

APSTA-GE 2094

APSY-GE 2524

Modern Approaches in Measurement: Lecture 6

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Check-In

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Table of Contents

1. Measurement - Week 6

1. Check-In

2. Table of Contents

3. Announcements

2. Modeling Response Processes

1. IRTrees

3. Fitting an IRTree model in `mirt`

4. Non-Monotonic Item Response Functions

1. Ideal Point Models

5. Competitions

1. A Problem (and a Break)

2. Elo Models

6. Wrap Up

Announcements

- PS2 is due tomorrow (2.13 @ 11.59p)
- PS0 and PS1 grades are posted
 - These were good
 - If I made mistakes, submit a regrade request through Gradescope
- PS0 and PS1 solutions are posted
 - These are available on the Problem Sets tab on Brightspace
- PS3 is posted (due 3.20 @ 11.59p)
- PS4 will be due 4.3 @ 11.59p

Modeling Response Processes

Response Processes

- The "response process" is the cognitive and physical process that individuals go through when they respond to an item
 - Physical processes include pushing buttons, filling in bubbles, sorting cards, etc.
 - Cognitive processes include understanding a question, understanding the response options, and going through a mental decision tree, etc.
- Think *metacognitively* about your own response process as you answer these questions:
 1. I am a hard worker.
 - (*Strongly Disagree, Disagree, Agree, Strongly Agree*)
 2. $8 \div 2(1 + 3) =$
 - (*A : 1, B : 4, C : 8, D : 16*)
 3. What is your gender?
 - (*Male, Female*)

IRTrees

- IRTrees is the idea that we write out a decision tree associated with the expected response process and use IRT to model each decision point
- Really flexible approach!
 - Leverages IRT's resilience to missing data
 - Can incorporate multiple latent traits!
 - Each node can use any type of IRT model

IRTrees

- Let's build decision trees for each of these:
 - I am a hard worker. (*Strongly Disagree, Disagree, Agree, Strongly Agree*)
 - What is your gender? (*Male, Female*)
- Let's write down the data structure
 - Follow an individual's response through the decision tree
 - Consider each node as its own item
 - If a respondent doesn't reach a node, mark it as `NA`
- You can fit these models in `mirt` with clever data recoding or using the `irtrees` package
- You'll try both in PS3

Fitting an IRTree model in `mirt`

- Let's fit an IRTree model to an empathizing–systemizing instrument
- Each respondent sees 120 statements that they rate on the following scale:
 - (1) strongly disagree
 - (2) slightly disagree
 - (3) slightly agree
 - (4) strongly agree
- Download the data here (redistributed from the Item Response Warehouse)

```
1 d <- read_csv('empathizing_systemizing.csv')
2
3 resp <- d |>
4   pivot_wider(
5     id_cols = id,
6     names_prefix = 'item_',
7     names_from = item,
8     values_from = resp
9   ) |>
10  select(-id)
```

Fitting an IRTree model in `mirt`

- We'll use the same decision tree we developed earlier that includes non-response
- We will model nonresponse, agreement, and extreme responses as separate latent traits
- We make responses for the nonresponse nodes first:

```
1 tree_resp_node_1 <- resp
2 tree_resp_node_1[is.na(resp)] <- 0
3 tree_resp_node_1[!is.na(resp)] <- 1
4 colnames(tree_resp_node_1) <- paste0('F1_', colnames(tree_resp_node_1))
```

Fitting an IRTree model in `mirt`

- Next we construct responses for the agreement nodes:

```
1 tree_resp_node_2 <- resp
2 tree_resp_node_2[resp <= 2] <- 0
3 tree_resp_node_2[resp >= 3] <- 1
4 colnames(tree_resp_node_2) <- paste0('F2_', colnames(tree_resp_node_2))
```

Fitting an IRTree model in mirt

- Next we construct responses for the agreement nodes:

```
1 tree_resp_node_3 <- resp
2 tree_resp_node_3[resp %in% c(2, 3)] <- 0
3 tree_resp_node_3[resp %in% c(1, 4)] <- 1
4 colnames(tree_resp_node_3) <- paste0('F3_', colnames(tree_resp_node_3))
```

level: 3

Fitting an IRTree model in `mirt`

- Next we combine the responses, free up some memory, and build out the `mirt.model` object

```
1 tree_resp <- bind_cols(tree_resp_node_1, tree_resp_node_2, tree_resp_node_3)
2
3 rm('tree_resp_node_1', 'tree_resp_node_2', 'tree_resp_node_3')
4
5 s <- 'RESPOND = F1_item_1-F1_item_120
6     AGREE = F2_item_1-F2_item_120
7     STRONG = F3_item_1-F3_item_120'
8
9 tree_model <- mirt.model(input = s, itemnames = names(tree_resp))
10
11 m <- mirt(data = tree_resp, model = tree_model, itemtype = 'Rasch')
12
13 thetas <- fscores(m)
14
15 tree_pars <- coef(m, IRTpars = TRUE, simplify = TRUE)
```

Non-Monotonic Item Response Functions

Different Shapes

- Until now, we've dealt with *monotonic* IRFs
 - Monotonic means probability of response is always increasing (or decreasing) with ability
 - More θ means more $P(X = 1|\theta)$
- This isn't the only reasonable IRF, though!
 - What about a Goldilocks situation?
 - $P(X = 1|\theta)$ is maximized when θ is "just right"

Let's buy jeans!



Buying Jeans

- We all have different body types and fit preferences!
- If the cut of the jeans are skinnier or baggier than you like, you're less likely to buy them ($P(X = 0)$)
- Is there something we could build an item response function out of?

Ideal Point Models

- We start from a normal pdf:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \cdot \exp\left[-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right]$$

- Notice that the mean of the distribution, μ , is a location parameter, which acts like a difficulty, b
- We also see that the inverse of the standard deviation, $\frac{1}{\sigma}$, functions like a discrimination, a
- The stuff up front is a normalization constant to make sure the pdf integrates to 1
- Let's write an example IRF:

$$P(X = 1|\theta) = c \cdot \exp\left[-a(\theta - b)^2\right]$$

- b is the location of the ideal point
- $a \in [0, \infty)$ is the discrimination
- $c \in [0, 1]$ is the upper bound on $P(X = 1)$

Unfolding Models

- Check out an unfolding IRF on [Desmos](#)
- In general, these are used for modeling preference data
- Often applied to Likert scale data, as well
- More generally called *unfolding models*, which is a reference to the theorized cognitive process that governs making choices
- In `mirt`, you can use `itemtype='ideal'` with dichotomous data
- `itemtype='ggum'` works with both dichotomous and polytomous data
 - `ggum` stands for "generalized graded unfolding model"

Competitions

A Problem (and a Break)

- Download the `squash-matches.rds` data
- The `player_1` and `player_2` columns have an integer that indicates which player is in the match
- The `result` column tells you if `player_1` won the match
- Using this data, rank the players from strongest to weakest

Elo Models

- Used in chess and other competitive sports
- We think the probability of winning is related to the difference in two players' abilities

$$P(A \text{ defeats } B | \theta_A, \theta_B) = \frac{1}{1 + \exp(-k(\theta_A - \theta_B))}$$

- Here, k is just a scaling factor that is preselected to work with the desired θ scale
- This functional form allows for making updates to individual abilities after each competition like this:

$$\theta_A^{i+1} = \theta_A^i + k(X_{AB} - P(x_{AB} = 1))$$

- Note adjustments to abilities are small if the win was a "sure thing" and huge if the win was an upset!

Back to Squash

- Turns out, `mirt` doesn't have an item type for Elo models
- We can, however, estimate this ourselves!
- The plan:
 - Write out a log likelihood function
 - Use `optim()` to find the solutions
 - Feel free to download my code [here](#)

```
1 LogLikMatch <- function(data, theta) {  
2   p <- plogis(theta[data$player_1] - theta[data$player_2])  
3   ll <- sum(data$result * log(p) + (1 - data$result) * log(1 - p))  
4   return(ll)  
5 }
```

Estimating the Model

- Using a single call to `optim()`, we can estimate all of our model parameters:

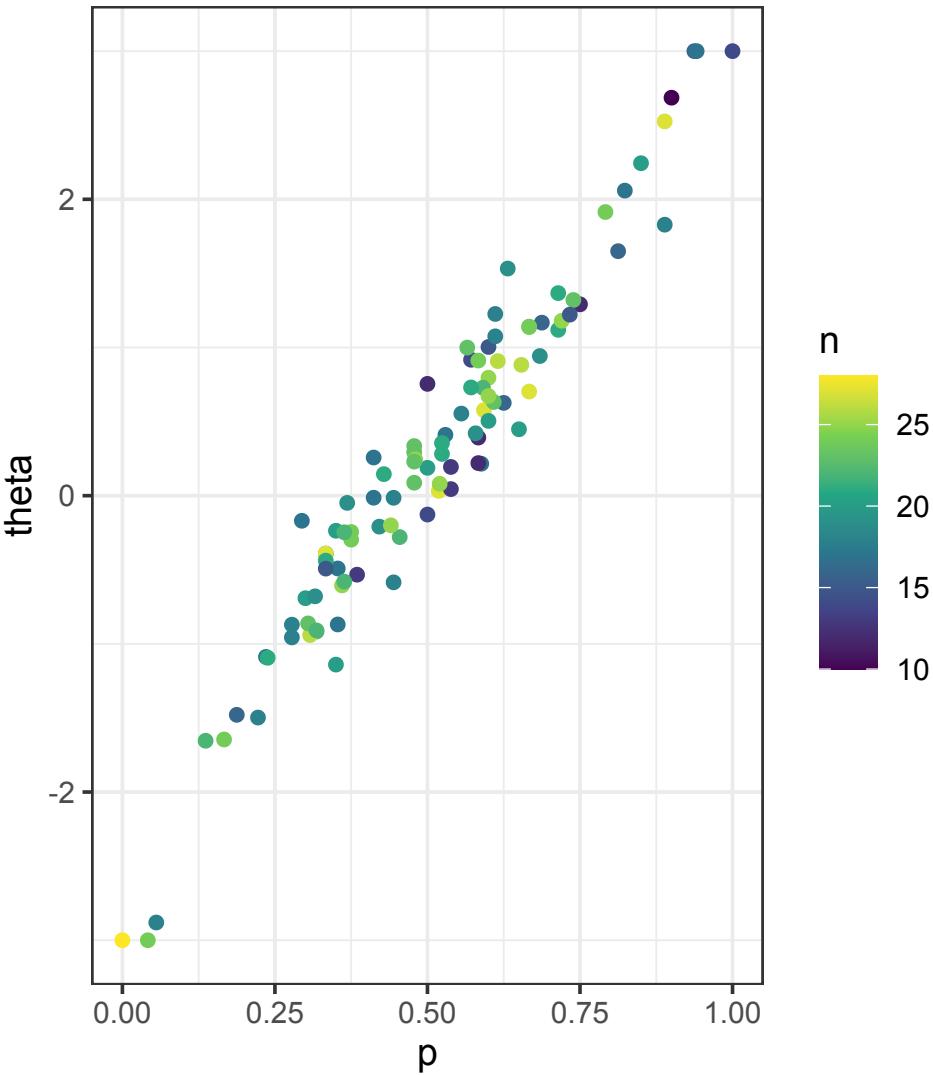
```
1 sol <- optim(  
2   starting_theta,  
3   LogLikMatch,  
4   data = d,  
5   method = 'L-BFGS-B',  
6   lower = -3,  
7   upper = 3,  
8   control = list(fnscale = -1, maxit = 1e6)  
9 )
```

Build an Output Object

```
1 tmp <- d |>
2   mutate(win = if_else(result == 1, player_1, player_2)) |>
3   mutate(loss = if_else(result == 0, player_1, player_2))
4
5 wins <- tmp |>
6   count(win) |>
7   select(player = win, wins = n)
8
9 losses <- tmp |>
10  count(loss) |>
11  select(player = loss, losses = n)
12
13 tot <- full_join(wins, losses, by = 'player') |>
14   arrange(player)
15
16 tot[is.na(tot)] <- 0
17
18 tot <- tot |>
19   mutate(p = wins / (wins + losses),
20         theta = sol$par,
21         n = wins + losses)
```

Visualizing the Solution

```
1 ggplot(tot, aes(x = p, y = theta, color = n))  
2   scale_color_viridis_c() +  
3   geom_point() +  
4   theme_bw()  
5  
6 cor(tot$p, tot$theta)  
  
1 [1] 0.9686027
```



Wrap Up

Recap

- IRTrees are *incredibly* flexible and useful for way more than you'd expect
- Unfolding models can be useful for expressing preferences with the Goldilocks property
- Elo-like systems can be useful for head-to-head competition
- This was our last lecture on vanilla-ish IRT!
- Next week we'll take a detour into topic models
 - Or, as we civilized folk say, "factor analysis for words"
- After next week, we'll bust into *categorical* latent variables
 - We'll start with clustering, then get kinda weird
- PS3 is out!
 - Polytomous IRT, IRTrees, and a fun surprise!

Check-Out

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