

Análises Fatoriais Confirmatorias - AFC

April 27, 2020

```
In [2]: library("tidyverse")
library("reshape2")
library("ggfortify")
library("ltm")
library(lavaan)
library(psych)
```

1 Ler "dados.csv"

```
In [4]: dados = read.csv("dados.csv", header = TRUE)
levels(dados$Escola) = c("Escola A", "Escola B")
dados$Série = factor(dados$Série, levels = c(6, 7, 8, 9, 1))
levels(dados$Série) = paste0(levels(dados$Série), "º ano")
dados$Turma = factor(paste(dados$Série, str_to_upper(as.character(dados$Turma))),
                      levels = c("6º ano A", "6º ano B", "7º ano A", "7º ano B", "7º ano C",
                                "7º ano E", "8º ano A", "8º ano C", "9º ano B", "9º ano C",
                                "1º ano A", "1º ano B"))
```

2 Ler "pontuacoes.csv"

```
In [5]: pontuacoes = read.csv("pontuacoes.csv", header = TRUE)
pontuacoes$Total = apply(pontuacoes[,2:26], 1, sum)
pontuacoes$Grau = factor(ceiling(pontuacoes$Total/25), levels = c(1, 2, 3, 4, 5))
levels(pontuacoes$Grau) = c("Nenhuma Ansiedade",
                             "Baixa Ansiedade",
                             "Ansiedade Moderada",
                             "Alta Ansiedade",
                             "Extrema Ansiedade")
```

3 Unir dados "pontuacoes" e "dados" por nome

```
In [7]: dados = left_join(dados, pontuacoes) %>%
  filter(!is.na(X1))
n_meninos = sum(dados$Gênero == "M" & !is.na(dados$X1))
n_meninas = sum(dados$Gênero == "F" & !is.na(dados$X1))
```

```
Joining, by = c("Nomes", "X1", "X2", "X3", "X4", "X5", "X6", "X7", "X8", "X9", "X10", "X11", "X12", "X13", "X14", "X15", "X16", "X17", "X18", "X19", "X20", "X21", "X22", "X23", "X24", "X25")
Warning message:
Column `Nomes` joining character vector and factor, coercing into character vector
```

4 Estudo de teste KMO e Bartlett

```
In [8]: M2 = as.matrix(dados[8:32])
```

4.1 KMO

```
In [9]: KMO(M2)
```

Kaiser-Meyer-Olkin factor adequacy

Call: KMO(r = M2)

Overall MSA = 0.76

MSA for each item =

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16
0.71	0.75	0.72	0.84	0.66	0.83	0.47	0.72	0.44	0.73	0.83	0.80	0.85	0.67	0.76	0.88	
	X17	X18	X19	X20	X21	X22	X23	X24	X25							
0.73	0.65	0.72	0.79	0.80	0.86	0.80	0.65	0.70								

4.2 Bartlett

```
In [10]: cortest.bartlett(M2)
```

R was not square, finding R from data

\$chisq 798.334619278655

\$p.value 6.87119867053906e-47

\$df 300

5 Estudos AFC

```
In [11]: modelo= 'F1 =~ X7 + X8 + X13 + X15 + X17 + X18 + X21 + X22 + X24 + X25
                  F2 =~ X1 + X2 + X4 + X5 + X6 + X9 + X10 + X14 + X16 + X20 + X23'
cfa1= cfa(modelo, data=dados)
summary(cfa1, standardized=FALSE, fit.measures=TRUE)
```

lavaan 0.6-5 ended normally after 101 iterations

Estimator	ML
Optimization method	NLMINB

Number of free parameters	43
Number of observations	73
Model Test User Model:	
Test statistic	340.668
Degrees of freedom	188
P-value (Chi-square)	0.000
Model Test Baseline Model:	
Test statistic	705.148
Degrees of freedom	210
P-value	0.000
User Model versus Baseline Model:	
Comparative Fit Index (CFI)	0.692
Tucker-Lewis Index (TLI)	0.656
Loglikelihood and Information Criteria:	
Loglikelihood user model (H0)	-1993.197
Loglikelihood unrestricted model (H1)	-1822.863
Akaike (AIC)	4072.395
Bayesian (BIC)	4170.885
Sample-size adjusted Bayesian (BIC)	4035.391
Root Mean Square Error of Approximation:	
RMSEA	0.105
90 Percent confidence interval - lower	0.087
90 Percent confidence interval - upper	0.123
P-value RMSEA <= 0.05	0.000
Standardized Root Mean Square Residual:	
SRMR	0.099
Parameter Estimates:	
Information	Expected
Information saturated (h1) model	Structured
Standard errors	Standard

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)
F1 =~				
X7	1.000			
X8	4.352	3.137	1.388	0.165
X13	4.084	2.874	1.421	0.155
X15	4.175	3.034	1.376	0.169
X17	5.390	3.827	1.408	0.159
X18	2.016	1.513	1.332	0.183
X21	5.675	3.999	1.419	0.156
X22	5.042	3.555	1.418	0.156
X24	3.731	2.760	1.352	0.176
X25	3.691	2.713	1.361	0.174
F2 =~				
X1	1.000			
X2	1.498	0.548	2.737	0.006
X4	2.433	0.787	3.091	0.002
X5	1.452	0.562	2.583	0.010
X6	2.560	0.842	3.039	0.002
X9	0.407	0.357	1.140	0.254
X10	1.812	0.649	2.790	0.005
X14	1.175	0.457	2.570	0.010
X16	2.821	0.889	3.172	0.002
X20	2.524	0.848	2.976	0.003
X23	1.972	0.637	3.098	0.002
Covariances:				
	Estimate	Std.Err	z-value	P(> z)
F1 ~~				
F2	0.037	0.028	1.295	0.195
Variances:				
	Estimate	Std.Err	z-value	P(> z)
.X7	0.606	0.101	6.011	0.000
.X8	0.993	0.175	5.682	0.000
.X13	0.359	0.070	5.155	0.000
.X15	1.109	0.193	5.745	0.000
.X17	0.957	0.175	5.467	0.000
.X18	0.441	0.075	5.868	0.000
.X21	0.750	0.144	5.224	0.000
.X22	0.611	0.116	5.250	0.000
.X24	1.225	0.210	5.828	0.000
.X25	1.076	0.185	5.803	0.000
.X1	0.483	0.082	5.890	0.000
.X2	0.603	0.104	5.767	0.000
.X4	0.615	0.115	5.329	0.000
.X5	0.763	0.131	5.838	0.000
.X6	0.816	0.150	5.448	0.000
.X9	0.643	0.107	6.023	0.000

.X10	0.787	0.137	5.735	0.000
.X14	0.511	0.088	5.843	0.000
.X16	0.585	0.116	5.031	0.000
.X20	0.964	0.174	5.554	0.000
.X23	0.394	0.074	5.311	0.000
F1	0.020	0.028	0.719	0.472
F2	0.088	0.054	1.645	0.100

6 Cronbach alpha

```
In [12]: questoes = 8:32
         cronbach.alpha(as.matrix(dados[,questoes]), CI = TRUE)
```

Cronbach's alpha for the 'as.matrix(dados[, questoes])' data-set

```
Items: 25
Sample units: 73
alpha: 0.897
```

```
Bootstrap 95% CI based on 1000 samples
 2.5% 97.5%
0.858 0.924
```