

Mixed Model PD

Data

```
Datos %>%  
  ungroup() %>%  
  dplyr::select(Subject,Level,PD) %>%  
  group_by(Subject,Level) %>%  
  mutate(mid = 1:n()) %>%  
  pivot_wider(names_from=mid,values_from=PD) %>%  
  arrange(Subject,Level) %>%  
  kable("latex", booktabs = T) %>%  
  kable_styling(latex_options = c("striped", "scale_down"))
```

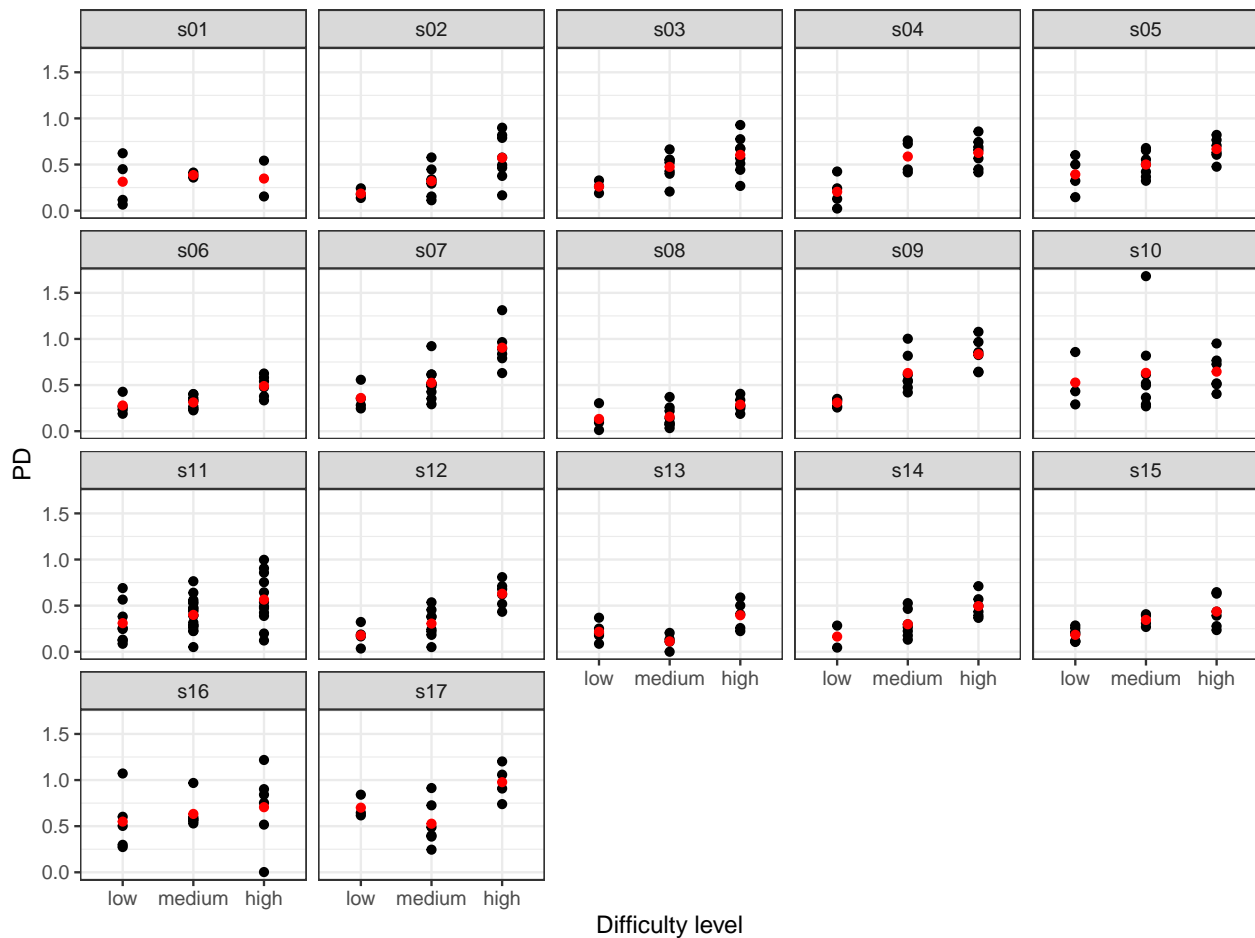
Subject	Level	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
s01	low	0.4496	0.0653	0.1166	0.6223															
s01	medium	0.3584	0.4130	0.3847																
s01	high	0.5421	0.1539																	
s02	low	0.1375	0.2422	0.1753																
s02	medium	0.5767	0.2926	0.1124	0.3179	0.3406	0.4468	0.1536												
s02	high	0.8992	0.8181	0.3766	0.4657	0.7887	0.5755	0.4946	0.1660											
s03	low	0.3274	0.2651	0.1895																
s03	medium	0.2070	0.5483	0.4275	0.5211	0.6642	0.5534	0.4001												
s03	high	0.2680	0.6748	0.9287	0.5675	0.7745	0.4426	0.5110	0.6703											
s04	low	0.4243	0.1281	0.0229	0.2419															
s04	medium	0.7608	0.7245	0.4148	0.4470															
s04	high	0.6576	0.8581	0.7439	0.4498	0.4149	0.5666	0.6897												
s05	low	0.4997	0.6024	0.1461	0.3229															
s05	medium	0.3668	0.4207	0.5019	0.3238	0.5547	0.6787	0.6535												
s05	high	0.6291	0.7662	0.7056	0.6060	0.8210	0.4763													
s06	low	0.4272	0.2644	0.2342	0.1891															
s06	medium	0.3336	0.3592	0.2426	0.4025	0.2681	0.3308	0.4009	0.2259	0.2440										
s06	high	0.5412	0.6253	0.4762	0.3785	0.3341	0.5811													
s07	low	0.2466	0.2825	0.5575	0.3538															
s07	medium	0.6131	0.4265	0.4856	0.5144	0.6161	0.5095	0.2921	0.9220	0.3530	0.5140									
s07	high	1.3118	0.8948	0.8379	0.7907	0.9658	0.6302													
s08	low	0.0127	0.3036	0.1198	0.0943															
s08	medium	0.3712	0.0756	0.2577	0.0335	0.0918	0.2190	0.0707	0.1411											
s08	high	0.4052	0.2488	0.2770	0.2709	0.1876	0.3389													
s09	low	0.2567	0.3433	0.3291	0.3505	0.2706														
s09	medium	1.0027	0.8177	0.6120	0.4199	0.5492	0.4736	0.5398												
s09	high	1.0774	0.9671	0.6386	0.8257	0.8564	0.6451													
s10	low	0.2907	0.8584	0.4327																
s10	medium	0.3656	0.6151	0.8187	0.2908	0.5207	0.2697	1.6808	0.4972											
s10	high	0.7261	0.7660	0.5185	0.4041	0.9512	0.5087													
s11	low	0.2465	0.5653	0.3812	0.1219	0.0865	0.1307	0.2564	0.6904											
s11	medium	0.7645	0.3942	0.4514	0.2239	0.6400	0.2855	0.5246	0.4775	0.4725	0.3922	0.2891	0.2262	0.0508	0.5389	0.4377	0.2605	0.2831	0.5613	0.3176
s11	high	0.9968	0.4234	0.8572	0.6441	0.3881	0.1980	0.4741	0.1219	0.9047	0.5377	0.7540	0.4890							
s12	low	0.3228	0.1867	0.0353	0.1662															
s12	medium	0.4543	0.3824	0.3775	0.5358	0.2197	0.1832	0.0503	0.2417											
s12	high	0.7105	0.8090	0.6212	0.6794	0.5191	0.4335													
s13	low	0.0867	0.1774	0.2510	0.3688	0.1978														
s13	medium	0.2045	0.1085	0.1366	0.0001															
s13	high	0.2570	0.5019	0.4069	0.5886	0.2239														
s14	low	0.0452	0.2838																	
s14	medium	0.2982	0.2244	0.5269	0.2667	0.1763	0.1307	0.4650												
s14	high	0.4335	0.3672	0.7113	0.4965	0.3929	0.5695													
s15	low	0.1109	0.2847	0.1180	0.1949	0.1068	0.2560	0.2141												
s15	medium	0.4068	0.3105	0.3933	0.2687															
s15	high	0.6461	0.3909	0.2775	0.4355	0.6300	0.2350													
s16	low	0.2737	0.5030	0.2979	0.6020	1.0714														
s16	medium	0.9685	0.5295	0.5974	0.5540	0.5707	0.5771													
s16	high	0.7535	0.5170	1.2180	0.9016	0.8415	0.0026													
s17	low	0.8413	0.6168	0.6444																
s17	medium	0.9135	0.3872	0.7261	0.4890	0.4003	0.2454													
s17	high	1.2019	1.0587	0.7393	0.9083															

Level	n	MD	SD
low	72	0.3046	0.2092
medium	124	0.4215	0.2314
high	106	0.6014	0.2541

Summary by group

```
Datos %>%
  group_by(Level) %>%
  summarise(n=n(),MD=mean(PD),SD=sd(PD)) %>%
  kable()%>%
  kable_styling(latex_options = c("striped"))
```

```
(q <-Datos %>% ggplot(aes(x=Level,y=PD)) +
  geom_point() + facet_wrap(~ Subject)+
  labs(x="Difficulty level")+theme_bw()+
  stat_summary(fun="mean", geom="point",color="red"))
```



Random Intercept and Slope Model

The following model is used to investigate whether there are significant differences between the study variables:

$$y_{ij} = \mu + l_k + s_j + (sl)_{jk} + \epsilon_{ij}, \quad (1)$$

where y_{ij} is the response variable (PD) for the i -th observation from the j -th subject, μ is the intercept, l_k is the k -th difficulty level, s_j is the j th subject effect, $(sl)_{jk}$ is the subject-level effect, i.e., the k -th level effect at the j -th subject, ϵ_{ij} is the error term (residual) for the i th observation from the j th subject.

We called *level* l a fixed effect, and ϵ is our *error term* that represent deviations from our predictions due to *random* factors that we cannot control experimentally. However, several measurements were taken for each subject at each difficulty level and that violates the assumption of independence of a linear model. On the other hand, each individual has a different cognitive load capacity, and this will be a characteristic factor that will affect all the responses of the same subject, which will make these responses interdependent instead of independent, see figure ???. The way we approaches this situation is adding a random effect to the subject and to the subject-level interaction. This allows us to solve this lack of independence by assuming a different intercept and slope for each subject. And finally, we assume that the residual, subject and subject-level effects are all relations of separate distributions, all with zero means:

$$\begin{aligned}\epsilon_{ij} &\sim N(0, \sigma^2), \\ s_j &\sim N(0, \sigma_s^2), \\ (sl)_{jk} &\sim N(0, \sigma_{sl}^2).\end{aligned}$$

Hence, s_j and $(sl)_{jk}$ are now random effects, and μ and l_k are fixed effects.

Using the **R** notation the model is

$$PD = (b_0 + u_{Subject}) + b_{Level}Level + \epsilon$$

In order to evaluate if there is an effect due to the difficulty level we will use the likelihood ratio test of the model with the *Level* effect against the model without the *Level* effect.

```
PD_mixed_reducido <- lme4::lmer(PD ~ 1 + (1+Level|Subject),data=Datos,REML=F)

PD_mixed_lme4 <- lme4::lmer(PD ~ Level + (1+Level|Subject),data=Datos,REML=F)

anova(PD_mixed_reducido,PD_mixed_lme4)

## Data: Datos
## Models:
## PD_mixed_reducido: PD ~ 1 + (1 + Level | Subject)
## PD_mixed_lme4: PD ~ Level + (1 + Level | Subject)
##          npar    AIC    BIC logLik deviance Chisq Df Pr(>Chisq)
## PD_mixed_reducido      8 -44.9 -15.2   30.4   -60.9
## PD_mixed_lme4         10 -71.5 -34.4   45.7   -91.5  30.6  2 0.00000023 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The p-value of the ratio test is significant at a level of 0.001.

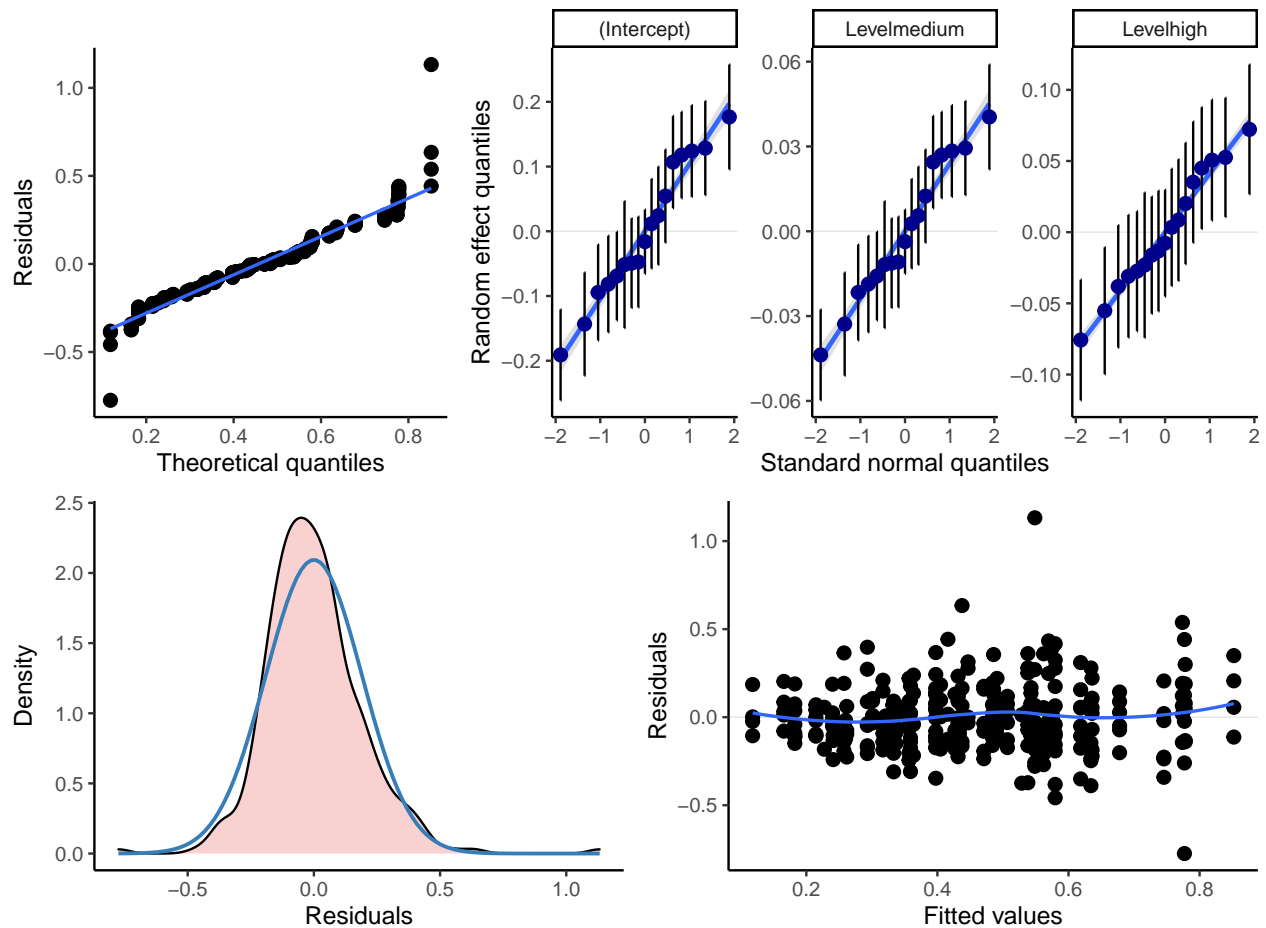
```
PD_mixed_lme4 <- lme4::lmer(PD ~ Level + (1+Level|Subject),data=Datos)
summary(PD_mixed_lme4)

## Linear mixed model fit by REML ['lmerMod']
## Formula: PD ~ Level + (1 + Level | Subject)
##      Data: Datos
```

```
##
## REML criterion at convergence: -75.7
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.950 -0.594 -0.100  0.464  5.776
##
## Random effects:
##   Groups   Name                Variance Std.Dev. Corr
##   Subject  (Intercept)  0.012463  0.1116
##             Levelmedium  0.000653  0.0256   1.00
##             Levelhigh    0.002185  0.0467   0.91  0.91
##   Residual                0.038427  0.1960
## Number of obs: 302, groups:  Subject, 17
##
## Fixed effects:
##              Estimate Std. Error t value
## (Intercept)   0.3091     0.0357    8.66
## Levelmedium   0.1081     0.0301    3.59
## Levelhigh     0.2943     0.0323    9.11
##
## Correlation of Fixed Effects:
##              (Intr) Lvlmdm
## Levelmedium -0.346
## Levelhigh   -0.225  0.630
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular

p<-plot_model(PD_mixed_lme4, type = "diag")

({p[[1]]+theme(plot.title=element_blank(),plot.subtitle=element_blank())+scale_x_continuous(name="Theor
```



```
contr <- glht(PD_mixed_lme4, linfct=mcp(Level="Tukey"))
summary(contr, test = adjusted("holm"))
```

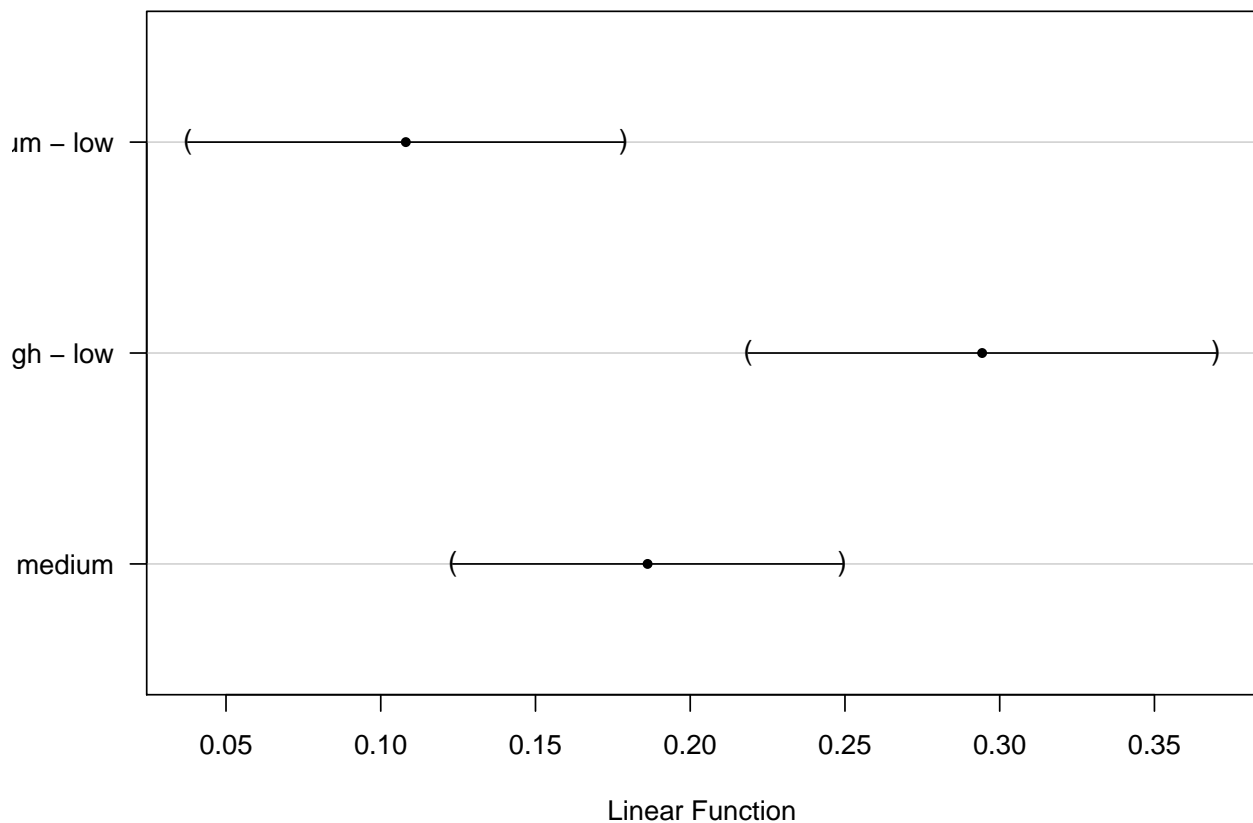
```
##
## Simultaneous Tests for General Linear Hypotheses
##
## Multiple Comparisons of Means: Tukey Contrasts
##
##
## Fit: lme4::lmer(formula = PD ~ Level + (1 + Level | Subject), data = Datos)
##
## Linear Hypotheses:
##           Estimate Std. Error z value      Pr(>|z|)
## medium - low == 0    0.1081    0.0301   3.59      0.00033 ***
## high - low == 0      0.2943    0.0323  9.11 < 0.0000000000000002 ***
## high - medium == 0   0.1862    0.0269  6.92      0.000000000000088 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## (Adjusted p values reported -- holm method)
```

```
confint(contr)
```

```
##
## Simultaneous Confidence Intervals
##
```

```
## Multiple Comparisons of Means: Tukey Contrasts
##
##
## Fit: lme4::lmer(formula = PD ~ Level + (1 + Level | Subject), data = Datos)
##
## Quantile = 2.34
## 95% family-wise confidence level
##
## Linear Hypotheses:
##               Estimate lwr    upr
## medium - low == 0  0.1081  0.0377 0.1785
## high - low == 0   0.2943  0.2188 0.3699
## high - medium == 0 0.1862  0.1233 0.2492
plot(confint(contr))
```

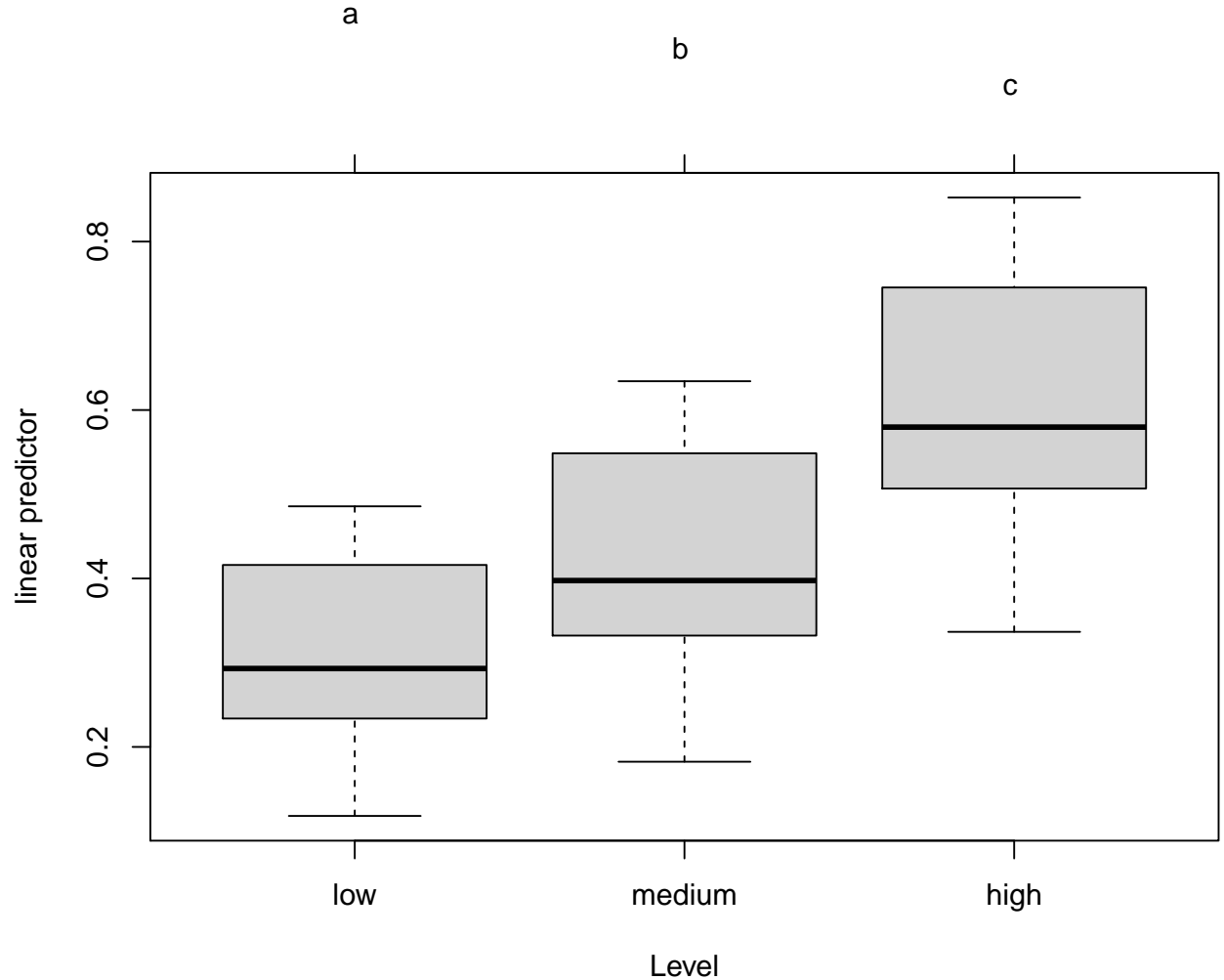
95% family-wise confidence level



```
contr.cld <- cld(contr)
old.par <- par(mai=c(1,1,1.25,1), no.readonly = TRUE)
plot(contr.cld)
```

Subject	Name	Training	Nivel	BLPS	MPDC	APCPS	PD	Entropy	TTP	PDS	SequenceMemory	SMN	id	Level	res	fit
s10	SequenceMemory_r24	FALSE	3	2.744	1.1568	0.4215	1.6808	-1.974	7176806	0	r24	24	14	medium	1.1322	0.5486
s16	SequenceMemory_r25	FALSE	1	4.300	0.0147	0.0034	1.0714	-2.111	3907135	0	r25	25	13	low	0.6338	0.4376
s07	SequenceMemory_r09	FALSE	6	3.654	0.3562	0.0975	1.3118	-2.009	8532099	0	r09	9	6	high	0.5381	0.7738
s10	SequenceMemory_r05	FALSE	1	3.083	0.4308	0.1397	0.8584	-1.820	8153300	0	r05	5	5	low	0.4424	0.4160
s16	SequenceMemory_r19	FALSE	6	4.291	0.1714	0.0399	1.2180	-2.159	13296613	0	r19	19	10	high	0.4411	0.7769
s09	SequenceMemory_r02	FALSE	3	3.637	0.4854	0.1335	1.0027	-2.046	5641562	0	r02	2	1	medium	0.4331	0.5696

Subject	Name	Training	Nivel	BLPS	MPDC	APCPS	PD	Entropy	TTP	PDS	SequenceMemory	SMN	id	Level	res	fit
s02	SequenceMemory_r30	FALSE	6	4.359	-0.1703	-0.0391	0.1660	-2.067	7794586	0	r30	30	17	high	-0.3721	0.5380
s01	SequenceMemory_r17	FALSE	6	4.023	-0.2674	-0.0665	0.1539	-1.911	2292544	0	r17	17	7	high	-0.3748	0.5287
s11	SequenceMemory_r15	FALSE	6	3.522	0.0065	0.0018	0.1980	-1.819	6498755	0	r15	15	20	high	-0.3817	0.5797
s17	SequenceMemory_r26	FALSE	3	3.706	-0.0342	-0.0092	0.2454	-1.877	5601869	0	r26	26	11	medium	-0.3888	0.6342
s11	SequenceMemory_r18	FALSE	6	3.521	-0.0856	-0.0243	0.1219	-1.781	7136712	0	r18	18		high	-0.4578	0.5797
s16	SequenceMemory_r28	FALSE	6	4.849	-0.3060	-0.0631	0.0026	-2.184	14432973	0	r28	28	15	high	-0.7743	0.7769



```

par(old.par)

Datos2 = Datos
Datos2$res = residuals(PD_mixed_lme4,type="pearson")
Datos2$fit = fitted(PD_mixed_lme4,type="pearson")

Datos2 %>% arrange(desc(res)) %>% head() %>% kable()%>%
  kable_styling(latex_options = c("striped", "scale_down"))

Datos2 %>% arrange(desc(res)) %>% tail() %>% kable()%>%
  kable_styling(latex_options = c("striped", "scale_down"))

```



```
shapiro.test(Datos2$res)

##
##  Shapiro-Wilk normality test
##
## data:  Datos2$res
## W = 0.95, p-value = 0.00000001

goftest::ad.test(Datos2$res,null="pnorm",mean=mean(Datos2$res), sd=sd(Datos2$res), estimated=TRUE)

##
##  Anderson-Darling test of goodness-of-fit
##  Braun's adjustment using 17 groups
##  Null hypothesis: Normal distribution
##  with parameters mean = -0.000000000000000270980301091141, sd =
##  0.190494627388844
##  Parameters assumed to have been estimated from data
##
## data:  Datos2$res
## Anmax = 1.8, p-value = 0.9

rstatix::levene_test(data=ungroup(Datos2),res~Level)

## # A tibble: 1 x 4
##   df1 df2 statistic p
##   <int> <int>   <dbl> <dbl>
## 1     2   299     1.41 0.245
```

The same model without the outliers

We repeat the analysis without the outlier

```
# we exclude the outlier
Datos <- Datos %>% filter(!(Subject=="s10" & SMN==24),
                          !(Subject=="s16" & SMN==28))

PD_mixed_lme4 <- lme4::lmer(PD ~ Level + (1+Level|Subject),data=Datos)
summary(PD_mixed_lme4)

## Linear mixed model fit by REML ['lmerMod']
## Formula: PD ~ Level + (1 + Level | Subject)
## Data: Datos
##
## REML criterion at convergence: -131.7
##
## Scaled residuals:
##   Min       1Q   Median       3Q      Max
## -2.635 -0.648 -0.095  0.516  3.337
##
## Random effects:
##   Groups   Name      Variance Std.Dev. Corr
##   Subject (Intercept) 0.01344  0.1159
##           Levelmedium 0.00185  0.0430  0.17
##           Levelhigh   0.00469  0.0685  0.75 0.78
##   Residual              0.03116  0.1765
```

```
## Number of obs: 300, groups: Subject, 17
##
## Fixed effects:
##           Estimate Std. Error t value
## (Intercept)  0.3083    0.0351    8.78
## Levelmedium  0.0997    0.0286    3.48
## Levelhigh    0.3033    0.0321    9.46
##
## Correlation of Fixed Effects:
##           (Intr) Lvlmdm
## Levelmedium -0.391
## Levelhigh   -0.083  0.640
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular
```

```
anova(PD_mixed_lme4)
```

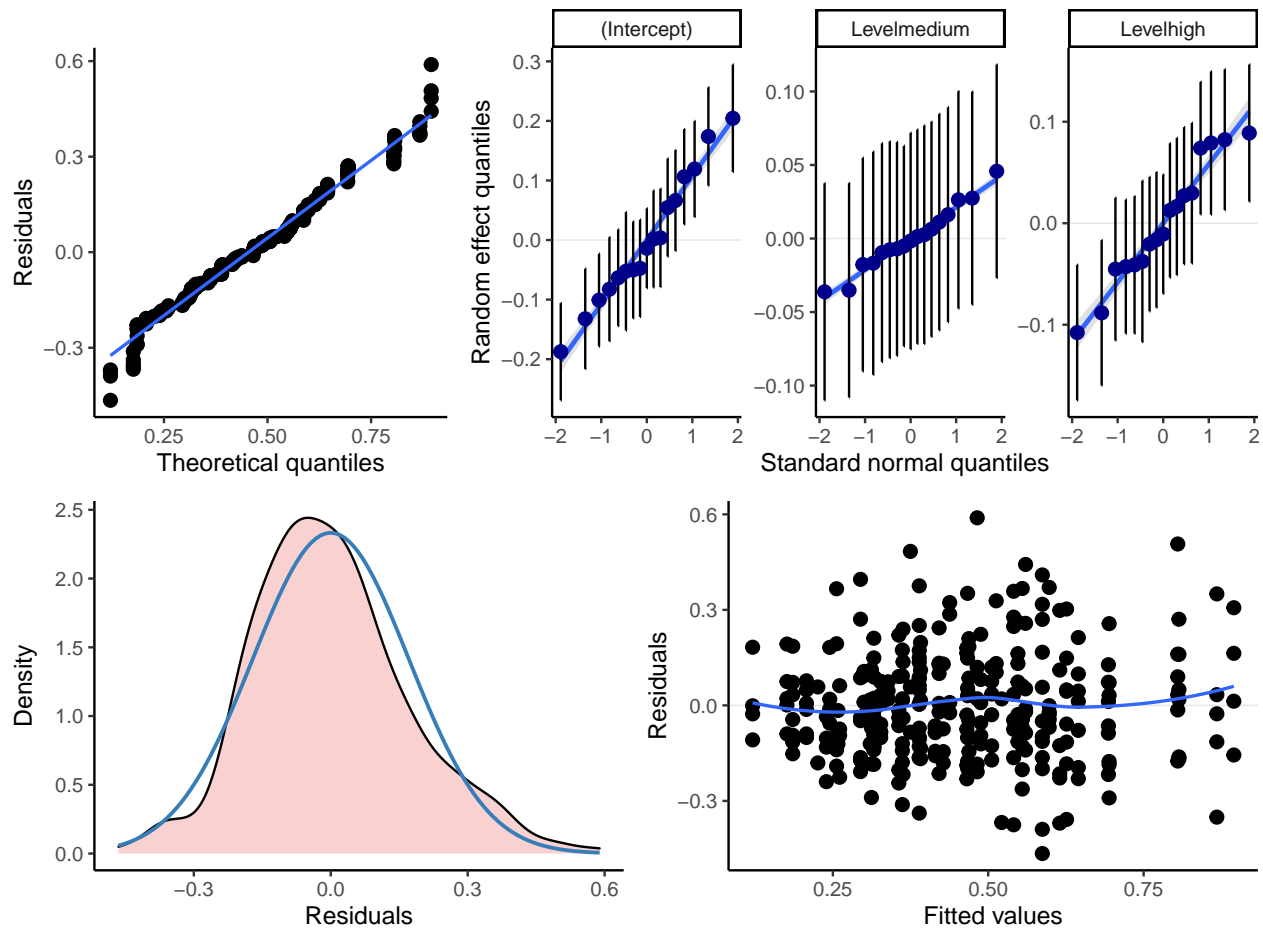
```
## Analysis of Variance Table
##           npar Sum Sq Mean Sq F value
## Level    2    3.14    1.57    50.4
```

```
coef(PD_mixed_lme4)
```

```
## $Subject
##           (Intercept) Levelmedium Levelhigh
## s01      0.2559      0.08288    0.2657
## s02      0.2581      0.09798    0.2827
## s03      0.3101      0.11083    0.3159
## s04      0.3120      0.12595    0.3329
## s05      0.3629      0.10598    0.3304
## s06      0.2450      0.08194    0.2605
## s07      0.4276      0.12713    0.3773
## s08      0.1209      0.06452    0.1955
## s09      0.4147      0.14542    0.3921
## s10      0.3747      0.09203    0.3198
## s11      0.2945      0.09450    0.2925
## s12      0.2609      0.10095    0.2869
## s13      0.1761      0.06344    0.2150
## s14      0.2258      0.09008    0.2622
## s15      0.2075      0.09261    0.2581
## s16      0.4822      0.11589    0.3856
## s17      0.5128      0.10227    0.3823
##
## attr(,"class")
## [1] "coef.mer"
```

```
p<-plot_model(PD_mixed_lme4, type = "diag")
```

```
(q<-p[[1]]+theme(plot.title=element_blank(),plot.subtitle=element_blank()))+scale_x_continuous(name="Th
```



```
# muy importante Tukey para lme4.
contr <- glht(PD_mixed_lme4, linfct=mcp(Level="Tukey"))
summary(contr, test = adjusted("holm"))

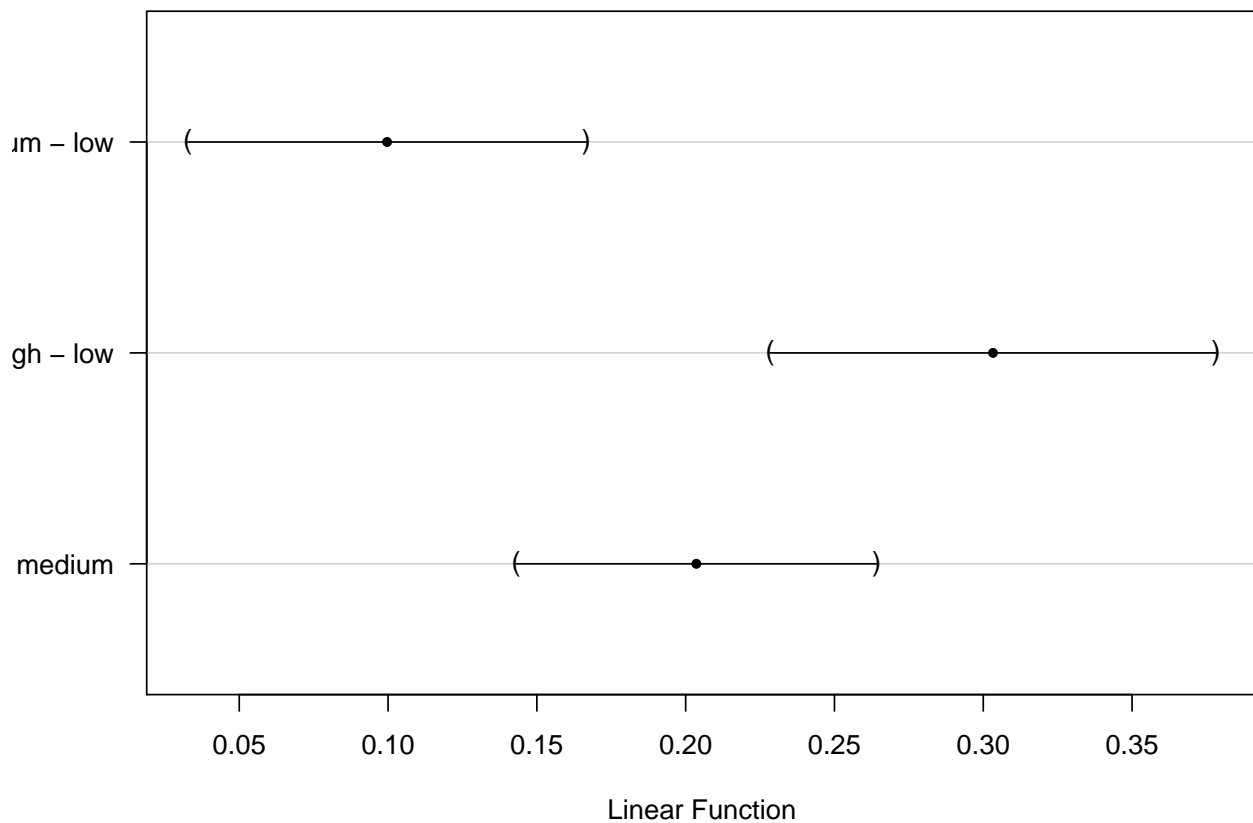
##
## Simultaneous Tests for General Linear Hypotheses
##
## Multiple Comparisons of Means: Tukey Contrasts
##
##
## Fit: lme4::lmer(formula = PD ~ Level + (1 + Level | Subject), data = Datos)
##
## Linear Hypotheses:
##           Estimate Std. Error z value      Pr(>|z|)
## medium - low == 0    0.0997    0.0286   3.48    0.0005 ***
## high - low == 0      0.3033    0.0321  9.46 < 0.0000000000000002 ***
## high - medium == 0   0.2036    0.0259  7.85    0.0000000000000008 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## (Adjusted p values reported -- holm method)

confint(contr)

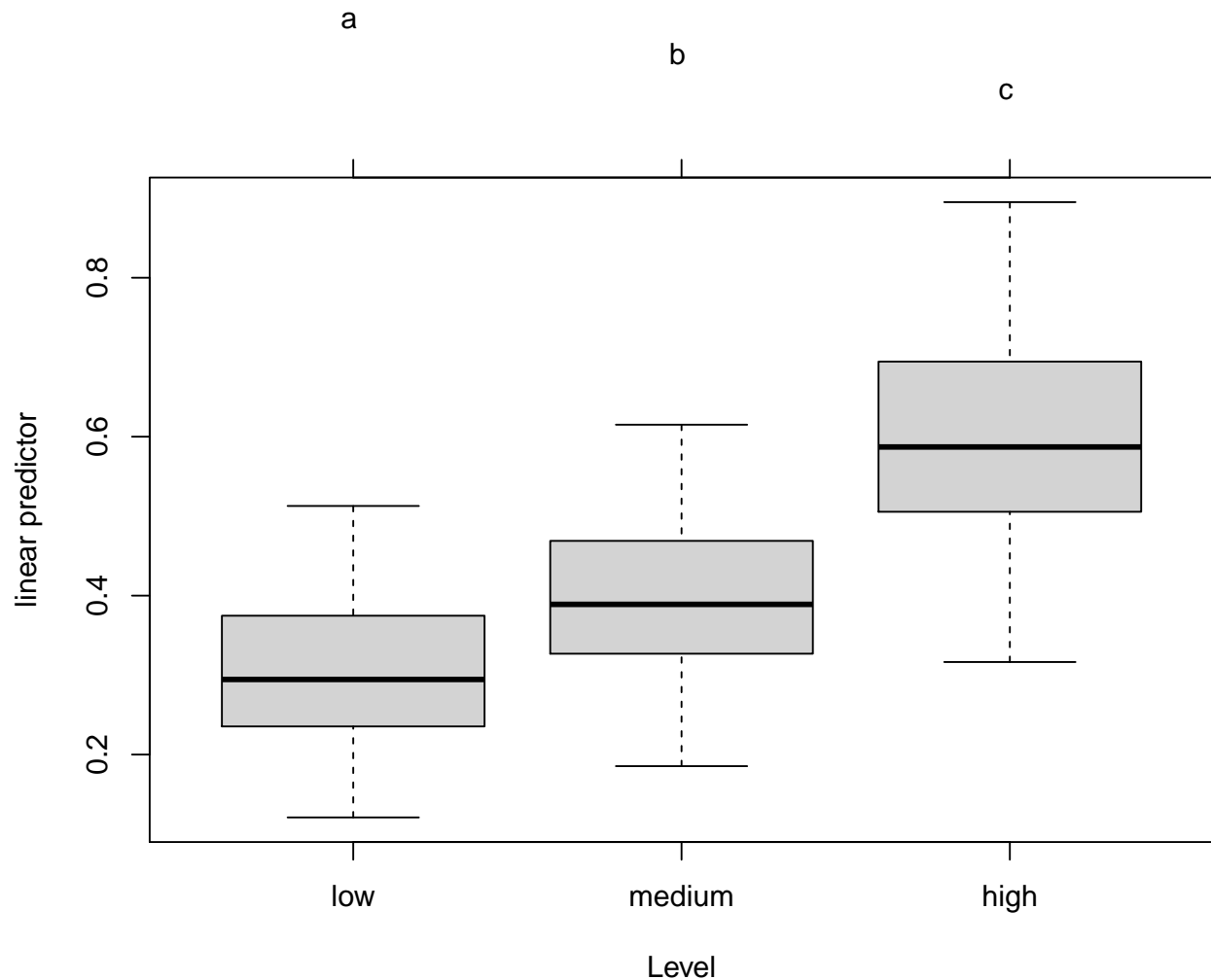
##
## Simultaneous Confidence Intervals
```

```
##
## Multiple Comparisons of Means: Tukey Contrasts
##
##
## Fit: lme4::lmer(formula = PD ~ Level + (1 + Level | Subject), data = Datos)
##
## Quantile = 2.339
## 95% family-wise confidence level
##
## Linear Hypotheses:
##               Estimate lwr      upr
## medium - low == 0  0.0997  0.0327 0.1666
## high - low == 0   0.3033  0.2283 0.3782
## high - medium == 0 0.2036  0.1430 0.2642
plot(confint(contr))
```

95% family-wise confidence level



```
contr.cld <- cld(contr)
### use sufficiently large upper margin
old.par <- par(mai=c(1,1,1.25,1), no.readonly = TRUE)
### plot
plot(contr.cld)
```



```
par(old.par)
```

```
Datos2=Datos
Datos2$res = residuals(PD_mixed_lme4,type="pearson")
Datos2$fit = fitted(PD_mixed_lme4,type="pearson")
shapiro.test(Datos2$res)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  Datos2$res
## W = 0.98, p-value = 0.002
```

```
goftest::ad.test(Datos2$res,null="pnorm",mean=mean(Datos2$res), sd=sd(Datos2$res), estimated=TRUE)
```

```
##
##  Anderson-Darling test of goodness-of-fit
##  Braun's adjustment using 17 groups
##  Null hypothesis: Normal distribution
##  with parameters mean = -0.000000000000000515008562371348, sd =
##  0.170981201138494
##  Parameters assumed to have been estimated from data
##
```

```
## data: Datos2$res
## Anmax = 2.3, p-value = 0.7
rstatix::levene_test(data=ungroup(Datos2),res~Level)
```

```
## # A tibble: 1 x 4
##   df1 df2 statistic    p
##   <int> <int>     <dbl> <dbl>
## 1     2   297       1.60 0.203
```

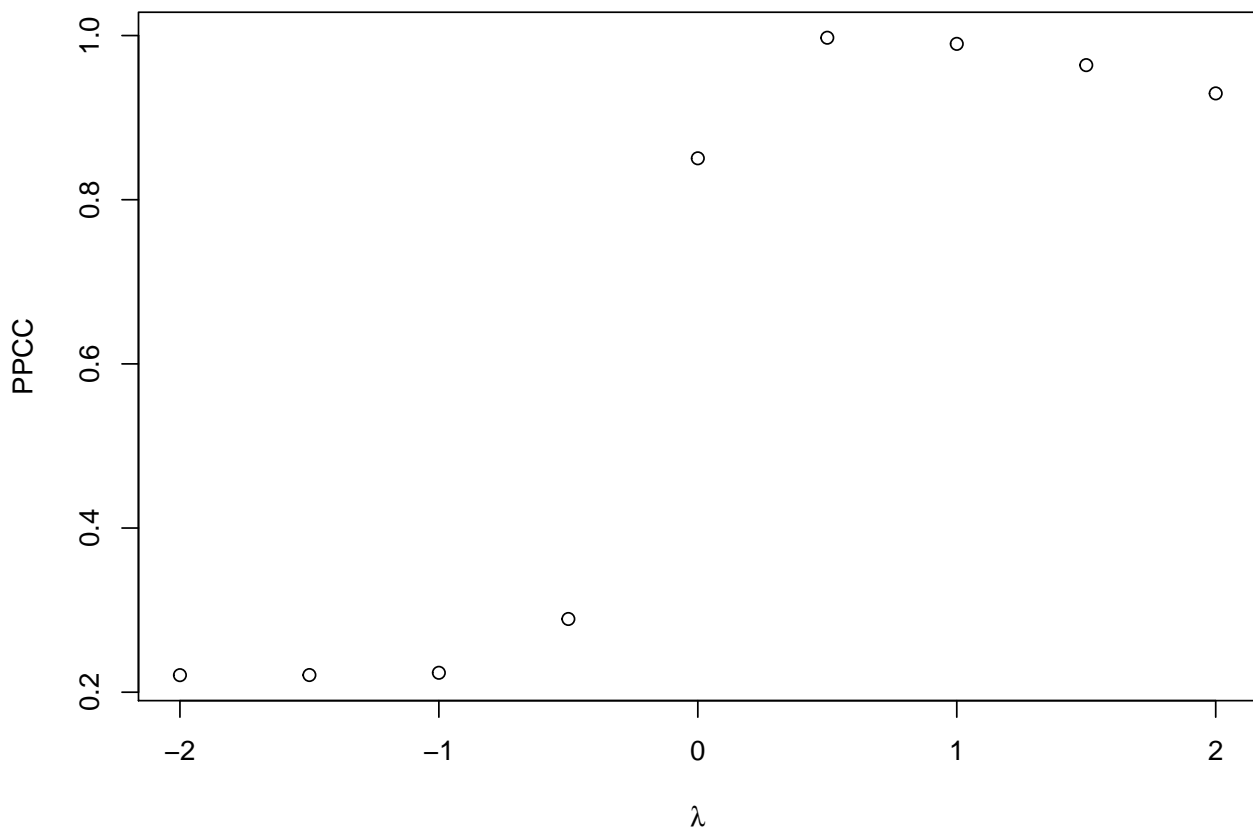
Box-Cox transformation

```
(PD_lm <- lm(PD ~ Level ,data=Datos))
```

```
##
## Call:
## lm(formula = PD ~ Level, data = Datos)
##
## Coefficients:
## (Intercept) Levelmedium Levelhigh
##          0.305         0.107         0.303
```

```
boxcox.list <- EnvStats::boxcox(PD_lm)
plot(boxcox.list)
```

Box-Cox Transformation Results: PPCC vs. lambda for PD_lm



Level	n	MD	SD
low	72	-0.8833	0.3183
medium	123	-0.7148	0.2983
high	105	-0.4545	0.3075

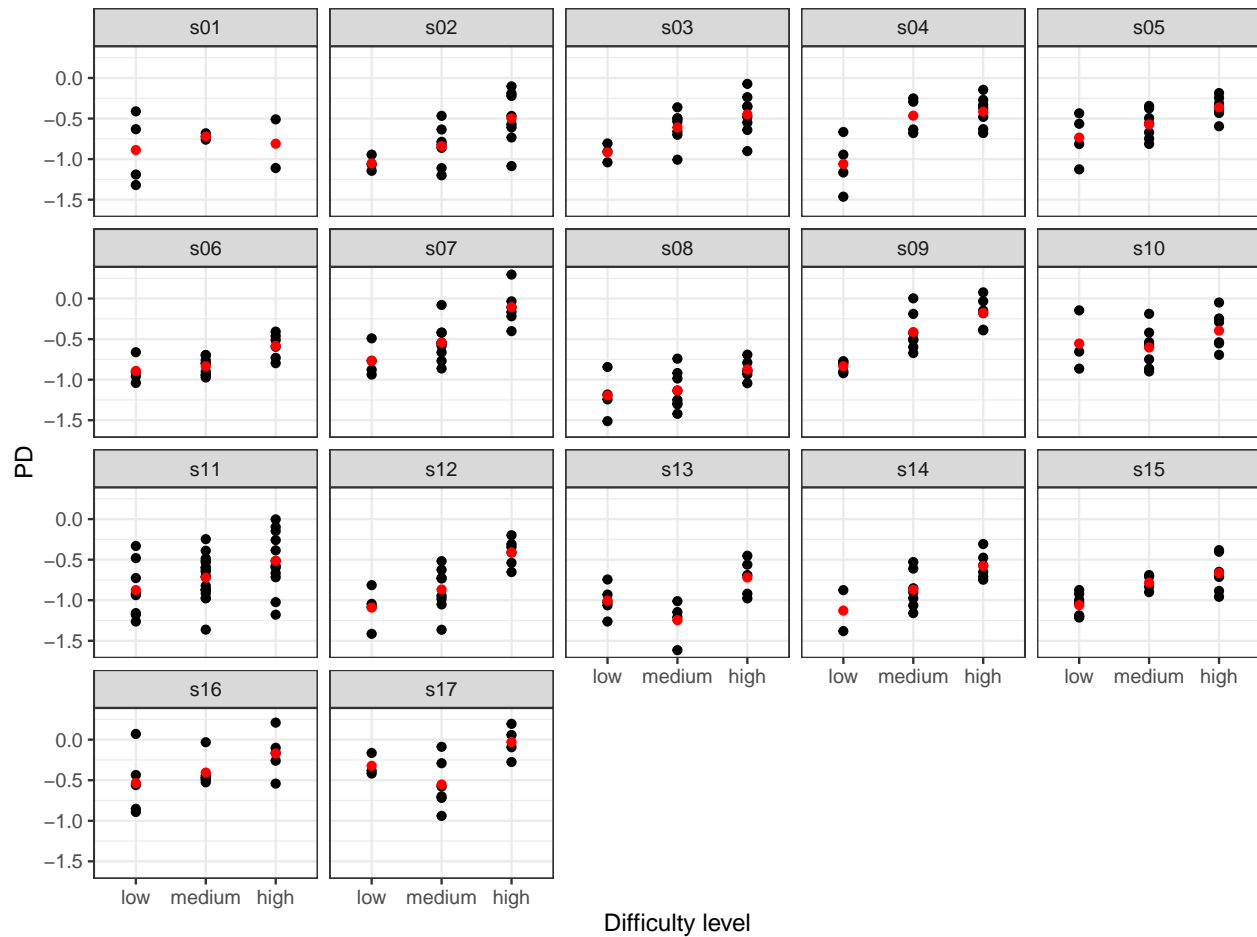
```
(boxcox.list <- EnvStats::boxcox(PD_lm,optimize = TRUE))

## $lambda
## [1] 0.6171
##
## $objective
## [1] 0.9987
##
## $objective.name
## [1] "PPCC"
##
## $optimize
## [1] TRUE
##
## $optimize.bounds
## lower upper
##      -2      2
##
## $eps
## [1] 0.0000000000000000222
##
## $lm.obj
##
## Call:
## lm(formula = PD ~ Level, data = Datos, y = TRUE, qr = TRUE)
##
## Coefficients:
## (Intercept) Levelmedium Levelhigh
##      0.305      0.107      0.303
##
##
## $sample.size
## [1] 300
##
## $data.name
## [1] "PD_lm"
##
## attr("class")
## [1] "boxcoxLm"

Datos$PD = (Datos$PD^(0.6171)-1)/(0.6171)
Datos %>%
  group_by(Level) %>%
  summarise(n=n(),MD=mean(PD),SD=sd(PD)) %>%
  kable()%>%
  kable_styling(latex_options = c("striped"))

(q <- Datos %>% ggplot(aes(x=Level,y=PD)) +
```

```
geom_point() + facet_wrap(~ Subject)+
labs(x="Difficulty level")+theme_bw()+
stat_summary(fun="mean", geom="point",color="red"))
```



```
PD_mixed_lme4 <- lme4::lmer(PD ~ Level + (1+Level|Subject),data=Datos)
summary(PD_mixed_lme4)
```

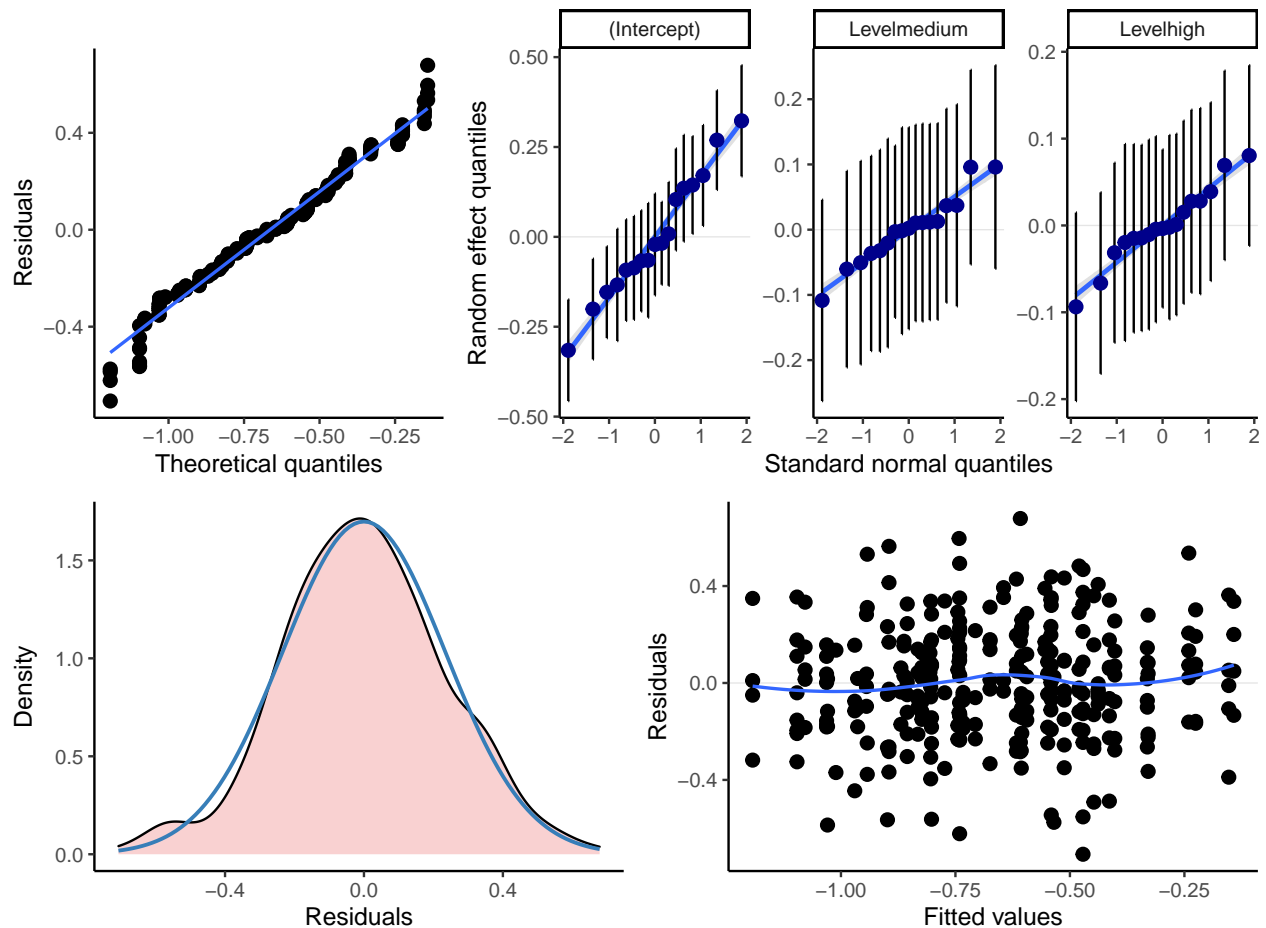
```
## Linear mixed model fit by REML ['lmerMod']
## Formula: PD ~ Level + (1 + Level | Subject)
## Data: Datos
##
## REML criterion at convergence: 62.1
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.9026 -0.6319 -0.0028  0.6138  2.7869
##
## Random effects:
## Groups   Name                Variance Std.Dev. Corr
## Subject (Intercept)  0.03419   0.1849
##           Levelmedium 0.00868   0.0932  -0.05
##           Levelhigh   0.00478   0.0691   0.14  0.98
## Residual                0.05930   0.2435
## Number of obs: 300, groups: Subject, 17
```



```
##
## Fixed effects:
##           Estimate Std. Error t value
## (Intercept) -0.8773    0.0535  -16.39
## Levelmedium  0.1574    0.0435   3.62
## Levelhigh    0.4272    0.0414  10.32
##
## Correlation of Fixed Effects:
##           (Intr) Lvlmdm
## Levelmedium -0.388
## Levelhigh   -0.337  0.691
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular
```

```
p<-plot_model(PD_mixed_lme4, type = "diag")
```

```
({p[[1]]+theme(plot.title=element_blank(),plot.subtitle=element_blank())+scale_x_continuous(name="Theoretical quantiles")})
```



```
contr <- glht(PD_mixed_lme4, linfct=mcp(Level="Tukey"))
summary(contr, test = adjusted("holm"))
```

```
##
## Simultaneous Tests for General Linear Hypotheses
##
## Multiple Comparisons of Means: Tukey Contrasts
```

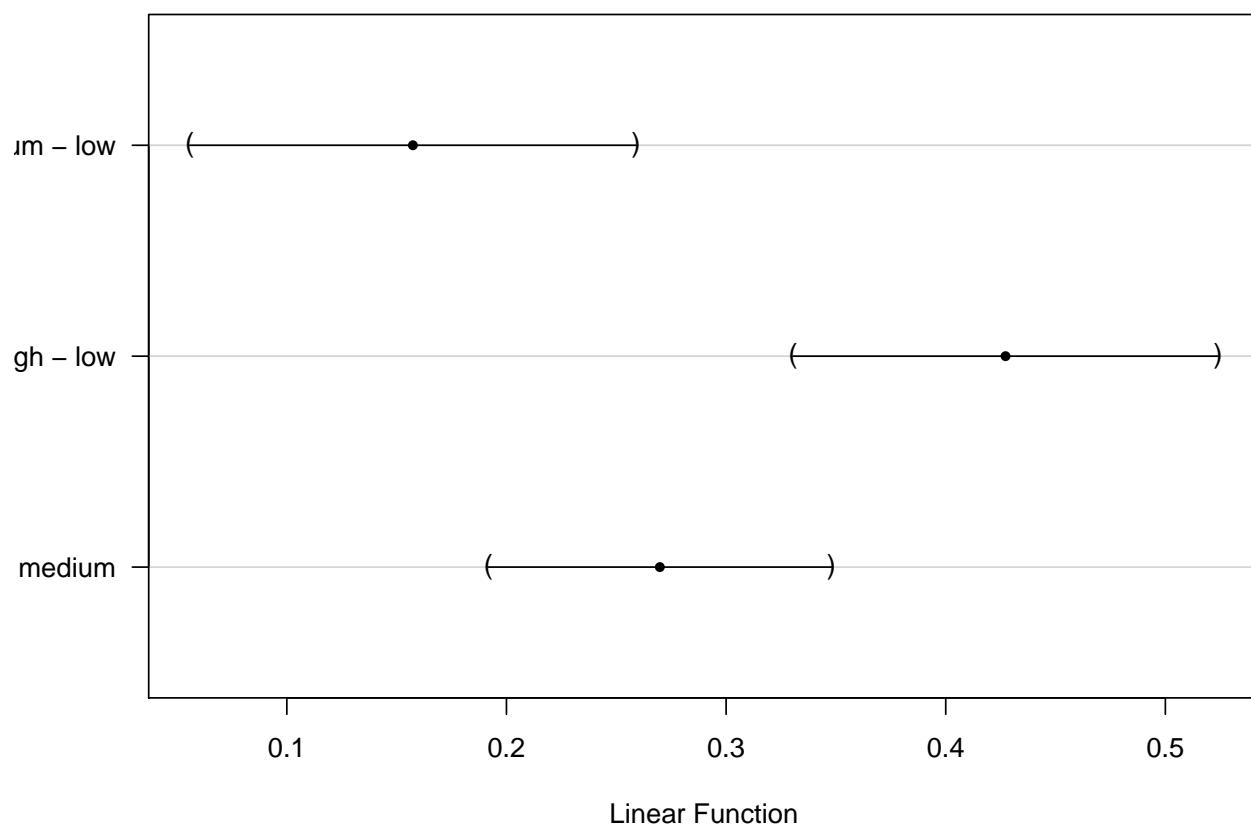
```
##
##
## Fit: lme4::lmer(formula = PD ~ Level + (1 + Level | Subject), data = Datos)
##
## Linear Hypotheses:
##           Estimate Std. Error z value      Pr(>|z|)
## medium - low == 0    0.1574    0.0435   3.62      0.00029 ***
## high - low == 0     0.4272    0.0414  10.32 < 0.0000000000000002 ***
## high - medium == 0  0.2698    0.0334   8.07  0.00000000000000013 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## (Adjusted p values reported -- holm method)

confint(contr)

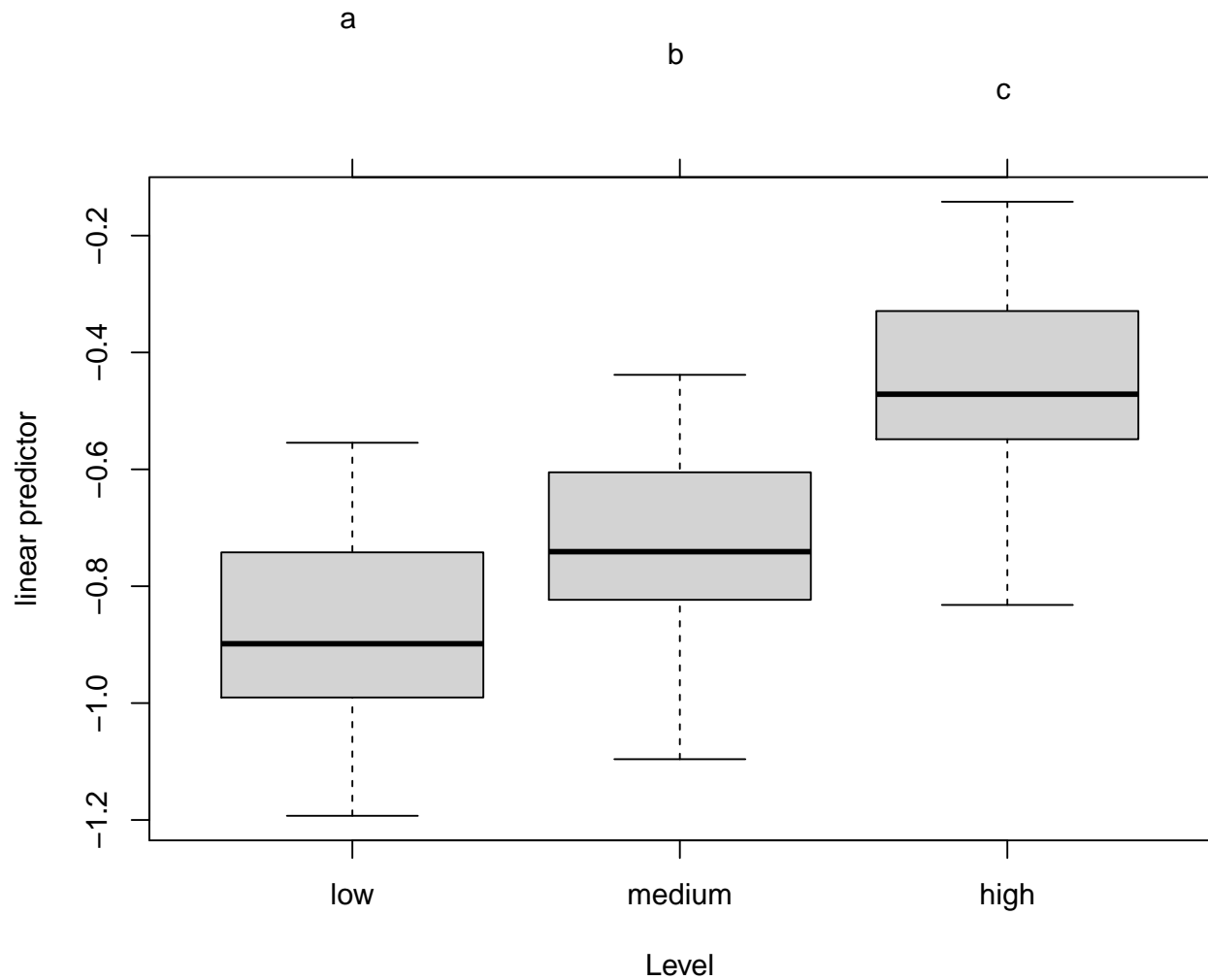
##
## Simultaneous Confidence Intervals
##
## Multiple Comparisons of Means: Tukey Contrasts
##
##
## Fit: lme4::lmer(formula = PD ~ Level + (1 + Level | Subject), data = Datos)
##
## Quantile = 2.337
## 95% family-wise confidence level
##
## Linear Hypotheses:
##           Estimate lwr    upr
## medium - low == 0  0.1574  0.0558 0.2590
## high - low == 0   0.4272  0.3304 0.5240
## high - medium == 0 0.2698  0.1917 0.3480

plot(confint(contr))
```

95% family-wise confidence level



```
contr.cld <- cld(contr)
old.par <- par(mai=c(1,1,1.25,1), no.readonly = TRUE)
plot(contr.cld)
```



```
par(old.par)
```

Non parametric tests

```
kruskal.test(PD ~ Level, data=Datos)
```

```
##
## Kruskal-Wallis rank sum test
##
## data: PD by Level
## Kruskal-Wallis chi-squared = 70, df = 2, p-value = 0.0000000000000005
```

```
PMCMR::posthoc.kruskal.nemenyi.test(data=Datos,PD~Level, dist="Tukey")
```

```
##
## Pairwise comparisons using Tukey and Kramer (Nemenyi) test
## with Tukey-Dist approximation for independent samples
##
## data: PD by Level
##
## low medium
## medium 0.0016 -
```

```
## high 0.000000000000037 0.000000094995046
```

```
##
```

```
## P value adjustment method: none
```

```
PMCMRplus::tukeyTest(data=Datos,PD~Level)
```

```
##          low          medium
```

```
## medium 0.00073      -
```

```
## high 0.00000000000009 0.000000018759
```