we would exclude options per filtering condition (C_F):

- (a) For **C_F1**: Products P2 and P3 are the best. -

- (b) For $\mathbf{C_F2}$: Products P3 and P4 are the best.

If the question asks to choose a product fulfilling both $\mathbf{C_F1}$ and $\mathbf{C_F2}$, then P3 is the best.

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21. Consider the tables below, which display the scores predicted by two recommender systems, called $\mathbf{rec_1}$ and $\mathbf{rec_2}$. Each system has computed predictions for the preferences of a user and scored the items to generate recommendations for her:

rec_1

Item	Score
Item1	0.5
Item2	0
Item3	0.3

rec_2

Item	Score
Item1	0.8
Item2	0.9
Item3	0.4

A weighted hybrid recommender system called $\mathbf{rec_{weighted}}$ will produce a new ranking by combining the scores from rec_1 and rec_2 . Assuming that the weights $\boldsymbol{\beta_1}$ = 0.5 and $\boldsymbol{\beta_2}$ = 0.5, which of the following options correctly represents the predicted scores by hybrid $rec_{weighted}$?

(A)

Item	Score
Item1	0.65
Item2	0.90
Item3	0.30

(B)

Item	Score
Item1	0.45
Item2	0.30
Item3	0.65

(C)

Item	Score
Item1	0.65
Item2	0.45
Item3	0.35

Note: The following is the formula:

$$rec_{weighted}(u,i) = \sum_{k=1}^{n} \beta_k \times rec_k(u,i)$$

Answer: Option (C). According to the provided formula, the following scores are computed by hybrid recommender system, $rec_{weighted}$:

- for Item 1: $\boldsymbol{\beta_1}$ * 0.5 + $\boldsymbol{\beta_2}$ * 0.8 = **0.5** * 0.5 + **0.5** * 0.8 = 0.65
- for Item 2: $\boldsymbol{\beta_1}$ * 0.0 + $\boldsymbol{\beta_2}$ * 0.9 = **0.5** * 0.0 + **0.5** * 0.9 = 0.45
- for Item 3: $\boldsymbol{\beta_1}$ * 0.3 + $\boldsymbol{\beta_2}$ * 0.4 = **0.5** * 0.3 + **0.5** * 0.4 = 0.35

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22. What does CF stand for in the recommender system approaches?

Answer: Collaborative Filtering.

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23. Consider the following scenario:

You have obtained a dataset that contains user ratings for shoes sold in an online store. To build a recommender model for shoes, you decide to perform an offline evaluation by predicting the Top 10 shoes to recommend for a user and then compare this to the 10 shoes the user actually liked.

Which metric is suitable for this evaluation?

(a) F1 score
(b) Root Mean Square Error
(c) Mean Absolute Error

Answer: (a) F1 score. The F1 score is the average (harmonic mean) of Precision and Recall. This metric is particularly suitable for classification tasks in recommender systems where the goal is to select a ranked list of Top-n items.

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24. A movie recommender system is used to recommend relevant movies to a user. The system generates a list of movie recommendations predicted to be relevant for the user. The following are the lists of movies recommended by the system and the movies that are relevant (actually good):

Recommended items (predicted as good)
Movie 10
Movie 24
Movie 23
Movie 14
Movie 11
Movie 21

Relevant items (actually good)
Movie 24
Movie 14
Movie 11
Movie 39
Movie 12

Calculate the Precision, Recall, and F1 Score for this movie recommender system using the provided lists. **Note:** here are the formulas:

$$Precision = \frac{tp}{tp + fp} = \frac{|good\ movies\ recommended|}{|\text{all recommendations}|}$$

$$Recall = \frac{tp}{tp + fn} = \frac{|good\ movies\ recommended|}{|all\ good\ movies|}$$

$$F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

Answer: The good movies that are recommended are: Movie 24, Movie 14, and Movie 11. We can proceed to calculate the requested metrics:

- Precision = 3 / 6 = 0.5
- Recall = 3 / 5 = 0.6
- F1 = 2 * (0.5 * 0.6) / (0.5 + 0.6) ≈ 0.54

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25. Which of the following recommendation approaches can utilize visual features extracted from movie items?

    (a) Collaborative Filtering
    (b) SVD
    (c) Content-based Filtering
    (d) Random
    (e) None of the given options.

Answer: (c) Content-based Filtering. This approach can utilize content features (attributes) of items, such as visual features, or audio features, extracted from movie files.

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26. Consider the following dataset of transactions:

Transaction ID	Items
1	Bread, Milk
2	Bread, Diaper, Beer, Eggs
3	Milk, Diaper, Beer, Coke
4	Bread, Milk, Diaper, Beer
5	Bread, Milk, Diaper, Coke

Calculate the support and confidence for the following association rule:

$$\{\text{Milk, Diaper}\} \Rightarrow \text{Beer}$$

Note: here are the formulas:

$$support = \frac{number\ of\ transactions\ containing\ X \cup Y}{number\ of\ transactions}$$

$$confidence = \frac{number\ of\ transactions\ containing\ X \cup Y}{number\ of\ transactions\ containing\ X}$$

Answer:

- Support: 2/5 = 0.4
- Confidence: 2/3 ≈ 0.66

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27. Imagine a scenario where you are developing a camera recommender system. You set up two algorithms (CF1 & CF2) to predict the most suitable cameras for users. In the end, your final rating prediction is based on 60% of the score predicted by CF1 and 40% of the score predicted by CF2.

Which of these alternatives best describes the type of recommender developed in this scenario?

(a) Monolithic Hybridization Design
(b) Parallelized Hybridization Design
(c) Pipelined Invocation Design
(d) Conjunctive Content Processing

Answer: (b) Parallelized Hybridization Design. This type of hybridization employs several recommenders side by side and uses a hybridization mechanism to aggregate their outputs. In the given scenario, two algorithms, CF1 and CF2, are working simultaneously, and their results are combined based on a weighted average, aligning with the characteristics of parallelized hybridization.

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28. The following figure represents the Confusion Matrix:

		Predicted Class *P*	Predicted Class *N*
Actual Class	*P*	True Positives (TP)	False Negatives (FN)
	N	False Positives (FP)	True Negatives (TN)

Considering that, what is the name of evaluation metric represented by the following formula?

$$? = \frac{TP}{FN + TP}$$

Answer: Recall.

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29. Determine the type of explanation provided by the following statement:

Laptop X has a longer battery life than Laptop Y due to its advanced lithium-ion technology, which allows for more efficient energy consumption.

- (a) Colourful explanation.
- (b) Intentional explanation.
- (c) Scientific explanation.
- (d) None of the given options.

Answer: (c) Scientific explanation. This type of explanation is used to express relations between the concepts formulated in various scientific fields and is typically based on refutable theories.

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30. Consider the following recommendation methods:

- Collaborative Filtering (CF)
- Content-based Filtering (CBF)
- Knowledge-based

Which of these methods best aligns with each of the following approaches?
- Approach 1: “Show me more of the same that I've liked.”
- Approach 2: “Show me what fits based on my needs.”
- Approach 3: “Show me what's popular among my peers.”

Answer:

Approach 1: Content-based Filtering
Approach 2: Knowledge-based
Approach 3: Collaborative Filtering

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31. Why using Term Frequency (TF) alone is not a good approach for modeling documents?

(a) It assumes all terms have similar importance.
(b) It doesn't consider the length of the document.
(c) It ignores the uniqueness of terms in different documents.
(d) All of the given options.

Answer: (d) All of the given options.

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32. Consider the following dataset of ratings:

	Item1	Item2	Item3	Item4	Item5
User1	1	0	0	1	1
User2	1	0	1	0	1
User3	0	0	0	1	1
User4	0	1	1	0	0

Calculate the support and confidence for the following association rule:

$$\text{Item1} \Rightarrow \text{Item5}$$

Note: here are the formulas:

$$support = \frac{number\ of\ transactions\ containing\ X \cup Y}{number\ of\ transactions}$$

$$confidence = \frac{number\ of\ transactions\ containing\ X \cup Y}{number\ of\ transactions\ containing\ X}$$

Answer:

- Support: 2/4 = 0.5
- Confidence: 2/2 = 1.0

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33. What do Precision and Recall measure?

Answer: Precision measures the proportion of retrieved instances that are relevant. Recall measures the proportion of relevant instances that are retrieved. For example, in a movie recommender, precision measures the proportion of recommended movies that are relevant (actually good). Recall measures the proportion of all good movies that are recommended.

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34. The dataset below represents the ratings provided by users for different items.

Rating dataset

	Item 1	Item 2	Item 3	Item 4	Item 5
User 1	5	3	4	4	**???**
User 2	3	1	2	3	3
User 3	3	3	1	5	4

What is the predicted rating of User 1 for Item 5 indicated with ‘ **???** ’ in the dataset based on user similarities? Briefly explain your answer.

In your calculation, consider using the following table with additional data, including similarities between User 1 and other users, as well as the average rating ($\overline{r_a}$) for each user:

Additional data

	sim(user 1,b)	$\overline{r_b}$
User 1	1	4.0
User 2	0.85	2.4
User 3	0	3.2

Note: The following is the formula to predict the rating user ***a*** for item ***p***, based on the similarity between user ***a*** and other users:

$$\boldsymbol{pred(a,p) = \overline{r_a} + \frac{\sum_{b \in N} sim(a,b) * (r_{b,p} - \overline{r_b})}{\sum_{b \in N} sim(a,b)}}$$

Answer: The following data is provided in the rating dataset and the table with additional data:

- *sim(user 1, user 2)* = 0.85
- *sim(user 1, user 3)* = 0.0
- $r_{user\ 2,\ item\ 5} = 3$
- $r_{user\ 3,\ item\ 5} = 4$

pred(user 1, item 5) = Predicted rating of User 1 for Item 5.
pred(user 1, item 5) = 4.0 + (**0.85** * (3 – 2.4) + **0.0** * (4 – 3.2)) / (**0.85** + **0.0**)
pred(user 1, item 5) = 4.6

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35. Which type of explanation deals with the functions of systems?
    (a) Scientific
    (b) Functional
    (c) Intentional
    (d) None of the given options.

Answer: (b) Functional
