Module Code: COMP3771 DO NOT REMOVE FROM THE EXAM VENUE

Module Title: User Adaptive Intelligent Systems © UNIVERSITY OF LEEDS

School of Computing Semester Two 2018/2019

May 2018/2019

(Delete as appropriate)

Calculator instructions:

 You are allowed to use a nonprogrammable calculator only from the following list of approved models in this exam:

o Casio fx-82, fx-83, fx-85, fx-350 series

o Sharp EL-531 series.

Dictionary instructions:

• You are not allowed to use your own dictionary in this exam. A basic English dictionary is available to use: raise your hand and ask an invigilator, if you need it.

Exam information:

- There are 6 pages to this exam.
- This is an open book exam. Any written or printed material is permitted.
- There will be **2 hours** to complete this exam.

Please do not remove this paper from the exam venue.

Question 1

Module Code: COMP3771

This question is related to a **hypothetical personalised news reader** system which maintains a profile of each user including:

gender, age, job, list-of-interests,

where list-of-interests is a subset of

{Art, Education, Finance, Politics, Science, Society, Sport, Travel}.

Consider the following stereotypes:

PROFESSIONAL_FINANCIAL_READER:

Trigger: (age>22) and (age<60) and (job in Professional-jobs) and ((list-of-interests includes Finance) or (list-of-interests includes Politics) or (list-of-interests includes Society))

P=0.7

Facets	Degree of interest	Ratings (out of 100)
Business news	High	90
Stocks and shares	High	80
Local news	High	70
International news	High	70
Holidays	Moderate	70
Online courses	Low	40
Music	Moderate	50
Sport	Moderate	50
Gossips	Low	70
Technology	High	70
Science	Moderate	60
Movies	Moderate	70

YOUNG_TRAVELLER:

Trigger: (age>16) and age<30) and (list-of-interests includes Travel)

P=0.8

Facets	Degree of interest	Ratings (out of 100)
Business news	Low	60
Stocks and shares	Low	60
Holidays	High	80
Online courses	Moderate	70
Music	High	80
Gossips	High	70
Movies	High	80

POLITICALLY_ENGAGED_ADULT:

Trigger: (age>25) and (age<60) and ((list-of-interests includes Politics) or (list-of-interests includes Society))

P = 0.9

Facets	Degree of interest	Ratings (out of 100)		
Business news	Moderate	60		
Stocks and shares	Moderate	90		
Local news	High	100		
International news	High	90		
Gossips	Low	80		
Technology	Moderate	60		
Science	Moderate	60		

(a) What do the values of the ratings for the facet **Business news** mean in the stereotypes **PROFESSIONAL_FINANCIAL_READER** and **YOUNG_TRAVELLER**?

[2 marks]

(b) Cite an example from the tables that illustrates one problem with stereotypes.

[2 marks]

(c) Consider a user U with the following profile:

Module Code: COMP3771

```
gender=male, age=40, job=manager,
list-of-interests = {Finance, Politics, Sport, Travel}
```

Calculate the probability for the user to have high interest in business news and high interest in local news. Show your working.

[6 marks]

(d) What is a **scrutable user model** and what are the claimed benefits? Suggest how a scrutable user model could be implemented for this scenario.

[6 marks]

(e) Imagine that you are a consultant with expertise in adaptive information systems. You are asked by the news publisher to suggest **one further adaptive feature** to add to this system and what extra information you would need to capture for the user profile.

[4 marks]

[question 1 total: 20 marks]

Sample solution for Question 1:

(a)

Users who belong to Professional_Financial_Reader are highly interested in Business news and this is valid for 90% of the cases, i.e. for such users the probability of this facet to take the value "high" is 0.9.

Users who belong to Young_Traveller have low interests in Business news and this is valid for 60% of the cases, i.e. for such users the probability of this facet to take the value "low" is 0.6.

2 marks for a correct and complete description (1 mark if the description is incomplete).

(b)

A correct answer should point either at a conflict between stereotypes by suggesting a user profile for which the facets values and ratings are in conflict (e.g. Male, 25, manager, {Art, Finance, Travel} – conflict with regard to Business news between Professional_Financial_Reader and Young_Traveller) or should discuss the reliability of the triggers, values, and ratings (pointing at an example from the stereotypes, e.g. the value and rating for the facet Music in the stereotype Young_Traveller).

1 mark for a correctly described problem.

1 mark for illustrating the problem with a specific situation from the example.

(c)

Module Code: COMP3771

U belongs to the stereotypes Professional_Financial_Reader and Politically_Engaged_Adult. [1 mark]

P(Business news=High) will be calculated only from the stereotype Professional_Financial_Reader P(Business news=High)=0.9*0.7=0.63 [1 mark]

P(Local news=High) will be calculated only both stereotypes Professional_Financial_Reader and Politically_Engaged_Adult.

Calculate the probability P(feature=value) for each stereotype using the formula P(feature=value)=P(feature=value|stereotye)*P(stereotype)

From Professional_Financial_Reader
X= P(Local news=High) = 0.7*0.7 = 0.49
From Politically_Engaged_Adult
Y= P(Local news=High) = 1*0.9 = 0.9

[2 marks]

Step 2 Combine the probabilities from each stereotype using the formula

P(feature=value)=X+(1-X)*Y where

X=P(feature=value) // from stereotype 1 Y=P(feature=value) // from stereotype 2

 $P(Local\ news=High) = 0.49 + 0.51*0.9=0.49+0.459=0.949$ [1 mark]

Overall probability = 0.63*0.95

[1 mark]

(d)

A scrutable user model is one that is open for the user to inspect the underlying facet/value held about himself/herself. (1 mark) Benefits – provide the user a control over the accuracy of the model held about him/her; by allowing the user to understand how the recommendation might be derived and an opportunity to amend any facet/value that is no longer true. (2 marks)

This is open to student's creative ideas – could be by providing an interface to the member to examine the information held on the member, and on the information derived for the member; what previous ratings he/she had put in for the articles read.. (3 marks)

(e)

This is a question looking for creative answer and any reasonable answer will be accepted. **1 mark** for a suggested new feature, **1 mark** for some information to add to the user profile, additional **2 marks** will be awarded if the adaptive feature and the extra information for the user model agree with each other, and properly explained (e.g. a more fine-tune adaptation to interests, by breaking the facet down into finer categories such as International news into Europe/Asia/Africa/etc., Sports news into football/basketball/tennis/cricket/etc.

Question 2

Module Code: COMP3771

A city council has a strategy to expand the tourism sector for the city. Part of their plan is to develop a mobile personalised city guide which can recommend to visitors nearby places of interests, good food and special events when they are visiting the city.

According to Burke (2002), three key features of recommender algorithms are:

- Background data;
- Input data;
- Algorithm.
- (a) Compare and contrast **collaborative filtering algorithms** with **content-based algorithms** on these three key features in the case of the mobile personalised city guide outlined above. You answer should include illustrative examples from the city guide, describing how the three key features of recommender algorithms are addressed by each of these two classes of algorithms.

[12 marks]

(b) Discuss **one benefit** and **one limitation** for both approaches (collaborative filtering and content-based filtering) to provide recommendations of nearby pleases of interest.

[4 marks]

(c) Assume that the city guide includes a new feature to recommend restaurants to a group of users. Paul, John, Marry, and Jane are registered users of the system and their prediction values for eight restaurants are given in the following matrix:

	<i>R</i> 1	R2	R3	<i>R</i> 4	R5	<i>R</i> 6	<i>R</i> 7	<i>R</i> 8
Paul	3	5	1	7	5	1	4	9
John	5	6	9	10	2	3	7	1
Marry	2	4	5	8	1	4	5	8
Jane	4	6	10	5	6	7	3	5

Use the **Least misery strategy** to identify a restaurant to recommend to the group. Show your working. Use the example to point at one advantage of the "Least misery strategy" over the "Average strategy".

[4 marks]

[question 2 total: 20 marks]

Turn the page over

Page 6 of 11

Sample solution for Question 2:

Module Code: COMP3771

(a)

There may be slight variations in how the students tackle this question. Any reasonable suggestions will be accepted. Better answer should also address the definition of 'nearby' places. Main points to include are:

For collaborative filtering algorithms -

Background data: Ratings from other visitors on items of interest in that city (attractions, food, events); Geolocations for items of interest.

Input data: ratings from the visitor of items of interest; GPS location.

Algorithm: Identify all the visitors in the database similar to the enquiring visitor; and extrapolate from their ratings on the attractions/food/events.

For content-based algorithms -

Background data: more detailed features of items of interest in that city (for attractions, food, events) – different from above. Geolocations for items of interest – similar to above.

Input data: visitor's ratings of items of interest; GPS location – similar to above Algorithm: Generate a classifier that fits the enquiring visitor's rating behaviour and use it to extra appropriate attractions/food/events – different to above.

[6 marks for each algorithm (2 marks for each point) = 12 marks]

(b)

Content of the answer depends on how (a) was answered. Based on the sample answer above, discussion can be along the line of –

The above are for a fairly basic recommender system, easy to implement for some degree of personalisation felt by users.

The power of recommendation can be increased with the level of details that the user characteristics/preferences and item features are being characterised and monitored. Too much explicit information capture may deter usage. Too much implicit information capture may cause privacy issue.

[1 mark for a good point, 4 marks in total]

(c)
The main idea of this strategy is that a group is as happy as its least happy member.
A new list with ratings is made with the lowest rating for each restaurant.

Module Code: COMP3771 DO NOT REMOVE FROM THE EXAM VENUE

	<i>R</i> 1	R2	<i>R</i> 3	<i>R</i> 4	<i>R</i> 5	<i>R</i> 6	<i>R</i> 7	<i>R</i> 8
Paul	3	5	1	7	5	1	4	9
John	5	6	9	5	2	3	7	1
Marry	2	4	9	8	1	4	5	8
Jane	4	6	10	5	6	7	3	5

Group 2 4 1 5 1 1 3 1

According to the least misery strategy, restaurant R4 will be recommended to the group.

Average strategy

Make a new list of ratings with the average of the individual ratings. Round to whole numbers.

Average 4 5 7 6 4 4 5 6

The students should point that the Least miserable strategy makes the negative opinions dominate, the average strategy may make some individual unhappy (as Paul in this case).

- **2 marks** for calculating the vector for the least misery strategy and the average strategy
- **2 marks** for correct and complete comparison (1 mark for incomplete but correct answer).

Question 3

This question relates to a **hypothetical regional newspaper** which covers a wide range of topics of local interests. The publisher plans to launch a personalised online service on a subscription basis. Readers can subscribe to a list of chosen topics, which allows them to access articles and announcements that are related to these topics. This regional newspaper plans to deliver an adaptive feature which will recommend new articles and announcements that are of interest to the readers.

(a) Use **Jameson's schema**, which was introduced in lectures, to explain how user subscription information can be used to offer personalised recommendation of new articles and announcements.

[6 marks]

(b) Consider an adaptive system that recommends articles to users. The matrix M below indicates which articles $a_1, ..., a_7$ were liked by which reader $r_1, ..., r_5$ (value 1 indicates that the reader liked the article). Assume that r_3 would like a suggestion for which articles may be interesting to read. Apply **Amazon's itemitem collaborative filtering** algorithm to find the most suitable article to recommend to r_3 . Show your working.

$$M = \begin{bmatrix} r_1 & r_2 & r_3 & r_4 & r_5 \\ a_1 & 1 & 1 & 0 & 1 & 1 \\ a_2 & 0 & 0 & 0 & 0 & 1 \\ a_3 & 0 & 1 & 0 & 1 & 0 \\ a_4 & 1 & 1 & 1 & 1 & 0 \\ a_5 & 1 & 1 & 0 & 0 & 1 \\ a_6 & 0 & 0 & 0 & 0 & 0 \\ a_7 & 1 & 0 & 1 & 0 & 1 \end{bmatrix}$$

[8 marks]

(c) Describe how Amazon's item-item filtering algorithm addresses the **scalability problem** usually associated with collaborative filtering algorithms.

[2 marks]

(d) Describe one **usability challenge** brought by Amazon's item-item filtering and suggest a way to overcome this.

[4 marks]

[question 3 total: 20 marks]

(a)
Jameson's schema contains the main stages of user model acquisition, user model and user model application. Expect a brief description of the types of subscription information available for capture (e.g. reader's login id, demographic details, interests and topic preferences) [2 marks]. The method of model acquisition would be mainly explicit via a subscription form at the outset and subsequent edit/update [1 mark]. The profile information will be stored based on some form of computational representation (e.g. relational DB, or XML, or semantics) which can be retrieved by a recommendation system [1 mark]. Depending on the algorithm(s) used in the recommender system, other sources for data on content (i.e. articles, announcements) and on other readers will be needed to detect relevance & apply strategy for adaptation [2 marks].

(b)
Amazon's item-item collaborative filtering

Module Code: COMP3771

Step 1: Identify readers who have liked the articles that r_3 has liked (a_4 and a_7). In this case, all five readers will be identified, as a_4 has been liked by everybody except r_5 , and r_5 liked a_7 . [**2 marks**]

Step 2: For each of the articles liked by r₃, identify pairs of articles that have been liked together by the readers identified in Step 1. The following pairs should be identified:

For a4: (a1, a4), (a3, a4), (a5, a4),

For a7: (a1, a7), (a2, a7), (a5, p7),

[2 marks]

Step 3: Calculate similarity values (applying the cosine similarity formula) and suggest the **article from the pair with highest similarity.**

$$|a_1| = 2$$
 $|a_2| = 1$ $|a_3| = \sqrt{2}$ $|a_4| = 2$ $|a_5| = \sqrt{3}$ $|a_7| = \sqrt{3}$ [1 mark]

Applying the cosine similarity formula, the following values are calculated:

$$sim(a_1, a_4) = \frac{3}{4} = 0.75$$
 $sim(a_3, a_4) = \frac{1}{\sqrt{2}} = 0.71$ $sim(a_5, a_4) = \frac{1}{\sqrt{3}} = 0.58$

$$sim(a_1, a_7) = \frac{1}{\sqrt{3}} = 0.58 \quad sim(a_2, a_7) = \frac{1}{\sqrt{3}} \quad sim(a_5, a_7) = \frac{2}{3} = 0.67$$
 [3 marks]

The most similar article is a₁ and will be recommended to the user.

(c)
The scalability problem with collaborative filtering comes from the excessive number of similarity comparisons between items or users. Amazon's algorithm reduces this number significantly by identifying pairs which are of interest and these are much less (due to the scarcity of the data) of the number of comparisons that would have to be done over all possible items. Also, Amazon pre-calculates the pairs and the

similarities, so that in real time no similarity calculations are made. This can be done only because they use a vast volume of data, which cannot be applied to the example here. So, the only possible answer is reduced number of similarity comparisons.

2 marks for the correct answer with appropriate description.

(d)

Appropriate answers include:

Module Code: COMP3771

- Diminish predictability and comprehensibility (related to adaptive features, usually addressed by adding explanations, particularly challenging for collaborative filtering algorithms)
- Diminish controllability (again, related to adaptivity features, addressed by adding appropriate adaptability features, such as asking for user's approval of or feedback on the recommendations)
- Obtrusiveness (this is typical for all features, one way to address it is to allow the users to turn on and off the adaptation features; systematic analysis whether the user follows the recommendations can be helpful too)
- Diminished breath of experience (this is the so called filter bubble; a way to address this is to include some algorithms for diversification).

2 marks for appropriate problem (based on features identified in the above points).

2 marks for suggesting an appropriate way to address the problem.

Page 11 of 11 End