Questions and Sample Answers for Chapter 6

Section 1 – Questions

Question 1

How is the NIDA model different from the DINA model?

Question 2

Some DCMs facilitate finer distinctions than others between respondents who possess different mastery profiles. Suppose that students with the following five mastery profiles completed Items 1-4 on the basic arithmetic assessment described on page 116 in Table 6.2.

	α_c
Student 1	[0,0,0,1]
Student 2	[0,0,1,0]
Student 3	[0,1,0,1]
Student 4	[1,0,0,1]
Student 5	[1,1,0,1]

Which of the non-compensatory DCMs would potentially distinguish between (a) Students 1 and 5, (b) Students 3 and 4, and (c) Students 2 and 3? Are there any instances in which none of the core non-compensatory DCMs would successfully distinguish between students possessing these mastery profiles? Explain.

Question 3

Which of the following core DCMs estimates slipping and guessing parameters for each attribute that are restricted across items?

a. DINA model
b. Reduced NC-RUM
c. DINO model
d. NIDO model
e. All of the above
f. None of the above

Question 4

The following two tables contain population parameter values for two items. Identify what kind of model is used for each item and determine any "unusual" values from a practitioner's perspective. Explain your reasoning.

Item 1

Baseline	**A 1**	**A 2**	**A 3**	**A 4**
π_1^*=.80	$r_{1,1}^*$=.20	$r_{1,2}^*$=.05	$r_{1,3}^*$=.30	$r_{1,4}^*$=.98

Model used:

Unusual value:

Item 2

Baseline	**A 1**	**A 2**	**A 3**	**A 4**
$\lambda_{2,0}$= 0.5	$\lambda_{2,1,(1)}$ =0.5		$\lambda_{2,1,(3)}$ =2.0	$\lambda_{2,1,(4)}$ =1.5

Model used:

Unusual value:

Question 5

The response probabilities of the first latent class $\boldsymbol{\alpha}$ = [0, 0, 0, 0, 0] to a group of six NC-RUM items are given by

Section 2 – Sample Answers

Question 1

The NIDA model is a noncompensatory model with a conjunctive condensation rule, just like the DINA model. The DINA model broadly separates respondents into two mastery classes for each item: one class with respondents who have mastered / possess all measured attributes and one class with respondents who have not mastered / do not possess at least one of the attributes measured by the item. The mastery / possession state is represented by a latent variable ζ_{ic} which assumes the value 1 if a respondent has mastered / possesses all measured attributes and the value 0 if at least one measured attribute is not mastered / not possessed. The probability of a correct response to an item given a respondent's class membership and associated attribute profile is computed by two item-level parameters, the slipping parameter (s_i) and the guessing parameter (g_i) and the latent variable using the following formula:

Question 2

The non-compensatory models that potentially differentiate between the three pairs of learners are shown in the following table:

Comparison	Model Type	Item 1	Item 2	Item 3	Item 4
Students 1 and 5	Non-compensatory	NIDA, DINA, NC-RUM	- -	NIDA, NC-RUM	NIDA, DINA, NC-RUM
Students 3 and 4	Non-compensatory	NIDA, NC-RUM	- -	NIDA, NC-RUM	NIDA, DINA, NC-RUM
Students 2 and 4	Non-compensatory	DINA, NC-RUM	NC-RUM	NC-RUM	DINA, NC-RUM

In no case did a model fail to differentiate between all of the pairs of students, but for Item 2 there were some pairs of students that would not be distinguishable using any of the core non-compensatory DCMS. Using any non-compensatory model, the predicted probability of a correct response to Item 2 by Students 1 and 5 would be identical; the likelihood of a correct response from Students 3 and 4 would also be identical.

Using any DCM, the likelihood of a correct response depends on whether or not the student has mastered all of the measured attributes. Item 2 requires only a single attribute, Attribute 4, which means that any DCM will only differentiate between respondents who have and have not mastered Attribute 4. Students 1, 3, 4, and 5 have all mastered Attribute 4 so they are all predicted to give the same response to Item even though their individual attribute profiles differ overall.

Question 3

Correct answer: d

The DINA and DINO models estimate slipping and guessing parameters that are constrained to equality across attributes, which is the opposite of what the question states. The Reduced NC-RUM model estimates slipping and guessing parameters for each combination of item and measured attribute, but it does not restrict these parameters across items. The C-RUM model also estimates slipping and guessing parameters for each combination of item and measured attributes, and similarly allows these parameters to vary across items. Only the NIDO model estimates slipping and guessing parameters that are restricted across items.

Question 4

1) Model: Reduced NC-RUM

Unusual value: The penalty probability parameter of Attribute 4 is close to 1 for this item. Because the penalty probability is defined as the ratio of "guessing" to "not slipping", if this parameter is close to 1 the attribute mastery state for a respondent does not influence the observed responses in any noticeable manner (i.e., the attribute is not measured in a reliable manner by this item / not required for responding to this item).

2) Model: C-RUM

Unusual value: The intercept parameter for this item is a positive value. This parameter is utilized to decide the baseline probability of correctly responding to the item when none of the required attributes has been mastered (i.e., for the first latent class). When this parameter is positive, it implies that even without mastering any of the required attributes the chance for the respondents to answer this item correctly is larger than 50%, which is an unusually high probability.

Question 5

The Q matrix for these items, with items as rows and attributes as columns, is