Reticular Action Model (RAM) Notation Notes

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2021-01-22

Contents

Chapter 1

Description

This is a collection of my personal notes on the Reticular Action Model (RAM) notation that accompanies the `ramR` package (Pesigan, 2021). You can install the released version of `ramR` from GitHub with:

```
remotes::install_github("jeksterslab/ramR")
```

These notes are based on the following resources:

- Boker and McArdle (2005)
- McArdle and McDonald (1984)
- McArdle (2005)

See GitHub Pages for the html deployment.

Chapter 2

Reticular Action Model (RAM) Matrix Notation

2.1 Full Model

Definition 2.1.

$$\mathbf{v} = \mathbf{A}\mathbf{v} + \mathbf{u} \tag{2.1}$$

where

- $\mathbf{v}$ and $\mathbf{u}$ are $t \times 1$ vectors of random variables
- $\mathbf{A}$ is a $t \times t$ matrix of *directed* or *asymmetric* relationship from column variable v_j to row variable v_i
  - $\mathbf{A}$ represent the regression of each of the t variables $\mathbf{v}$ on the other $t - 1$ variables
  - diagonal $a_{i,i}$ is zero
  - u_i represent the residual of v_i
  - if all regression coefficients on other variables are zero, then the variable v_i is considered the same as its own residual u_i

Definition 2.2.

$$\mathbf{S} = \mathbb{E}\left\{\mathbf{u}\mathbf{u}'\right\}, \tag{2.2}$$

where

- $\mathbf{S}$ is a $t \times t$ matrix of *undirected* or *symmetric* relationship
  - the notation Ω is used in other sources for $\mathbf{S}$
- $\mathbb{E}$ is the expectation operator

Definition 2.3.

$$\mathbf{C} = \mathbb{E}\left\{\mathbf{v}\mathbf{v}'\right\}, \tag{2.3}$$

where

- $\mathbf{C}$ is a $t \times t$ variance-covariance matrix
  - the notation Σ is used in other sources for $\mathbf{C}$

Definition 2.4.

$$\mathbf{v} = \mathbf{A}\mathbf{v} + \mathbf{u}$$

can be rewritten as

$$\begin{aligned} \mathbf{v} - \mathbf{A}\mathbf{v} &= \mathbf{u} \\ \mathbf{u} &= \mathbf{v} - \mathbf{A}\mathbf{v} \\ \mathbf{u} &= \left(\mathbf{I} - \mathbf{A}\right)\mathbf{v} \end{aligned} \tag{2.4}$$

assuming that $(\mathbf{I} - \mathbf{A})$ is non-singular,

$$\mathbf{E} = \left(\mathbf{I} - \mathbf{A}\right)^{-1} \tag{2.5}$$

then

$$\begin{aligned} \mathbf{v} &= \left(\mathbf{I} - \mathbf{A}\right)^{-1}\mathbf{u} \\ &= \mathbf{E}\mathbf{u}. \end{aligned} \tag{2.6}$$

Using the definitions above, $\mathbf{S}$ and $\mathbf{C}$ are given by

$$\begin{aligned} \mathbf{S} &= \left(\mathbf{I} - \mathbf{A}\right)\mathbf{C}\left(\mathbf{I} - \mathbf{A}\right)^{-1} \\ &= \mathbf{E}^{-1}\mathbf{C}\left(\mathbf{E}^{-1}\right)^{\intercal} \end{aligned} \tag{2.7}$$

$$\begin{aligned} \mathbf{C} &= \left(\mathbf{I} - \mathbf{A}\right)^{-1}\mathbf{S}\left[\left(\mathbf{I} - \mathbf{A}\right)^{-1}\right]^{\intercal} \\ &= \mathbf{E}\mathbf{S}\mathbf{E}^{\intercal} \end{aligned} \tag{2.8}$$

2.2 Observed/Manifest/Given Variables vs. Unobserved/Latent/Hidden Variables

Definition 2.5.

$$\mathbf{v} = \begin{bmatrix} \mathbf{g}_{p \times 1} \\ \mathbf{h}_{q \times 1} \end{bmatrix} \tag{2.9}$$

$$t = p + q \tag{2.10}$$

- $\mathbf{g}$ may be considered observed, manifest or *given* variables
- $\mathbf{h}$ may be considered unobserved, latent, or *hidden* variables

Definition 2.6.

$$\mathbf{F} = \left[\mathbf{I}_{p \times p} : \mathbf{0}_{p \times q}\right] \tag{2.11}$$

- the $\mathbf{F}$ matrix acts as a *filter* to select the manifest variables out of the full set of manifest and latent variables

$$\mathbf{g} = \mathbf{F}\mathbf{v} \tag{2.12}$$

$$\begin{aligned} \mathbf{g} &= \mathbf{F}\left(\mathbf{I} - \mathbf{A}\right)^{-1} \mathbf{u} \\ &= \mathbf{F}\mathbf{E}\mathbf{u} \end{aligned} \tag{2.13}$$

Definition 2.7.

$$\mathbf{M} = \mathbb{E}\left\{\mathbf{g}\mathbf{g}^{\mathsf{T}}\right\} \tag{2.14}$$

$$\begin{aligned} \mathbf{M} &= \mathbf{F}\left(\mathbf{I} - \mathbf{A}\right)^{-1} \mathbf{S} \left[\left(\mathbf{I} - \mathbf{A}\right)^{-1}\right]^{\mathsf{T}} \mathbf{F}^{\mathsf{T}} \\ &= \mathbf{F}\mathbf{E}\mathbf{S}\mathbf{E}^{\mathsf{T}}\mathbf{F}^{\mathsf{T}} \\ &= \mathbf{F}\mathbf{C}\mathbf{F}^{\mathsf{T}} \end{aligned} \tag{2.15}$$

- when components of $\mathbf{v}$ are permuted, the columns of $\mathbf{F}$ can be correspondingly permuted
- the rows and columns of $\mathbf{C}$ that are filtered out by $\mathbf{F}$ contain useful information about the latent variable structure.

The equations above completely define RAM.

Chapter 3

Reticular Action Model (RAM) Path Diagram

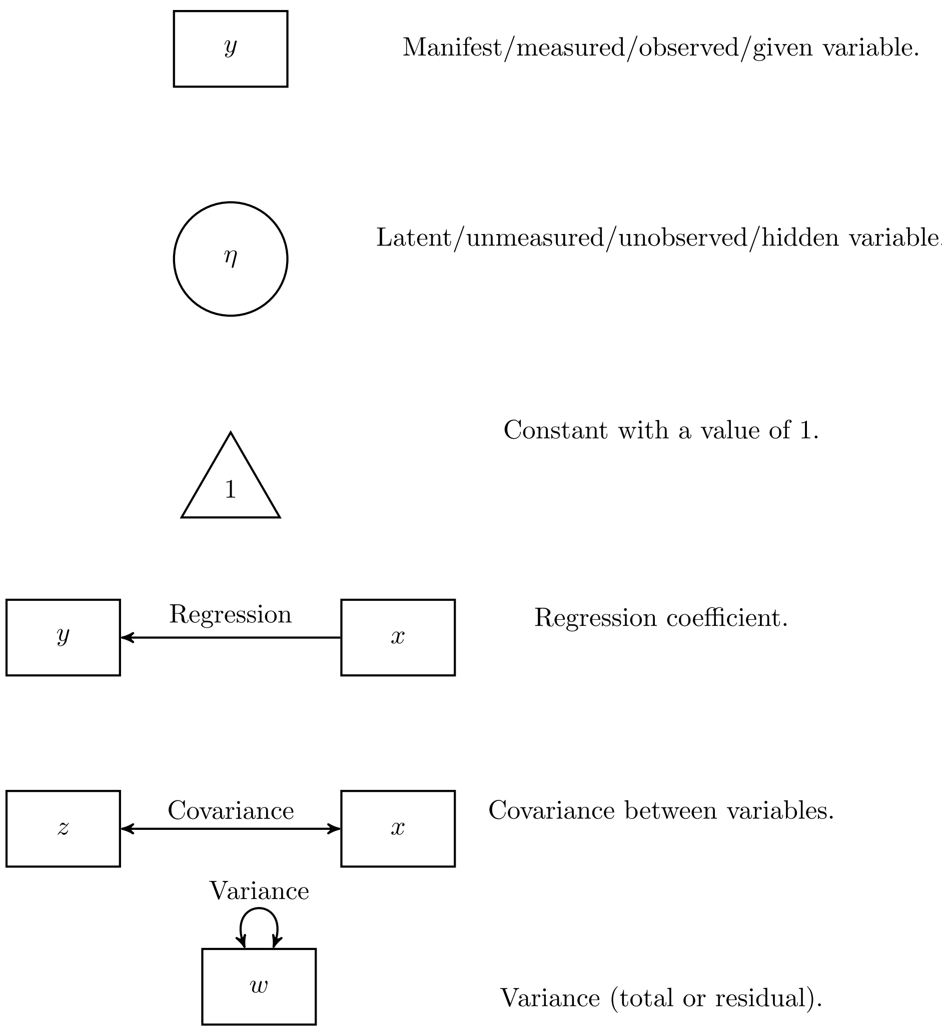
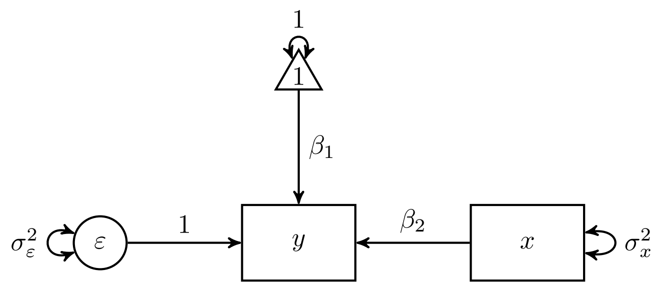
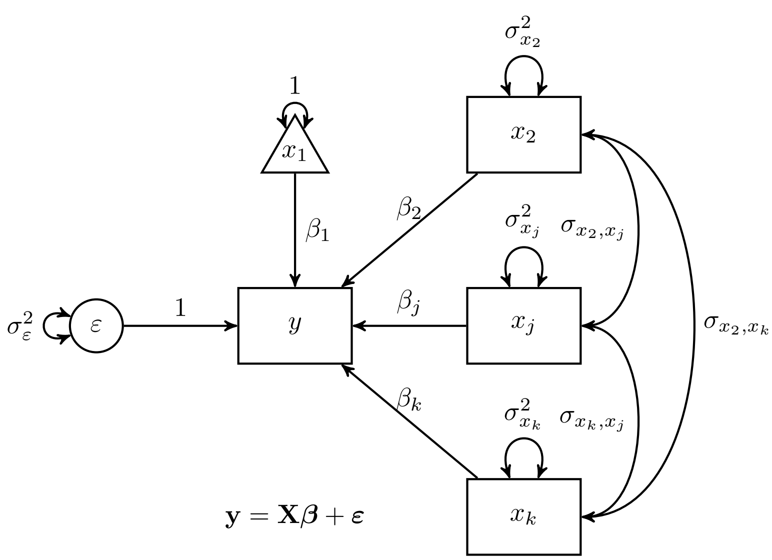


Figure 3.1: Path Diagram Elements



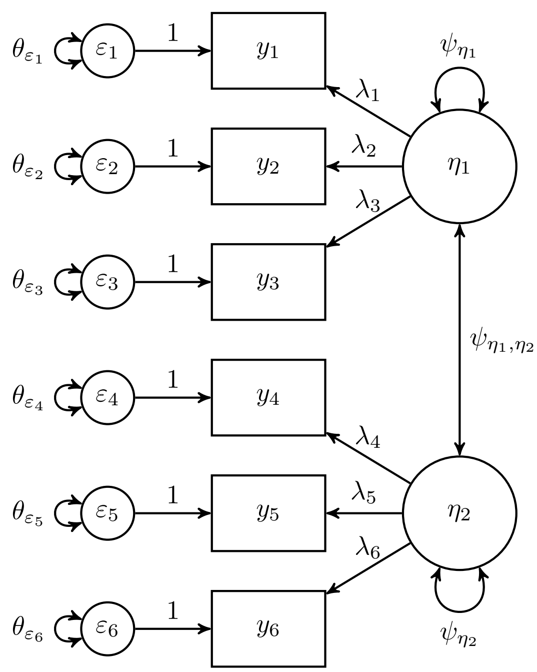
$$y = \alpha + \beta x + \varepsilon$$

Figure 3.2: Two-Variable Regression Model



$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

Figure 3.3: k-Variable Regression Model



$$\mathbf{y} = \boldsymbol{\Lambda}\boldsymbol{\eta} + \boldsymbol{\varepsilon}$$

Figure 3.4: Two-Factor Confirmatory Factor Analysis Model

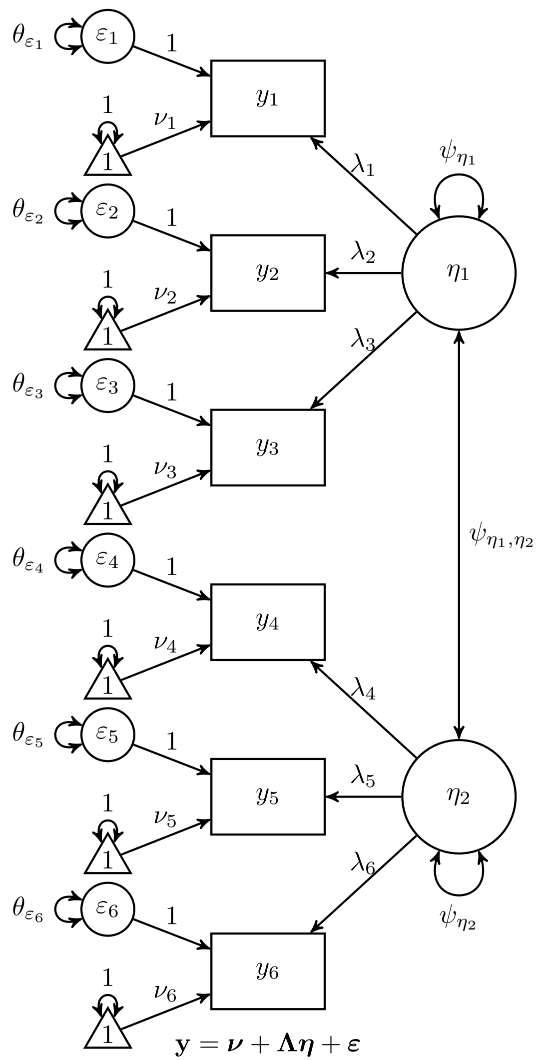
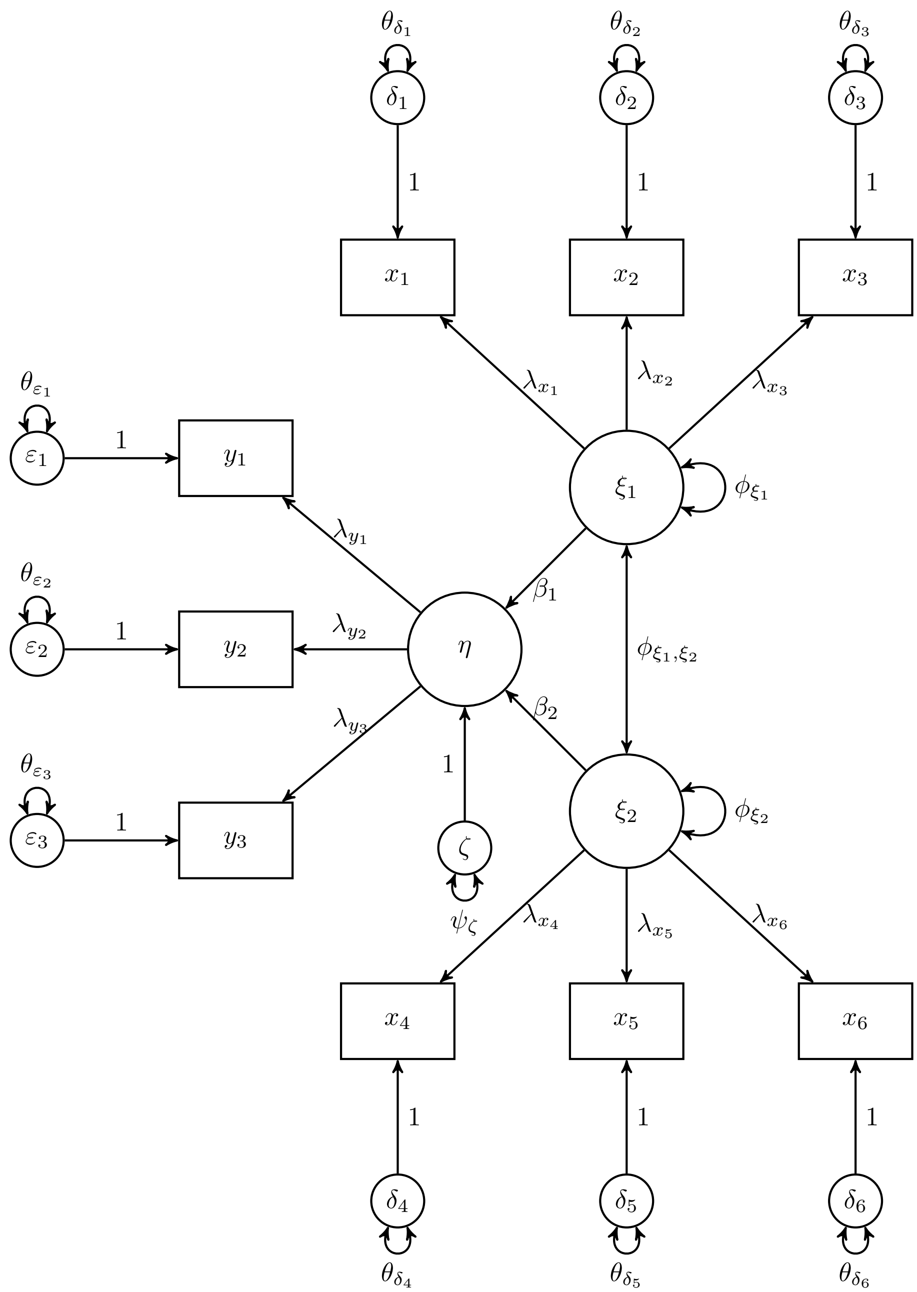


Figure 3.5: Two-Factor Confirmatory Factor Analysis Model with Mean Structure



$$\boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta}, \mathbf{y} = \boldsymbol{\Lambda}_y\boldsymbol{\eta} + \boldsymbol{\varepsilon}, \mathbf{x} = \boldsymbol{\Lambda}_x\boldsymbol{\xi} + \boldsymbol{\delta}$$

Figure 3.6: Path Model with Latent Variables

Chapter 4

Student's t-test

In this section, the Student's t-test is presented as a structural equation model using the RAM notation. Let y be a continuous dependent variable, x be a dichotomous independent variable ($x = \{0, 1\}$), and ε be the stochastic error term with mean 0 and constant variance of σ^2_{ε} across the values of x. The associations of the variables are given by

$$y = \alpha + \beta x + \varepsilon$$

where

- α is the expected value of y when $x = 0$
- β is the unit change in y for unit change in x
- $\alpha + \beta$ is the expected value of y when $x = 1$

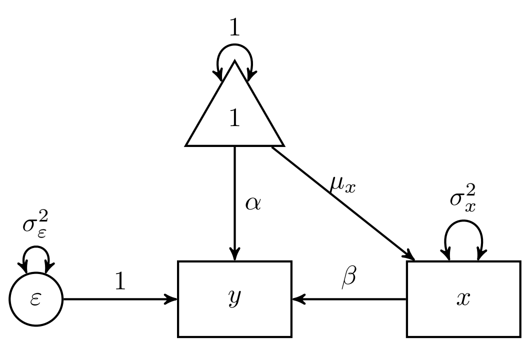


Figure 4.1: Student's t-test

4.1 Symbolic

Let $\{y, x, \varepsilon\}$ be the variables of interest.

$$\mathbf{A} = \begin{pmatrix} 0 & \beta & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

$$\mathbf{S} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & \sigma_x^2 & 0 \\ 0 & 0 & \sigma_\varepsilon^2 \end{pmatrix}$$

$$\begin{aligned}
\mathbf{C} &= (\mathbf{I} - \mathbf{A})^{-1}\,\mathbf{S}\left[(\mathbf{I} - \mathbf{A})^{-1}\right]^{\mathsf{T}} \\
&= \mathbf{E}\mathbf{S}\mathbf{E}^{\mathsf{T}} \\
&= \begin{pmatrix} 1 & \beta & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 & 0 & 0 \\ 0 & \sigma_x^2 & 0 \\ 0 & 0 & \sigma_\varepsilon^2 \end{pmatrix} \begin{pmatrix} 1 & \beta & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}^{\mathsf{T}} \\
&= \begin{pmatrix} \sigma_x^2\beta^2 + \sigma_\varepsilon^2 & \beta\sigma_x^2 & \sigma_\varepsilon^2 \\ \sigma_x^2\beta & \sigma_x^2 & 0 \\ \sigma_\varepsilon^2 & 0 & \sigma_\varepsilon^2 \end{pmatrix}
\end{aligned}$$

$$\mathbf{F} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}$$

$$\begin{aligned}
\mathbf{M} &= \mathbf{F}\,(\mathbf{I} - \mathbf{A})^{-1}\,\mathbf{S}\left[(\mathbf{I} - \mathbf{A})^{-1}\right]^{\mathsf{T}}\mathbf{F}^{\mathsf{T}} \\
&= \mathbf{F}\mathbf{E}\mathbf{S}\mathbf{E}^{\mathsf{T}}\mathbf{F}^{\mathsf{T}} \\
&= \mathbf{F}\mathbf{C}\mathbf{F}^{\mathsf{T}} \\
&= \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} \sigma_x^2\beta^2 + \sigma_\varepsilon^2 & \beta\sigma_x^2 & \sigma_\varepsilon^2 \\ \sigma_x^2\beta & \sigma_x^2 & 0 \\ \sigma_\varepsilon^2 & 0 & \sigma_\varepsilon^2 \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}^{\mathsf{T}} \\
&= \begin{pmatrix} \sigma_x^2\beta^2 + \sigma_\varepsilon^2 & \beta\sigma_x^2 \\ \sigma_x^2\beta & \sigma_x^2 \end{pmatrix}
\end{aligned}$$

$$\begin{aligned}
\mathbf{v} &= (\mathbf{I} - \mathbf{A})^{-1}\,\mathbf{u} \\
&= \left[\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} - \begin{pmatrix} 0 & \beta & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}\right]^{-1} \begin{pmatrix} \alpha \\ \mu_x \\ 0 \end{pmatrix} \\
&= \begin{pmatrix} \alpha + \beta\mu_x \\ \mu_x \\ 0 \end{pmatrix}
\end{aligned}$$

$$
\begin{aligned}
\mathbf{u} &= \left(\mathbf{I} - \mathbf{A}\right)\mathbf{v} \\
&= \left[\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} - \begin{pmatrix} 0 & \beta & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}\right] \begin{pmatrix} \alpha + \beta\mu_x \\ \mu_x \\ 0 \end{pmatrix} \\
&= \begin{pmatrix} \alpha \\ \mu_x \\ 0 \end{pmatrix}
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{g} &= \mathbf{F}\left(\mathbf{I} - \mathbf{A}\right)^{-1}\mathbf{u} \\
&= \left[\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} - \begin{pmatrix} 0 & \beta & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}\right]^{-1} \begin{pmatrix} \alpha \\ \mu_x \\ 0 \end{pmatrix} \\
&= \begin{pmatrix} \alpha + \beta\mu_x \\ \mu_x \end{pmatrix}
\end{aligned}
$$

4.1.1 Using the `ramR` Package

```
A
```

```
##   y   x      e  
## y "0" "beta" "1"
## x "0" "0"    "0"
## e "0" "0"    "0"
```

```
S
```

```
##   y   x            e                     
## y "0" "0"          "0"                   
## x "0" "sigma[x]^2" "0"                   
## e "0" "0"          "sigma[varepsilon]^2"
```

```
u
```

```
##   u      
## y "alpha"
## x "mu[x]"
## e "0"
```

```
filter
```

```
##   y x e
## y 1 0 0
## x 0 1 0
```

The covariance expectations can be symbolically derived using the `ramR::C_sym()` function.

```
ramR::C_sym(A, S)
```

```
## {{sigma[x]^2*beta^2+sigma[varepsilon]^2,                    beta*sigma[x]^2,            si
##  {                       sigma[x]^2*beta,                        sigma[x]^2,
##  {                    sigma[varepsilon]^2,                                 0,            si
```

$$\mathbf{C} = \begin{pmatrix} \sigma_x^2\beta^2 + \sigma_\varepsilon^2 & \beta\sigma_x^2 & \sigma_\varepsilon^2 \\ \sigma_x^2\beta & \sigma_x^2 & 0 \\ \sigma_\varepsilon^2 & 0 & \sigma_\varepsilon^2 \end{pmatrix}$$

The covariance expectations for the observed variables can be symbolically derived using the `ramR::M_sym()` function.

```
ramR::M_sym(A, S, filter)
```

```
## {{sigma[x]^2*beta^2+sigma[varepsilon]^2,                    beta*sigma[x]^2},
##  {                       sigma[x]^2*beta,                        sigma[x]^2}}
```

$$\mathbf{M} = \begin{pmatrix} \sigma_x^2\beta^2 + \sigma_\varepsilon^2 & \beta\sigma_x^2 \\ \sigma_x^2\beta & \sigma_x^2 \end{pmatrix}$$

The mean expectations can be symbolically derived using the `ramR::v_sym()` function.

```
ramR::v_sym(A, u)
```

```
## {{alpha+beta*mu[x]},
##  {           mu[x]},
##  {               0}}
```

$$\mathbf{v} = \begin{pmatrix} \alpha + \beta\mu_x \\ \mu_x \\ 0 \end{pmatrix}$$

The mean expectations for the observed variables can be symbolically derived using the `ramR::g_sym()` function.

```
ramR::g_sym(A, u, filter)
```

```
## {{alpha+beta*mu[x]},
##  {           mu[x]}}
```

$$\mathbf{g} = \begin{pmatrix} \alpha + \beta\mu_x \\ \mu_x \end{pmatrix}$$

4.2 Numerical Example

Let `df` be a random sample with the following parameters

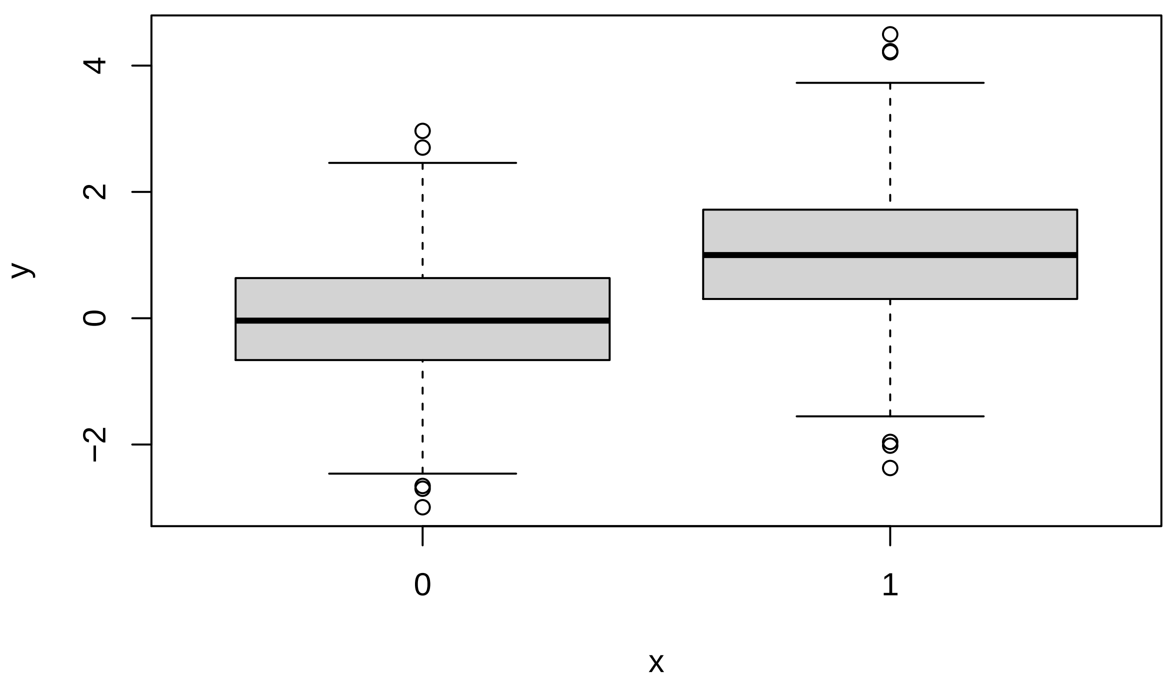
Parameter	\$x = 0\$	\$x = 1\$
Sample Size	500	500
\$\mu\$	0	1
\$\sigma^2\$	1	1

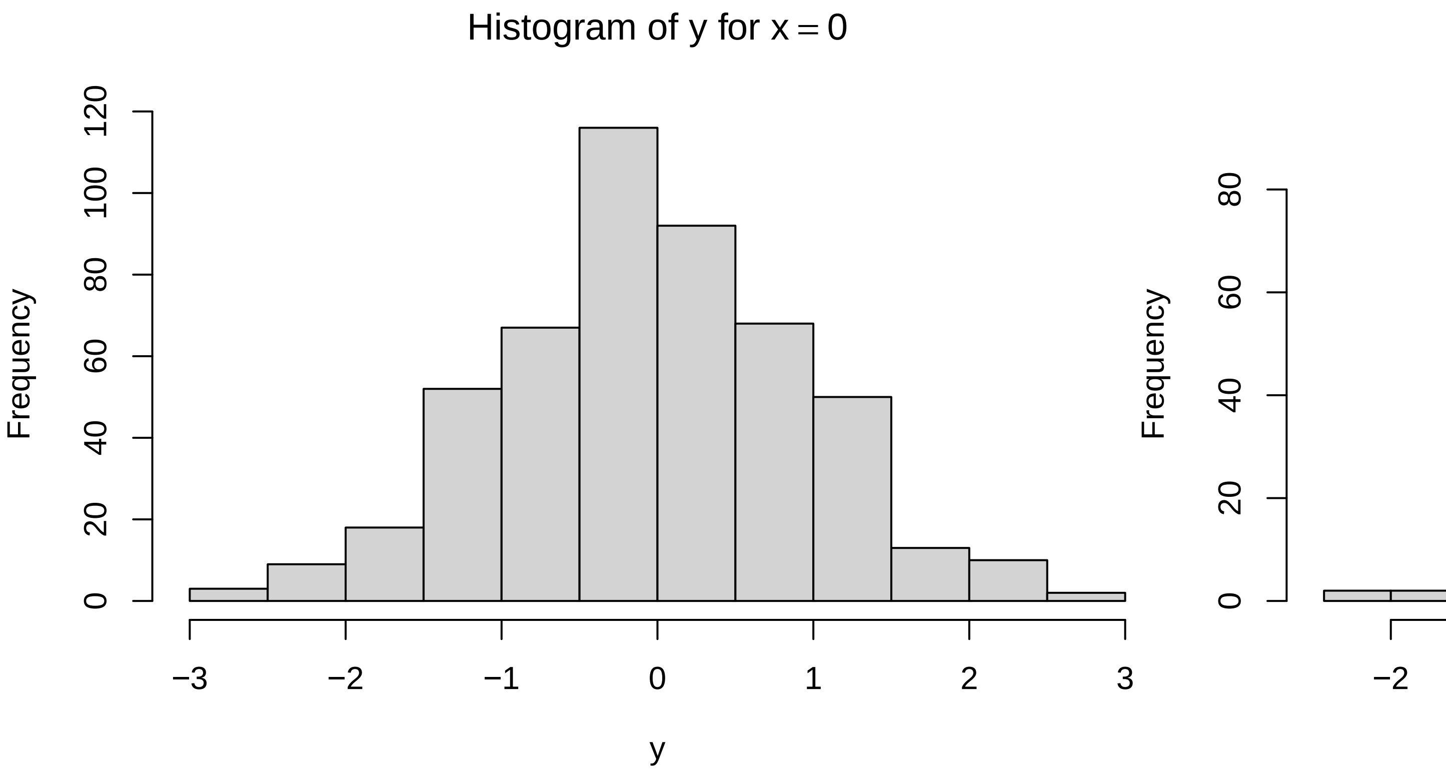
```
head(df)
```

```
##            y x
## 1  1.3709584 0
## 2 -0.5646982 0
## 3  0.3631284 0
## 4  0.6328626 0
## 5  0.4042683 0
## 6 -0.1061245 0
```

```
summary(df)
```

```
##        y                  x
##  Min.   :-2.9931   Min.   :0.0
##  1st Qu.:-0.2770   1st Qu.:0.0
##  Median : 0.4503   Median :0.5
##  Mean   : 0.4742   Mean   :0.5
##  3rd Qu.: 1.2492   3rd Qu.:1.0
##  Max.   : 4.4953   Max.   :1.0
```





4.2.1 t-test

```
t.test(y ~ x, data = df)
```

```
##
##  Welch Two Sample t-test
##
## data:  y by x
## t = -15.897, df = 994.36, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -1.1329278 -0.8839594
## sample estimates:
## mean in group 0 mean in group 1
##     -0.03004622      0.97839737
```

4.2.2 Linear Regression

```
summary(lm(y ~ x, data = df))
```

```
##
## Call:
## lm(formula = y ~ x, data = df)
##
```

```
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -3.3501 -0.6517  0.0086  0.6858  3.5169 
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept) -0.03005    0.04486   -0.67    0.503    
## x            1.00844    0.06344   15.90   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 1.003 on 998 degrees of freedom
## Multiple R-squared:  0.2021, Adjusted R-squared:  0.2013 
## F-statistic: 252.7 on 1 and 998 DF,  p-value: < 2.2e-16
```

4.2.3 Structural Equation Modeling

```
model <- "
  y ~ x
"
fit <- lavaan::sem(
  model,
  data = df,
  meanstructure = TRUE,
  fixed.x = FALSE
)
lavaan::summary(fit)
```

```
## lavaan 0.6-7 ended normally after 12 iterations
## 
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of free parameters                          5
##                                                       
##   Number of observations                          1000
##                                                       
## Model Test User Model:
##                                                       
##   Test statistic                                 0.000
##   Degrees of freedom                                 0
## 
## Parameter Estimates:
## 
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
## 
## Regressions:
##                    Estimate  Std.Err  z-value  P(>|z|)
##   y ~                                                 
##     x                 1.008    0.063   15.913    0.000
## 
```

```
## Intercepts:
##                   Estimate  Std.Err  z-value  P(>|z|)
##    .y               -0.030    0.045   -0.671    0.503
##     x                0.500    0.016   31.623    0.000
##
## Variances:
##                   Estimate  Std.Err  z-value  P(>|z|)
##    .y                1.004    0.045   22.361    0.000
##     x                0.250    0.011   22.361    0.000
```

Parameter	Estimate
α	-0.03
β	1.01
σ^{2}_{x}	0.25
σ^{2}_{ε}	1.01
μ_x	0.5

4.2.4 Using the `ramR` Package

```
A
```

```
##   y        x e
## y 0 1.008444 1
## x 0 0.000000 0
## e 0 0.000000 0
```

```
S
```

```
##   y         x        e
## y 0 0.0000000 0.000000
## x 0 0.2502503 0.000000
## e 0 0.0000000 1.006038
```

```
u
```

```
##             u
## y -0.03004622
## x  0.50000000
## e  0.00000000
```

```
filter
```

```
##   y x e
## y 1 0 0
## x 0 1 0
```

The covariance expectations can be numerically derived using the `ramR::C_num()` function.

```r
ramR::C_num(A, S)
```

```
##           y         x        e
## y 1.2605321 0.2523633 1.006038
## x 0.2523633 0.2502503 0.000000
## e 1.0060380 0.0000000 1.006038
```

The covariance expectations for the observed variables can be numerically derived using the `ramR::M_num()` function.

```r
ramR::M_num(A, S, filter)
```

```
##           y         x
## y 1.2605321 0.2523633
## x 0.2523633 0.2502503
```

The mean expectations can be numerically derived using the `ramR::v_num()` function.

```r
ramR::v_num(A, u)
```

```
##           v
## y 0.4741756
## x 0.5000000
## e 0.0000000
```

The mean expectations for the observed variables can be numerically derived using the `ramR::v_num()` function.

```r
ramR::g_num(A, u, filter)
```

```
##           g
## y 0.4741756
## x 0.5000000
```

4.3 Equations to RAM

The `ramR` package has a utility function to convert structural equations to RAM notation. The Student's *t*-test can be expressed in the following equations

```r
eq <- "
  # VARIABLE1 OPERATION VARIABLE2 LABEL
  e         by        y         1;
  y         on        x         beta;
  e         with      e         sigma[varepsilon]^2;
  x         with      x         sigma[x]^2;
  y         on        1         alpha;
  x         on        1         mu[x]
"
```

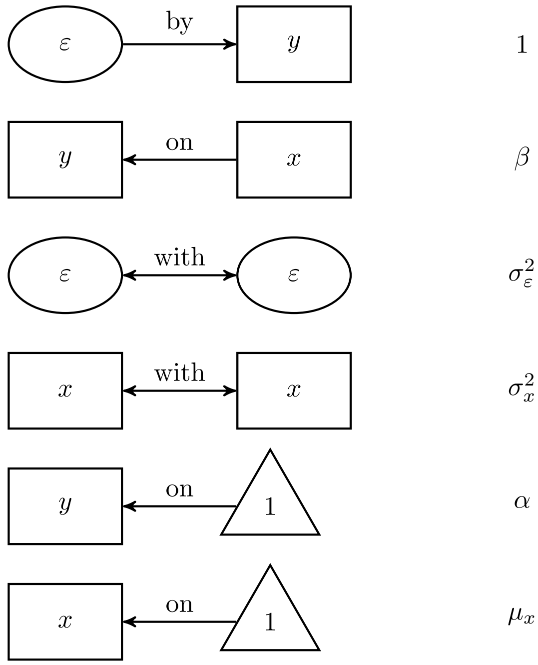


Figure 4.2: Student's t-test's Structural Equations

The error term is treated as a latent variable and defined with the operation `by`. It's value is constrained to 1. The regression of y on x is defined by operation `on`. It is labeled as `beta`. The variance of x and the error variance are defined using the operation `with`. These are labeled `sigma[x]^2` and `sigma[varepsilon]^2` respectively. The intercept and the mean of x are defined using the operation `on 1`. These are labeled `alpha` and `mu[x]` respectively.

The `ramR::eq2ram` converts the equations to RAM notation.

```
ramR::eq2ram(eq)
```

```
## $eq
##   var1   op var2               label
## 1    e   by    y                   1
## 2    y   on    x                beta
## 3    e with    e sigma[varepsilon]^2
## 4    x with    x         sigma[x]^2
## 5    y   on    1               alpha
## 6    x   on    1               mu[x]
##
## $variables
## [1] "y" "x" "e"
##
## $A
##   y   x      e
## y "0" "beta" "1"
## x "0" "0"    "0"
## e "0" "0"    "0"
##
## $S
##   y   x             e
```

```
## y "0" "0"          "0"
## x "0" "sigma[x]^2" "0"
## e "0" "0"          "sigma[varepsilon]^2"
##
## $filter
##   y x e
## y 1 0 0
## x 0 1 0
##
## $u
##   u
## y "alpha"
## x "mu[x]"
## e "0"
```

4.4 Equations to Expectations

The `ramR` package has a utility function to convert structural equations to expectations both symbolically and numerically.

```
eq <- "
  # VARIABLE1 OPERATION VARIABLE2 LABEL
  e           by        y         1;
  y           on        x         beta;
  e           with      e         sigma[varepsilon]^2;
  x           with      x         sigma[x]^2;
  y           on        1         alpha;
  x           on        1         mu[x]
"
```

```
ramR::eq2exp_sym(eq)
```

```
## $variables
## [1] "y" "x" "e"
##
## $A
## {{   0, beta,    1},
##  {   0,    0,    0},
##  {   0,    0,    0}}
##
## $S
## {{                  0,                   0,                   0},
##  {                  0,          sigma[x]^2,                   0},
##  {                  0,                   0, sigma[varepsilon]^2}}
##
## $u
## {{alpha},
##  {mu[x]},
##  {    0}}
##
## $filter
## {{1, 0, 0},
```

```
##  {0, 1, 0}}
##
## $v
## {{alpha+beta*mu[x]},
##  {           mu[x]},
##  {               0}}
##
## $g
## {{alpha+beta*mu[x]},
##  {           mu[x]}}
##
## $C
## {{sigma[x]^2*beta^2+sigma[varepsilon]^2,                        beta*sigma[x]^2,                   sig
##  {                      sigma[x]^2*beta,                             sigma[x]^2,
##  {                  sigma[varepsilon]^2,                                      0,                   sig
##
## $M
## {{sigma[x]^2*beta^2+sigma[varepsilon]^2,                        beta*sigma[x]^2},
##  {                      sigma[x]^2*beta,                             sigma[x]^2}}
```

```
eq <- "
  # VARIABLE1 OPERATION VARIABLE2 VALUE
  e           by        y         1.00;
  y           on        x         1.00;
  e           with      e         1.00;
  x           with      x         0.25;
  y           on        1         0.00;
  x           on        1         0.50
"
```

```
ramR::eq2exp_num(eq)
```

```
## $variables
## [1] "y" "x" "e"
##
## $A
##   y x e
## y 0 1 1
## x 0 0 0
## e 0 0 0
##
## $S
##   y    x e
## y 0 0.00 0
## x 0 0.25 0
## e 0 0.00 1
##
## $u
##     u
## y 0.0
## x 0.5
## e 0.0
##
```

```
## $filter
##   y x e
## y 1 0 0
## x 0 1 0
##
## $v
##     v
## y 0.5
## x 0.5
## e 0.0
##
## $g
##     g
## y 0.5
## x 0.5
##
## $C
##      y    x e
## y 1.25 0.25 1
## x 0.25 0.25 0
## e 1.00 0.00 1
##
## $M
##      y    x
## y 1.25 0.25
## x 0.25 0.25
```

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