Replication File Chapter 4

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Packages and Data Preparation

Packages

```
library(brms)
library(dplyr)

# run the following for two lines parallel estimation of brms models
# library(parallel)
# options(mc.cores = parallel::detectCores())

data_paper3_gles <- "../data/"

# load the data
# selected and clean variables from the original data, one subject is
# one observation
load(file = paste0(data_paper3_gles, "befragung_selection.Rda"))
# long dataframe whith one subject-politican combination is one observation;
# used to estimate the models
load(file = paste0(data_paper3_gles, "befragung_per_candidate.Rda"))
```

Model 4.1: All Politicians

```
# This code load the brms-object reported in the Dissertation. If you wish to
# estimate the model again, either change or remove the filenname under the
# 'file = ' argument or run the code in comments below.
symp_brm_post_pos5 <- brm(
  symp_post_positive ~
    (1|symp_pre_positive + age_decades + a145 + match_id) +
    (0 + angst_dif + aversion_scale_dif + enth_scale_dif | follower_dummy) +
    female_dummy,
              data = filter(befragung_per_candidate, !name == "herrmann"),
              family=cumulative("logit"),
              control = list(adapt_delta = 0.999, max_treedepth = 15),
                  iter = 6000,
             file = paste0(data_paper3_gles, "symp_brm_post_pos5"))

summary(symp_brm_post_pos5)
```

```
##  Family: cumulative
##   Links: mu = logit; disc = identity
## Formula: symp_post_positive ~ (1 | symp_pre_positive + age_decades + a145 + match_id) + (0 + angst_di
##    Data: filter(befragung_per_candidate, !name == "herrmann (Number of observations: 590)
## Samples: 4 chains, each with iter = 6000; warmup = 3000; thin = 1;
##          total post-warmup samples = 12000
##
## Group-Level Effects:
## ~a145 (Number of levels: 5)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.24      0.27     0.01     0.94 1.00     4753     6128
##
## ~age_decades (Number of levels: 6)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.19      0.17     0.01     0.62 1.00     4545     5065
##
## ~follower_dummy (Number of levels: 2)
##                                     Estimate Est.Error l-95% CI u-95% CI
## sd(angst_dif)                           0.48      0.67     0.02     2.30
## sd(aversion_scale_dif)                  0.88      0.88     0.14     3.29
## sd(enth_scale_dif)                      0.99      0.89     0.23     3.37
## cor(angst_dif,aversion_scale_dif)       0.12      0.51    -0.84     0.93
## cor(angst_dif,enth_scale_dif)          -0.14      0.50    -0.93     0.80
## cor(aversion_scale_dif,enth_scale_dif) -0.16      0.49    -0.93     0.78
##                                     Rhat Bulk_ESS Tail_ESS
## sd(angst_dif)                       1.00     4129     3653
## sd(aversion_scale_dif)              1.00     6265     7420
## sd(enth_scale_dif)                  1.00     6312     7466
## cor(angst_dif,aversion_scale_dif)   1.00     8552     7601
## cor(angst_dif,enth_scale_dif)       1.00     9735     8209
## cor(aversion_scale_dif,enth_scale_dif) 1.00     9236     9594
##
## ~match_id (Number of levels: 187)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.62      0.18     0.22     0.95 1.00     1986     1917
##
## ~symp_pre_positive (Number of levels: 11)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     4.14      0.92     2.77     6.32 1.00     2717     5008
##
## Population-Level Effects:
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept[1]     -4.80      0.92    -6.67    -3.05 1.00     2429     4717
## Intercept[2]     -3.82      0.90    -5.64    -2.09 1.00     2401     4700
## Intercept[3]     -2.71      0.89    -4.49    -0.99 1.00     2349     4696
## Intercept[4]     -1.79      0.88    -3.54    -0.07 1.00     2328     4472
## Intercept[5]     -1.15      0.88    -2.90     0.57 1.00     2330     4327
## Intercept[6]     -0.06      0.87    -1.82     1.63 1.00     2306     4597
## Intercept[7]      1.20      0.88    -0.54     2.92 1.00     2313     4322
## Intercept[8]      2.83      0.89     1.04     4.59 1.00     2337     4329
## Intercept[9]      4.98      0.92     3.16     6.80 1.00     2383     4555
## Intercept[10]     7.40      0.97     5.46     9.30 1.00     2556     4790
## female_dummy      0.14      0.19    -0.24     0.52 1.00    12705     9716
##
```

```
## Family Specific Parameters:
##      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## disc     1.00      0.00     1.00     1.00 1.00    12000    12000
##
## Samples were drawn using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

```
prior_summary(symp_brm_post_pos5)
```

```
##                 prior     class               coef             group resp dpar
##                (flat)         b
##                (flat)         b       female_dummy
##  student_t(3, 0, 2.5) Intercept
##  student_t(3, 0, 2.5) Intercept                  1
##  student_t(3, 0, 2.5) Intercept                 10
##  student_t(3, 0, 2.5) Intercept                  2
##  student_t(3, 0, 2.5) Intercept                  3
##  student_t(3, 0, 2.5) Intercept                  4
##  student_t(3, 0, 2.5) Intercept                  5
##  student_t(3, 0, 2.5) Intercept                  6
##  student_t(3, 0, 2.5) Intercept                  7
##  student_t(3, 0, 2.5) Intercept                  8
##  student_t(3, 0, 2.5) Intercept                  9
##  lkj_corr_cholesky(1)         L
##  lkj_corr_cholesky(1)         L                        follower_dummy
##  student_t(3, 0, 2.5)        sd
##  student_t(3, 0, 2.5)        sd                                  a145
##  student_t(3, 0, 2.5)        sd          Intercept              a145
##  student_t(3, 0, 2.5)        sd                           age_decades
##  student_t(3, 0, 2.5)        sd          Intercept       age_decades
##  student_t(3, 0, 2.5)        sd                        follower_dummy
##  student_t(3, 0, 2.5)        sd          angst_dif    follower_dummy
##  student_t(3, 0, 2.5)        sd aversion_scale_dif    follower_dummy
##  student_t(3, 0, 2.5)        sd     enth_scale_dif    follower_dummy
##  student_t(3, 0, 2.5)        sd                              match_id
##  student_t(3, 0, 2.5)        sd          Intercept          match_id
##  student_t(3, 0, 2.5)        sd                     symp_pre_positive
##  student_t(3, 0, 2.5)        sd          Intercept symp_pre_positive
##  nlpar bound       source
##                   (unknown)
##                (vectorized)
##                   (unknown)
##                (vectorized)
##                (vectorized)
##                (vectorized)
##                (vectorized)
##                (vectorized)
##                (vectorized)
##                (vectorized)
##                (vectorized)
##                (vectorized)
##                (vectorized)
##                   (unknown)
```

```
##              (vectorized)
##                 (unknown)
##              (vectorized)
##              (vectorized)
##              (vectorized)
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##              (vectorized)
##              (vectorized)
##              (vectorized)
##              (vectorized)
##              (vectorized)
##              (vectorized)
##              (vectorized)
##              (vectorized)
```

```
rm(symp_brm_post_pos5)

# # estimate the model from scratch if you wish
# symp_brm_post_pos_new_estimation <- brm(symp_post_positive ~ (1|symp_pre_positive + age_decades + a14
#               data = filter(befragung_per_candidate, !name == "herrmann"),
#               family=cumulative("logit"),
#               control = list(adapt_delta = 0.999, max_treedepth = 15),
#                   iter = 6000,
#              file = paste0(data_paper3_gles, "symp_brm_post_pos5_new_estimation"))
```

Model 4.2: Merkel

```
# loading the object
symp_brm_post_pos_merkel <- brm(
  symp_post_positive ~
    (1|symp_pre_positive + age_decades + a145 + match_id) +
    (0 + angst_dif + aversion_scale_dif + enth_scale_dif | follower_dummy) +
    female_dummy,
             data = filter(befragung_per_candidate, name == "merkel"),
             family=cumulative("logit"),
             control = list(adapt_delta = 0.999, max_treedepth = 15),
                 iter = 6000,
            file = paste0(data_paper3_gles, "symp_brm_post_pos_merkel"))

summary(symp_brm_post_pos_merkel)
```

```
##  Family: cumulative
##   Links: mu = logit; disc = identity
## Formula: symp_post_positive ~ (1 | symp_pre_positive + age_decades + a145 + match_id) + (0 + angst_di
##    Data: filter(befragung_per_candidate, name == "merkel") (Number of observations: 180)
## Samples: 4 chains, each with iter = 6000; warmup = 3000; thin = 1;
##          total post-warmup samples = 12000
##
## Group-Level Effects:
## ~a145 (Number of levels: 5)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
```

```
## sd(Intercept)     0.47      0.52     0.01     1.85 1.00     4489     6473
##
## ~age_decades (Number of levels: 6)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.26      0.24     0.01     0.90 1.00     5555     6736
##
## ~follower_dummy (Number of levels: 2)
##                                     Estimate Est.Error l-95% CI u-95% CI
## sd(angst_dif)                           0.76      0.85     0.03     3.06
## sd(aversion_scale_dif)                  1.67      1.53     0.04     5.37
## sd(enth_scale_dif)                      0.91      0.90     0.06     3.42
## cor(angst_dif,aversion_scale_dif)      -0.11      0.50    -0.92     0.85
## cor(angst_dif,enth_scale_dif)          -0.02      0.51    -0.89     0.87
## cor(aversion_scale_dif,enth_scale_dif)    -0.18      0.48    -0.93     0.78
##                                     Rhat Bulk_ESS Tail_ESS
## sd(angst_dif)                       1.00     4552     5313
## sd(aversion_scale_dif)              1.00     3905     4932
## sd(enth_scale_dif)                  1.00     5341     5376
## cor(angst_dif,aversion_scale_dif)   1.00     8821     7457
## cor(angst_dif,enth_scale_dif)       1.00    11007     8716
## cor(aversion_scale_dif,enth_scale_dif) 1.00    10003     8176
##
## ~match_id (Number of levels: 180)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.74      0.57     0.03     2.20 1.01      527      714
##
## ~symp_pre_positive (Number of levels: 11)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     4.48      1.19     2.82     7.37 1.00     1803     2223
##
## Population-Level Effects:
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept[1]     -5.98      1.36    -9.02    -3.64 1.00     1472     1608
## Intercept[2]     -4.74      1.22    -7.37    -2.61 1.00     1742     2042
## Intercept[3]     -3.22      1.09    -5.54    -1.21 1.00     2704     3012
## Intercept[4]     -2.02      1.02    -4.11    -0.11 1.00     3526     4693
## Intercept[5]     -1.03      0.98    -3.01     0.85 1.00     3873     5107
## Intercept[6]      0.44      0.98    -1.47     2.40 1.00     3935     5811
## Intercept[7]      1.58      1.01    -0.34     3.65 1.00     3421     4337
## Intercept[8]      3.60      1.14     1.61     6.03 1.00     2176     2497
## Intercept[9]      5.40      1.30     3.21     8.29 1.00     1559     1611
## Intercept[10]     8.49      1.66     5.91    12.50 1.00     1158     1082
## female_dummy     -0.04      0.35    -0.73     0.65 1.00     9796     6798
##
## Family Specific Parameters:
##      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## disc     1.00      0.00     1.00     1.00 1.00    12000    12000
##
## Samples were drawn using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

```
prior_summary(symp_brm_post_pos_merkel)
```

```
##                prior     class               coef            group resp dpar
##               (flat)         b
##               (flat)         b       female_dummy
##  student_t(3, 0, 2.5) Intercept
##  student_t(3, 0, 2.5) Intercept                  1
##  student_t(3, 0, 2.5) Intercept                 10
##  student_t(3, 0, 2.5) Intercept                  2
##  student_t(3, 0, 2.5) Intercept                  3
##  student_t(3, 0, 2.5) Intercept                  4
##  student_t(3, 0, 2.5) Intercept                  5
##  student_t(3, 0, 2.5) Intercept                  6
##  student_t(3, 0, 2.5) Intercept                  7
##  student_t(3, 0, 2.5) Intercept                  8
##  student_t(3, 0, 2.5) Intercept                  9
##  lkj_corr_cholesky(1)         L
##  lkj_corr_cholesky(1)         L                     follower_dummy
##  student_t(3, 0, 2.5)        sd
##  student_t(3, 0, 2.5)        sd                               a145
##  student_t(3, 0, 2.5)        sd          Intercept            a145
##  student_t(3, 0, 2.5)        sd                        age_decades
##  student_t(3, 0, 2.5)        sd          Intercept     age_decades
##  student_t(3, 0, 2.5)        sd                     follower_dummy
##  student_t(3, 0, 2.5)        sd          angst_dif  follower_dummy
##  student_t(3, 0, 2.5)        sd aversion_scale_dif  follower_dummy
##  student_t(3, 0, 2.5)        sd     enth_scale_dif  follower_dummy
##  student_t(3, 0, 2.5)        sd                           match_id
##  student_t(3, 0, 2.5)        sd          Intercept        match_id
##  student_t(3, 0, 2.5)        sd                   symp_pre_positive
##  student_t(3, 0, 2.5)        sd          Intercept symp_pre_positive
##  nlpar bound       source
##                  (unknown)
##               (vectorized)
##                  (unknown)
##               (vectorized)
##               (vectorized)
##               (vectorized)
##               (vectorized)
##               (vectorized)
##               (vectorized)
##               (vectorized)
##               (vectorized)
##               (vectorized)
##               (vectorized)
##                  (unknown)
##               (vectorized)
##                  (unknown)
##               (vectorized)
##               (vectorized)
##               (vectorized)
##               (vectorized)
##               (vectorized)
##               (vectorized)
##               (vectorized)
##               (vectorized)
```

```
##              (vectorized)
##              (vectorized)
##              (vectorized)
##              (vectorized)
```

```
rm(symp_brm_post_pos_merkel)
```

Model 4.3: Schulz

```
symp_brm_post_pos_schulz <- brm(
  symp_post_positive ~
    (1|symp_pre_positive + age_decades + a145 + match_id) +
    (0 + angst_dif + aversion_scale_dif + enth_scale_dif | follower_dummy) +
    female_dummy,
             data = filter(befragung_per_candidate, name == "schulz"),
             family=cumulative("logit"),
             control = list(adapt_delta = 0.999, max_treedepth = 15),
                 iter = 6000,
            file = paste0(data_paper3_gles, "symp_brm_post_pos_schulz"))

summary(symp_brm_post_pos_schulz)
```

```
##  Family: cumulative
##   Links: mu = logit; disc = identity
## Formula: symp_post_positive ~ (1 | symp_pre_positive + age_decades + a145 + match_id) + (0 + angst_di
##    Data: filter(befragung_per_candidate, name == "schulz") (Number of observations: 179)
## Samples: 4 chains, each with iter = 6000; warmup = 3000; thin = 1;
##          total post-warmup samples = 12000
##
## Group-Level Effects:
## ~a145 (Number of levels: 5)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.55      0.52     0.02     1.88 1.00     3629     5011
##
## ~age_decades (Number of levels: 6)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.39      0.35     0.02     1.28 1.00     3521     5797
##
## ~follower_dummy (Number of levels: 2)
##                                          Estimate Est.Error l-95% CI u-95% CI
## sd(angst_dif)                                0.58      0.76     0.01     2.64
## sd(aversion_scale_dif)                       1.81      1.37     0.26     5.26
## sd(enth_scale_dif)                           0.82      0.87     0.06     3.17
## cor(angst_dif,aversion_scale_dif)            0.09      0.51    -0.85     0.91
## cor(angst_dif,enth_scale_dif)                0.01      0.51    -0.88     0.89
## cor(aversion_scale_dif,enth_scale_dif)      -0.03      0.48    -0.87     0.84
##                                          Rhat Bulk_ESS Tail_ESS
## sd(angst_dif)                            1.00     5267     6538
## sd(aversion_scale_dif)                   1.00     4460     4071
## sd(enth_scale_dif)                       1.00     4905     5203
```

```
## cor(angst_dif,aversion_scale_dif)      1.00     6668     7430
## cor(angst_dif,enth_scale_dif)          1.00     9337     8223
## cor(aversion_scale_dif,enth_scale_dif) 1.00     9714     9041
##
## ~match_id (Number of levels: 179)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     1.26      0.75     0.08     2.91 1.01      419      843
##
## ~symp_pre_positive (Number of levels: 11)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     4.88      1.44     2.80     8.39 1.00      962     2175
##
## Population-Level Effects:
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept[1]     -5.59      1.46    -8.95    -3.17 1.00     1158     1553
## Intercept[2]     -4.62      1.33    -7.58    -2.32 1.00     1434     2003
## Intercept[3]     -3.55      1.20    -6.18    -1.37 1.00     1885     2433
## Intercept[4]     -2.68      1.12    -5.05    -0.58 1.00     2345     2821
## Intercept[5]     -1.96      1.08    -4.18     0.11 1.00     2756     3208
## Intercept[6]     -0.26      1.06    -2.28     1.90 1.00     2755     4164
## Intercept[7]      1.18      1.13    -0.86     3.64 1.00     1426     2230
## Intercept[8]      2.82      1.30     0.64     5.79 1.01      871     1616
## Intercept[9]      5.39      1.66     2.81     9.34 1.01      622     1215
## Intercept[10]     8.06      2.12     4.93    13.16 1.01      565     1102
## female_dummy      0.20      0.39    -0.56     1.01 1.00     8186     5307
##
## Family Specific Parameters:
##      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## disc     1.00      0.00     1.00     1.00 1.00    12000    12000
##
## Samples were drawn using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

```r
prior_summary(symp_brm_post_pos_schulz)
```

```
##                 prior     class               coef             group resp dpar
##                (flat)         b
##                (flat)         b       female_dummy
##  student_t(3, 0, 2.5) Intercept
##  student_t(3, 0, 2.5) Intercept                  1
##  student_t(3, 0, 2.5) Intercept                 10
##  student_t(3, 0, 2.5) Intercept                  2
##  student_t(3, 0, 2.5) Intercept                  3
##  student_t(3, 0, 2.5) Intercept                  4
##  student_t(3, 0, 2.5) Intercept                  5
##  student_t(3, 0, 2.5) Intercept                  6
##  student_t(3, 0, 2.5) Intercept                  7
##  student_t(3, 0, 2.5) Intercept                  8
##  student_t(3, 0, 2.5) Intercept                  9
##  lkj_corr_cholesky(1)         L
##  lkj_corr_cholesky(1)         L                          follower_dummy
##  student_t(3, 0, 2.5)        sd
##  student_t(3, 0, 2.5)        sd                                    a145
```

```
## student_t(3, 0, 2.5)       sd          Intercept              a145
## student_t(3, 0, 2.5)       sd                          age_decades
## student_t(3, 0, 2.5)       sd          Intercept       age_decades
## student_t(3, 0, 2.5)       sd                       follower_dummy
## student_t(3, 0, 2.5)       sd          angst_dif    follower_dummy
## student_t(3, 0, 2.5)       sd aversion_scale_dif    follower_dummy
## student_t(3, 0, 2.5)       sd     enth_scale_dif    follower_dummy
## student_t(3, 0, 2.5)       sd                             match_id
## student_t(3, 0, 2.5)       sd          Intercept          match_id
## student_t(3, 0, 2.5)       sd                    symp_pre_positive
## student_t(3, 0, 2.5)       sd          Intercept symp_pre_positive
## nlpar bound       source
##                (unknown)
##             (vectorized)
##                (unknown)
##             (vectorized)
##             (vectorized)
##             (vectorized)
##             (vectorized)
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##             (vectorized)
##             (vectorized)
##             (vectorized)
```

```r
rm(symp_brm_post_pos_schulz)
```

Average Fear and Anger among Merkel & Schulz Partisans

```r
# Merkel Partisans, who are more angry -> take negative sides and fear
angry_merkel <- befragung_per_candidate %>%
  filter(name == "merkel" & follower_dummy == 1 & aversion_scale_dif>0) %>%
  select(schlechte_seiten_post, angst_dif)

# Merkel Partisans, who are less or same angry -> take negative sides and fear
```

```r
non_angry_merkel <- befragung_per_candidate %>%
  filter(name == "merkel" & follower_dummy == 1 & aversion_scale_dif<=0) %>%
  select(schlechte_seiten_post, angst_dif)

# t-test
t.test(angry_merkel$angst_dif, non_angry_merkel$angst_dif, alternative = "g")
```

```
##
##  Welch Two Sample t-test
##
## data:  angry_merkel$angst_dif and non_angry_merkel$angst_dif
## t = 2.0901, df = 4.2085, p-value = 0.05069
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval:
##  -0.008096411          Inf
## sample estimates:
##   mean of x   mean of y
##  1.40000000 -0.03571429
```

```r
# Schulz Partisans, who are more angry -> take negative sides and fear
angry_schulz <- befragung_per_candidate %>%
  filter(name == "schulz" & follower_dummy == 1 & aversion_scale_dif>0) %>%
  select(schlechte_seiten_post, gute_seiten_post, angst_dif)

# Schulz Partisans, who are less or same angry -> take negative sides and fear
non_angry_schulz <- befragung_per_candidate %>%
  filter(name == "schulz" & follower_dummy == 1 & aversion_scale_dif<=0) %>%
  select(schlechte_seiten_post, gute_seiten_post, angst_dif)

# t-test
t.test(angry_schulz$angst_dif, non_angry_schulz$angst_dif, alternative = "g")
```

```
##
##  Welch Two Sample t-test
##
## data:  angry_schulz$angst_dif and non_angry_schulz$angst_dif
## t = 1.2383, df = 23, p-value = 0.1141
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval:
##  -0.09601903         Inf
## sample estimates:
## mean of x mean of y
##      0.00     -0.25
```

Print Negative Sides Angry Merkel Follower

```r
angry_merkel$schlechte_seiten_post
```

```
## [1] "Nicht ehrlich, redet viel ohne etwas zusagen  nicht authentisch"
## [2] "um den heißen Brei herumreden"
```

```
## [3] "sehr schlecht in solchen Duellen  hebt sich nicht ab  zu konservativ"
## [4] "gelegentlich nicht konservativ genug"
## [5] "Hält mit Entscheidungen zurück.  Zu unternehmerfreundlich"
```

Negative Sides Angry Schulz Follower

```
angry_schulz$schlechte_seiten_post
```

```
## [1] "kampflustig  fällt der Kanzlerin ins Wort  kommt bei seinen Aussagen nicht auf den Punkt"
## [2] "aufbrausend"
## [3] "keine"
## [4] "/"
## [5] "-99 keine Angabe"
```