Assignment 3

study group no 8

23/11/2022

Part I - simulating the data

Use the meta-analysis reported in Parola et al (2020), create a simulated dataset with 100 matched pairs of schizophrenia and controls, each participant producing 10 repeated measures (10 trials with their speech recorded). for each of these "recordings" (data points) produce 10 acoustic measures: 6 from the meta-analysis, 4 with just random noise. Do the same for a baseline dataset including only 10 noise variables. Tip: see the slides for the code.

```
simulate_data <- function(pop_effects, n = 100, n_trails = 10, individual_sd = 1, trail_sd = 0.5, error

  set.seed(seed)

  tibble(
    variable = map_chr(seq_along(pop_effects), ~ paste0('v_', .)),
    population_value = pop_effects) %>%
  mutate(id = seq(1, n, by = 1) %>% list) %>%
    unnest(id) %>%
  rowwise %>%
  mutate(condition = c('sz', 'hc') %>% list,
         true_effect = rnorm(1, population_value, individual_sd) / 2,
         true_effect = c(true_effect, - true_effect) %>% list,
         trail = seq(1, n_trails, by = 1) %>% list) %>%
    unnest(c(condition, true_effect)) %>% unnest(trail) %>%
  rowwise %>%
  mutate(measurment = rnorm(1, true_effect, trail_sd) %>% rnorm(1, ., error),
         across(c(variable, id, condition), as_factor)) %>%
  relocate(c(variable, population_value), .after = condition)
}
```

```
m_a_values <- c(0.253, -0.546, 0.739, -1.26, -0.155, -0.75, 1.891, 0.046)

set.seed(1)
informed_pop_effects <- c(sample(m_a_values, 6, replace = F), rep(0, 4))


skeptic_pop_effects <- rep(0, 10)
```

```
dfs_long <- map(list(informed_pop_effects, skeptic_pop_effects), simulate_data)

names(dfs_long) <- c('informed', 'skeptic')
```

```r
head(dfs_long[[1]])
```

```
## # A tibble: 6 x 7
## # Rowwise:
##   id    condition variable population_value true_effect trail measurment
##   <fct> <fct>     <fct>               <dbl>       <dbl> <dbl>      <dbl>
## 1 1     sz        v_1                 0.253      -0.187     1      0.603
## 2 1     sz        v_1                 0.253      -0.187     2     -0.580
## 3 1     sz        v_1                 0.253      -0.187     3     -0.485
## 4 1     sz        v_1                 0.253      -0.187     4     -0.164
## 5 1     sz        v_1                 0.253      -0.187     5     -0.610
## 6 1     sz        v_1                 0.253      -0.187     6     -0.500
```

```r
head(dfs_long[[2]])
```

```
## # A tibble: 6 x 7
## # Rowwise:
##   id    condition variable population_value true_effect trail measurment
##   <fct> <fct>     <fct>               <dbl>       <dbl> <dbl>      <dbl>
## 1 1     sz        v_1                     0      -0.313     1      0.477
## 2 1     sz        v_1                     0      -0.313     2     -0.706
## 3 1     sz        v_1                     0      -0.313     3     -0.611
## 4 1     sz        v_1                     0      -0.313     4     -0.290
## 5 1     sz        v_1                     0      -0.313     5     -0.737
## 6 1     sz        v_1                     0      -0.313     6     -0.627
```

#“‘{r} #checking whether the simulation works fine

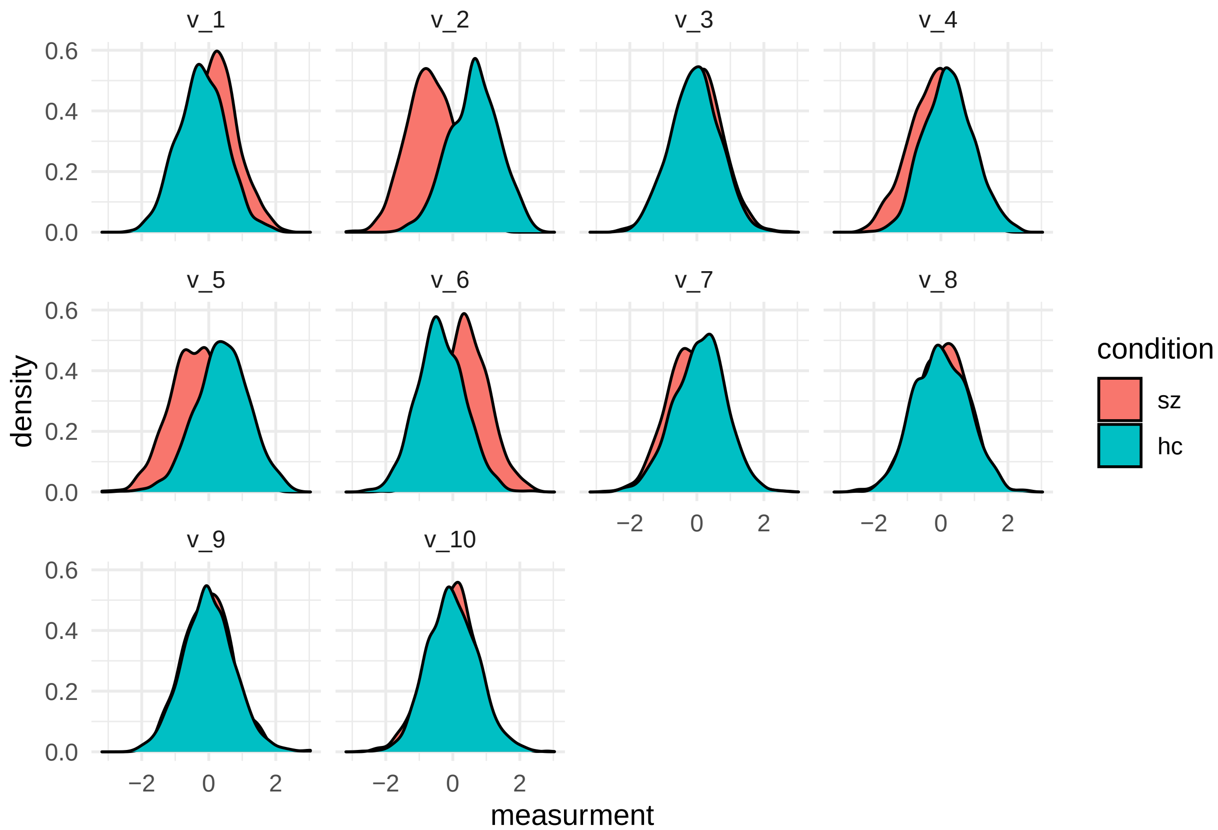
check <- map(list(informed_pop_effects, skeptic_pop_effects), ~ simulate_data(pop_effects = .x, n = 1000))

check[[1]] %>% group_by(variable) %>% summarise(mean = true_effect %>% mean, sd = true_effect %>% sd) %>% mutate(true_mean = population_value, true_sd = 1)

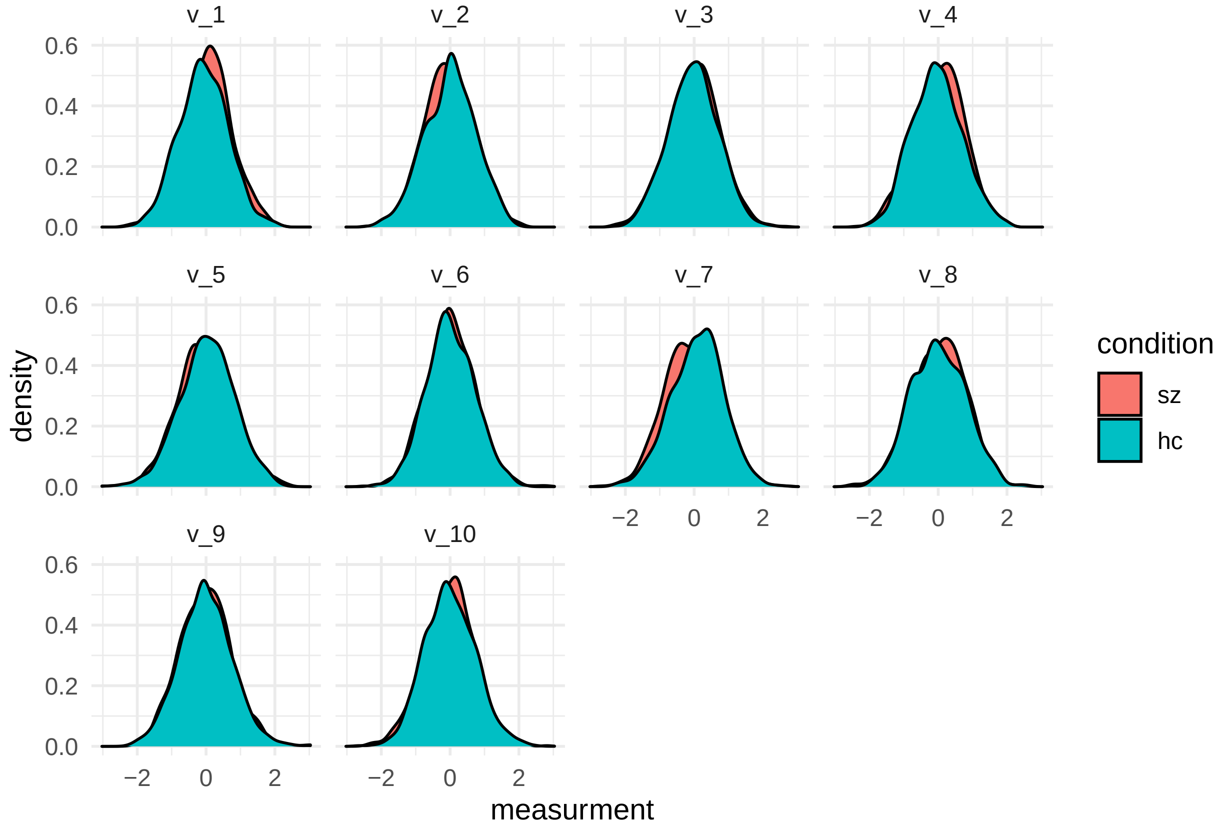
check[[1]] %>% group_by(id) %>% summarise(mean = measurment %>% mean, sd = measurment %>% sd) %>% mutate(true_mean = true_effect) #“‘

```r
#visualising the simulated data


map(dfs_long,
    ~ .x %>%
      ggplot(aes(x = measurment, fill = condition)) +
        geom_density()+
        facet_wrap(vars(variable)) +
        theme_minimal()
)
```

```
## $informed
```


v_1
v_2
v_3
v_4
v_5
v_6
v_7
v_8
v_9
v_10
0.6
0.4
0.2
0.0
density
−2
0
2
measurment
condition
sz
hc

```
##
## $skeptic
```




```r
dfs_wide <- map(dfs_long,
  ~ .x %>%
      pivot_wider(id_cols = c(id, trail, condition),
                  names_from = variable,
                  values_from = measurment)
)
head(dfs_wide[[1]])
```

```
## # A tibble: 6 x 13
##   id    trail condit~1    v_1    v_2    v_3     v_4    v_5   v_6     v_7     v_8
##   <fct> <dbl> <fct>     <dbl>  <dbl>  <dbl>   <dbl>  <dbl> <dbl>   <dbl>   <dbl>
## 1 1         1 sz        0.603 -1.57  -0.570  0.123  0.745  0.155 -0.156  -0.167
## 2 1         2 sz       -0.580 -1.54   0.414 -0.647  0.646  0.951  0.330   0.478
## 3 1         3 sz       -0.485 -0.629  0.818  0.0598 0.0165 0.996  0.297   0.104
## 4 1         4 sz       -0.164 -1.44  -0.212  0.540  0.864  0.314  0.222   0.0444
## 5 1         5 sz       -0.610 -0.813 -0.516  0.425  0.283  0.237  0.0142 -1.09
## 6 1         6 sz       -0.500 -1.32   0.642 -0.307  0.335  0.582  0.905  -0.0668
## # ... with 2 more variables: v_9 <dbl>, v_10 <dbl>, and abbreviated variable
## #   name 1: condition
```

```r
head(dfs_wide[[2]])
```

```
## # A tibble: 6 x 13
##   id    trail condition    v_1      v_2    v_3     v_4   v_5     v_6     v_7
##   <fct> <dbl> <fct>      <dbl>    <dbl>  <dbl>   <dbl> <dbl>   <dbl>   <dbl>
```

```
## 1 1         1 sz         0.477 -0.943   -0.593  0.396  1.12  -0.214  -0.156
## 2 1         2 sz        -0.706 -0.913    0.391 -0.374  1.02   0.582   0.330
## 3 1         3 sz        -0.611  0.00110  0.795  0.333  0.392  0.626   0.297
## 4 1         4 sz        -0.290 -0.806   -0.235  0.813  1.24  -0.0557  0.222
## 5 1         5 sz        -0.737 -0.183   -0.539  0.698  0.658 -0.132   0.0142
## 6 1         6 sz        -0.627 -0.691    0.619 -0.0336 0.710  0.212   0.905
## # ... with 3 more variables: v_8 <dbl>, v_9 <dbl>, v_10 <dbl>
```

Part II - machine learning pipeline on simulated data

On the two simulated datasets (separately) build a machine learning pipeline: i) create a data budget (e.g. balanced training and test sets); ii) pre-process the data (e.g. scaling the features); iii) fit and assess a classification algorithm on the training data (e.g. Bayesian multilevel logistic regression); iv) assess performance on the test set; v) discuss whether performance is as expected and feature importance is as expected.

Bonus question: replace the bayesian multilevel regression with a different algorithm, e.g. SVM or random forest (but really, anything you'd like to try). ## Budgeting the data:

```
# We know that using map() for a list of 2 elements might probably be considered an overkill, but we th


splits <- map(dfs_wide, ~ .x %>% initial_split(prop = 4/5))

dfs_training <- map(splits, ~ .x %>% training)
dfs_testing <- map(splits, ~ .x %>% testing)

rm(splits)
```

Preprocessing the data

```
recipes <- map(dfs_training,
               ~ recipe(condition ~ 1 + ., data = .x) %>%
                   update_role(id, trail, new_role = 'id') %>%
                   step_normalize(all_numeric())
)
```

Fitting (training) the models

Creating the models

```
prior_b <- normal(location = c(rep(0, 10)), scale = c(rep(0.3, 10)))
prior_intercept <- normal(0, 1)


prior_model <- logistic_reg() %>%
  set_engine('stan',
             prior = prior_b,
```

```
             prior_intercept = prior_intercept,
             prior_PD = T,
             cores = 3)


model <- logistic_reg() %>%
  set_engine('stan',
             prior = prior_b,
             prior_intercept = prior_intercept,
             cores = 3)
```

Workflows

```
wflows <- map(recipes,
              ~  workflow() %>%
                  add_model(model) %>%
                  add_recipe(.x)
)

prior_wflows <- map(recipes,
                       ~ workflow() %>%
                         add_model(prior_model) %>%
                         add_recipe(.x))
```

Model fitting

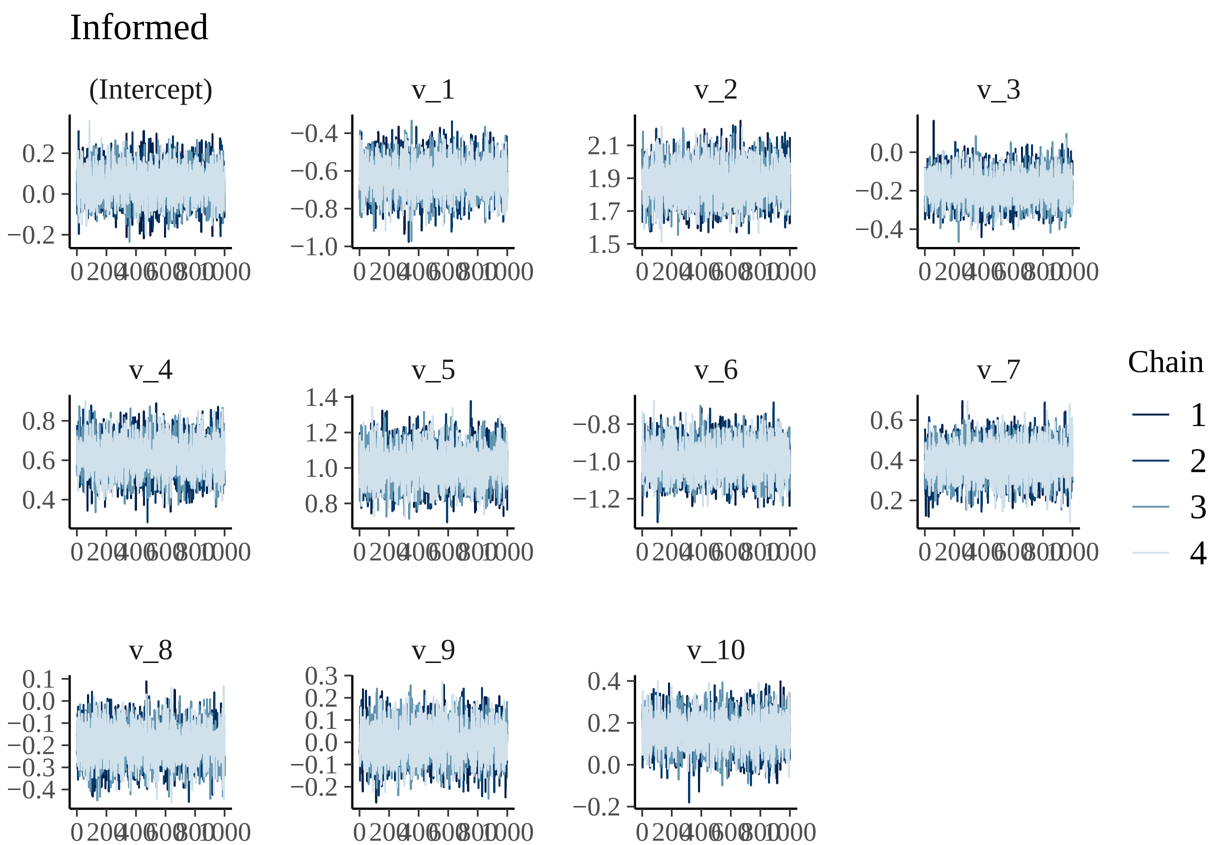
```
prior_models <- list(prior_wflows[[1]] %>% fit(dfs_training[[1]]),
                     prior_wflows[[2]] %>% fit(dfs_training[[2]])
                     ) %>% map(extract_fit_engine)


fitted <- list(wflows[[1]] %>% fit(dfs_training[[1]]),
               wflows[[2]] %>% fit(dfs_training[[2]])
               )
names(fitted) <- c('Informed', 'Sceptic')


fitted_models <- fitted %>% map(extract_fit_engine)

rm(prior_wflows)
```

Convergance checks

```
convergance_plots <- map2(
  fitted_models,
  names(fitted_models),
  function(.x, .y){
```

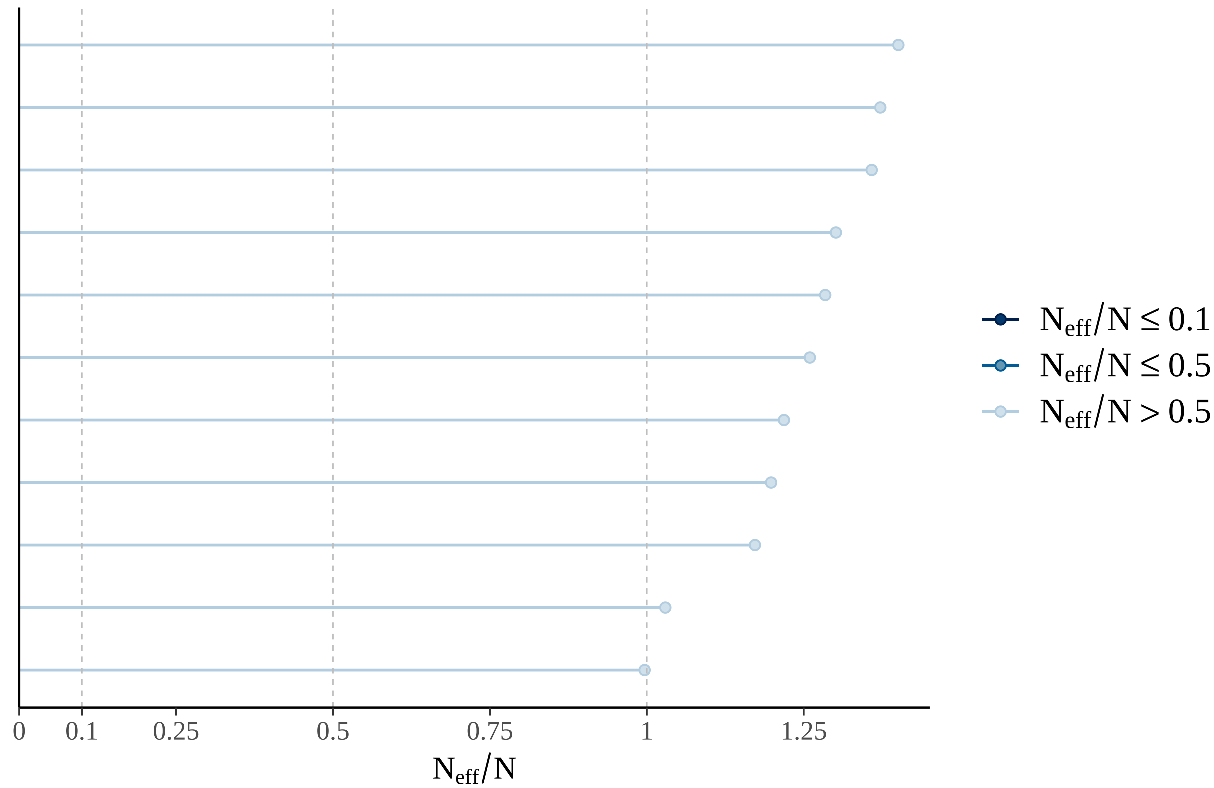
```
    list(
      plot(.x, 'trace'),
      plot(.x, 'neff'),
      plot(.x, 'rhat')
      ) %>%
    map(function(.x){.x + ggtitle(.y)})
  }
)

convergance_plots %>% print
```

```
## $Informed
## $Informed[[1]]
```



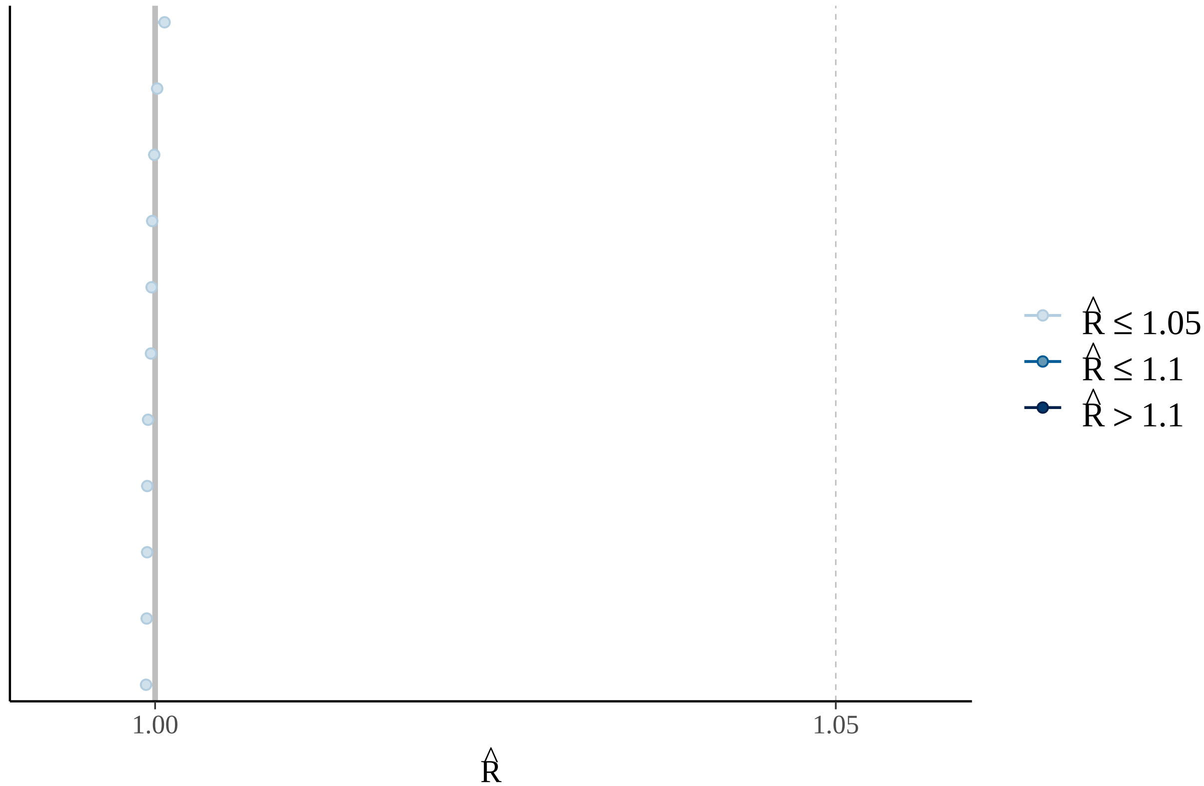

```
##
## $Informed[[2]]
```

Informed

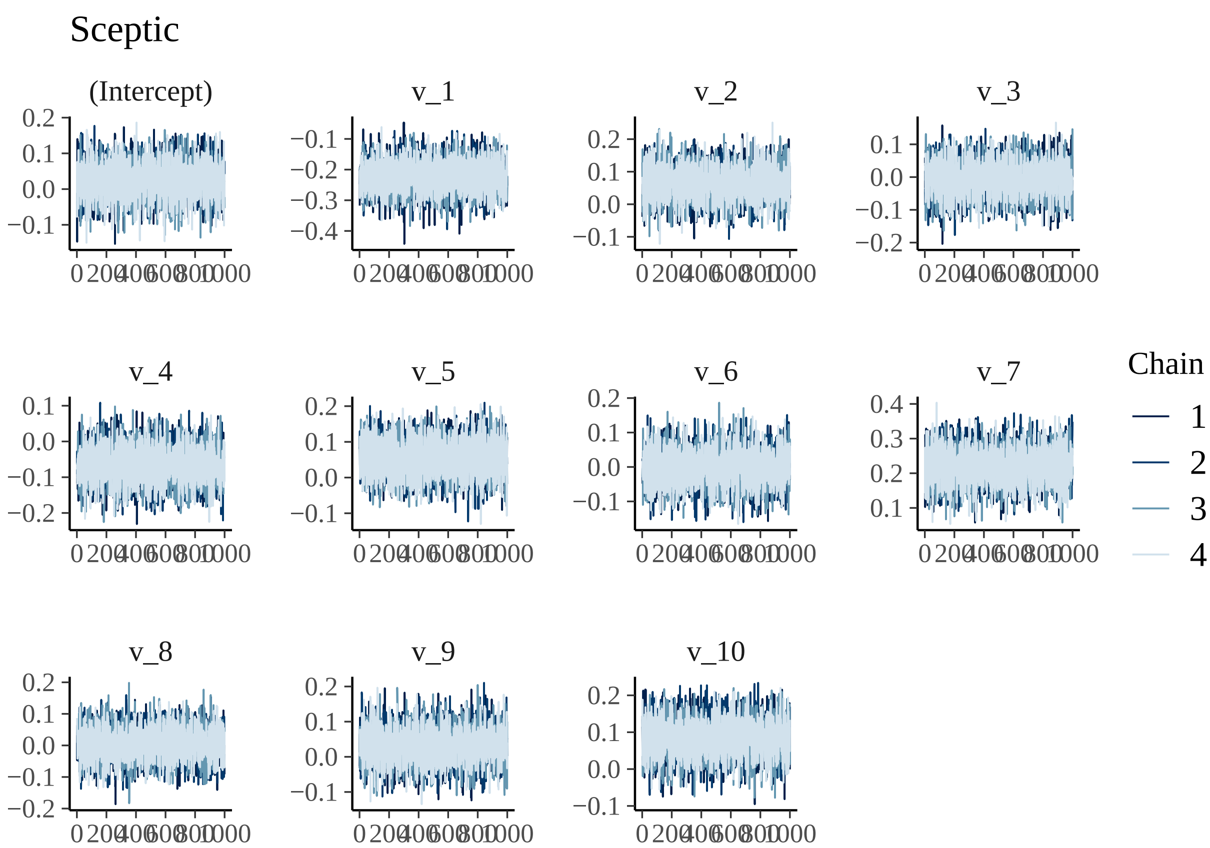



```
##
## $Informed[[3]]
```

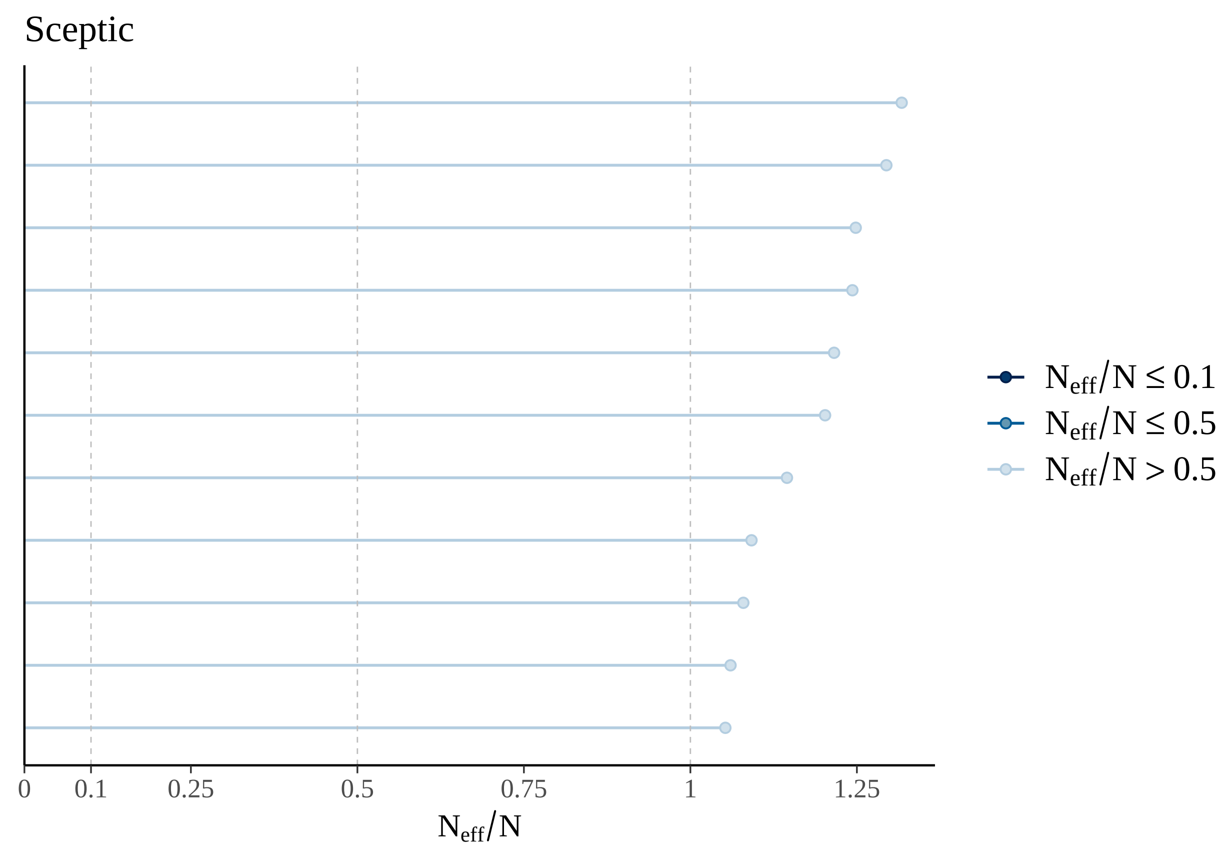
Informed



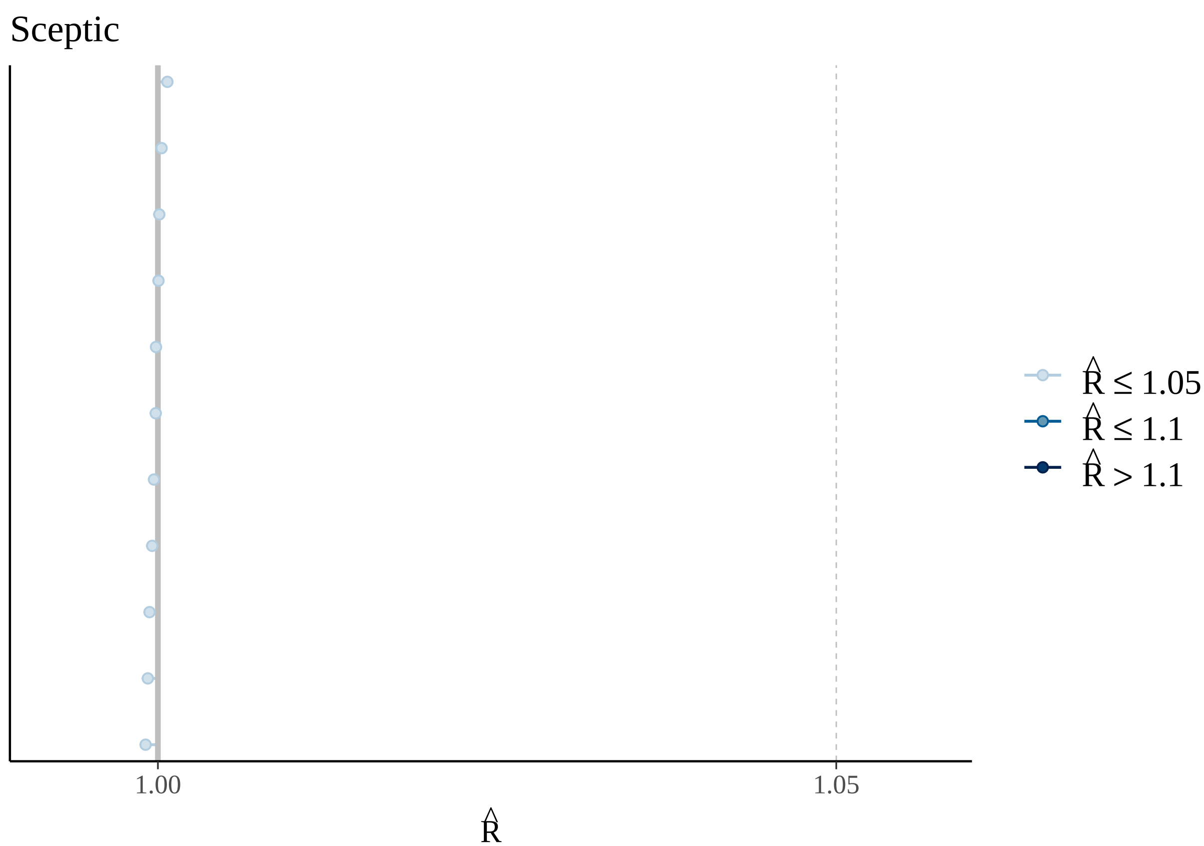

```
##
##
## $Sceptic
## $Sceptic[[1]]
```




```
##
## $Sceptic[[2]]
```


Sceptic
0
0.1
0.25
0.5
0.75
1
1.25
N_{eff}/N
$N_{eff}/N \leq 0.1$
$N_{eff}/N \leq 0.5$
$N_{eff}/N > 0.5$

```
##
## $Sceptic[[3]]
```




```
rm(convergance_plots)
```

Checking the priors

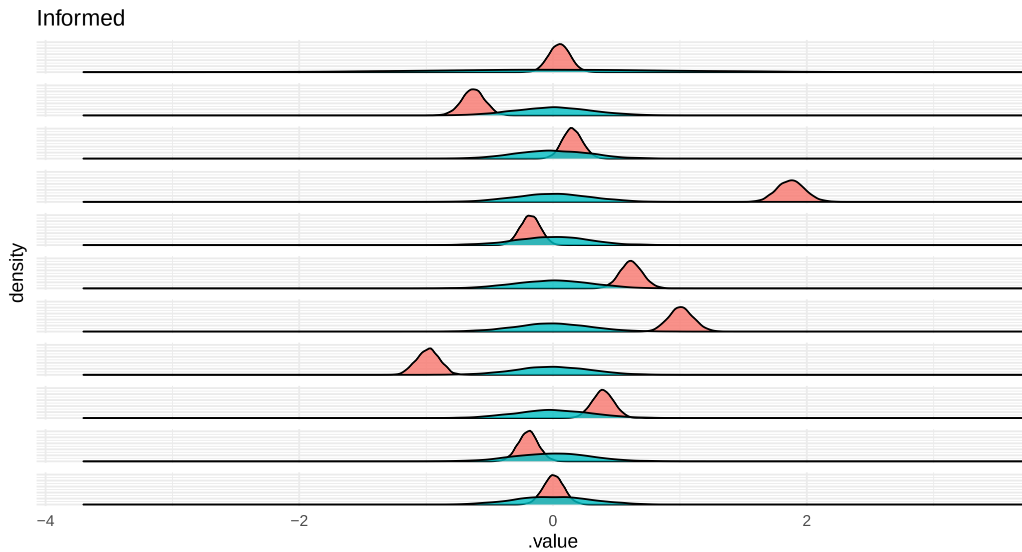
```
#make prior visualisation like the one on the slides (week 10)
```

Visualising the prior distributions

```
pp_update_plot <- function(prior_model, posterior_model){
  df_draws <-
    bind_rows(
      bind_rows(
        prior_model %>% gather_draws(`(Intercept)`),
        prior_model %>% gather_draws(`v_.*`, regex = T)
        ) %>%
        mutate(type = 'prior'),

      bind_rows(
        posterior_model %>% gather_draws(`(Intercept)`),
```

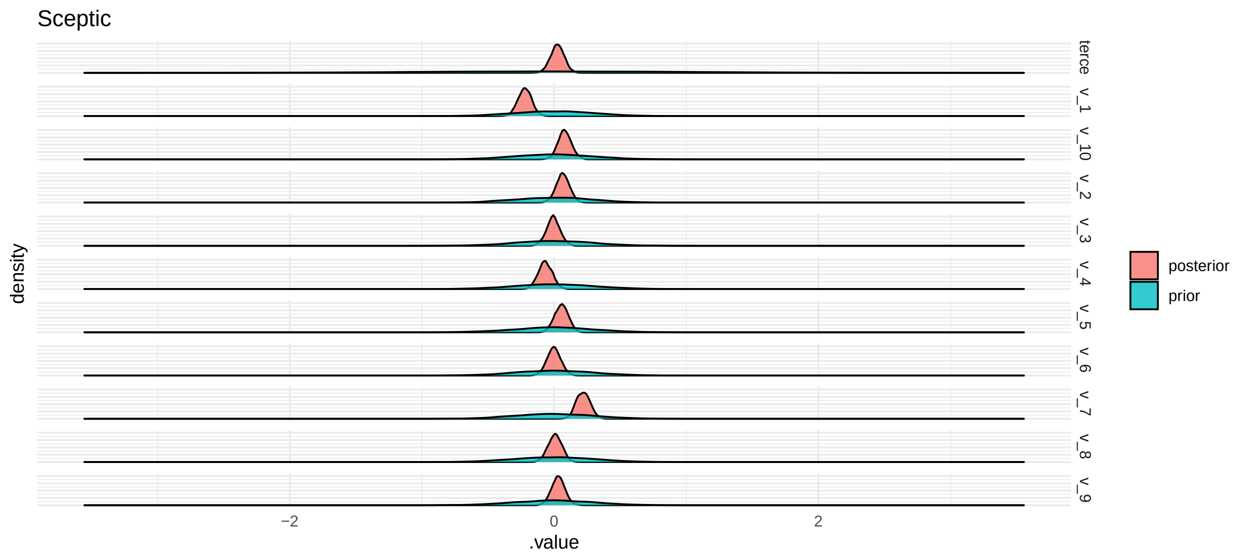
```
        posterior_model %>% gather_draws(`v_.*`, regex = T)
        ) %>%
        mutate(type = 'posterior')
      )

  df_draws <- df_draws %>%
    group_by(.variable) %>%
    mutate(upp_lim = if_else((max(.value) + min(.value)) > 0, max(.value), - min(.value)),
           low_lim = - upp_lim) %>%
    ungroup



  df_draws %>%
    ggplot(aes(x = .value, fill = type)) +
      geom_density(alpha = 0.8) +
      labs(fill = element_blank()) +
      xlim(df_draws$low_lim[[1]], df_draws$upp_lim[[1]]) +
      facet_grid(vars(df_draws$.variable)) +
      theme_minimal() +
      theme(axis.ticks.y = element_blank(),
            axis.text.y = element_blank())
}
```

```
pp_update_plot(prior_models[[1]], fitted_models[[1]])+
  ggtitle('Informed')
```



Prior-posterior update checks

```
pp_update_plot(prior_models[[2]], fitted_models[[2]])+
  ggtitle('Sceptic')
```



Visualising the model

```
#add a plot of the regression line on the log-odds scale and on the probability scale
```

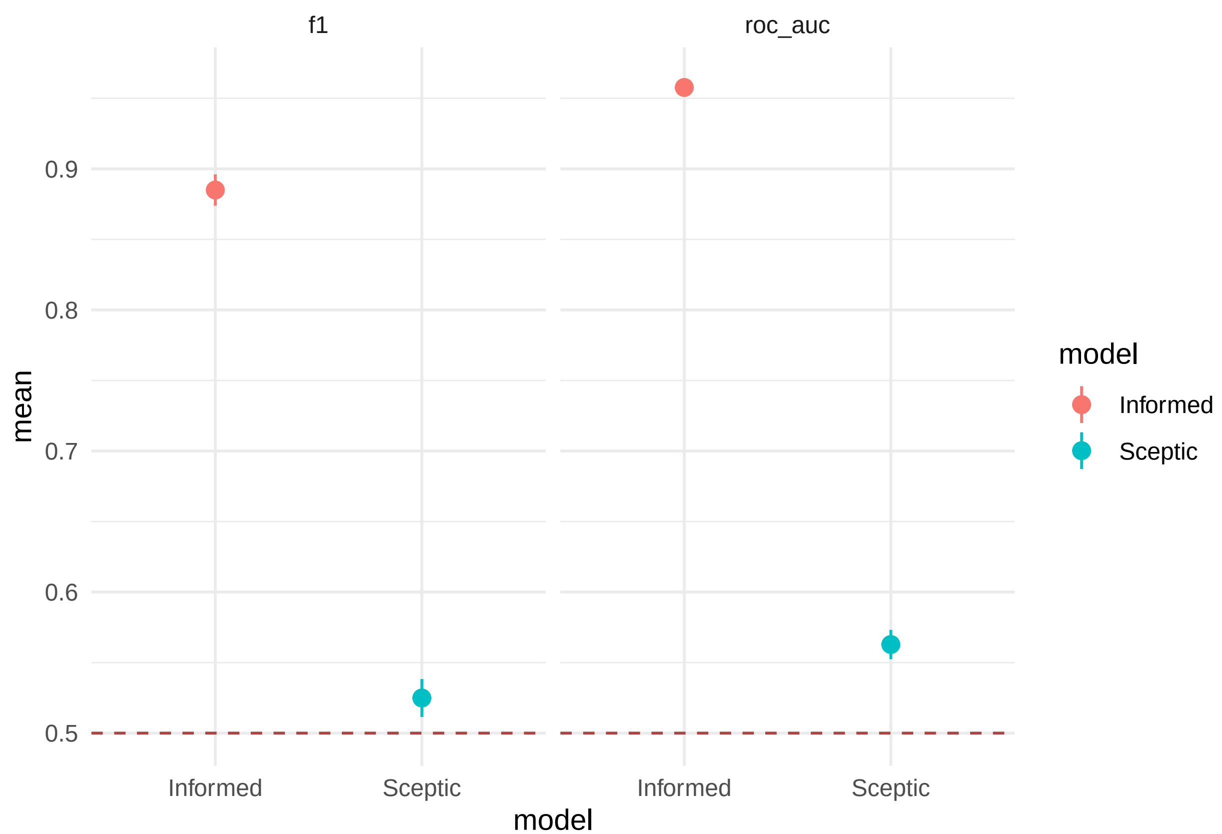
Accessing model performance

Cross-validation

```
dfs_folded <- map(dfs_training, ~ vfold_cv(.x, v = 8))



cv_data <- map2(wflows, dfs_folded, ~ fit_resamples(.x, .y, metrics = metric_set(f_meas, roc_auc)))

cv_results <- map(cv_data, ~ collect_metrics(.x) %>%
                    mutate(upper = mean + std_err,
                           lower = mean - std_err))

cv_results <- bind_rows(
    cv_results[[1]] %>% mutate(model = 'Informed'),
    cv_results[[2]] %>% mutate(model = 'Sceptic')
  )

cv_results <- cv_results %>%
  rename_with(.cols = everything(), ~ str_remove(.x, stringr::fixed("."))) %>%
  mutate(metric = if_else(metric == 'f_meas', 'f1', metric))
```

```
cv_results%>%
  ggplot(aes(x = mean, y = model, xmax = upper, xmin = lower, colour = model)) +
    geom_pointrange()+
    facet_wrap(vars(metric)) +
```

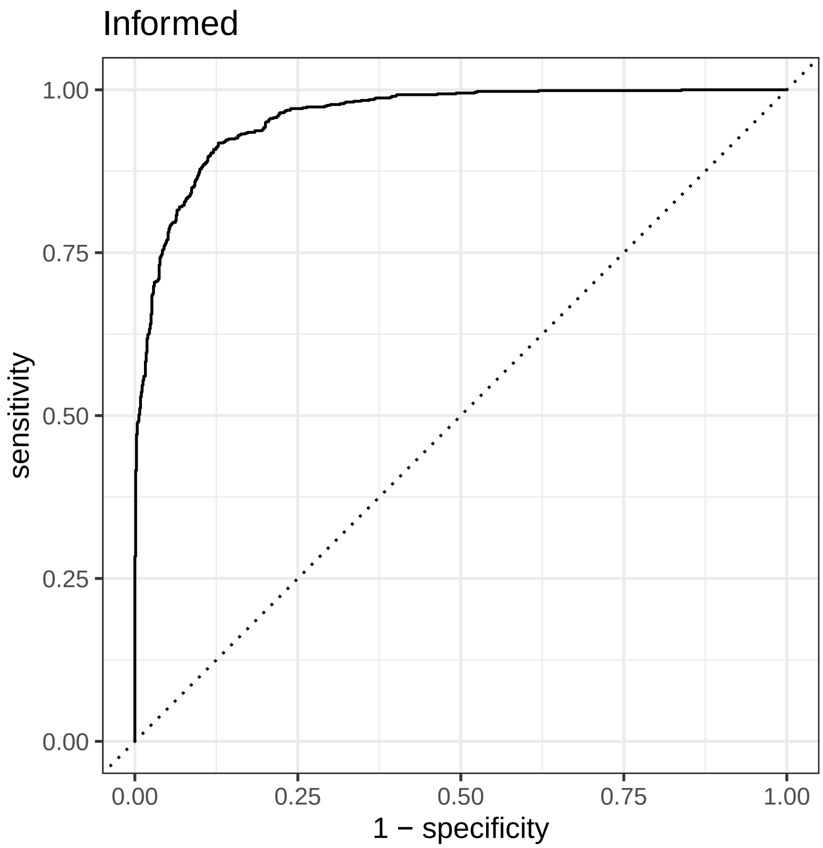
```
    geom_vline(xintercept = 0.5, colour = 'darkred', linetype = 'dashed', alpha = 0.7) +
    theme_minimal() +
    coord_flip()
```



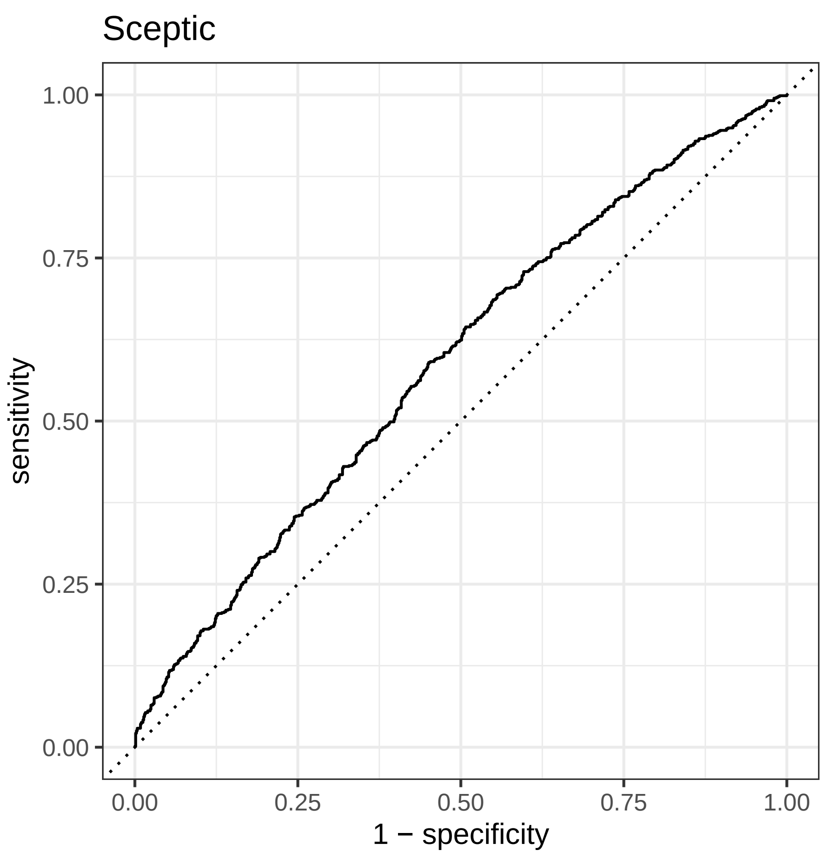
Test data

```
test_preds <- map2(fitted, dfs_training, ~ augment(.x, .y))


map2(test_preds, names(test_preds),
     ~ .x %>%
          roc_curve(truth = condition, .pred_sz) %>%
            autoplot +
            ggtitle(.y)
)
```

```
## $Informed
```

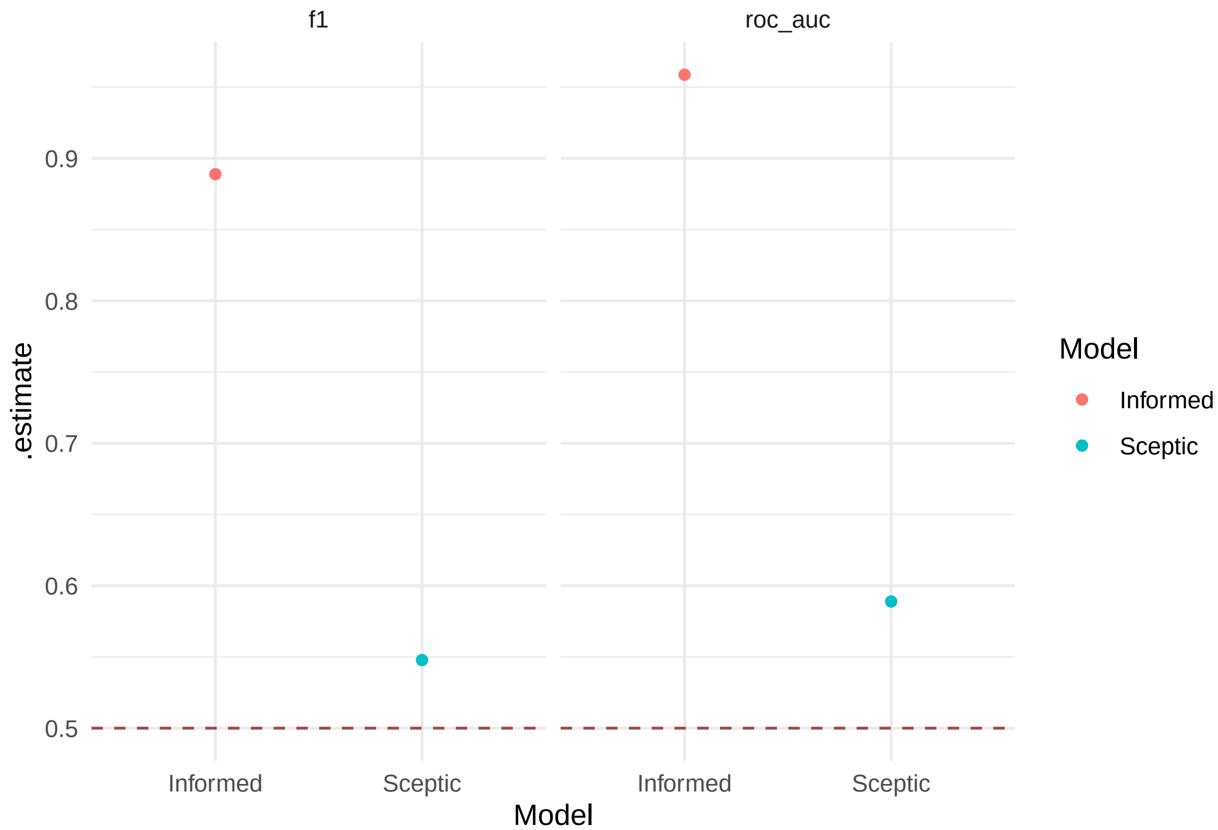

Informed
1.00
0.75
0.50
0.25
0.00
sensitivity
0.00
0.25
0.50
0.75
1.00
1 − specificity

```
##
## $Sceptic
```



Conclusions (is performance and feature importance as expected)

```
#without uncertanity


# come up with a better name for this one
test_results_mean_only <- map2_df(test_preds, names(test_preds),
             ~ bind_rows(
                 .x %>% roc_auc(truth = condition, .pred_sz),
                 .x %>% f_meas(truth = condition, .pred_class, beta = 1) %>% mutate(.metric = 'f1')
             ) %>%
               mutate(Model = .y)
)






test_results_mean_only %>%
  ggplot(aes(x = Model, y = .estimate, colour = Model)) +
    geom_point()+
    facet_wrap(vars(.metric)) +
    geom_hline(yintercept = 0.5, colour = 'darkred', linetype = 'dashed', alpha = 0.7) +
    theme_minimal()
```

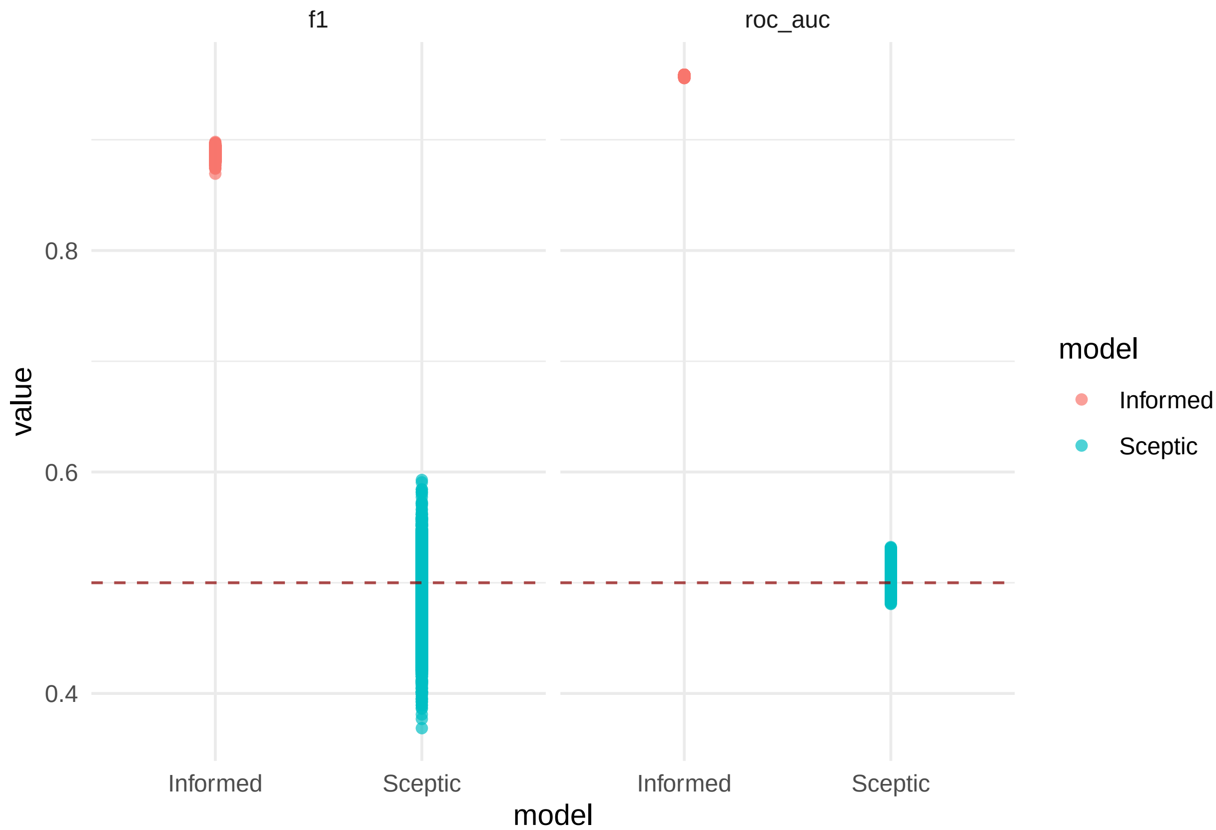



```
#with the uncertanity

test_results <- tibble(draw = NULL,
                       f1 = NULL,
                       model = NULL)


for (i in seq_along(fitted_models)){

  m <- fitted_models[[i]]
  name <- names(fitted_models)[[i]]

  draws_matrix <- posterior_epred(m)

  roc_aucs <- map_dbl(
    draws_matrix %>% split(row(draws_matrix)),
    ~ roc_auc_vec(truth = dfs_training[[1]]$condition, estimate = .x)
    )

  roc_aucs <- tibble(
    value = roc_aucs,
    metric = 'roc_auc',
    draw = seq_along(nrow)
    )
```

```r
  preds_class <- map(
    draws_matrix %>% split(row(draws_matrix)),
    ~ if_else(.x < 0.5, 'sz', 'hc') %>% as_factor %>% relevel('sz')
    )


  fs <- map_dbl(
    preds_class,
    ~ f_meas_vec(truth = dfs_training[[1]]$condition, estimate = .x, beta = 1)
    )

  fs <- tibble(
    value = fs,
    metric = 'f1',
    draw = seq_along(nrow)
    )


  test_results <- bind_rows(
    test_results,
    bind_rows(fs, roc_aucs) %>% mutate(model = name)
  )
}
rm(i, m, name, draws_matrix, roc_aucs, preds_class, fs)


test_results <- test_results %>%
  mutate(value = if_else(metric == 'roc_auc', 1 - value, value))

test_results_summary <- test_results %>%
  group_by(model, metric) %>%
  summarise(mean = mean(value), std_err = sd(value),
            #because we're dealing the the estimates of the population parameters, the sd already is th
            lower = mean - 1.96*std_err,
            upper = mean + 1.96*std_err)
```

```
## `summarise()` has grouped output by 'model'. You can override using the
## `.groups` argument.
```

```r
test_results %>%
    ggplot(aes(x = model, y = value, colour = model)) +
      geom_point(alpha = 0.7) +
      geom_hline(yintercept = 0.5, color = 'darkred', linetype = 'dashed', alpha = 0.7) +
      theme_minimal() +
      facet_wrap(vars(metric))
```

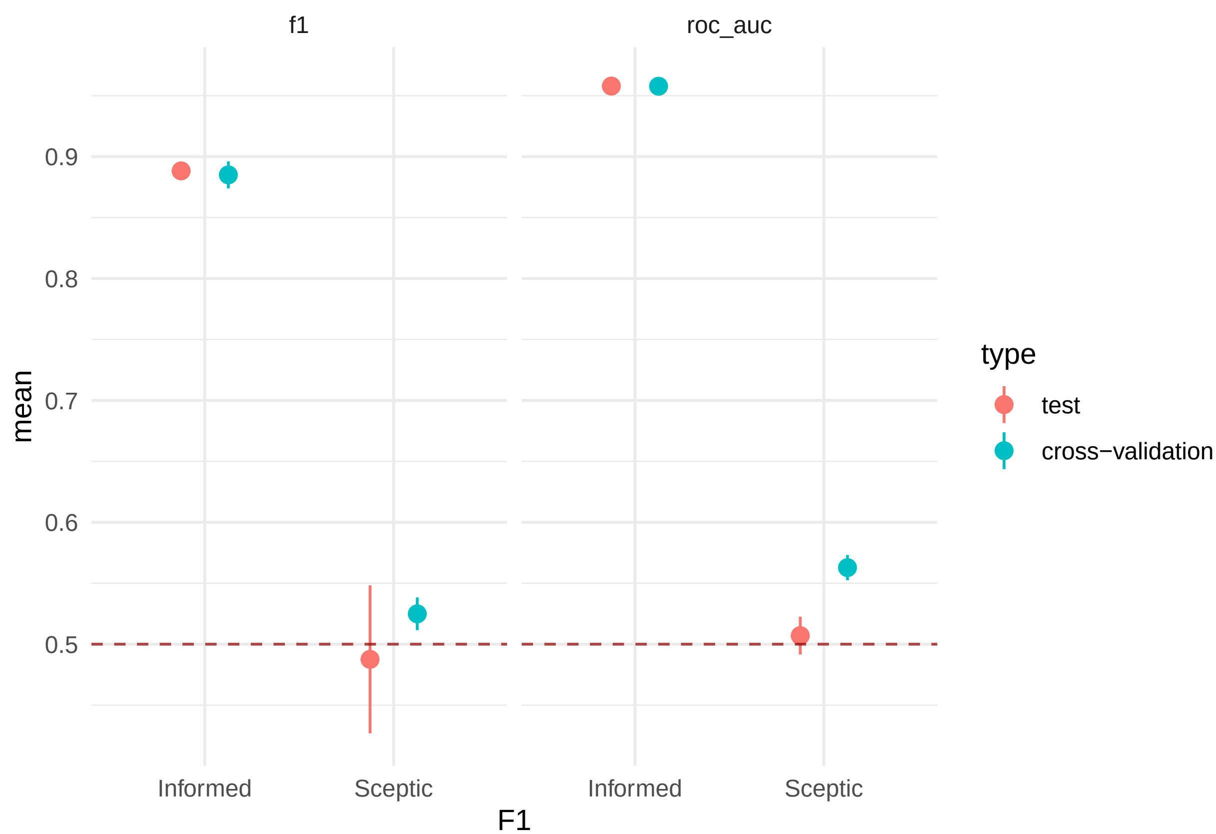



```
# Just realised this might actually not work

  # 1. mean accuracy of all draws is something very different from the accuracy of the mean linear pred

  #2. Second problem is that the confidence intervals in cross-validation and test might not show the s

        # What to do about it?
          # - plot only the accuracies only for the mean + ci of final model estimates?
          # - just back out of the confidence intervals and do all the dots for cross-validation as wel
                # - you then have to code the cross-validation 'by hand'


performance_data <- bind_rows(
  test_results_summary %>% mutate(type = 'test'),
  cv_results %>% mutate(type = 'cross-validation')) %>%
  ungroup

performance_data <- performance_data %>%
  mutate(across(where(is.character), as_factor))

glimpse(performance_data)
```

```
## Rows: 8
## Columns: 10
## $ model      <fct> Informed, Informed, Sceptic, Sceptic, Informed, Informed, Sc~
## $ metric     <fct> f1, roc_auc, f1, roc_auc, f1, roc_auc, f1, roc_auc
```

```
## $ mean      <dbl> 0.8882674, 0.9578412, 0.4875699, 0.5070287, 0.8849941, 0.957~
## $ std_err   <dbl> 0.0029913341, 0.0004801837, 0.0309563668, 0.0079182479, 0.01~
## $ lower     <dbl> 0.8824044, 0.9569001, 0.4268954, 0.4915089, 0.8738774, 0.952~
## $ upper     <dbl> 0.8941305, 0.9587824, 0.5482444, 0.5225485, 0.8961109, 0.962~
## $ type      <fct> test, test, test, test, cross-validation, cross-validation, ~
## $ estimator <fct> NA, NA, NA, NA, binary, binary, binary, binary
## $ n         <int> NA, NA, NA, NA, 8, 8, 8, 8
## $ config    <fct> NA, NA, NA, NA, Preprocessor1_Model1, Preprocessor1_Model1, ~
```

```
performance_data %>%
    ggplot(aes(x = mean, y = model, xmin = lower, xmax = upper, colour = type)) +
      geom_pointrange(position = position_dodge(width = 0.5)) +
      geom_vline(aes(xintercept = 0.5), color = 'darkred', linetype = 'dashed', alpha = 0.7) +
      labs(y = 'F1') +
      theme_minimal()+
      coord_flip() +
      facet_wrap(vars(metric))
```

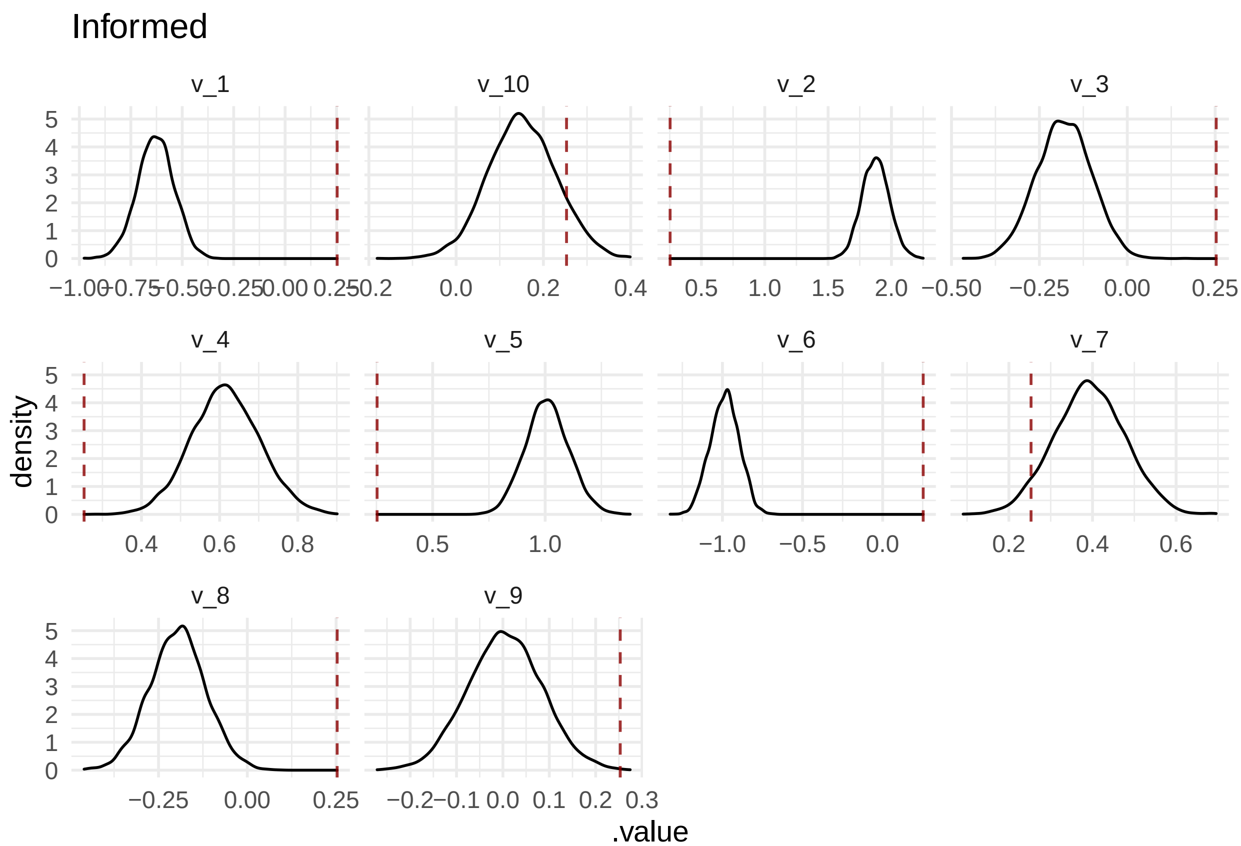


Feature importance

```
vim_simulated <- function(model, truth){
vim_df <- model %>% gather_draws(`v_.*`, regex = T)
vim_df <- map2_df(vim_df %>% group_split(.variable), truth,
                  ~ .x %>% mutate(truth = .y)
                  )
```

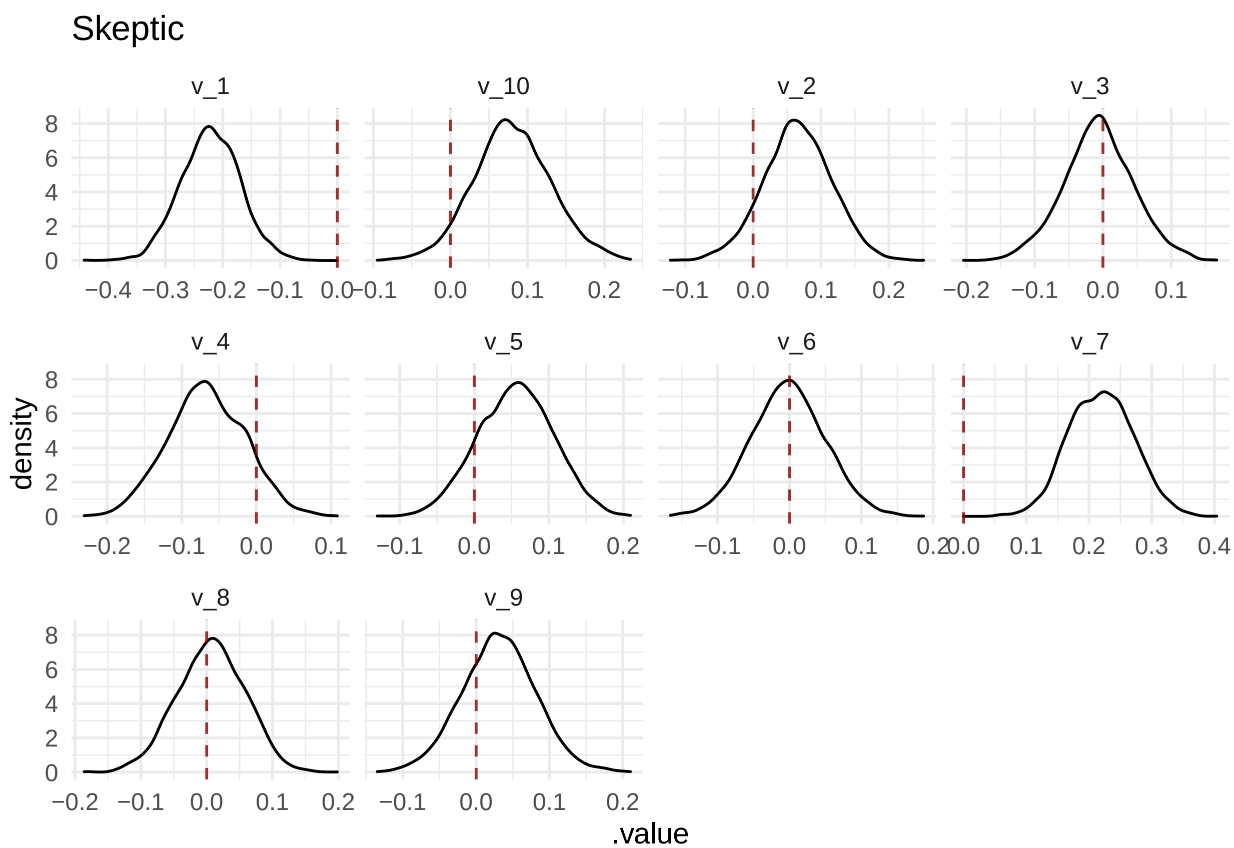
```
vim_df %>%
ggplot(aes(x = .value)) +
  geom_density() +
  geom_vline(aes(xintercept = truth[[1]]), color = 'darkred', linetype = 'dashed', alpha = 0.8) +
  facet_wrap(vars(.variable), nrow = , scales = 'free_x') +
  theme_minimal()
}

vip_simulated(fitted_models[[1]], informed_pop_effects) + ggtitle('Informed')
```

```
## Warning: ... is ignored in group_split(<grouped_df>), please use group_by(..., .add =
## TRUE) %>% group_split()
```




```
vip_simulated(fitted_models[[2]], skeptic_pop_effects) + ggtitle('Skeptic')
```

```
## Warning: ... is ignored in group_split(<grouped_df>), please use group_by(..., .add =
## TRUE) %>% group_split()
```




```
#how to make v_10 appear as last? (mutating to factor before ggplot and inside facet_wrap doesn't work)
```

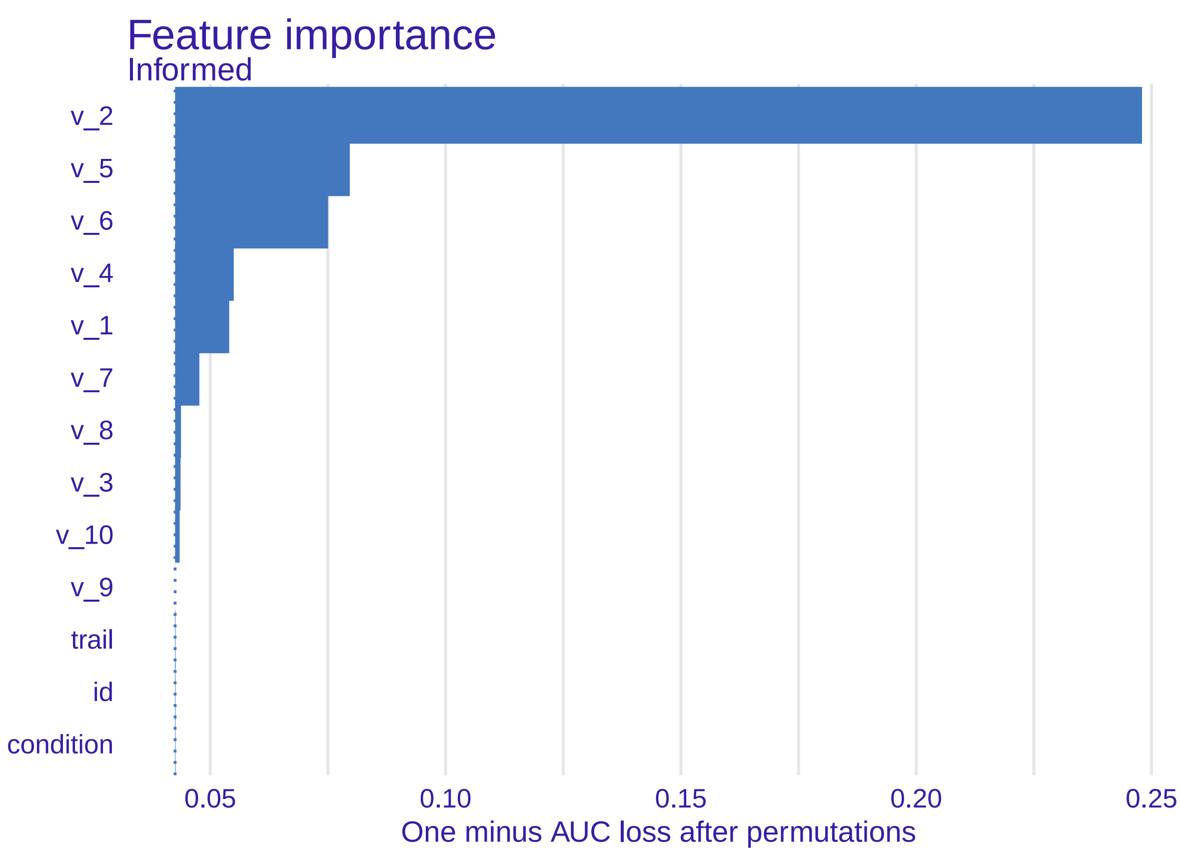
```
vips <- map(
  c(1,2),
  ~ explain_tidymodels(
      fitted[[.x]] %>% extract_fit_parsnip,
      data = dfs_training[[.x]],
      y = dfs_training[[.x]]$condition %>% as.numeric - 1,
      label = names(fitted)[[.x]]
      )
)
```

```
## Preparation of a new explainer is initiated
##   -> model label       :  Informed
##   -> data              :  1600  rows  13  cols
##   -> data              :  tibble converted into a data.frame
##   -> target variable   :  1600  values
##   -> predict function  :  yhat.model_fit  will be used (  default  )
##   -> predicted values  :  No value for predict function target column. (  default  )
##   -> model_info        :  package parsnip , ver. 1.0.2 , task classification (  default  )
##   -> predicted values  :  numerical, min =  0.000284271 , mean =  0.4993827 , max =  0.9995609
##   -> residual function :  residual_function
##   -> residuals         :  numerical, min =  0 , mean =  0 , max =  0
##   A new explainer has been created!
## Preparation of a new explainer is initiated
```

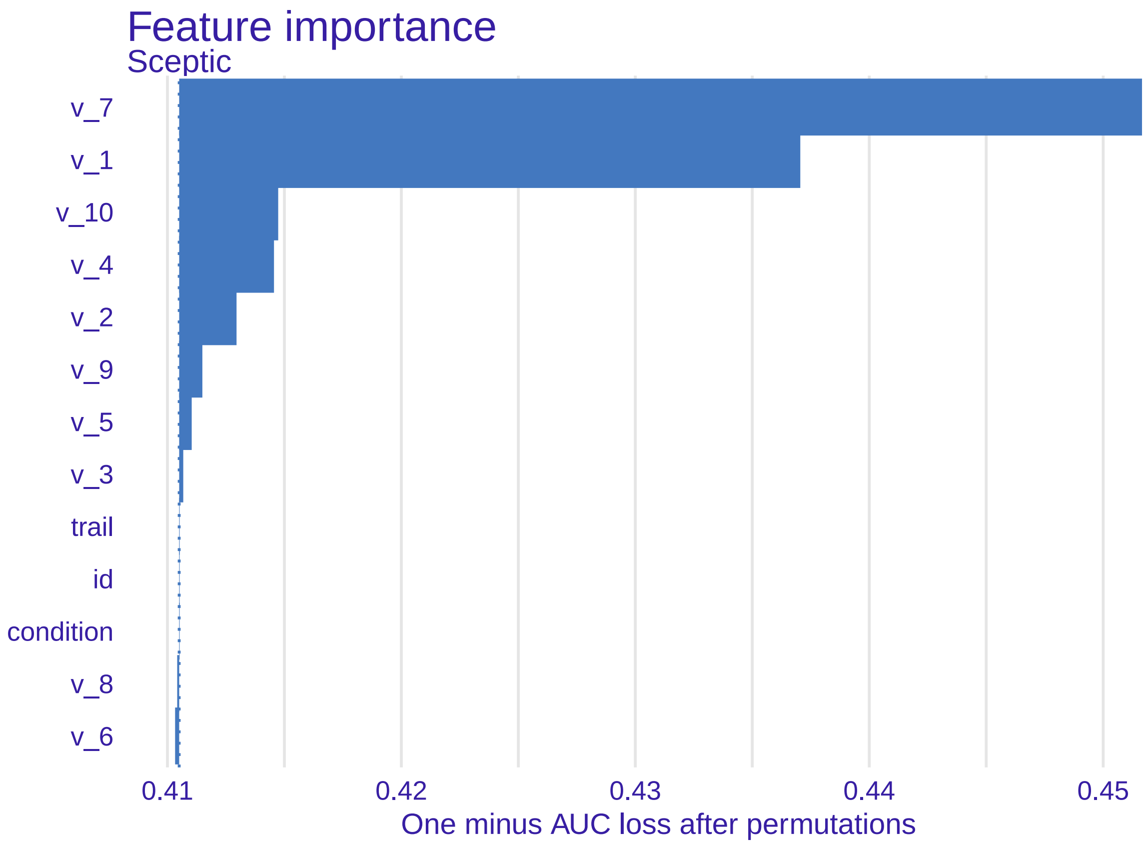
```
##   -> model label       :  Sceptic
##   -> data              :  1600  rows  13  cols
##   -> data              :  tibble converted into a data.frame
##   -> target variable   :  1600  values
##   -> predict function  :  yhat.model_fit  will be used (  default  )
##   -> predicted values  :  No value for predict function target column. (  default  )
##   -> model_info        :  package parsnip , ver. 1.0.2 , task classification (  default  )
##   -> predicted values  :  numerical, min =  0.2986658 , mean =  0.5047465 , max =  0.7008366
##   -> residual function :  residual_function
##   -> residuals         :  numerical, min =  0 , mean =  0 , max =  0
##   A new explainer has been created!
```

```
map(
  vips,
  ~ .x %>%
    model_parts %>%
    plot(show_boxplots = F) +
      labs(title = 'Feature importance',
         subtitle = NULL)
)
```

```
## [[1]]
```

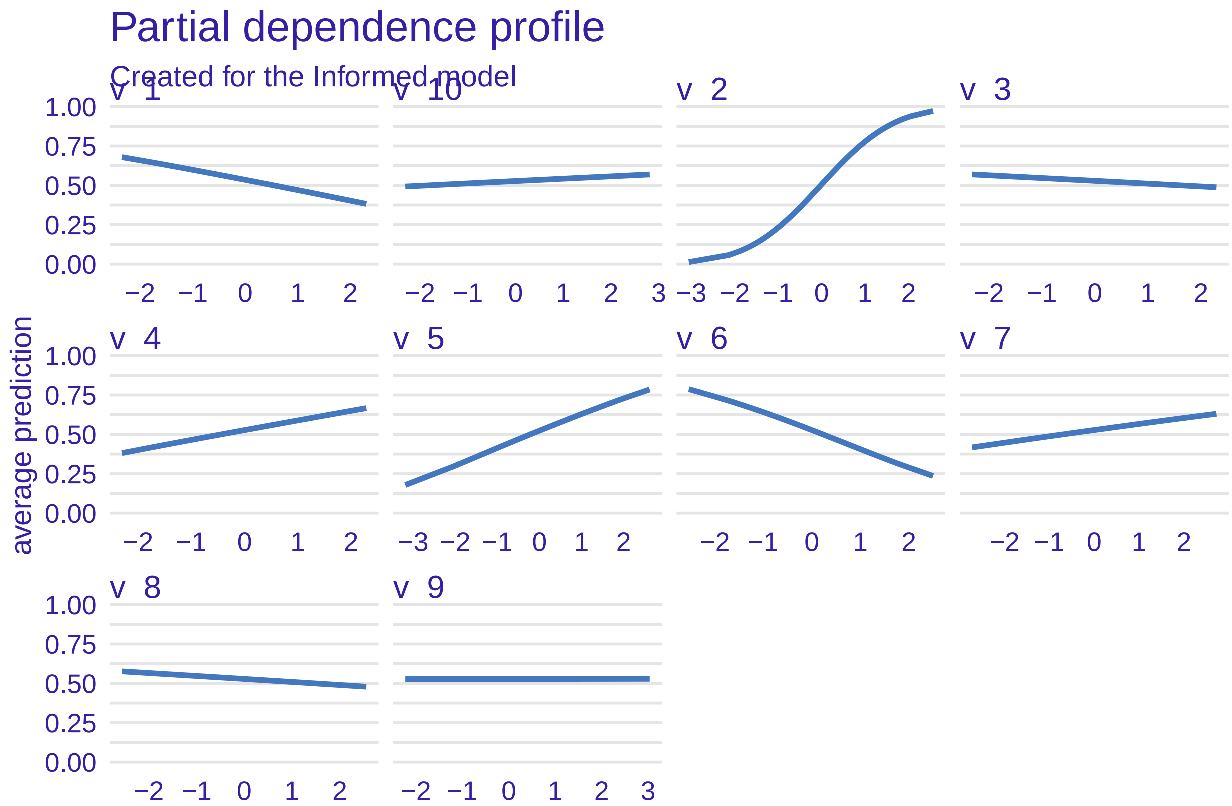



```
##
## [[2]]
```



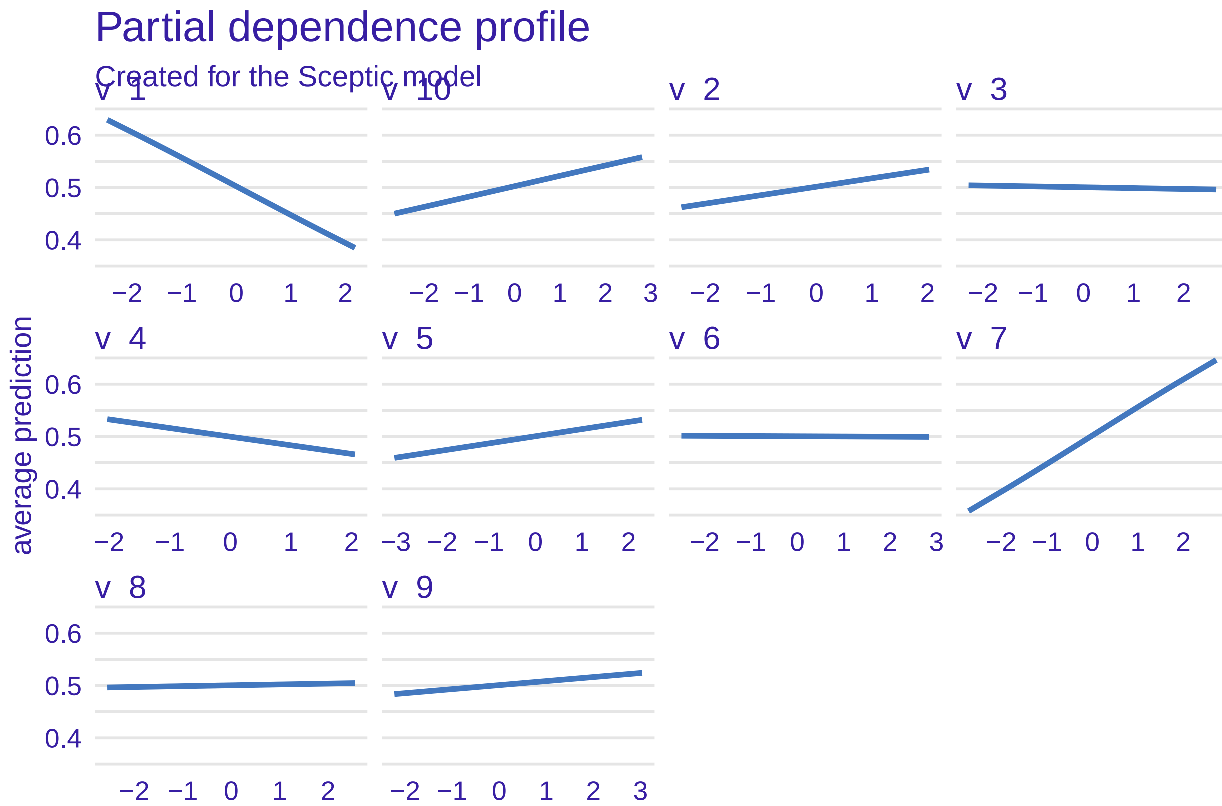

```
map(
  vips,
  ~ .x %>%
    model_profile(
      type = 'partial',
      variables = paste0('v_', seq(10))
      ) %>%
    plot() +
      labs(title = 'Partial dependence profile')
)
```

```
## [[1]]
```



Partial dependence profile
Created for the Informed model
average prediction
v 1
v 10
v 2
v 3
v 4
v 5
v 6
v 7
v 8
v 9


```
##
## [[2]]
```




```
#save.image(file = "/rdata/a3_part2.Rdata")
```

Part III

Download the empirical dataset from brightspace and apply your ML pipeline to the new data, adjusting where needed. Warning: in the simulated dataset we only had 10 features, now you have many more! Such is the life of the ML practitioner. Consider the impact a higher number of features will have on your ML inference, and decide whether you need to cut down the number of features before running the pipeline (or alternatively expand the pipeline to add feature selection).

```
rm(list = ls())
# removing all objects from the global environment
```

```
data_raw <- read_csv('real_data.csv')
```

```
## Rows: 1889 Columns: 398
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr   (5): NewID, Diagnosis, Language, Gender, Trial
## dbl (393): PatID, Corpus, Duration_Praat, F0_Mean_Praat, F0_SD_Praat, Intens...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
glimpse(data_raw)
```

```
## Rows: 1,889
## Columns: 398
## $ PatID                    <dbl> 101, 101, 101, 101, 101, 101, 101, 101, 1~
## $ NewID                    <chr> "101CT1", "101CT1", "101CT1", "101CT1", "~
## $ Diagnosis                <chr> "CT", "CT", "CT", "CT", "CT", "CT", "CT",~
## $ Language                 <chr> "D", "D", "D", "D", "D", "D", "D", "D", "~
## $ Gender                   <chr> "M", "M", "M", "M", "M", "M", "M", "M", "~
## $ Trial                    <chr> "T7", "T8", "T4", "T2", "T3", "T5", "T9",~
## $ Corpus                   <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,~
## $ Duration_Praat           <dbl> 5.62, 2.82, 9.49, 8.92, 6.00, 12.62, 10.4~
## $ F0_Mean_Praat            <dbl> 157.4865, 115.4691, 125.3085, 133.1547, 1~
## $ F0_SD_Praat              <dbl> 37.226724, 5.037427, 9.099214, 19.466738,~
## $ Intensity_Mean_Praat     <dbl> 70.16840, 67.47500, 70.23711, 70.42194, 6~
## $ Intensity_SD_Praat       <dbl> 6.114989, 5.396695, 6.733844, 6.293483, 6~
## $ PauseDuration_Praat      <dbl> 3.31, 2.00, 5.03, 5.93, 3.57, 9.22, 5.53,~
## $ TurnDuration_Praat       <dbl> 2.31, 0.82, 4.46, 2.99, 2.43, 3.40, 4.92,~
## $ TurnNumber_Praat         <dbl> 12, 5, 19, 10, 20, 23, 22, 7, 6, 9, 38, 2~
## $ PauseNumber_Praat        <dbl> 12, 6, 20, 10, 21, 24, 23, 8, 6, 10, 38, ~
## $ PercentSpoke_Praat       <dbl> 0.4110320, 0.2907801, 0.4699684, 0.335201~
## $ PercentSilence_Praat     <dbl> 0.5889680, 0.7092199, 0.5300316, 0.664798~
## $ NHR_mean                 <dbl> 1.0762909, 1.7420739, 0.8930114, 1.405997~
## $ NHR_std                  <dbl> 1.0974521, 1.5076043, 1.1247343, 1.365611~
## $ Duration_Cova            <dbl> 5.70, 2.90, 9.57, 9.00, 6.08, 12.70, 10.5~
## $ PauseDuration_Cova       <dbl> 3.62, 2.10, 4.75, 5.99, 3.50, 9.26, 5.76,~
## $ TurnDuration_Cova        <dbl> 2.08, 0.80, 4.82, 3.01, 2.58, 3.44, 4.77,~
## $ TurnNumber_Cova          <dbl> 19, 9, 27, 28, 24, 40, 36, 15, 10, 15, 48~
## $ PauseNumber_Cova         <dbl> 19, 9, 27, 28, 24, 40, 36, 15, 10, 15, 48~
## $ PercentSpoke_Cova        <dbl> 0.3649123, 0.2758621, 0.5036573, 0.334444~
## $ PercentSilence_Cova      <dbl> 0.6350877, 0.7241379, 0.4963427, 0.665555~
## $ Pitch_Mean               <dbl> 5.004515, 4.823150, 4.854354, 4.878221, 4~
## $ Pitch_Median             <dbl> 4.969807, 4.762174, 4.832306, 4.844187, 4~
## $ Pitch_SD                 <dbl> 0.20531669, 0.17566305, 0.11439739, 0.136~
## $ Pitch_IQR                <dbl> 0.27026462, 0.05577301, 0.10887925, 0.115~
## $ Pitch_MAD                <dbl> 0.20509209, 0.03202284, 0.07263167, 0.071~
## $ F0_Mean                  <dbl> 152.4279, 126.5938, 129.2510, 132.7043, 1~
## $ F0_Median                <dbl> 144.00, 117.00, 125.50, 127.00, 123.50, 1~
## $ F0_SD                    <dbl> 34.171980, 28.166559, 18.064082, 20.47695~
## $ F0_IQR                   <dbl> 38.750, 6.625, 13.875, 15.000, 6.875, 16.~
## $ F0_MAD                   <dbl> 28.91070, 3.70650, 8.89560, 8.89560, 5.18~
## $ F1_Mean                  <dbl> 474.3766, 590.4291, 479.5878, 539.8825, 5~
## $ F1_Median                <dbl> 477.8326, 596.2321, 489.8214, 504.4456, 4~
## $ F1_SD                    <dbl> 123.33146, 118.70444, 138.64037, 173.5359~
## $ F1_IQR                   <dbl> 156.48211, 111.39806, 150.95069, 154.2735~
## $ F1_MAD                   <dbl> 119.55121, 87.83947, 109.97878, 115.86091~
## $ F2_Mean                  <dbl> 1379.245, 1604.363, 1642.664, 1591.472, 1~
## $ F2_Median                <dbl> 1320.325, 1298.711, 1613.912, 1532.705, 1~
## $ F2_SD                    <dbl> 359.8170, 537.6798, 442.4514, 441.9225, 4~
## $ F2_IQR                   <dbl> 338.8416, 814.1942, 509.2859, 618.9723, 6~
## $ F2_MAD                   <dbl> 251.7420, 284.0742, 378.3801, 450.8429, 4~
## $ F3_Mean                  <dbl> 2588.769, 2725.858, 2708.497, 2575.991, 2~
## $ F3_Median                <dbl> 2668.810, 2779.451, 2682.219, 2563.081, 2~
```

```
## $ F3_SD                    <dbl> 408.1128, 398.5884, 348.2637, 348.0087, 3~
## $ F3_IQR                   <dbl> 289.6221, 418.5070, 438.6633, 559.2186, 4~
## $ F3_MAD                   <dbl> 171.3690, 305.8763, 341.0985, 394.4439, 3~
## $ F4_Mean                  <dbl> 3378.862, 3481.532, 3584.281, 3487.865, 3~
## $ F4_Median                <dbl> 3451.576, 3542.469, 3645.670, 3552.070, 3~
## $ F4_SD                    <dbl> 410.0392, 494.4055, 326.6898, 383.0070, 3~
## $ F4_IQR                   <dbl> 590.2965, 859.3307, 412.4021, 521.6006, 3~
## $ F4_MAD                   <dbl> 363.4770, 592.0502, 266.3483, 344.6552, 2~
## $ F5_Mean                  <dbl> 4201.605, 4253.272, 4542.009, 4517.439, 4~
## $ F5_Median                <dbl> 4340.185, 4365.997, 4603.801, 4651.156, 4~
## $ F5_SD                    <dbl> 456.6505, 530.5366, 325.3482, 374.0563, 2~
## $ F5_IQR                   <dbl> 745.2826, 934.3287, 428.5955, 435.8510, 2~
## $ F5_MAD                   <dbl> 580.2267, 546.9331, 312.7858, 242.7380, 1~
## $ NAQ_Mean                 <dbl> 0.06180290, 0.04635425, 0.07702477, 0.043~
## $ NAQ_Median               <dbl> 0.05702131, 0.03949889, 0.07097532, 0.039~
## $ NAQ_SD                   <dbl> 0.03384222, 0.03439789, 0.04596121, 0.030~
## $ NAQ_IQR                  <dbl> 0.04679950, 0.04546405, 0.05426564, 0.034~
## $ NAQ_MAD                  <dbl> 0.03489768, 0.03222384, 0.03949983, 0.025~
## $ QOQ_Mean                 <dbl> 0.2284831, 0.1746557, 0.2585948, 0.161105~
## $ QOQ_Median               <dbl> 0.2105338, 0.1607614, 0.2298884, 0.153294~
## $ QOQ_SD                   <dbl> 0.11634157, 0.12148572, 0.14146882, 0.088~
## $ QOQ_IQR                  <dbl> 0.13750215, 0.12728650, 0.13913989, 0.107~
## $ QOQ_MAD                  <dbl> 0.10112211, 0.09477261, 0.10050534, 0.077~
## $ H1H2_Mean                <dbl> -2.690729, -3.462465, -6.724419, -5.75338~
## $ H1H2_Median              <dbl> -3.9527000, -2.8253954, -7.9101788, -6.97~
## $ H1H2_SD                  <dbl> 9.903949, 9.542624, 9.448744, 9.085656, 8~
## $ H1H2_IQR                 <dbl> 14.195829, 10.139859, 12.107344, 11.26088~
## $ H1H2_MAD                 <dbl> 10.598792, 8.434327, 9.022037, 8.413112, ~
## $ PSP_Mean                 <dbl> 0.4155799, 0.5096232, 0.5365308, 0.677747~
## $ PSP_Median               <dbl> 0.3856743, 0.4434876, 0.5113159, 0.654711~
## $ PSP_SD                   <dbl> 0.2332902, 0.3638096, 0.2725629, 0.367708~
## $ PSP_IQR                  <dbl> 0.3265878, 0.6215354, 0.3690651, 0.465478~
## $ PSP_MAD                  <dbl> 0.22695909, 0.40013808, 0.27969538, 0.346~
## $ HRF_Mean                 <dbl> 25.63492, 26.19126, 30.71390, 31.48877, 3~
## $ HRF_Median               <dbl> 25.85260, 22.61750, 30.39679, 30.27583, 3~
## $ HRF_SD                   <dbl> 7.417731, 21.510680, 12.444059, 16.179379~
## $ HRF_IQR                  <dbl> 8.994097, 24.682586, 9.573233, 9.185110, ~
## $ HRF_MAD                  <dbl> 6.761540, 18.082763, 7.055838, 7.070440, ~
## $ MDQ_Mean                 <dbl> 0.1102170, 0.1334687, 0.1154243, 0.128729~
## $ MDQ_Median               <dbl> 0.1109119, 0.1375647, 0.1158310, 0.128661~
## $ MDQ_SD                   <dbl> 0.03080837, 0.02964374, 0.03133302, 0.023~
## $ MDQ_IQR                  <dbl> 0.04498629, 0.05090973, 0.04364999, 0.031~
## $ MDQ_MAD                  <dbl> 0.03284165, 0.03223560, 0.03258088, 0.023~
## $ peakSlope_Mean           <dbl> -0.3314857, -0.2978618, -0.3399992, -0.34~
## $ peakSlope_Median         <dbl> -0.3307617, -0.2949662, -0.3406523, -0.34~
## $ peakSlope_SD             <dbl> 0.08814333, 0.08688939, 0.09960372, 0.085~
## $ peakSlope_IQR            <dbl> 0.1004853, 0.1174296, 0.1268701, 0.112550~
## $ peakSlope_MAD            <dbl> 0.07490536, 0.09788425, 0.09669734, 0.080~
## $ Rd_Mean                  <dbl> 1.423645, 1.355995, 1.387245, 1.609067, 1~
## $ Rd_Median                <dbl> 1.414300, 1.324520, 1.341969, 1.596359, 1~
## $ Rd_SD                    <dbl> 0.4628926, 0.4884298, 0.4772106, 0.515868~
## $ Rd_IQR                   <dbl> 0.6859440, 0.7441651, 0.7387420, 0.783192~
## $ Rd_MAD                   <dbl> 0.5103568, 0.5689866, 0.5373712, 0.589471~
## $ Rd_conf_Mean             <dbl> 0.5205419, 0.5037996, 0.5403747, 0.443519~
```

```
## $ Rd_conf_Median                <dbl> 0.5093454, 0.5153203, 0.5337394, 0.438403~
## $ Rd_conf_SD                    <dbl> 0.11268859, 0.07871862, 0.10851630, 0.081~
## $ Rd_conf_IQR                   <dbl> 0.13331901, 0.11781373, 0.15594084, 0.109~
## $ Rd_conf_MAD                   <dbl> 0.09982159, 0.08450161, 0.11357995, 0.076~
## $ VAD_Mean                      <dbl> 0.09273929, 0.05074510, 0.09563633, 0.086~
## $ MCEP0_Mean                    <dbl> -7.800048, -8.576307, -7.848345, -7.79173~
## $ MCEP0_Median                  <dbl> -7.466394, -8.378789, -7.630364, -7.39657~
## $ MCEP0_SD                      <dbl> 1.4010125, 0.9047833, 1.4079963, 1.246560~
## $ MCEP0_IQR                     <dbl> 2.519754, 1.219289, 1.766956, 1.564649, 1~
## $ MCEP0_MAD                     <dbl> 1.6556223, 0.5363446, 1.2693449, 0.984502~
## $ MCEP1_Mean                    <dbl> 2.780916, 3.021607, 2.762131, 3.016723, 2~
## $ MCEP1_Median                  <dbl> 3.070201, 3.208075, 2.838830, 3.137675, 2~
## $ MCEP1_SD                      <dbl> 1.0526957, 0.8032844, 0.8947056, 0.788233~
## $ MCEP1_IQR                     <dbl> 0.6737240, 0.5889144, 1.0237569, 0.849630~
## $ MCEP1_MAD                     <dbl> 0.4734662, 0.4230775, 0.7667883, 0.630019~
## $ MCEP2_Mean                    <dbl> -0.31957158, -0.90633955, -0.45911659, -0~
## $ MCEP2_Median                  <dbl> -0.386224463, -0.995711955, -0.568981375,~
## $ MCEP2_SD                      <dbl> 0.8361694, 0.6931855, 0.8851594, 0.898476~
## $ MCEP2_IQR                     <dbl> 1.4352173, 1.1267430, 1.4676696, 1.361394~
## $ MCEP2_MAD                     <dbl> 1.0446619, 0.7028617, 1.0742934, 0.933227~
## $ MCEP3_Mean                    <dbl> 0.52587771, -0.05046947, 0.58634110, 0.37~
## $ MCEP3_Median                  <dbl> 0.4320123, -0.1913579, 0.5971787, 0.38349~
## $ MCEP3_SD                      <dbl> 0.4859120, 0.5651418, 0.4582939, 0.393721~
## $ MCEP3_IQR                     <dbl> 0.6738033, 0.3542476, 0.6360194, 0.576670~
## $ MCEP3_MAD                     <dbl> 0.5026710, 0.2633475, 0.4768839, 0.438343~
## $ MCEP4_Mean                    <dbl> -0.7003233, -0.9826797, -0.5998804, -0.52~
## $ MCEP4_Median                  <dbl> -0.6777626, -1.1284020, -0.6356815, -0.52~
## $ MCEP4_SD                      <dbl> 0.4936995, 0.3922649, 0.4408092, 0.392671~
## $ MCEP4_IQR                     <dbl> 0.6991296, 0.6156483, 0.5549506, 0.505118~
## $ MCEP4_MAD                     <dbl> 0.5242759, 0.4336825, 0.4063606, 0.367032~
## $ MCEP5_Mean                    <dbl> -2.265027e-01, -3.760730e-01, -4.205528e-~
## $ MCEP5_Median                  <dbl> -0.189869096, -0.373225135, -0.413290762,~
## $ MCEP5_SD                      <dbl> 0.4288621, 0.3344166, 0.3508698, 0.289449~
## $ MCEP5_IQR                     <dbl> 0.5620242, 0.4506707, 0.4443000, 0.304058~
## $ MCEP5_MAD                     <dbl> 0.4053460, 0.2573561, 0.3389200, 0.227060~
## $ MCEP6_Mean                    <dbl> 0.07553752, -0.05573101, -0.14504608, -0.~
## $ MCEP6_Median                  <dbl> 0.04392212, -0.11108834, -0.14859093, -0.~
## $ MCEP6_SD                      <dbl> 0.2976298, 0.3234591, 0.3279043, 0.364046~
## $ MCEP6_IQR                     <dbl> 0.3407936, 0.3525973, 0.4895238, 0.553154~
## $ MCEP6_MAD                     <dbl> 0.2520758, 0.2462648, 0.3665046, 0.414260~
## $ MCEP7_Mean                    <dbl> -0.4457810785, -0.0017213469, -0.40583462~
## $ MCEP7_Median                  <dbl> -0.4426901477, 0.0017575745, -0.390821270~
## $ MCEP7_SD                      <dbl> 0.2969627, 0.2423995, 0.3227063, 0.236961~
## $ MCEP7_IQR                     <dbl> 0.4169535, 0.3339511, 0.4421994, 0.300219~
## $ MCEP7_MAD                     <dbl> 0.2972967, 0.2491468, 0.3334111, 0.224476~
## $ MCEP8_Mean                    <dbl> -0.039303411, -0.226372038, 0.052734711, ~
## $ MCEP8_Median                  <dbl> -0.05549179, -0.19439660, 0.03797236, -0.~
## $ MCEP8_SD                      <dbl> 0.3431017, 0.2352191, 0.2904116, 0.282241~
## $ MCEP8_IQR                     <dbl> 0.4515983, 0.2854237, 0.3586195, 0.340595~
## $ MCEP8_MAD                     <dbl> 0.3605354, 0.2160354, 0.2668115, 0.248315~
## $ MCEP9_Mean                    <dbl> 1.539128e-01, -1.947572e-02, -7.018876e-0~
## $ MCEP9_Median                  <dbl> 0.1083735455, -0.0332572012, -0.087571055~
## $ MCEP9_SD                      <dbl> 0.2527215, 0.1818983, 0.2321234, 0.195758~
## $ MCEP9_IQR                     <dbl> 0.4277931, 0.2881567, 0.3079276, 0.232201~
```

```
## $ MCEP9_MAD                   <dbl> 0.2930839, 0.2027145, 0.2248219, 0.173099~
## $ MCEP10_Mean                 <dbl> 0.015567172, 0.190576580, 0.052467563, 0.~
## $ MCEP10_Median               <dbl> 0.035034816, 0.164430460, 0.056071360, 0.~
## $ MCEP10_SD                   <dbl> 0.2055490, 0.2352665, 0.1647975, 0.160535~
## $ MCEP10_IQR                  <dbl> 0.2671504, 0.2831755, 0.1984662, 0.225709~
## $ MCEP10_MAD                  <dbl> 0.2044624, 0.1965240, 0.1455495, 0.166113~
## $ MCEP11_Mean                 <dbl> -0.05285422, -0.22262581, -0.07242971, -0~
## $ MCEP11_Median               <dbl> -0.04361598, -0.18393433, -0.06076622, -0~
## $ MCEP11_SD                   <dbl> 0.3420598, 0.2062883, 0.1977763, 0.194204~
## $ MCEP11_IQR                  <dbl> 0.3288330, 0.1964233, 0.2524433, 0.248262~
## $ MCEP11_MAD                  <dbl> 0.2505081, 0.1767264, 0.1898152, 0.186048~
## $ MCEP12_Mean                 <dbl> -8.009303e-02, 7.094762e-02, -4.301525e-0~
## $ MCEP12_Median               <dbl> -0.0738974724, 0.0290061666, -0.041927605~
## $ MCEP12_SD                   <dbl> 0.2199786, 0.2713073, 0.1644384, 0.155547~
## $ MCEP12_IQR                  <dbl> 0.3119040, 0.2979355, 0.1963599, 0.196165~
## $ MCEP12_MAD                  <dbl> 0.2229825, 0.2204087, 0.1466897, 0.144399~
## $ MCEP13_Mean                 <dbl> 0.03534516, -0.21369482, 0.01668160, -0.0~
## $ MCEP13_Median               <dbl> 0.067398181, -0.170491744, -0.002495087, ~
## $ MCEP13_SD                   <dbl> 0.2419947, 0.2434436, 0.1639809, 0.171371~
## $ MCEP13_IQR                  <dbl> 0.2330868, 0.2434911, 0.2047924, 0.201847~
## $ MCEP13_MAD                  <dbl> 0.1785131, 0.1643662, 0.1461172, 0.142785~
## $ MCEP14_Mean                 <dbl> -0.03624464, -0.01700709, -0.08812533, -0~
## $ MCEP14_Median               <dbl> -0.06599079, -0.04405941, -0.10138297, -0~
## $ MCEP14_SD                   <dbl> 0.2126561, 0.1728301, 0.1715754, 0.185861~
## $ MCEP14_IQR                  <dbl> 0.2645698, 0.1919640, 0.2094784, 0.203211~
## $ MCEP14_MAD                  <dbl> 0.19393336, 0.15052423, 0.15546220, 0.147~
## $ MCEP15_Mean                 <dbl> 0.029339533, 0.075035394, 0.039228518, 0.~
## $ MCEP15_Median               <dbl> 0.06326352, 0.09617531, 0.03428203, 0.071~
## $ MCEP15_SD                   <dbl> 0.1687383, 0.1198379, 0.1745691, 0.135412~
## $ MCEP15_IQR                  <dbl> 0.2274155, 0.1911718, 0.1844297, 0.182000~
## $ MCEP15_MAD                  <dbl> 0.1576012, 0.1291894, 0.1370157, 0.136579~
## $ MCEP16_Mean                 <dbl> -0.018902212, -0.007332804, -0.054915496,~
## $ MCEP16_Median               <dbl> -0.031415519, 0.003973841, -0.047630039, ~
## $ MCEP16_SD                   <dbl> 0.1671133, 0.1200883, 0.1412939, 0.135579~
## $ MCEP16_IQR                  <dbl> 0.2325541, 0.1863602, 0.1674624, 0.168561~
## $ MCEP16_MAD                  <dbl> 0.16898038, 0.13035156, 0.12042533, 0.125~
## $ MCEP17_Mean                 <dbl> 0.062222806, 0.158139342, 0.130739580, 0.~
## $ MCEP17_Median               <dbl> 0.0650740054, 0.1487444829, 0.1205964152,~
## $ MCEP17_SD                   <dbl> 0.15203571, 0.15779716, 0.13289068, 0.144~
## $ MCEP17_IQR                  <dbl> 0.1621526, 0.2051570, 0.1674744, 0.192940~
## $ MCEP17_MAD                  <dbl> 0.12444558, 0.15133865, 0.12455968, 0.144~
## $ MCEP18_Mean                 <dbl> -0.120433671, -0.172700271, -0.014428218,~
## $ MCEP18_Median               <dbl> -0.0904101351, -0.1174760728, -0.00742910~
## $ MCEP18_SD                   <dbl> 0.2056625, 0.2006196, 0.1670167, 0.139316~
## $ MCEP18_IQR                  <dbl> 0.2243093, 0.2308869, 0.1827712, 0.191223~
## $ MCEP18_MAD                  <dbl> 0.16063479, 0.13986433, 0.13624502, 0.142~
## $ MCEP19_Mean                 <dbl> 0.117159546, 0.114212584, 0.008380285, 0.~
## $ MCEP19_Median               <dbl> 0.114921223, 0.077127419, 0.004291641, 0.~
## $ MCEP19_SD                   <dbl> 0.19393664, 0.15471220, 0.15677018, 0.098~
## $ MCEP19_IQR                  <dbl> 0.1963855, 0.1779120, 0.2007070, 0.119655~
## $ MCEP19_MAD                  <dbl> 0.15462003, 0.12523672, 0.14870920, 0.087~
## $ MCEP20_Mean                 <dbl> 0.083725299, -0.003770943, 0.127305887, 0~
## $ MCEP20_Median               <dbl> 0.096173766, -0.006621202, 0.110219812, 0~
## $ MCEP20_SD                   <dbl> 0.16630486, 0.14166424, 0.13939016, 0.131~
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## $ MCEP20_IQR                <dbl> 0.1848750, 0.2215488, 0.1759195, 0.197436~
## $ MCEP20_MAD                <dbl> 0.13790607, 0.15687353, 0.13287525, 0.141~
## $ MCEP21_Mean               <dbl> -0.157253275, -0.008839917, -0.147938954,~
## $ MCEP21_Median             <dbl> -0.1635386362, 0.0072850838, -0.128554507~
## $ MCEP21_SD                 <dbl> 0.14139349, 0.10105277, 0.14877063, 0.145~
## $ MCEP21_IQR                <dbl> 0.1978189, 0.1139186, 0.2086274, 0.205675~
## $ MCEP21_MAD                <dbl> 0.14979538, 0.08170653, 0.15652125, 0.148~
## $ MCEP22_Mean               <dbl> 0.10734900, 0.09166880, 0.13374899, 0.132~
## $ MCEP22_Median             <dbl> 0.07511721, 0.06684783, 0.10965862, 0.111~
## $ MCEP22_SD                 <dbl> 0.14857784, 0.15284477, 0.15545739, 0.165~
## $ MCEP22_IQR                <dbl> 0.1996835, 0.1749956, 0.1896957, 0.219032~
## $ MCEP22_MAD                <dbl> 0.13574833, 0.13419483, 0.13656928, 0.161~
## $ MCEP23_Mean               <dbl> -0.064468403, -0.082254478, -0.110631028,~
## $ MCEP23_Median             <dbl> -0.031075494, -0.078492269, -0.079121400,~
## $ MCEP23_SD                 <dbl> 0.14843412, 0.12471937, 0.16704872, 0.132~
## $ MCEP23_IQR                <dbl> 0.1893956, 0.1735505, 0.2073757, 0.186646~
## $ MCEP23_MAD                <dbl> 0.13618216, 0.12673728, 0.14732736, 0.133~
## $ MCEP24_Mean               <dbl> 0.0624111217, -0.0255798885, 0.0155992170~
## $ MCEP24_Median             <dbl> 0.0827723291, -0.0184776351, 0.0090141200~
## $ MCEP24_SD                 <dbl> 0.16058747, 0.11330836, 0.14423073, 0.118~
## $ MCEP24_IQR                <dbl> 0.22968498, 0.14107863, 0.15687874, 0.149~
## $ MCEP24_MAD                <dbl> 0.16670648, 0.09981928, 0.11437897, 0.108~
## $ HMPDM10_Mean              <dbl> 0.462916208, 0.299164268, 0.619238809, -0~
## $ HMPDM10_Median            <dbl> 0.247548945, 0.242225778, 0.672442600, -0~
## $ HMPDM10_SD                <dbl> 0.57935011, 0.38817217, 0.51994772, 0.507~
## $ HMPDM10_IQR               <dbl> 0.96944020, 0.59651784, 0.67857881, 0.666~
## $ HMPDM10_MAD               <dbl> 0.53871105, 0.53139045, 0.42084892, 0.442~
## $ HMPDM11_Mean              <dbl> 0.785720168, 0.354838597, 1.058612078, -0~
## $ HMPDM11_Median            <dbl> 0.92712842, 0.19708433, 1.35632912, -0.53~
## $ HMPDM11_SD                <dbl> 1.3148847, 1.9199271, 1.2388222, 0.861318~
## $ HMPDM11_IQR               <dbl> 1.8103453, 3.7029098, 1.2299072, 0.886903~
## $ HMPDM11_MAD               <dbl> 1.4482975, 2.8997051, 0.8583449, 0.666904~
## $ HMPDM12_Mean              <dbl> -0.26059899, -2.05737648, 0.74462738, -0.~
## $ HMPDM12_Median            <dbl> -0.13783108, -2.65844078, 1.61451117, -0.~
## $ HMPDM12_SD                <dbl> 2.1154896, 1.3339112, 2.0844224, 1.206198~
## $ HMPDM12_IQR               <dbl> 4.0736177, 1.0636729, 2.8746027, 1.123186~
## $ HMPDM12_MAD               <dbl> 2.9898295, 0.4623250, 1.5077382, 0.782046~
## $ HMPDM13_Mean              <dbl> 0.097822351, -0.496628148, 0.494025741, -~
## $ HMPDM13_Median            <dbl> -0.07348105, -0.84379036, 1.99950613, -0.~
## $ HMPDM13_SD                <dbl> 2.2328497, 2.0002194, 2.4765841, 1.303406~
## $ HMPDM13_IQR               <dbl> 4.6036754, 3.9970797, 5.1415816, 2.150568~
## $ HMPDM13_MAD               <dbl> 3.4267581, 2.4003871, 1.4064338, 1.205070~
## $ HMPDM14_Mean              <dbl> 0.29256032, 1.72669905, 1.73035387, -0.50~
## $ HMPDM14_Median            <dbl> 1.002958614, 1.910295614, 2.427255232, -0~
## $ HMPDM14_SD                <dbl> 2.3590339, 0.6923295, 1.8515397, 0.852251~
## $ HMPDM14_IQR               <dbl> 4.9092249, 1.0648298, 0.8444969, 0.816712~
## $ HMPDM14_MAD               <dbl> 2.6559172, 0.6799794, 0.5552898, 0.594781~
## $ HMPDM15_Mean              <dbl> 0.17156419, 1.97277606, 0.90510418, -0.23~
## $ HMPDM15_Median            <dbl> -0.28239919, 2.02609243, 2.10470053, 0.01~
## $ HMPDM15_SD                <dbl> 2.3635938, 0.9175364, 2.2677094, 0.995837~
## $ HMPDM15_IQR               <dbl> 4.7651908, 0.5229397, 4.2615835, 0.984093~
## $ HMPDM15_MAD               <dbl> 3.6137636, 0.2738011, 0.8966952, 0.727603~
## $ HMPDM16_Mean              <dbl> 0.56299793, 1.10772412, 1.43354852, -0.21~
## $ HMPDM16_Median            <dbl> 1.83403750, 2.26266763, 2.31948061, -0.13~
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## $ HMPDM16_SD                <dbl> 2.3660132, 2.1633942, 1.9803967, 1.199829~
## $ HMPDM16_IQR               <dbl> 4.7938983, 2.0415720, 1.1010347, 1.299731~
## $ HMPDM16_MAD               <dbl> 1.7062209, 0.5225194, 0.5902522, 0.960349~
## $ HMPDM17_Mean              <dbl> -0.14891508, 0.76087307, 0.65391101, -0.0~
## $ HMPDM17_Median            <dbl> -0.13637987, 1.50257720, 1.48832050, -0.0~
## $ HMPDM17_SD                <dbl> 2.2660741, 1.6564394, 2.1785880, 1.554046~
## $ HMPDM17_IQR               <dbl> 4.6286819, 1.7477955, 4.6375379, 1.986361~
## $ HMPDM17_MAD               <dbl> 3.4579266, 1.0500901, 1.7415496, 1.381364~
## $ HMPDM18_Mean              <dbl> -0.14745062, -0.89027935, 1.58018005, 0.1~
## $ HMPDM18_Median            <dbl> -0.80476168, -1.56266609, 2.25468713, -0.~
## $ HMPDM18_SD                <dbl> 2.1839925, 1.0650795, 1.6333817, 1.524495~
## $ HMPDM18_IQR               <dbl> 4.5327626, 1.7430205, 1.0521880, 2.029207~
## $ HMPDM18_MAD               <dbl> 2.8487966, 0.7780924, 0.5903986, 1.757841~
## $ HMPDM19_Mean              <dbl> 0.213523473, -0.528374511, 0.420239997, 1~
## $ HMPDM19_Median            <dbl> 0.346446386, -1.304565990, 0.930928035, 1~
## $ HMPDM19_SD                <dbl> 2.2084954, 1.9435859, 2.2619935, 1.645159~
## $ HMPDM19_IQR               <dbl> 4.5546990, 3.6124929, 4.2801849, 1.997815~
## $ HMPDM19_MAD               <dbl> 3.0771108, 1.5480793, 2.6015180, 1.409637~
## $ HMPDM20_Mean              <dbl> -1.194983939, 0.331909980, 0.984798155, 0~
## $ HMPDM20_Median            <dbl> -1.716786707, 0.492041931, 2.296511339, -~
## $ HMPDM20_SD                <dbl> 1.3754961, 1.5342994, 2.1564130, 1.372549~
## $ HMPDM20_IQR               <dbl> 2.4752775, 1.4055726, 3.3378901, 1.778124~
## $ HMPDM20_MAD               <dbl> 1.5573955, 1.0305474, 1.1540370, 1.321572~
## $ HMPDM21_Mean              <dbl> -0.648115956, -0.144724354, 0.947089615, ~
## $ HMPDM21_Median            <dbl> -0.501558665, -0.065206616, 2.278419332, ~
## $ HMPDM21_SD                <dbl> 2.2195806, 1.5470122, 2.3032490, 1.025915~
## $ HMPDM21_IQR               <dbl> 4.1148162, 1.5703220, 4.5685775, 0.968569~
## $ HMPDM21_MAD               <dbl> 3.1805463, 1.5739852, 1.0357899, 0.677026~
## $ HMPDM22_Mean              <dbl> 0.36327975, 0.07293082, 0.83382914, -0.24~
## $ HMPDM22_Median            <dbl> 0.73558804, 0.48903061, 2.10661438, -0.24~
## $ HMPDM22_SD                <dbl> 1.9309571, 1.8676068, 2.2065057, 1.678771~
## $ HMPDM22_IQR               <dbl> 3.1388046, 3.5682869, 4.3203887, 2.360193~
## $ HMPDM22_MAD               <dbl> 1.9920810, 2.4503021, 1.2341223, 1.918375~
## $ HMPDM23_Mean              <dbl> -0.66428089, -0.22894930, -0.18222487, -0~
## $ HMPDM23_Median            <dbl> -0.999385670, -0.004583891, -0.276236113,~
## $ HMPDM23_SD                <dbl> 1.3087729, 1.1947151, 1.5207685, 2.018825~
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## $ HMPDM23_MAD               <dbl> 1.5649485, 1.3485971, 1.7435392, 2.439599~
## $ HMPDM24_Mean              <dbl> -0.135118031, 0.133342098, 0.584839923, -~
## $ HMPDM24_Median            <dbl> -0.04389285, -1.00946570, 0.39765459, -1.~
## $ HMPDM24_SD                <dbl> 1.329261, 2.090515, 1.756946, 1.808786, 1~
## $ HMPDM24_IQR               <dbl> 1.681760, 4.235691, 3.135425, 2.915209, 3~
## $ HMPDM24_MAD               <dbl> 1.3540894, 2.4167004, 2.5441505, 1.098470~
## $ HMPDD0_Mean               <dbl> -0.3408285, -0.1645714, -0.2692037, -0.25~
## $ HMPDD0_Median             <dbl> -0.3075534, -0.1522718, -0.2520761, -0.21~
## $ HMPDD0_SD                 <dbl> 0.5174648, 0.1015647, 0.1197612, 0.447922~
## $ HMPDD0_IQR                <dbl> 0.1048730, 0.1412477, 0.1470585, 0.115853~
## $ HMPDD0_MAD                <dbl> 0.07421019, 0.09621325, 0.10612883, 0.089~
## $ HMPDD1_Mean               <dbl> -1.2535007, -0.9959845, -1.1447973, -1.11~
## $ HMPDD1_Median             <dbl> -1.266898, -1.022398, -1.134259, -1.13271~
## $ HMPDD1_SD                 <dbl> 0.1623235, 0.1391240, 0.1353228, 0.151761~
## $ HMPDD1_IQR                <dbl> 0.12033199, 0.09390683, 0.14035092, 0.170~
## $ HMPDD1_MAD                <dbl> 0.08675471, 0.06950135, 0.10316261, 0.130~
## $ HMPDD2_Mean               <dbl> -1.0933339, -0.8545146, -0.9924906, -0.99~
```

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## $ HMPDD2_Median                <dbl> -1.1045322, -0.8761917, -0.9852409, -1.00~
## $ HMPDD2_SD                    <dbl> 0.12948211, 0.09619218, 0.09781110, 0.113~
## $ HMPDD2_IQR                   <dbl> 0.13966772, 0.13723257, 0.09755791, 0.105~
## $ HMPDD2_MAD                   <dbl> 0.10226742, 0.08835237, 0.07426567, 0.076~
## $ HMPDD3_Mean                  <dbl> -0.9779883, -0.8063730, -0.9194741, -0.91~
## $ HMPDD3_Median                <dbl> -0.9766211, -0.8210046, -0.9173615, -0.92~
## $ HMPDD3_SD                    <dbl> 0.14187276, 0.08538769, 0.07739077, 0.110~
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## $ HMPDD3_MAD                   <dbl> 0.13187451, 0.08532394, 0.07236728, 0.081~
## $ HMPDD4_Mean                  <dbl> -0.8284356, -0.7477489, -0.8013249, -0.80~
## $ HMPDD4_Median                <dbl> -0.8555960, -0.7756226, -0.8025337, -0.81~
## $ HMPDD4_SD                    <dbl> 0.14579275, 0.07962604, 0.07937704, 0.105~
## $ HMPDD4_IQR                   <dbl> 0.19246413, 0.05958430, 0.10207012, 0.127~
## $ HMPDD4_MAD                   <dbl> 0.12848827, 0.04271755, 0.07693148, 0.096~
## $ HMPDD5_Mean                  <dbl> -0.7964747, -0.6979204, -0.7347430, -0.73~
## $ HMPDD5_Median                <dbl> -0.7897005, -0.7097710, -0.7404063, -0.73~
## $ HMPDD5_SD                    <dbl> 0.08228026, 0.07613074, 0.08130780, 0.095~
## $ HMPDD5_IQR                   <dbl> 0.09774727, 0.06568892, 0.08540655, 0.124~
## $ HMPDD5_MAD                   <dbl> 0.06738755, 0.05046784, 0.06329457, 0.092~
## $ HMPDD6_Mean                  <dbl> -0.7154683, -0.6693892, -0.6814118, -0.68~
## $ HMPDD6_Median                <dbl> -0.7244345, -0.6868018, -0.6922698, -0.69~
## $ HMPDD6_SD                    <dbl> 0.10084335, 0.06852692, 0.07377278, 0.090~
## $ HMPDD6_IQR                   <dbl> 0.11685441, 0.04693702, 0.06503571, 0.083~
## $ HMPDD6_MAD                   <dbl> 0.08499778, 0.03363377, 0.04865246, 0.061~
## $ HMPDD7_Mean                  <dbl> -0.5872387, -0.6134421, -0.5931024, -0.60~
## $ HMPDD7_Median                <dbl> -0.5869346, -0.6180031, -0.5994557, -0.61~
## $ HMPDD7_SD                    <dbl> 0.08509958, 0.06776318, 0.06519572, 0.107~
## $ HMPDD7_IQR                   <dbl> 0.11087414, 0.11045517, 0.07996860, 0.110~
## $ HMPDD7_MAD                   <dbl> 0.08270070, 0.08096909, 0.05920412, 0.085~
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## $ HMPDD8_SD                    <dbl> 0.07939885, 0.06533846, 0.06643105, 0.079~
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## $ HMPDD8_MAD                   <dbl> 0.09147356, 0.05137329, 0.07175205, 0.074~
## $ HMPDD9_Mean                  <dbl> -0.338200382, -0.449000122, -0.414840764,~
## $ HMPDD9_Median                <dbl> -0.333857995, -0.442950807, -0.416892315,~
## $ HMPDD9_SD                    <dbl> 0.08174587, 0.05630173, 0.05954582, 0.066~
## $ HMPDD9_IQR                   <dbl> 0.08666532, 0.08180327, 0.07048822, 0.082~
## $ HMPDD9_MAD                   <dbl> 0.06503703, 0.06169567, 0.05192746, 0.062~
## $ HMPDD10_Mean                 <dbl> -0.239247045, -0.389175838, -0.314760191,~
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## $ HMPDD10_SD                   <dbl> 0.09501607, 0.06001945, 0.08044657, 0.073~
## $ HMPDD10_IQR                  <dbl> 0.11864709, 0.09641070, 0.10179278, 0.107~
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## $ HMPDD11_SD                   <dbl> 0.10154515, 0.05720821, 0.07671794, 0.078~
## $ HMPDD11_IQR                  <dbl> 0.12123917, 0.08738290, 0.10245011, 0.083~
## $ HMPDD11_MAD                  <dbl> 0.09402148, 0.06778729, 0.07595104, 0.054~
## $ HMPDD12_Mean                 <dbl> -0.08097356, -0.23458833, -0.17156862, -0~
## $ HMPDD12_Median               <dbl> -0.08285349, -0.23010835, -0.18476613, -0~
## $ HMPDD12_SD                   <dbl> 0.09529543, 0.06127831, 0.07358020, 0.073~
## $ HMPDD12_IQR                  <dbl> 0.11987141, 0.08167643, 0.09139550, 0.072~
## $ HMPDD12_MAD                  <dbl> 0.08947968, 0.05861450, 0.06553915, 0.054~
```

```
## $ Harmonicity_Mean            <dbl> 0.6462543, 0.7163654, 0.8055542, 0.709283~
## $ Harmonicity_SD              <dbl> 0.4555504, 0.4600380, 0.4762750, 0.432797~
## $ Clarity_Mean                <dbl> 0.6575821, 0.6804585, 0.7029027, 0.671836~
## $ Clarity_SD                  <dbl> 0.1593496, 0.1467127, 0.1449230, 0.131540~
## $ LPerror_Mean                <dbl> 6.911738, 8.040148, 7.026986, 7.208061, 6~
## $ LPerror_SD                  <dbl> 2.229282, 1.674179, 2.013750, 1.865100, 2~
## $ HarmonicProductSpectrum_Mean <dbl> -13.785519, -42.346709, -9.642031, -6.450~
## $ HarmonicProductSpectrum_SD  <dbl> 92.39493, 55.07227, 94.35489, 101.06790, ~
## $ CepstralPeakProminence_Mean <dbl> 4.545577, 4.397983, 4.547749, 4.383870, 4~
## $ CepstralPeakProminence_SD   <dbl> 0.5295720, 0.4481834, 0.6342335, 0.502741~
## $ Srh1_Mean                   <dbl> 0.1962962, 0.1807567, 0.1951253, 0.190560~
## $ Srh1_SD                     <dbl> 0.03753496, 0.03224129, 0.03797110, 0.038~
## $ Srh2_Mean                   <dbl> 13.321604, 5.053818, 8.798485, 13.324161,~
## $ Srh2_SD                     <dbl> 10.728828, 3.842785, 7.440368, 13.270542,~
## $ creakF0_Mean                <dbl> 149.1352, 119.1684, 128.7470, 129.9000, 1~
## $ creakF0_SD                  <dbl> 28.846649, 17.551321, 15.329024, 12.77894~
## $ CreakProbability_Mean       <dbl> 0.107691033, 0.322322607, 0.150356314, 0.~
## $ CreakProbability_SD         <dbl> 0.15440934, 0.24655873, 0.18271252, 0.169~
## $ PauseNumMin_Cova            <dbl> 3.333333, 3.103448, 2.821317, 3.111111, 3~
## $ MeanPauseDur_Cova           <dbl> 0.19052632, 0.23333333, 0.17592593, 0.213~
## $ TurnNumMin_Cova             <dbl> 3.333333, 3.103448, 2.821317, 3.111111, 3~
## $ MeanTurnDur_Cova            <dbl> 0.10947368, 0.08888889, 0.17851852, 0.107~
## $ PauseNumMin_Praat           <dbl> 2.135231, 2.127660, 2.107482, 1.121076, 3~
## $ TurnNumMin_Praat            <dbl> 2.135231, 1.773050, 2.002107, 1.121076, 3~
## $ MeanTurnDur_Praat           <dbl> 0.1925000, 0.1640000, 0.2347368, 0.299000~
```

```r
data <- data_raw %>%
  rename_with(.cols = everything(), str_to_lower) %>%
  rename(id = patid,
         condition = diagnosis) %>%
  mutate(across(where(is.character), str_to_lower),
         across(1:7, as_factor),
         condition = if_else(condition != 'ct', 'sz', 'hc') %>% as_factor %>% relevel('sz')) %>%
  select(-newid)

data$language %>% summary
```

```
##    d
## 1889
```

```r
data$corpus %>% summary
```

```
##   1   2   3   4
## 681 363 375 470
```

```r
data <- data %>%
  select(-language)


head(data)
```

```
## # A tibble: 6 x 396
```

```
##   id    condition gender trial corpus duration~1 f0_me~2 f0_sd~3 inten~4 inten~5
##   <fct> <fct>     <fct>  <fct> <fct>       <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
## 1 101   hc        m      t7    1            5.62    157.   37.2     70.2    6.11
## 2 101   hc        m      t8    1            2.82    115.    5.04    67.5    5.40
## 3 101   hc        m      t4    1            9.49    125.    9.10    70.2    6.73
## 4 101   hc        m      t2    1            8.92    133.   19.5     70.4    6.29
## 5 101   hc        m      t3    1            6       122.   13.5     67.4    6.59
## 6 101   hc        m      t5    1           12.6     132.   22.9     69.2    6.26
## # ... with 386 more variables: pauseduration_praat <dbl>,
## #   turnduration_praat <dbl>, turnnumber_praat <dbl>, pausenumber_praat <dbl>,
## #   percentspoke_praat <dbl>, percentsilence_praat <dbl>, nhr_mean <dbl>,
## #   nhr_std <dbl>, duration_cova <dbl>, pauseduration_cova <dbl>,
## #   turnduration_cova <dbl>, turnnumber_cova <dbl>, pausenumber_cova <dbl>,
## #   percentspoke_cova <dbl>, percentsilence_cova <dbl>, pitch_mean <dbl>,
## #   pitch_median <dbl>, pitch_sd <dbl>, pitch_iqr <dbl>, pitch_mad <dbl>, ...
```

Describing the data

Condition

```
data %>%
  count(condition) %>%
  mutate(pct = n / sum(n), pct = pct %>% round(2))
```

```
## # A tibble: 2 x 3
##   condition     n   pct
##   <fct>     <int> <dbl>
## 1 sz          900  0.48
## 2 hc          989  0.52
```

Gender

```
data %>%
  count(gender) %>%
  mutate(pct = n / sum(n), pct = pct %>% round(2))
```

```
## # A tibble: 2 x 3
##   gender     n   pct
##   <fct>  <int> <dbl>
## 1 m       1081  0.57
## 2 f        808  0.43
```

```
# pct should have grouped n in the denominator
data %>%
  count(gender, condition) %>%
  group_by(condition) %>%
  mutate(pct = n / sum(n), pct = pct %>% round(2))
```

```
## # A tibble: 4 x 4
## # Groups:   condition [2]
##   gender condition     n   pct
##   <fct>  <fct>     <int> <dbl>
## 1 m      sz          515  0.57
## 2 m      hc          566  0.57
## 3 f      sz          385  0.43
## 4 f      hc          423  0.43
```

```
data %>%
  count(corpus) %>%
  mutate(pct = n / sum(n), pct = pct %>% round(2))
```

```
## # A tibble: 4 x 3
##   corpus     n   pct
##   <fct>  <int> <dbl>
## 1 1        681  0.36
## 2 2        363  0.19
## 3 3        375  0.2
## 4 4        470  0.25
```

```
data %>%
  count(condition, corpus) %>%
  group_by(condition) %>%
  mutate(pct = n / sum(n), pct = pct %>% round(2))
```

```
## # A tibble: 8 x 4
## # Groups:   condition [2]
##   condition corpus     n   pct
##   <fct>     <fct>  <int> <dbl>
## 1 sz        1        333  0.37
## 2 sz        2        179  0.2
## 3 sz        3        151  0.17
## 4 sz        4        237  0.26
## 5 hc        1        348  0.35
## 6 hc        2        184  0.19
## 7 hc        3        224  0.23
## 8 hc        4        233  0.24
```

Modeling the data

Budgeting

```
data_background <- data %>% select(1:5)
data <- data %>% select(-c(gender, corpus))

split <- initial_split(data, prop = 4/5)

data_training <- training(split)
data_testing <- testing(split)

rm(split)
```

Preprocessing the data

```
recipes <- list()

recipes[[1]] <- recipe(condition ~ 1 + ., data = data_training) %>%
                    update_role(id, trial, new_role = 'id') %>%
                    step_normalize(all_numeric())


recipes[[2]] <- recipes[[1]] %>% step_corr(all_predictors())
recipes[[3]] <- recipes[[1]] %>% step_pca(all_predictors())

names(recipes) <- c('lasso', 'corr', 'pca')


# Right now you need to do this only with corr and pca
recipes <- recipes[2:3]
#remove this later
```

Creating the models

```
prior_b <- normal(location = 0, scale = 0.3)
prior_intercept <- normal(0, 1)


model_prior <- logistic_reg() %>%
  set_engine('stan',
             prior = prior_b,
             prior_intercept = prior_intercept,
             prior_PD = T,
             cores = 3)


model <- logistic_reg() %>%
  set_engine('stan',
             prior = prior_b,
             prior_intercept = prior_intercept,
             cores = 3)

model_lasso <- logistic_reg(penalty = 0.01, mixture = 1) %>%
    set_engine('stan',
             prior = prior_b,
             prior_intercept = prior_intercept,
             cores = 3)
```

Workflows

```
wflows <- map(recipes,
              ~ workflow() %>%
```

```
                  add_model(model) %>%
                  add_recipe(.x))
#un # this after you decide what to do about the lasso regression

#wflows[[1]] <- workflow() %>%
 #   add_model(model_lasso) %>%
  #  add_recipe(recipes[[1]])
```

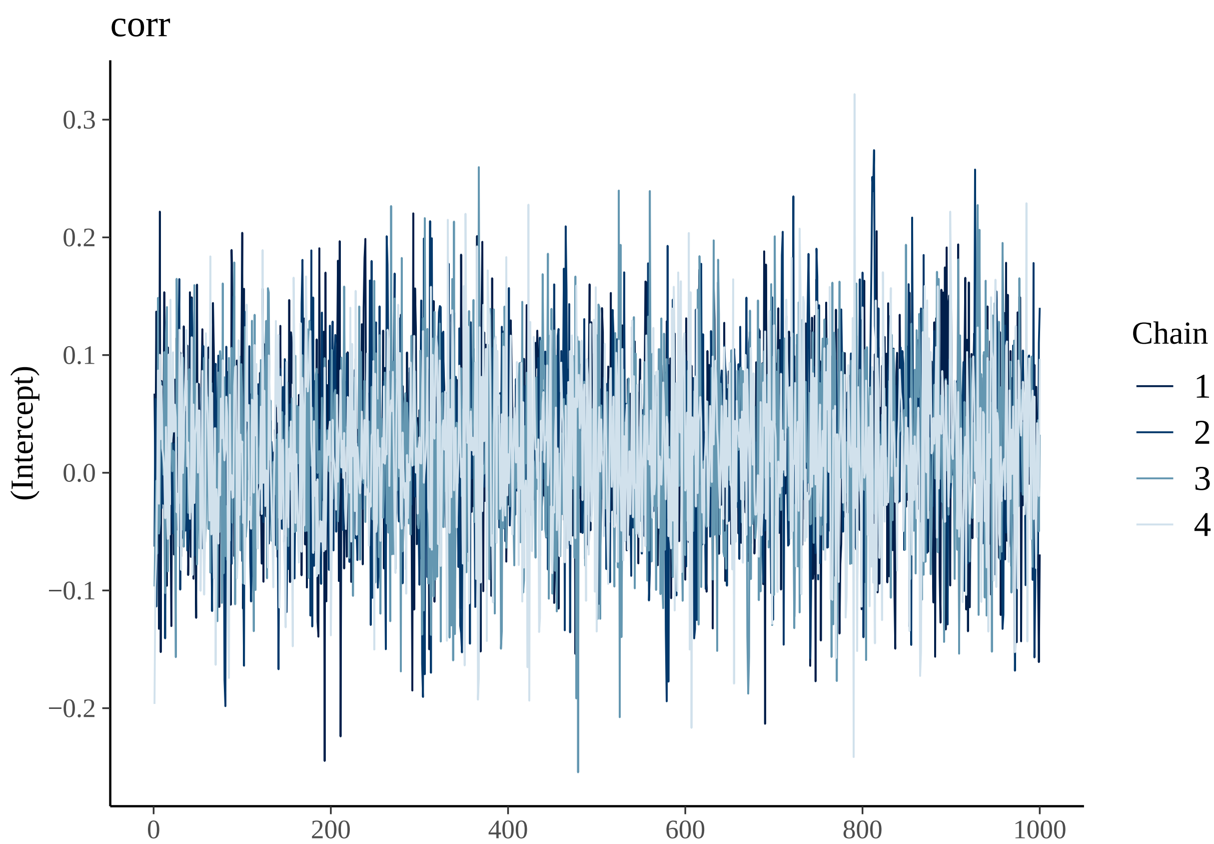
Fitting the models

```
set.seed(1)
fitted <- map(wflows,
              ~ .x %>% fit(data_training))

fitted_models <- map(fitted, extract_fit_engine)

set.seed(1)
prior_fitted <- map(recipes,
  ~ workflow() %>%
     add_model(model_prior) %>%
     add_recipe(.x) %>%
     fit(data_training) %>%
     extract_fit_engine()
)
```

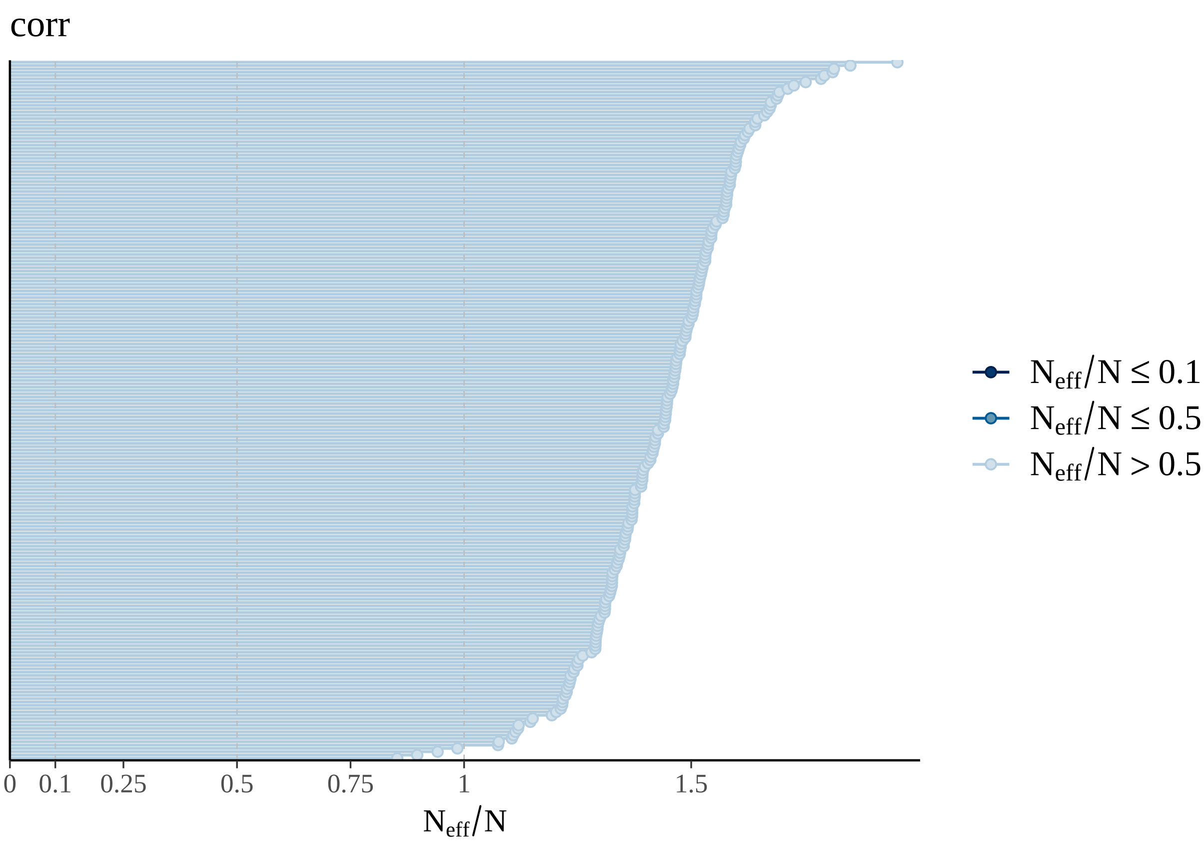
Convergance checks

```
convergance_plots <- map2(
  fitted_models,
  names(fitted_models),
  function(.x, .y){
    list(
      plot(.x, 'trace', pars = '(Intercept)'),
      #think about which estimates to include and add this here
      plot(.x, 'neff'),
      plot(.x, 'rhat')
      ) %>%
    map(function(.x){.x + ggtitle(.y)})
  }
)

convergance_plots %>% print
```

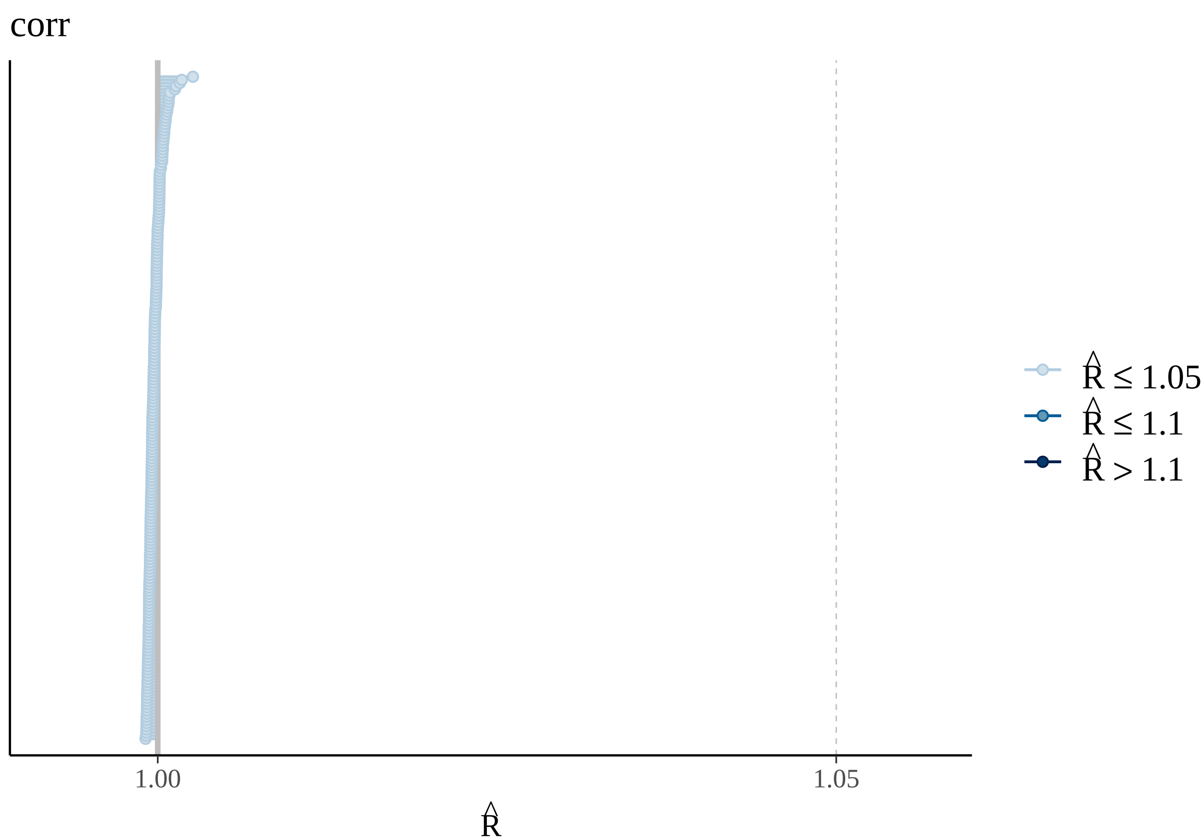
```
## $corr
## $corr[[1]]
```


corr
0.3
0.2
0.1
0.0
−0.1
−0.2
(Intercept)
0
200
400
600
800
1000
Chain
1
2
3
4

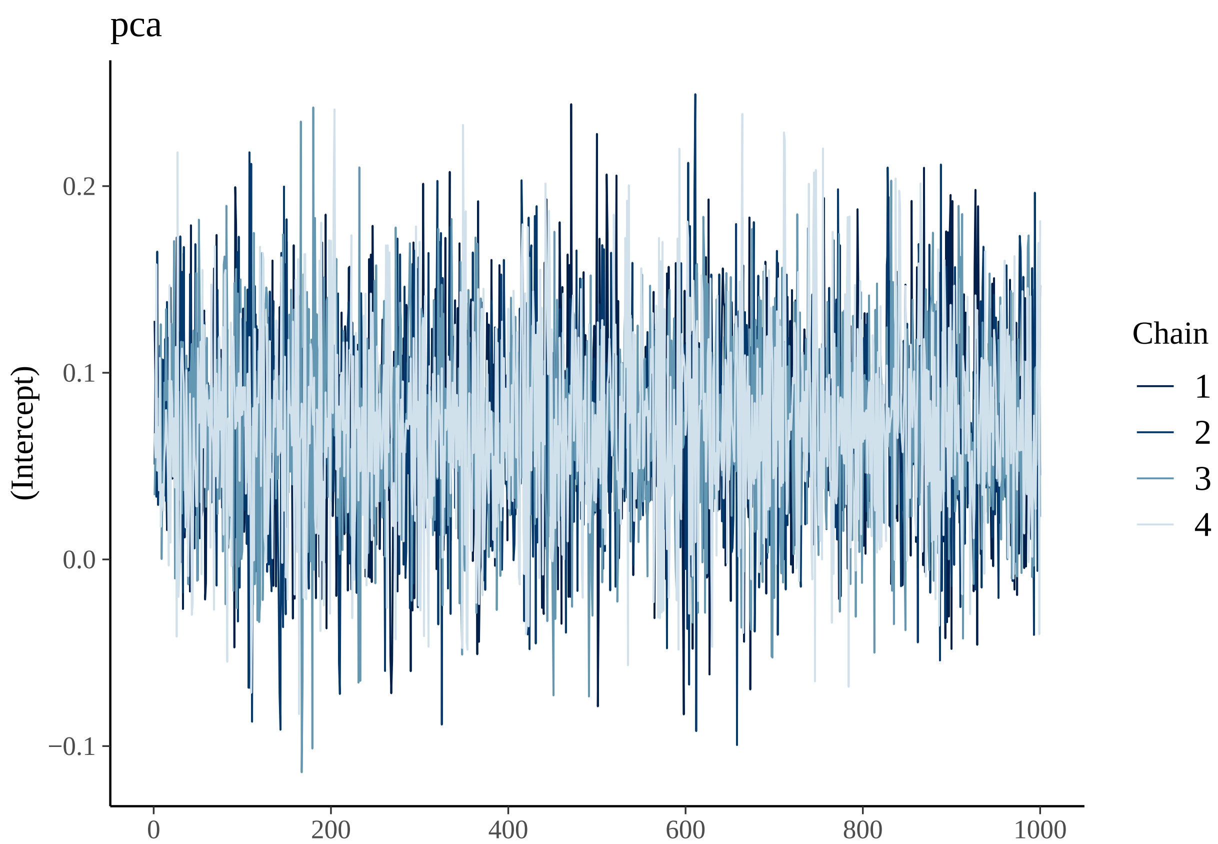
```
##
## $corr[[2]]
```



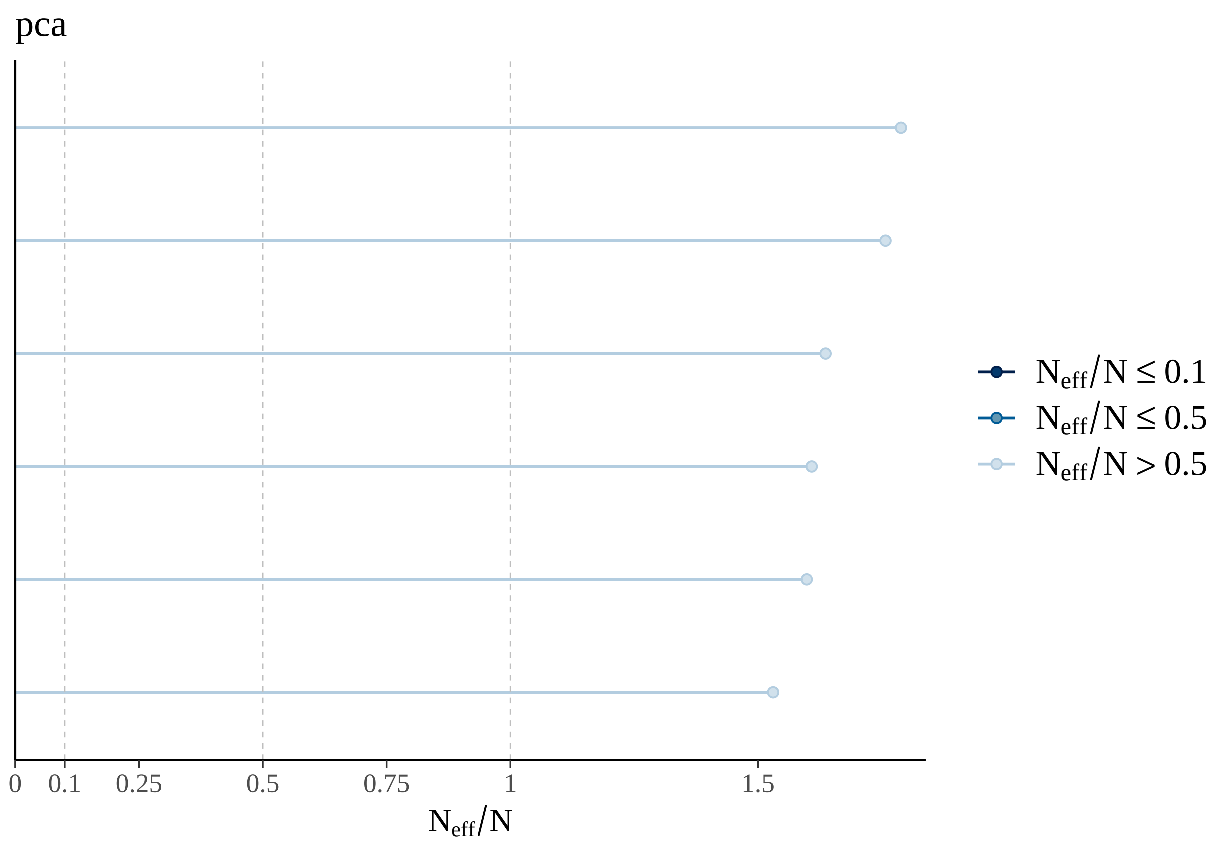

```
##
## $corr[[3]]
```



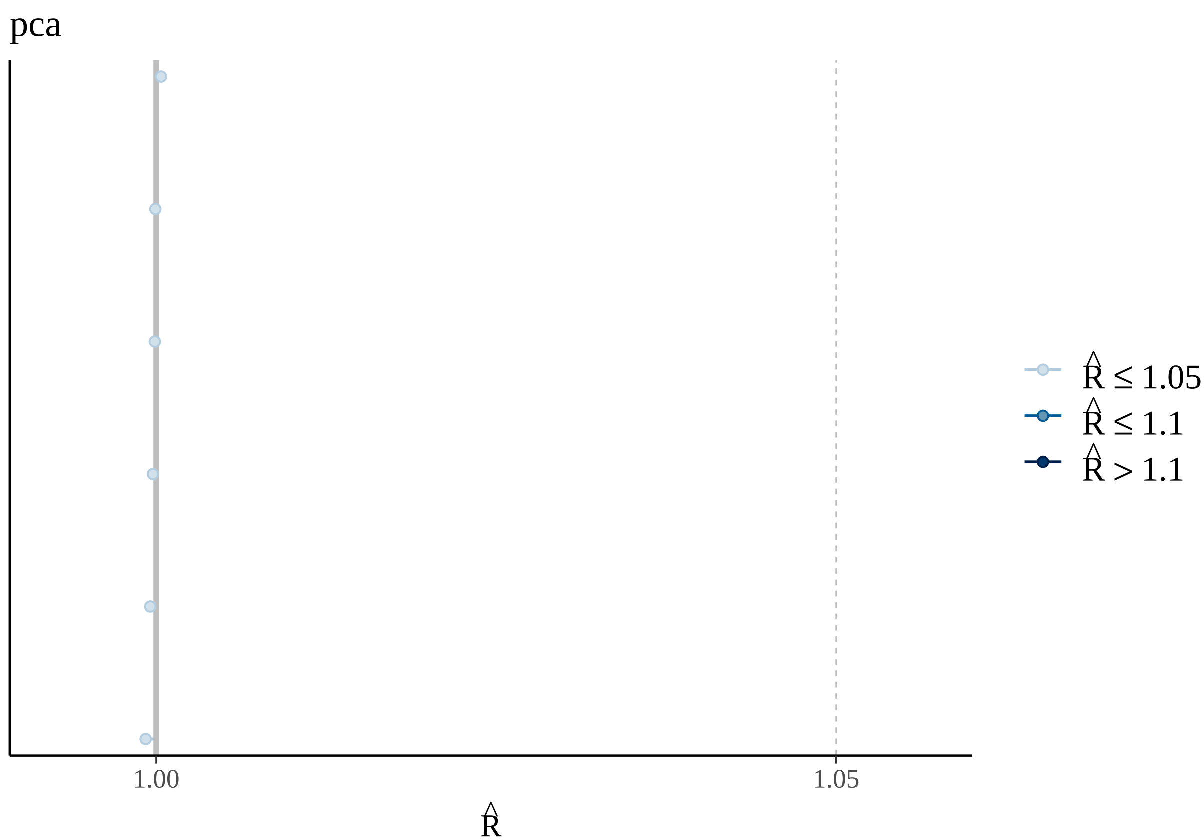

```
##
##
## $pca
## $pca[[1]]
```




```
##
## $pca[[2]]
```




```
##
## $pca[[3]]
```




```
rm(convergance_plots)
```

```
tidy_pca <- tidy(fitted[[2]] %>% extract_recipe, 2)

tidy_pca %>%
  filter(component %in% paste0('PC', 1:5)) %>%
  group_by(component) %>%
  top_n(15, abs(value)) %>%
  ungroup() %>%
  mutate(terms = reorder_within(terms, abs(value), component)) %>%
  ggplot(aes(value, terms)) +
  geom_col() +
  facet_wrap(~component, scale = 'free_y') +
  scale_y_reordered() +
  theme_minimal()
```

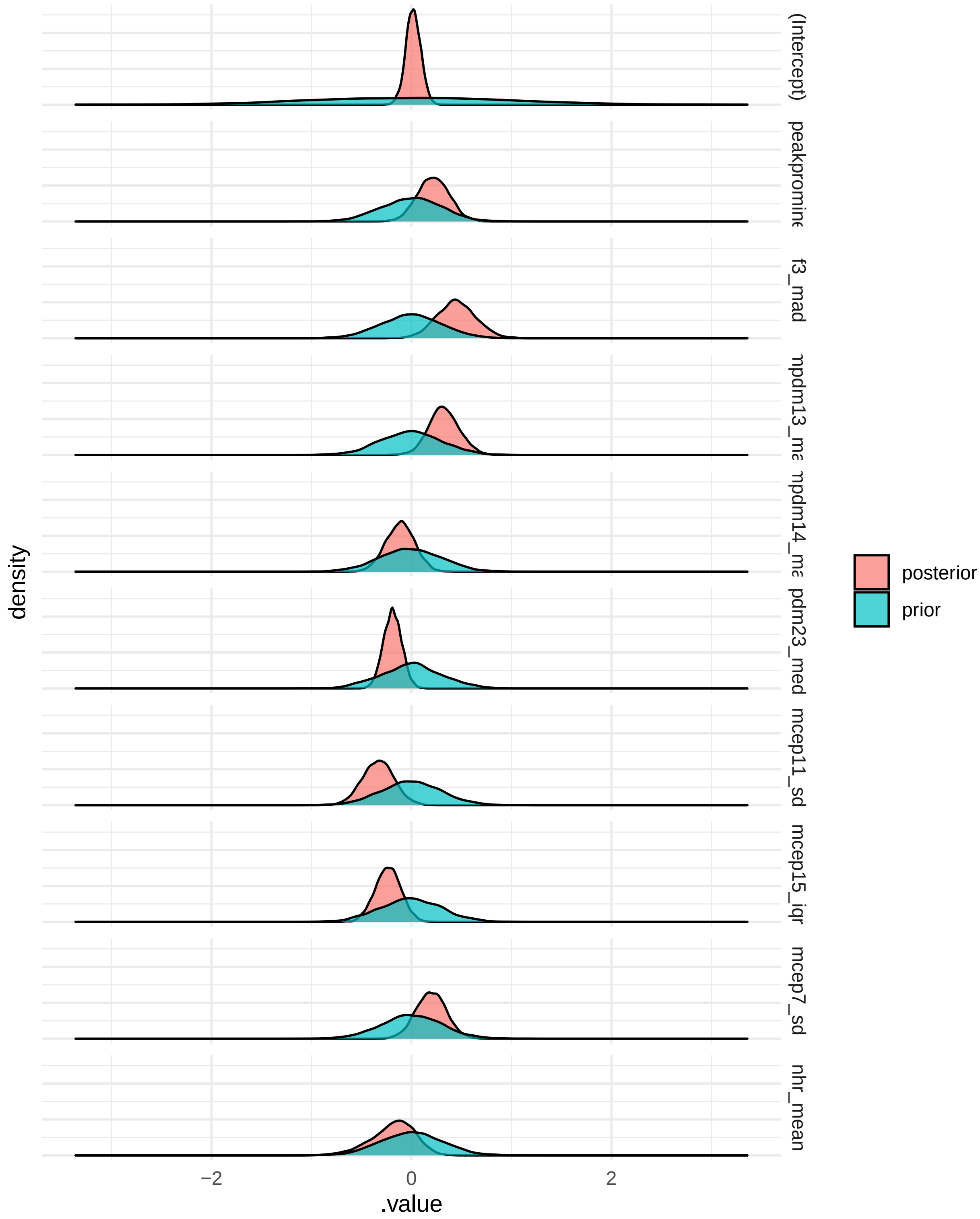

```r
#ggsave('pca_interpretation.png', height = 10, width = 12, bg = 'white')
```

```r
variables_corr <- get_variables(fitted_models[[1]]) %>%
    str_subset('.*__', negate = T) %>%
      #removing all the 'technical' variables (e.g. 'treedepth__', 'stepsize__')
    str_subset('(Intercept)', negate = T)

variables_corr <- c(
  '(Intercept)',
  variables_corr %>% str_subset('mcep.*') %>% sample(3, replace = F),
  variables_corr %>% str_subset('hmpdm.*') %>% sample(3, replace = F),
  variables_corr %>% str_subset(.,'mcep.*|hmpd.*', negate = T) %>% sample(3, replace = F)
)
#drawing different variables from different types of measures to plot as a sample in the pior-posterior

variables_pca <- get_variables(fitted_models[[2]]) %>% str_subset('.*__', negate = T)
```

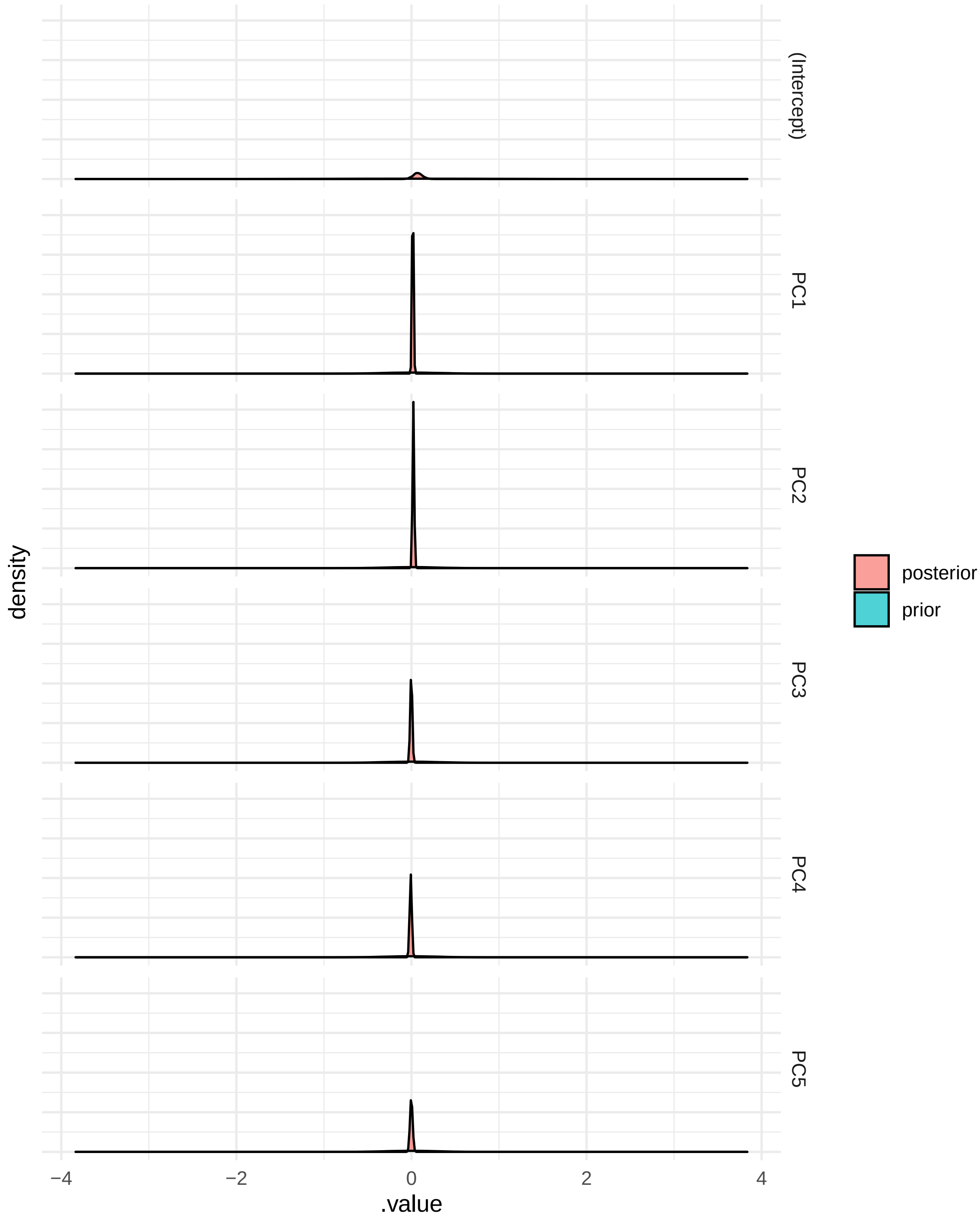
```r
pp_update_plot <- function(prior_model, posterior_model, variables){

  df_draws <-  bind_rows(
```

```
    prior_model %>% gather_draws(!!!syms(variables))%>%
      mutate(type = 'prior'),

      posterior_model %>% gather_draws(!!!syms(variables))%>%
        mutate(type = 'posterior')
      )

  df_draws <- df_draws %>%
    group_by(.variable) %>%
    mutate(upp_lim = if_else((max(.value) + min(.value)) > 0, max(.value), - min(.value)),
           low_lim = - upp_lim) %>%
    ungroup



  df_draws %>%
    ggplot(aes(x = .value, fill = type)) +
      geom_density(alpha = 0.7) +
      labs(fill = element_blank()) +
      xlim(df_draws$low_lim[[1]], df_draws$upp_lim[[1]]) +
      facet_grid(vars(df_draws$.variable)) +
      theme_minimal() +
      theme(axis.ticks.y = element_blank(),
            axis.text.y = element_blank())
}
```

```
pp_update_plot(prior_fitted[[1]], fitted_models[[1]], variables_corr)
```




```r
#ggsave('pp_upadte_corr.png', height = 8, bg = 'white')

pp_update_plot(prior_fitted[[2]], fitted_models[[2]], variables_pca)
```

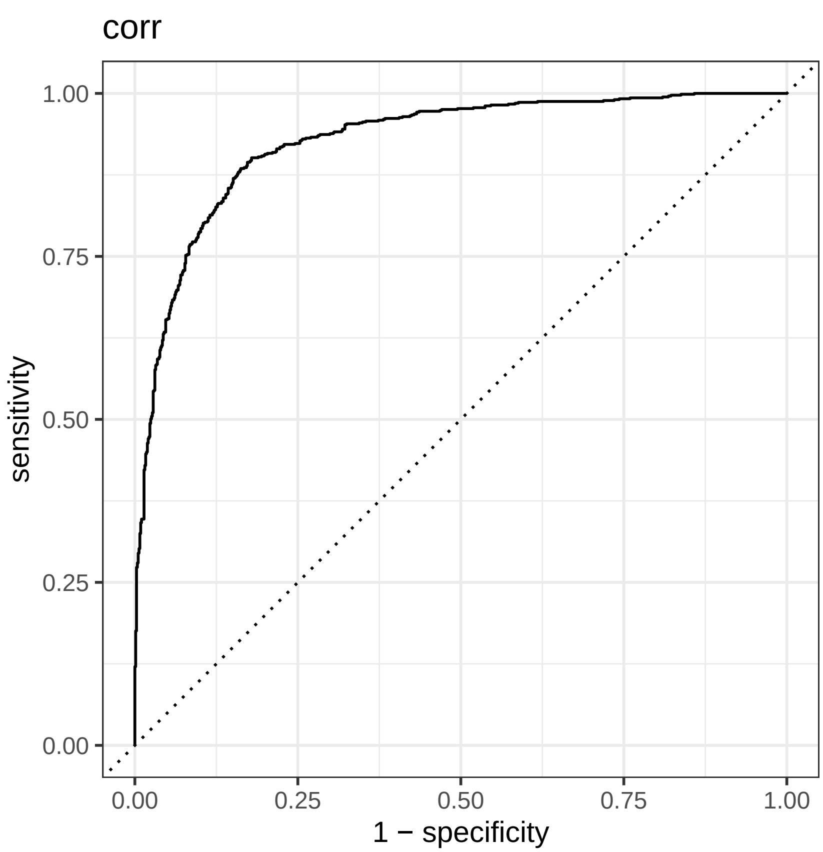



```r
#ggsave('pp_update_pca.png', height = 8, bg = 'white')
```

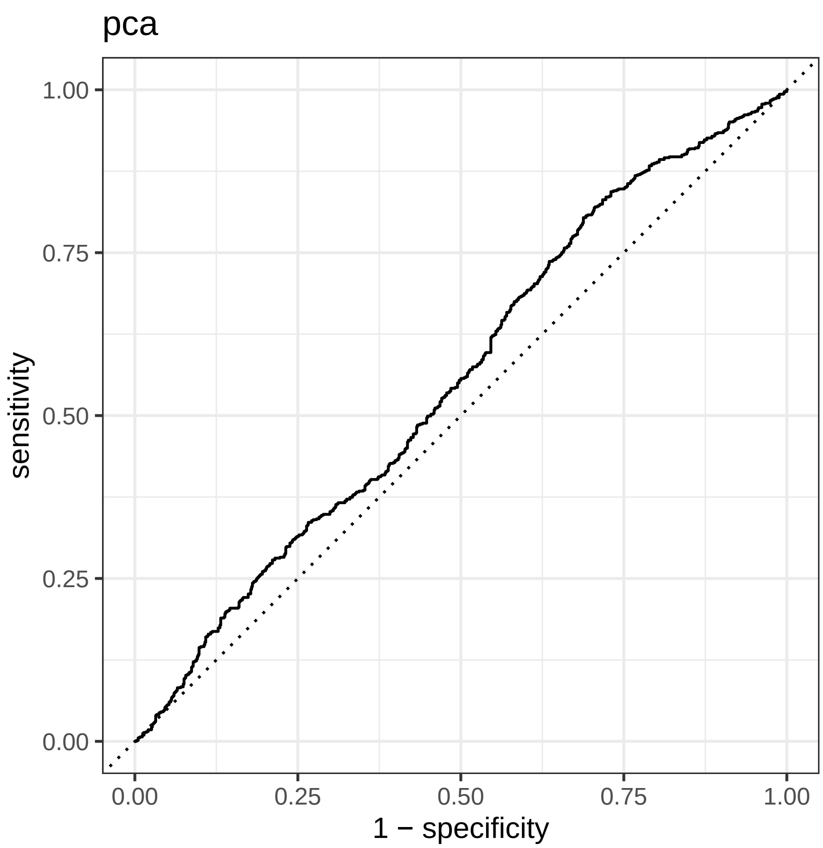
```r
test_preds <- map(fitted, ~ augment(.x, data_training))
```

```
rocs <- map2(test_preds, names(test_preds),
      ~ .x %>%
          roc_curve(truth = condition, .pred_sz) %>%
            autoplot +
            ggtitle(.y)
)
rocs
```

```
## $corr
```



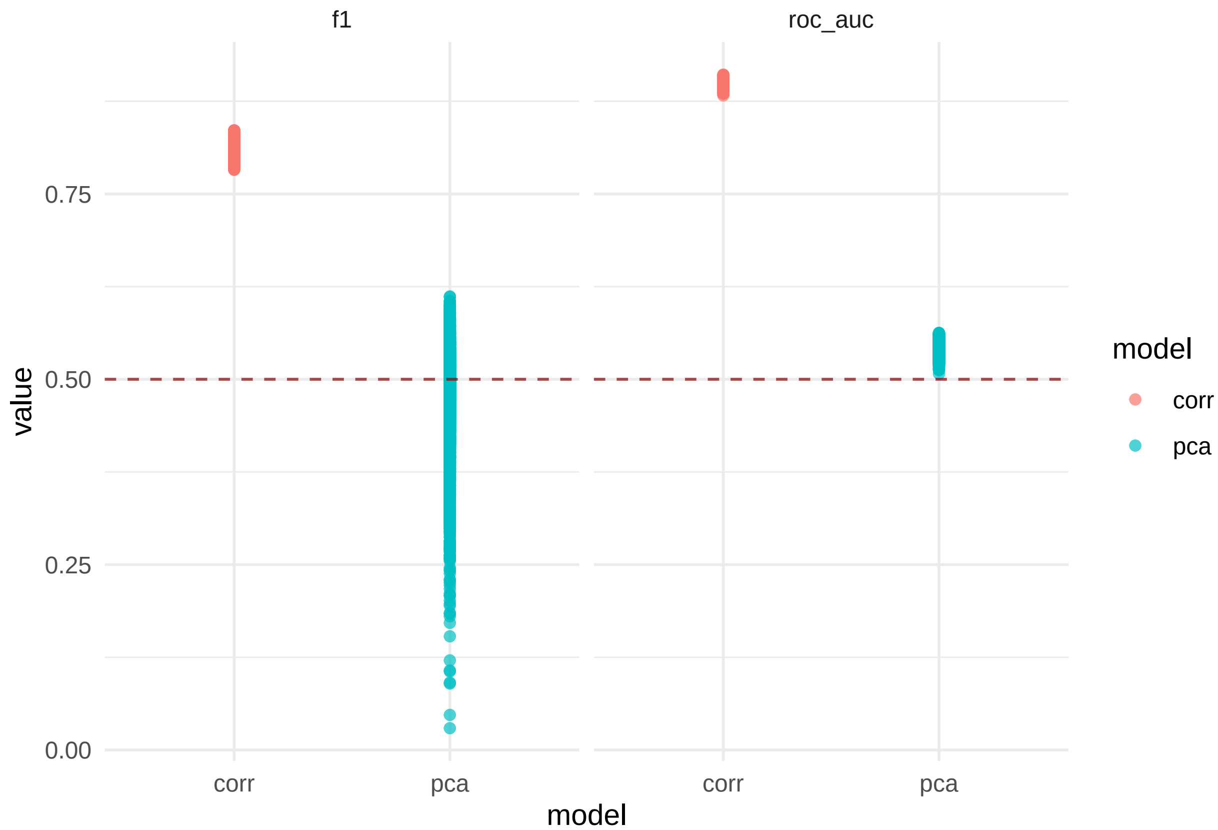

```
##
## $pca
```




```
#ggsave(plot = rocs[[1]], filename = 'roc_corr.png')
#ggsave(plot = rocs[[2]], filename =  'roc_pca.png')
```

```
#with the uncertanity

test_results <- tibble(draw = NULL,
                       f1 = NULL,
                       model = NULL)


for (i in seq_along(fitted_models)){

  m <- fitted_models[[i]]
  name <- names(fitted_models)[[i]]

  draws_matrix <- posterior_epred(m)

  roc_aucs <- map_dbl(
    draws_matrix %>% split(row(draws_matrix)),
    ~ roc_auc_vec(truth = data_training$condition, estimate = .x)
    )
  roc_aucs <- tibble(
    value = roc_aucs,
    metric = 'roc_auc',
    draw = seq_along(nrow)
    )
```

```r
  preds_class <- map(
    draws_matrix %>% split(row(draws_matrix)),
    ~ if_else(.x < 0.5, 'sz', 'hc') %>% as_factor %>% relevel('sz')
    )


  fs <- map_dbl(
    preds_class,
    ~ f_meas_vec(truth = data_training$condition, estimate = .x)
    )
  fs <- tibble(
    value = fs,
    metric = 'f1',
    draw = seq_along(nrow)
    )


  test_results <- bind_rows(
    test_results,
    bind_rows(fs, roc_aucs) %>% mutate(model = name)
  )
}
rm(i, m, name, draws_matrix, roc_aucs, preds_class, fs)


test_results <- test_results %>%
  mutate(value = if_else(metric == 'roc_auc', 1 - value, value))

test_results %>%
    ggplot(aes(x = model, y = value, colour = model)) +
      geom_point(alpha = 0.7) +
      geom_hline(yintercept = 0.5, color = 'darkred', linetype = 'dashed', alpha = 0.7) +
      theme_minimal() +
      facet_wrap(vars(metric))
```




```
#ggsave('test_results.png', bg = 'white')
```

```
#save.image(file = "/rdata/a3_part3.Rdata")
```