



University of Antwerp  
Faculty of Social Sciences

# Objective rating method: Entropy

Speech intelligibility estimation

Jose Rivera

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# What are we going to talk about?

## 1 Preliminars

- Research question
- Research hypothesis production

## 2 Research hypothesis procedure

- Estimand and process model
- Synthetic data generation
- Statistical model design and testing
- Apply statistical model to data

## 3 References

# 1. Preliminars

Research question

# Research question

On two fronts:

1. Can comparative judgement (CJ) methods be used to assess speech intelligibility (SI)?,

To investigate this we need:

- an objective measure of SI

2. where CJ stands versus absolute holistic judgement (HJ) methods?,

In terms of:

- validity
- reliability
- statistical efficiency
- time efficiency

# Objective measure of SI

the most objective (we know of) measure of SI comes from a transcription task:

1. transcribe children's utterances (made by multiple judges),
2. align transcriptions at the utterance level,
3. calculate an entropy measure ( $H$ ), per utterance per child:

$$H = H(\mathbf{p}) = \frac{-\sum_{i=1}^n p_i \cdot \log_2(p_i)}{\log_2(N)}$$

4. characteristics of  $H$  [3, 7]
  - bounded in  $[0, 1]$  space,
  - utterances with more agreement are more intelligible, and therefore  $H \rightarrow 0$ ,
  - utterances with low agreement are less intelligible, and therefore  $H \rightarrow 1$ .

# 1. Preliminars

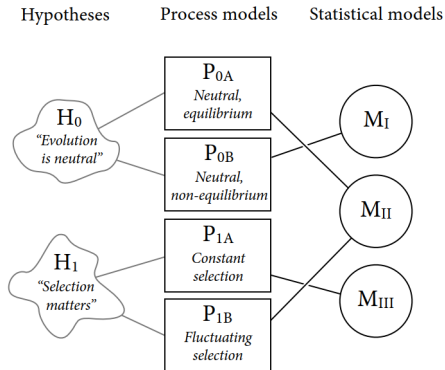
Research hypothesis production

# A typical scientific lab

What is needed / deal with<sup>a</sup>

1. Quality of theory
2. Quality of data
3. Reliable procedures and code
4. Quality of data analysis
5. Documentation
6. Reporting

<sup>a</sup>Figure extracted from McElreath [11]



# Research hypothesis production<sup>1</sup>

## Well known challenges

- Insufficient data
- Wrong population
- Measurement error
- Selection bias
- Confounding

## Known challenges in our research;

- Insufficient data (possibly)
- Wrong population
- Measurement error
- Selection bias
- Confounding

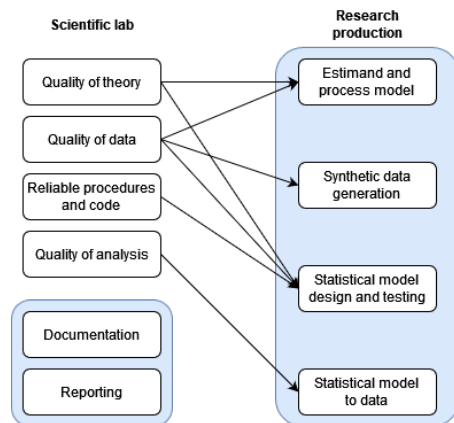
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<sup>1</sup>Hernán [9], lesson 4



# Research hypothesis schematics<sup>2</sup>

- Estimand and process model
- Synthetic data generation
- Statistical model design and testing
- Apply statistical model to data



<sup>2</sup>McElreath [12], lecture 20, Pearl [13]. Follow Fogarty et al. [8] on item (c).

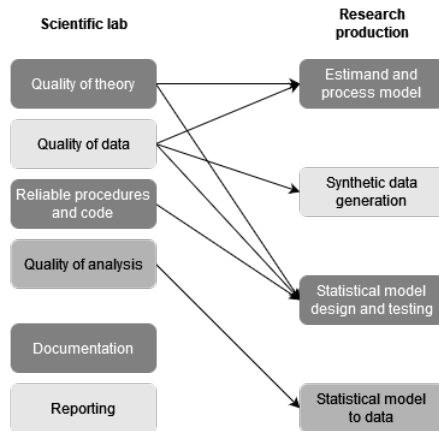
# Why do we need to follow this?

Because the improvement of:

- A clear definition of the estimand and process model (assumptions).
- An improved the reliability of your procedures.
- As a documentation procedure.

leads to:

- A sound analysis and results  
(even when we cannot answer our question).
- An improved planning to get data.

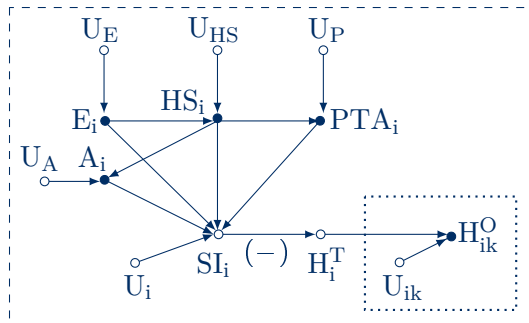


## 2. Research hypothesis procedure

Estimand and process model

# The theory behind our research

- $H_{ik}$  = (observed) entropy replicates
- $H_i$  = (latent) “true” entropy
- $SI_i$  = (latent) SI score  
(inversely related to  $H_i^T$ )
- $A_i$  = “hearing” age (minimum)
- $E_i$  = etiology of disease
- $HS_i$  = hearing status
- $PTA_i$  = pure tone average (standardized)
- variables **assumed independent**, beyond the described relationships,



General causal diagram

$$\begin{aligned} P(\mathbf{U}) &= P(U_{ik}, U_i, U_A, U_E, U_{HS}, U_P) \\ &= P(U_{ik})P(U_i)P(U_A)P(U_E)P(U_{HS})P(U_P) \end{aligned}$$

# Probabilistic (causal) model

## First form

$$H_{ik}^O \leftarrow f(H_i^T, U_{ik})$$

$$H_i^T \leftarrow f(SI_i)$$

$$SI_i \leftarrow f(HS_i, A_i, E_i, PTA_i, U_i)$$

$$HS_i \leftarrow f(U_{HS})$$

$$A_i \leftarrow f(U_A)$$

$$E_i \leftarrow f(U_E)$$

$$PTA_i \leftarrow f(U_P)$$

$$U \sim P(\mathbf{U})$$

(a) general structural model

$$H_{ik}^O \sim \text{BetaProp}(H_i^T, M_{ik})$$

$$H_i^T = \text{inv\_logit}(-SI_i)$$

$$SI_i \sim \text{Normal}(\mu_{SI}, \sigma_{U_i})$$

$$\begin{aligned} \mu_{SI} = & \alpha + \alpha_{HS[i]} + \alpha_{E[i]} \\ & + \beta_{A,HS[i]}(A_i - \bar{A}) + \beta_P PTA_i \end{aligned}$$

$$HS_i \sim \text{data}$$

$$A_i \sim \text{data}$$

$$E_i \sim \text{data}$$

$$PTA_i \sim \text{data}$$

$$U \sim \text{unobservable}$$

(a) general probabilistic model

# Probabilistic (causal) model

## First form

Notice,

- $\alpha, \alpha_{\text{HS}[i]}, \alpha_{\text{E}[i]}, \beta_{\text{A,HS}[i]}, \beta_{\text{P}}$   
are structural parameters (as in SEM)
- $U_{ik}$  = replicates measurement error  
 $U_i$  = between child SI variability
- variability of  $U_{ik}$  is modeled by  $M_{ik}$   
variability of  $U_i$  is modeled by  $\sigma_{U_i}$

$$H_{ik}^O \sim \text{BetaProp}(H_i^T, M_{ik})$$

$$H_i^T = \text{inv\_logit}(-SI_i)$$

$$SI_i \sim \text{Normal}(\mu_{SI}, \sigma_{U_i})$$

$$\begin{aligned} \mu_{SI} = & \alpha + \alpha_{\text{HS}[i]} + \alpha_{\text{E}[i]} \\ & + \beta_{\text{A,HS}[i]}(A_i - \bar{A}) + \beta_{\text{P}}PTA_i \end{aligned}$$

$$HS_i \sim \text{data}$$

$$A_i \sim \text{data}$$

$$E_i \sim \text{data}$$

$$PTA_i \sim \text{data}$$

$$U \sim \text{unobservable}$$

(a) general probabilistic model

# Probabilistic (causal) model

Express variability in BetaProp

$$H_{ik}^O \sim \text{BetaProp}(H_i^T, M_{ik})$$

$$H_i^T = \alpha / (\alpha + \beta)$$

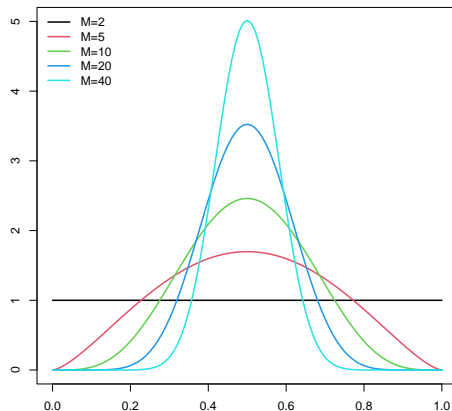
$$M_{ik} = \alpha + \beta$$

$$\alpha = H_i^T \cdot M_{ik}$$

$$\beta = (1 - H_i^T) \cdot M_{ik}$$

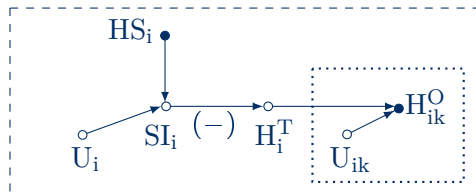
$$\alpha = 0.5 \cdot 2$$

$$\beta = (1 - 0.5) \cdot 2$$

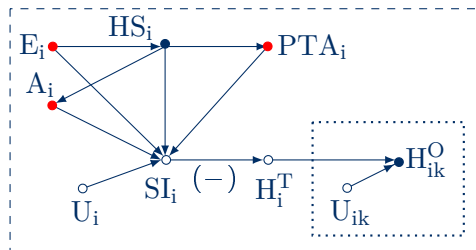


# Interested in two effects

1. **total effects** model inherits:
  - children's characteristics that lead to the fitting of specific apparatus,
  - the (convenience of) sample selection (fixed with post-stratification)
2. to do the last, we stratify for all variables that explain variability, ergo, use a **direct effects** model
3. two levels: replicates (k), children (i), denoted by discontinuous squares



(b) total effects



(a) direct effects



# Probabilistic (causal) model

## Second form

$$H_{ik}^O \leftarrow f(H_i^T, U_{ik})$$

$$H_i^T \leftarrow f(SI_i)$$

$$SI_i \leftarrow f(HS_i, \textcolor{red}{A}_i, \textcolor{red}{E}_i, \textcolor{red}{PTA}_i, U_i)$$

$$HS_i \leftarrow f(U_{HS})$$

$$A_i \leftarrow f(U_A)$$

$$E_i \leftarrow f(U_E)$$

$$PTA_i \leftarrow f(U_P)$$

$$U \sim P(\mathbf{U})$$

(a) general structural model

$$H_{ik}^O \sim \text{BetaProp}(H_i^T, M_{ik})$$

$$H_i^T = \text{inv\_logit}(-SI_i)$$

$$SI_i = a_i + \alpha + \alpha_{HS[i]} + \textcolor{red}{\alpha}_{E[i]} \\ + \textcolor{red}{\beta}_{A,HS[i]}(\textcolor{red}{A}_i - \bar{A}) + \textcolor{red}{\beta}_P \textcolor{red}{PTA}_i$$

$$a_i \sim \text{Normal}(0, \sigma_{U_i})$$

$$HS_i \sim \text{data}$$

$$A_i \sim \text{data}$$

$$E_i \sim \text{data}$$

$$PTA_i \sim \text{data}$$

$$U \sim \text{unobservable}$$

(a) general probabilistic model

## 2. Research hypothesis procedure

Synthetic data generation

# Idealized data<sup>3</sup>

Simulation data can serve as [10, 11],

1. A place where to test your model, on multiple purposes,
  - parameter recovery
  - power
2. A reflection of a population,
  - De Raeve [6]:  
70 HI/CI, 130 HI/HA
  - Our idealized data:  
150 NH, 70 HI/CI, 130 HI/HA
3. A reflection of a hypothesis,
  - size of effects

```
(sim_name=NULL, # file_name ne
sim_save=NULL, # file_save ne
seed=NULL, # seed
I=350, # experimental units (
K=10, # replicates (utterance
p=c(0.50, 0.175, 0.325), # ch
par=list( m_i=0, s_i=0.5, # h
          m_M=10, s_M=NULL, #
          a=0,
          aE=rep(0,4),
          aHS=c(0.4,0,-0.4),
          bP=-0.1,
          bA=0.15,
          bAHS=rep(0,3) ) ) {
```

---

<sup>3</sup>more details in file: [1\\_2\\_E\\_sim\\_fun.R](#)

# Idealized data

About the size of the effects

(in logits, no previous info)

1.  $aE = 0$ , ordered by severity  
( $\text{cor}(E, HS) \approx 1$ , ordering might not be possible) ,
2.  $aHS = -0.4$ , difference between  
NH children and HI/CI,
3.  $bP = -0.1$ , per PTA unit  
(+10 PTA units  $\Rightarrow$  -1 logit),
4.  $bA = -0.15$ , per A unit, above the  
minimum  
(+10 A units  $\Rightarrow$  +1.5 logits),

```
(sim_name=NULL, # file_name ne
sim_save=NULL, # file_save ne
seed=NULL, # seed
I=350, # experimental units (
K=10, # replicates (utterance
p=c(0.50, 0.175, 0.325), # ch
par=list( m_i=0, s_i=0.5, # h
          m_M=10, s_M=NULL, #
          a=0,
          aE=rep(0,4),
          aHS=c(0.4,0,-0.4),
          bP=-0.1,
          bA=0.15,
          bAHS=rep(0,3) ) ) {
```

# Idealized data

1. variables are generated in a random fashion
2. between children SI variability are defined by the random effects

```
# 1. true data ###
dT = data.frame(matrix(NA, nrow=I, ncol=1))
names(dT) = c('child_id')
dT$child_id = 1:I

# assigning children to groups
n = round( p*I )
if( sum(n) != I ){
  if( I - sum(n[c(1,3)]) > n[2] ){
    n[2] = I - sum(n[c(1,3)]) # to sum the right amount
  } else {
    n[3] = I - sum(n[c(1,3)]) # to sum the right amount
  }
}

# generating covariates
if(!is.null(seed)){
  set.seed(seed+1)
}
dT$HS = c( rep(1, n[1]), rep(2, n[2]), rep(3, n[3]))
dT$A = round( rnorm( sum(n), 5, 1) )
dT$A = with(dT, ifelse(A>7, 7, A) )

dT$E = c( rep(1, n[1]), # no way to know true effects
  sample(2:3, size=n[2], replace=T),
  sample(3:4, size=n[3], replace=T))

dT$PTA = c( round(rnorm(n[1], 60, 15)), # first 12 NH
  round(rnorm(n[2], 90, 15)), # next 10
  round(rnorm(n[3], 110, 15))) # last 10

# children's random effects
if(!is.null(seed)){
  set.seed(seed-1)
}
par$re_i = rnorm(I, par$m_i, par$s_i)
dT$re_i = par$re_i # children's random effects (between SI)
```

# Idealized data

1. we use **second form** of the probabilistic model
2. “true” entropy (Ht) is inversely related to SI
3. we simulate measurement error through M from BetaProp() distribution.

```
# linear predictor / SI index
dT$SI = with(dT, re_i + par$a + par$aE[E] + par$aHS[HS] +
             par$bA*(A - min(A)) +
             par$bAHS[HS]*(A - min(A)) +
             par$bP*c( standardize(PTA) ) )

# true entropy
dT$Ht = inv_logit(-dT$SI) # true entropy (SI -> Ht: negativ

# variability of H
if(!is.null(seed)){
  set.seed(seed+2)
}
if( is.numeric(par$m_M) & !is.numeric(par$s_M) ){
  par$m = rep(par$m_M, I)
} else{
  par$m = round( rlnorm(I, meanlog=par$m_M, sdlog= par$s_M)
}
dT$m = par$m # same df for all children (not same shape!!)

# rounding
dT[,6:ncol(dT)] = round( dT[,6:ncol(dT)], 5)

# 2. observed data ####
N = I*K
do = data.frame(matrix(NA, nrow=N, ncol=3))
names(do) = c('child_id', 'utt_id', 'H')
do$child_id = rep(1:I, each=K)
do$utt_id = rep(1:K, I)

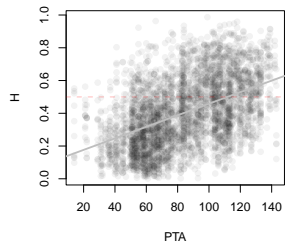
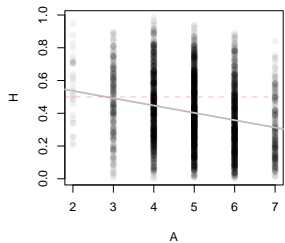
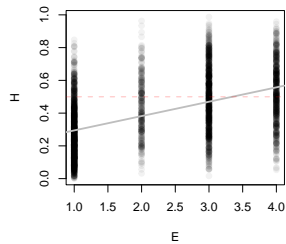
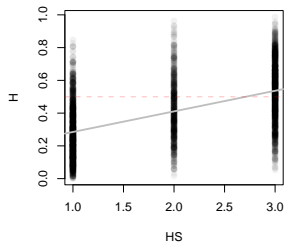
# generating observed H
# i=1
if(!is.null(seed)){
  set.seed(seed-2)
}
```

# Idealized data

1. we simulate replicate measures of entropy (H)
2. we storage all relevant parameters and data

```
for(i in 1:I){  
  # identify data  
  idx = d0$child_id == i  
  
  # linear predictor  
  d0$H[idx] = rbeta2(n=K, prob=dT$Ht[i], theta=dT$M[i])  
}  
  
# round  
d0$H = round( d0$H, 5)  
  
# 3. list data ####  
dL = list(  
  # dimensions  
  N = nrow(d0), # observations  
  I = max(d0$child_id), # children  
  K = max(d0$utt_id), # utterances  
  
  # category numbers  
  CHS = max(dT$HS),  
  cE = max(dT$E),  
  
  # child's data  
  HS = dT$HS,  
  Am = with(dT, A-min(A) ), # centered at minimum  
  E = dT$E,  
  sPTA = c( standardize( dT$PTA ) ),  
  
  # observed data  
  H = with(d0, ifelse(H==0, 0.0001, ifelse(H==1, 0.9999, H)) ),  
  cid = d0$child_id,  
  uid = d0$utt_id  
)  
  
# 4. save data ####  
mom = list(dS=list( dT=dT, d0=d0, par=par), dL=dL)
```

# Example





## 2. Research hypothesis procedure

Statistical model design and testing

# Model design and test<sup>4</sup>

## Purpose:

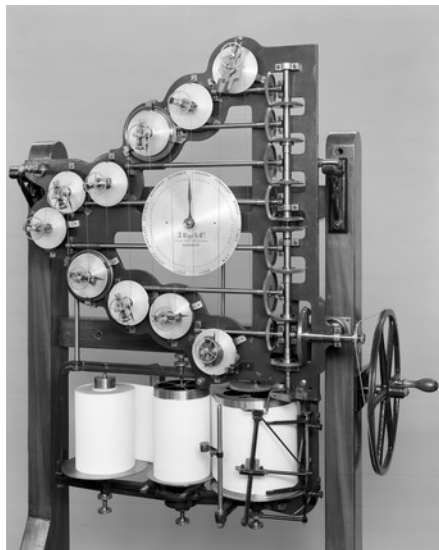
- to have reliable procedures,
- to maintain a clear documentation,
- to have a sound analysis

## Procedure:

- step by step, instantiating one difficulty at the time
- use probabilistic assumptions defined in **estimand** and **process model**
- is like running **synthetic data generation** backwards

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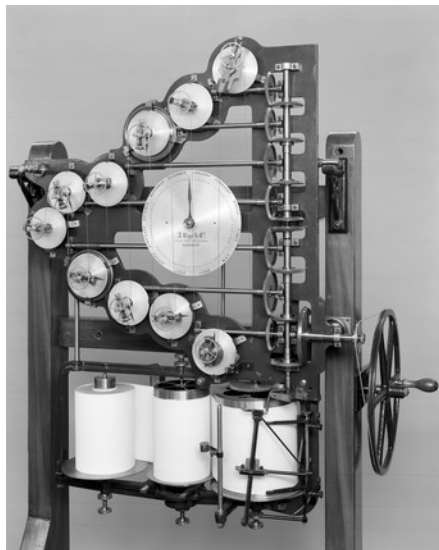
<sup>4</sup>Following Fogarty et al. [8]



# Model design and test

We evaluate,

- the probabilistic model implementation [11, 2]  
(centered and non-centered versions)
- prior predictive
- “health” of MCMC chains
- parameter recovery
- posterior predictive
- power



# Probabilistic model

starts with,

- the simplest model
- the simplest data generating procedure

```
transformed parameters{  
  vector[I] SI;           // SI index (per child)  
  vector[I] Ht;           // true entropy (per child)  
  
  SI = a + re_i;           // linear predictor  
  Ht = inv_logit(-SI);     // average entropy (SI -> 0)  
}  
model{  
  
  // hyperpriors  
  m_i ~ normal( 0 , 0.2 );  
  s_i ~ exponential( 1 );  
  
  // priors  
  a ~ normal( 0 , 0.2 );  
  re_i ~ normal( m_i , s_i );  
  
  // likelihood  
  for(n in 1:N){  
    H[n] ~ beta_proportion( Ht[cid[n]] , 10 );  
  }  
}
```

# Probabilistic model

try,

- the centered and non-centered parametrization

```
transformed parameters{
  vector[I] re_i;      // random intercepts (per
  vector[I] SI;        // SI index
  vector[I] Ht;        // true entropy (per child

  re_i = m_i + s_i*z_re; // non-centered RE
  SI = a + re_i;         // linear predictor
  Ht = inv_logit(-SI);   // average entropy (SI ->

}
model{

  // hyperpriors
  m_i ~ normal( 0 , 0.2 );
  s_i ~ exponential( 1 );

  // priors
  a ~ normal( 0 , 0.2 );
  z_re ~ std_normal();

  // likelihood
  for(n in 1:N){
    H[n] ~ beta_proportion( Ht[cid[n]] , 10 );
  }
}
```

# Probabilistic model

escalate,

- complexity of model
- traits of the data

```
transformed parameters{
  vector[I] SI;           // SI index (per child)
  vector[I] Ht;           // true entropy (per child)

  // linear predictor
  for(i in 1:I){
    SI[i] = re_i[i] + a + aHS[HS[i]] +
            bA*Am[i] + bP*sPTA[i];
    // no multicollinearity between E and HS
  }

  // average entropy (SI -> Ht: negative)
  Ht = inv_logit(-SI);    // average entropy (SI -> Ht)
}

model{

  // hyperpriors
  m_i ~ normal( 0 , 0.2 );
  s_i ~ exponential( 1 );

  // priors
  a ~ normal( 0 , 0.2 );
  re_i ~ normal( m_i , s_i );
  //aE ~ normal( 0 , 0.5 );
  aHS ~ normal( 0 , 0.5 );
  bP ~ normal( 0 , 0.3 );
  bA ~ normal( 0 , 0.3 );
  m_M ~ lognormal( 1.5 , 0.5 );

  // likelihood
  for(n in 1:N){
    H[n] ~ beta_proportion( Ht[cid[n]] , m_M );
  }
}
```

# Probabilistic model

We tested 5 random effects models:

(from 5 synthetic data types)

(centered, and non-centered)

- only intercept,  $M = 10$ ,
- causal model,  $M = 10$ ,
- causal model,  $M$  per individual,
- no known process,
- causal model with interaction,  $M$  per individual,

```
transformed parameters{
  vector[I] SI;          // SI index (per child)
  vector[I] Ht;          // true entropy (per child)

  // linear predictor
  for(i in 1:I){
    SI[i] = re_i[i] + a + aHS[HS[i]] +
      bA*Am[i] + bP*sPTA[i];
    // no multicollinearity between E and HS
  }

  // average entropy (SI -> Ht: negative)
  Ht = inv_logit(-SI); // average entropy (SI -> Ht)
}

model{

  // hyperpriors
  m_i ~ normal( 0 , 0.2 );
  s_i ~ exponential( 1 );

  // priors
  a ~ normal( 0 , 0.2 );
  re_i ~ normal( m_i , s_i );
  //aE ~ normal( 0 , 0.5 );
  aHS ~ normal( 0 , 0.5 );
  bP ~ normal( 0 , 0.3 );
  bA ~ normal( 0 , 0.3 );
  m_M ~ lognormal( 1.5 , 0.5 );

  // likelihood
  for(n in 1:N){
    H[n] ~ beta_proportion( Ht[cid[n]] , m_M );
  }
}
```

# Prior predictive

## Priors and hyper-priors

- In the probabilistic (causal) model there were no priors for our parameters,
- To decide our priors we follow McElreath [11]:  
“priors are part of the assumptions, and should be inspected as such”,
- We will evaluate the implications of our priors on the outcome scale.  
We have three outcomes scales:  
 $SI_i$ ,  $H_i^T$ , and  $H_{ik}^O$

## Priors

$$a_i \sim \text{Normal}(\mu_a, \sigma_a)$$

$$M_i \sim \text{LogNormal}(\mu_M, \sigma_M)$$

$$\alpha \sim \text{Normal}(0, 0.2)$$

$$\alpha_{HS[i]} \sim \text{Normal}(0, 0.3)$$

$$\alpha_{E[i]} \sim \text{Normal}(0, 0.3)$$

$$\beta_{A,HS[i]} \sim \text{Normal}(0, 0.3)$$

$$\beta_P \sim \text{Normal}(0, 0.3)$$

## Hyper-priors

$$\mu_a \sim \text{Normal}(0, 0.2)$$

$$\sigma_a \sim \text{Exp}(1)$$

$$\mu_M \sim \text{Normal}(0, 0.5)$$

$$\sigma_M \sim \text{Exp}(1)$$



# Prior predictive

Undesired assumptions can easily creep  
in **non-linear models**<sup>a</sup>

Example:

(black line)

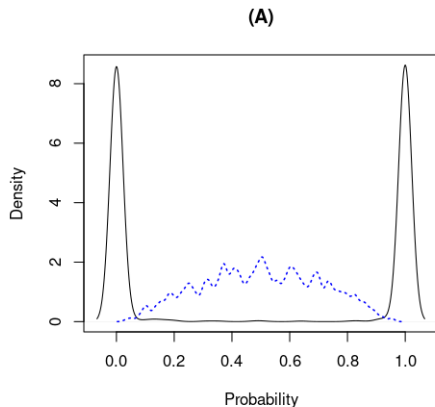
$$\theta \sim N(0, 100)$$

$$\text{logit}(p) = \theta$$

(blue line)

$$\theta \sim N(0, 1)$$

$$\text{logit}(p) = \theta$$



<sup>a</sup>Figure extracted from Rivera [14].

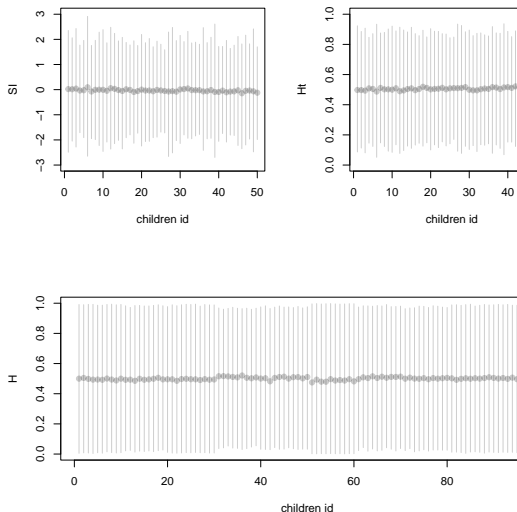
# Prior predictive

What our priors imply?

NO undesired assumption has crept in:

- the  $SI_i$  scale,
- the  $H_i^T$  scale,
- the  $H_{ik}^O$  scale

i.e. the scales' full space can be reached  
by (a combination of) the parameters

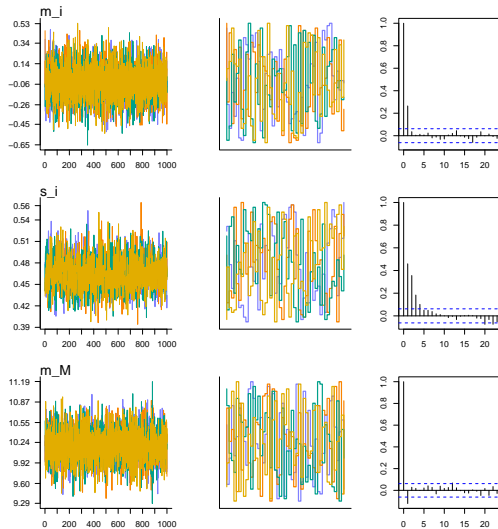


# “Health” of MCMC chains

The MCMC chains achieve,

- good convergence
- good mixing
- lack of autocorrelation

same results on the  $n_{\text{eff}}$  and  $R\hat{\text{H}}\text{at}$  statistics.

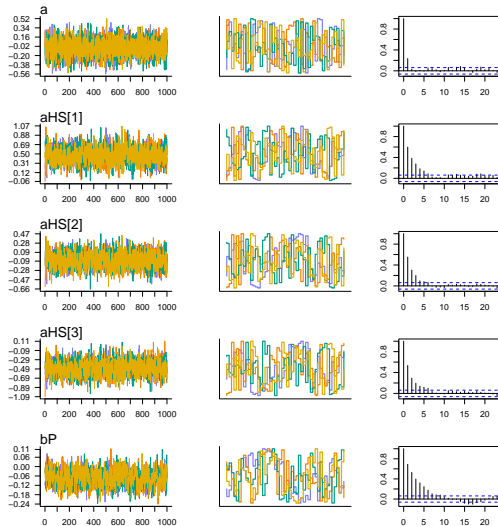


# “Health” of MCMC chains

The MCMC chains achieve,

- good convergence
- good mixing
- lack of autocorrelation

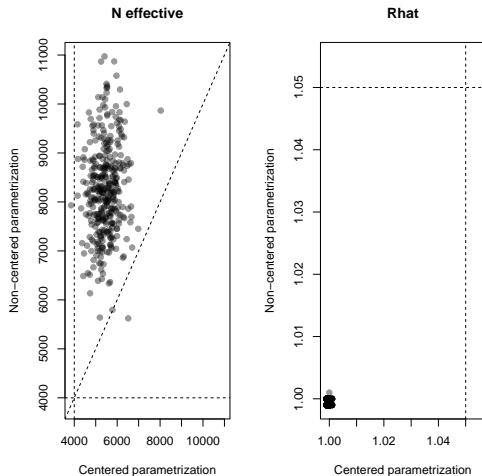
same results on the  $n_{\text{eff}}$  and  $R\text{Hat}$  statistics.



# “Health” of MCMC chains

The non-centered parametrization has,

- better  $n_{\text{eff}}$   
(denoting lack of autocorrelation)
- better  $R_{\text{hat}}$   
(denoting good convergence)
- better mixing  
(inspected visually, not shown)

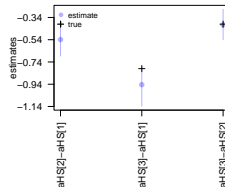
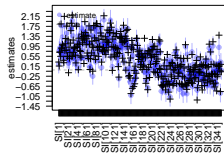
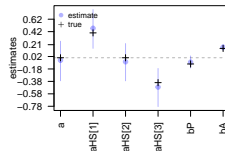
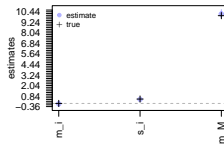


# Parameter recovery

On idealized data

The model,

- recovers the parameters in the right scale,
- most of the “true” parameters are inside of the compatibility intervals (CI)
- contrast are approximately correct



# Posterior predictive

But how well reproduces the data?,  
The model with **less working assumptions**<sup>a</sup>,

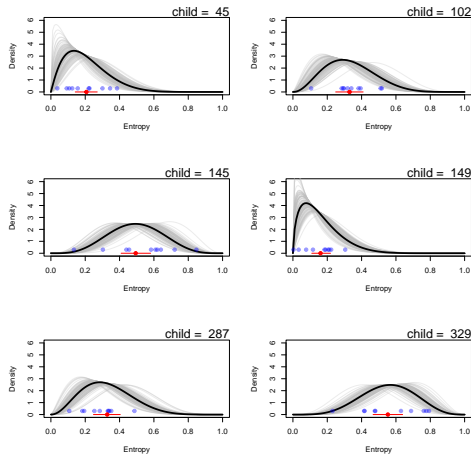
- captures the variability of the replicates,
- provides a “true” H and SI

More complex models,

- captures even better the data, but might **overfit**,
- avoid **overfit** when the model is fit to the data (ITA [1, 4])

---

<sup>a</sup>random effects causal model, with  $M = 10$



# Power

Equivalent prior sampling method [18, 10]

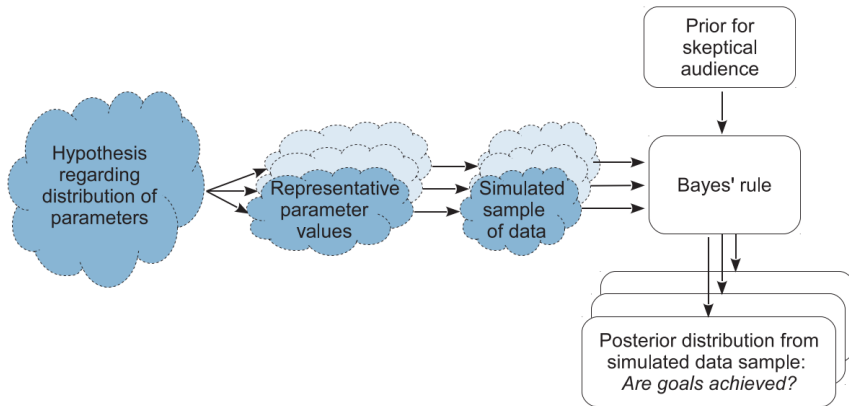


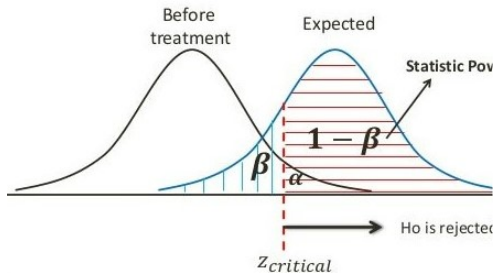
Figure: Flow of information in a power analysis, in which simulated data come from random hypothetical parameters. Extracted from Kruschke [10].



# Power

## Equivalent prior sampling method

1. generate idealized data
2. generate parameters' distribution  
(with Bayes theorem)
3. simulate data sample  
(variability in data and parameters)
4. apply models to simulated data  
(include priors)
5. evaluate desire goals
  - reject the null hypothesis
  - affirm predicted value
  - achieve precision in estimate
6. repeat procedure  
(to approximate power)



# Power

## Equivalent prior sampling method

1. ~~generate idealized data~~
2. ~~generate parameters' distribution~~  
(with Bayes theorem)
3. **simulate data sample**  
(variability in data and parameters)
4. **apply models to simulated data**  
(include priors)
5. evaluate desire goals
  - reject the null hypothesis
  - affirm predicted value
  - achieve precision in estimate
6. repeat procedure  
(to approximate power)

```
Epower( power_save=file.path(getwd(), 'sim_chain'), # po
sim_name='Hbeta_sim2_power.RData', # file_save n
sim_save=file.path(getwd(), 'sim_data'), # file_
model_name='Hbeta_NC_sim2', # model for which we
model_in=file.path(getwd(), 'sim_models'), # loc
model_out=file.path(getwd(), 'sim_chain'), # loc
Nsim=100, # number of simulation for power
I_grid = c(48, 60), # experimental units (childr
K_grid = c(10, 20), # replicates (utterances)
p=c(0.34, 0.33, 0.33), # children prop. on each
par_int=c('aHS','bP','bA','m_i','s_i','m_M','SI'
par_cont=c('aHS','SI') ) # parameters to contras
```

# Power

## Equivalent prior sampling method

1. generate idealized data
2. generate parameters' distribution  
(with Bayes theorem)
3. simulate data sample  
(variability in data and parameters)
4. apply models to simulated data  
(include priors)
5. evaluate desire goals<sup>a</sup>
  - reject the null hypothesis
  - affirm predicted value
  - achieve precision in estimate
6. repeat procedure  
(to approximate power)

```
(true_par,  
cuts=c(0,0.1,0.2,0.5,0.8,1.2,2), # based  
rvalues=c(0.2,0.2,0.15,0.3,0.3,0.4,0.8))
```

Effect size	<i>d</i>
Very small	0.01
Small	0.20
Medium	0.50
Large	0.80
Very large	1.20
Huge	2.0

<sup>a</sup>use ROPE [10], and effect sizes [5, 15]

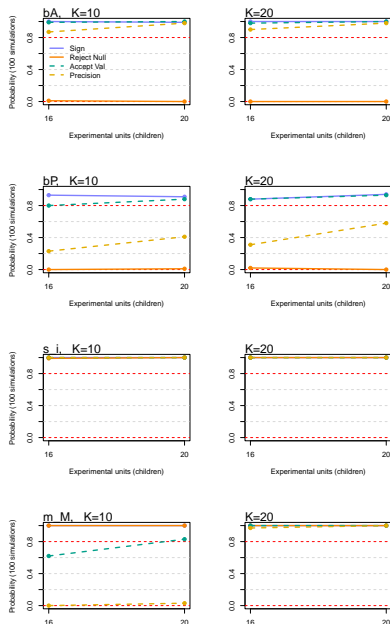
# Power results

For this parameter set,

- reject the null hypothesis, never achieved in structural parameters,
- affirm predicted value, in all shown parameters
- achieve precision in estimate, in some parameters is reached

Notice,

- between child SI variability,
- replicates measurement error (M),
- not much difference with 2x comparisons (except for M)



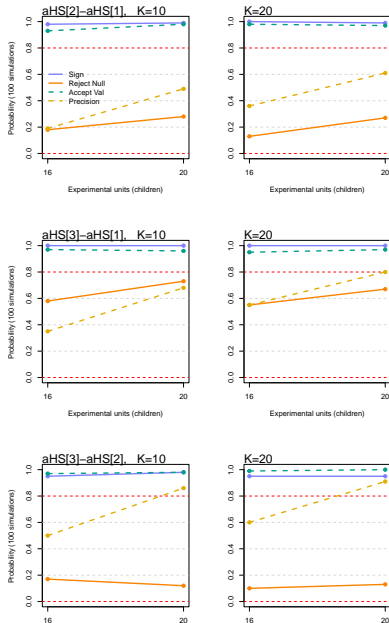
# Power results

For group contrasts,

- reject the null hypothesis, closest for the **largest contrast**,
- affirm predicted value, in **all** shown contrasts,
- achieve precision in estimate, **grows** with more children

Notice,

- not much difference with 2x comparisons
- group contrasts are easier to identify (larger sample size per comparison)



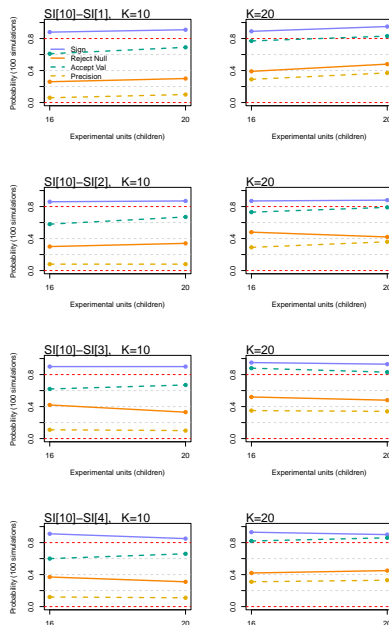
# Power results

For individual contrasts,

- reject the null hypothesis, depends on the contrast of interest,
- affirm predicted value, for some is achieved,
- achieve precision in estimate, clearly requires more sample size

Notice,

- we see a clear difference with 2x comparisons (more sample at the appropriate level)

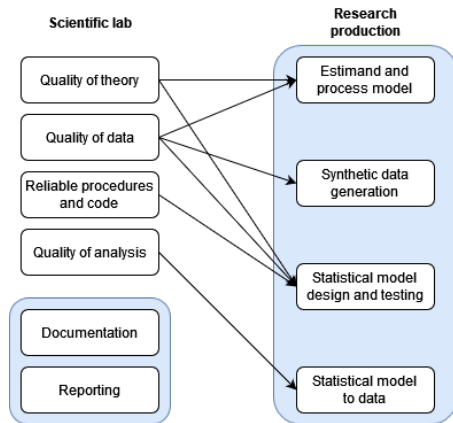


## 2. Research hypothesis procedure

Apply statistical model to data

# What we have so far

1. measure:  
replicated entropies  $H_{ik}^O$
2. estimand:  
SI index, structural parameters,  
contrasts
3. structural models:  
total and direct effects
4. probabilistic models:  
three possible fitting models
5. statistical models:  
works as intended
6. power:  
enough





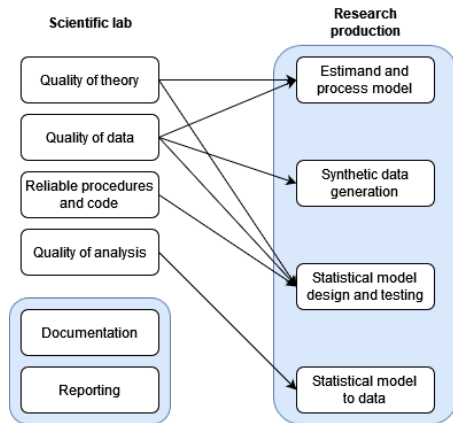
# Information Theoretic Approach [1, 4]

The last step would be to select the most fitting model, and we do it with the ITA,

1. ~~hypothesis into statistical models~~,
2. select among competing models,
3. make inferences based on one or multiple models.

Select models with information criteria,

1. WAIC [17]
2. PSIS [16]



# Competing models

models\_table.png

### 3. References

### 3. References

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