1 Dataset

86 subjects, mean age 144.1 ($\sim$ 12 years), sd 30.90.

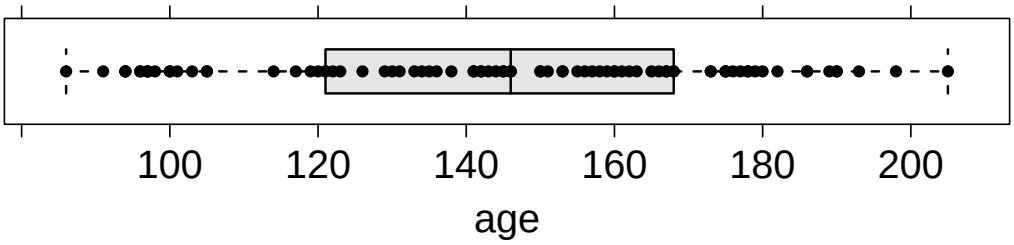


Figure 1: Age distribution.

Clinical profile:

- DSM5: classification of dyslexia in 'low' (class 1), 'medium' (class 2), 'high' (class 3).

DSM5 class	number of subjects
class 1	42
class 2	14
class 3	30

Table 1: Clinical profile. DSM5 classification.

Cognitivie profile:

- WISC-III/IV: 5 *scores*, 7 *subscales*.
  Only the subscale scores are considered. This in order to perform machine learning procedures without involving dependent variables.
  The subscale scores were reduced to 7 after the two instruments, WISC-III and WISC-IV, were merged.

  Subscale mean: 10.
  Subscale standard deviation: 3.

WISC subscales	range	mean	sd
dc	6 : 18	11.13	2.86
so	4 : 17	10.36	2.79
mc	2 : 15	8.40	2.75
cf	1 : 14	7.60	2.67
vc	3 : 17	10.02	2.73
co	5 : 19	11.08	2.70
rs	2 : 16	9.36	2.88

Table 2: Cognitive profile. WISC subscales.

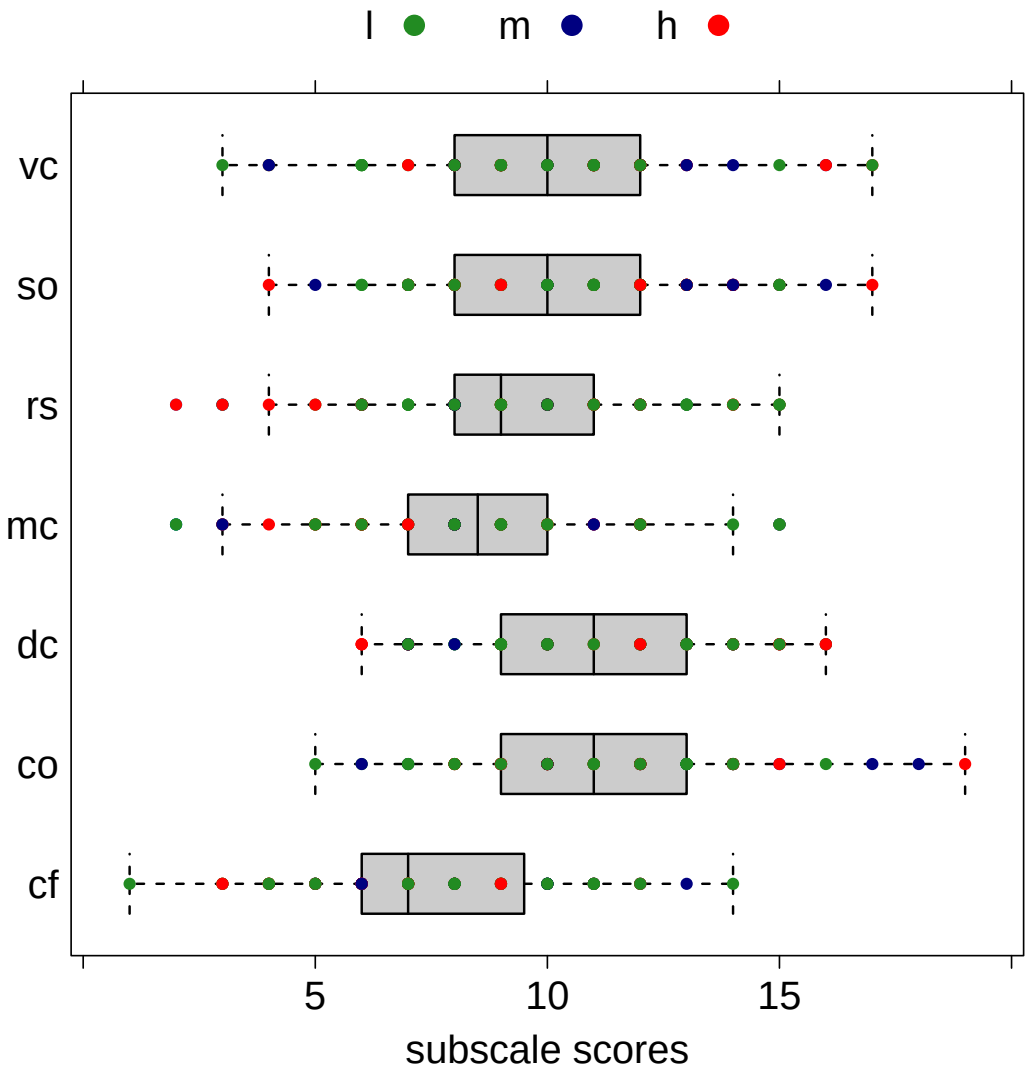


Figure 2: WISC subscale distribution.

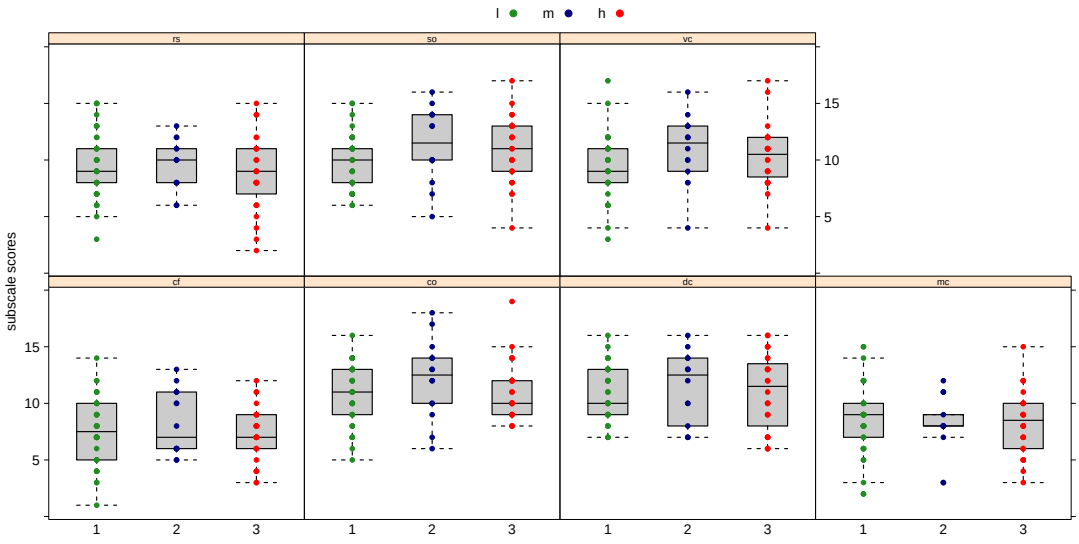


Figure 3: WISC subscale distribution by class.

- DDE: 4 *scores* measuring word/non-word reading speed (wspeed, nwspeed) and accuracy (wacc, nwacc).
  DDE scores are sigma values, with -2.0 as the threshold for impairment. These values are computed with respect to age.

DDE scores	range	mean	sd
wspeed	$-13.43 : -0.46$	-3.93	2.61
wacc	$-10.30 : 1.00$	-2.50	2.40
nwspeed	$-9.90 : 0.20$	-3.57	2.24
nwacc	$-9.00 : 1.30$	-1.33	1.74

Table 3: Cognitive profile. DDE scores.

Outliers: subject 5, 673.
Subject 5 $\longrightarrow$ wspeed= -13.43, new range $-11.60 : -0.46$
Subject 673 $\longrightarrow$ nwacc= -9.00, new range $-4.40 : 1.30$

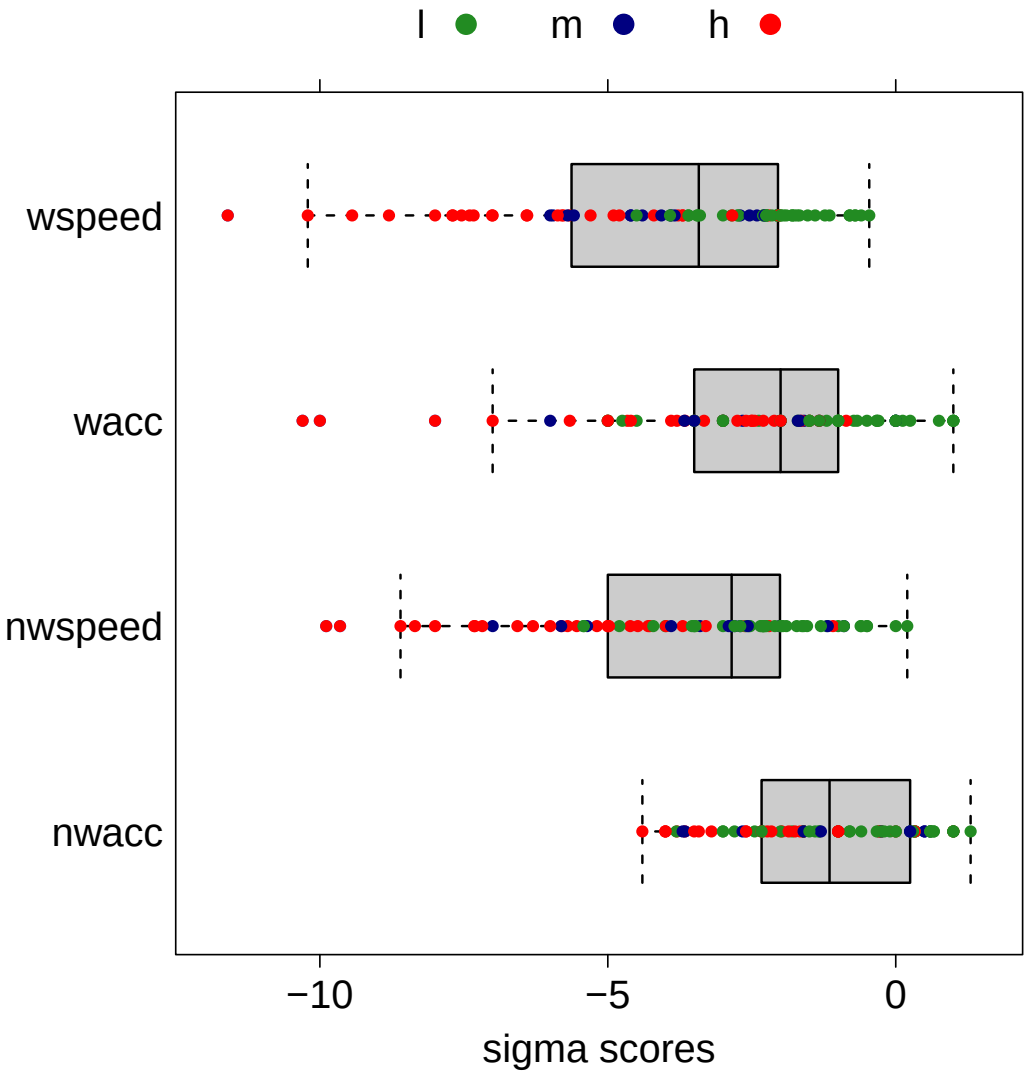


Figure 4: DDE score distribution.

In order to investigate the distribution of DSM5 classes and the correlation between the scores we provide the graph below.

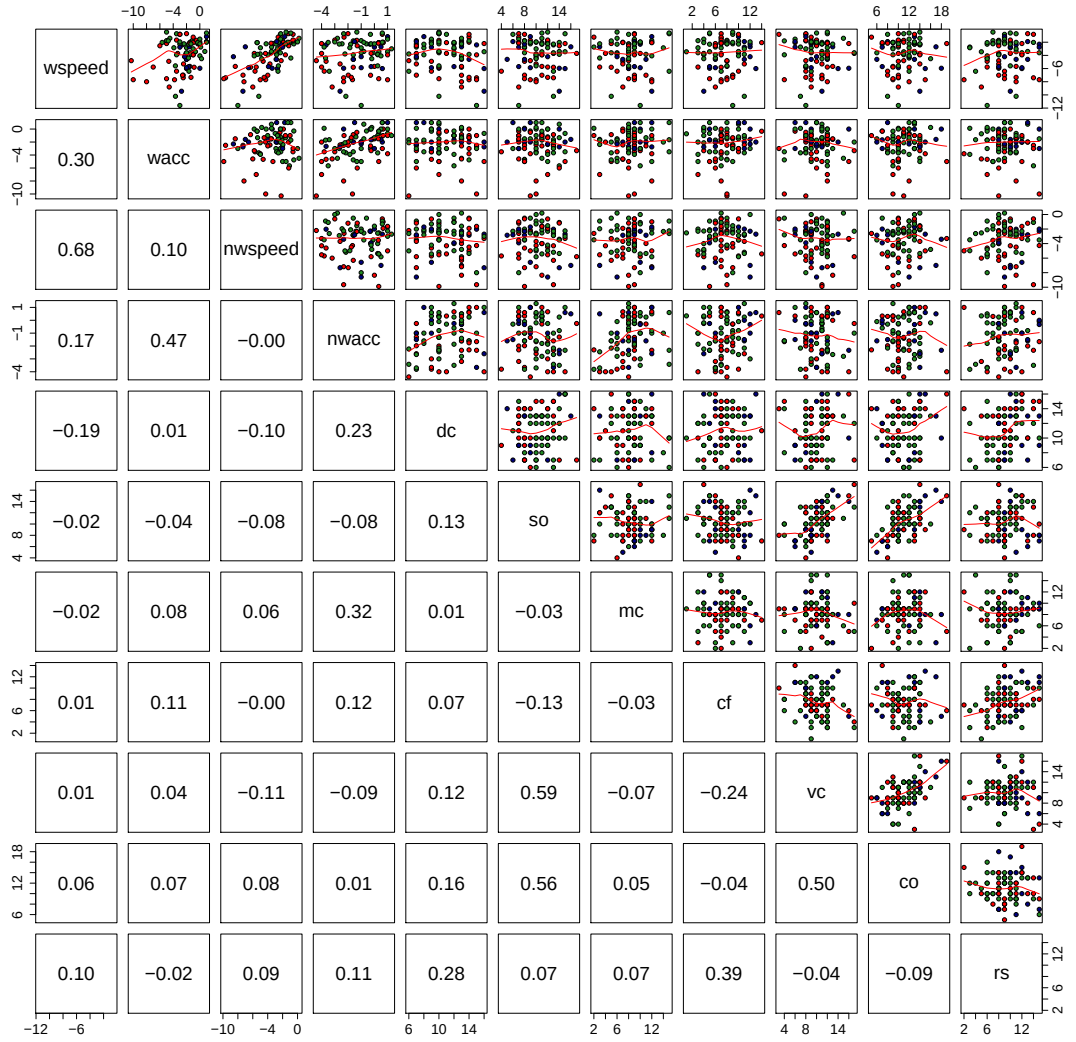
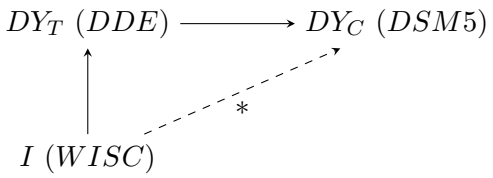


Figure 5: Pair graph with DDE scores and WISC subscales. Correlation coefficient in the lower panel.

2 Visual Data Analysis

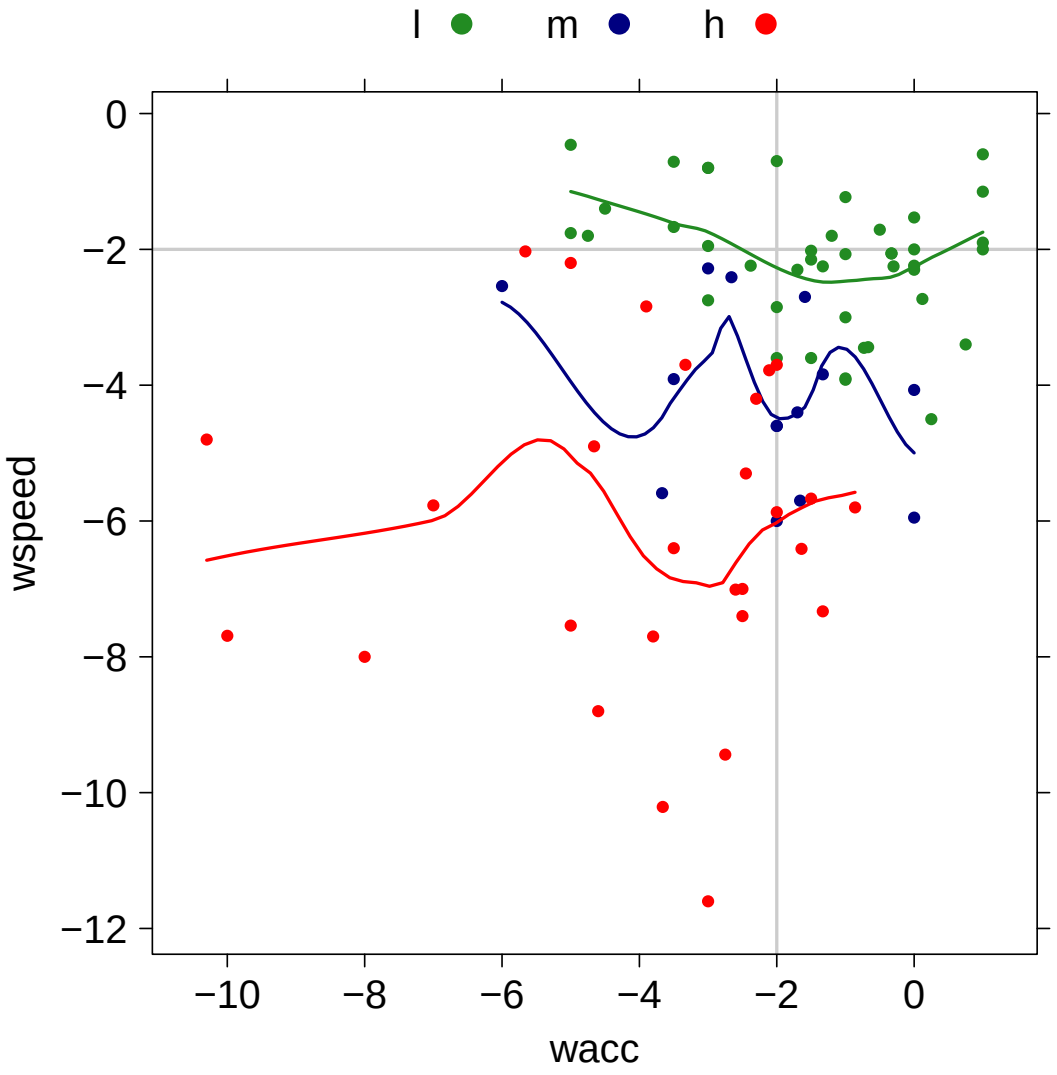
From previous Figures we can suppose that DSM5 classification can be driven from DDE scores, hence DDE is a classifier, while WISC subscales work as a modulator. We want to assess the following diagram in order to provide a cognitive profile to the DSM5 classification (*).



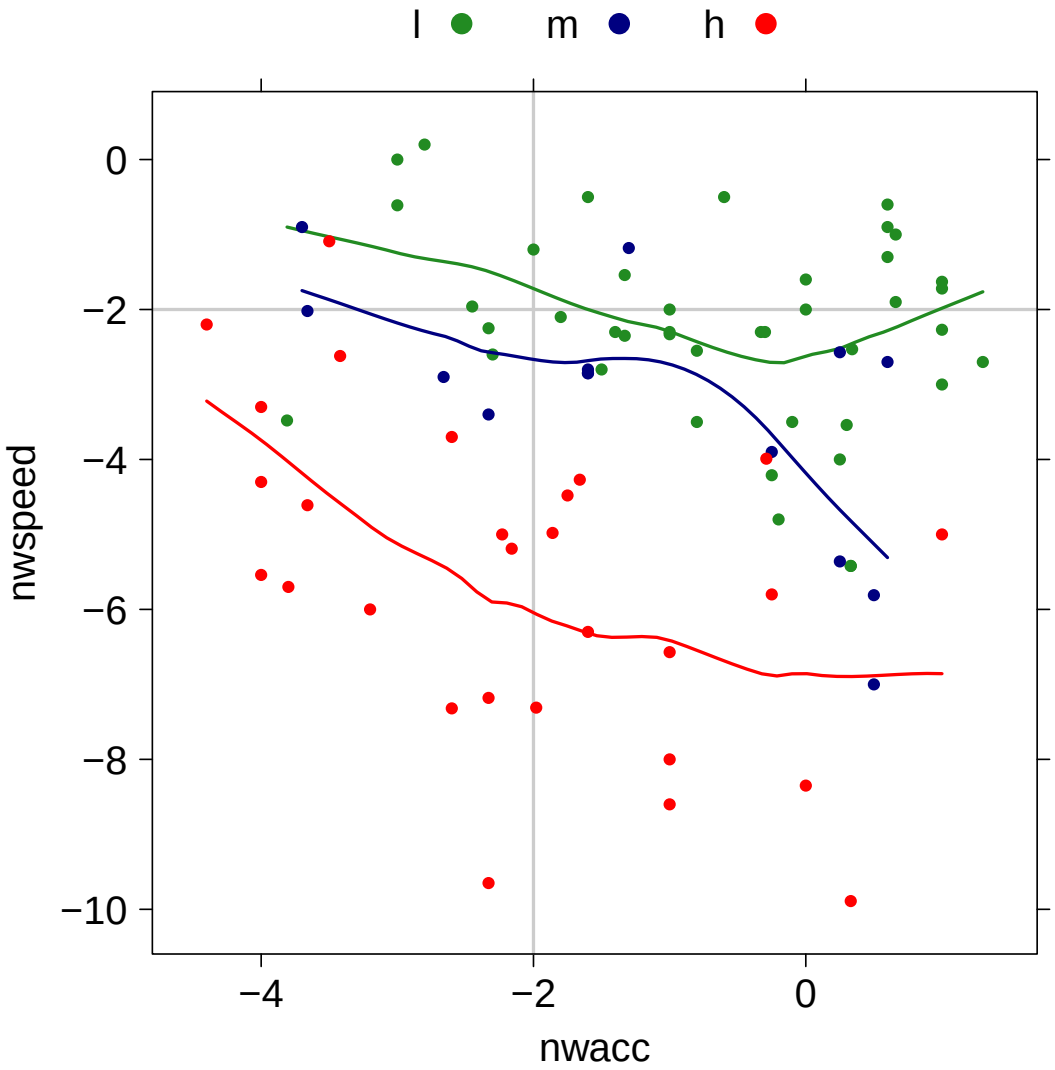
DY_T: technical dyslexia, DY_C: clinical dyslexia, I: intelligence.

2.1 DDE scores

Firstly we want to see if it is possible to reduce the number of DDE variables, from 4 to 2, expressing the processing speed in function of the processing accuracy.



(a) Scatterplot word accuracy against word speed in the three classes.

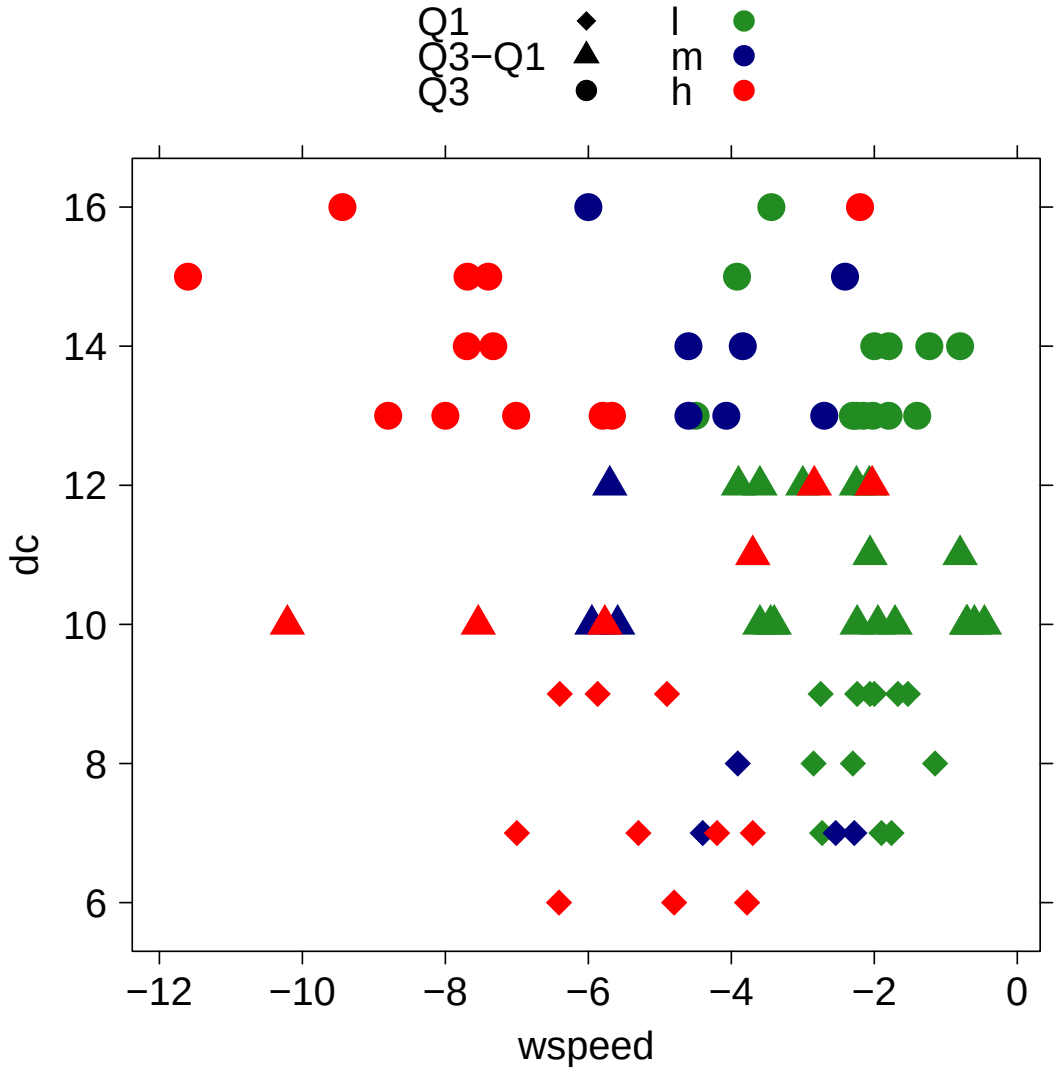


(b) Scatterplot non-word accuracy against non-word speed in the three classes.

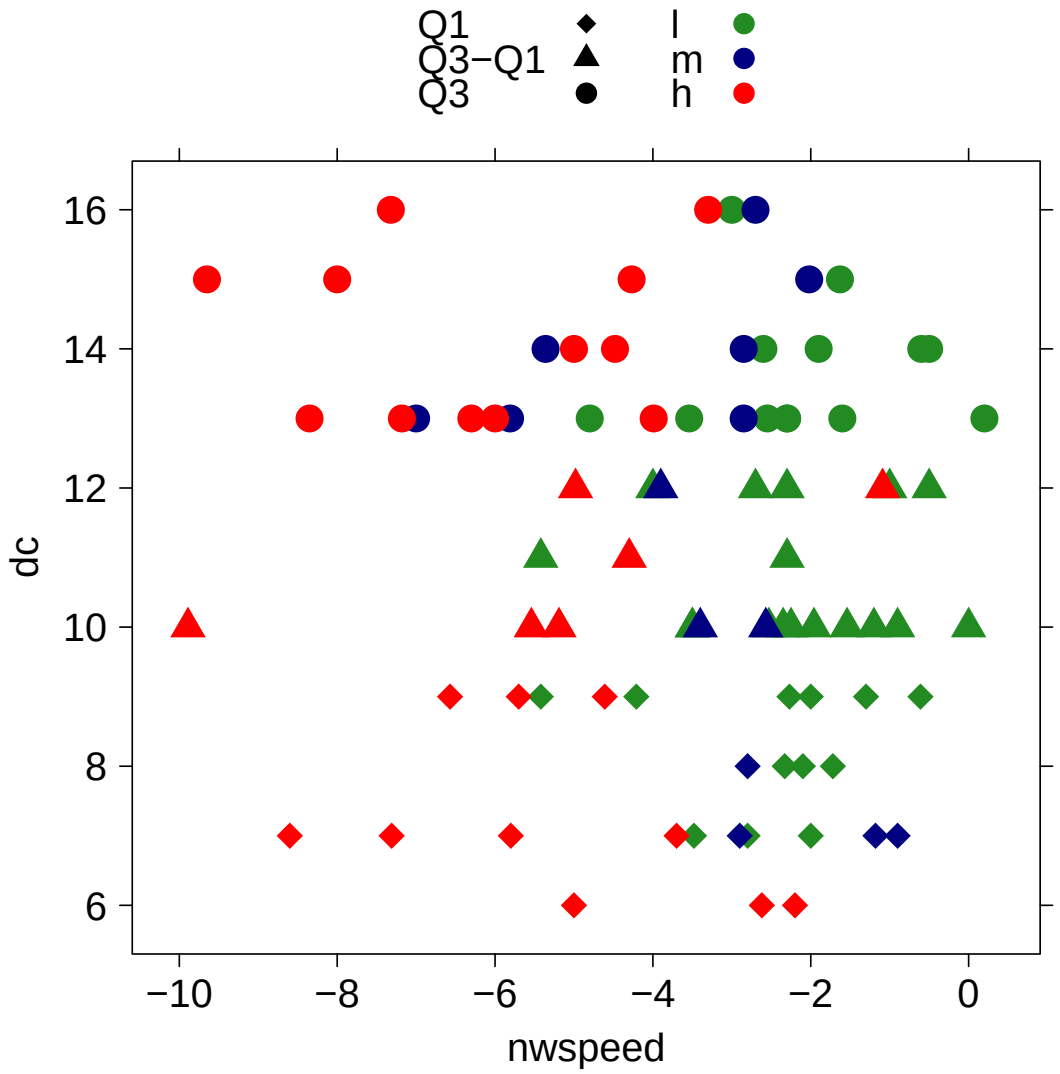
Figure 6

2.2 WISC subscales

We would like to parametrize the loess lines in Figures 6a-6b in order to see if the variation of WISC subscales determines a shift from the curve of one class to the curve of another.
Let us now see how the WISC subscales vary according to the DDE word/non-word speed scores. We highlight the first and third quantile, along with the DSM5 classes.

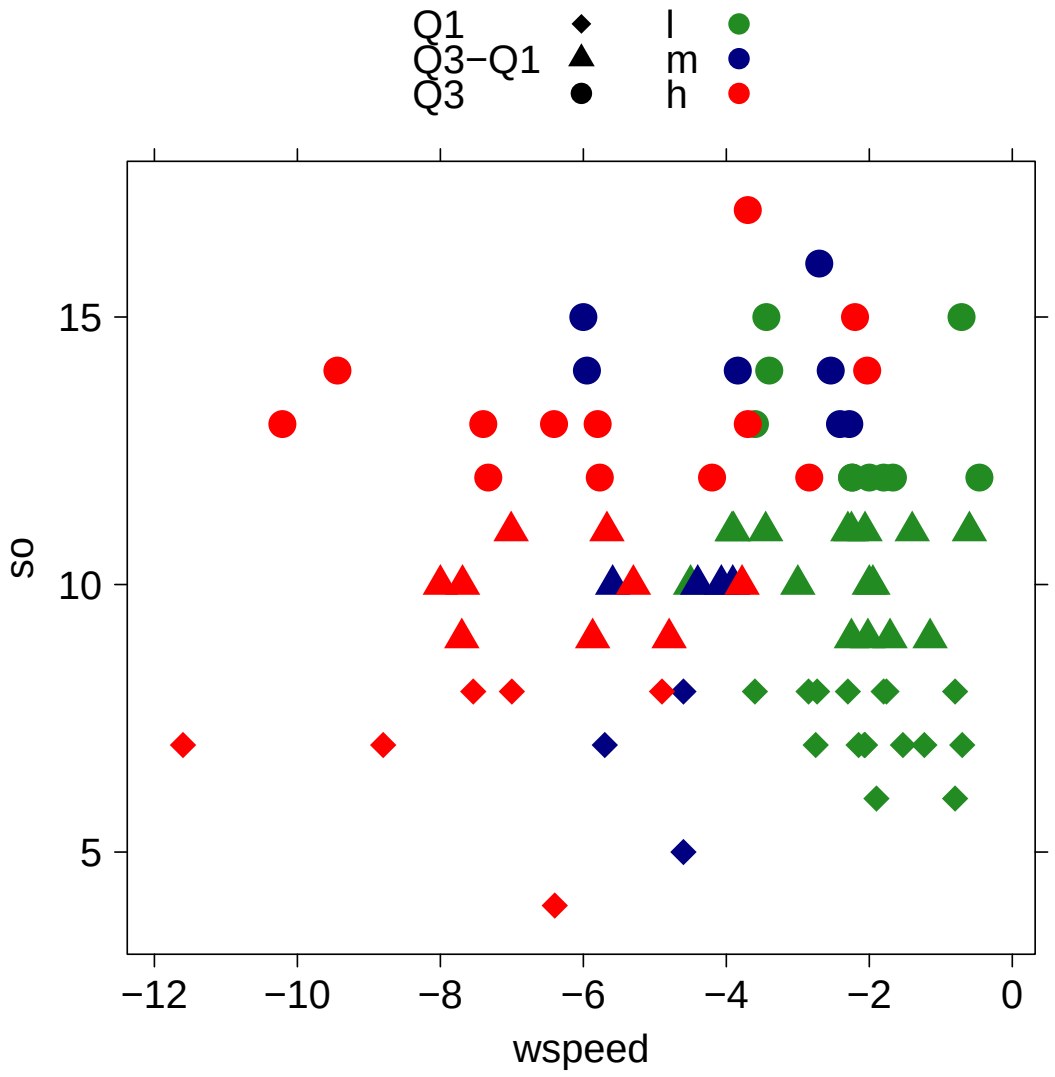


(a)

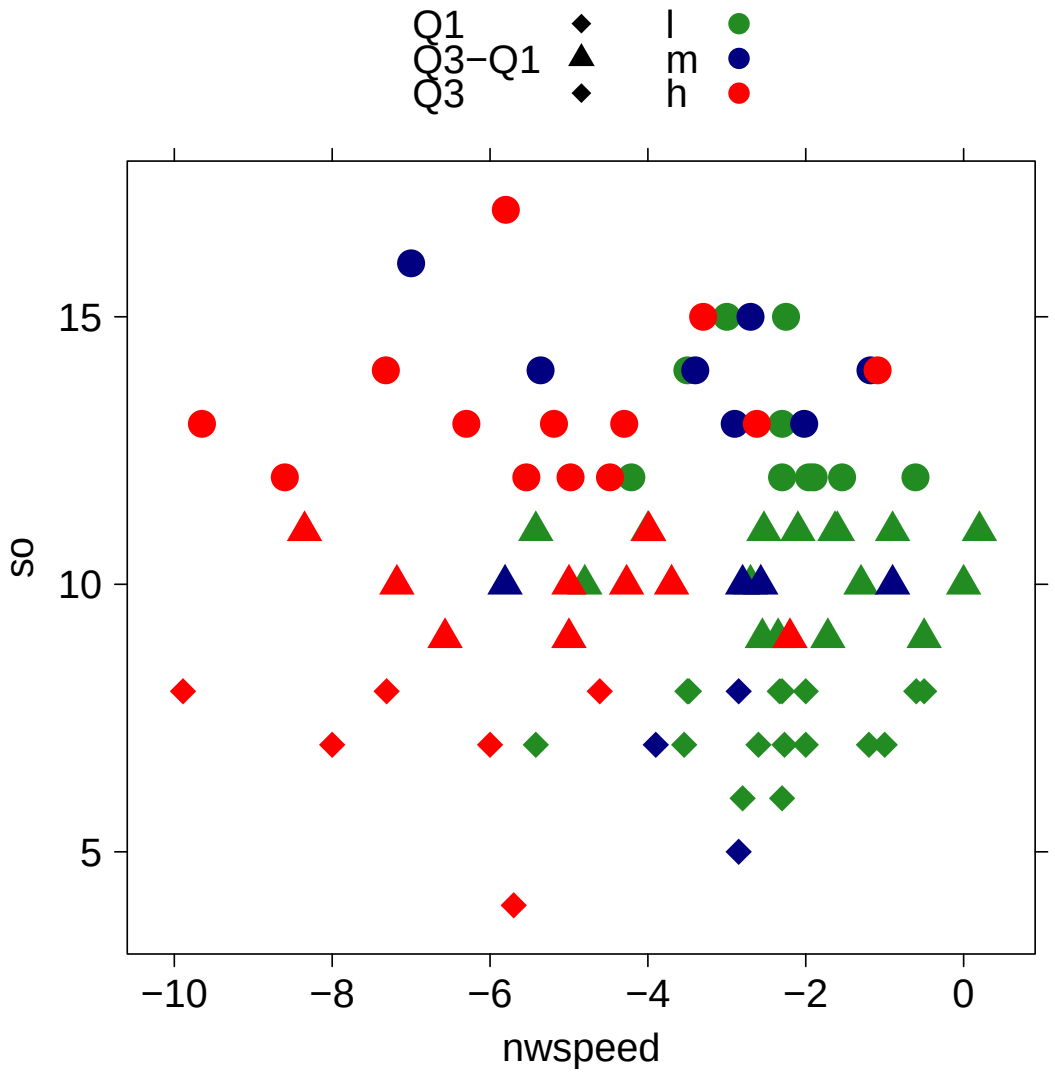


(b)

Figure 7: Reading speed of words and non-words against subscale dc.

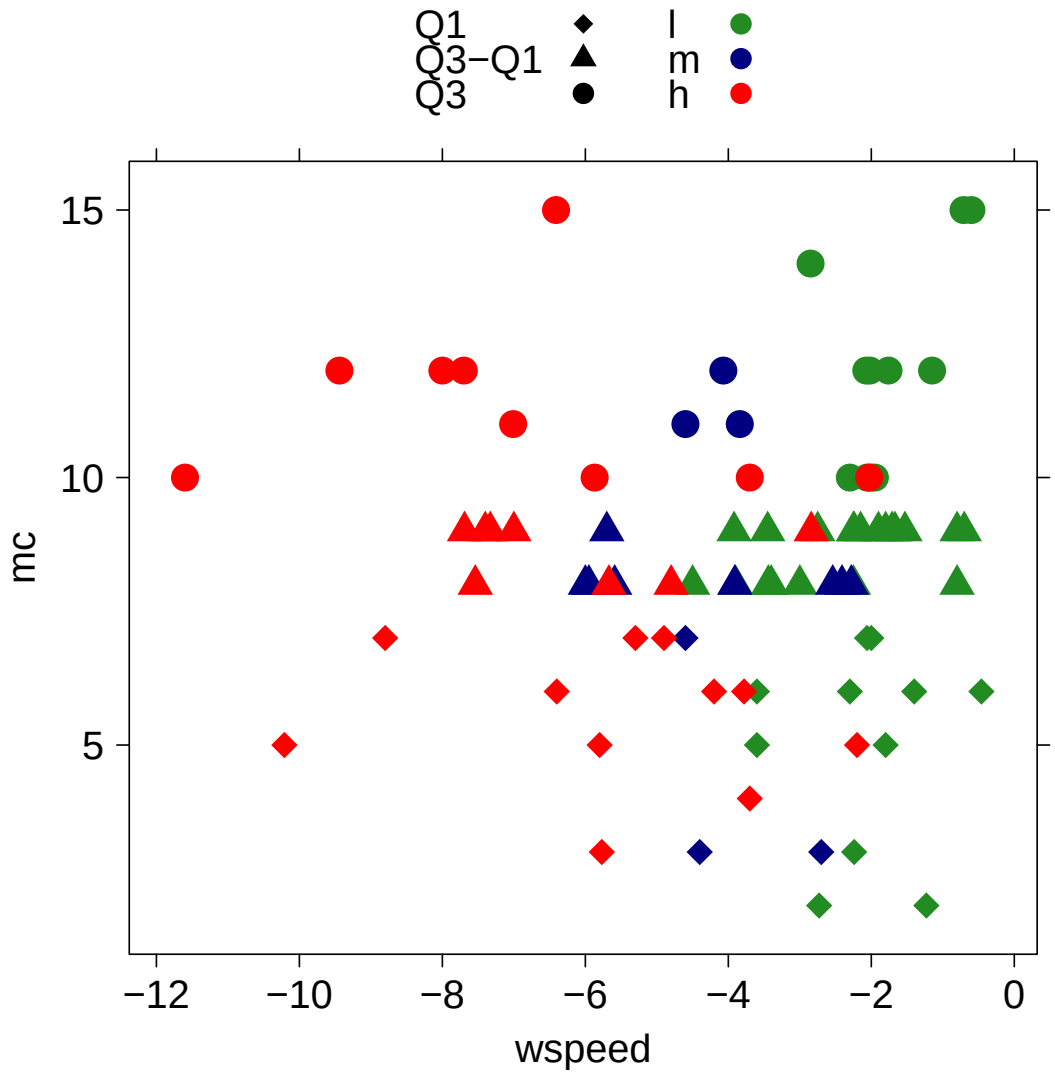


(a)

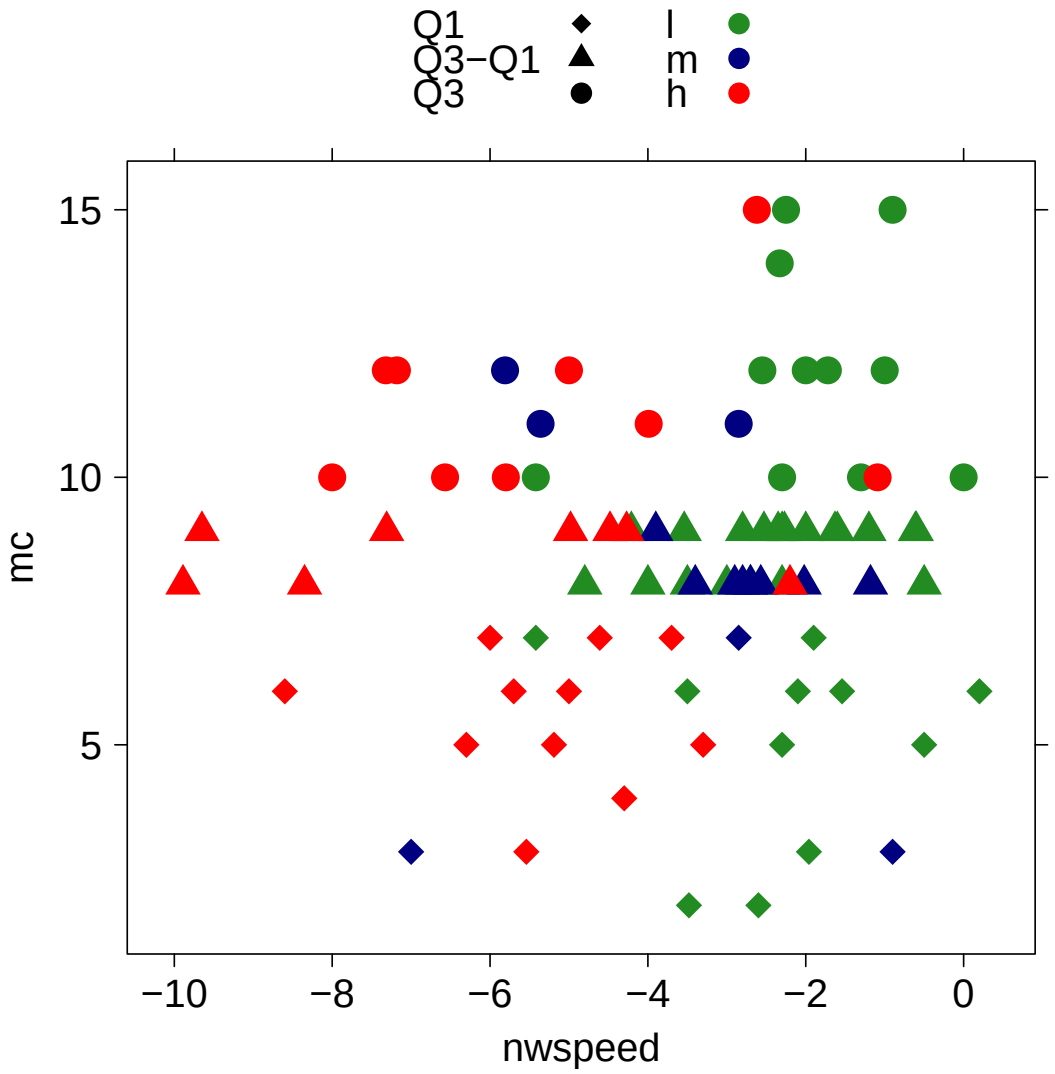


(b)

Figure 8: Reading speed of words and non-words against subscale so.

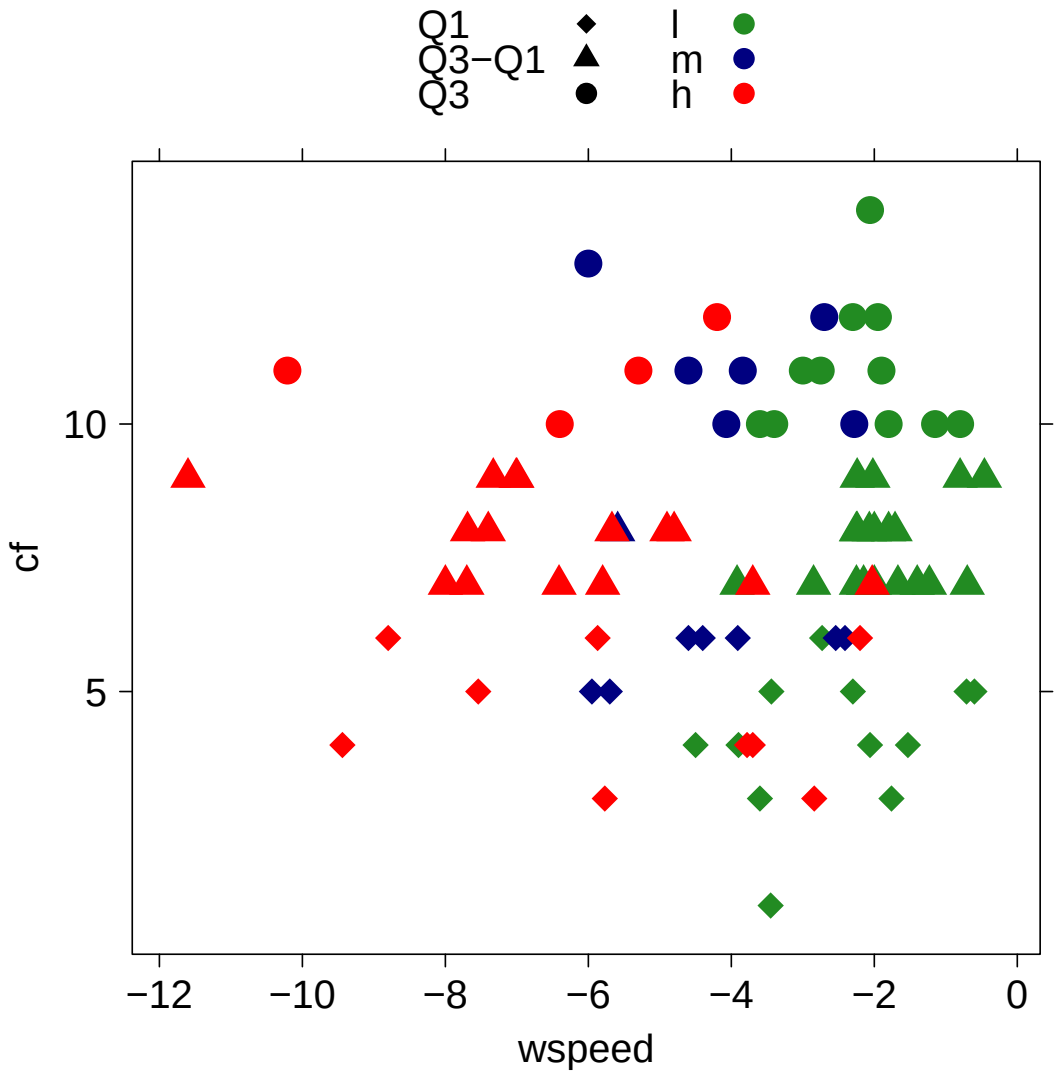


(a)

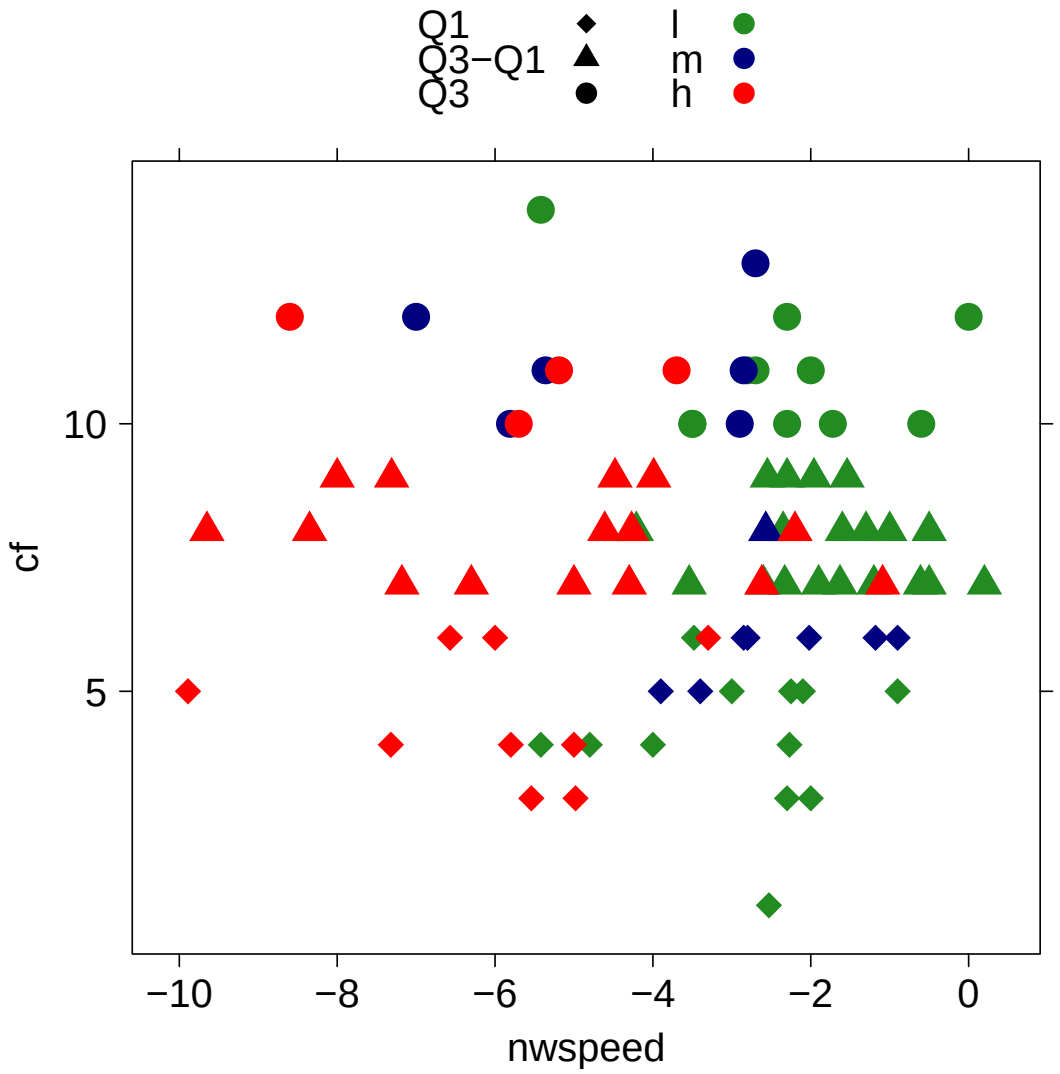


(b)

Figure 9: Reading speed of words and non-words against subscale mc.

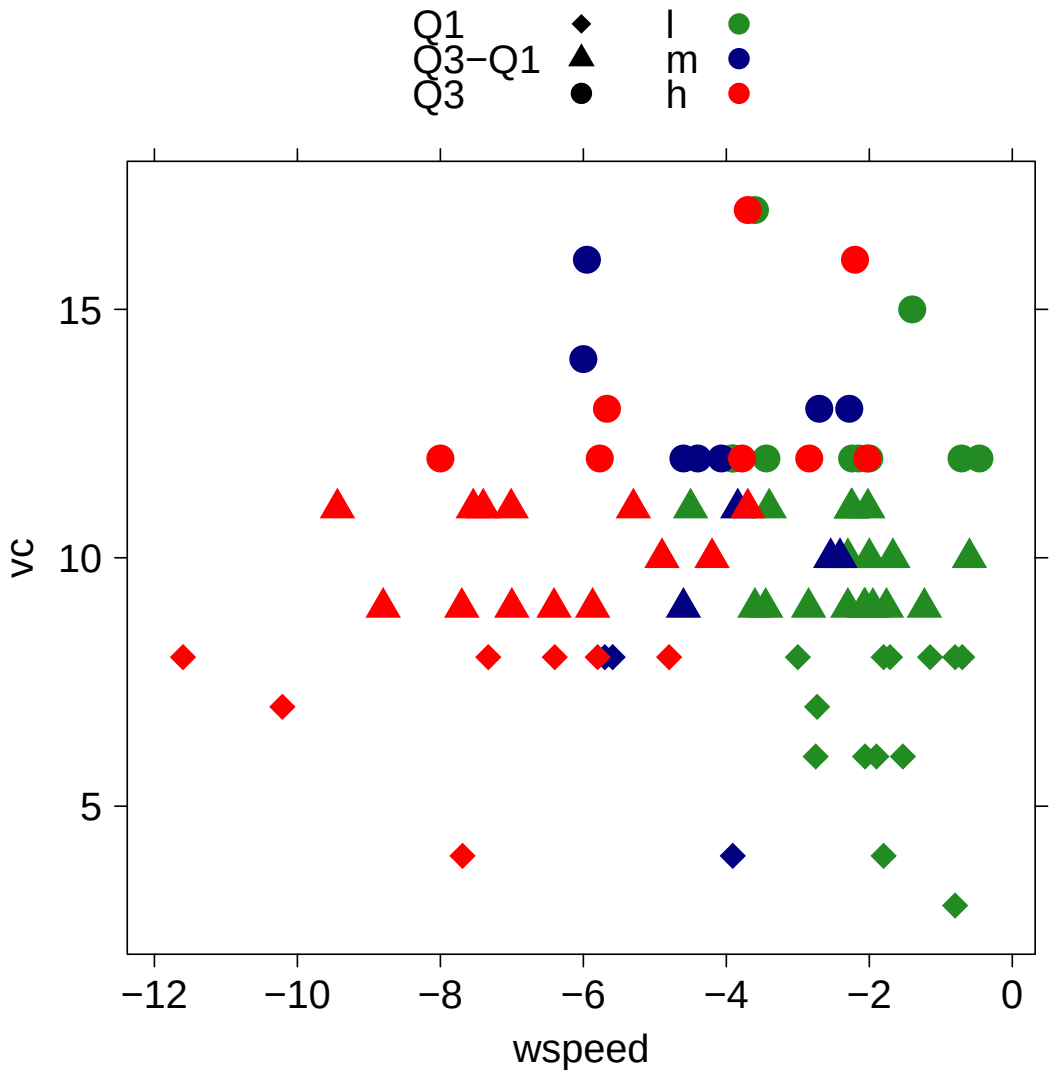


(a)

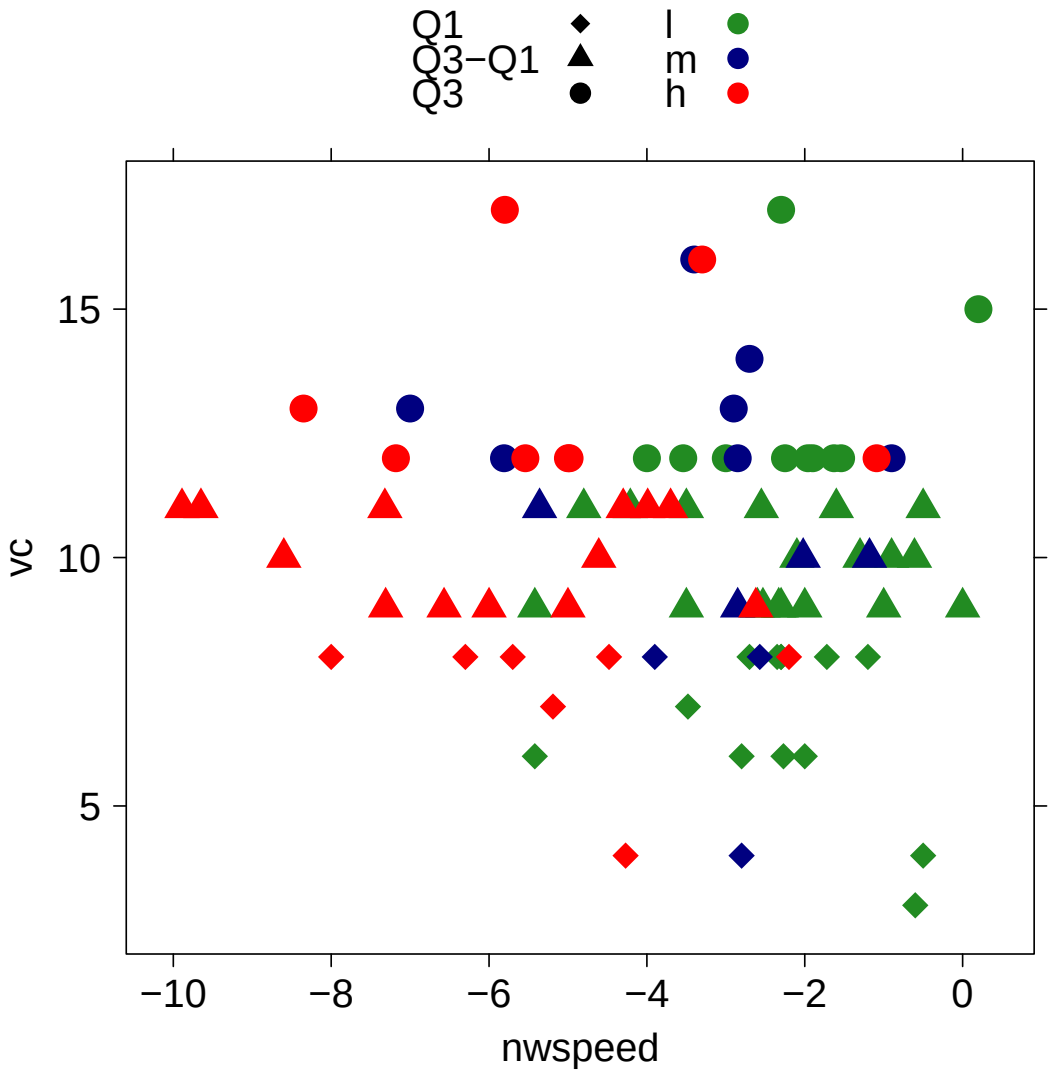


(b)

Figure 10: Reading speed of words and non-words against subscale cf.

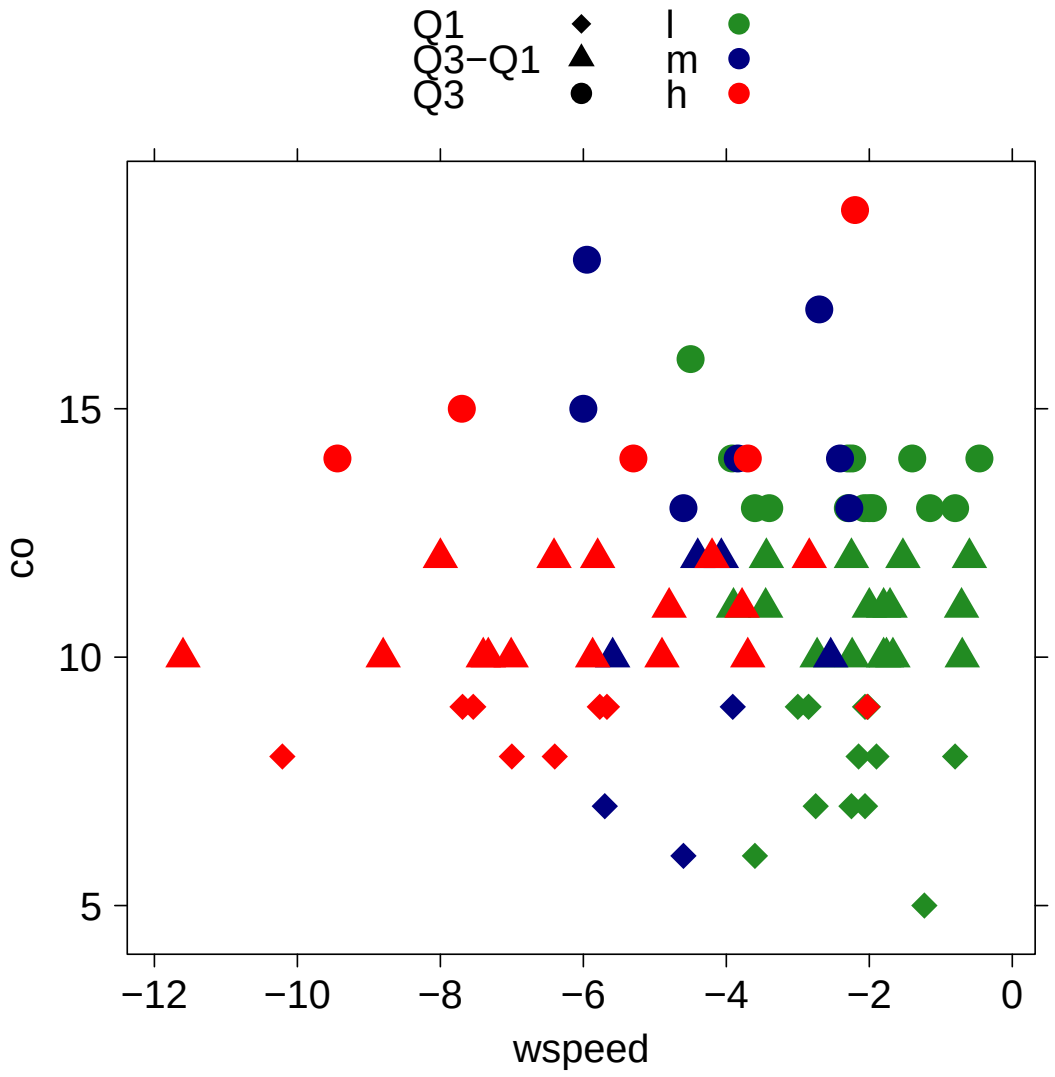


(a)

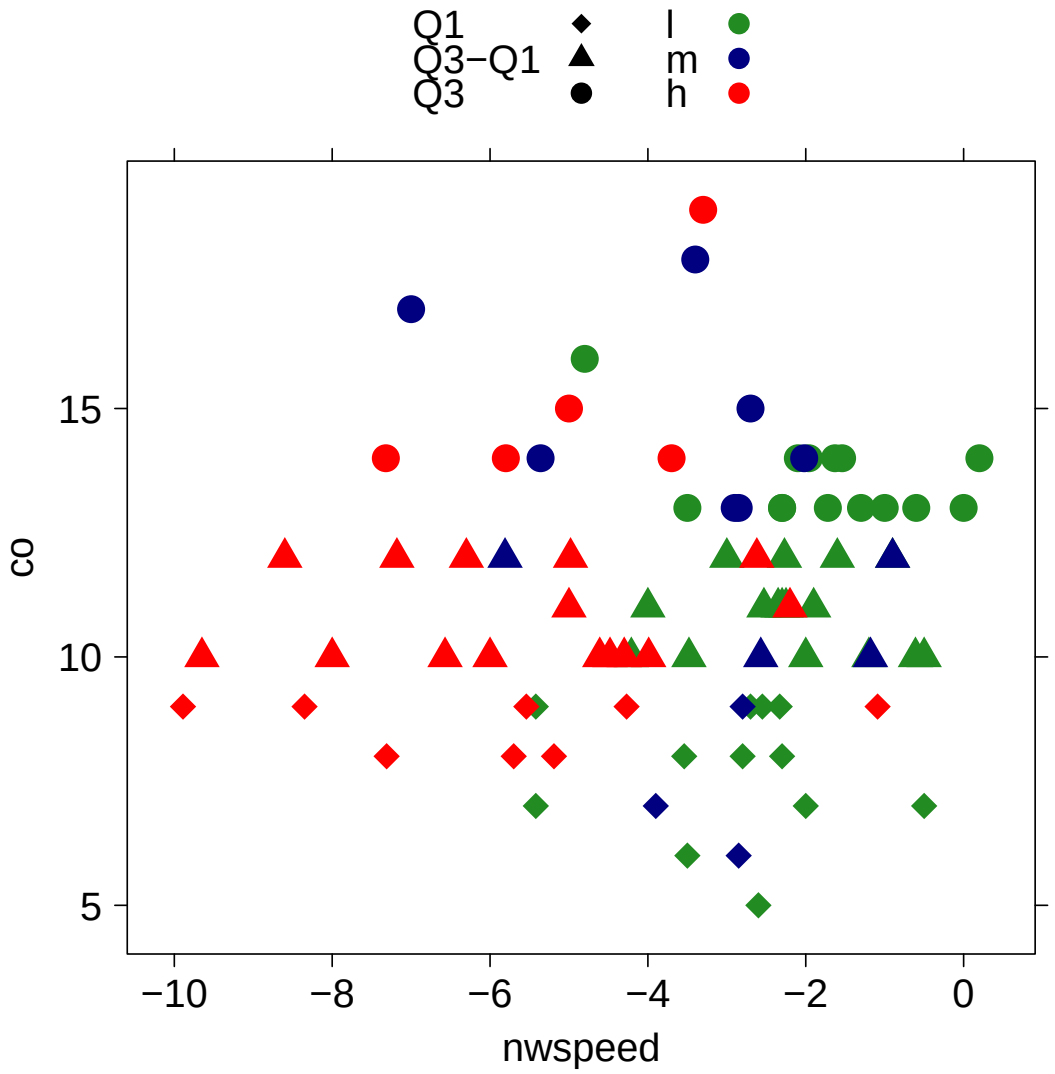


(b)

Figure 11: Reading speed of words and non-words against subscale vc.



(a)



(b)

Figure 12: Reading speed of words and non-words against subscale co.

3 Data Analysis

3.1 Random Forest

Firstly we perform a random forest with classification trees, where we try to perform the DSM5 classification with DDE scores. As we can see in Figure 13 the most important variables are the ones concerning the reading speed ability. This supports the thesis that dde scores can be reduced from 4 to 2 variables.

```
Type of random forest: classification
                      Number of trees: 500
No. of variables tried at each split: 2

        OOB estimate of  error rate: 20.93%
Confusion matrix:
   1 2  3 class.error
1 39 3  0  0.07142857
2  6 5  3  0.64285714
3  3 3 24  0.20000000
```

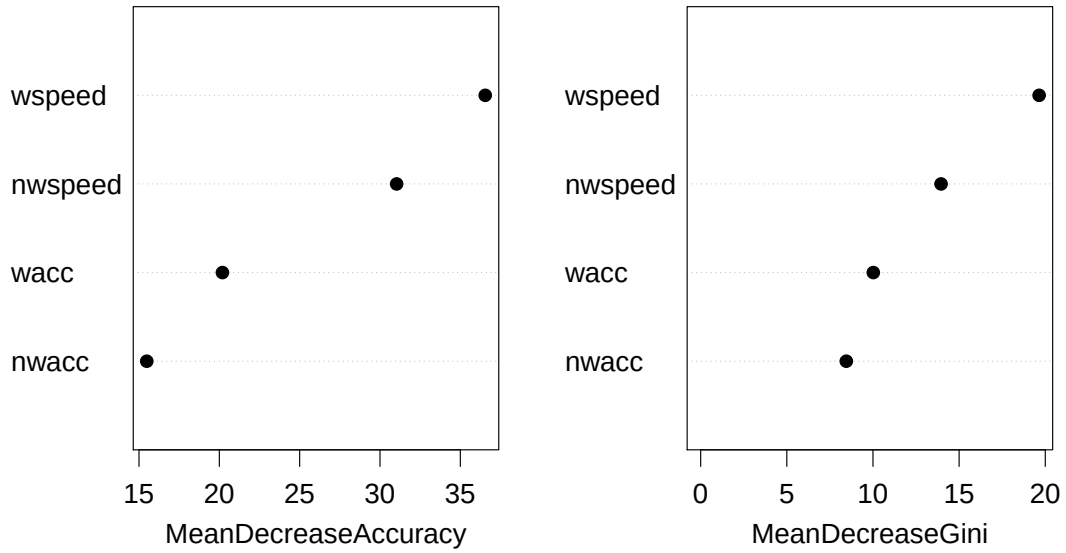


Figure 13: Classification tree with DDE scores. Variable importance.

Performing the classification with WISC subscales we obtain the following result:

```
Type of random forest: classification
                      Number of trees: 500
No. of variables tried at each split: 2
        OOB estimate of  error rate: 58.14%
Confusion matrix:
   1 2  3 class.error
1 27 1 14   0.3571429
2  5 1  8   0.9285714
3 20 2  8   0.7333333
```

Now we try the following approach in order to seek for a relationship between WISC subscales a DDE scores:

1. we fit a random forest model with classification trees on WISC subscales considering only classes 1 (low dyslexia) and 3 (high dyslexia).
2. we select the most important variables.
3. we fit a random forest model with regression trees with DDE speed score (word/non-word) as response and selected WISC subscales as regressors.
4. we fit the model at Step 3. to the full database, in order to check if the selected variables correctly predict the class 1 (medium dyslexia) scores.

DDE Word Reading Speed Scores

First step:

```
Type of random forest: classification
                      Number of trees: 500
No. of variables tried at each split: 2

        OOB estimate of  error rate: 48.61%
Confusion matrix:
   1  3 class.error
1 30 12   0.2857143
3 23  7   0.7666667
```

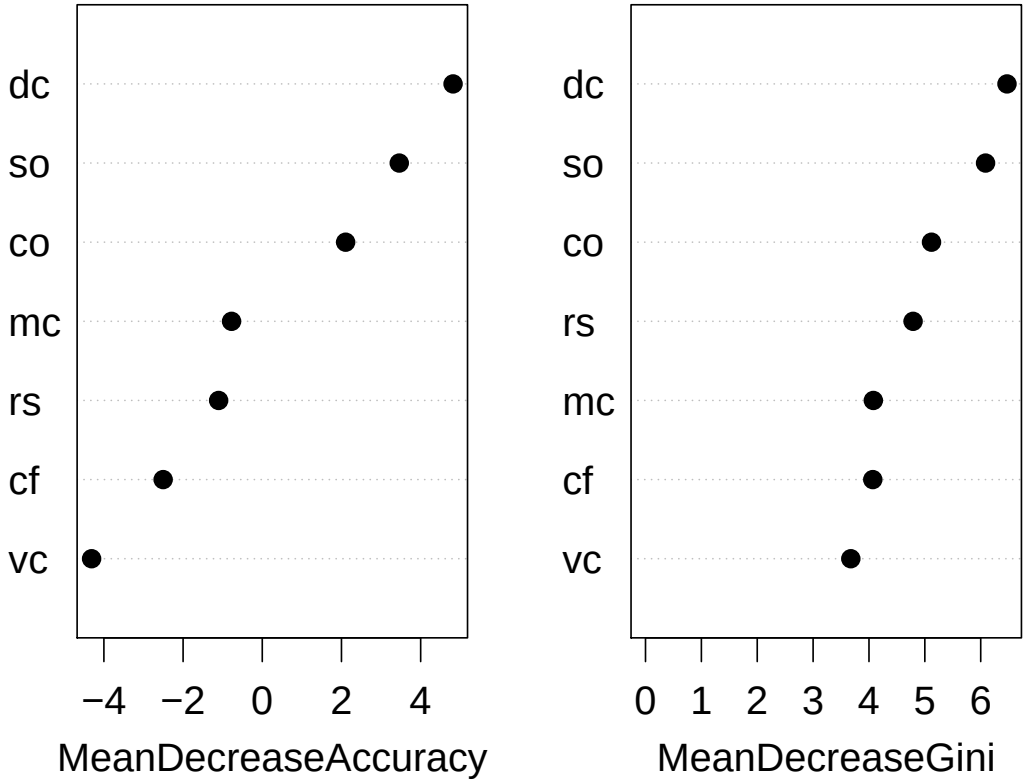


Figure 14: Classification tree of low (1) and high (3) dyslexia classes with WISC scores. Variable importance.

Second step: Selected dc, so, co.
Third step:

```
Type of random forest: regression
                      Number of trees: 500
No. of variables tried at each split: 1

          Mean of squared residuals: 8.060252
                    % Var explained: -4.31
```

Fourth step:

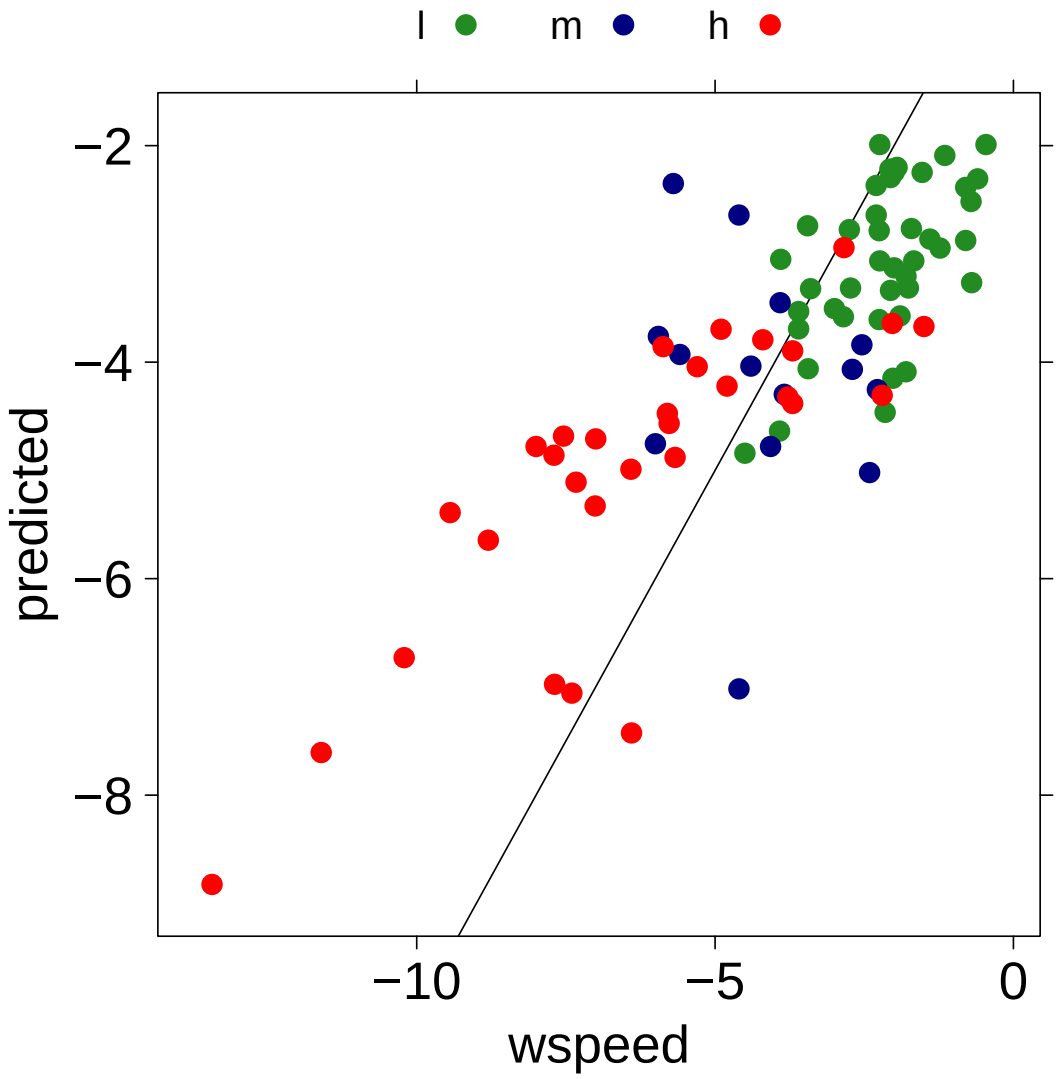


Figure 15: Predicted wspeed values with dc, so, co subscales as regressors.

DDE Non-Word Reading Speed Scores

Third step:

```
Type of random forest: regression
                      Number of trees: 500
No. of variables tried at each split: 1

          Mean of squared residuals: 6.229219
```

```
% Var explained: -15.4
```

Fourth step:

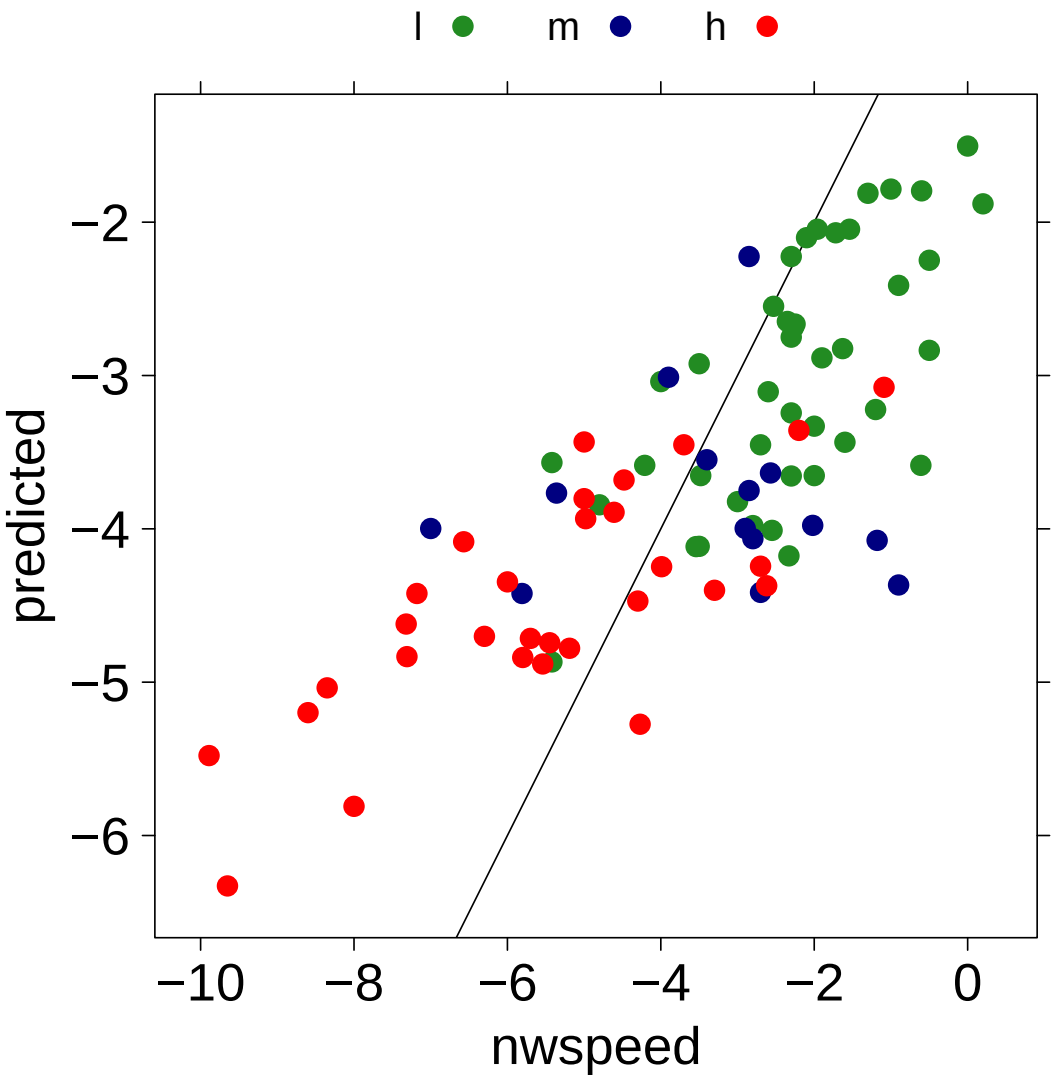


Figure 16: Predicted nwspeed values with dc, so, co subscales as regressors.

3.2 Logistic Regression

1. We perform a generalized linear model with DSM5 classes as response and $(wspeed + nwspeed) * (dc + so + mc + cf + vc + co + rs)$ as regressors.

```
Call:
glm(formula = as.numeric(class) ~ (wspeed + nwspeed) * (dc +
    so + mc + cf + vc + co + rs), data = db)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.0819  -0.3673   0.0273   0.2924   1.3917

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.4527523  1.1786947  -1.233   0.2224
```

```
wspeed      -0.7192542  0.2955793  -2.433   0.0179 *
nwspeed     -0.0379841  0.3332131  -0.114   0.9096
dc           0.0531177  0.0561646   0.946   0.3479
so           0.0509453  0.0702433   0.725   0.4710
mc          -0.0157737  0.0535120  -0.295   0.7692
cf           0.0120412  0.0661857   0.182   0.8562
vc           0.0458190  0.0642764   0.713   0.4786
co          -0.0205524  0.0689815  -0.298   0.7667
rs           0.0837888  0.0643954   1.301   0.1980
wspeed:dc    0.0278732  0.0156406   1.782   0.0796 .
wspeed:so   -0.0003371  0.0160713  -0.021   0.9833
wspeed:mc   -0.0099392  0.0147529  -0.674   0.5030
wspeed:cf   -0.0080491  0.0165237  -0.487   0.6279
wspeed:vc    0.0340400  0.0220449   1.544   0.1276
wspeed:co   -0.0116266  0.0226920  -0.512   0.6102
wspeed:rs    0.0150460  0.0156261   0.963   0.3394
nwspeed:dc  -0.0042277  0.0170771  -0.248   0.8053
nwspeed:so   0.0010863  0.0235441   0.046   0.9633
nwspeed:mc   0.0090118  0.0167042   0.539   0.5915
nwspeed:cf   0.0119266  0.0175343   0.680   0.4989
nwspeed:vc  -0.0272551  0.0249071  -1.094   0.2781
nwspeed:co   0.0049547  0.0246277   0.201   0.8412
nwspeed:rs   0.0009999  0.0223444   0.045   0.9644
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 0.346641)

    Null deviance: 70.326  on 85  degrees of freedom
Residual deviance: 21.492  on 62  degrees of freedom
AIC: 174.8

Number of Fisher Scoring iterations: 2
```

2. We perform a generalized linear model as before, but only with wspeed as DDE score.

```
Call:
glm(formula = as.numeric(class) ~ (wspeed) * (dc + so + mc +
    cf + vc + co + rs), data = db)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.09783  -0.38314  -0.01877   0.31199   1.46870

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.536257   1.050852  -1.462  0.14824
wspeed      -0.763376   0.249875  -3.055  0.00318 **
dc           0.062294   0.052323   1.191  0.23784
so           0.070691   0.061652   1.147  0.25545
mc          -0.025985   0.047962  -0.542  0.58970
cf           0.023843   0.059087   0.404  0.68779
vc           0.041189   0.063746   0.646  0.52030
co          -0.005472   0.061786  -0.089  0.92968
rs           0.061151   0.053304   1.147  0.25520
wspeed:dc    0.026036   0.011205   2.324  0.02306 *
wspeed:so   -0.002213   0.011844  -0.187  0.85229
wspeed:mc   -0.006564   0.012072  -0.544  0.58836
wspeed:cf    0.005038   0.013625   0.370  0.71265
```

```
wspeed:vc    0.005968   0.014774   0.404  0.68749
wspeed:co    0.004074   0.016744   0.243  0.80846
wspeed:rs    0.013701   0.010941   1.252  0.21464
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 0.3738487)

    Null deviance: 70.326  on 85  degrees of freedom
Residual deviance: 26.169  on 70  degrees of freedom
AIC: 175.74

Number of Fisher Scoring iterations: 2
```

3. We perform a generalized linear model as before, but only with nwspeed as DDE score.

```
Call:
glm(formula = as.numeric(class) ~ (nwspeed) * (dc + so + mc +
    cf + vc + co + rs), data = db)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.45153  -0.48069  -0.03166   0.46398   1.52062

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.8018996  1.2816080  -0.626   0.5335
nwspeed     -0.6344651  0.3267787  -1.942   0.0562 .
dc          -0.0167730  0.0632053  -0.265   0.7915
so           0.1513009  0.0823838   1.837   0.0705 .
mc          -0.0105356  0.0597755  -0.176   0.8606
cf           0.0671982  0.0723314   0.929   0.3561
vc           0.0066307  0.0703881   0.094   0.9252
co          -0.0253525  0.0765273  -0.331   0.7414
rs           0.0126075  0.0752521   0.168   0.8674
nwspeed:dc  -0.0008382  0.0146107  -0.057   0.9544
nwspeed:so   0.0260926  0.0205275   1.271   0.2079
nwspeed:mc  -0.0004094  0.0161121  -0.025   0.9798
nwspeed:cf   0.0178704  0.0167581   1.066   0.2899
nwspeed:vc   0.0084209  0.0194769   0.432   0.6668
nwspeed:co  -0.0113936  0.0211721  -0.538   0.5922
nwspeed:rs   0.0010554  0.0183193   0.058   0.9542
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 0.5281967)

    Null deviance: 70.326  on 85  degrees of freedom
Residual deviance: 36.974  on 70  degrees of freedom
AIC: 205.46

Number of Fisher Scoring iterations: 2
```

It is worth observing the significance of the interaction $wspeed * dc$ ($p < 0.05$) in the second model. *dc* is the most important variable selected by the random forest model implemented in the previous subsection. Moreover we can observe the lower significance ($p < 0.1$) of the subscale *so* in the third model. *so* is the second subscale value selected by the random forest model implemented in the previous subsection.

4 Multinomial Logistic Regression

1. Regressors: dde variables (wspeed,nwspeed,wacc,nwacc). Reference level $\longrightarrow$ class 3.

```
Call:
multinom(formula = form.dde, data = db.tmp)

Coefficients:
  (Intercept)    wspeed   nwspeed      wacc    nwacc
1   197.58085 17.493015 20.179414 18.755749 16.97987
2    72.10549  4.504629  6.428822  6.531223  6.56515

Std. Errors:
  (Intercept)   wspeed   nwspeed      wacc    nwacc
1   104.88858 9.866885 11.586665 10.739339 9.701778
2    57.39051 4.164916  5.752461  6.223839 6.106167

Residual Deviance: 0.8815825
AIC: 20.88158

P-values:
  (Intercept)     wspeed    nwspeed      wacc      nwacc
1  0.05960269 0.07624501 0.08157729 0.0807323 0.08008696
2  0.20897067 0.27944577 0.26374742 0.2939995 0.28229995
```

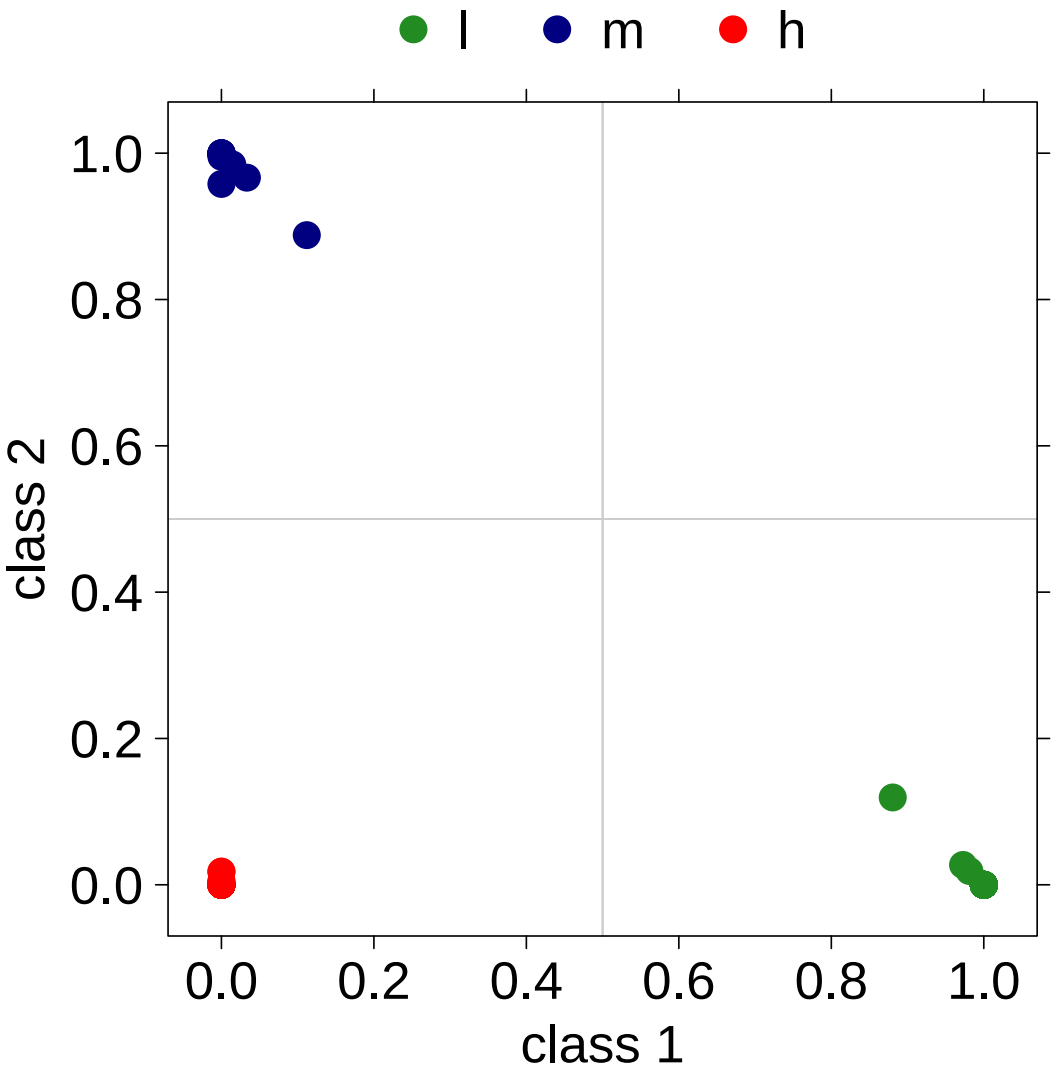


Figure 17: Multinomial logistic regression on dyslexia class, with dde scores as regressors.

2. Regressors: dde variables:wisc subscales (dc+cf+rs+so+vc+co+mc). Reference level ⟶ class 3.

```
Call:
multinom(formula = form.inter, data = db.tmp)

Coefficients:
  (Intercept)  wspeed:dc  wspeed:cf  wspeed:rs wspeed:mc wspeed:so wspeed:vc
1   155.71909  0.3342648 0.03952001  0.9264321 2.2657407 0.8902855 -1.509521
2    70.17509 -0.8217690 2.15442465 -3.8670681 0.3964486 6.0207881 -2.854898
   wspeed:co    wacc:dc   wacc:cf   wacc:rs  wacc:mc   wacc:so   wacc:vc
1 -0.0667730 -2.1048418 -2.814648 0.8747144 1.610395  2.413544 -2.480102
2 -0.5481724 -0.5554065 -5.768567 3.5798315 3.703040 -5.383504  2.095209
   wacc:co nwspeed:dc nwspeed:cf nwspeed:rs nwspeed:mc nwspeed:so nwspeed:vc
1 1.881738 -0.7359609  1.5059307 -0.9581549  -1.447987 -0.6769544   2.874844
2 2.727121 -0.2459587 -0.6291299  3.3131139  -1.736066 -5.4680130   4.315976
  nwspeed:co nwacc:dc  nwacc:cf   nwacc:rs   nwacc:mc  nwacc:so   nwacc:vc
1  0.1885891 2.632224 0.5703178 -0.7755046 -0.9244619 -1.285881  3.8711319
2  1.3454552 3.770200 4.9178314 -4.2213342 -1.5216561  3.250182 -0.5353119
   nwacc:co
1 -2.097886
2 -4.677192

Std. Errors:
  (Intercept) wspeed:dc wspeed:cf wspeed:rs wspeed:mc wspeed:so wspeed:vc
1    198.3953  619.0846 1573.2037  520.3707 1155.7102  596.9785 1320.9672
2    181.1330  377.2129  318.4729  345.0649  441.5142  427.4253  481.9091
  wspeed:co  wacc:dc  wacc:cf  wacc:rs  wacc:mc   wacc:so   wacc:vc   wacc:co
1  402.7968 414.7655 697.8195 518.0233 373.2299 1708.0067  461.8061 1212.9684
2  639.4655 684.3562 201.6864 539.2540 822.2969  952.6766 1356.6554  738.0164
  nwspeed:dc nwspeed:cf nwspeed:rs nwspeed:mc nwspeed:so nwspeed:vc nwspeed:co
1   363.9444   675.9214   781.5355   648.1829   370.0346   505.6632   457.1549
2   421.8806   870.6919   256.1981   345.1745   253.9231   619.9579   448.3060
  nwacc:dc nwacc:cf nwacc:rs nwacc:mc nwacc:so nwacc:vc  nwacc:co
1 993.3434  209.252 751.7241 784.8282 435.3508 305.2842  490.4145
2 902.9500 1322.052 653.5004 581.7775 908.1572 564.2960 1412.9238

Residual Deviance: 0.0001232419
AIC: 116.0001


P-values:
  (Intercept) wspeed:dc wspeed:cf wspeed:rs wspeed:mc wspeed:so wspeed:vc
1   0.4325164 0.9995692 0.9999800 0.9985795 0.9984358 0.9988101 0.9990882
2   0.6984430 0.9982618 0.9946025 0.9910585 0.9992836 0.9887612 0.9952732
  wspeed:co   wacc:dc   wacc:cf   wacc:rs   wacc:mc   wacc:so   wacc:vc
1 0.9998677 0.9959509 0.9967817 0.9986527 0.9965573 0.9988725 0.9957150
2 0.9993160 0.9993525 0.9771823 0.9947033 0.9964069 0.9954912 0.9987678
    wacc:co nwspeed:dc nwspeed:cf nwspeed:rs nwspeed:mc nwspeed:so nwspeed:vc
1 0.9987622  0.9983865  0.9982223  0.9990218  0.9982176  0.9985403  0.9954638
2 0.9970517  0.9995348  0.9994235  0.9896822  0.9959870  0.9828196  0.9944454
  nwspeed:co  nwacc:dc  nwacc:cf  nwacc:rs  nwacc:mc  nwacc:so  nwacc:vc
1  0.9996709 0.9978857 0.9978254 0.9991769 0.9990602 0.9976433 0.9898828
2  0.9976054 0.9966685 0.9970320 0.9948460 0.9979131 0.9971445 0.9992431
   nwacc:co
1 0.9965868
2 0.9973588
```

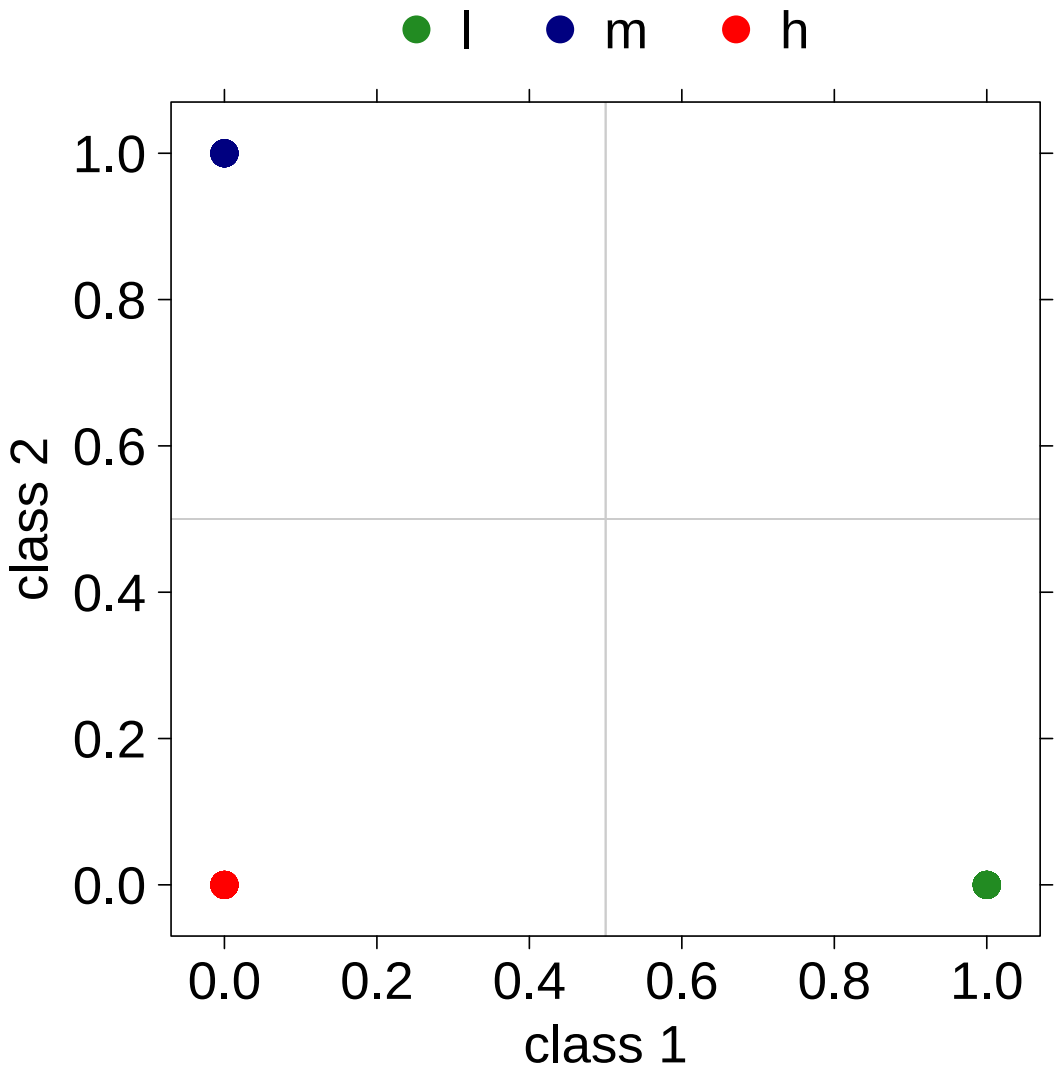


Figure 18: Multinomial logistic regression on dyslexia class, with interaction dde scores and wisc subscales as regressors.

3. Regressors: dde speed scores $*$ visual wisc subscales (dc+cf+rs).

```
Call:
multinom(formula = form.visivispeed, data = db.tmp)

Coefficients:
  (Intercept)  wspeed:dc wspeed:cf  wspeed:rs  nwspeed:dc nwspeed:cf nwspeed:rs
1    6.277681 0.00611342 0.2584666 -0.1146242  0.06079504 -0.1850473  0.1639073
2    2.039740 0.02950453 0.1529593 -0.1650891 -0.01074398 -0.1737438  0.2351008

Std. Errors:
  (Intercept)  wspeed:dc  wspeed:cf  wspeed:rs nwspeed:dc nwspeed:cf nwspeed:rs
1    1.298233 0.08365329 0.09530742 0.12434004 0.07698627 0.07868204  0.1160773
2    1.112825 0.05578426 0.06819754 0.08080758 0.06453172 0.07505726  0.1043742

Residual Deviance: 103.2073
AIC: 131.2073

P-values:
   (Intercept) wspeed:dc   wspeed:cf  wspeed:rs nwspeed:dc nwspeed:cf
1 1.327723e-06 0.9417421 0.006689371 0.35660142  0.4297108 0.01868099
2 6.681165e-02 0.5968719 0.024904171 0.04105346  0.8677702 0.02062300
  nwspeed:rs
1  0.1579344
2  0.0242920
```

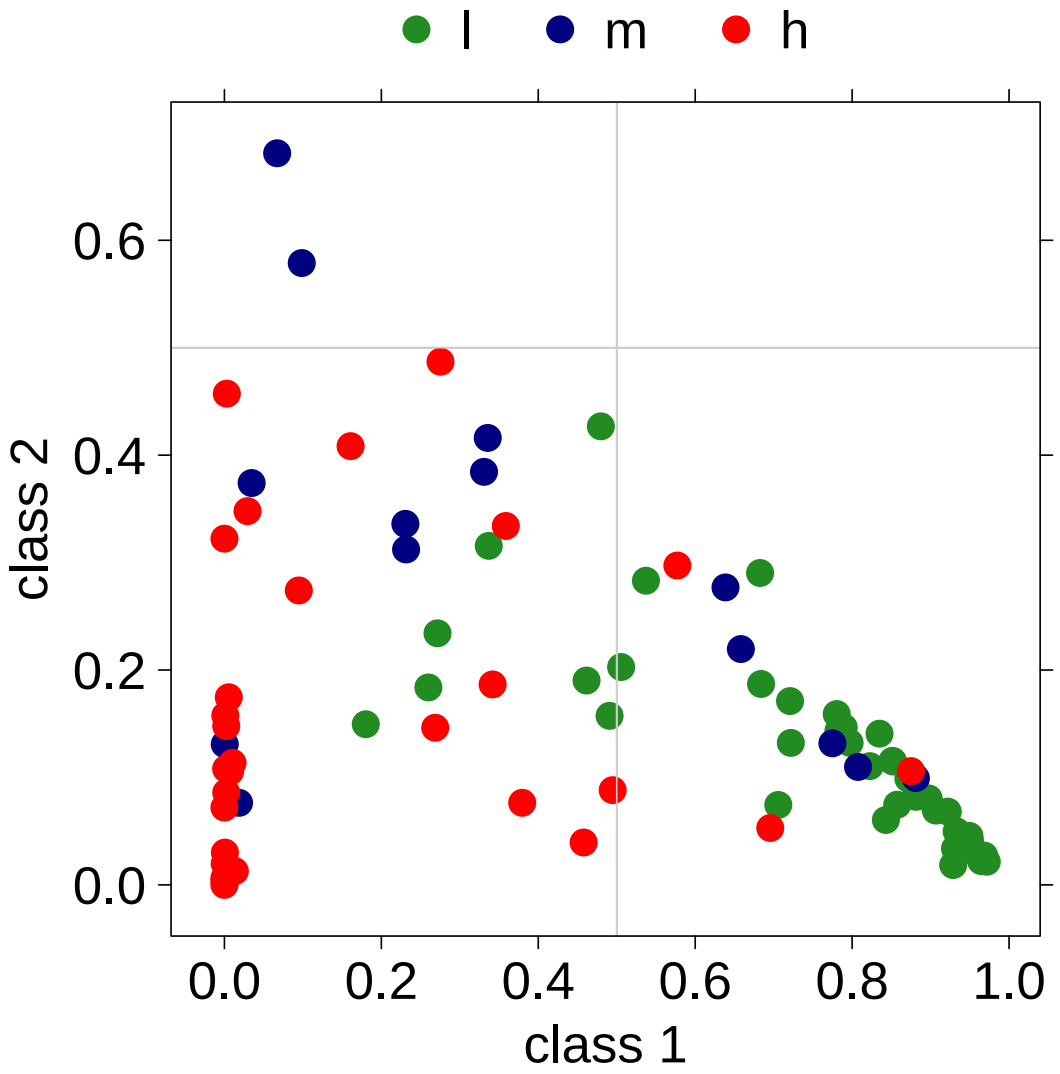


Figure 19: Multinomial logistic regression on dyslexia class, with interaction dde speed scores and visual wisc subscales as regressors.

4. Regressors: dde speed scores $*$ verbal wisc subscales (so+vc+co).

```
Call:
multinom(formula = form.verbspeed, data = db.tmp)

Coefficients:
  (Intercept)    wspeed:so  wspeed:vc wspeed:co  nwspeed:so nwspeed:vc
1    6.649187 0.1411143522 -0.1372634 0.1040200 -0.06918093  0.2415311
2    2.224401 0.0008399367 -0.2385547 0.2326216  0.02172425  0.3298946
  nwspeed:co
1 -0.1119064
2 -0.2798262

Std. Errors:
  (Intercept)  wspeed:so wspeed:vc wspeed:co nwspeed:so nwspeed:vc nwspeed:co
1    1.361804 0.12371457 0.1244158 0.1449235  0.1379826  0.1392925  0.1556190
2    1.248451 0.07401035 0.1072877 0.1242906  0.1083624  0.1344208  0.1515837

Residual Deviance: 97.91408
AIC: 125.9141

P-values:
   (Intercept) wspeed:so  wspeed:vc  wspeed:co nwspeed:so nwspeed:vc nwspeed:co
1 1.046801e-06 0.2540179 0.26991283 0.47290648  0.6161076 0.08292065 0.47207613
2 7.479351e-02 0.9909451 0.02618173 0.06126276  0.8411069 0.01412014 0.06488965
```

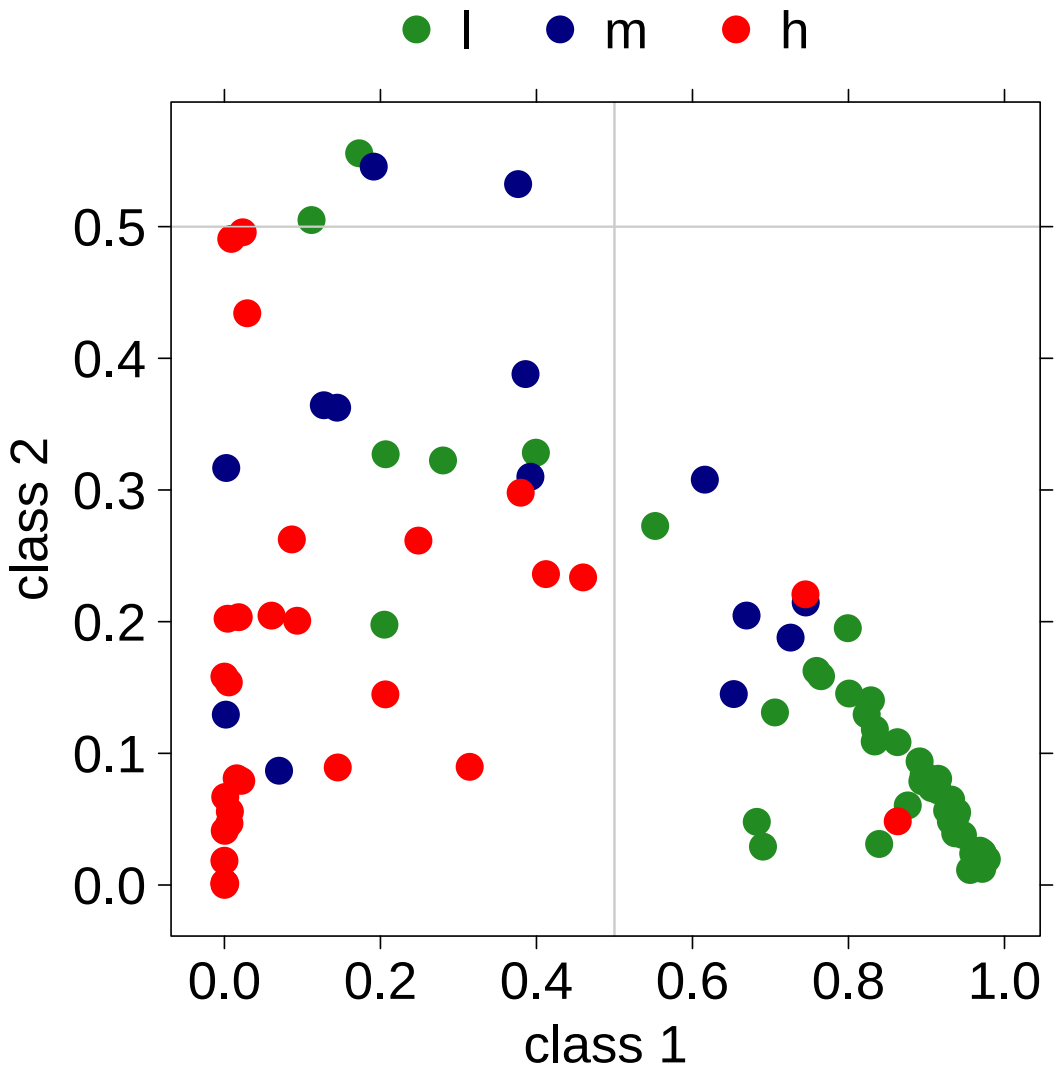


Figure 20: Multinomial logistic regression on dyslexia class, with interaction dde speed scores and verbal wisc subscales as regressors.

5. Regressors: wisc subscales (dc+cf+rs+so+vc+co+mc). Reference level ⟶ class 3.

```
Call:
multinom(formula = form.sub, data = db.tmp)

Coefficients:
  (Intercept)          dc          cf         rs           mc          so
1    1.341380 -0.07089792 -0.05945828 0.12023871  0.009459909 -0.18255369
2   -3.057193 -0.04641101  0.10046204 0.04019967 -0.036906151 -0.02193856
            vc        co
1 -0.077716873 0.1542340
2  0.008973166 0.1838802

Std. Errors:
  (Intercept)         dc        cf        rs         mc        so        vc
1    1.823957 0.09420951 0.1087047 0.1044373 0.09065468 0.1228189 0.1220454
2    2.445674 0.12552842 0.1405156 0.1455718 0.12152918 0.1679099 0.1723151
         co
1 0.1238968
2 0.1650733

Residual Deviance: 164.6416
AIC: 196.6416

P-values:
  (Intercept)        dc        cf        rs        mc        so        vc
1   0.4620820 0.4517169 0.5843989 0.2496088 0.9168908 0.1371825 0.5242638
2   0.2112846 0.7115873 0.4746380 0.7824327 0.7613706 0.8960469 0.9584696
         co
1 0.2131839
2 0.2653091
```

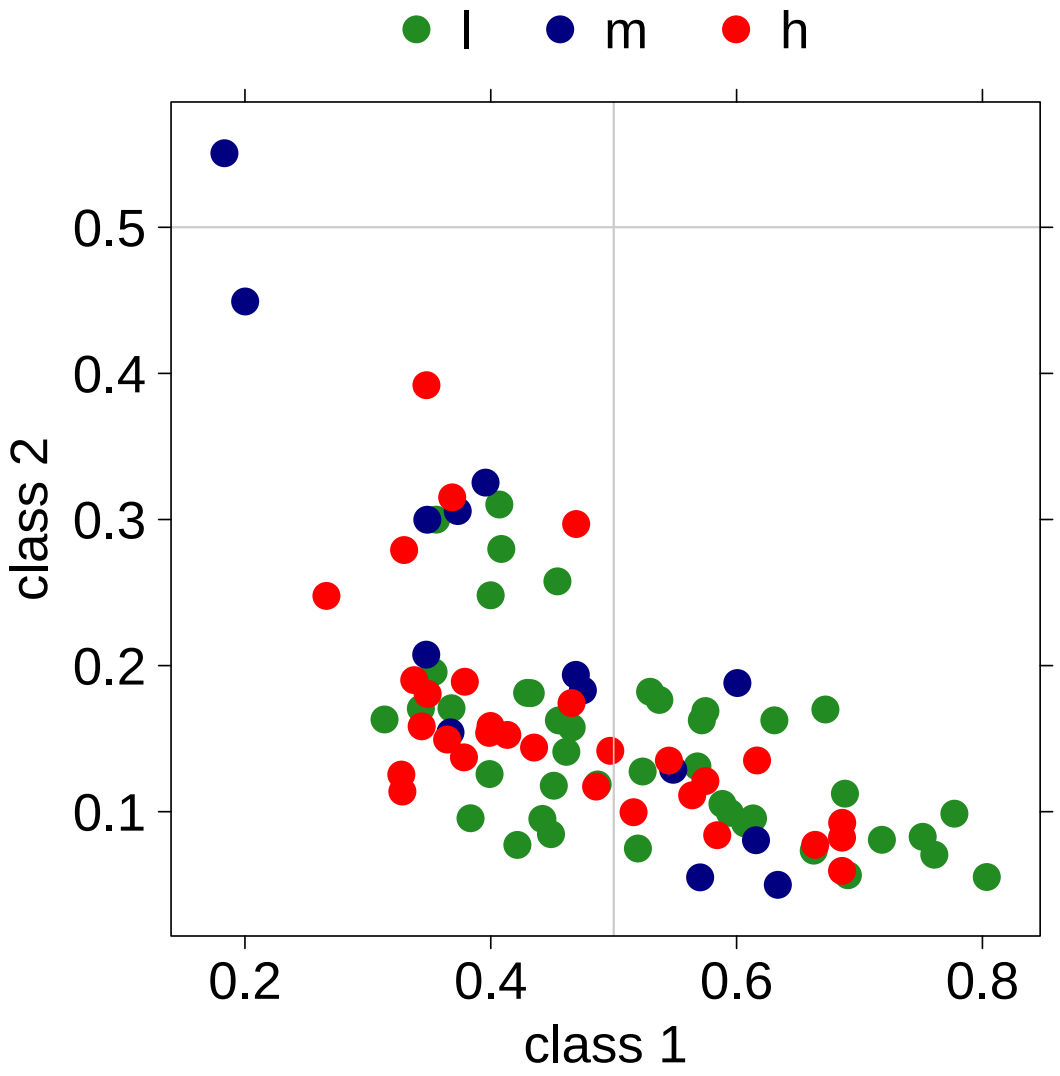


Figure 21: Multinomial logistic regression on dyslexia class, with wisc subscales as regressors.

If we reduce to only consider classes 1 and 3 we obtain:

- $class\ (wacc + nwacc + wspeed + nwspeed) * (dc + so + mc + cf + vc + co + rs)$

```
Warning messages:
1: glm.fit: algorithm did not converge
2: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

- $class\ wspeed + nwspeed + wacc + nwacc$

```
Call:
glm(formula = form, family = binomial, data = data)

Deviance Residuals:
       Min          1Q      Median          3Q         Max
-3.414e-05  -2.100e-08   2.100e-08   2.100e-08   4.329e-05

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)    170.93  106509.49   0.002    0.999
wspeed          12.42   22953.48   0.001    1.000
nwspeed         15.27   19789.85   0.001    0.999
wacc            16.20   11885.89   0.001    0.999
nwacc           16.76   14639.62   0.001    0.999

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 9.7804e+01  on 71  degrees of freedom
Residual deviance: 4.5129e-09  on 67  degrees of freedom
AIC: 10

Number of Fisher Scoring iterations: 25
```

- $class\ (wspeed + wacc + nwspeed + nwacc) : (dc + cf + rs + mc + so + vc + co)$

```
Warning messages:
1: glm.fit: algorithm did not converge
2: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

- $class\ dc + cf + rs + mc + so + vc + co$

```
Call:
glm(formula = form, family = binomial, data = data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6764  -1.1531   0.7178   1.0841   1.3691

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  1.643483   2.026490   0.811    0.417
dc          -0.064009   0.094734  -0.676    0.499
cf          -0.079863   0.114484  -0.698    0.485
rs           0.121840   0.101854   1.196    0.232
mc           0.008063   0.089418   0.090    0.928
so          -0.181098   0.127121  -1.425    0.154
vc          -0.076115   0.129030  -0.590    0.555
co           0.130424   0.121668   1.072    0.284

(Dispersion parameter for binomial family taken to be 1)
```

```
    Null deviance: 97.804  on 71  degrees of freedom
Residual deviance: 92.919  on 64  degrees of freedom
AIC: 108.92

Number of Fisher Scoring iterations: 4
```

- $class\ (wspeed + nwspeed) : (dc + cf + rs)$ (VISIVI)

```
Call:
glm(formula = form, family = binomial, data = data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.9962  -0.1195   0.1354   0.3802   1.6085

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  6.42550    1.67242   3.842 0.000122 ***
wspeed:dc   -0.04907    0.08932  -0.549 0.582720
wspeed:cf    0.29366    0.11144   2.635 0.008408 **
wspeed:rs   -0.11524    0.12159  -0.948 0.343227
nwspeed:dc   0.11803    0.08430   1.400 0.161474
nwspeed:cf  -0.19764    0.08638  -2.288 0.022134 *
nwspeed:rs   0.14482    0.11464   1.263 0.206504
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 97.804  on 71  degrees of freedom
Residual deviance: 38.843  on 65  degrees of freedom
AIC: 52.843

Number of Fisher Scoring iterations: 7
```

- $class\ (wspeed + nwspeed) : (so + vc + co)$ (VERBALI)

```
Call:
glm(formula = form, family = binomial, data = data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.6944  -0.2183   0.1092   0.3165   1.7802

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  6.43340    1.59738   4.027 5.64e-05 ***
wspeed:so    0.11347    0.12399   0.915   0.3601
wspeed:vc   -0.17754    0.14304  -1.241   0.2145
wspeed:co    0.14524    0.16208   0.896   0.3702
nwspeed:so  -0.07763    0.13232  -0.587   0.5574
nwspeed:vc   0.29298    0.16694   1.755   0.0793 .
nwspeed:co  -0.13971    0.17006  -0.821   0.4114
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)
```

```
    Null deviance: 97.804  on 71  degrees of freedom
Residual deviance: 35.733  on 65  degrees of freedom
AIC: 49.733

Number of Fisher Scoring iterations: 7
```