SF12_Multinom

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LCM

Model 1: Baseline (1 class, no classificaiton) Model 2: LCM (2 classes) Model 3: LCM (3 classes)

Model comparison results in favor of *Model 3* with 3 latent classes. Proceed with this model for multinomial logistic regression analyses.

```
#LCM: Baseline (1 class)
mod.pcs1<-mdirt(pcs, 1)
```

```
## Iteration: 1, Log-Lik: -3454.332, Max-Change: 5.10615Iteration: 2, Log-Lik: -2137.719, Max-Change: 0
```

```
#LCM: 2 classes
mod.pcs2<-mdirt(pcs, 2)
```

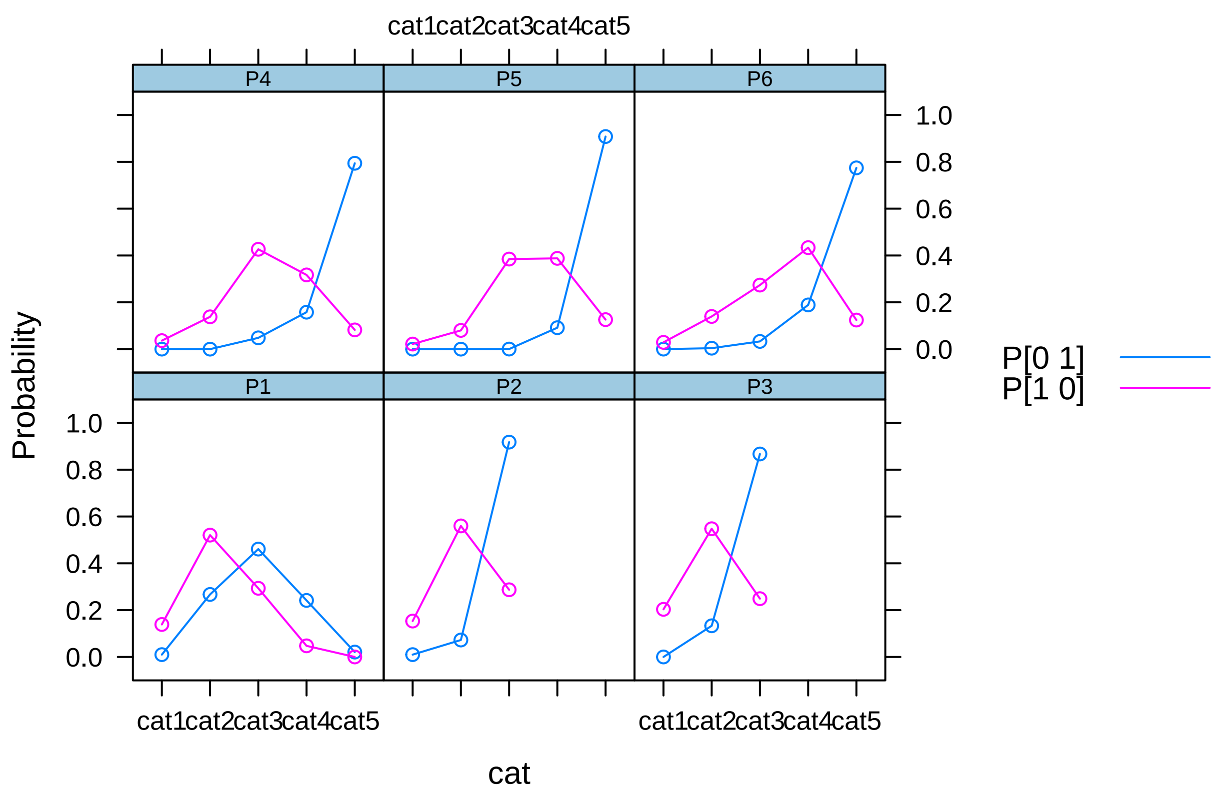
```
## Iteration: 1, Log-Lik: -2683.246, Max-Change: 3.76044Iteration: 2, Log-Lik: -1970.096, Max-Change: 0
```

```
summary(mod.pcs2)
```

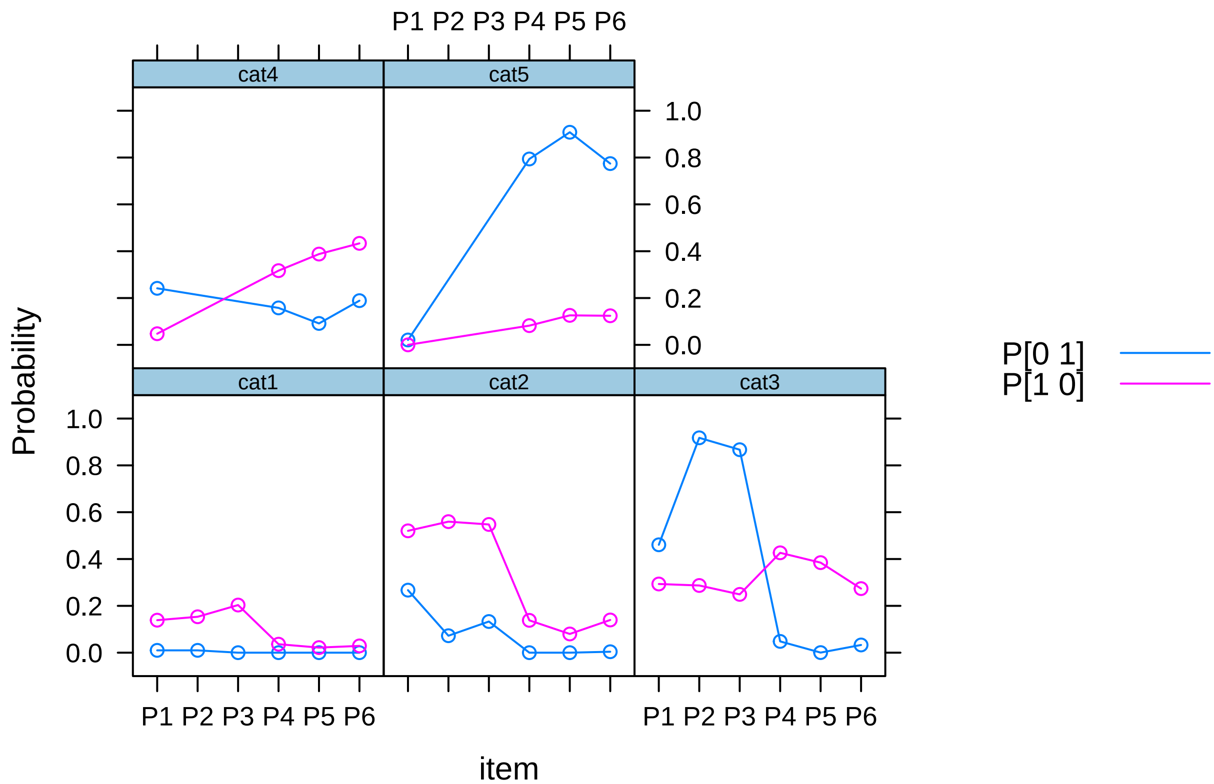
```
## $P1
##         category_1 category_2 category_3 category_4 category_5
## P[1 0]       0.139      0.520      0.293      0.048      0.000
## P[0 1]       0.010      0.267      0.461      0.242      0.021
##
## $P2
##         category_1 category_2 category_3
## P[1 0]       0.153      0.560      0.287
## P[0 1]       0.010      0.072      0.918
##
## $P3
##         category_1 category_2 category_3
## P[1 0]       0.203      0.548      0.249
## P[0 1]       0.000      0.133      0.867
##
## $P4
##         category_1 category_2 category_3 category_4 category_5
## P[1 0]       0.036      0.138      0.427      0.317      0.082
## P[0 1]       0.000      0.000      0.048      0.158      0.794
##
## $P5
```

```
##          category_1 category_2 category_3 category_4 category_5
## P[1 0]        0.022       0.08      0.385      0.388      0.126
## P[0 1]        0.000       0.00      0.000      0.092      0.908
##
## $P6
##          category_1 category_2 category_3 category_4 category_5
## P[1 0]        0.029      0.140      0.274      0.434      0.124
## P[0 1]        0.000      0.004      0.033      0.189      0.774
##
## $Class.Probability
##             F1 F2  prob
## Profile_1  1  0 0.417
## Profile_2  0  1 0.583
```

```
plot(mod.pcs2)
```




```
plot(mod.pcs2, profile=TRUE)
```




```
# # Classification based on posterior
# fs.pcs2<-fscores(mod.pcs2)
# head(fs.pcs2)
# classes.pcs2<-1:2
# class_max.pcs2<-classes.pcs2[apply(apply(fs.pcs2,1,max)==fs.pcs2, 1,which)]
# table(class_max.pcs2)

#LCM: 3 classes
mod.pcs3<-mdirt(pcs, 3)
```

```
## Iteration: 1, Log-Lik: -2697.630, Max-Change: 3.88443Iteration: 2, Log-Lik: -1978.671, Max-Change: 1
```

```
mod.pcs3
```

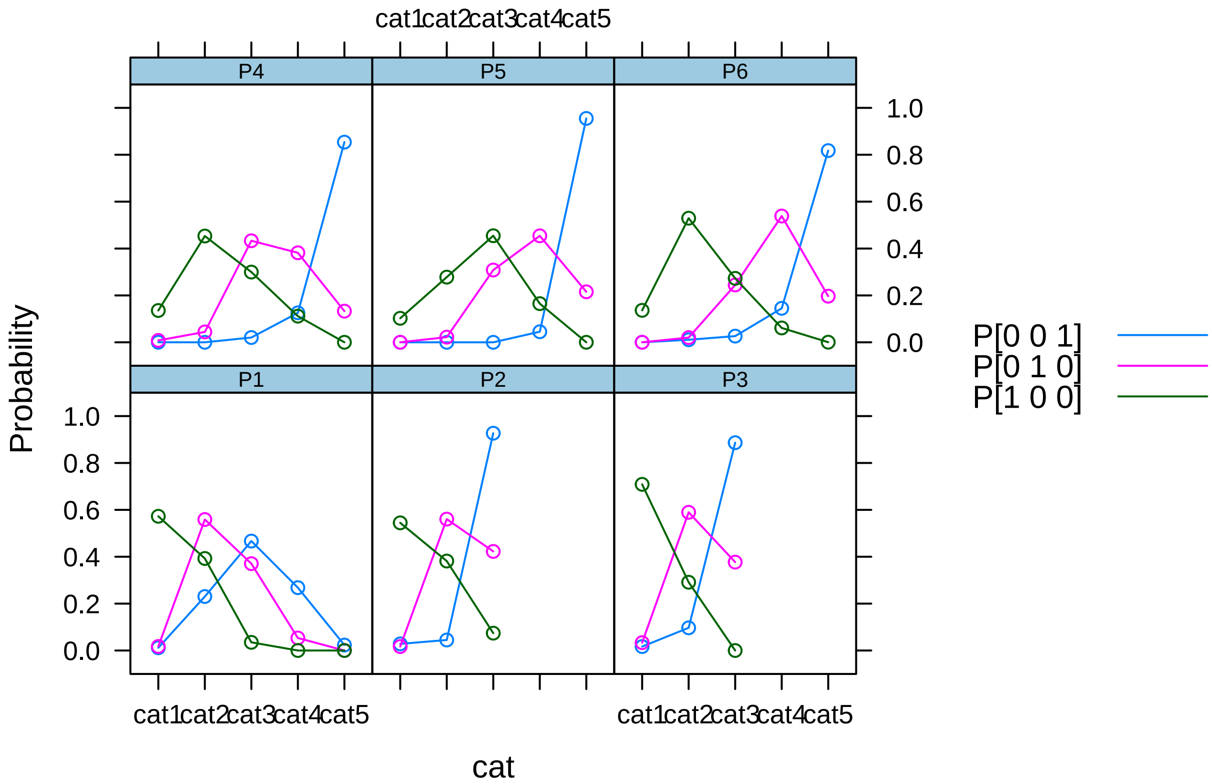
```
##
## Call:
## mdirt(data = pcs, model = 3)
##
## Latent class model with 3 classes and 3 profiles.
## Converged within 1e-04 tolerance after 20 EM iterations.
## mirt version: 1.34
## M-step optimizer: nlminb
## EM acceleration: Ramsay
## Latent density type: discrete
##
```

```
## Log-likelihood = -1732.386
## Estimated parameters: 62
## AIC = 3588.771; AICc = 3618.03
## BIC = 3824.315; SABIC = 3627.65
## G2 (5562) = 635.23, p = 1, RMSEA = 0
```

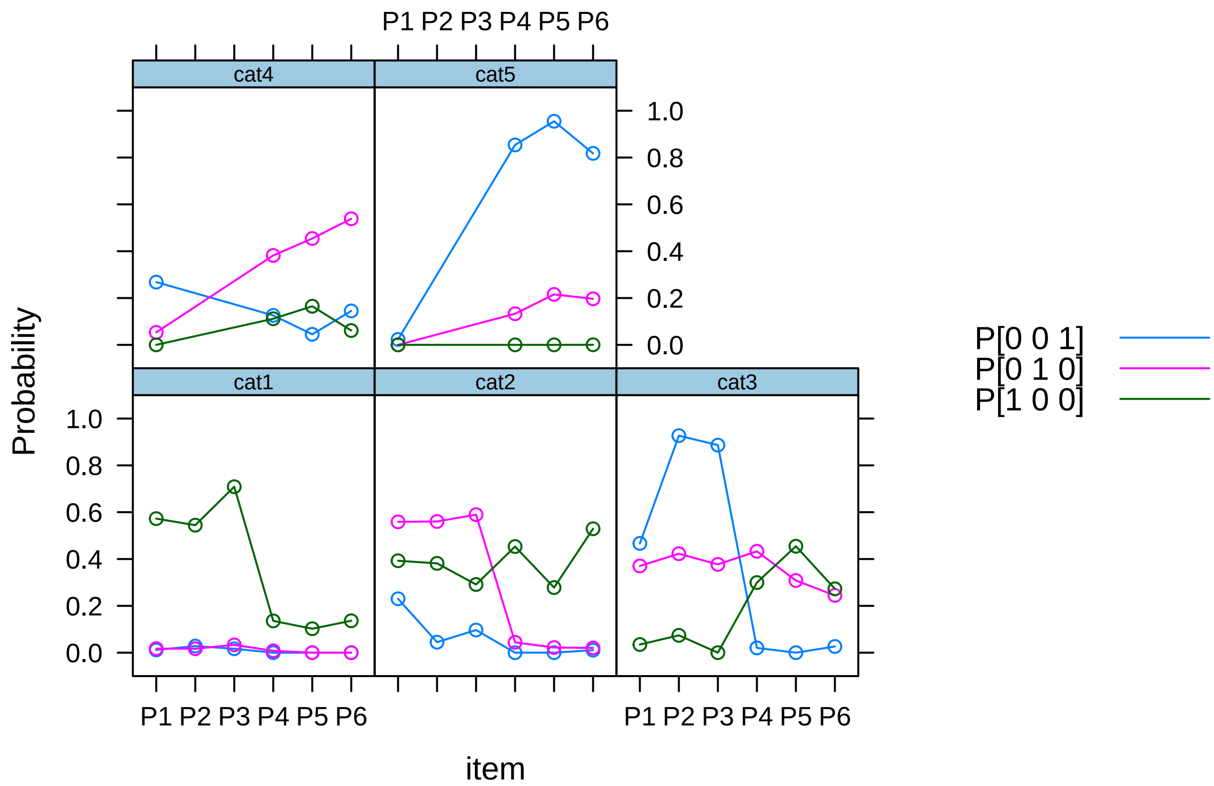
```
summary(mod.pcs3)
```

```
## $P1
##           category_1 category_2 category_3 category_4 category_5
## P[1 0 0]       0.573      0.393      0.035      0.000      0.000
## P[0 1 0]       0.017      0.559      0.371      0.053      0.000
## P[0 0 1]       0.012      0.230      0.467      0.268      0.023
##
## $P2
##           category_1 category_2 category_3
## P[1 0 0]       0.545      0.382      0.074
## P[0 1 0]       0.017      0.560      0.423
## P[0 0 1]       0.028      0.045      0.927
##
## $P3
##           category_1 category_2 category_3
## P[1 0 0]       0.709      0.291      0.000
## P[0 1 0]       0.033      0.590      0.377
## P[0 0 1]       0.017      0.097      0.887
##
## $P4
##           category_1 category_2 category_3 category_4 category_5
## P[1 0 0]       0.136      0.453      0.300      0.112      0.000
## P[0 1 0]       0.008      0.044      0.433      0.382      0.133
## P[0 0 1]       0.000      0.000      0.020      0.126      0.854
##
## $P5
##           category_1 category_2 category_3 category_4 category_5
## P[1 0 0]       0.102      0.278      0.455      0.165      0.000
## P[0 1 0]       0.000      0.022      0.308      0.454      0.215
## P[0 0 1]       0.000      0.000      0.000      0.045      0.955
##
## $P6
##           category_1 category_2 category_3 category_4 category_5
## P[1 0 0]       0.136      0.529      0.273      0.061      0.000
## P[0 1 0]       0.000      0.020      0.245      0.539      0.197
## P[0 0 1]       0.000      0.011      0.026      0.145      0.818
##
## $Class.Probability
##            F1 F2 F3  prob
## Profile_1  1  0  0 0.089
## Profile_2  0  1  0 0.389
## Profile_3  0  0  1 0.521
```

```
plot(mod.pcs3)
```




```
plot(mod.pcs3, profile = TRUE)
```




```
# model comparison
anova(mod.pcs2, mod.pcs1)
```

```
##
## Model 1: mdirt(data = pcs, model = 1)
## Model 2: mdirt(data = pcs, model = 2)

##        AIC     AICc    SABIC       HQ      BIC    logLik      X2  df   p
## 1 4315.421 4318.139 4327.963 4345.729 4391.403 -2137.711     NaN NaN NaN
## 2 3743.086 3755.045 3768.797 3805.218 3898.849 -1830.543 614.335  21   0
```

```
anova(mod.pcs2, mod.pcs3)
```

```
##
## Model 1: mdirt(data = pcs, model = 2)
## Model 2: mdirt(data = pcs, model = 3)

##        AIC     AICc    SABIC       HQ      BIC    logLik      X2  df   p
## 1 3743.086 3755.045 3768.797 3805.218 3898.849 -1830.543     NaN NaN NaN
## 2 3588.771 3618.030 3627.650 3682.726 3824.315 -1732.386 196.315  21   0
```

```
#classification based on posterior
fs.pcs3<-fscores(mod.pcs3)
head(fs.pcs3)
```

```
##        Class_1      Class_2    Class_3
## 1 2.569162e-12 0.5381314131 0.46186859
## 2 5.356504e-09 0.9289362329 0.07106376
## 3 3.778848e-15 0.0415547658 0.95844523
## 4 8.568590e-23 0.0002434768 0.99975652
## 5 8.568590e-23 0.0002434768 0.99975652
## 6 2.237398e-08 0.9972161078 0.00278387
```

```
classes.pcs3<-1:3
class_max.pcs3<-classes.pcs3[apply(apply(fs.pcs3,1,max)==fs.pcs3, 1,which)]
table(class_max.pcs3)
```

```
## class_max.pcs3
##   1   2   3
##  28 125 177
```

Multinomial Logistic Regression

```
## # weights:  27 (16 variable)
## initial  value 361.443443
## iter  10 value 272.147795
## iter  20 value 267.262187
## final  value 267.261625
## converged
```

```
## Call:
## multinom(formula = pcs_group ~ Age + Gender + employ2 + marital2 +
##     edu2 + famhx + years_dgx, data = dat)
##
## Coefficients:
##   (Intercept)        Age    GenderM   employ22  marital21      edu22     famhx1
## 1  -2.8314816 0.05743305 -1.8286518 -1.1339931 -1.2046264 -0.2723257 -0.2249540
## 2  -0.5357432 0.02049665 -0.4575071 -0.6018189 -0.3421662 -0.1276181 -0.4341028
##      years_dgx
## 1 -0.006798982
## 2  0.008158174
##
## Std. Errors:
##   (Intercept)        Age   GenderM  employ22 marital21      edu22    famhx1
## 1   2.0260995 0.02805665 0.5958263 0.5530143 0.4886606 0.4620763 0.4844214
## 2   0.9312544 0.01359084 0.2558327 0.2808116 0.3330059 0.2512391 0.2614281
##    years_dgx
## 1 0.02254839
## 2 0.01270368
##
## Residual Deviance: 534.5232
## AIC: 566.5232
```

```
##   (Intercept)      Age   GenderM  employ22 marital21      edu22     famhx1
## 1   -1.397504 2.047039 -3.069102 -2.050568 -2.465160 -0.5893522 -0.4643768
## 2   -0.575292 1.508122 -1.788306 -2.143141 -1.027508 -0.5079547 -1.6605052
##    years_dgx
```

```
## 1 -0.3015285
## 2  0.6421899

##   (Intercept)        Age     GenderM   employ22  marital21     edu22     famhx1
## 1   0.1622621 0.04065429 0.002147033 0.04030907 0.01369522 0.5556250 0.64237783
## 2   0.5650938 0.13152322 0.073726712 0.03210177 0.30418136 0.6114851 0.09681286
##   years_dgx
## 1 0.7630115
## 2 0.5207499

##   (Intercept)      Age   GenderM  employ22 marital21     edu22    famhx1
## 1  0.05892548 1.059114 0.1606300 0.3217459 0.2998040 0.7616062 0.7985529
## 2  0.58523417 1.020708 0.6328593 0.5478143 0.7102302 0.8801895 0.6478457
##   years_dgx
## 1 0.9932241
## 2 1.0081915

##           3           1         2
## 1 0.5370555 0.029090495 0.4338540
## 2 0.6191488 0.012997809 0.3678533
## 3 0.6452718 0.032453683 0.3222746
## 4 0.7800748 0.007741918 0.2121833
## 5 0.6957778 0.013572699 0.2906495
## 6 0.6139999 0.013651685 0.3723484
```

Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.