Determining the number of factors using personality data

S. Mason Garrison
VANDERBILT
PEABODY COLLEGE

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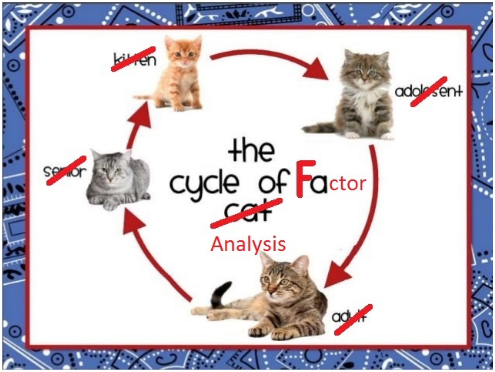
Introduction

Differential Psychology and Factor Analysis

- The study of individual differences (*i.e.* intelligence, personality) is inexorably with factor analysis.
- Many generally accepted theories, such as the
    - General factor of Intelligence (Spearman, 1904) and the
    - Five Factor Model of Personality (**?**),
  - were developed, using factor analysis.
- Measures, based on those theories were developed,
  - using factor analysis.
- In turn, those measures were used to refine the theories,
  - which are used to create new measures...

- This cycle leaves Differential Psychology vulnerable



  - because factor analysis is misused often in construct validation research (Distefano & Hess, 2005),
  - conventional methods for determining the number of factors are subjective (Zwick & Velicer, 1986), and the
  - standard cut points for determining good fit aren't designed for personality-like data (Kang, McNeish, & Hancock, 2016).

Present Study

- The current study is designed to examine the effectiveness of factor enumeration rules on personality data;
- do the commonly used methods actually recover the correct number of factors?
- Specifically, how well do the following perform in recovering the correct number of factors?:
  - Minimum Average Partial procedure, and
  - various goodness-of-fit indices,
    - using classic (Hu & Bentler, 1998) thresholds.

Design Constants

- Five factors
- Estimated using MLE with Oblimin Rotation
- Adapted the vss function from Revelle's Psych package, using R 3.2.4 revised.
- Extracted maximum of 9 factors
- 100 Data Sets per condition

Data Generation

```
## Generate Data from factor loadings
# need a factor model and an effects matrix
GenData = function(fmodel,effect,n,names) {
  numberofvariables = dim(fmodel)[1]
  numberoflatent = dim(fmodel)[2]
  tmodel = t(fmodel)
  communality = diag(fmodel%*%tmodel)    #weight true
      scores and errors given the measurement model
  uniqueness = 1-communality
  errorweight = diag(sqrt(uniqueness))   #weight the
      errors
```

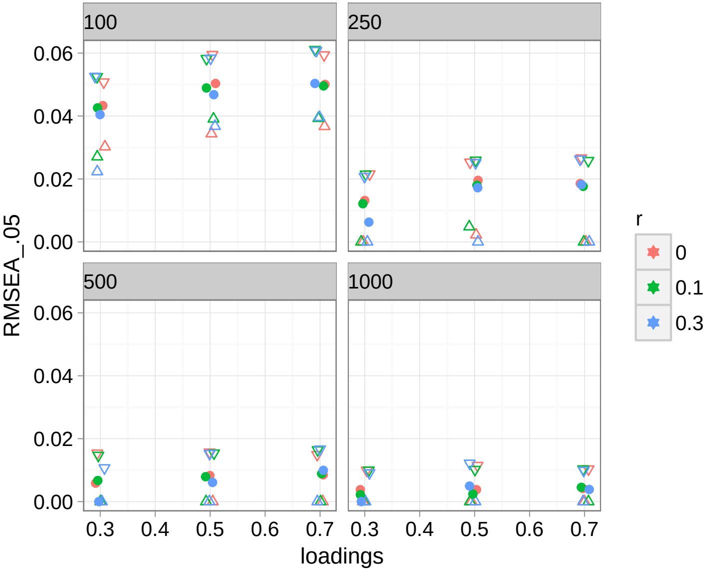
Data Generation

```
#create true scores for the latent variables
  latentscores = matrix(rnorm(n*(numberoflatent)),n)
  latentscores = latentscores%*%effect
  truescores = latentscores%*%tmodel

#create normal error scores
  error = matrix(rnorm(n*(numberofvariables)),n)
  error = error%*%errorweight

#create observed scores
  observedscore = truescores+error
  observedscore = data.frame(observedscore)
  names(observedscore)= names
  return(observedscore)}
```

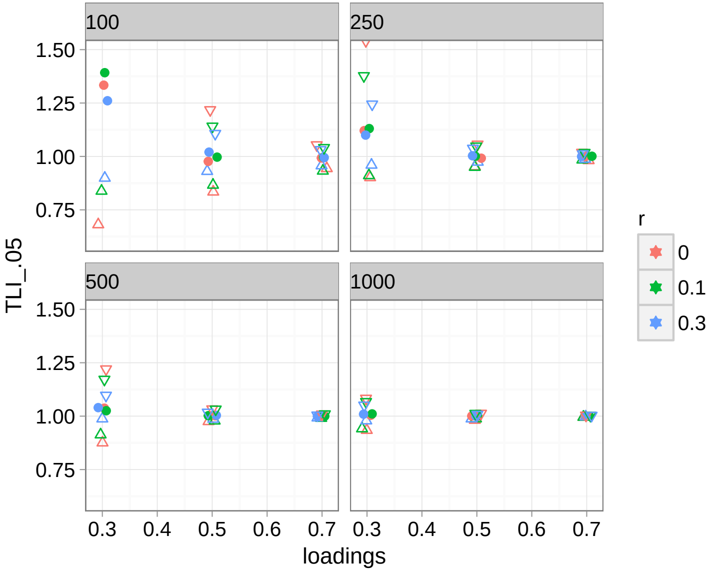
Design Conditions (3x3x3x4)

- Test Structure
  - Big Five Inventory (BFI; **?**)
    - 44 items, 16 reverse coded
  - International Personality Item Pool-NEO (IPIP-NEO; Goldberg, 1999)
    - 50 items, 24 reverse coded
    - 100 items, 47 reverse coded
- Item Loadings
  - .3, .5, .7
- Correlation between Factors
  - 0, .1, .3
- Sample Size
  - 100, 250, 500, 1000

Fit Statistics for True Model:RMSEA



TLI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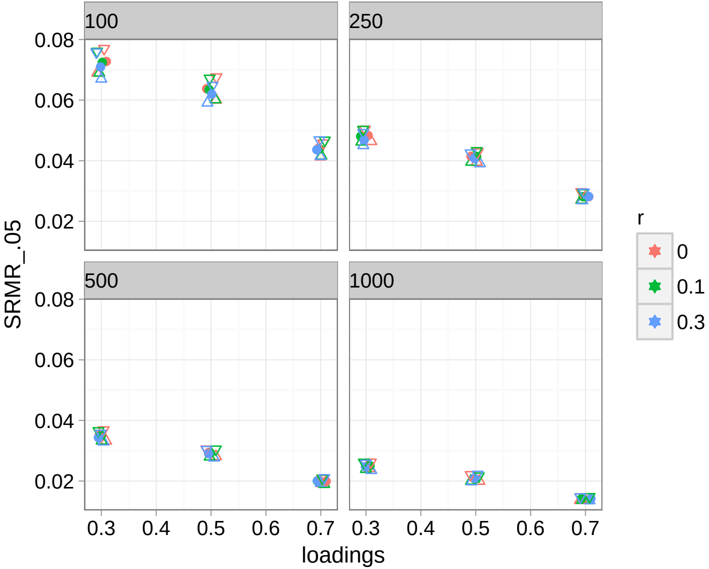
SRMR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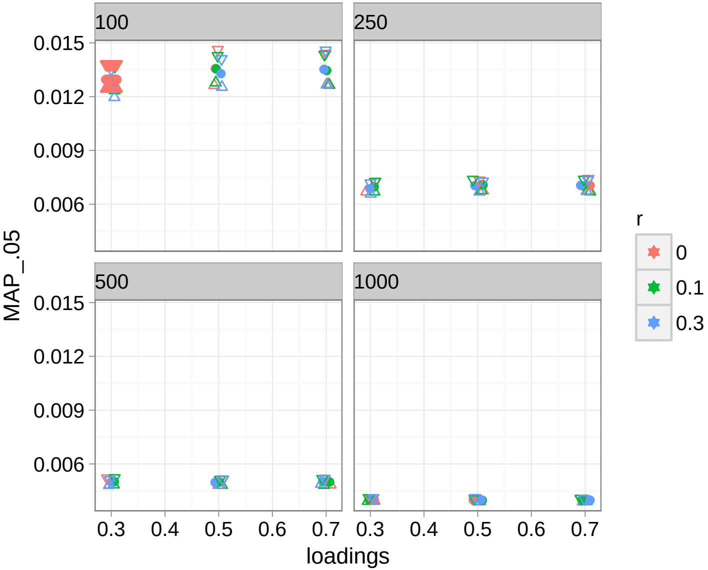
MAP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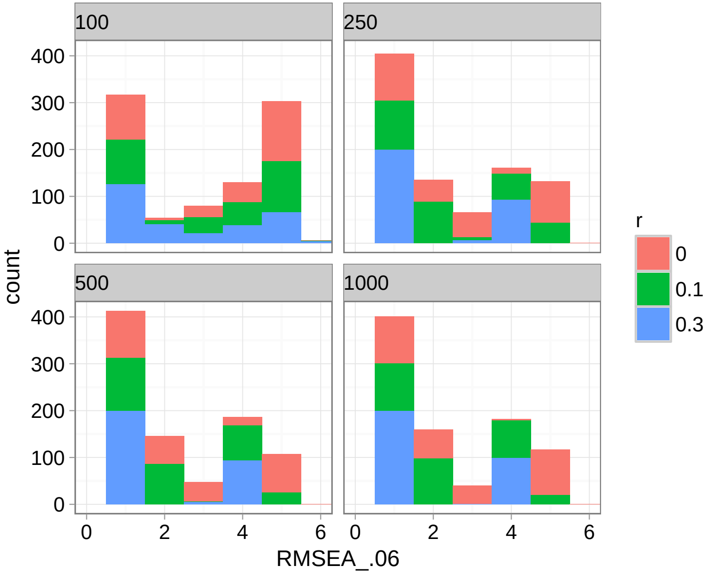
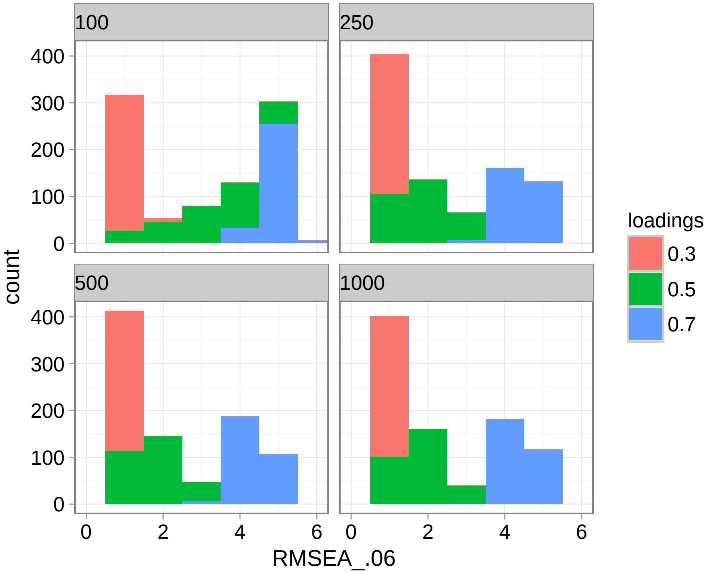
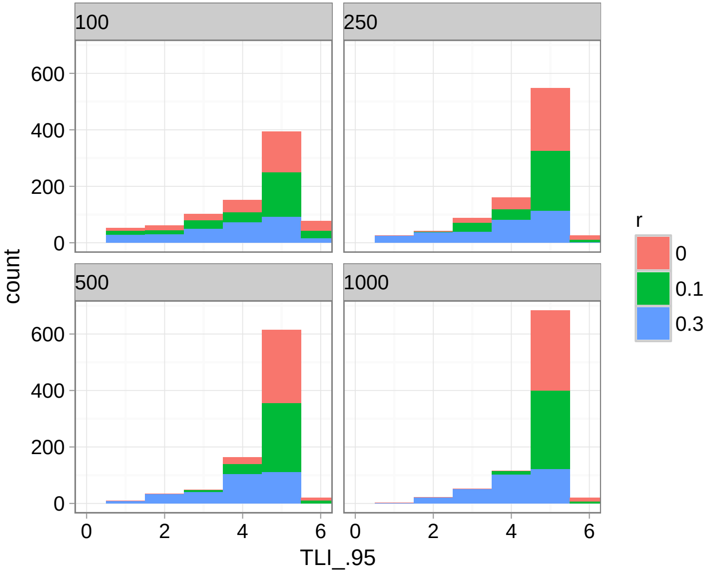
RMSEA Point Estimate by Correlated Factors



RMSEA Point by Loading



TLI by Correlated Factors



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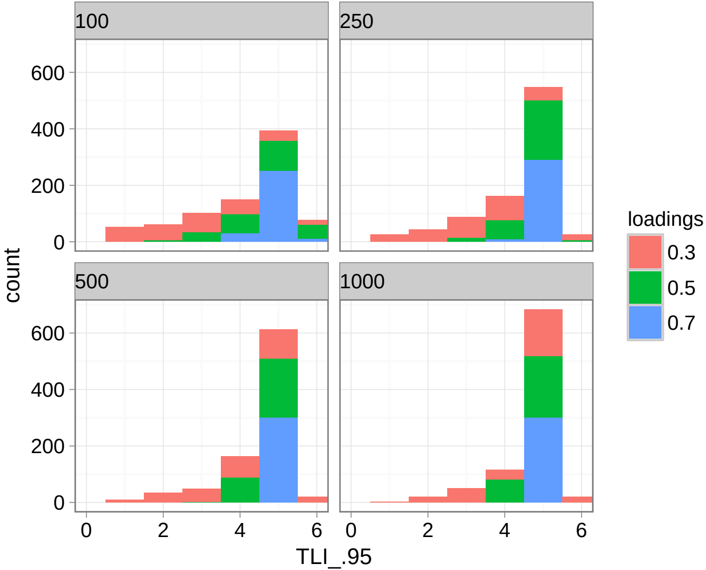

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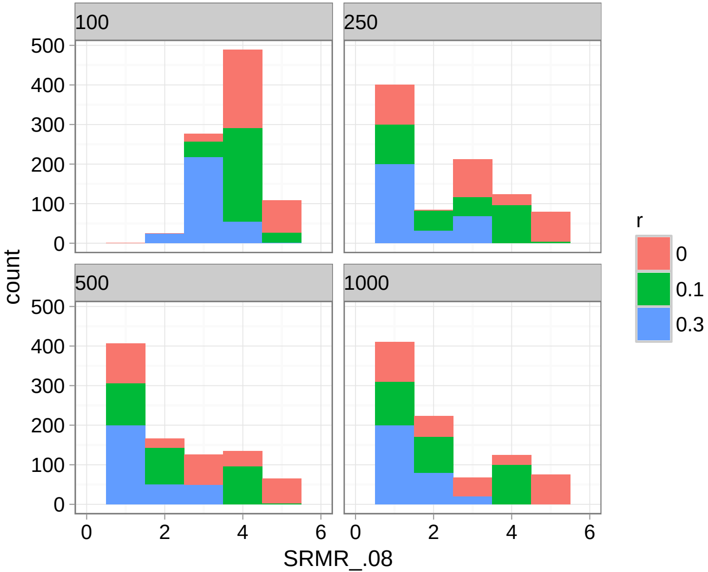

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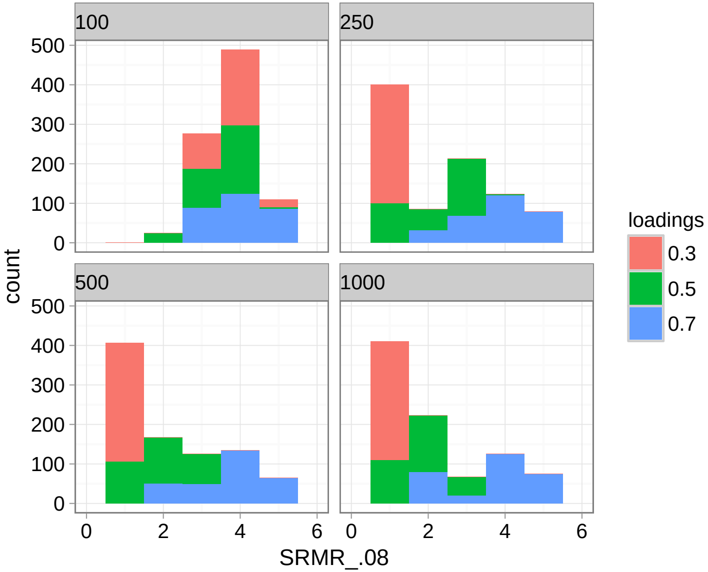

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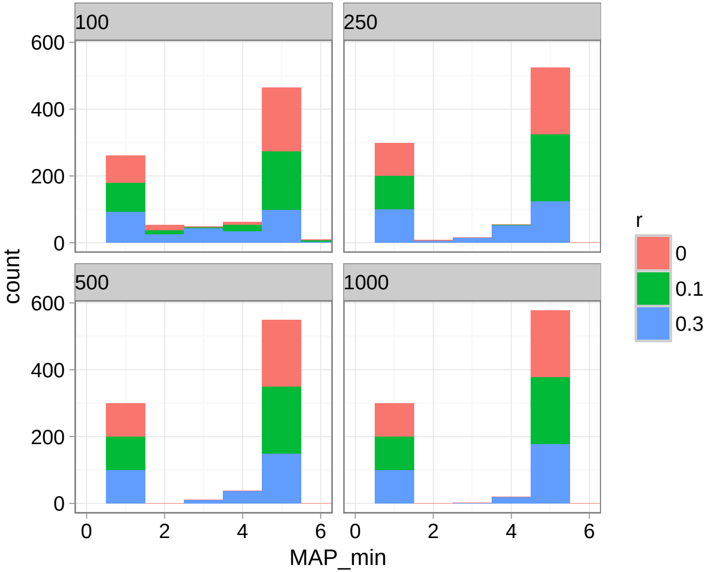

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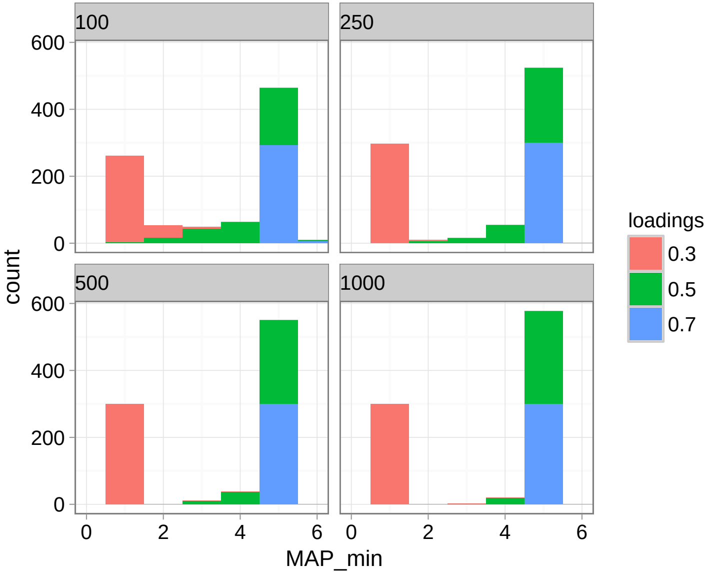
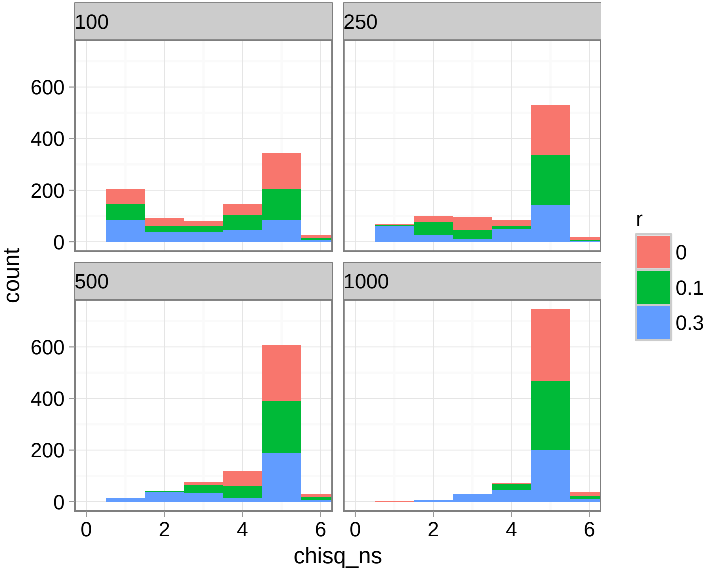


CHI^2 BY CORRELATED FACTORS



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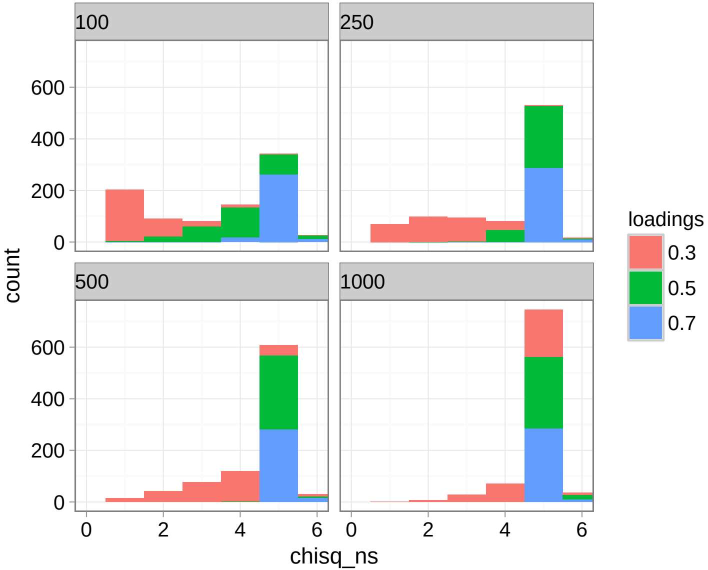
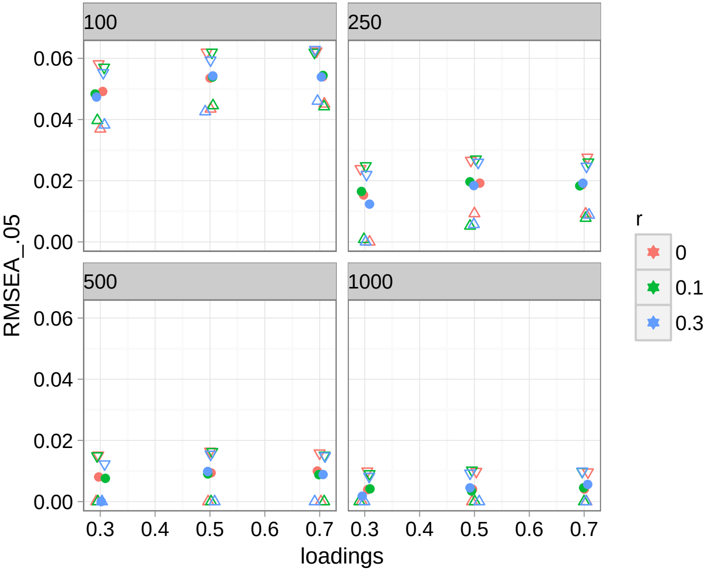


Fit Statistics for True Model:RMSEA



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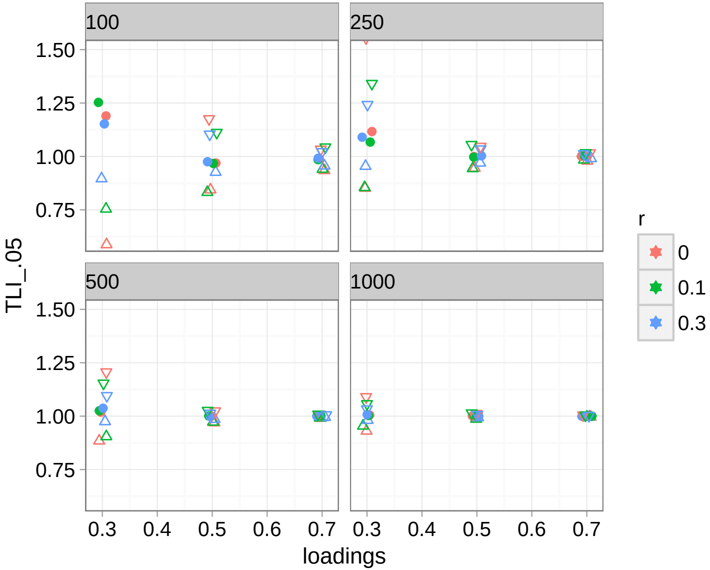
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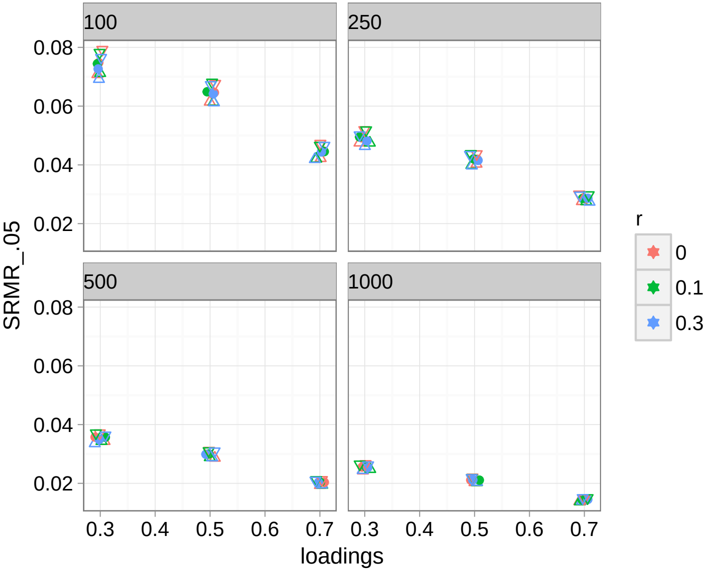
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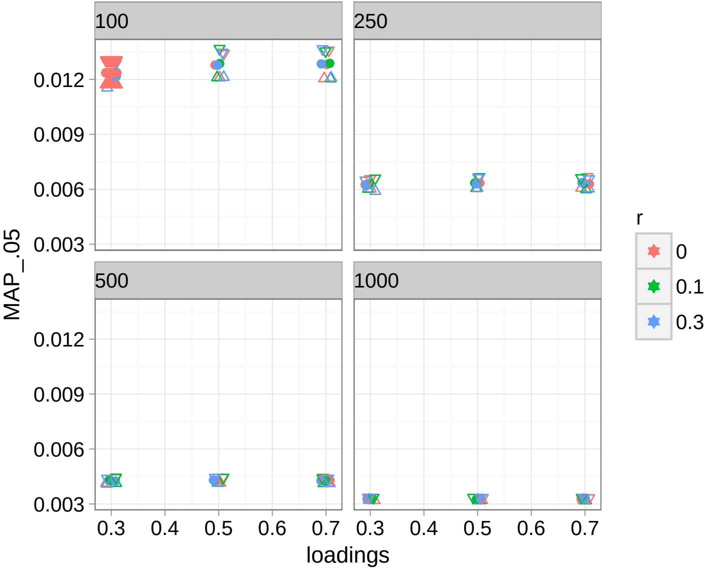
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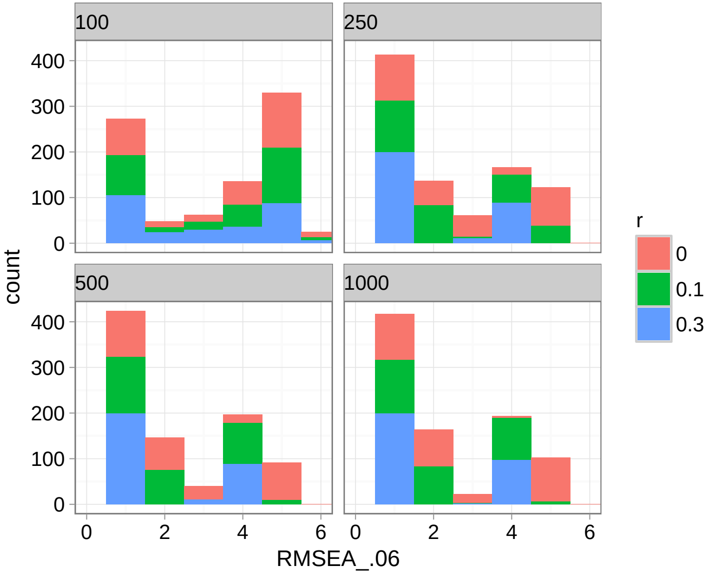

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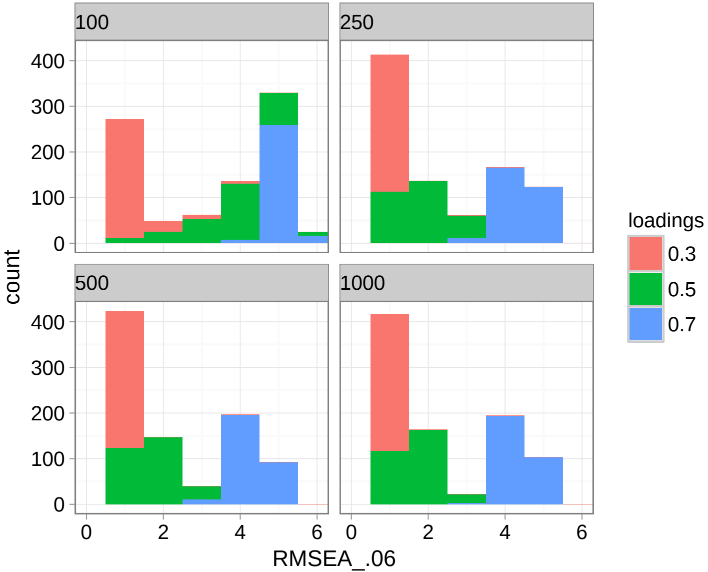

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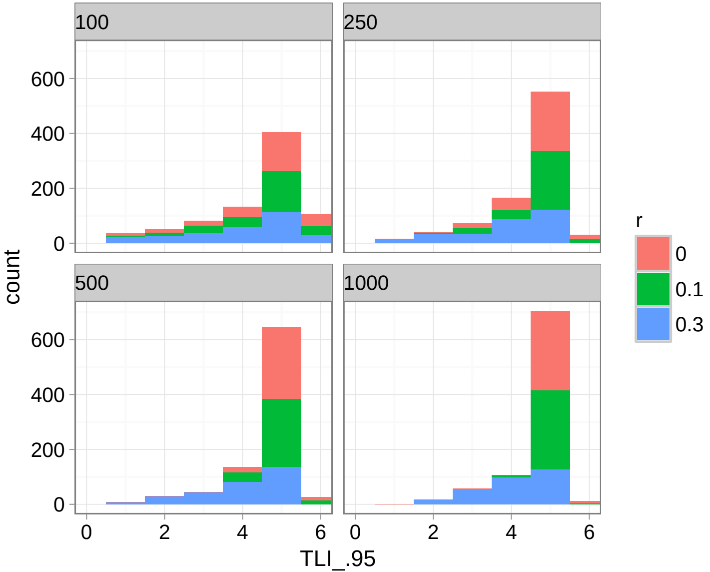

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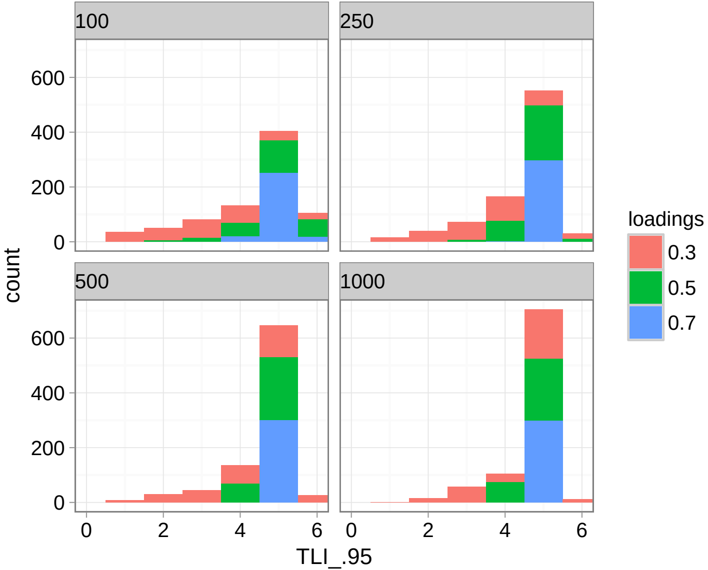
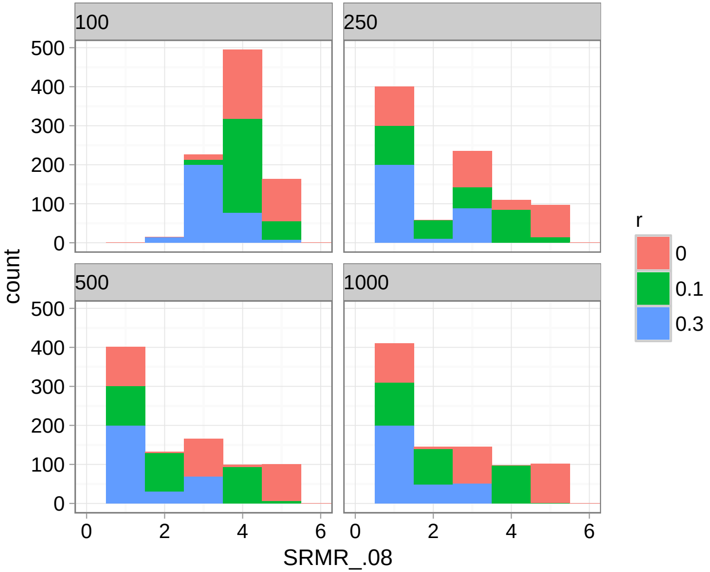


SRMR by Correlated Factors



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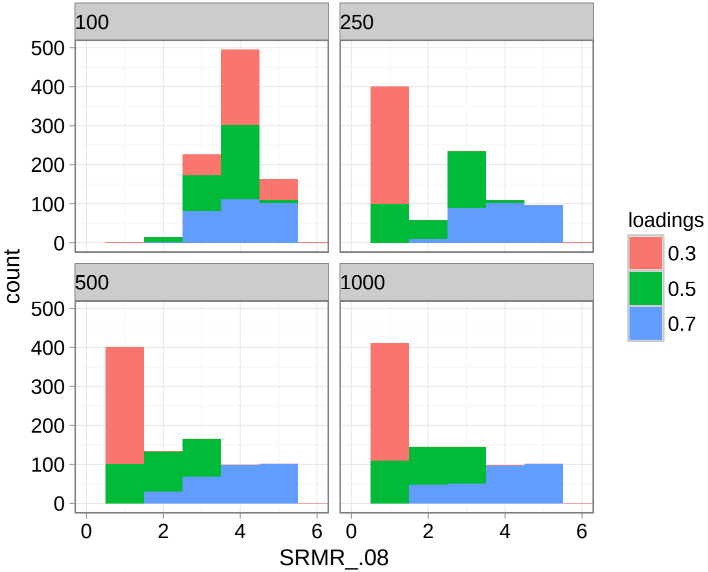

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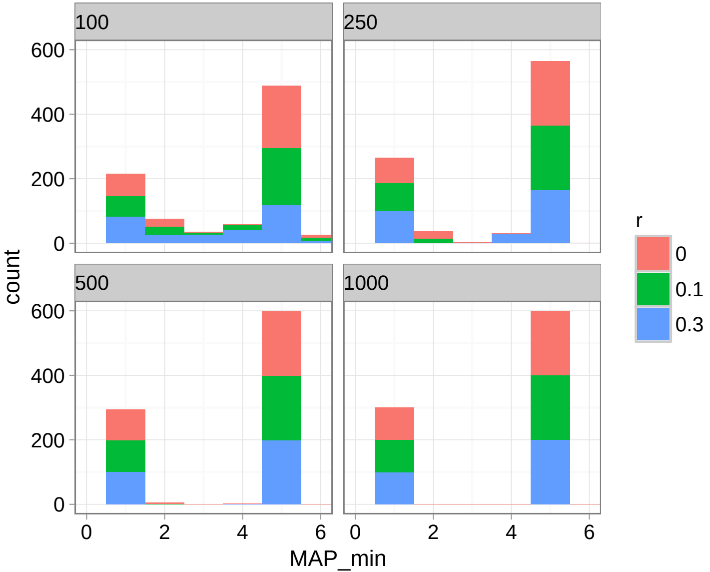

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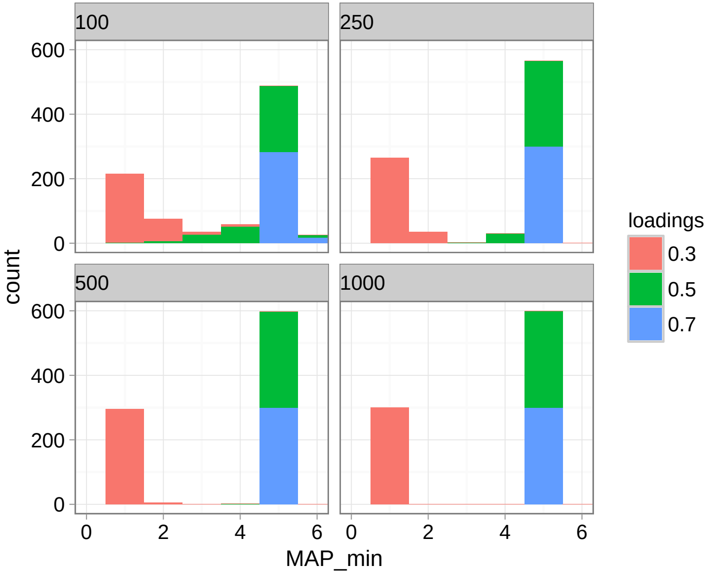
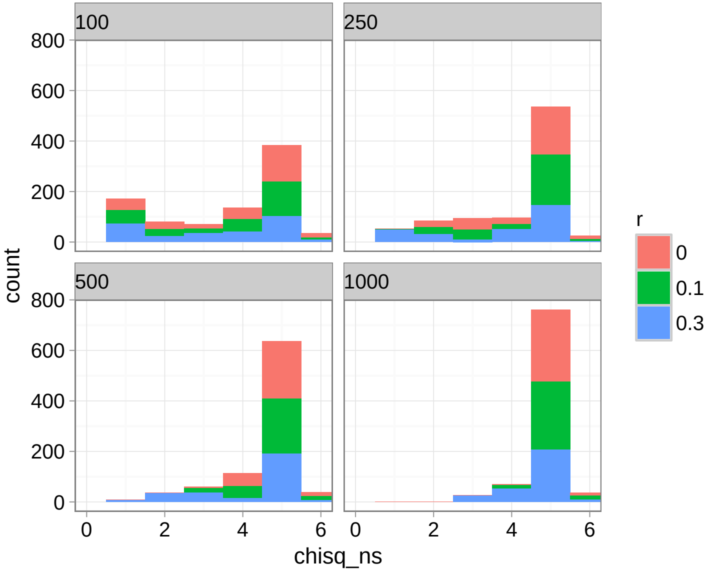


Chi^2 by Correlated Factors



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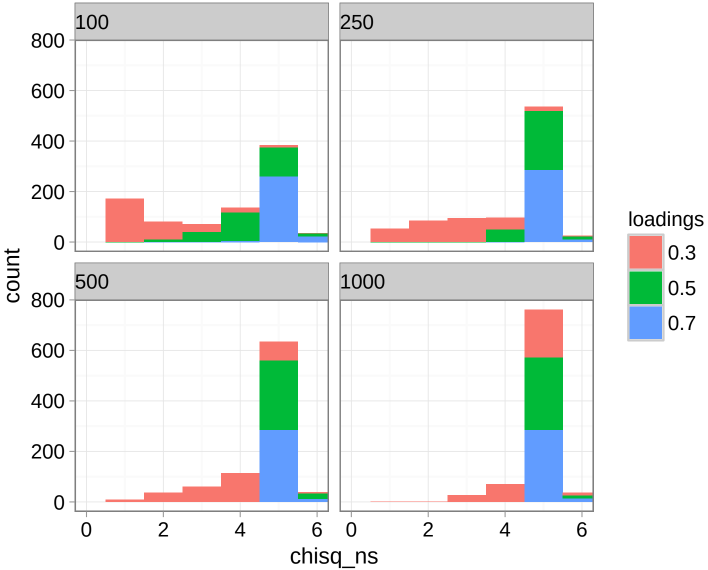

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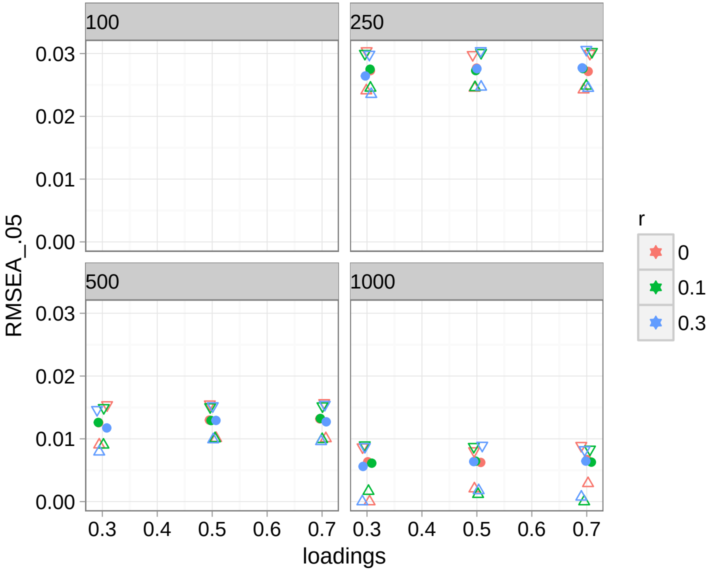

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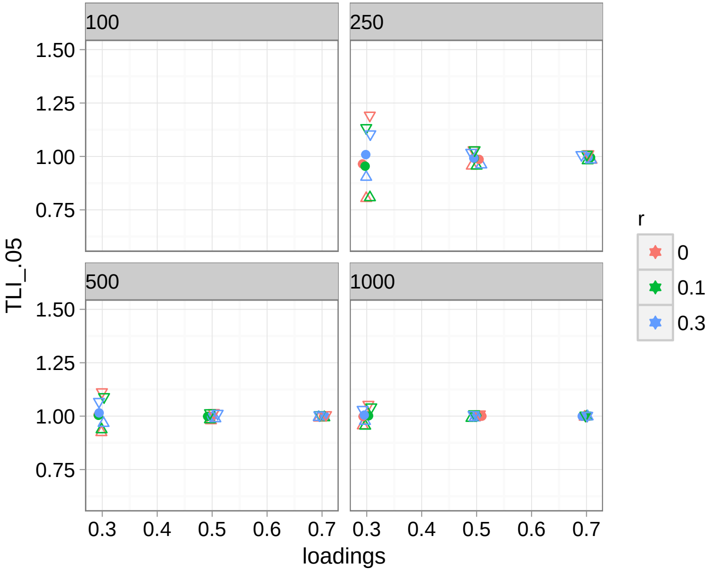
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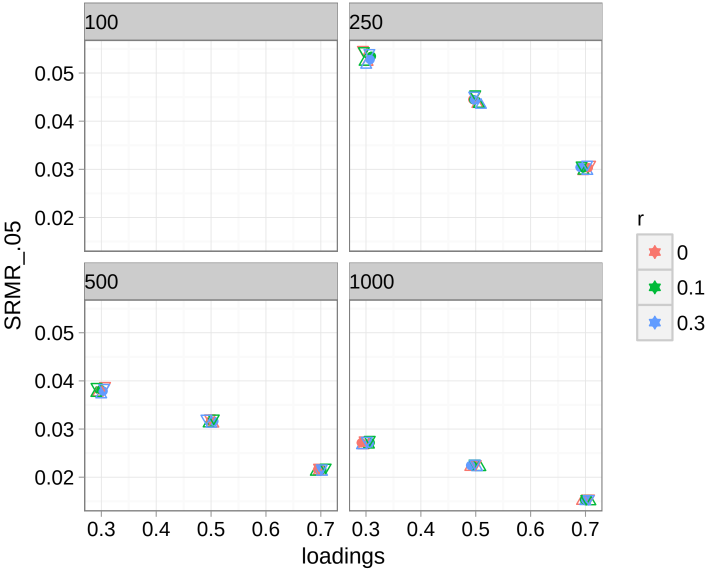
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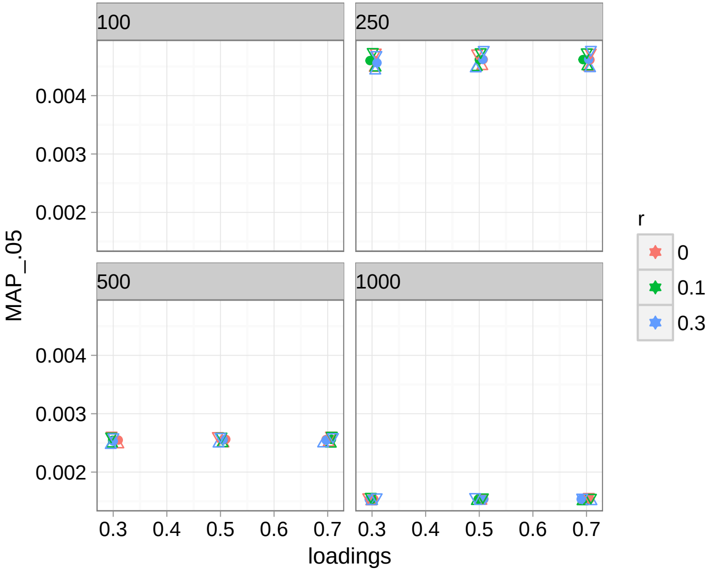
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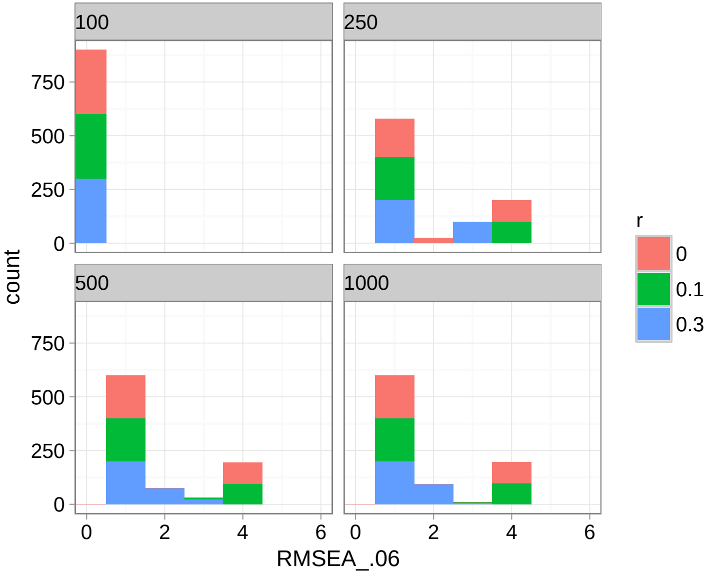

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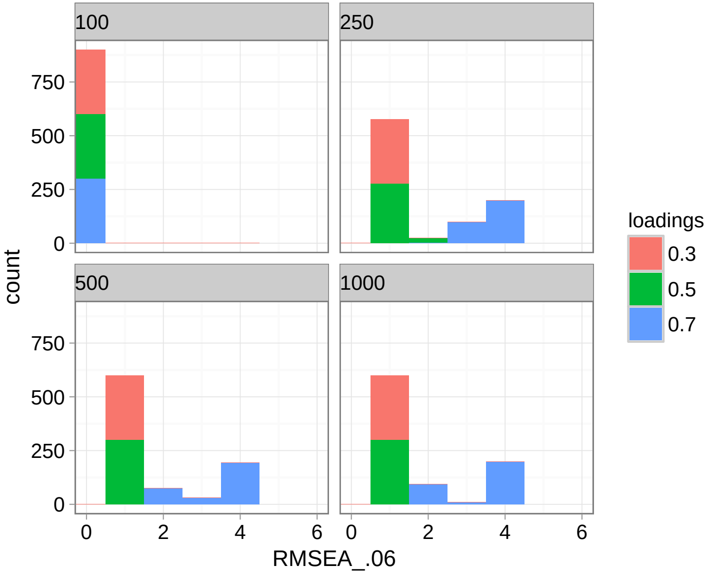
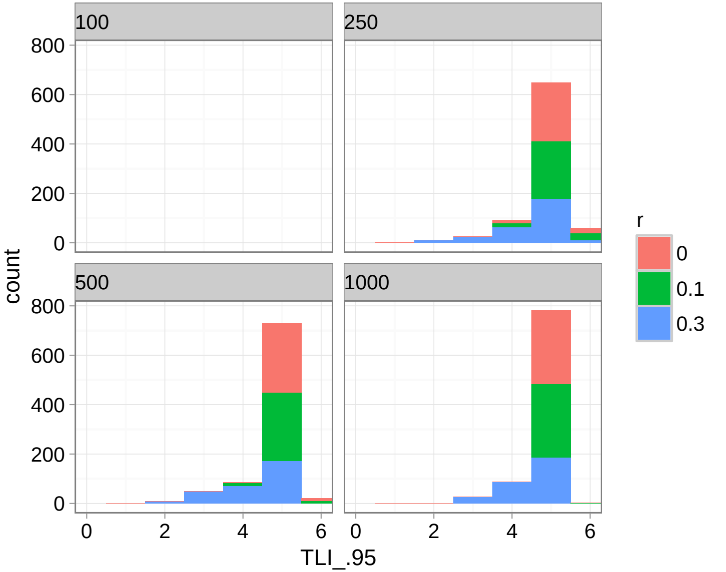


TLI by Correlated Factors



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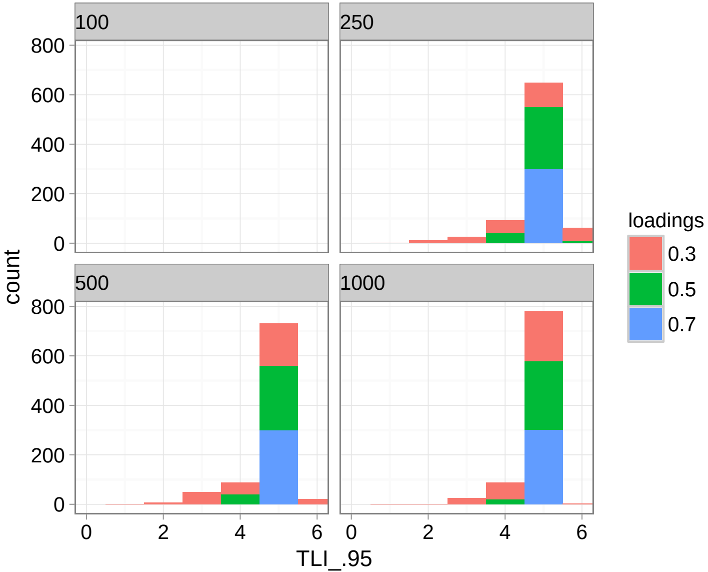
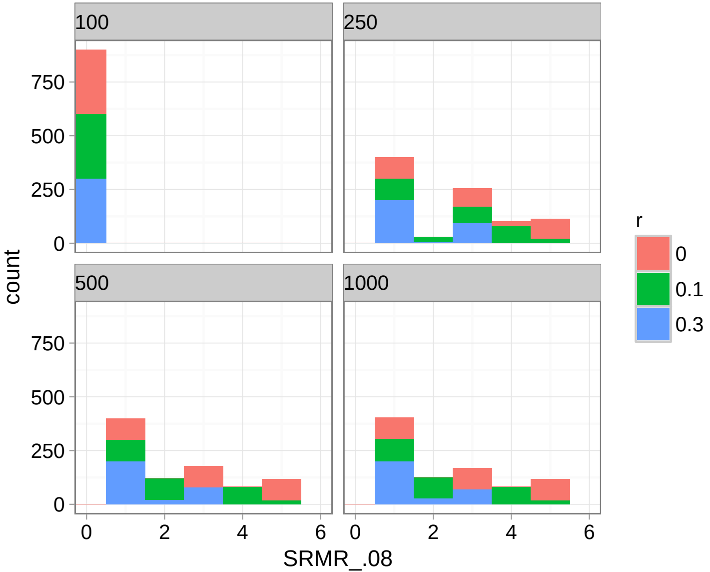
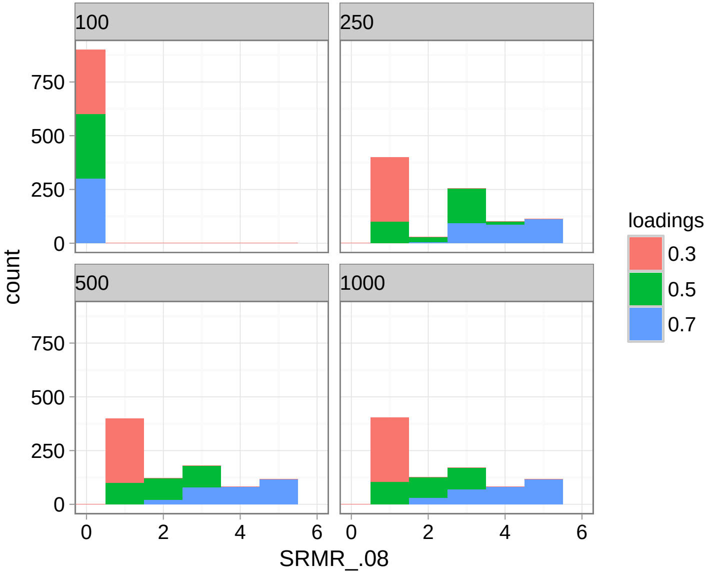


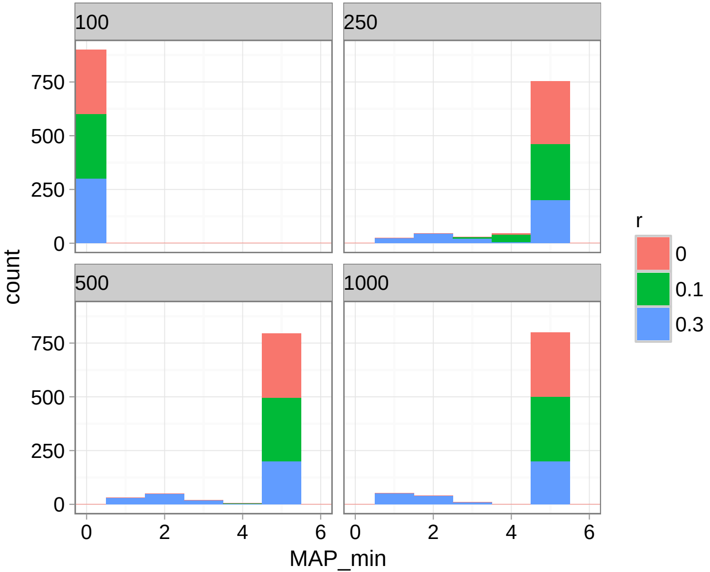
SRMR by Correlated Factors



SRMR BY LOADING



MAP by Correlated Factors



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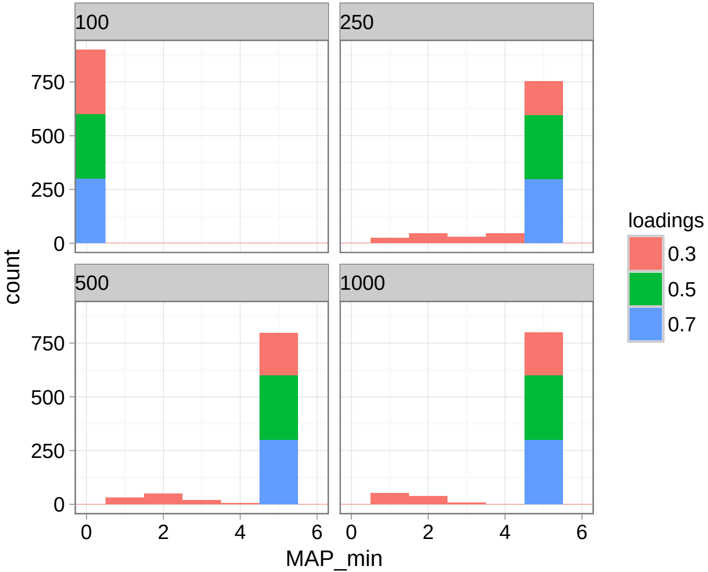
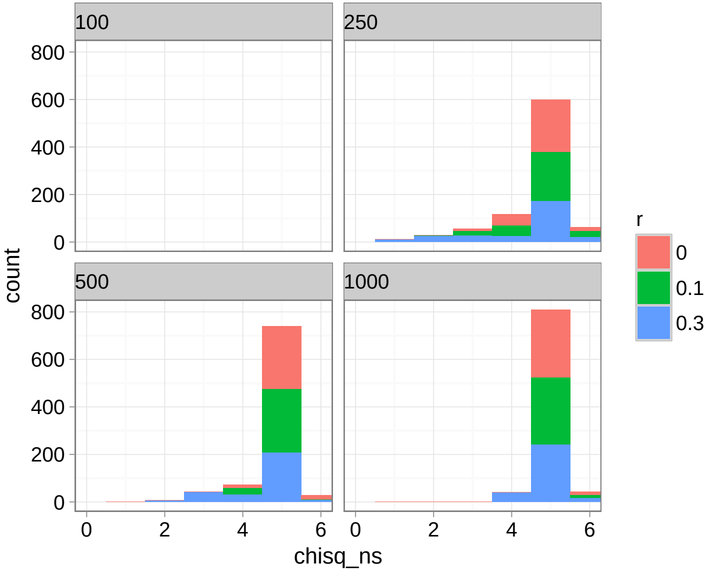


CHI^2 BY CORRELATED FACTORS



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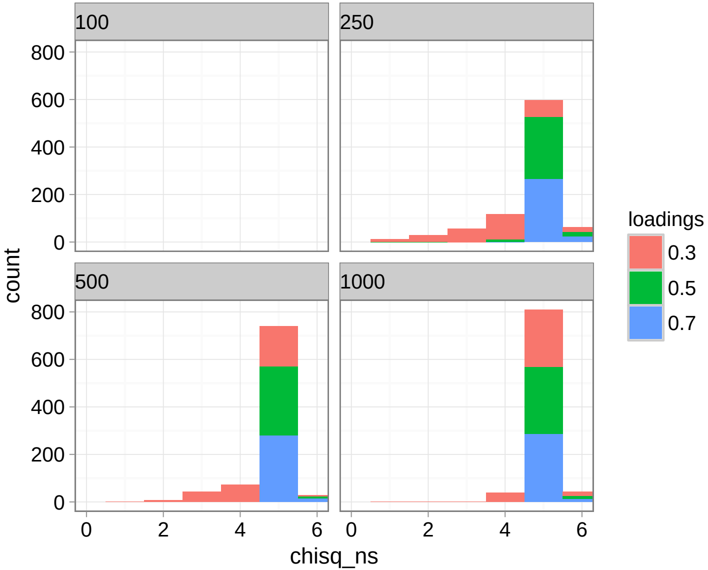

Discussion

- Interpretation
  - Tendency to underfactor
  - High Correlations between factors
  - Low Factor Loadings
- Recommendations
  - Sample Size
  - Measurement Matters
- Future Directions

References

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