***MUPPscore: An R Script for Expected A Posteriori Scoring
of Multi-Unidimensional Pairwise Preference Items***

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DRAFT version.

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Abstract

In this manual, we present a flexible and freely available tool for obtaining latent trait scores from multi-unidimensional pairwise preference (MUPP) tests: An R script named *MUPPscore*. The development of the *MUPPscore* script provides a solution to the issue that is the previously inconvenient estimation of forced choice item pairs. Instead of using the computationally-intensive multidimensional Bayes modal procedure, the *MUPPscore* script employs the expected a posterior (EAP) scoring procedure, which provides plausible latent trait score estimates and is also consistent with scoring algorithms used in existing software programs intended for single stimulus measures (e.g., GGUM2004, IRTPRO). The *MUPPscore* script also returns the empirical marginal reliability of EAP theta estimates and outputs a series of files that can be used to easily create and modify three-dimensional surface charts for plotting MUPP item response function (IRF) in Microsoft Excel.

Keywords:

item response theory; multi-unidimensional pairwise preference; forced-choice measures; Bayesian estimation; R program

**MUPPscore: An R Script for Expected A Posteriori Scoring
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Recent research has presented evidence that personality assessment conducted using forced-choice (FC) formats may recover more accurate estimates of personality traits than traditional self-report methods. In particular, researchers have been interested in this approach to personality testing for high-stakes situations in which respondents are motivated to distort their responses to appear more favorable, such as employment testing (e.g., Chernyshenko et al., 2009; Drasgow et al., 2012). Under this approach to personality testing, respondents are asked to choose between two statements, each designed to tap into a different personality trait, which is presumed to lower the chances that respondents can successfully distort responses. However, as Chernyshenko et al. (2009) have indicated, multi-statement multidimensional FC items may increase the cognitive load on respondents leading to greater errors, a less accurate score may occur due to the complex judgement process. Further, recent results have questioned the ability of multidimensional FC tests to solve the problem of response distortion in employment tests (Guan et al., 2015). Given this recent surge of interest and its application to crucial and high-profile testing programs, such as the United States Army's tailored adaptive personality assessment system (TAPAS; see Drasgow et al., 2012), more research on this method of assessment is greatly needed.

For research in this area to progress, a flexible and freely available tool for obtaining latent trait scores from multi-unidimensional pairwise preference (MUPP) tests should be essential in both research and applied settings. However, no such program is currently publicly available to conveniently accomplish latent trait score estimation for the MUPP model. The development of the *MUPPscore* script provides a solution to this issue. Instead of using the

computationally-intensive multidimensional Bayes modal procedure, the *MUPPscore* script employs the expected a posterior (EAP) scoring procedure, which provides plausible latent trait score estimates (see Hontangas et al., 2015) and is also consistent with scoring algorithms used in software programs intended for single stimulus measures (e.g., GGUM2004, IRTPRO). Note that our EAP algorithm does not integrate across dimensions (unlike the Bayes modal procedure adopted by Stark et al. [2005] which would greatly complicate and bog down the scoring) and should be considered a more simplistic approach. The *MUPPscore* script also returns the empirical marginal reliability of EAP theta (θ) estimates and outputs a series of files that can be used to easily create and modify three-dimensional surface charts for plotting MUPP item response function (IRF) in Microsoft Excel.

Technical Details of the *MUPPscore* Script

The *MUPPscore* script utilizes the generalized graded unfolding model (GGUM; Roberts et al., 2000) item parameters as the basis for the MUPP model. Although the MUPP model can be implemented with any item response theory (IRT) model as its basis, the GGUM has been used in all available research and applications of the MUPP model. The full GGUM for dichotomous data, which is adapted in the *MUPPscore* script is stated as:

$$P(X_i = 1|\theta_j) = \frac{\exp[\alpha_i(\theta_j - \delta_i - \tau_i)] + \exp[\alpha_i[2(\theta_j - \delta_i - \tau_i)]]}{1 + \exp[\alpha_i[3(\theta_j - \delta_i)]] + \exp[\alpha_i(\theta_j - \delta_i - \tau_i)] + \exp[\alpha_i[2(\theta_j - \delta_i - \tau_i)]]}. \quad (1)$$

The GGUM states that the probability that the response to the item, $P(X_i = 1|\theta_j)$, will be affirmative as a function of (i) the latent trait standing of person j (denoted as θ_j), (ii) the location of the of the i^{th} item on the latent trait continuum (denoted as δ_i), (iii) the discrimination of the item (denoted as α_i), and (iv) the location of the item threshold (denoted as τ_i).

In applying the MUPP model, the focal trait (i.e., the trait to be estimated, θ_s) is estimated by first estimating the unidimensional GGUM in *Equation (1)* utilizing data in which persons

selecting the statement reflecting θ_s receive a score of $X_s = 1$, whereas those choosing the statement reflecting a trait other than s (i.e., the non-focal trait, denoted as t) receive a score of $X_s = 0$. Next, a new dataset is created in which all responses are reverse-scored, such that those whom choose option s receive a score of $X_t = 0$, and those choosing option t receive a score of $X_t = 1$. The GGUM is then estimated with these data. Using the two resulting sets of estimated item parameters as a starting point, the MUPP can be stated as:

$$P(s > t | \theta_s, \theta_t) = \frac{P(X_s = 1 | \theta_s)P(X_t = 0 | \theta_t)}{P(X_s = 1 | \theta_s)P(X_t = 0 | \theta_t) + P(X_s = 0 | \theta_s)P(X_t = 1 | \theta_t)}. \quad (2)$$

The MUPP states that the probability that the person will choose option s over option t is a function of the conditional probabilities derived from the item parameters of the two aforementioned datasets under the unidimensional GGUM. The *MUPPscore* script calculates these probabilities and uses them as inputs for the calculation of EAP θ estimates. This is accomplished by evaluating the likelihood of each response pattern at various potential levels of θ (i.e., quadrature points) and calculating the expected value and standard error of θ from these likelihoods by mixing them with theoretical likelihoods based on the assumption that θ is distributed normally with a mean of 0 and unit variance.

Demonstration of the *MUPPscore* Script

To demonstrate the capability of the *MUPPscore* script, we first compared our scoring using the simplistic EAP approach to the latent trait scores estimated using Stark et al.' (2005) Bayes modal approach. Using an empirical dataset, designed to measure the Five Factor Model of personality, 1,130 participants responded to 46 MUPP pairs to reflect their personality dimensions: Agreeableness (8 pairs), Extraversion (10 pairs), Conscientiousness (10 pairs), Openness (8 pairs) and Emotional Stability (10 pairs). Latent trait score estimations were consistent with the Bayes modal approach (Boyce et al., 2015) as same-trait correlations

were .81, .94, .93, .90 and .80, respectively. With regard to the processing speed, each run of the *MUPPscore* script required about 20 seconds to complete.

To demonstrate the accuracy of estimates calculated using *MUPPscore*, we simulated a 20-pair, two-dimensional MUPP test. Latent trait scores (i.e., θ_s) for two traits were simulated from a multivariate normal distribution with $\mu = 0$ and $\sigma = 1$ for both traits; the correlation between two traits was set to .20. Random discrimination values (i.e., α_i) were sampled from a uniform distribution with values ranging from 1 to 2 to represent both moderate and high discrimination. Item location parameters (i.e., δ_i) were generated from a uniform (-2, 2) distribution, and response thresholds (i.e., τ_i) were simulated from a uniform distribution with values ranging from -2 to -1. Responses were simulated for a sample size of 2,000. Using the simulated dataset, the correlation between the true theta and estimated theta for the 20-pair test was .72, consistent with the results of Hontangas et al. (2015) under similar data-analytic conditions. Overall, this program has the capability of delivering plausible latent trait estimates for the MUPP model.

Use of the *MUPPscore* Script

MUPPscore is a user-defined function script written in the free software programming language R (R Core Team, 2018). Source code for the *MUPPscore* can be found in Appendix A. The *MUPPscore* script is free-of-charge for noncommercial use only. The *MUPPscore* script estimates one trait (i.e., focal trait) for each run with no limit on the number of respondents or the number of total pairs. There are a few precursory steps before the *MUPPscore* can execute successfully. First, the user needs to specify the working directory to indicate where the input files are. Notably, all \ in the file location must be replaced with a / or \\. The working directory can be replaced in the first line of the R code. Second, the users also need to install and load the

LearnBayes R package (Albert, 2018). In addition, the user needs to specify the number of respondents (i.e., N), and the number of total pairs (i.e., $PAIRS$) in the following two lines of the R code to reflect the dataset. Next, the user needs to place two files that are in .csv format under the same folder specified in the working directory: 1) a “Parameters.csv” file of two statements for each pair (i.e., α , δ , and τ), and the format can be found in Figure 1; and 2) a “Responses.csv” file of the focal trait only (i.e., 0 for non-endorsement, 1 for endorsement, and code 9 for missing values), it is important to note that the order of responses must be consistent with the pair order specified in the item parameters file. Then, the user can now run the program after all these steps are properly completed.

The *MUPPscore* will produce three sets of output files and will be stored under the same folder specified in the working directory: 1) a “TraitScores.csv” file with latent trait scores of the focal trait and corresponding standard errors; 2) a “ScaleReliability.csv” file with the scale marginal reliability, which is defined as $(\sigma_{\theta}^2 - \bar{\sigma}_e^2) / \sigma_{\theta}^2$, where σ_{θ}^2 is the population variance of the trait scores, and $\bar{\sigma}_e^2$ is the average of the squared standard errors for trait scores; 3) the probabilities for plotting the IRF for each pair, and the IRF can be drew directly using the “surface” function in Microsoft Excel. An example IRF can be found in Figure 2.

Discussion and Conclusion

The *MUPPscore* script presented in this manual represents the first publicly available tool for estimating latent trait scores for the MUPP model for FC items. The script may help researchers get a better understanding of the MUPP format of testing and increase inquiries into and applications of IRT-based FC measurement in psychological research and practice.

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Figure 1. Format of the Item Parameter File.

		A	B	C	
	1	Alpha	Delta	Tau	
Pair 1	2	0.91989	1.87539	-2.419	← Statement 1: Focal trait
	3	0.1737	10.6528	-6.7758	← Statement 2: Other trait
Pair 2	4	2.08324	0.82328	-1.2661	← Statement 1: Focal trait
	5	1.19928	4.01641	-3.5203	← Statement 2: Other trait
	6	2.39414	0.65158	-1.1774	
	7	1.38169	3.71992	-3.2214	
	8	0.60325	3.38045	-4.1987	
	9	0.72267	3.57175	-2.6011	
	10	0.82505	2.46168	-1.7647	
	11	0.66006	3.53449	-4.0765	
	12	1.59665	-0.9489	-0.5186	
	13	0.42509	-2.2652	-3.0782	
	14	1.01428	-1.6138	-0.2814	
	15	0.99213	-1.9585	-3.0691	
	16	0.58305	-1.461	-2.5772	
	17	1.28519	-0.9702	-0.2375	
	18	1.60636	-0.7872	-0.7135	
	19	0.95978	-0.445	-0.8798	
	20	1.57116	-0.6931	-1.1329	
	21	0.78017	-4.2625	-3.6568	

Figure 2. Example Item Response Function Using Data Generated by *MUPPscore* Using the Microsoft Excel Surface Charts function.

Note. Item parameters for θ_s were: $\alpha_s = 1.57$, $\delta_s = -.35$, $\tau_s = -1.03$; item parameters for θ_t were: $\alpha_t = 1.55$, $\delta_t = -.16$, $\tau_t = -.40$.

Appendix A. R code for running the *MUPPscore* script.

```

setwd("~/newMUPPscore") ## Change working directory (Note: replace \ with / or \\)

if(!require(LearnBayes)){
  install.packages("LearnBayes")
}
library(LearnBayes)

N=1130 ## Change sample size
PAIRS=10 ##Change number of pairs

P=29 ## number of quadrature points (ONLY advanced users are allowed to change)
PS=841 ## square the P (ONLY advanced users are allowed to change)

Parameters=read.csv("Parameters.csv",header=T)

Response=read.csv("Responses.csv",header=T)
NewResponse=Response[rep(1:nrow(Response),each=PS),]

prior=t(t(seq(-3.5,3.5,.25)))
PriorSForOne=t(t(prior[rep(1:nrow(prior),each=P),]))
PriorS=PriorSForOne[rep(1:PS,N)]

PriorT=prior[rep(1:P,N*P),]
PriorTForOne=prior[rep(1:P,P),]

mu=c(0,0)
Sigma=matrix(c(1,0,0,1),2,2)

PriorST=matrix(c(PriorS,PriorT),,2)
ProbS=dnorm(PriorS, mu, Sigma, log=FALSE)
ProbT=dnorm(PriorT, mu, Sigma, log=FALSE)
ProbST=dmnorm(PriorST, mu, Sigma, log=FALSE)

OneItemResponse=matrix(,nrow=(PS*N),ncol=1)
PickedProb=matrix(,nrow=(PS*N),ncol=PAIRS)
ThetaNumerator=matrix(,nrow=N,ncol=1)
ThetaDenominator=matrix(,nrow=N,ncol=1)
Theta=matrix(,nrow=N,ncol=1)
StdErrorNumeratorAll=matrix(,nrow=(PS*N),ncol=1)
StdErrorNumerator=matrix(,nrow=N,ncol=1)
StdError=matrix(,nrow=N,ncol=1)
ProbSgreaterTIRF=matrix(,nrow=PS,ncol=1)

for (i in 1:PAIRS)
{
  AlphaS=Parameters[(2*i-1),1]
  BetaS=Parameters[(2*i-1),2]

```

```

TauS=Parameters[(2*i-1),3]
AlphaT=Parameters[(2*i),1]
BetaT=Parameters[(2*i),2]
TauT=Parameters[(2*i),3]

GammaS=1+exp(AlphaS*(3*(PriorS-BetaS)))+exp(AlphaS*((PriorS-BetaS)-TauS))+exp(AlphaS*(2*(PriorS-BetaS)-TauS))
GammaT=1+exp(AlphaT*(3*(PriorT-BetaT)))+exp(AlphaT*((PriorT-BetaT)-TauT))+exp(AlphaT*(2*(PriorT-BetaT)-TauT))
PS1=(exp(AlphaS*((PriorS-BetaS)-TauS))+exp(AlphaS*(2*(PriorS-BetaS)-TauS)))/GammaS
PS0=(1+exp(AlphaS*(3*(PriorS-BetaS))))/GammaS
PT1=(exp(AlphaT*((PriorT-BetaT)-TauT))+exp(AlphaT*(2*(PriorT-BetaT)-TauT)))/GammaT
PT0=(1+exp(AlphaT*(3*(PriorT-BetaT))))/GammaT
ProbSgreaterT=(PS1*PT0)/(PS1*PT0+PS0*PT1)
ProbSlessT=(PS0*PT1)/(PS1*PT0+PS0*PT1)

GammaSIRF=1+exp(AlphaS*(3*(PriorSForOne-BetaS)))+exp(AlphaS*((PriorSForOne-BetaS)-TauS))+exp(AlphaS*(2*(PriorSForOne-BetaS)-TauS))
GammaTIRF=1+exp(AlphaT*(3*(PriorTForOne-BetaT)))+exp(AlphaT*((PriorTForOne-BetaT)-TauT))+exp(AlphaT*(2*(PriorTForOne-BetaT)-TauT))
PS1IRF=(exp(AlphaS*((PriorSForOne-BetaS)-TauS))+exp(AlphaS*(2*(PriorSForOne-BetaS)-TauS)))/GammaSIRF
PS0IRF=(1+exp(AlphaS*(3*(PriorSForOne-BetaS))))/GammaSIRF
PT1IRF=(exp(AlphaT*((PriorTForOne-BetaT)-TauT))+exp(AlphaT*(2*(PriorTForOne-BetaT)-TauT)))/GammaTIRF
PT0IRF=(1+exp(AlphaT*(3*(PriorTForOne-BetaT))))/GammaTIRF
ProbSgreaterTIRF=(PS1IRF*PT0IRF)/(PS1IRF*PT0IRF+PS0IRF*PT1IRF)
Table=matrix(ProbSgreaterTIRF,ncol=P)
colnames(Table)=c(seq(-3.5,3.5,.25))
rownames(Table)=c(seq(-3.5,3.5,.25))
IRF_Table=paste("IRFTable_",i,".csv",sep="")
write.csv(Table,file=IRF_Table)

OneItemResponse=NewResponse[,i]

for (j in 1:(PS*N))
{
  if(OneItemResponse[j]==1){
    PickedProb[j,i]=ProbSgreaterT[j]}
  if(OneItemResponse[j]==0){
    PickedProb[j,i]=ProbSlessT[j]}
  else if (OneItemResponse[j]==9){
    PickedProb[j,i]=1}
}

rowProds=function(X){apply(X,1,FUN="prod")}
LVfA=rowProds(PickedProb)
LVf=LVfA*ProbST

Af=ProbST

NumeratorRaw=t(t(PriorS*LVf*Af))

DenominatorRaw=t(t(LVf*Af))

```

```

for (k in 1:N)
{
  ThetaNumerator[k]=sum(NumeratorRaw[(PS*(k-1)+1):(PS*(k-1)+PS),])
  ThetaDenominator[k]=sum(DenominatorRaw[(PS*(k-1)+1):(PS*(k-1)+PS),])
  Theta[k]=ThetaNumerator[k]/ThetaDenominator[k]
}

Theta=t(t(Theta))
ThetaAll=Theta[rep(1:nrow(Theta),each=PS),]
StdErrorNumeratorAll=t(t(Af*LVf*((PriorS-ThetaAll)^2)))

for (m in 1:N)
{
  StdErrorNumerator[m]=sum(StdErrorNumeratorAll[(PS*(m-1)+1):(PS*(m-1)+PS),])
  ThetaDenominator[m]=sum(DenominatorRaw[(PS*(m-1)+1):(PS*(m-1)+PS),])
  StdError[m]=sqrt(StdErrorNumerator[m]/ThetaDenominator[m])
}

TraitScores=cbind(Theta,StdError)
colnames(TraitScores)=c("Theta","StdError")
write.csv(TraitScores,file="TraitScores.csv")

Reliability=1-(median(StdError^2)/(var(Theta)+median(StdError^2)))
colnames(Reliability)=c("Reliability")
write.csv(Reliability,file="ScaleReliability.csv")

```