Cognitive Bias and Symptom Importance, Supplemental Analyses

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Supplemental analyses

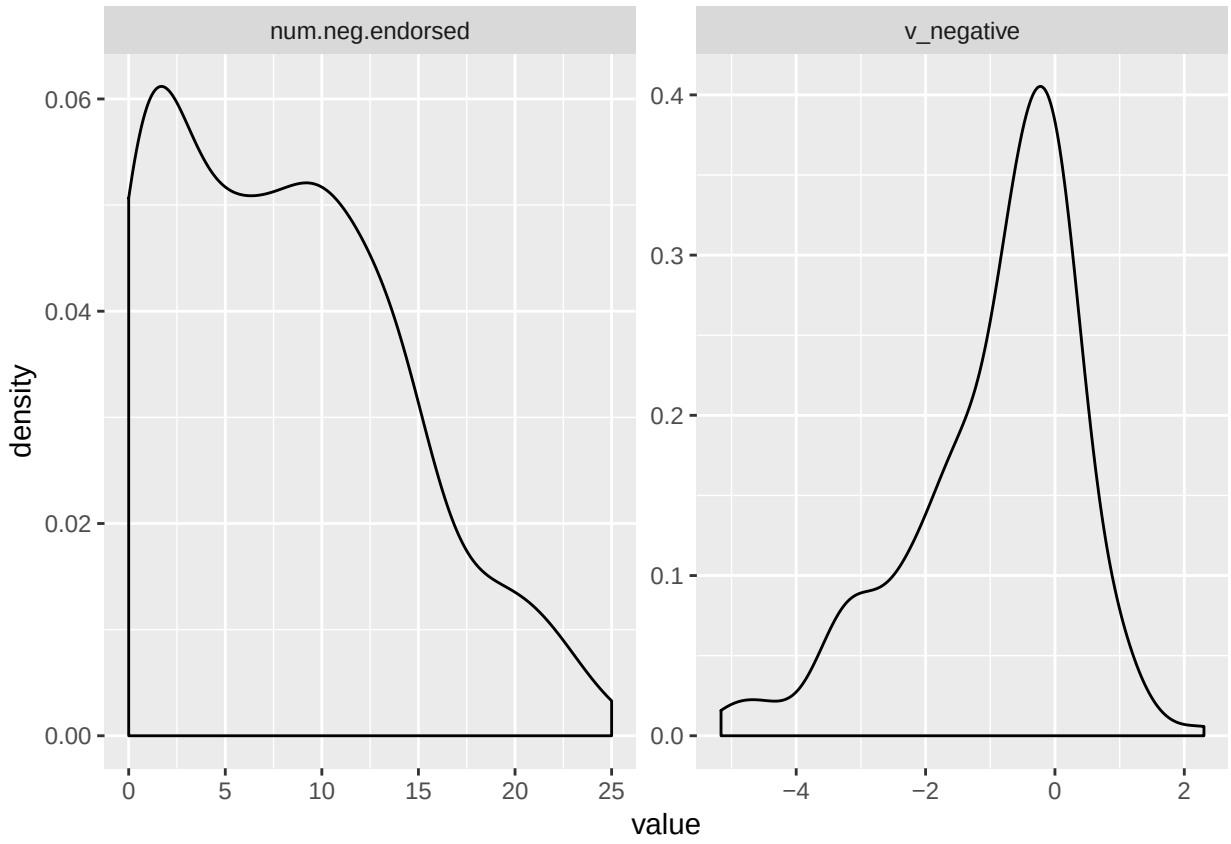
This file includes code snippets used to generate the supplemental analyses for *Association between negative cognitive bias and depression: A symptom-level approach* by Beevers et al.

Packages used for this analysis. Note that the beset package is not available on CRAN, but can be found here: https://github.com/jashu/beset

```
library(knitr); library(haven)
library(tidyverse); library(beset)
library(ggpubr)
```

Section 1.0: Distribution of SRET metrics

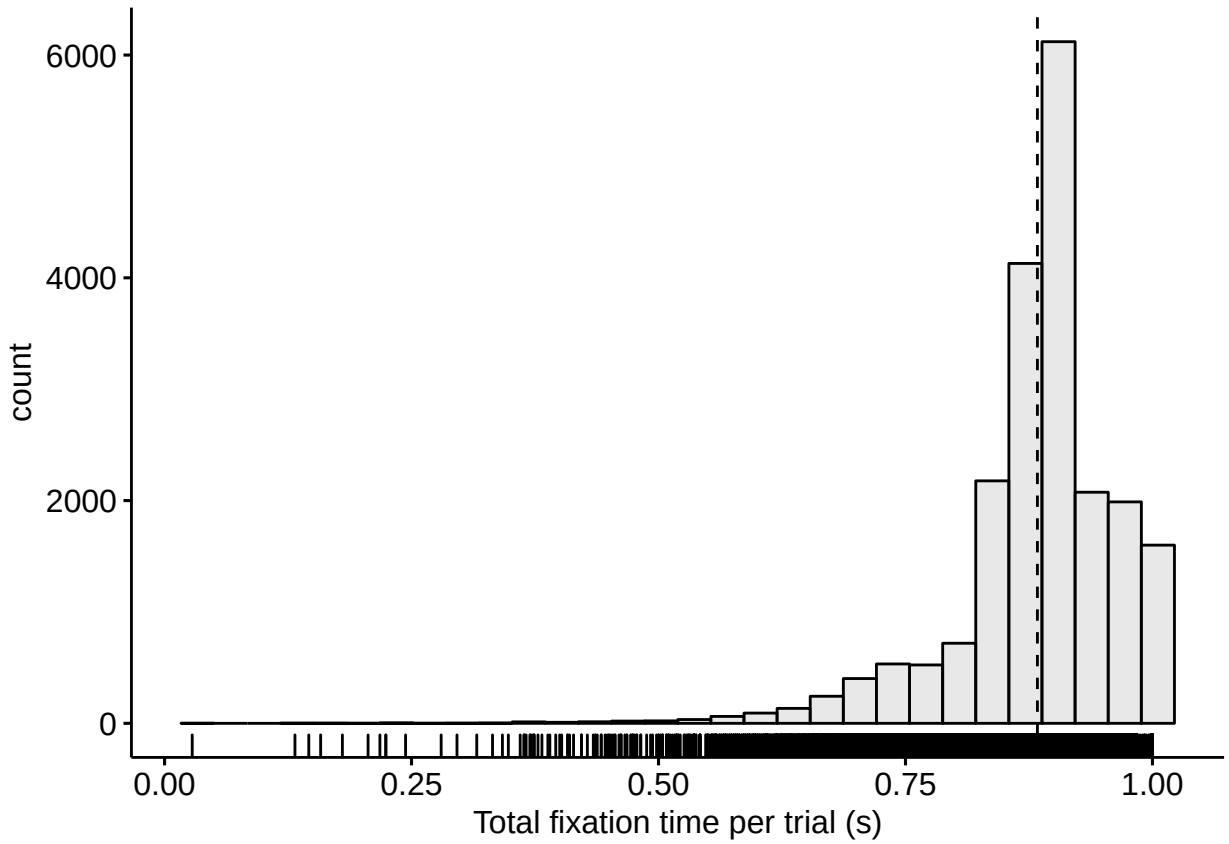
```
sret %>%
  select(num.neg.endorsed, v_negative) %>%
  gather() %>%
  ggplot(aes(value)) +
    facet_wrap(~ key, scales = "free") +
    geom_density()
```



As expected and can be seen in the figure on the left, the count data for number of negative words endorsed as self-descriptive (num.neg.endorsed) is highly non-normally distributed. The distribution for drift rate for negative words (v_negative) does not appear to strongly deviate from a normal distribution.

Section 1.1: Distribution of total fixation data across all trials

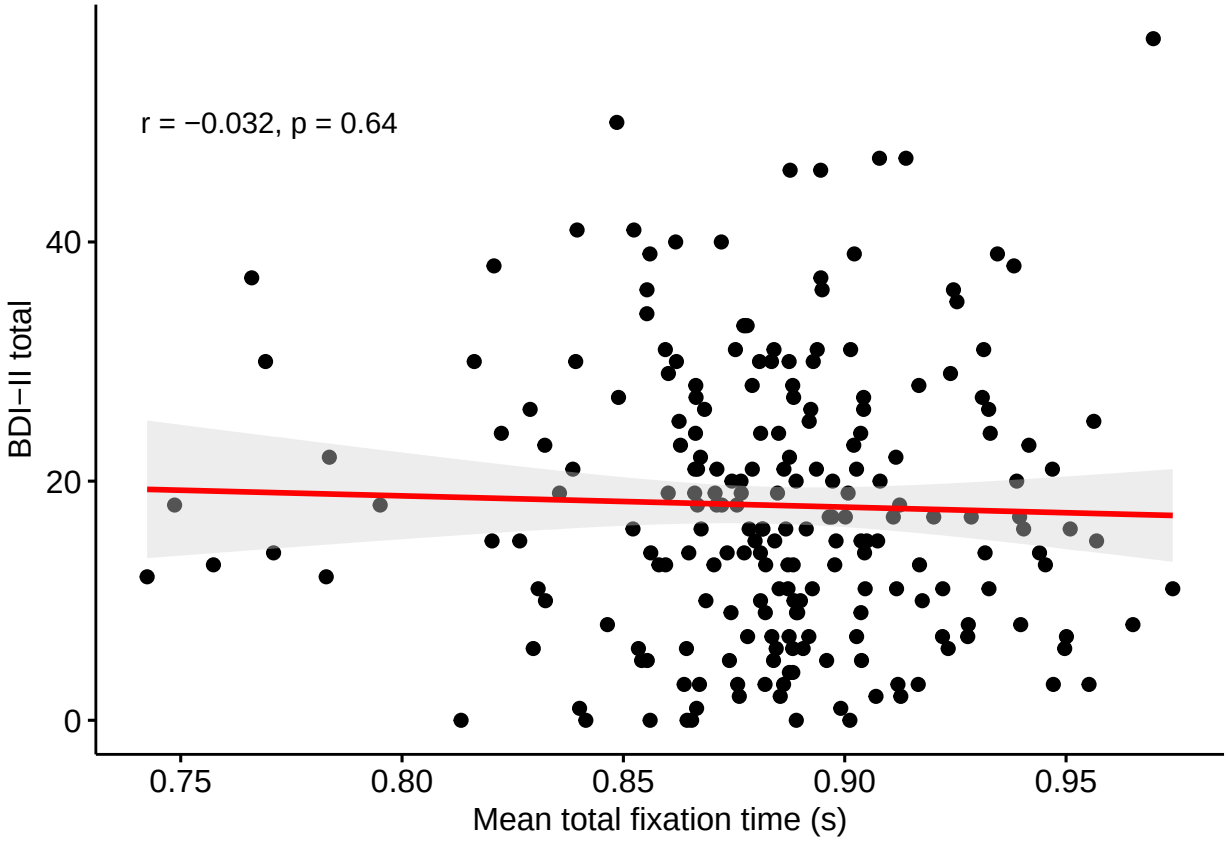
```
library(ggpubr)
gghistogram(tot_fix, x = "total_fixation", fill = "lightgray",
            add = "mean", rug = TRUE) +
  labs(x = "Total fixation time per trial (s)")
```



Histrogram of trial level data indicates that most trials had relatively little missing fixation data. Fixation is primarily missing due to blinks or significant head movement. Dashed line indicates mean total fixation per trial in seconds.

Section 1.2: Correlation between BDI-II and mean total fixation time

```
sp <- ggscatter(tot_fix, x = "mean_tot_fix", y = "bdi_total",
   add = "reg.line",  # Add regressin line
   add.params = list(color = "red", fill = "lightgray"), # Customize reg. line
   conf.int = TRUE # Add confidence interval
   )
# Add correlation coefficient
sp + stat_cor(method = "pearson", label.x = .77, label.y = 50) +
  labs(x = "Mean total fixation time (s)",
       y = "BDI-II total")
```

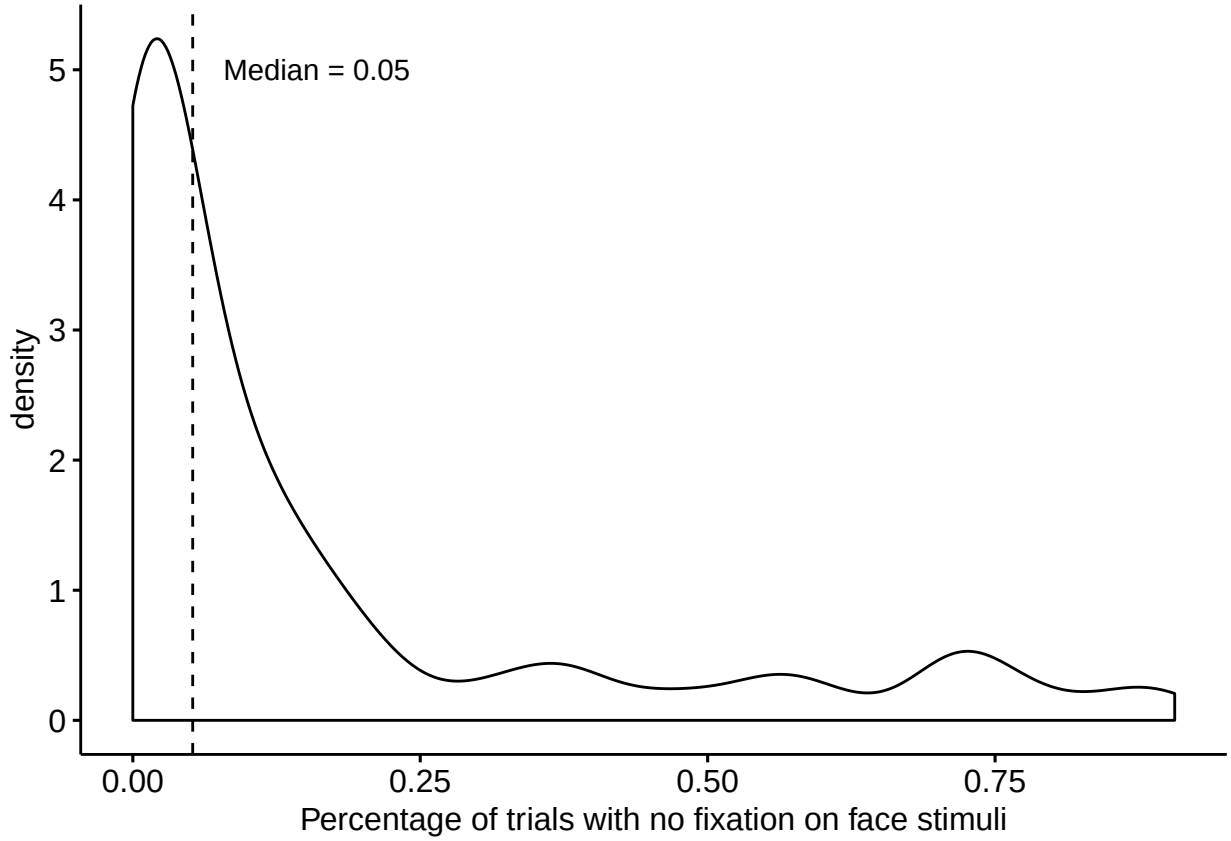


As can be seen in the scatterplot, depression severity and mean total fixation time were very weakly correlated (r = -0.032). Rather than making an arbitrary decision about a cut-point for an acceptable amount of missing eye tracking data, we created means that are weighted by total fixation time. This should allow us to analyze all available data and reduce the influence of trials where total fixation time is relatively low. Notably, no participant had less than .75 seconds of total fixation time.

Section 1.21: Percentage of trials that only looked at center

```
## # A tibble: 1 x 3
##    mean    sd median
##   <dbl> <dbl>  <dbl>
## 1 0.168 0.242 0.0521
```

```
ggdensity(dp_bias, x = "pct_gaze_center", add = "median", rug = FALSE,
          xlab = "Percentage of trials with no fixation on face stimuli") +
  annotate("text", x = .16, y=5, label = "Median = 0.05")
```



Using the median as a measure of central tendency, this figure shows that participants did not look at the negative or neutral face stimulus on approximately 5% of the trials (the mean was 17%, but that is driven by a long right tail). That is, participants maintained their gaze at the former location of the fixation cross on about 5% of the trials. Given that we are interested in measuring biased attention for negative stimuli, we required participants to have a fixation on the neutral or sad face on 80% or more trials. This reduced our sample from N = 215 (we could not collect eye tracking data for 3 people) to 165. We reasoned that fixating on the face stimuli would also be important for measuring attention bias with reaction time as well. Further, in order for our analyses to be consistent across eye gaze and behavioral metrics, we used this same requirement (>= 80% of trials with a fixation on either face stimulus) for the behavioral indices of attention bias. Thus, our *n* for all attention bias analyses was 165.

Next, we examined whether people retained for dot-probe analyses differed from those dropped from analyses in terms of depression severity, age, or gender.

```
#n per cell
kable(count(demo, dp_keep))
```

dp_keep	n
0	52
1	165
NA	1

```
#depression severity
t.test(demo$bdi_total~demo$dp_keep)
```

```
##
##  Welch Two Sample t-test
```

```
##
## data:  demo$bdi_total by demo$dp_keep
## t = -0.42045, df = 90.067, p-value = 0.6752
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -4.297129  2.795964
## sample estimates:
## mean in group 0 mean in group 1
##        17.46154        18.21212
```

```
#age
t.test(demo$age~demo$dp_keep)
```

```
##
##  Welch Two Sample t-test
##
## data:  demo$age by demo$dp_keep
## t = 1.2425, df = 76.345, p-value = 0.2179
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.6279301  2.7111469
## sample estimates:
## mean in group 0 mean in group 1
##        24.09615        23.05455
```

```
#gender
table(demo$female, demo$dp_keep)
```

```
##
##       0   1
##   0  21  52
##   1  31 113
```

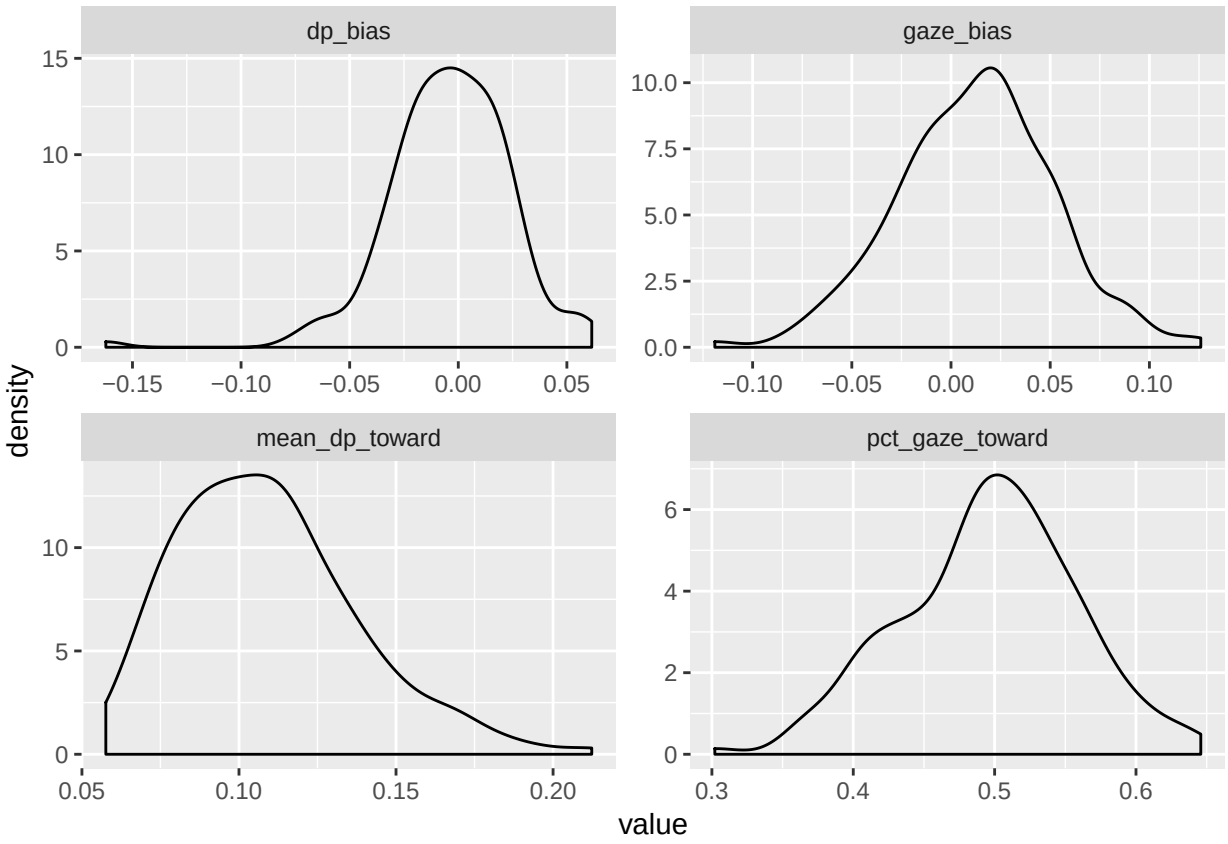
```
chisq.test(demo$female, demo$dp_keep)
```

```
##
##  Pearson's Chi-squared test with Yates' continuity correction
##
## data:  demo$female and demo$dp_keep
## X-squared = 1.0243, df = 1, p-value = 0.3115
```

Importantly, participants dropped because of poor quality eye tracking data ($n = 52$) did not differ from those retained ($n = 165$) in terms of depression symptom severity, age, or gender.

Section 1.3: Distribution of dot-probe variables

```
dp_bias %>%
  select(dp_bias, mean_dp_toward, gaze_bias, pct_gaze_toward) %>%
  gather() %>%
  ggplot(aes(value)) +
    facet_wrap(~ key, scales = "free") +
    geom_density()
```



The four dot-probe metrics are approxmiately normally distributed, although the traditional dot-probe bias score does have a longish tail on the left. Thus, we will do an outlier analysis for elastic net models involving the traditional bias score in section 3.0. Random forest models are not strongly impacted by outliers.

Section 1.4: Symptom importance analyses with additional TLBS metrics.

Random forest for TLBS bias away from sad stimuli.

```
rt_bias_rf <- beset_rf(mean_dp_away ~ ., data=dp_bias[,c(1:21, 28)])
summary(rt_bias_rf)
```

```
## Type of random forest: regression
## Number of trees: 500
## No. of variables tried at each split: 7
## =========================================================
## OOB estimate of % Var explained: -3.12
## CV estimate of % Var explained: 0.63
##
##            Importance    Min    Max
## pre_bdi_13      0.297  0.258  0.337
## pre_bdi_15      0.183  0.154  0.212
## pre_bdi_16      0.127  0.102  0.152
## pre_bdi_8       0.099  0.076  0.122
## pre_bdi_17      0.069  0.048  0.090
## pre_bdi_10      0.065  0.047  0.082
```

```
## pre_bdi_12      0.053  0.034  0.073
## pre_bdi_20      0.051  0.028  0.074
## pre_bdi_19      0.048  0.025  0.072
## pre_bdi_5       0.039  0.018  0.059
## pre_bdi_14      0.015  0.001  0.029
## pre_bdi_11      0.013 -0.006  0.033
## pre_bdi_6       0.011 -0.002  0.025
## pre_bdi_2       0.010 -0.007  0.027
## pre_bdi_1       0.006 -0.014  0.026
## pre_bdi_21     -0.001 -0.016  0.015
## pre_bdi_4      -0.001 -0.017  0.014
## pre_bdi_9      -0.002 -0.013  0.009
## pre_bdi_7      -0.015 -0.033  0.004
## pre_bdi_18     -0.026 -0.040 -0.013
## pre_bdi_3      -0.042 -0.057 -0.027
##
##
## Prediction Metrics
## (Results of 10-fold cross-validation repeated 10 times)
##                          Mean     S.E.       Min      Max
## Mean Absolute Error   0.02460 0.001160  0.024100  0.02510
## Mean Cross Entropy   -2.03000 0.059200 -2.050000 -2.01000
## Mean Squared Error    0.00101 0.000122  0.000978  0.00105
## Variance Explained   -0.02120 0.055700 -0.057200  0.01440
## =====================================================
```

Using 10-fold cross-validation repeated 10 times, the random forest model with all 21 BDI-II symptoms entered as predictors explained less than 0% (Mean = -0.02, SE = 0.056, Min = -0.057 Max = 0.014) of the out-of-sample variance in TLBS away from sad stimuli. Thus, no depression symptoms were reliably associated with this TLBS metric.

Random forest for TLBS variability for sad stimuli.

```
rt_bias_rf <- beset_rf(var_dp_bias ~ ., data=dp_bias[,c(1:21, 29)])
summary(rt_bias_rf)
```

```
## Type of random forest: regression
## Number of trees: 500
## No. of variables tried at each split: 7
## =====================================================
## OOB estimate of % Var explained: -1.53
## CV estimate of % Var explained: 2.11
##
##             Importance    Min    Max
## pre_bdi_13      0.250  0.220  0.280
## pre_bdi_15      0.133  0.111  0.155
## pre_bdi_20      0.084  0.062  0.106
## pre_bdi_10      0.078  0.064  0.092
## pre_bdi_16      0.077  0.058  0.096
## pre_bdi_8       0.075  0.058  0.092
## pre_bdi_1       0.063  0.046  0.080
## pre_bdi_19      0.060  0.042  0.078
## pre_bdi_5       0.058  0.040  0.075
## pre_bdi_14      0.038  0.026  0.051
## pre_bdi_6       0.037  0.025  0.049
## pre_bdi_12      0.031  0.019  0.044
```

```
## pre_bdi_17      0.018  0.004  0.031
## pre_bdi_11      0.017  0.001  0.032
## pre_bdi_7       0.007 -0.008  0.022
## pre_bdi_2       0.004 -0.010  0.018
## pre_bdi_4       0.002 -0.009  0.012
## pre_bdi_9       0.001 -0.006  0.008
## pre_bdi_21      0.000 -0.011  0.011
## pre_bdi_3      -0.006 -0.019  0.008
## pre_bdi_18     -0.027 -0.038 -0.015
##
##
## Prediction Metrics
## (Results of 10-fold cross-validation repeated 10 times)
##                          Mean     S.E.      Min      Max
## Mean Absolute Error   0.02480 0.001290  0.02420  0.02530
## Mean Cross Entropy   -2.00000 0.056800 -2.01000 -1.98000
## Mean Squared Error    0.00108 0.000127  0.00104  0.00112
## Variance Explained    0.00183 0.072400 -0.03110  0.03580
## =========================================================
```

Using 10-fold cross-validation repeated 10 times, the random forest model with all 21 BDI-II symptoms entered as predictors explained approxmiately 0% (Mean = 0.001, SE = 0.072, Min = -0.031 Max = 0.036) of the out-of-sample variance in TLBS variability in attention bias. Thus, no depression symptoms were reliably associated with this TLBS metric.

Section 2.0: SRET Drift Rate and Elastic Net

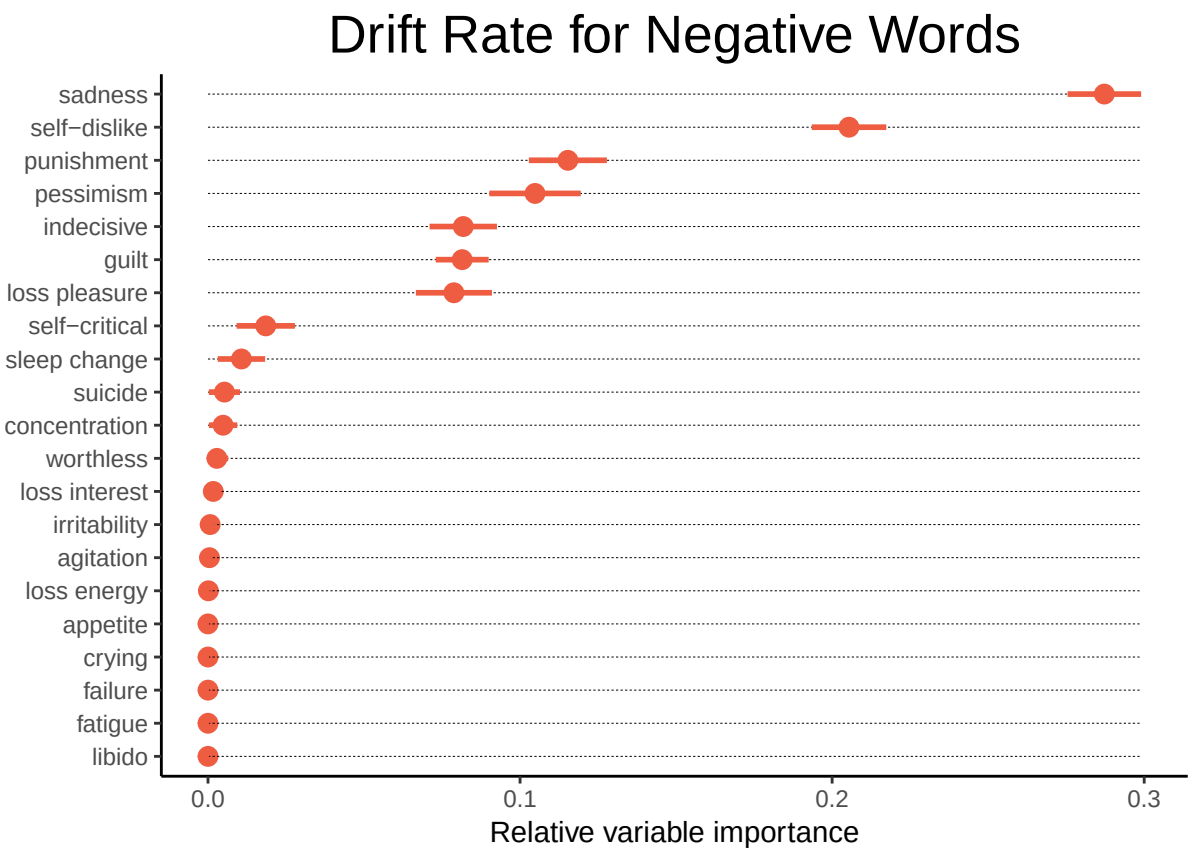
```r
#nested cross-validation to tune and then test
drift_elnet <- beset_elnet(v_negative ~ ., data=bdi[,c(2:23)], nest_cv = TRUE)
summary(drift_elnet)
```

```
##
## Results of nested 10-fold cross-validation repeated 10 times
## =========================================================
## Most conservative tuning parameters within
## 1 SE of best cross-validation Mean Squared Error:
##         Mean  S.E.          Range
## alpha  0.990 0.000   0.99 - 0.99
## lambda 0.247 0.013 0.239 - 0.256
##
##
## Non-zero coefficients ranked in order of importance:
##            Stnd.Coef.  S.E.   Min   Max
## pre_bdi_1       0.163 0.007 0.161 0.164
## pre_bdi_7       0.116 0.007 0.114 0.120
## pre_bdi_6       0.065 0.007 0.062 0.068
## pre_bdi_2       0.059 0.008 0.058 0.063
## pre_bdi_5       0.046 0.005 0.043 0.048
## pre_bdi_13      0.046 0.006 0.043 0.050
## pre_bdi_4       0.045 0.007 0.043 0.046
## pre_bdi_8       0.010 0.005 0.006 0.016
## pre_bdi_16      0.006 0.004 0.003 0.009
## pre_bdi_9       0.003 0.003 0.000 0.006
```

```
## pre_bdi_19      0.003 0.003 0.001 0.004
## pre_bdi_14      0.002 0.002 0.000 0.005
## pre_bdi_12      0.001 0.001 0.000 0.004
##
##
## Prediction Metrics:
##                 Variance Explained   S.E.   Min   Max
## Train Sample                 0.383 0.0082 0.379 0.390
## CV-Tune Holdout              0.337 0.0418 0.330 0.343
## CV-Test Holdout              0.341 0.0269 0.322 0.353
## ========================================================
```

We selected the optimal alpha using the 1 SD rule, which also tends to encourage sparsity. This model retains 13 symptoms and predicts 34.1% of the out-of-sample variance in drift rate. Next, plot the importance metrics to visualize which symptoms are most important.

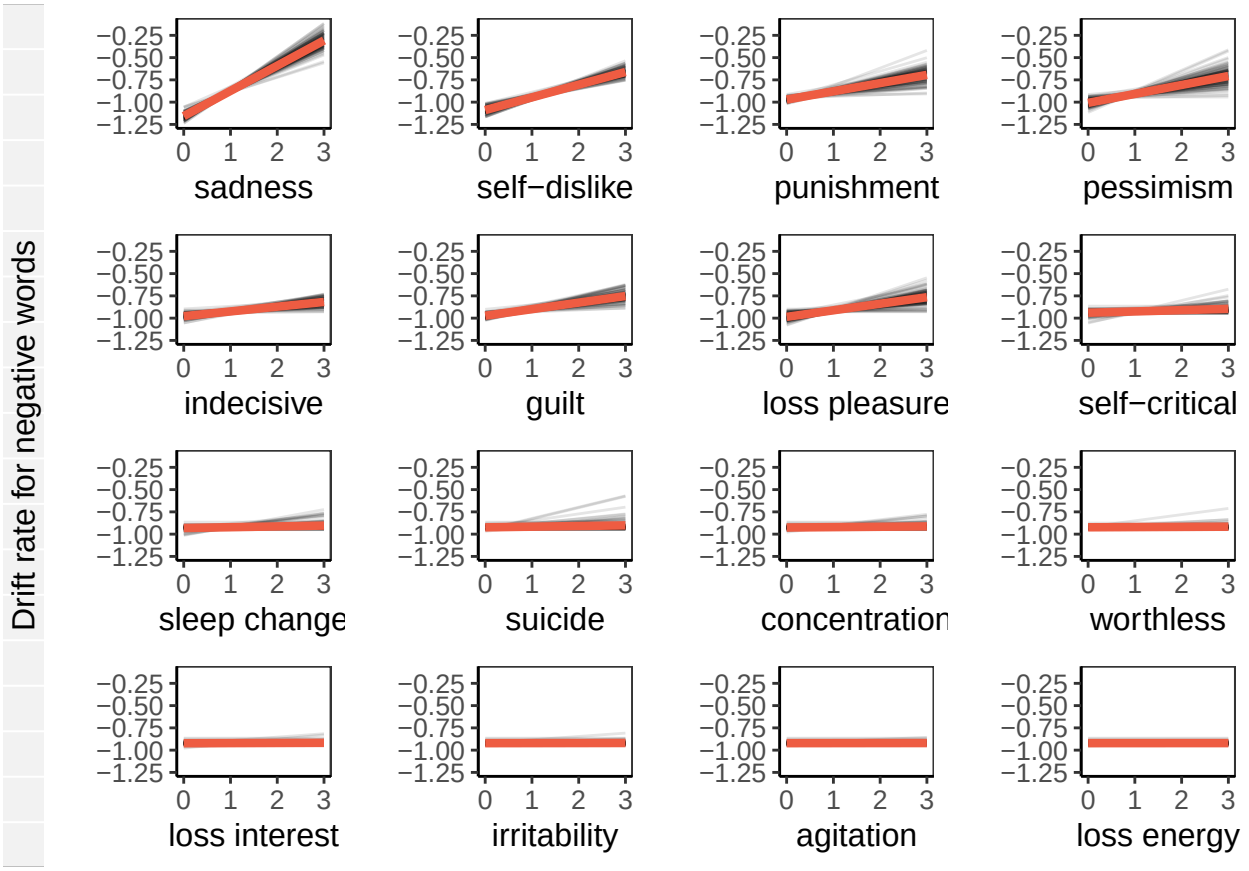
```r
#create df with variables and variable lables
names_bdi <- data_frame(var = names(bdi)[3:23],
                        label =  c("sadness", "pessimism", "failure", "loss pleasure",
                                   "guilt", "punishment", "self-dislike",
                                   "self-critical", "suicide", "crying", "agitation",
                                   "loss interest", "indecisive", "worthless",
                                   "loss energy", "sleep change", "irritability",
                                   "appetite", "concentration", "fatigue", "libido")
)

#plot the importance variables
p1 <- beset::importance(drift_elnet)
plot(p1, p_max = 21, labels = names_bdi) + ggtitle("Drift Rate for Negative Words") +
  theme(plot.title = element_text(hjust = 0.5))
```



Sadness is clearly the most important symptom, followed by self-dislike. Punishment and pessimissm are next, followed by guilt, indecision, and loss of pleasure. The remaining symptoms are relatively unimportant.

Now examine the partial dependence plots.

```
#dependence plots
p2 <- beset::dependence(drift_elnet,
                        y_lab = "Drift rate for negative words",
                        x_lab = c("sadness", "pessimism", "failure",
                                  "loss pleasure", "guilt", "punishment",
                                  "self-dislike", "self-critical",
                                  "suicide", "crying", "agitation",
                                  "loss interest", "indecisive",
                                  "worthless", "loss energy", "sleep change",
                                  "irritability", "appetite", "concentration",
                                  "fatigue", "libido"))
plot(p2, order = "import")
```

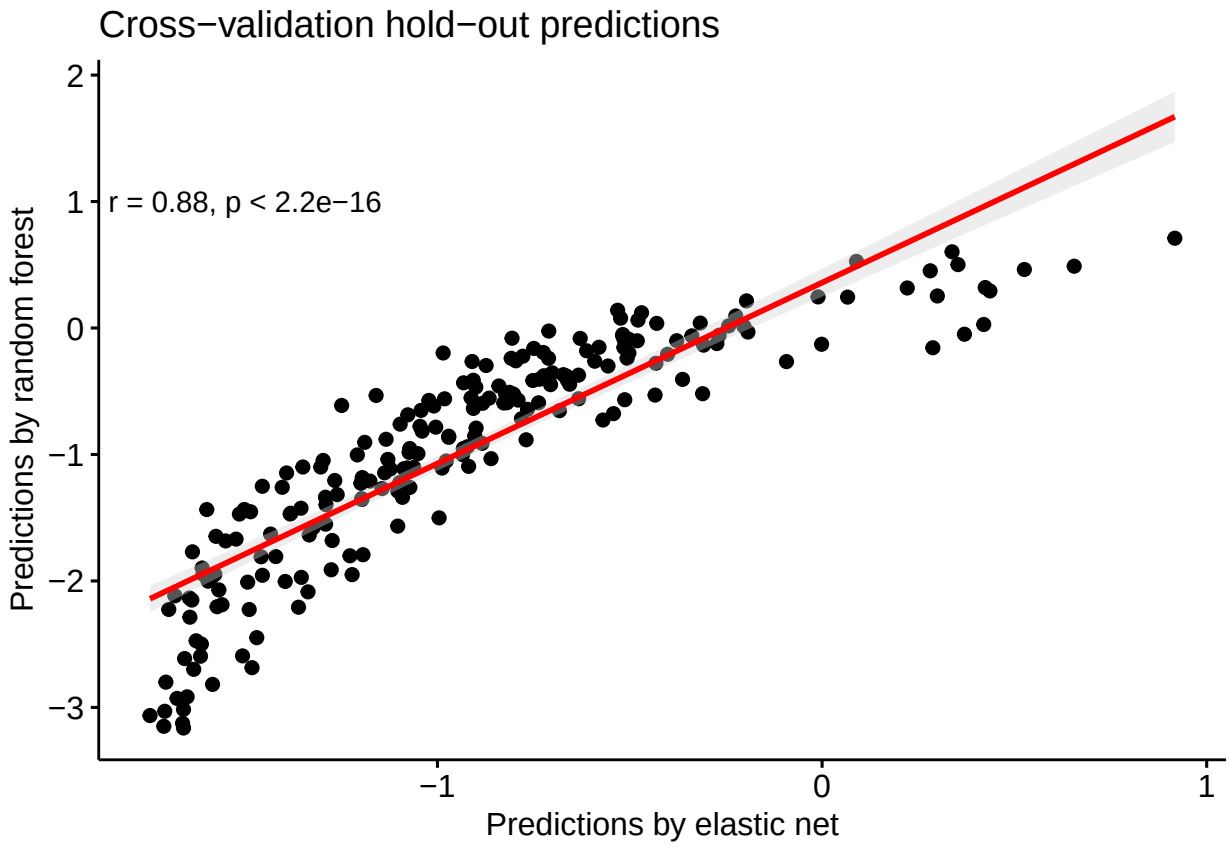



```
## TableGrob (4 x 5) "arrange": 17 grobs
##                 z     cells    name                grob
## sadness         1 (1-1,2-2) arrange       gtable[layout]
## self-dislike    2 (1-1,3-3) arrange       gtable[layout]
## punishment      3 (1-1,4-4) arrange       gtable[layout]
## pessimism       4 (1-1,5-5) arrange       gtable[layout]
## indecisive      5 (2-2,2-2) arrange       gtable[layout]
## guilt           6 (2-2,3-3) arrange       gtable[layout]
## loss pleasure   7 (2-2,4-4) arrange       gtable[layout]
## self-critical   8 (2-2,5-5) arrange       gtable[layout]
## sleep change    9 (3-3,2-2) arrange       gtable[layout]
## suicide        10 (3-3,3-3) arrange       gtable[layout]
## concentration  11 (3-3,4-4) arrange       gtable[layout]
## worthless      12 (3-3,5-5) arrange       gtable[layout]
## loss interest  13 (4-4,2-2) arrange       gtable[layout]
## irritability   14 (4-4,3-3) arrange       gtable[layout]
## agitation      15 (4-4,4-4) arrange       gtable[layout]
## loss energy    16 (4-4,5-5) arrange       gtable[layout]
##                17 (1-4,1-1) arrange text[GRID.text.1257]
```

We can see here that there is a fairly clear linear (by definition) relationship between the top variables and the first seven bdi symptoms. After the first seven variables, the lines are relatively flat.

Section 2.1: Correlation between predictions from random forest and elastic net for drift rate

```
drift_rf <- beset_rf(v_negative ~ ., data=bdi[,c(2:23)])
rf_preds <- validate(drift_rf, keep_pred = TRUE)

el_preds <- validate(drift_elnet, keep_pred = TRUE)

plot_data <- data_frame(
  elnet = rowMeans(el_preds$predictions),
  rf = rowMeans(rf_preds$predictions)
)

ggscatter(plot_data, x = "elnet", y = "rf",
   add = "reg.line",
   add.params = list(color = "red", fill = "lightgray"),
   conf.int = TRUE,
   title = "Cross-validation hold-out predictions") +
  stat_cor(method = "pearson", label.x = -1.5, label.y = 1) +
  labs(x = "Predictions by elastic net",
       y = "Predictions by random forest")
```



The predictions across models are strongly correlated. It is interesting that there is clear nonlinear relationship here–the random forest tends to cap its predictions around 0, whereas the elastic net is more aggressive with predicting positive drift rates for a small set of cases.

Section 2.2: SRET Number of negative words endorsed and best subset with negative binomial distribution

Given the distribution of the count data for number of negative words endorsed, we decided to use a best subsets regression. Because this approach is very computationally expensive, we limited this to no more than 10 predictors.

```
sret_negbin <- beset_glm(num.neg.endorsed ~ ., data=bdi[,c(1, 3:23)],
                         p_max = 10, family = "negbin")
```

```
sret_negbin <- readRDS(file = rds_file)

summary(sret_negbin)
```

```
##
## ============================================================
## Best Model:
##   ~ pre_bdi_1 + pre_bdi_6
##
## Nearly Equivalent Model:
##   ~ pre_bdi_1 + pre_bdi_5
##
## Coefficients:
##             Estimate
## (Intercept)   1.3040
## pre_bdi_1     0.5963
## pre_bdi_6     0.2510
##
## (Dispersion parameter for Negative Binomial(2.5903) family taken to be 1)
##
## Log-likelihood: -624.8 on 4 Df
## AIC: 1257.6
##
## Number of Fisher Scoring iterations: 1
##
## Train-sample R-squared = 0.31
## Cross-validated R-squared =  0.29
## ============================================================
```

```
summary(sret_negbin, oneSE = FALSE)
```

```
##
## ============================================================
## Best Model:
##   ~ pre_bdi_1 + pre_bdi_5 + pre_bdi_6 + pre_bdi_7 + pre_bdi_9 + pre_bdi_13 + pre_bdi_16
##
## 82 Nearly Equivalent Models:
##   ~ pre_bdi_1 + pre_bdi_2 + pre_bdi_4 + pre_bdi_5 + pre_bdi_6 + pre_bdi_9 + pre_bdi_16
##   ~ pre_bdi_1 + pre_bdi_2 + pre_bdi_5 + pre_bdi_6 + pre_bdi_7 + pre_bdi_9 + pre_bdi_11
##   ~ pre_bdi_1 + pre_bdi_2 + pre_bdi_5 + pre_bdi_6 + pre_bdi_7 + pre_bdi_9 + pre_bdi_13
##   ~ pre_bdi_1 + pre_bdi_2 + pre_bdi_5 + pre_bdi_6 + pre_bdi_7 + pre_bdi_9 + pre_bdi_16
##   ~ pre_bdi_1 + pre_bdi_2 + pre_bdi_5 + pre_bdi_6 + pre_bdi_7 + pre_bdi_9 + pre_bdi_19
##   ...
##    + 77 more
##   ...
```

```
##
## Coefficients:
##             Estimate
## (Intercept)  1.04300
## pre_bdi_1    0.33390
## pre_bdi_5    0.11770
## pre_bdi_6    0.15900
## pre_bdi_7    0.10090
## pre_bdi_9    0.20490
## pre_bdi_13   0.07407
## pre_bdi_16   0.13160
##
## (Dispersion parameter for Negative Binomial(3.3748) family taken to be 1)
##
## Log-likelihood: -609.6 on 9 Df
## AIC: 1237.1
##
## Number of Fisher Scoring iterations: 1
##
## Train-sample R-squared = 0.39
## Cross-validated R-squared =  0.35
## ============================================================
```

Section 3.0: Dot-Probe (RT) and Elastic Net

First, traditional RT dot-probe.

```
#nested cross-validation to tune and then test
rt_bias <- beset_elnet(dp_bias ~ ., data=dp_bias[,c(1:21, 24)], nest_cv = TRUE)
summary(rt_bias)
```

```
##
## Results of nested 10-fold cross-validation repeated 10 times
## ============================================================
## Most conservative tuning parameters within
## 1 SE of best cross-validation Mean Squared Error:
##           Mean     S.E.             Range
## alpha  0.99000 0.000000       0.99 - 0.99
## lambda 0.00444 0.000185 0.00441 - 0.00448
##
##
## No reliable predictors.
##
## Prediction Metrics:
##                 Variance Explained    S.E.      Min      Max
## Train Sample               0.00000 0.00000  0.00000  0.00000
## CV-Tune Holdout           -0.00709 0.00883 -0.00861 -0.00644
## CV-Test Holdout           -0.00315 0.00640 -0.00638 -0.00102
## ============================================================
```

To be consistent with prior symptom importance work (e.g., network analyses), which uses Lasso to reduce redundant variables, we are selecting a model that is within 1 SD of the best model, which will encourage model sparsity. This model does not find any reliable associations between symptoms and RT attention bias.

We can also look at the solution when we do not use the one standard error rule.

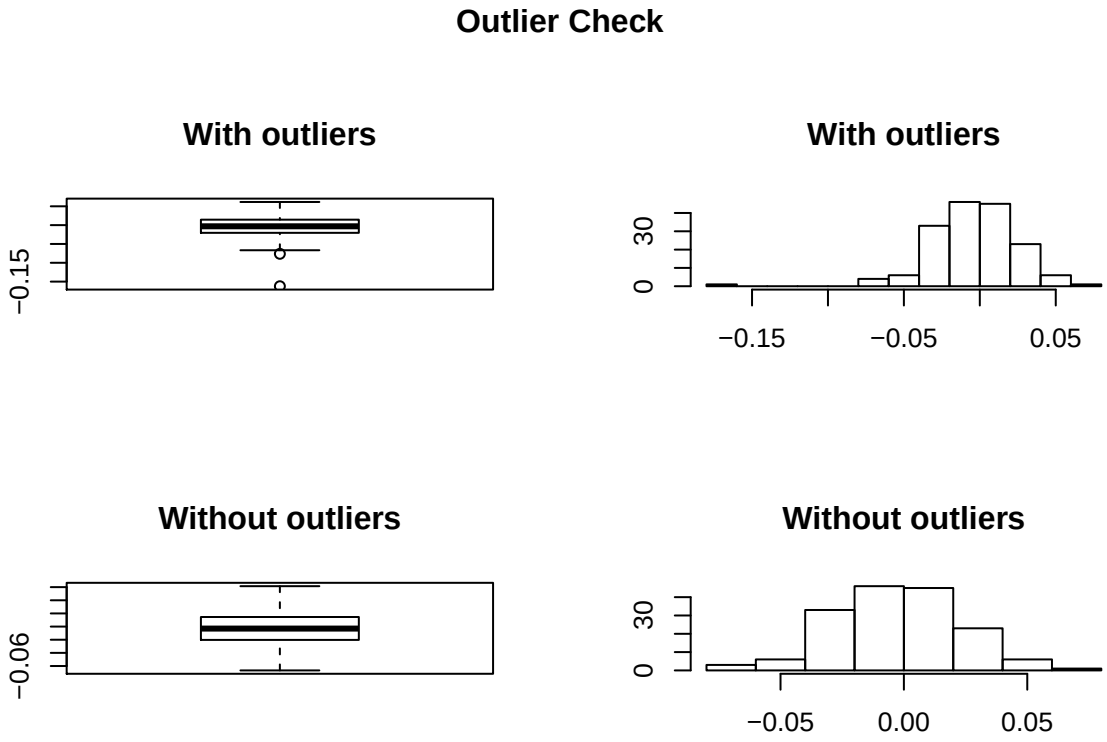
```
summary(rt_bias, oneSE = FALSE)
```

```
##
## Results of nested 10-fold cross-validation repeated 10 times
## ========================================================
## Tuning parameters with best cross-validation Mean Squared Error :
##         Mean   S.E.         Range
## alpha  0.363 0.1290   0.157 - 0.5
## lambda 0.188 0.0607 0.131 - 0.275
##
##
## Non-zero coefficients ranked in order of importance:
##            Stnd.Coef.  S.E.    Min    Max
## pre_bdi_12     -0.030 0.012 -0.047 -0.016
## pre_bdi_11      0.005 0.004  0.000  0.011
## pre_bdi_3       0.003 0.003  0.000  0.008
## pre_bdi_6       0.003 0.003  0.000  0.007
## pre_bdi_14      0.003 0.003  0.000  0.009
## pre_bdi_7       0.002 0.003  0.000  0.009
## pre_bdi_16     -0.002 0.004 -0.010  0.000
## pre_bdi_17     -0.002 0.002 -0.005  0.000
## pre_bdi_19      0.002 0.002  0.000  0.008
## pre_bdi_1       0.001 0.002  0.000  0.006
## pre_bdi_5       0.001 0.001  0.000  0.003
## pre_bdi_15     -0.001 0.002 -0.005  0.000
##
##
## Prediction Metrics:
##                  Variance Explained    S.E.      Min      Max
## Train Sample               0.01280 0.00601  0.00533  0.02010
## CV-Tune Holdout           -0.00134 0.01130 -0.00344  0.00086
## CV-Test Holdout           -0.01300 0.01310 -0.02180 -0.00113
## ========================================================
```

This model selects a lower alpha and finds several variables with non-zero coefficients and explains about 1.2% of the variance in dot-probe RT bias in the train sample. However, cross-validation finds that this finding is not reliable, as these symptoms predict less than 0% variance in the test sample. Thus, no reliable predictors. Also note that the standard coefficients for all of the predictors contain 0 or less than 0 across the iterations, suggesting that there were models in which each predictor was not retained.

Given the long left tail of the dp_bias variable (traditional dot-probe bias score), we performed a sensitivity test to see whether there are any univariate outliers and, if so, whether removing them impacts the elastic net model. To detect the outliers we will use Tukey's method which identifies outliers above and below the 1.5*IQR.

```r
dp_bias_miss <- dp_bias

outlierKD <- function(dt, var) {
     var_name <- eval(substitute(var),eval(dt))
     na1 <- sum(is.na(var_name))
     m1 <- mean(var_name, na.rm = T)
     par(mfrow=c(2,2), oma=c(0,0,3,0))
     boxplot(var_name, main="With outliers")
     hist(var_name, main="With outliers", xlab=NA, ylab=NA)
     outlier <- boxplot.stats(var_name)$out
     mo <- mean(outlier)
     var_name <- ifelse(var_name %in% outlier, NA, var_name)
     boxplot(var_name, main="Without outliers")
     hist(var_name, main="Without outliers", xlab=NA, ylab=NA)
     title("Outlier Check", outer=TRUE)
     na2 <- sum(is.na(var_name))
     cat("Outliers identified:", na2 - na1, "\n")
     cat("Propotion (%) of outliers:", round((na2 - na1) / sum(!is.na(var_name))*100, 1), "/n")
     cat("Mean of the outliers:", round(mo, 2), "\n")
     m2 <- mean(var_name, na.rm = T)
     cat("Mean without removing outliers:", round(m1, 2), "\n")
     cat("Mean if we remove outliers:", round(m2, 2), "\n")
     response <- "y"
     if(response == "y" | response == "yes"){
          dt[as.character(substitute(var))] <- invisible(var_name)
          assign(as.character(as.list(match.call())$dt), dt, envir = .GlobalEnv)
          cat("Outliers successfully removed", "\n")
          return(invisible(dt))
     } else{
          cat("Nothing changed", " ")
          return(invisible(var_name))
     }
}

outlierKD(dp_bias_miss, dp_bias)
```




```
## Outliers identified: 2
## Propotion (%) of outliers: 1.2 /nMean of the outliers: -0.12
## Mean without removing outliers: 0
## Mean if we remove outliers: 0
## Outliers successfully removed
```

There appear to be 2 potential outliers in the dp_bias variable. The distribution looks better when these variables are removed (see second row in figure). Thus, I will re-run the elastic net with these outliers removed.

```
rt_bias <- beset_elnet(dp_bias ~ ., data=dp_bias_miss[,c(1:21, 24)], nest_cv = TRUE)
summary(rt_bias)
```

```
##
## Results of nested 10-fold cross-validation repeated 10 times
## ======================================================
## Most conservative tuning parameters within
## 1 SE of best cross-validation Mean Squared Error:
##           Mean     S.E.             Range
## alpha  0.99000 0.000000       0.99 - 0.99
## lambda 0.00428 0.000162 0.00426 - 0.00434
##
##
## No reliable predictors.
##
## Prediction Metrics:
##                 Variance Explained    S.E.      Min      Max
## Train Sample               0.00000 0.00000  0.00000  0.00000
## CV-Tune Holdout           -0.00639 0.00693 -0.00871 -0.00459
## CV-Test Holdout           -0.00212 0.00471 -0.00295 -0.00147
## ======================================================
```

As before, this model also does not find any reliable symptom predictors, suggesting that the presence of outliers in the traditional measure of attention bias was not significantly influencing the results.

Next, we examine TLBS towards sad stimuli.

```
#nested cross-validation to tune and then test
tlbs_bias <- beset_elnet(mean_dp_toward ~ ., data=dp_bias[,c(1:21, 27)],
                         nest_cv = TRUE)
summary(tlbs_bias)
```

```
##
## Results of nested 10-fold cross-validation repeated 10 times
## ============================================================
## Most conservative tuning parameters within
## 1 SE of best cross-validation Mean Squared Error:
##           Mean     S.E.             Range
## alpha  0.99000 0.000000       0.99 - 0.99
## lambda 0.00733 0.000255 0.00729 - 0.00742
##
##
## No reliable predictors.
##
## Prediction Metrics:
##                 Variance Explained    S.E.      Min      Max
## Train Sample               0.00000 0.00000  0.00000  0.00000
## CV-Tune Holdout           -0.00770 0.00768 -0.01020 -0.00572
## CV-Test Holdout           -0.00179 0.00440 -0.00317 -0.00112
## ============================================================
```

This model does not find any reliable associations between symptoms and RT attention bias.

As before, we can also look at the solution when we do not use the one standard error rule.

```
summary(tlbs_bias, oneSE = FALSE)
```

```
##
## Results of nested 10-fold cross-validation repeated 10 times
## ============================================================
## Tuning parameters with best cross-validation Mean Squared Error :
##          Mean   S.E.          Range
## alpha  0.0737 0.0752   0.01 - 0.157
## lambda 0.1110 0.0168 0.0867 - 0.154
##
##
## Non-zero coefficients ranked in order of importance:
##            Stnd.Coef.  S.E.    Min   Max
## pre_bdi_15      0.035 0.010  0.026 0.043
## pre_bdi_16      0.021 0.003  0.018 0.024
## pre_bdi_14      0.019 0.002  0.017 0.020
## pre_bdi_20      0.018 0.002  0.017 0.021
## pre_bdi_6       0.016 0.003  0.014 0.020
## pre_bdi_21      0.016 0.003  0.015 0.018
## pre_bdi_3       0.014 0.002  0.013 0.016
## pre_bdi_5       0.013 0.002  0.012 0.014
## pre_bdi_8       0.012 0.003  0.010 0.015
## pre_bdi_17      0.009 0.002  0.007 0.010
## pre_bdi_2       0.008 0.002  0.007 0.009
```

```
## pre_bdi_1       0.006 0.002  0.005 0.007
## pre_bdi_7       0.001 0.001  0.000 0.001
## pre_bdi_11      0.001 0.001  0.000 0.001
## pre_bdi_12     -0.001 0.001 -0.004 0.000
## pre_bdi_18      0.001 0.001  0.000 0.003
##
##
## Prediction Metrics:
##                 Variance Explained   S.E.     Min    Max
## Train Sample                0.0612 0.0058  0.0574 0.0654
## CV-Tune Holdout             0.0223 0.0273  0.0175 0.0263
## CV-Test Holdout             0.0127 0.0244 -0.0016 0.0277
## =========================================================
```

This model selects a lower alpha and finds several variables with non-zero coefficients and explains about 6.1% of the variance in dot-probe RT bias in the train sample. However, variance explained in cross-validation test sample is 1.2%, which suggests that if there is an effect, it is quite small. Given the results of the random forest, the more stringent elastic net, we are concluding that there are no reliable symptom predictors of bias towards sad stimuli.

Section 3.1: Dot-Probe (eye gaze) and Elastic Net

```
#nested cross-validation to tune and then test
gz_bias <- beset_elnet(gaze_bias ~ ., data=dp_bias[,c(1:21, 30)], nest_cv = TRUE)
summary(gz_bias)
```

```
##
## Results of nested 10-fold cross-validation repeated 10 times
## =========================================================
## Most conservative tuning parameters within
## 1 SE of best cross-validation Mean Squared Error:
##           Mean     S.E.             Range
## alpha  0.99000 0.000000       0.99 - 0.99
## lambda 0.00695 0.000243 0.00683 - 0.00711
##
##
## No reliable predictors.
##
## Prediction Metrics:
##                 Variance Explained    S.E.      Min      Max
## Train Sample                0.00000 0.00000  0.00000  0.00000
## CV-Tune Holdout            -0.00811 0.00714 -0.00998 -0.00650
## CV-Test Holdout            -0.00266 0.00486 -0.00460 -0.00114
## =========================================================
```

This model does not find any reliable associations between symptoms and eye gaze bias for sad stimuli.

As before, we can also look at the solution when we do not use the one standard error rule.

```
summary(gz_bias, oneSE= FALSE)
```

```
##
## Results of nested 10-fold cross-validation repeated 10 times
## =========================================================
```

```
## Tuning parameters with best cross-validation Mean Squared Error :
##         Mean   S.E.         Range
## alpha  0.201 0.1100 0.059 - 0.304
## lambda 0.366 0.0841 0.269 - 0.457
##
##
## Non-zero coefficients ranked in order of importance:
##            Stnd.Coef.  S.E.    Min    Max
## pre_bdi_15     -0.023 0.011 -0.031 -0.010
## pre_bdi_12     -0.008 0.007 -0.016 -0.003
## pre_bdi_7       0.005 0.006  0.000  0.010
## pre_bdi_4      -0.002 0.002 -0.006  0.000
## pre_bdi_19      0.002 0.003  0.000  0.005
## pre_bdi_10      0.001 0.002  0.000  0.005
## pre_bdi_11      0.001 0.001  0.000  0.002
## pre_bdi_21     -0.001 0.001 -0.003  0.000
##
##
## Prediction Metrics:
##                  Variance Explained    S.E.      Min      Max
## Train Sample               0.01140 0.00551  0.00526  0.01570
## CV-Tune Holdout           -0.00048 0.00871 -0.00255  0.00152
## CV-Test Holdout           -0.01000 0.01100 -0.02350 -0.00232
## =========================================================
```

This model identifies several non-zero symptoms but cross-validation indicates less than 0 variance explained, thus, no reliable symptom predictors. There are no reliable symptom predictors of eye gaze bias, with or without conservative model tuning.

Finally, let's look at percentage of trials with gaze towards sad stimuli.

```
#nested cross-validation to tune and then test
pct_tw_bias <- beset_elnet(pct_gaze_toward ~ ., data=dp_bias[,c(1:21, 34)],
                           nest_cv = TRUE)
summary(pct_tw_bias)
```

```
##
## Results of nested 10-fold cross-validation repeated 10 times
## =========================================================
## Most conservative tuning parameters within
## 1 SE of best cross-validation Mean Squared Error:
##          Mean     S.E.           Range
## alpha  0.9900 0.000000     0.99 - 0.99
## lambda 0.0125 0.000514 0.0124 - 0.0128
##
##
## No reliable predictors.
##
## Prediction Metrics:
##                  Variance Explained    S.E.      Min      Max
## Train Sample               0.00000 0.00000  0.00000  0.00000
## CV-Tune Holdout           -0.00600 0.00601 -0.00686 -0.00435
## CV-Test Holdout           -0.00192 0.00450 -0.00335 -0.00101
## =========================================================
```

```r
summary(pct_tw_bias, oneSE = FALSE)
```

```
##
## Results of nested 10-fold cross-validation repeated 10 times
## ========================================================
## Tuning parameters with best cross-validation Mean Squared Error :
##         Mean  S.E.         Range
## alpha  0.255 0.131 0.108 - 0.549
## lambda 0.420 0.135 0.216 - 0.623
##
##
## Non-zero coefficients ranked in order of importance:
##            Stnd.Coef.  S.E.    Min    Max
## pre_bdi_4      -0.034 0.011 -0.054 -0.022
## pre_bdi_12     -0.010 0.004 -0.013 -0.005
## pre_bdi_15     -0.010 0.004 -0.015 -0.006
## pre_bdi_2      -0.005 0.003 -0.010 -0.002
## pre_bdi_21     -0.005 0.002 -0.007 -0.003
## pre_bdi_6       0.004 0.003  0.002  0.007
## pre_bdi_17     -0.004 0.002 -0.007 -0.002
## pre_bdi_20     -0.004 0.002 -0.006 -0.002
## pre_bdi_11     -0.003 0.002 -0.007  0.000
## pre_bdi_18     -0.003 0.001 -0.005 -0.001
## pre_bdi_5       0.002 0.002  0.000  0.004
## pre_bdi_9      -0.002 0.002 -0.006  0.000
##
##
## Prediction Metrics:
##                  Variance Explained    S.E.      Min     Max
## Train Sample               0.02430 0.00619  0.01980 0.02880
## CV-Tune Holdout            0.00533 0.01170  0.00232 0.00769
## CV-Test Holdout           -0.01480 0.01400 -0.02510 0.00040
## ========================================================
```

Based on cross-validated variance explained, this model also does not find any reliable symptom predictors of percentage of trials with gaze toward sad stimuli, with or without conservative model tuning.

Section 4.0: Examining associations between depression symptoms and cognitive bias for positive stimuli

At the request of a reviewer, we also report below the findings for positive cognitive biases, as the abscence of such biases may also be improtant for understanding the maintenance of depression.

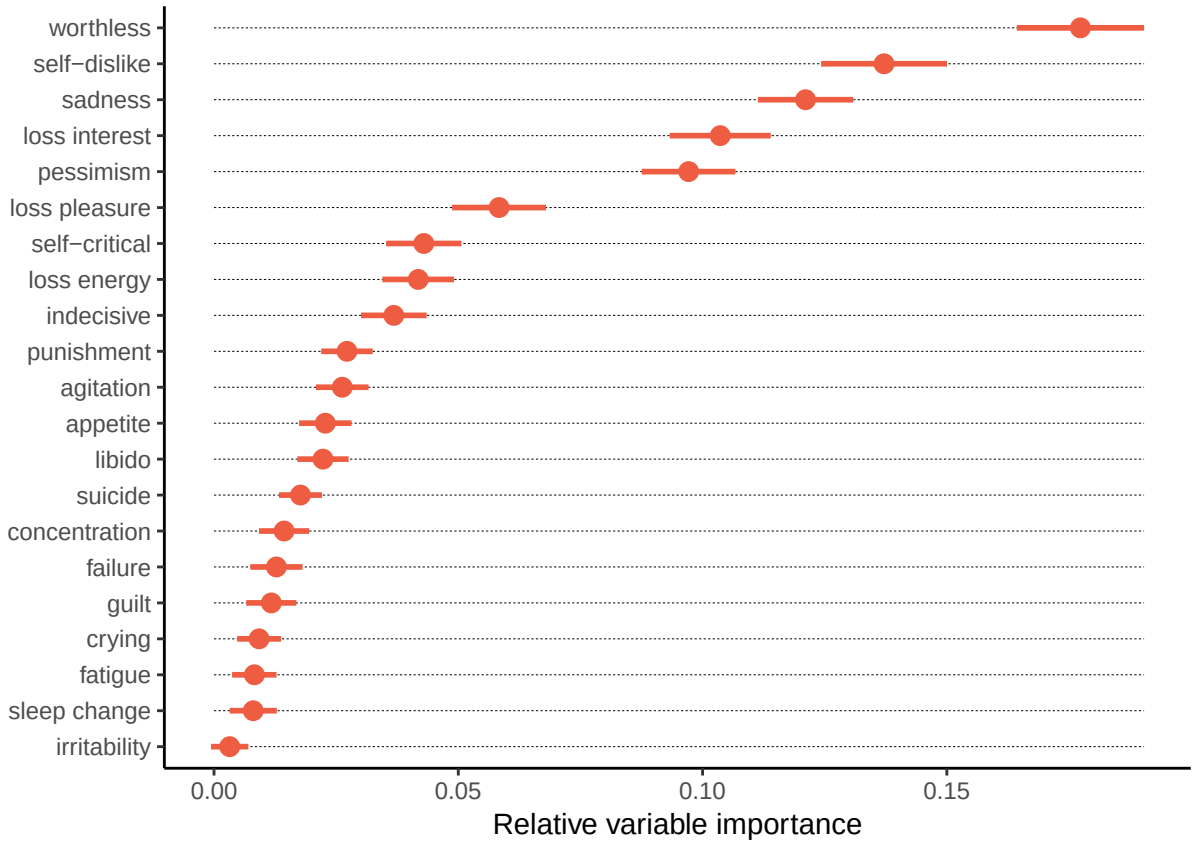
SRET: Drift rate for positive words

```r
#nested cross-validation to tune and then test
pos_drift_rf <- beset_rf(v_positive ~ ., data=bdi[,c(2:23)])
summary(pos_drift_rf)
```

```
## Type of random forest: regression
## Number of trees: 500
```

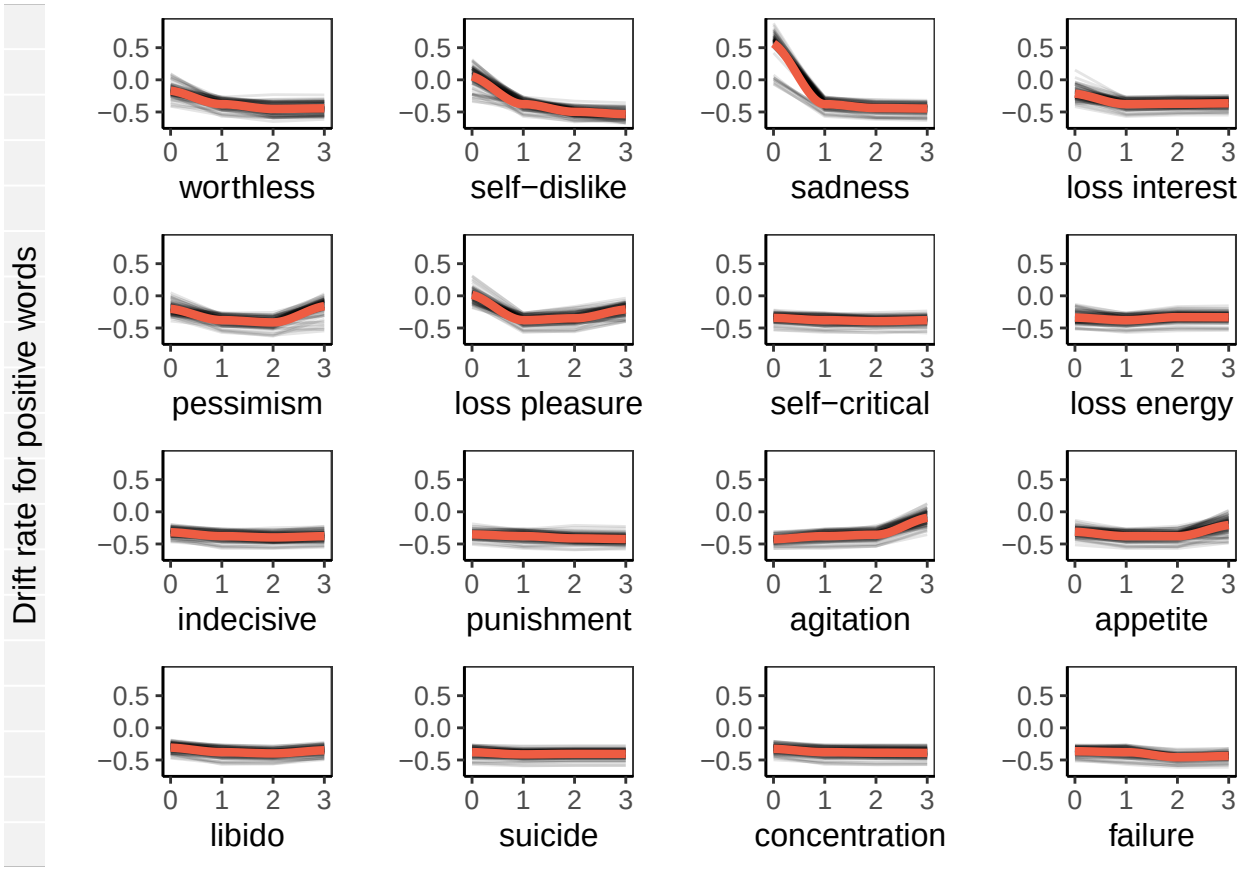
```
## No. of variables tried at each split: 7
## ======================================================
## OOB estimate of % Var explained: 36.08
## CV estimate of % Var explained: 38.79
##
##            Importance    Min   Max
## pre_bdi_14      0.177  0.164 0.190
## pre_bdi_7       0.137  0.124 0.150
## pre_bdi_1       0.121  0.111 0.131
## pre_bdi_12      0.104  0.093 0.114
## pre_bdi_2       0.097  0.088 0.107
## pre_bdi_4       0.058  0.049 0.068
## pre_bdi_8       0.043  0.035 0.051
## pre_bdi_15      0.042  0.034 0.049
## pre_bdi_13      0.037  0.030 0.044
## pre_bdi_6       0.027  0.022 0.032
## pre_bdi_11      0.026  0.021 0.032
## pre_bdi_18      0.023  0.017 0.028
## pre_bdi_21      0.022  0.017 0.028
## pre_bdi_9       0.018  0.013 0.022
## pre_bdi_19      0.014  0.009 0.019
## pre_bdi_3       0.013  0.007 0.018
## pre_bdi_5       0.012  0.007 0.017
## pre_bdi_10      0.009  0.005 0.014
## pre_bdi_20      0.008  0.004 0.013
## pre_bdi_16      0.008  0.003 0.013
## pre_bdi_17      0.003 -0.001 0.007
##
##
## Prediction Metrics
## (Results of 10-fold cross-validation repeated 10 times)
##                        Mean   S.E.   Min   Max
## Mean Absolute Error   0.917 0.0391 0.899 0.944
## Mean Cross Entropy    1.600 0.0462 1.580 1.620
## Mean Squared Error    1.450 0.1320 1.370 1.510
## Variance Explained    0.374 0.0487 0.348 0.405
## ======================================================
```

```
#importance plot
imp_pos_drift_rf <- beset::importance(pos_drift_rf)
fig_pos_imp_drift_rf <- plot(imp_pos_drift_rf, p_max = 21, labels = names_bdi)
fig_pos_imp_drift_rf
```



Using 10-fold cross validation repeated 10 times with all 21 BDI-II symptoms entered as predictors, out-of-sample R_pred^2 = 37.4% (SE = 0.048, Min = 0.348, Max = 0.405) for drift rate for positive words. As seen in the figure above, the most important symptom was worthlessness, although self-dislike was similarly important. Other important symptoms included sadness, loss of interest, and pessimism. The remaining symptoms made relatively smaller contributions to the prediction of drift rate for positive words.

```
#dependence plots
dep_pos_drift_rf <- beset::dependence(pos_drift_rf,
                        y_lab = "Drift rate for positive words",
                        x_lab = c("sadness", "pessimism", "failure",
                                  "loss pleasure", "guilt", "punishment",
                                  "self-dislike", "self-critical",
                                  "suicide", "crying", "agitation",
                                  "loss interest", "indecisive",
                                  "worthless", "loss energy", "sleep change",
                                  "irritability", "appetite", "concentration",
                                  "fatigue", "libido"))
fig_pos_dep_drift_rf <- plot(dep_pos_drift_rf, order = "import")
```




```
fig_pos_dep_drift_rf
```

```
## TableGrob (4 x 5) "arrange": 17 grobs
##                 z     cells    name                grob
## worthless       1 (1-1,2-2) arrange       gtable[layout]
## self-dislike    2 (1-1,3-3) arrange       gtable[layout]
## sadness         3 (1-1,4-4) arrange       gtable[layout]
## loss interest   4 (1-1,5-5) arrange       gtable[layout]
## pessimism       5 (2-2,2-2) arrange       gtable[layout]
## loss pleasure   6 (2-2,3-3) arrange       gtable[layout]
## self-critical   7 (2-2,4-4) arrange       gtable[layout]
## loss energy     8 (2-2,5-5) arrange       gtable[layout]
## indecisive      9 (3-3,2-2) arrange       gtable[layout]
## punishment     10 (3-3,3-3) arrange       gtable[layout]
## agitation      11 (3-3,4-4) arrange       gtable[layout]
## appetite       12 (3-3,5-5) arrange       gtable[layout]
## libido         13 (4-4,2-2) arrange       gtable[layout]
## suicide        14 (4-4,3-3) arrange       gtable[layout]
## concentration  15 (4-4,4-4) arrange       gtable[layout]
## failure        16 (4-4,5-5) arrange       gtable[layout]
##                17 (1-4,1-1) arrange text[GRID.text.2088]
```

The above partial dependence plots indicate the relationship between each symptom and drift rate for positive words holding all other predictors constant at their mean. This figure reveals that individuals who report no worthlessness, self-dislike, or sadness (i.e., report a 0 on the item) have a relatively high drift rate, indicating it was easy to endorse positive words as self-descriptive. Other symptoms had a similar but less pronounced pattern with the exception of agitation, which unexpectedly showed a higher drift rate at higher levels of

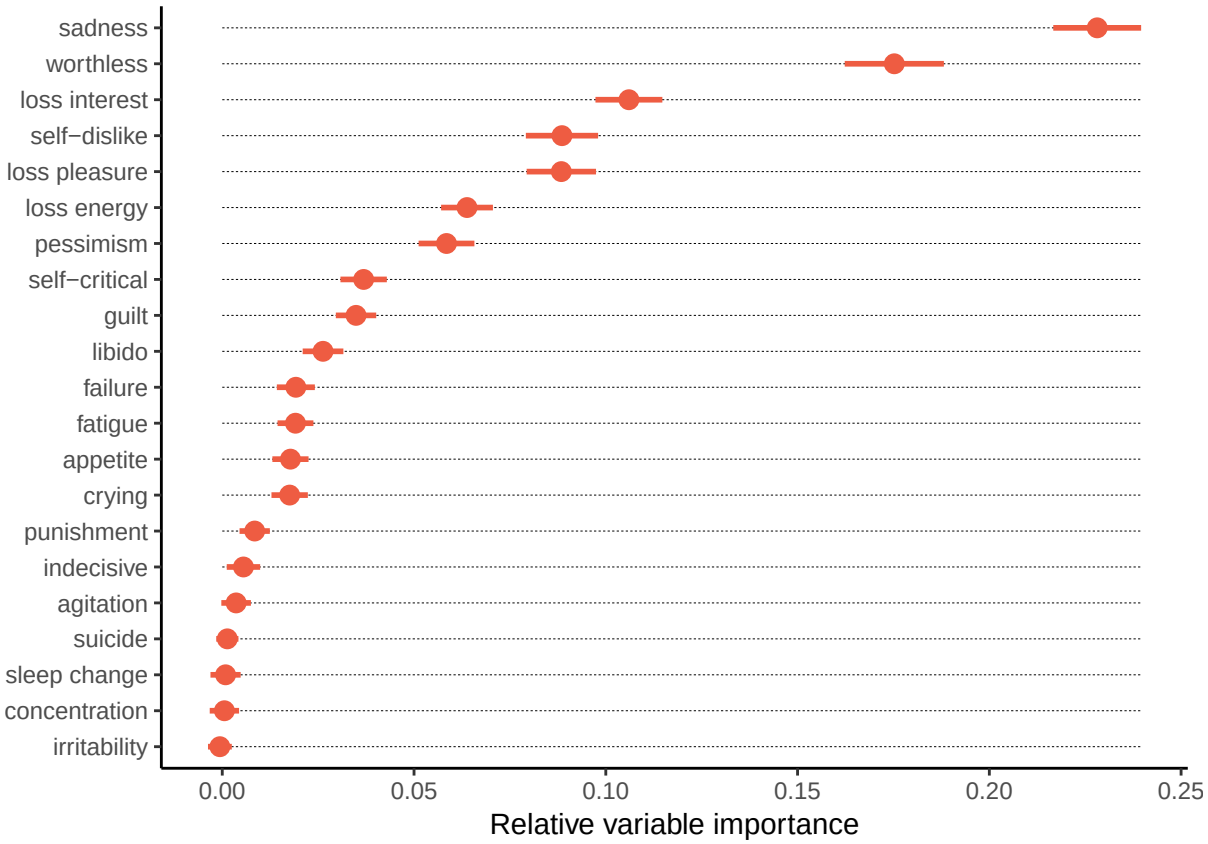
agitation.

SRET: Endosement of positive words

```
#nested cross-validation to tune and then test
pos_end_rf <- beset_rf(num.pos.endorsed ~ ., data=bdi[,c(1, 3:23)])
summary(pos_end_rf)
```

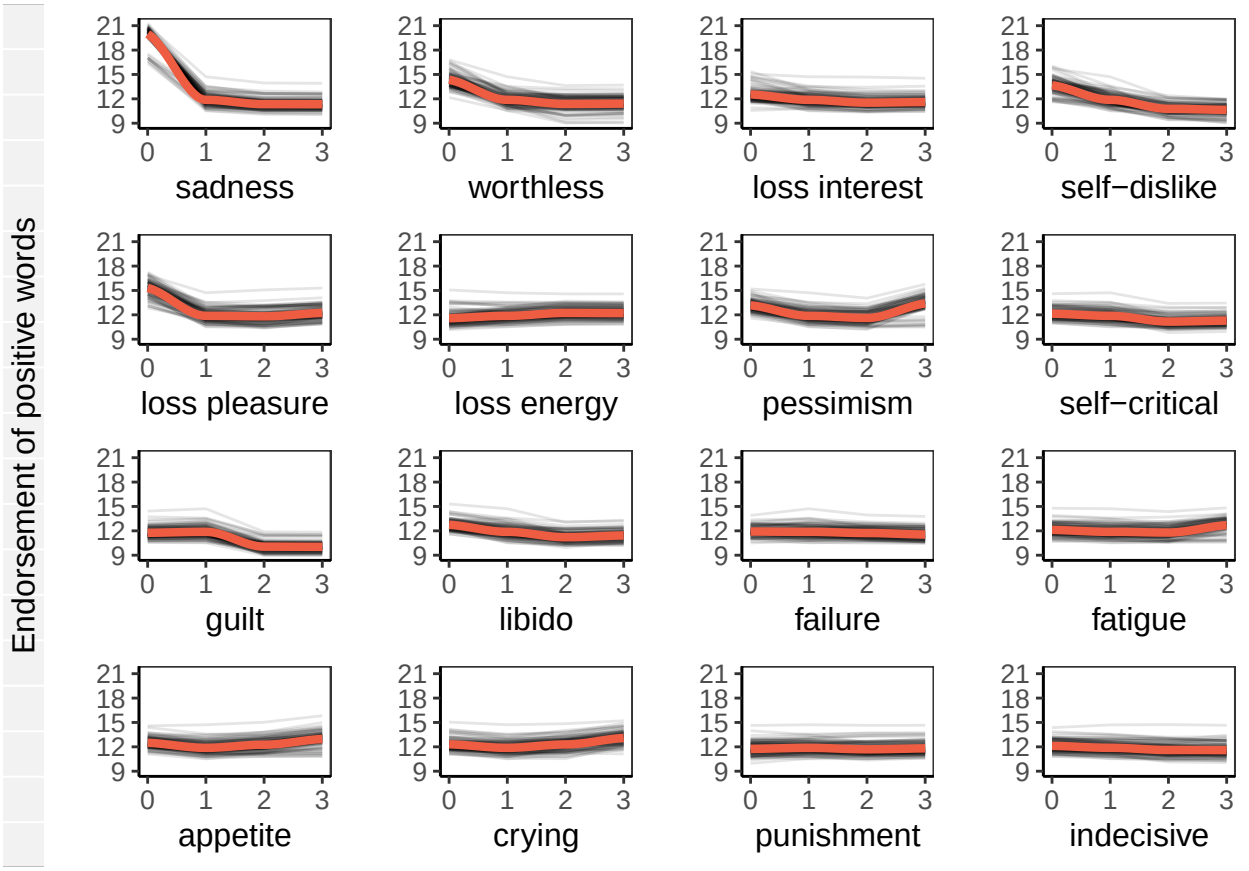
```
## Type of random forest: regression
## Number of trees: 500
## No. of variables tried at each split: 7
## ========================================================
## OOB estimate of % Var explained: 43.87
## CV estimate of % Var explained: 45.73
##
##            Importance    Min   Max
## pre_bdi_1       0.228  0.217 0.240
## pre_bdi_14      0.175  0.162 0.188
## pre_bdi_12      0.106  0.097 0.115
## pre_bdi_7       0.089  0.079 0.098
## pre_bdi_4       0.088  0.079 0.097
## pre_bdi_15      0.064  0.057 0.071
## pre_bdi_2       0.058  0.051 0.066
## pre_bdi_8       0.037  0.031 0.043
## pre_bdi_5       0.035  0.030 0.040
## pre_bdi_21      0.026  0.021 0.032
## pre_bdi_3       0.019  0.014 0.024
## pre_bdi_20      0.019  0.014 0.024
## pre_bdi_18      0.018  0.013 0.022
## pre_bdi_10      0.018  0.013 0.022
## pre_bdi_6       0.008  0.005 0.012
## pre_bdi_13      0.006  0.001 0.010
## pre_bdi_11      0.004  0.000 0.007
## pre_bdi_9       0.001 -0.002 0.004
## pre_bdi_16      0.001 -0.003 0.005
## pre_bdi_19      0.001 -0.003 0.004
## pre_bdi_17     -0.001 -0.004 0.002
##
##
## Prediction Metrics
## (Results of 10-fold cross-validation repeated 10 times)
##                        Mean   S.E.    Min    Max
## Mean Absolute Error   4.700 0.2210  4.640  4.790
## Mean Cross Entropy    3.160 0.0441  3.150  3.180
## Mean Squared Error   32.800 2.9300 32.200 33.900
## Variance Explained    0.444 0.0532  0.426  0.455
## ========================================================
```

```
#importance plot
imp_pos_end_rf <- beset::importance(pos_end_rf)
fig_pos_imp_end_rf <- plot(imp_pos_end_rf, p_max = 21, labels = names_bdi)
fig_pos_imp_end_rf
```



Using 10-fold cross validation repeated 10 times with all 21 BDI-II symptoms entered as predictors, out-of-sample R_pred^2 = 44.4% (SE = 0.053, Min = 0.426, Max = 0.455) for endorsement of positive words. As seen in the above symptom importance plot, the most important symptom was sadness. Other important symptoms included worthlessness, loss of interest, self-dislike, loss of pleasure, low energy, and pessimism. The remaining symptoms made relatively small contributions to the prediction of endorsement of positive words.

```
#dependence plots
dep_pos_end_rf <- beset::dependence(pos_end_rf,
                        y_lab = "Endorsement of positive words",
                        x_lab = c("sadness", "pessimism", "failure",
                                  "loss pleasure", "guilt", "punishment",
                                  "self-dislike", "self-critical",
                                  "suicide", "crying", "agitation",
                                  "loss interest", "indecisive",
                                  "worthless", "loss energy", "sleep change",
                                  "irritability", "appetite", "concentration",
                                  "fatigue", "libido"))
fig_pos_dep_end_rf <- plot(dep_pos_end_rf, order = "import")
```




```
fig_pos_dep_end_rf
```

```
## TableGrob (4 x 5) "arrange": 17 grobs
##                 z     cells    name                grob
## sadness         1 (1-1,2-2) arrange       gtable[layout]
## worthless       2 (1-1,3-3) arrange       gtable[layout]
## loss interest   3 (1-1,4-4) arrange       gtable[layout]
## self-dislike    4 (1-1,5-5) arrange       gtable[layout]
## loss pleasure   5 (2-2,2-2) arrange       gtable[layout]
## loss energy     6 (2-2,3-3) arrange       gtable[layout]
## pessimism       7 (2-2,4-4) arrange       gtable[layout]
## self-critical   8 (2-2,5-5) arrange       gtable[layout]
## guilt           9 (3-3,2-2) arrange       gtable[layout]
## libido         10 (3-3,3-3) arrange       gtable[layout]
## failure        11 (3-3,4-4) arrange       gtable[layout]
## fatigue        12 (3-3,5-5) arrange       gtable[layout]
## appetite       13 (4-4,2-2) arrange       gtable[layout]
## crying         14 (4-4,3-3) arrange       gtable[layout]
## punishment     15 (4-4,4-4) arrange       gtable[layout]
## indecisive     16 (4-4,5-5) arrange       gtable[layout]
##                17 (1-4,1-1) arrange text[GRID.text.2870]
```

Partial dependence plots indicate that people with no sadness endorsed a high number of adjectives as self-descriptive. Those who endorsed some level of sadness endorsed fewer positive words as self-descriptive, although endorsement appeared fairly similar at all levels of sadness. A similar but less robust pattern was observed for the other symptoms. After about the first 10 symptoms, the relationship the relationship between endorsement of positive words and symptom severity was relatively flat, indicating the absence of a

strong relationship.

Dot-probe: Bias for positive stimuli (RT)

Random forest for traditional dot-probe metric for positive stimuli.

```
rt_bias_rf <- beset_rf(dp_bias ~ ., data=dp_bias[,c(1:21, 24)])
summary(rt_bias_rf)
```

```
## Type of random forest: regression
## Number of trees: 500
## No. of variables tried at each split: 7
## ==========================================================
## OOB estimate of % Var explained: -17.55
## CV estimate of % Var explained: -15
##
##            Importance    Min   Max
## pre_bdi_12      0.166  0.133 0.199
## pre_bdi_4       0.156  0.119 0.193
## pre_bdi_17      0.150  0.117 0.183
## pre_bdi_14      0.088  0.063 0.113
## pre_bdi_1       0.086  0.057 0.115
## pre_bdi_3       0.050  0.028 0.072
## pre_bdi_18      0.046  0.027 0.066
## pre_bdi_13      0.043  0.018 0.069
## pre_bdi_5       0.036  0.012 0.060
## pre_bdi_19      0.036  0.017 0.055
## pre_bdi_20      0.030  0.016 0.043
## pre_bdi_2       0.022  0.005 0.039
## pre_bdi_9       0.018  0.004 0.032
## pre_bdi_21      0.017  0.001 0.034
## pre_bdi_7       0.017 -0.006 0.040
## pre_bdi_6       0.013 -0.002 0.029
## pre_bdi_10      0.011 -0.008 0.029
## pre_bdi_8       0.010 -0.010 0.030
## pre_bdi_15      0.005 -0.010 0.019
## pre_bdi_11      0.002 -0.014 0.018
## pre_bdi_16     -0.003 -0.022 0.016
##
##
## Prediction Metrics
## (Results of 10-fold cross-validation repeated 10 times)
##                         Mean     S.E.      Min      Max
## Mean Absolute Error   0.0255 0.001520  0.02510  0.02630
## Mean Cross Entropy   -1.9000 0.086000 -1.92000 -1.88000
## Mean Squared Error    0.0013 0.000291  0.00125  0.00135
## Variance Explained   -0.1640 0.061700 -0.21300 -0.12300
## ==========================================================
```

Using 10-fold cross-validation repeated 10 times with all 21 BDI-II symptoms entered as predictors, out-of-sample R_pred^2 was < 0% (Mean = -0.16, SE = 0.062, Min = -0.213 Max = -0.123) for traditional reaction time attention bias for positive stimuli. Thus, no depression symptoms were reliably associated with the traditional reaction time metric for positive attention bias.

Random forest for TLBS bias towards positive stimuli.

```
tlbs_bias_rf <- beset_rf(mean_dp_toward ~ ., data=dp_bias[,c(1:21, 27)])
summary(tlbs_bias_rf)
```

```
## Type of random forest: regression
## Number of trees: 500
## No. of variables tried at each split: 7
## ======================================================
## OOB estimate of % Var explained: -4.89
## CV estimate of % Var explained: -2.44
##
##             Importance    Min    Max
## pre_bdi_13       0.225  0.203  0.248
## pre_bdi_1        0.146  0.130  0.162
## pre_bdi_19       0.084  0.070  0.097
## pre_bdi_15       0.065  0.050  0.080
## pre_bdi_17       0.063  0.050  0.076
## pre_bdi_12       0.063  0.050  0.076
## pre_bdi_8        0.057  0.042  0.071
## pre_bdi_4        0.050  0.037  0.064
## pre_bdi_2        0.045  0.033  0.056
## pre_bdi_20       0.040  0.029  0.052
## pre_bdi_14       0.035  0.024  0.047
## pre_bdi_6        0.032  0.023  0.041
## pre_bdi_11       0.029  0.019  0.039
## pre_bdi_7        0.023  0.010  0.035
## pre_bdi_10       0.019  0.009  0.029
## pre_bdi_3        0.011  0.000  0.022
## pre_bdi_21       0.011  0.002  0.020
## pre_bdi_9        0.011  0.004  0.017
## pre_bdi_5        0.007 -0.002  0.017
## pre_bdi_16      -0.003 -0.013  0.007
## pre_bdi_18      -0.012 -0.020 -0.004
##
##
## Prediction Metrics
## (Results of 10-fold cross-validation repeated 10 times)
##                           Mean     S.E.      Min      Max
## Mean Absolute Error    0.02480 0.001310  0.02400  0.02520
## Mean Cross Entropy    -2.01000 0.065000 -2.03000 -2.00000
## Mean Squared Error     0.00105 0.000141  0.00101  0.00108
## Variance Explained    -0.04940 0.064100 -0.07480 -0.00196
## ======================================================
```

The same analysis was performed for TLBS towards positive stimuli. Using 10-fold cross-validation repeated 10 times with all 21 BDI-II symptoms entered as predictors, out-of-sample R_pred^2 was $< 0\%$ (Mean = -0.049, SE = 0.064, Min = -0.074, Max = -0.002). Thus, no depression symptoms were reliably associated with the TLBS metric for bias towards positive stimuli.

Random forest for eye gaze bias.

```
gz_bias_rf <- beset_rf(gaze_bias ~ ., data=dp_bias[,c(1:21, 30)])
summary(gz_bias_rf)
```

```
## Type of random forest: regression
## Number of trees: 500
```

```
## No. of variables tried at each split: 7
## ==========================================================
## OOB estimate of % Var explained: -11.4
## CV estimate of % Var explained: -11.2
##
##             Importance    Min    Max
## pre_bdi_4        0.327  0.295  0.359
## pre_bdi_12       0.243  0.219  0.268
## pre_bdi_18       0.064  0.051  0.077
## pre_bdi_1        0.051  0.034  0.068
## pre_bdi_3        0.048  0.036  0.059
## pre_bdi_21       0.032  0.021  0.042
## pre_bdi_19       0.031  0.020  0.042
## pre_bdi_15       0.029  0.018  0.040
## pre_bdi_14       0.029  0.015  0.043
## pre_bdi_10       0.025  0.015  0.036
## pre_bdi_5        0.024  0.011  0.037
## pre_bdi_17       0.024  0.009  0.038
## pre_bdi_7        0.023  0.010  0.036
## pre_bdi_13       0.018  0.003  0.033
## pre_bdi_2        0.017  0.008  0.026
## pre_bdi_6        0.017  0.007  0.027
## pre_bdi_8        0.015  0.003  0.027
## pre_bdi_20       0.014  0.005  0.023
## pre_bdi_9       -0.002 -0.009  0.006
## pre_bdi_16      -0.010 -0.018 -0.002
## pre_bdi_11      -0.017 -0.027 -0.007
##
##
## Prediction Metrics
## (Results of 10-fold cross-validation repeated 10 times)
##                           Mean    S.E.      Min      Max
## Mean Absolute Error    0.05500 0.00292  0.05250  0.05640
## Mean Cross Entropy    -1.19000 0.06510 -1.23000 -1.18000
## Mean Squared Error     0.00538 0.00087  0.00502  0.00554
## Variance Explained    -0.10100 0.06770 -0.13500 -0.02750
## ==========================================================
```

Using 10-fold cross-validation repeated 10 times with all 21 BDI-II symptoms entered as predictors, out-of-sample R_pred^2 was < 0% (Mean = -0.101, SE = 0.067, Min = -0.135, Max = -0.027). Thus, no depression symptoms were reliably associated with the eye gaze metric for bias towards positive stimuli.

Random forest for percentage of trials towards positive stimuli.

```
pct_gz_bias <- beset_rf(pct_gaze_toward ~ ., data=dp_bias[,c(1:21, 34)])
summary(pct_gz_bias)
```

```
## Type of random forest: regression
## Number of trees: 500
## No. of variables tried at each split: 7
## ==========================================================
## OOB estimate of % Var explained: -13.97
## CV estimate of % Var explained: -11.63
##
##             Importance    Min    Max
## pre_bdi_12       0.229  0.203  0.256
```

```
## pre_bdi_14      0.109  0.084  0.133
## pre_bdi_4       0.106  0.082  0.130
## pre_bdi_10      0.077  0.060  0.093
## pre_bdi_18      0.075  0.057  0.093
## pre_bdi_9       0.057  0.040  0.074
## pre_bdi_21      0.056  0.042  0.071
## pre_bdi_7       0.053  0.034  0.072
## pre_bdi_2       0.044  0.029  0.058
## pre_bdi_20      0.043  0.028  0.059
## pre_bdi_13      0.035  0.016  0.055
## pre_bdi_3       0.034  0.018  0.050
## pre_bdi_8       0.027  0.010  0.044
## pre_bdi_1       0.025  0.008  0.041
## pre_bdi_15      0.016  0.001  0.031
## pre_bdi_19      0.012 -0.004  0.028
## pre_bdi_17      0.011 -0.004  0.026
## pre_bdi_5       0.007 -0.009  0.023
## pre_bdi_6       0.006 -0.007  0.019
## pre_bdi_16     -0.002 -0.017  0.013
## pre_bdi_11     -0.022 -0.033 -0.010
##
##
## Prediction Metrics
## (Results of 10-fold cross-validation repeated 10 times)
##                          Mean     S.E.      Min      Max
## Mean Absolute Error   0.06880 0.003470  0.06810  0.06950
## Mean Cross Entropy   -0.98000 0.057500 -0.98900 -0.96700
## Mean Squared Error    0.00825 0.000964  0.00809  0.00846
## Variance Explained   -0.13700 0.056400 -0.16600 -0.11500
## =========================================================
```

Using 10-fold cross-validation repeated 10 times with all 21 BDI-II symptoms entered as predictors, out-of-sample R_pred^2 was $< 0\%$ (Mean = -0.137, SE = 0.056, Min = -0.166, Max = -0.115). Thus, no depression symptoms were reliably associated with perentage of trials where gaze was directed towards positive stimuli.

In summary, findings for the positive cognitive biases mirrored what we observed for negative cognitive bias: affective and cognitive symptoms of depression were strongly (positively) correlated with positive self-referent processing whereas there were no associations between depression symptoms and positive attention bias.