DSSFA Project

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Upload data from 'psych'

This dataset contains 25 self-report personality items from the International Personality Item Pool (ipip.ori.org). It was developed as part of the Personality Assessment Project. The data contains the responses of 2800 people and can be used for demonstration purposes, as well as for the factor analysis that we will use here. We try to reduce the dimension to at least 25-1 = 24 factors, but we can even be more ambitious and propose directly k_max = 15 for the speed of implementation of the following algorithms. More information here.

```
data(bfi)
bfi = na.omit(bfi)
bfi = bfi[which(bfi$age>50),1:25]
```

```
##       A1 A2 A3 A4 A5 C1 C2 C3 C4 C5 E1 E2 E3 E4 E5 N1 N2 N3 N4 N5 O1 O2 O3 O4
## 61661 -1  5  6  5  6  4  3  2 -4 -5 -2 -1  2  5  2  2  2  2  2  2  6 -1  5  5
## 61669 -2  4  4  4  3  6  5  6 -1 -1 -2 -4  4  2  6  3  3  5  3  2  5 -2  6  6
## 61782 -1  2  2  4  2  2  4  2 -5 -1 -2 -2  4  2  2  4  2  2  2  4  2 -3  4  2
## 61813 -1  5  5  5  5  5  2  4 -1 -2 -4 -1  5  5  5  1  1  1  4  1  6 -1  5  5
## 62013 -3  5  4  4  4  3  3  4 -4 -4 -5 -4  3  2  4  2  3  2  3  2  5 -4  4  3
## 62197 -1  5  5  5  5  5  4  5 -1 -1 -2 -2  3  5  5  1  2  2  2  2  2 -2  5  4
## 62260 -1  5  5  5  4  4  4  4 -2 -2 -4 -4  4  2  5  1  2  1  1  2  4 -2  5  6
## 62267 -1  6  5  6  5  5  6  6 -2 -1 -5 -2  5  1  6  5  4  5  4  2  6 -5  3  6
## 62333 -1  6  6  6  6  6  6  6 -1 -1 -5 -1  6  6  6  1  6  1  1  1  6 -1  3  6
## 62345 -2  4  4  6  5  4  4  4 -3 -4 -1 -1  5  5  6  2  4  3  3  1  6 -1  6  4
## 62368 -1  6  1  6  5  4  1  2 -5 -6 -1 -1  5  5  6  2  4  6  6  5  6 -1  6  6
## 62423 -2  6  5  6  3  5  6  5 -2 -3 -3 -2  5  5  5  3  5  5  1  4  4 -2  4  6
## 62448 -1  6  2  6  5  5  5  5 -4 -2 -2 -6  1  4  5  4  2  1  2  3  6 -5  3  6
## 62498 -1  5  6  6  6  1  5  6 -4 -1 -6 -6  3  2  5  4  1  2  6  6  6 -5  2  6
## 62518 -2  6  6  6  6  6  6  5 -1 -1 -1 -1  6  5  6  1  1  2  2  1  6 -1  6  5
## 62577 -2  5  5  5  5  2  1  2 -5 -4 -5 -5  5  4  2  5  5  5  6  4  5 -6  4  6
## 62597 -2  5  5  5  4  6  2  4 -2 -5 -1 -2  5  5  5  4  5  5  5  4  6 -2  5  6
## 62599 -1  5  5  6  6  6  1  5 -3 -1 -6 -6  1  5  1  4  5  5  6  1  6 -5  1  6
## 62617 -2  6  6  6  6  6  6  6 -1 -1 -3 -6  6  1  6  4  4  1  1  3  6 -1  6  2
## 62622 -1  6  6  6  6  6  6  5 -1 -4 -1 -1  6  6  6  4  6  5  2  4  6 -5  6  6
## 62638 -2  6  6  2  6  6  3  5 -1 -2 -1 -1  5  5  6  1  2  2  1  1  5 -1  6  4
## 62664 -1  5  6  5  6  6  5  5 -1 -2 -2 -1  5  1  5  4  5  4  5  4  5 -4  4  6
## 62688 -1  6  5  6  4  6  6  5 -1 -2 -1 -5  2  5  6  5  6  4  4  3  4 -5  5  5
## 62712 -1  6  5  5  6  6  5  5 -1 -3 -1 -1  5  6  6  1  2  1  1  1  6 -1  6  6
## 62719 -1  4  6  5  6  5  2  6 -1 -1 -1 -3  5  1  5  6  6  6  6  6  4 -1  5  6
## 62750 -2  4  4  6  5  5  2  5 -1 -2 -2 -2  3  5  4  2  5  2  2  1  4 -3  4  4
## 62874 -1  6  6  6  6  5  6  6 -1 -1 -1 -1  6  6  6  1  1  1  1  2  5 -2  3  4
## 66965 -2
## 67026 -5
## 67029 -5
## 67055 -5
## 67098 -1
## 67232 -2
## 67342 -4
## 67388 -3
## 67406 -2
## 67453 -1
```

These data are preprocessed by us. Here, we hide a part of the code if it is not directly related to the subject, for a better readability.

Note : The algorithms called with "source()" are presented in the appendix, to ease the reading.

Gibbs Sampler

```
source("GIBBS.R")
gibbs = gibbs_sampler(y,my_seed=6784,N_sampl=15000,
                           alpha=5,a_sig=1,b_sig=0.3,a_theta=2,b_theta=2,theta_inf=0.05,
                           start_adapt=500,Hmax=dim(y)[2]+1,alpha0=-1,alpha1=-5*10^(-4))
```

```
burn_in = 5000
```

Burn-in for the sampler

```
p = dim(gibbs$y)[2]
```

Number of variables : 25

```
thin = 5
thinning = seq(burn_in+1,gibbs$N_sampl,by=thin)
```

Thinning

```
Omega_post = array(NA,c(p,p,length(thinning)))
```

Posterior sample of the covaraince matrix

Object to build

```
obj = list()
```

```
obj$P = p
```

Number of variables in the sample : 25

```
obj$samp.size = length(thinning)
```

Sample size : 2000

```
obj$post.cov = Omega_post
```

Posterior sample covariance matrix

```
obj$nsim = 2000
obj$thin = 1
```

Posterior sample size : 2000

DSSFA Method applied to our object (k_max = 15) :

```
source("DSSFA.R")
obj.bfa.list.CUSP = DSSFA(obj, length.lambda = 2, k.max = 15, print.out = T, tol.em = 0.00001)
```

```
## Factor =  1
## Factor =  2
## Factor =  3
## Factor =  4
## Factor =  5
## Factor =  6
## Factor =  7
## Factor =  8
## Factor =  9
## Factor =  10
## Factor =  11
## Factor =  12
## Factor =  13
## Factor =  14
## Factor =  15
```

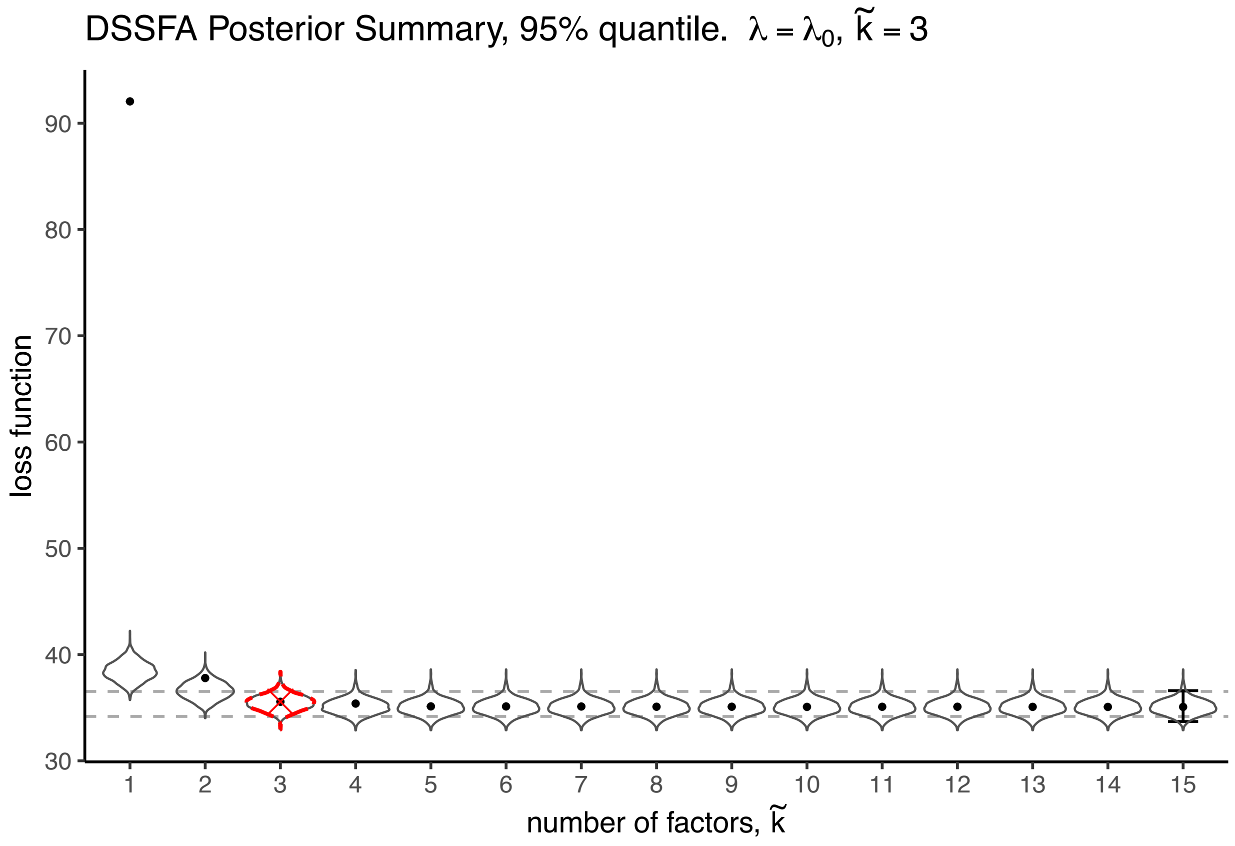
Creation of the 95% confidence interval :

```
CI = list()
CI$CI.85 = list(c("85"),c(0.075,0.925))
CI$CI.90 = list(c("90"),c(0.05,0.95))
CI$CI.95 = list(c("95"),c(0.025,0.975))
CI$CI.99 = list(c("99"),c(0.005,0.995))
```

Plots that summarize the DSSFA method :

```
source("summary_plot.R")
summary.plot(obj.bfa.list.CUSP,CI[[3]],cov.dssfa = T, text_main_prior = "CUSP prior,", col.lambda = 1,l
```

```
## Warning: Using ‘size‘ aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use ‘linewidth‘ instead.
```



“Summary.plot” creates a summary graph for the Bayesian factor analysis model, as above. This function uses a default CI of 95%. It uses the fit values of the model to select the best number of factors and the best lambda value of the loss. Then the function uses the selected loadings and uniquenesses to calculate the Omega matrices. In this case, we can see the selected number of factors : k=3.

Select the right number of factors :

```
source("DSSFA_sel_mat.R")
mat.sel = sel.model.dssfa(obj.bfa.list.CUSP,CI[[3]])
sel = min(which(lapply(mat.sel$mat.sel.ksel,is.null) == F))
cat('The right number of factors is : k =', sel)
```

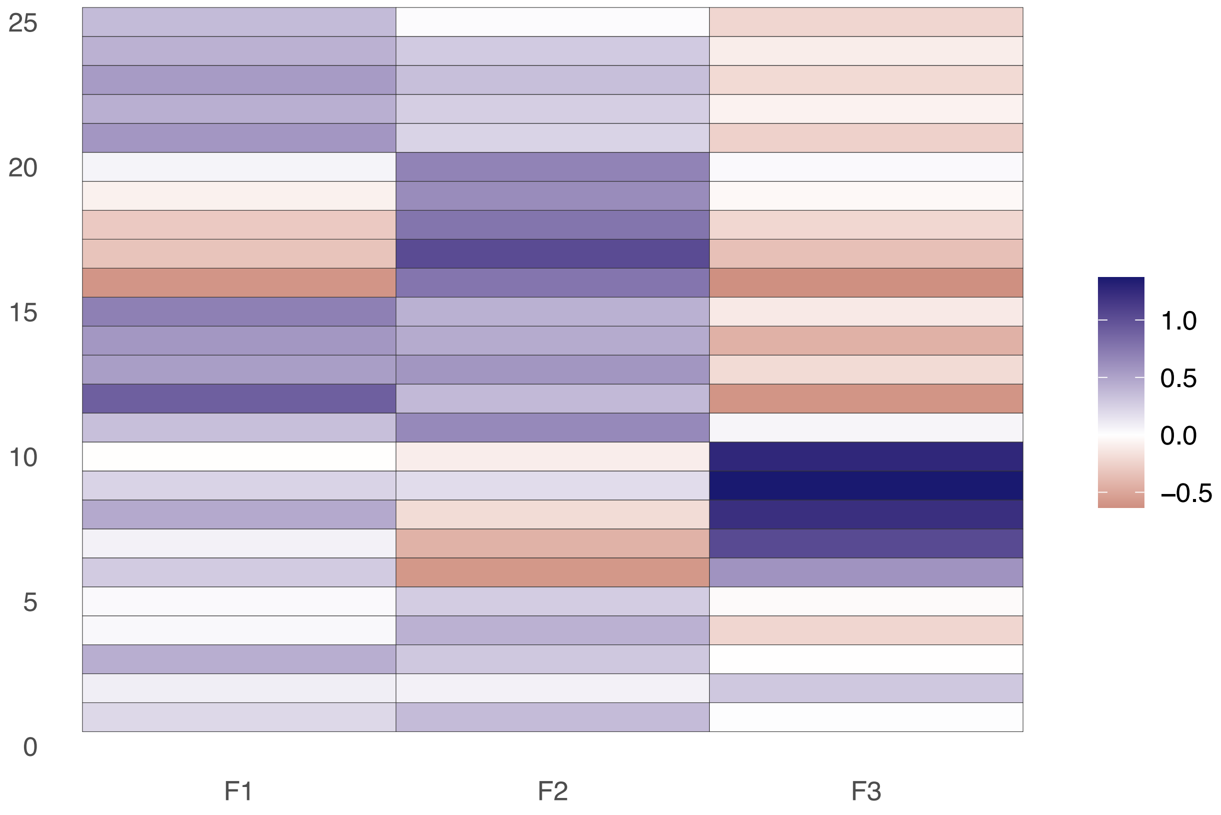
```
## The right number of factors is : k = 3
```

"Sel.model.dssfa" selects the "best" model from a list of models based on the confidence interval. The function checks if a k-value has been provided (number of factors), otherwise it uses all k-values between 1 and the maximum k-value provided in the input list, here k_max=15. Then, it calculates the quantiles of the credible interval using the fit values of the models and loops over the selected k-values and checks whether the fit value of each model is within the credible interval. If this is the case, the function saves the parameters of the corresponding model, otherwise it saves a null value. It also records uniquenesses and correlation matrices if they have been provided in the input list. Here, the function returns "3" : the selected model (ie. the selected number of factors).

Loadings Matrix :

We finally obtain the loadings matrix from the DSSFA method, for k=3 number of factors (F1, F2, and F3). A clear and interpretable pattern is observed in the loadings from the DSSFA method, despite the reduction of the factor dimension.

```
mat = mat.sel$mat.sel.ksel[[sel]]
mat = mat[,c(3,1,2)]
make.plot.mat(mat,fact.name = c("F1","F2","F3"))
```



Appendix

You will find the functions useful for the realization of our code.

Gibbs sampler

```
gibbs_sampler <- function(y,my_seed,N_sampl,alpha,a_sig,b_sig,a_theta,b_theta,
                              theta_inf,start_adapt,Hmax,alpha0,alpha1){
  set.seed(my_seed)
  n<-dim(y)[1]
  p<-dim(y)[2]
  u<-runif(N_sampl)

  H<-rep(NA,N_sampl)
  Hstar<-rep(NA,N_sampl)
  Lambda_post<-vector("list",N_sampl)
  eta_post<-vector("list",N_sampl)
  theta_inv_post<-vector("list",N_sampl)
  w_post<-vector("list",N_sampl)
  z_post<-vector("list",N_sampl)
  inv_sigma_sq_post<-matrix(NA,p,N_sampl)

  H[1]<-p+1
  Hstar[1]<-p
  Lambda_post[[1]]<-matrix(rnorm(p*H[1]),p,H[1])
  eta_post[[1]]<-matrix(rnorm(n*H[1]),n,H[1])
  theta_inv_post[[1]]<-rep(1,H[1])
  w_post[[1]]<-rep(1/H[1],H[1])
  z_post[[1]]<-rep(H[1],H[1])
  inv_sigma_sq_post[,1]<-1

  t0 <- proc.time()
  for (t in 2:N_sampl){
    Lambda_post[[t]]<-matrix(NA,p,H[t-1])
    eta_post[[t]]<-matrix(NA,n,H[t-1])
    theta_inv_post[[t]]<-rep(NA,H[t-1])
    w_post[[t]]<-rep(NA,H[t-1])
    z_post[[t]]<-rep(NA,H[t-1])

    for (j in 1:p){
      V_j<-chol2inv(chol(diag(theta_inv_post[[t-1]],nrow=H[t-1])+inv_sigma_sq_post[j,t-1]*(t(eta_post[[t
      mu_j<-V_j%*%t(eta_post[[t-1]])%*%(y[,j])*inv_sigma_sq_post[j,t-1]
      Lambda_post[[t]][j,]<-mvrnorm(1,mu_j,V_j)
    }

    diff_y<-apply((y-(eta_post[[t-1]]%*%t(Lambda_post[[t]])))^2,2,sum)
    for (j in 1:p){
      inv_sigma_sq_post[j,t]<-rgamma(n=1,shape=a_sig+0.5*n,rate=b_sig+0.5*diff_y[j])
    }

    V_eta<-chol2inv(chol(diag(H[t-1])+t(Lambda_post[[t]])%*%diag(inv_sigma_sq_post[,t])%*%Lambda_post[[t
    for (i in 1:n){
```

```
    mu_eta_i<-V_eta%*%t(Lambda_post[[t]])%*%diag(inv_sigma_sq_post[,t])%*%y[i,]
    eta_post[[t]][i,]<-mvrnorm(1,mu_eta_i,V_eta)
  }

  lhd_spike<-rep(0,H[t-1])
  lhd_slab<-rep(0,H[t-1])
  for (h in 1:H[t-1]){
    lhd_spike[h]<-exp(sum(log(dnorm(Lambda_post[[t]][,h], mean = 0, sd = theta_inf^(1/2), log = FALSE
    lhd_slab[h]<-dmvt(x=Lambda_post[[t]][,h], mu=rep(0,p), S=(b_theta/a_theta)*diag(p), df=2*a_theta)
    prob_h<-w_post[[t-1]]*c(rep(lhd_spike[h],h),rep(lhd_slab[h],H[t-1]-h))
    if (sum(prob_h)==0){
      prob_h<-c(rep(0,H[t-1]-1),1)
    }
    else{
      prob_h<-prob_h/sum(prob_h)
    }
    z_post[[t]][h]<-c(1:H[t-1])%*%rmultinom(n=1, size=1, prob=prob_h)
  }

  v<-rep(NA,H[t-1])
  for (h in 1:(H[t-1]-1)){
    v[h]<-rbeta(1, shape1 = 1+sum(z_post[[t]]==h), shape2 = alpha+sum(z_post[[t]]>h))
  }
  v[H[t-1]]<-1
  w_post[[t]][1]<-v[1]
  for (h in 2:H[t-1]){
    w_post[[t]][h]<-v[h]*prod(1-v[1:(h-1)])
  }

  for (h in 1:H[t-1]){
    if (z_post[[t]][h]<=h){
      theta_inv_post[[t]][h]<-theta_inf^(-1)
    }
    else{
      theta_inv_post[[t]][h]<-rgamma(n=1,shape=a_theta+0.5*p,rate=b_theta+0.5*t(Lambda_post[[t]][,h])
    }
  }

  active <- which(z_post[[t]]>c(1:H[t-1]))
  Hstar[t] <- length(active)
  H[t]<-H[t-1]

  if (t>=start_adapt & u[t]<=exp(alpha0+alpha1*t)){
    if (Hstar[t]<H[t-1]-1){
      H[t]<-Hstar[t]+1
      eta_post[[t]]<-cbind(eta_post[[t]][,active],rnorm(n))
      theta_inv_post[[t]]<-c(theta_inv_post[[t]][active],theta_inf^(-1))
      w_post[[t]]<-c(w_post[[t]][active],1-sum(w_post[[t]][active]))
      Lambda_post[[t]]<-cbind(Lambda_post[[t]][,active],rnorm(p,mean=0,sd=sqrt(theta_inf)))
    } else if (H[t-1]<Hmax) {
      H[t]<-H[t-1]+1
      eta_post[[t]]<-cbind(eta_post[[t]],rnorm(n))
      v[H[t-1]]<-rbeta(1,shape1=1,shape2=alpha)
```

```
        v<-c(v,1)
        w_post[[t]]<-rep(NA,H[t])
        w_post[[t]][1]<-v[1]
        for (h in 2:H[t]){
          w_post[[t]][h]<-v[h]*prod(1-v[1:(h-1)])
        }
        theta_inv_post[[t]]<-c(theta_inv_post[[t]],theta_inf^(-1))
        Lambda_post[[t]]<-cbind(Lambda_post[[t]],rnorm(p,mean=0,sd=sqrt(theta_inf)))
      }
    }
  }
  runtime <- proc.time()-t0
  output<-list("y"=y,"my_seed"=my_seed,"N_sampl"=N_sampl,
               "alpha"=alpha,"a_sig"=a_sig,"b_sig"=b_sig,"a_theta"=a_theta,"b_theta"=b_theta,
               "theta_inf"=theta_inf,"start_adapt"=start_adapt,"Hmax"=Hmax,
               "alpha0"=alpha0,"alpha1"=alpha1,
               "H"=H,"Hstar"=Hstar,"Lambda_post"=Lambda_post,"eta_post"=eta_post,
               "theta_inv_post"=theta_inv_post,"w_post"=w_post,"z_post"=z_post,
               "inv_sigma_sq_post"=inv_sigma_sq_post,"runtime"=runtime)
  return(output)
}
```

DSSFA function

Here are some intermediate functions that we had to set up to use our objects.

```
require(fanc)
fitcpp.post.fanc.cov <- function(Mat1, Mat2) {
  OmegaSamp <- array(Mat1, dim = c(dim(Mat1)[-3], dim(Mat1)[3]))
  OmegaBar <- as.matrix(Mat2)

  M <- dim(OmegaSamp)[2]
  fit <- numeric(M)

  for (i in 1:M) {
    fit[i] <- log(det(OmegaBar)) + sum(solve(OmegaBar) * OmegaSamp[,,i])
  }
  return(fit)
}

fitcpp.fanc <- function(Mat1, Mat2, Mat3) {
  c1 <- array(Mat1, dim = c(dim(Mat1)[-3], dim(Mat1)[3]))
  m2 <- as.matrix(Mat2)
  OmegaBar <- as.matrix(Mat3)

  lambda <- dim(c1)[3]
  fit <- numeric(lambda)
  for (i in 1:lambda) {
    if(all(dim(c1[,,i]) == dim(m2[i,]))){
      fit[i] <- log(det(c1[,,i] + diag(m2[i,]))) + sum(OmegaBar %*% solve(c1[,,i] + diag(m2[i,])))
    } else {
      stop("Input matrices have different dimensions.")
    }
  }
  return(fit)
}

fit.fanc.post.cov = function(list.bfa){

  list.bfa$fit.post.fanc.cov = fitcpp.post.fanc.cov(list.bfa$post.cov,list.bfa$Omega.kmax)
  return(list.bfa)
}

fit.fanc = function(list.bfa){

  list.bfa$fit.fanc = fitcpp.fanc(list.bfa$betas.prod.fanc,list.bfa$fanc.sigma,list.bfa$Omega.bar)
  return(list.bfa)
}
```

And the main function (from here, partly modified)

```
DSSFA = function(obj,length.lambda = 1, k.max = 1, print.out = F, plot.summary = F, cor.factor = F, tol
  if(cor.factor){
    cat("Oblique - Sparse")
    cat("\n")
  }
  list.bfa = list()
  list.bfa$prior.bfa = obj$prior.bfa
  list.bfa$k.max = k.max
  list.bfa$M = obj$samp.size
  list.bfa$p = obj$P
  list.bfa$length.lambda = length.lambda
  list.bfa$cor.factor = cor.factor
  list.bfa$post.cov = obj$post.cov
  list.bfa$Omega.bar = apply(obj$post.cov,c(1,2),mean)

  fit.fanc.mat  = matrix(0,length.lambda,list.bfa$k.max)
  num.zero.mat  = matrix(0,length.lambda,list.bfa$k.max)
  lambda.mat    = matrix(0,length.lambda,list.bfa$k.max)
  fit.sel       = vector("list",list.bfa$k.max)
  num.zero.list = vector("list",list.bfa$k.max)
  list.sel      = vector("list",list.bfa$k.max)
  list.full     = vector("list",list.bfa$k.max)
  uniq.full     = list()

  if(list.bfa$cor.factor == T){
    phi.full      = list()
    phi.list = vector("list",list.bfa$k.max)
  }
  for(k.temp in 1:list.bfa$k.max){
    if(length.lambda >= 2){
      fanc.bfa = fanc(covmat = list.bfa$Omega.bar, factors = k.temp,
                      gamma = Inf, control = list(start = "warm", min.rhozero = T, cor.factor = cor.fac
    }else{
      fanc.bfa = fanc(covmat = list.bfa$Omega.bar, factors = k.temp, rho = 0,
                      gamma = Inf, control = list(start = "warm", min.rhozero = T, cor.factor = cor.fac
    }
    list.bfa$lambda = fanc.bfa$rho
    lambda.mat[,k.temp] = fanc.bfa$rho
    list.bfa$loadings.fanc.bfa = as.array(fanc.bfa$loadings$gamma1)
    list.bfa$fanc.sigma.bfa = fanc.bfa$uniquenesses[,,1]

    if(length.lambda < 2){
      list.bfa$fanc.sigma.bfa = matrix(list.bfa$fanc.sigma.bfa,nrow = 1)
    }
    fanc.matrix.bfa = matrix(0,length(list.bfa$lambda),list.bfa$p*k.temp)
    for(i in 1:length(list.bfa$lambda)){
      fanc.matrix.bfa[i,] = as.numeric(list.bfa$loadings.fanc.bfa[[i]])
    }
    list.bfa$fanc.matrix.bfa = fanc.matrix.bfa
    betas.bfa.fanc.full = replicate(length(list.bfa$lambda),matrix(0,list.bfa$p,k.temp))
    for(i in 1:length(list.bfa$lambda)){
      betas.bfa.fanc.full[,,i] = as.matrix(list.bfa$loadings.fanc.bfa[[i]])
    }
    list.bfa$fanc.matrix.sel = betas.bfa.fanc.full
    mat_dif_zero = which(apply(betas.bfa.fanc.full,3,function(x) sum(colSums(x) == 0)) != 0)

    if(length(mat_dif_zero) == length.lambda){
      cat("Zeroed Columns")
      fanc.bfa  = fanc(covmat = list.bfa$Omega.bar, factors = k.temp, gamma = Inf, control = list(start
      list.bfa$lambda = fanc.bfa$rho
      lambda.mat[,k.temp] = fanc.bfa$rho
      list.bfa$loadings.fanc.bfa = as.array(fanc.bfa$loadings$gamma1)
      list.bfa$fanc.sigma.bfa = t(as.matrix(fanc.bfa$uniquenesses[,,1]))
      if(length.lambda < 2){
        list.bfa$fanc.sigma.bfa = matrix(list.bfa$fanc.sigma.bfa,nrow = 1)
      }
      fanc.matrix.bfa = matrix(0,length(list.bfa$lambda),list.bfa$p*k.temp)
      for(i in 1:length(list.bfa$lambda)){
        fanc.matrix.bfa[i,] = as.numeric(list.bfa$loadings.fanc.bfa[[i]])
      }
      list.bfa$fanc.matrix.bfa = fanc.matrix.bfa
      betas.bfa.fanc.full = replicate(length(list.bfa$lambda),matrix(0,list.bfa$p,k.temp))
      for(i in 1:length(list.bfa$lambda)){
        betas.bfa.fanc.full[,,i] = as.matrix(list.bfa$loadings.fanc.bfa[[i]])
      }
      list.bfa$fanc.matrix.sel = betas.bfa.fanc.full
      if(apply(betas.bfa.fanc.full,3,function(x) sum(colSums(x) == 0)) == 0) cat(" - FULL Matrix") else
      mat_dif_zero = length.lambda-1
    }
    num.zero.mat[,k.temp] = apply(fanc.matrix.bfa, 1, function(x) sum(x != 0))
    list.sel[[k.temp]]  = betas.bfa.fanc.full
    list.full[[k.temp]] = betas.bfa.fanc.full

    if(list.bfa$cor.factor){
      phi.full[[k.temp]] = fanc.bfa$Phi[,,,1]
    }
    betas.prod.bfa.fanc = replicate(length(list.bfa$lambda),matrix(0,list.bfa$p,list.bfa$p))
    if(cor.factor == T & k.temp > 1){
      for(i in 1:length(list.bfa$lambda)){
        betas.prod.bfa.fanc[,,i] = betas.bfa.fanc.full[,,i]%*%fanc.bfa$Phi[,,i,1]%*%t(betas.bfa.fanc.ful
      }
      list.bfa$betas.prod.fanc = betas.prod.bfa.fanc
    }else{
      for(i in 1:length(list.bfa$lambda)){
        betas.prod.bfa.fanc[,,i] = betas.bfa.fanc.full[,,i]%*%t(betas.bfa.fanc.full[,,i])
      }
      list.bfa$betas.prod.fanc = betas.prod.bfa.fanc
    }
    if(k.temp == list.bfa$k.max){
      Omega.kmax = list.bfa$betas.prod.fanc[,,length(list.bfa$lambda)]+diag(fanc.bfa$uniquenesses[lengt
      list.bfa$Omega.kmax = Omega.kmax
      list.bfa = fit.fanc.post.cov(list.bfa)
    }
    list.bfa = fit.fanc(list.bfa)
    fit.fanc.mat[,k.temp] = list.bfa$fit.fanc
    if(length(mat_dif_zero) == 0){
      fit.sel[[k.temp]] = list.bfa$fit.fanc
      num.zero.list[[k.temp]] = apply(fanc.matrix.bfa, 1, function(x) sum(x == 0))
      uniq.full[[k.temp]] = fanc.bfa$uniquenesses[,,1]
      if(length.lambda < 2){
        uniq.full[[k.temp]] = matrix(fanc.bfa$uniquenesses[,,1],nrow = 1)
      }
      if(list.bfa$cor.factor == T){
        phi.list[[k.temp]] = fanc.bfa$Phi[,,,1]
      }
    }else{
      fit.sel[[k.temp]] = list.bfa$fit.fanc[-mat_dif_zero]
      num.zero.list[[k.temp]] = apply(fanc.matrix.bfa, 1, function(x) sum(x == 0))[-mat_dif_zero]
      if(k.temp == 1){
        dim.array = dim(list.sel[[k.temp]][,,-mat_dif_zero])[2]
        list.sel[[k.temp]] = array(list.sel[[k.temp]][,,-mat_dif_zero],dim = c(list.bfa$p,k.temp,dim.ar
      }else{
        list.sel[[k.temp]] = list.sel[[k.temp]][,,-mat_dif_zero]
      }
      uniq.full[[k.temp]] = fanc.bfa$uniquenesses[-mat_dif_zero,,1]
      if(length.lambda < 2){
        uniq.full[[k.temp]] = matrix(fanc.bfa$uniquenesses[,,1],nrow = 1)
      }
      if(list.bfa$cor.factor == T){
        phi.list[[k.temp]] = fanc.bfa$Phi[,,-mat_dif_zero,1]
      }
    }
    if(print.out == T){
      cat("Factor = ",k.temp)
      cat("\n")
    }
  }

  if(list.bfa$cor.factor){
    list.bfa$phi.list = phi.list
    list.bfa$phi.full = phi.full
```

```r
  }
  list.bfa$uniq.full = uniq.full
  list.bfa$fit.sel = fit.sel
  list.bfa$num.zero.list = num.zero.list
  list.bfa$list.sel = list.sel
  list.bfa$list.full = list.full
  list.bfa$rho.mat = lambda.mat

  return(list.bfa)
}
```

Summary plot function

Intermediate function :

```r
fitcpp.post.plot.cov <- function(Mat1, Mat2) {
  Omegacov <- array(Mat1, dim = c(dim(Mat1)[-3], dim(Mat1)[3]))
  Omegakmax <- array(Mat2, dim = c(dim(Mat2)[-3], dim(Mat2)[3]))

  M <- dim(Omegacov)[3]
  kmax <- dim(Omegakmax)[3]
  Omega_lamb <- matrix(nrow = M, ncol = kmax)

  for (i in 1:kmax) {
    val <- log(det(Omegakmax[,,i]))
    for (j in 1:M) {
      Omega_lamb[j,i] <- val+sum(solve(Omegakmax[,,i]) * Omegacov[,,j])
    }
  }
  return(Omega_lamb)
}
```

Main function (from here, partly modified) :

```r
summary.plot = function(list.bfa,CI = NULL, cov.dssfa = F, reg = T, text_main_prior = "", col.lambda =

  if(is.null(CI)){
    ic.1 = 0.025
    ic.2 = 0.975
    CI.text = "95"
  }else{
    ic.1 = CI[[2]][1]
    ic.2 = CI[[2]][2]
    CI.text = CI[[1]]
  }
  q1 = quantile(list.bfa$fit.post.fanc,probs = c(ic.1,ic.2))[1]
  q2 = quantile(list.bfa$fit.post.fanc,probs = c(ic.1,ic.2))[2]

  k.sel = min(which(lapply(list.bfa$fit.sel, function(x) length(which(x < q2))) != 0))
  lamb.sel = lapply(list.bfa$fit.sel, function(x) list.bfa$length.lambda-length(which(x < q2))+1)
  lamb.sel = lamb.sel[[k.sel]]

```

```r
fit.list.plot = list()
for(i in 1:list.bfa$k.max){
  if(length(dim(list.bfa$list.sel[[i]])) == 3){
    dim.size = dim(list.bfa$list.sel[[i]])[3]
    Omega.temp = array(0,dim = c(list.bfa$p,list.bfa$p,dim.size))
    for(j in 1:dim.size){
      beta.max = as.matrix(list.bfa$list.sel[[i]][,,j])
      uniq.sel = list.bfa$uniq.full[[i]][j,]
      Omega.temp[,,j] = beta.max%*%t(beta.max)+diag(uniq.sel)
    }
  }else if(length(dim(list.bfa$list.sel[[i]])) != 3){
    dim.size = 1
    Omega.temp = array(0,dim = c(list.bfa$p,list.bfa$p,1))
    beta.max = as.matrix(list.bfa$list.sel[[i]])
    uniq.sel = list.bfa$uniq.full[[i]]
    Omega.temp[,,1] = beta.max%*%t(beta.max)+diag(uniq.sel)
  }
  if(cov.dssfa == T){
    fit.list.plot[[i]] = as.matrix(fitcpp.post.plot.cov(list.bfa$post.cov,Omega.temp))
  }
  colnames(fit.list.plot[[i]]) = ((list.bfa$length.lambda-dim.size)+1):list.bfa$length.lambda
}

temp.melt = lapply(fit.list.plot, melt)

for(i in 1:list.bfa$k.max){
  temp.melt[[i]]$kmax = as.numeric(i)
}

temp = bind_rows(temp.melt)
temp = data.frame(temp)

max.lamb = max(temp$Var2)
temp$Var2 = factor(temp$Var2,levels = 1:max.lamb,ordered = T)

temp.melt2 = lapply(list.bfa$fit.sel,melt)
for(i in 1:list.bfa$k.max){
  temp.melt2[[i]]$kmax = as.numeric(i)
  dim.size = dim(temp.melt2[[i]])[1]
  temp.melt2[[i]]$lamb = ((list.bfa$length.lambda-dim.size)+1):list.bfa$length.lambda
}

temp2 = bind_rows(temp.melt2)

mygreys = colorRampPalette(brewer.pal(9,"Greys"))(max.lamb + 7)
mygreys = mygreys[-((max.lamb+6):(max.lamb+7))]
mygreys = mygreys[-(1:5)]

min = min(temp2$lamb)

g = ggplot() + geom_point(data = temp2, aes(factor(kmax),value, col = factor(lamb, labels = (max.lamb
  scale_color_manual(values = mygreys, aesthetics = c("col")) + theme(legend.position = legend.pos) +
  guides(colour = guide_legend(ncol = col.lambda))
  temp.data.reg = temp[which(temp$kmax == k.sel & temp$Var2 == lamb.sel),]
  temp.point.reg = temp2[which(temp2$kmax == k.sel & temp2$lamb == lamb.sel),]

  g = g + geom_hline(yintercept = q2, lty = "dashed", col = "darkgrey") + geom_hline(yintercept = q1, lt

  for(i in 1:max.lamb){

    temp.data = temp[which(temp$Var2 == i),]
    temp.point = temp2[which(temp2$lamb ==  i),]

    if(i == max.lamb){
      df.summary <- temp.data %>% group_by(kmax) %>%
        summarize(mid = mean(value),
                  lo = quantile(value, ic.1),
                  hi = quantile(value, ic.2))

      g = g + geom_errorbar(data = df.summary[list.bfa$k.max,],aes(factor(max(kmax)),ymin = lo, ymax = h
    }

    g = g + geom_violin(data  = temp.data,aes(factor(kmax), value), alpha = 0, size = 0.4, col = mygreys

    if(i == max.lamb){
      g = g + geom_point(data = temp.point, aes(kmax,value,col = factor(lamb)), col = "#000000", size =
    }else{
      g = g + geom_point(data = temp.point, aes(kmax,value,col = factor(lamb)), col = mygreys[i], size =
    }

    if(reg == T & i == lamb.sel){
      g = g + geom_violin(data = temp.data.reg, aes(factor(kmax),value),col = "red", lty = "twodash", al
    }
  }
  g = g + geom_point(data = temp.point.reg, aes(kmax,value), col = "red", size = 4, shape = 4)

  if(reg == T){
    lamb.sel = max.lamb-lamb.sel
    text.lambda = paste("$\\lambda = \\lambda_{",lamb.sel,"}$", sep = "")
    text.main = paste("DSSFA Posterior Summary, ", CI.text, "% quantile.  ",text.lambda,", $\\tilde{k} =
  }else{
    text.main = paste("DSSFA Posterior Summary, ", CI.text, "% quantile.  ",sep = "")
  }
  g = g  + labs(title = TeX(text.main), x = TeX("number of factors, $\\tilde{k}$"), y = TeX("loss functi

  g
}
```

Function that selects the right model

This one is from this repo.

```r
sel.model.dssfa = function(list.bfa,CI = NULL, k.sel = NULL, fast = F){

  if(length(CI) == 0){
    ic.1 = 0.025
    ic.2 = 0.975
  }else{
    ic.1 = CI[[2]][1]
    ic.2 = CI[[2]][2]
  }
  if(is.null(k.sel)){
    k.sel = 1:list.bfa$k.max
  }
  q1 = quantile(list.bfa$fit.post.fanc,probs = c(ic.1,ic.2))[1]
  q2 = quantile(list.bfa$fit.post.fanc,probs = c(ic.1,ic.2))[2]

  sel.model     = list()
  mat.sel.ksel  = vector("list",length(k.sel))
  uniq.sel.ksel = vector("list",length(k.sel))
  phi.sel.ksel  = vector("list",length(k.sel))
  mat.sel.CI    = vector("list",list.bfa$k.max)
  uniq.sel.CI   = vector("list",list.bfa$k.max)
  phi.sel.CI    = vector("list",list.bfa$k.max)

  l = 1 # count the number of select factors
  if(fast){
    for(i in k.sel){
      if(sum(which(list.bfa$fit.sel[[i]] < q2)) == 0){
        # cat("aqui11")
        mat.sel.ksel[[l]]  = NULL
        uniq.sel.ksel[[l]] = NULL
        if(list.bfa$cor.factor){
          phi.sel.ksel[[l]] = NULL
        }
        l = l+1
      }else{
        # cat("aqui12")
        min.sel = min(which(list.bfa$fit.sel[[i]] < q2))
        mat.sel.ksel[[l]]  = list.bfa$betas.full[[i]]
        uniq.sel.ksel[[l]] = list.bfa$list.uniqueness[[i]]
        if(list.bfa$cor.factor){
          phi.sel.ksel[[l]] = list.bfa$phi.full[[i]]
        }
        l = l+1
      }
    }
  }else{
    for(i in k.sel){
      if(sum(which(list.bfa$fit.sel[[i]] < q2)) == 0){
        # cat("aqui11")
        mat.sel.ksel[[l]]  = NULL
        uniq.sel.ksel[[l]] = NULL
        if(list.bfa$cor.factor){
          phi.sel.ksel[[l]] = NULL
        }
        l = l+1
      }else{
        if(length(dim(list.bfa$list.sel[[i]])) != 3){
          # cat("aqui12")
          min.sel = min(which(list.bfa$fit.sel[[i]] < q2))
          mat.sel.ksel[[l]]  = list.bfa$list.sel[[i]]
          uniq.sel.ksel[[l]] = list.bfa$uniq.full[[i]]
          if(list.bfa$cor.factor){
            phi.sel.ksel[[l]] = list.bfa$list.bfa$phi.list[[i]]
          }
          l = l+1
        }else{
          # cat("aqui13")
          min.sel = min(which(list.bfa$fit.sel[[i]] < q2))
          mat.sel.ksel[[l]]  = list.bfa$list.sel[[i]][,,min.sel]
          if(list.bfa$length.lambda < 2){
            uniq.sel.ksel[[l]] = list.bfa$uniq.full[[i]]
          }else{
            uniq.sel.ksel[[l]] = list.bfa$uniq.full[[i]][min.sel,]
          }
          if(list.bfa$cor.factor){
            if(i == 1){
              phi.sel.ksel[[l]] = 1
            }else{
              phi.sel.ksel[[l]] = list.bfa$phi.list[[i]][,,min.sel]
            }
          }
          l = l+1
        }
      }
    }
  }
  sel.model$mat.sel.ksel  = mat.sel.ksel
  sel.model$uniq.sel.ksel = uniq.sel.ksel
  if(list.bfa$cor.factor){
    sel.model$phi.sel.ksel = phi.sel.ksel
  }
  return(sel.model)
}
make.plot.mat = function(mat,col.names,fact.name){
  rownames(mat) = col.names
  colnames(mat) = fact.name
  mat = apply(mat, 2, rev)
  longmat = melt(mat)

  names(longmat)[2] = "factors"
  names(longmat)[1] = "variable"

  g1 = ggplot(longmat, aes(x = factors, y = variable)) + geom_tile(aes(fill = value),colour = "grey20")

  g2 = g1 + scale_fill_gradient2(low = "#800000", high = "#191970", mid = "white")+ theme(
    axis.title.x = element_blank(),
    axis.title.y = element_blank(),
    # panel.grid.major = element_blank(),
    text = element_text(size = 12),
    panel.border = element_blank(),
    panel.background = element_blank(),
    axis.ticks = element_blank(),
    # axis.text = element_blank(),
    legend.title = element_text(),
    plot.title = element_text(hjust = 0.5)) + labs(fill = " ")
  g2
}
```