

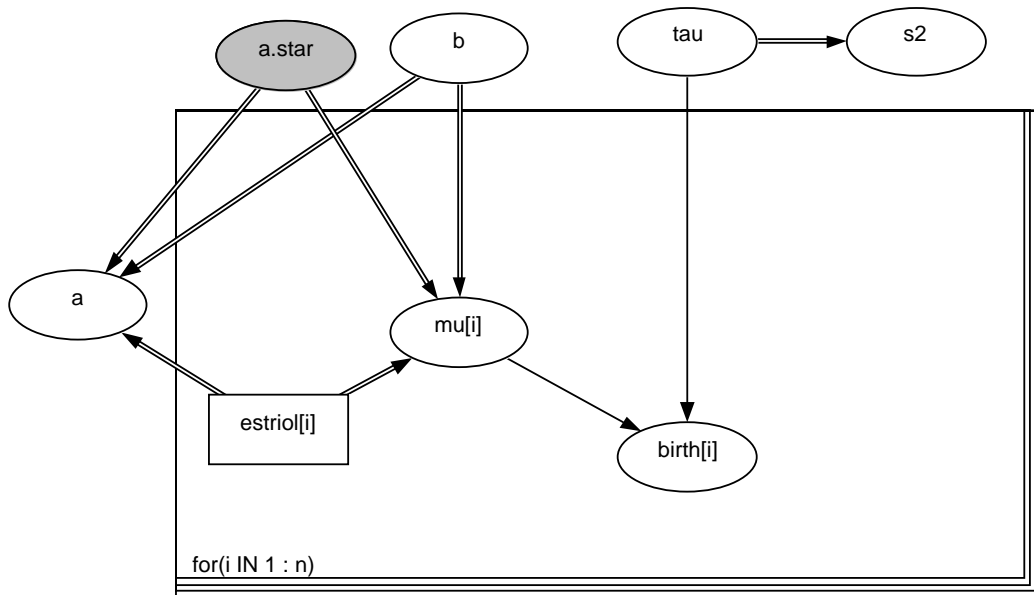
## ΠΑΡΑΡΤΗΜΑ Δ1 (4<sup>ο</sup> ΜΑΘΗΜΑΤΟΣ): ΠΑΡΑΔΕΙΓΜΑΤΑ ΕΛΕΓΧΩΝ ΥΠΟΘΕΣΕΩΝ, ΕΠΙΛΟΓΗΣ ΜΟΝΤΕΛΩΝ ΚΑΙ ΜΕΤΑΒΛΗΤΩΝ

### 1 ΠΑΡΑΔΕΙΓΜΑ WINBUGS 1: Ένας Απλός Έλεγχος Υπόθεσης (ESTRIOL DATASET)

```
model estriol;
{
#   definition of likelihood function
#
  for (i in 1:n) {
    birth[i]~dnorm( mu[i], tau ); # random component
    mu[i]<-a.star+gamma*b*(estriol[i]-mean(estriol[])); # systematic component
    # & link function
  }
#   prior distributions
#
  a.star~dnorm( 0, 1.0E-04 ); # normal prior for a
  b~dnorm( 0, 1.575); # normal prior for b
  gamma~dbern(0.5);
  tau~dgamma( 1.0E-04 , 1.0E-04 ); # gamma prior for precision
  s2<-1/tau;
  a<-a.star-b*mean(estriol[]);
}
list(a.star=0.0, b=0.0, tau=1.0,gamma=1)

list(n=31)
estriol[] birth[]
7      25
9      25
9      25
12     27
14     27
16     27
16     24
14     30
16     30
16     31
17     30
19     31
21     30
24     28
15     32
16     32
17     32
25     32
27     34
15     34
15     34
15     35
16     35
19     34
18     35
17     36
18     37
20     38
22     40
25     39
24     43
END
```

name: a.star      type: stochastic      density: dnorm  
mean: 0.0      precision: 1.0E-6      lower bound:      upper bound:



## 2 ΠΑΡΑΔΕΙΓΜΑ WINBUGS 2: Διαγνωστικά Τέστ και Συγκρίσεις μοντέλων (ESTRIOL DATASET)

```

model estriol_AIC_BIC;
{
#   definition of likelihood function
#
    pi<-3.14
    for (i in 1:n) {
        birth[i]~dnorm( mu[i], tau );           # random component
        mu[i]<-a.star+b*(estriol[i]-mean(estriol[])); # systematic component
                                                # & link function
        birth.pred[i]~dnorm( mu[i], tau )
        loglike1[i]<- -0.5*log(2*pi)+0.5*log(tau)-0.5*pow( birth[i]-mu[i],2 )*tau
        loglike1.pred[i]<- -0.5*log(2*pi)+0.5*log(tau)-0.5*pow( birth.pred[i]-mu[i],2 )*tau
        like1[i]<- exp( loglike1[i] )

#
#           model m_0
        birth0[i]~dnorm( mu0[i], tau0 );           # random component
        mu0[i]<-a0;                                # systematic component
                                                # & link function
        birth0.pred[i]~dnorm( mu0[i], tau0 )
        loglike0[i]<- -0.5*log(2*pi)+0.5*log(tau0)-0.5*pow( birth0[i]-mu0[i],2 )*tau0
        loglike0.pred[i]<- -0.5*log(2*pi)+0.5*log(tau0)-0.5*pow( birth0.pred[i]-mu0[i],2 )*tau0
        like0[i]<- exp( loglike0[i] )

#
#
        ss1[i] <- pow( birth.pred[i]-birth[i], 2 )
        ss0[i] <- pow( birth0.pred[i]-birth0[i], 2 )
    }
#   prior distributions for model m1
#
    a.star~dnorm( 0, 1.0E-04 ); # normal prior for a
    b~dnorm( 0, 1.0E-04 ); # normal prior for b
    tau~dgamma( 1.0E-04 , 1.0E-04 ); # gamma prior for precision
    s2<-1/tau;
    a<-a.star-b*mean(estriol[]);

#
#           prior distributions for model m0
    a0~dnorm( 0, 1.0E-04 ); # normal prior for a
    tau0~dgamma( 1.0E-04 , 1.0E-04 ); # gamma prior for precision

#
#           Bayesian versions of LogLikelihood
    L1<-sum( loglike1[] )
    L0<-sum( loglike0[] )

#
#           Bayesian versions of BIC
    BIC1<- -2*L1 + 3*log(n)
    BIC0<- -2*L0 + 2*log(n)

#
#           Bayesian versions of AIC
    AIC1<- -2*L1 + 3*2
    AIC0<- -2*L0 + 2*2

#
#           Lm criterion
    Lm1<- sum( ss1[] )
    Lm0<- sum( ss0[] )

#
#           Mm criterion
    Mm1<-exp( sum(loglike1.pred[] ) )
    Mm0<-exp( sum(loglike0.pred[] ) )

#
    Mm1.star<-exp( -sum(loglike1.pred[])/n )
    Mm0.star<-exp( -sum(loglike0.pred[])/n )

#
# parallel differences
    DBIC10<- BIC0-BIC1
    DAIC10<- AIC0-AIC1
    diff[1]<-DAIC10
    diff[2]<-DBIC10
    diff[3]<- Lm0-Lm1
    diff[4]<-Mm1-Mm0

```

```

diff[5]<-Mm0.star-Mm1.star
PBF<-Mm1/Mm0
PBFn<-Mm0.star/Mm1.star
#
# parallel probabilities
for (i in 1:5){
    prob[i]<-step(diff[i])
}
}

```

### 3 ΠΑΡΑΔΕΙΓΜΑ WINBUGS 3: Διαγνωστικά Τέστ και Συγκρίσεις μοντέλων (LINE DATASET)

```

model{
  pi<-3.14
  #
  # Likelihood
  for( i in 1 : N ) {
    y[i] ~ dnorm(mu[i],tau)
    mu[i] <- alpha + beta * (x[i] - mean(x[]))
  }
  #
  # residuals
  resid[i]<-y[i]-mu[i]
  sresid[i]<-resid[i]*sqrt(tau)
  #
  # predicted values
  y.pred[i]~dnorm(mu[i],tau)
  #
  # predicted standardised residuals
  sr.pred[i]<-(y[i]-y.pred[i])*sqrt(tau)
  #
  # p.smaller
  p.smaller[i]<-step(y[i]-y.pred[i])
  #
  #
  sresid.pred[i]<-(y.pred[i]-mu[i])*sqrt(tau)
  sresid3[i]<-pow( sresid[i] , 3 )
  sresid3.pred[i]<-pow( sresid.pred[i] , 3 )
  }
  #
  # Prior distributions
  tau ~ dgamma(0.001,0.001)
  sigma <- 1 / sqrt(tau)
  alpha ~ dnorm(0.0,1.0E-6)
  beta ~ dnorm(0.0,1.0E-6)
  #
  #
  skew.obs<-mean(sresid3[])
  skew.pred<-mean(sresid3.pred[])
  pval.pred<-step(skew.pred-skew.obs)
}

```

**Data(WITHOUT OUTLIER):** list(x = c(1, 2, 3, 4, 5), y= c(1, 3, 3, 3, 5), N = 5)

**Data(WITH OUTLIER):** list(x = c(1, 2, 3, 4, 5), y= c(1, 10000, 3, 3, 5), N = 5)

**Inits:** list(alpha = 0, beta = 0, tau = 1)

## 4 ΠΑΡΑΔΕΙΓΜΑ WINBUGS 4: Πλήρες Μοντέλο για το Antitoxin dataset

```
model{
#
# model likelihood
for (i in 1:4) {
  r[i]~dbin(p[i],n[i]);
  logit(p[i])<-b[1] + x[i,2]* b[2]
                + x[i,3]* b[3]
                + x[i,4]* b[4]; }
# priors and pseudopriors

b[1]~dnorm(0.0, 0.0001)
for (i in 2:4) { b[i]~dnorm( 0.0 , 0.0001) ; }

}

DATA
r[] n[] x[,1] x[,2] x[,3] x[,4]
5 12 1 -1 -1 1
4 26 1 1 -1 -1
15 20 1 -1 1 -1
6 21 1 1 1 1
END

INITS
list( b=c(1,0,0,0))
```

## 5 ΠΑΡΑΔΕΙΓΜΑ WINBUGS 5: Gibbs Variable Selection για το Antitoxin dataset

```
model {
#
# model likelihood
for (i in 1:4) {
  r[i]~dbin(p[i],n[i]);
  logit(p[i])<-b[1] + x[i,2]* g[2]* b[2]
                    + x[i,3]* g[3]* b[3]
                    + x[i,4]* g[4]* b[4]; }
# priors and pseudopriors
b[1]~dnorm( 0.0, 0.0001 )
for (i in 2:4) {
  tau[i]<-g[i]/8+(1-g[i])/(se[i]*se[i]);
  bpriorm[i]<-mean[i]*(1-g[i]);
  b[i]~dnorm(bpriorm[i],tau[i]); }

  mdl<-g[2]+2*g[3]+3*g[4];
  pmdl[1]<-equals(mdl,0)
  pmdl[2]<-equals(mdl,1)
  pmdl[3]<-equals(mdl,2)
  pmdl[4]<-equals(mdl,3)
  pmdl[5]<-equals(mdl,6)

for (i in 1:4) { g[i]~dbern( pi[i] ) }
pi[1]<-1.0
pi[2]<-0.5*(1-g[4])+g[4]
pi[3]<-0.5*(1-g[4])+g[4]
pi[4]<-0.20
}
```

### DATA

```
r[] n[] x[,1] x[,2] x[,3] x[,4]
  5 12 1 -1 -1 1
  4 26 1 1 -1 -1
 15 20 1 -1 1 -1
  6 21 1 1 1 1
END
```

### PROPOSAL/PSEUDOPRIOR VALUES

```
mean[] se[]
-0.4889 0.2823
-0.8919 0.2798
 0.5866 0.2824
-0.1773 0.272
END
```

### INITS

```
list( g=c(1,1,1,1), b=c(1,0,0,0))
```

**ΠΑΡΑΡΤΗΜΑ Δ2: ΒΙΒΛΙΟΓΡΑΦΙΑ ΚΑΙ ΔΗΜΟΣΙΕΥΣΕΙΣ ΣΧΕΤΙΚΕΣ ΜΕ  
BAYESIAN MODEL AND VARIABLE SELECTION**

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