

Modellazione multilevel

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```
library(rstanarm)
library(bayesplot)
library(tidybayes)
library(ggplot2)
library(magrittr)
library(lme4)
library(dplyr)
library(gtools)
library(tidyverse)
```

Preprocessing

```
mandarino_temp = mandarino[ , -6 ]
mandarino_wide = spread(mandarino_temp, time, "f0")
Y = as.matrix(mandarino_wide[ , 5:(NCOL(mandarino_wide)) ])      # Funzioni osservate
```

Analisi con componenti principali funzionali (fPCA)

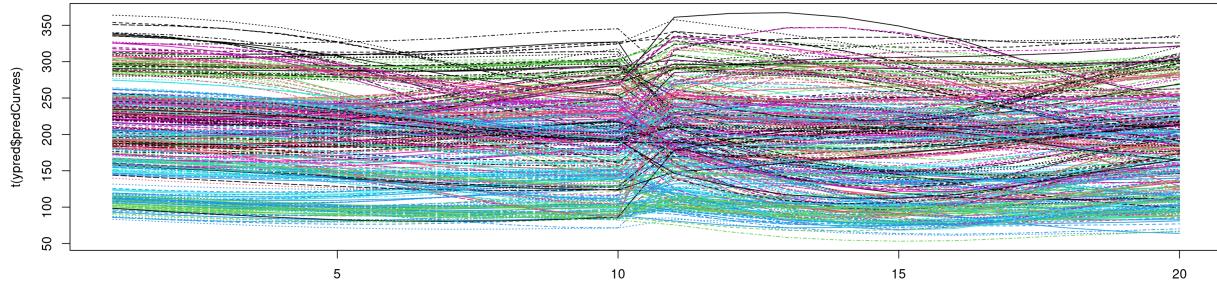
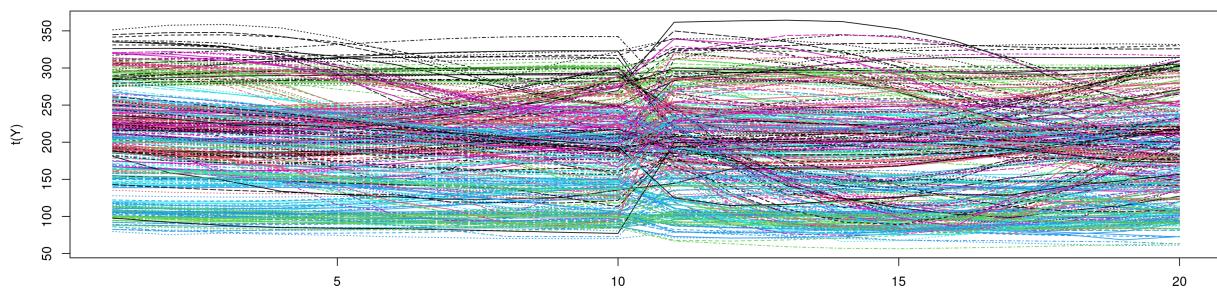
Stima delle funzioni principali che spieghino il 95% della varianza funzionale:

```
library(fdapace)

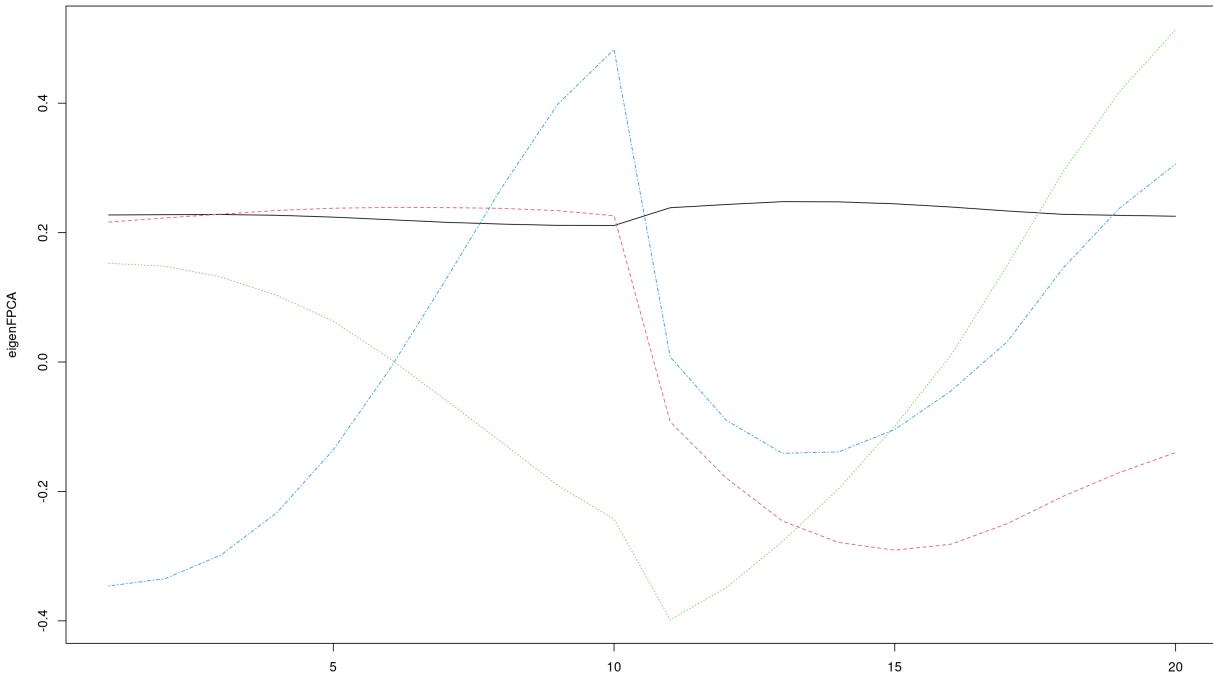
Y_list = lapply(seq_len(NROW(Y)), function(i) Y[i,])
t_list = lapply(seq_len(NROW(Y)), function(i) 1:20)

f pca = FPCA(Ly = Y_list, Lt = t_list, optns = list(FVEthreshold = 0.99))

ypred = predict(f pca, Y_list, t_list)
{
  # Confronto fPCA univariate con MFPCA
  par(mfrow = c(2,1))
  matplot(t(Y), type = "l")
  matplot(t(ypred$predCurves), type = "l")
  par(mfrow = c(1,1))
}
```



```
K = fPCA$selectK  
eigenFPCA = fPCA$phi  
# Estimated eigenfunctions  
matplot(eigenFPCA, type = "l")
```



```

# Add eigenfunctions as covariates
eigenColumns = NULL
for(i in 1:NROW(Y)){
  eigenColumns = rbind(eigenColumns, eigenPCA)
}

mandarino_fPCA = cbind(mandarino, eigenColumns)
colnames(mandarino_fPCA) = c(colnames(mandarino), paste0("PC", 1:K))

if(file.exists("fitStanLmer2.Rdata")){
  load("fitStanLmer2.Rdata")
} else{
  fitStanLmer2 = stan_glmer(f0 ~ cog_load + current +
    PC1 + PC2 + PC3 + PC4 +
    PC1:syllable1 + PC1:syllable2 +
    PC2:syllable1 + PC2:syllable2 +
    PC3:syllable1 + PC3:syllable2 +
    PC4:syllable1 + PC4:syllable2 +
    (1 | subject) +
    (0 + current|subject) +
    (0 + PC1 + PC2 + PC3 + PC4|subject) +
    (0 + PC1:syllable1 | subject) +
    (0 + PC1:syllable2 | subject) +
    (0 + PC2:syllable1 | subject) +
    (0 + PC2:syllable2 | subject) +
    (0 + PC3:syllable1 | subject) +
    (0 + PC3:syllable2 | subject) +
    (0 + PC4:syllable1 | subject) +
    (0 + PC4:syllable2 | subject))
}

```

```

        ,
        data = mandarino_fPCA,
        algorithm = "meanfield",
        prior = hs(),
        iter = 20000,
        QR = TRUE)
save(fitStanLmer2, file="fitStanLmer2.Rdata")
}

plot(fitStanLmer2, pars=names(fitStanLmer2$coefficients)[1:48])

```

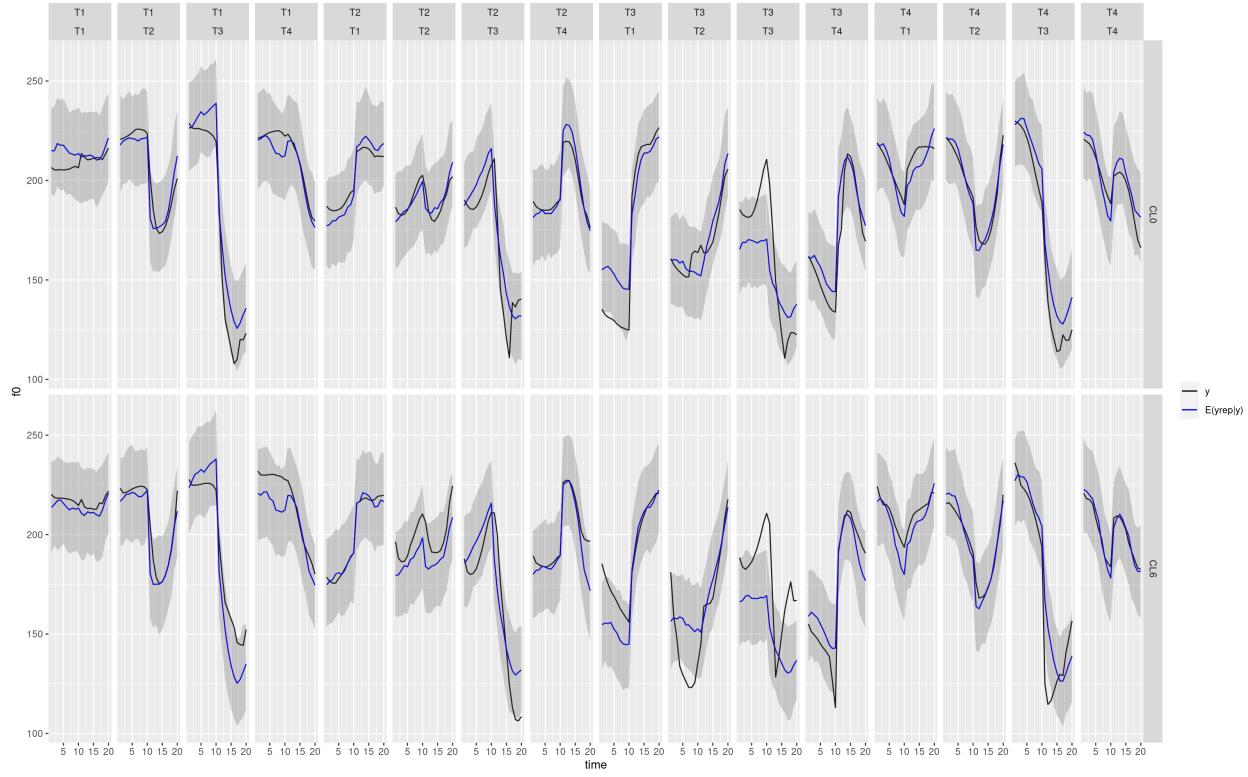
The figure is a dot plot with 48 data points. The x-axis ranges from 0 to 1200 with major ticks at 0, 400, 800, and 1200. The y-axis lists parameter names. Most points are clustered between 0 and 400. A few points are outliers: '(Intercept)' is at approximately 100, 'cog_loadCL6' is at approximately 1000, and 'currentT1' is at approximately 1150.

```

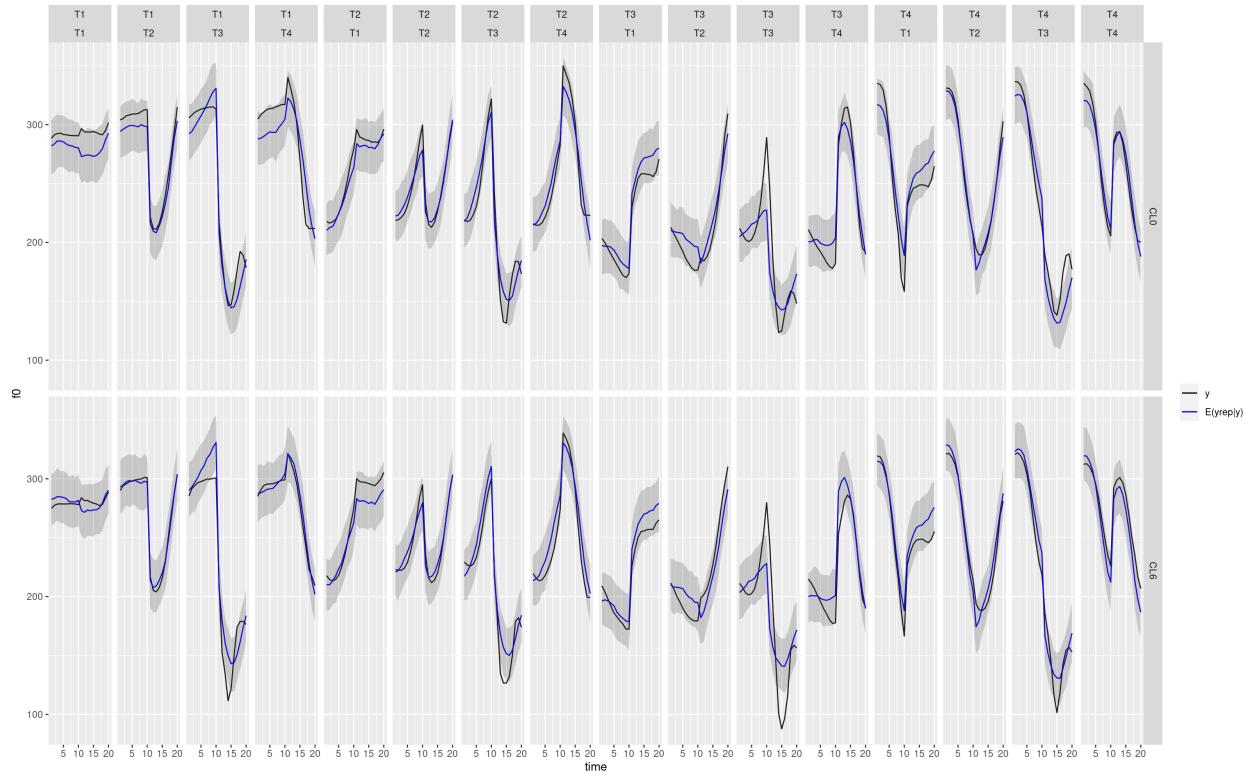
ypredStanLmer2 = posterior_predict(fitStanLmer2, draws = 500)
ypred = apply(ypredStanLmer2, 2, mean)
stdev = apply(ypredStanLmer2, 2, sd)
lmin = apply(ypredStanLmer2, 2, function(col) quantile(col, p = 0.05))
lmax = apply(ypredStanLmer2, 2, function(col) quantile(col, p = 0.95))

ppc_subject("S1", mandarino, ypred, lmin, lmax)

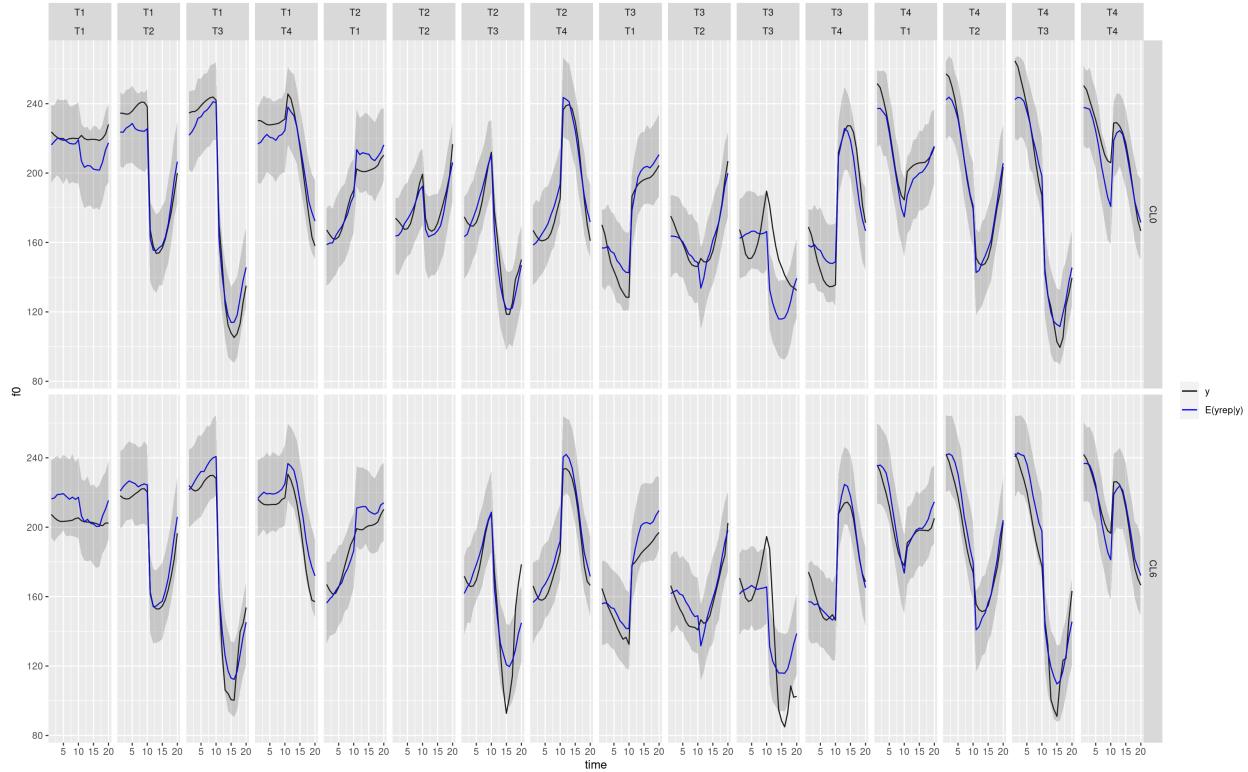
```



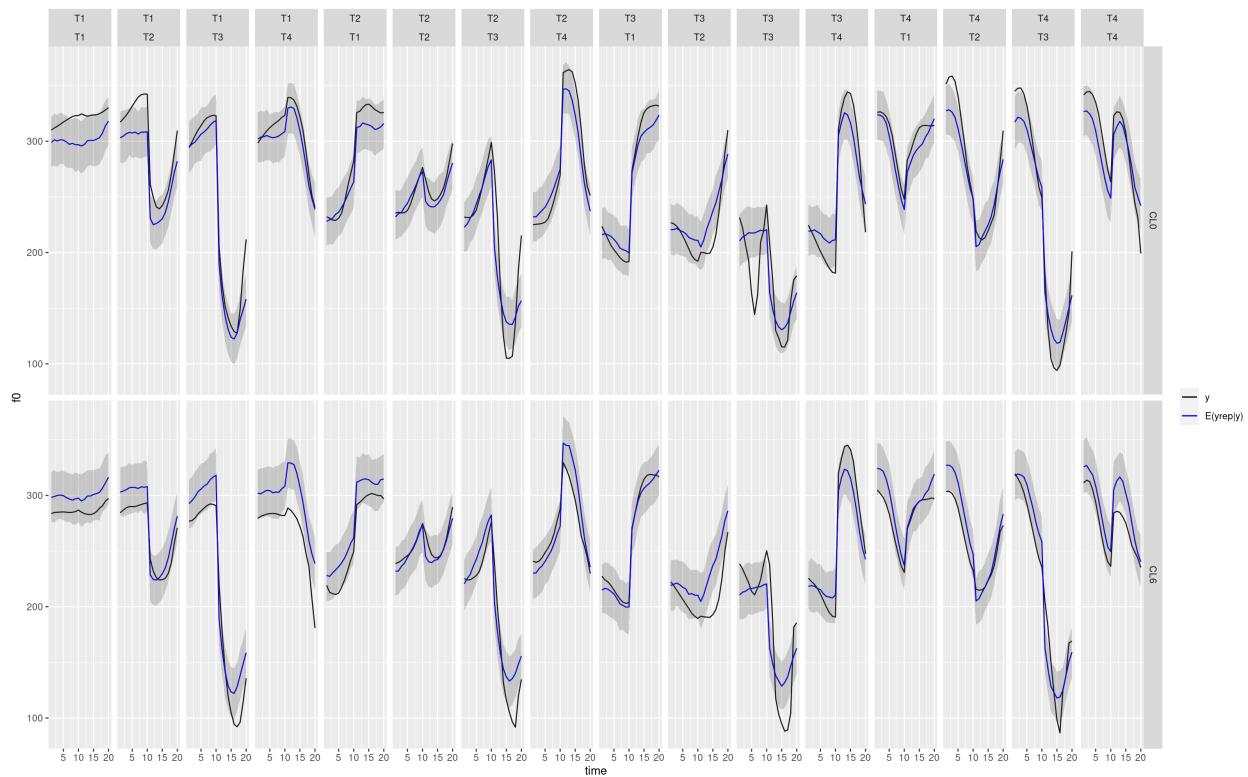
ppc_subject("S2", mandarino, ypred, lmin, lmax)



```
ppc_subject("S3", mandarino, ypred, lmin, lmax)
```



```
ppc_subject("S4", mandarino, ypred, lmin, lmax)
```



```

# ppc_subject("S5", mandarino, ypred, lmin, lmax)
# ppc_subject("S6", mandarino, ypred, lmin, lmax)
# ppc_subject("S7", mandarino, ypred, lmin, lmax)
# ppc_subject("S8", mandarino, ypred, lmin, lmax)
# ppc_subject("S9", mandarino, ypred, lmin, lmax)
# ppc_subject("S10", mandarino, ypred, lmin, lmax)
# ppc_subject("S11", mandarino, ypred, lmin, lmax)
# ppc_subject("S12", mandarino, ypred, lmin, lmax)

ppc_full(mandarino, ypred)

```

