HW4 - Past Linearity [MACS 30100]

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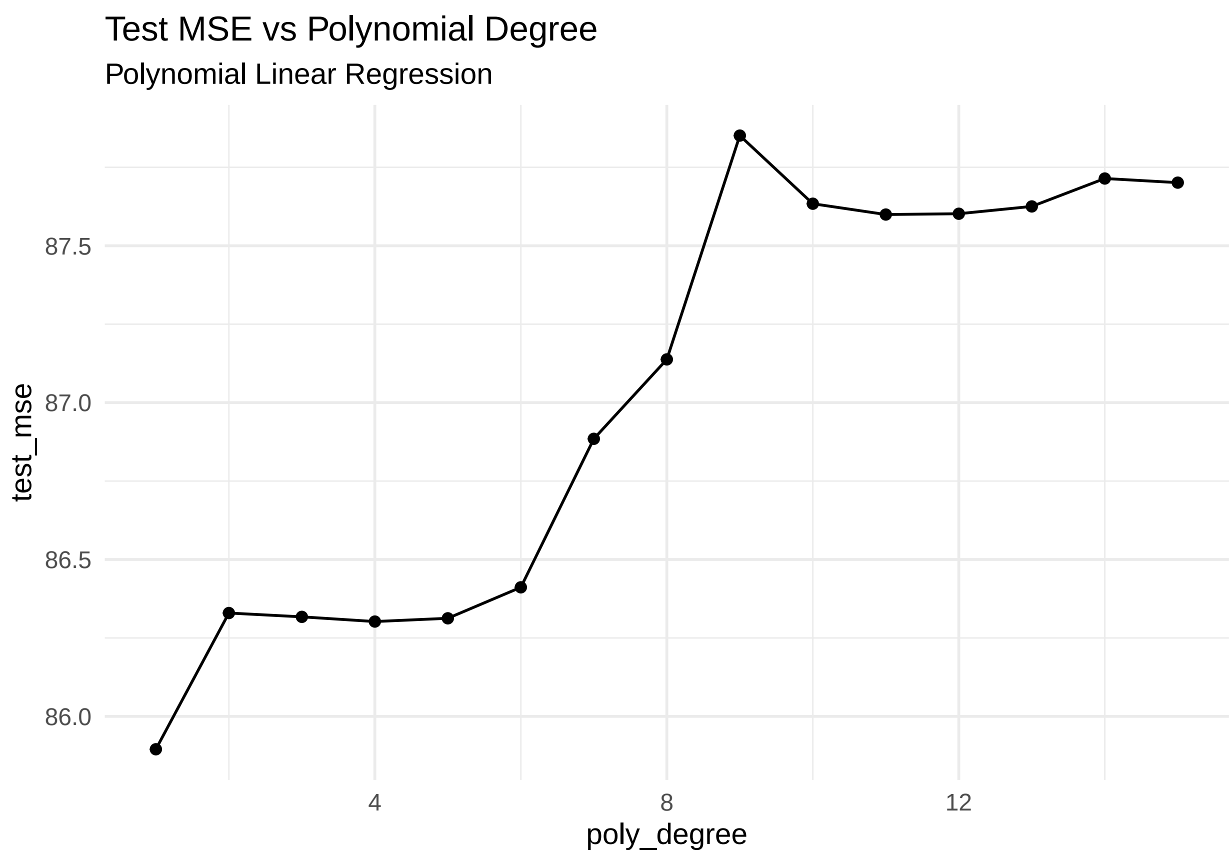
Setup - Reading and Cleaning Data

```
gss_train_dfmin <- read_csv("../data/gss_train.csv") %>%
  select(egalit_scale, income06) %>%
  #mutate(egalit_scale =  as.factor(egalit_scale)) %>%
  na.omit()

gss_test_dfmin <- read_csv("../data/gss_test.csv") %>%
  select(egalit_scale, income06) %>%
  #mutate(egalit_scale =  as.factor(egalit_scale)) %>%
  na.omit()
```

Q1: Polynomial Regression

```
polyreg_mse <- function(degree_val){
  set.seed(02162020)

  poly_control <- trainControl(method = "cv", number = 10)

  polyreg_mod <- train(form = egalit_scale ~ poly(income06, degree = degree_val),
                       data = gss_train_dfmin %>% mutate(degree_val = degree_val), method = "lm", prePr
                       metric = "RMSE", trControl = poly_control)

  #summary(polyreg_mod)

  train_mse <- mean((predict(polyreg_mod, newdata = gss_train_dfmin) - gss_train_dfmin$egalit_scale)^2)
  test_mse <- mean((predict(polyreg_mod, newdata = gss_test_dfmin) - gss_test_dfmin$egalit_scale)^2)

  out_tbl <- tibble(train_mse = train_mse,
                    test_mse = test_mse)

  return(out_tbl)
}

polyreg_df <- c(1:15) %>%
  enframe(name = NULL, value= "poly_degree") %>%
  mutate(mse_values = map(poly_degree, ~polyreg_mse(.x))) %>%
  unnest(mse_values)

polyreg_df %>%
```

```r
ggplot(aes(x = poly_degree, y = test_mse)) +
  geom_line() +
  geom_point() +
  theme_minimal() +
  ggtitle("Test MSE vs Polynomial Degree", subtitle = "Polynomial Linear Regression")
```



The best MSE is from `degree = 1`.

```r
polymod_best <- lm(egalit_scale ~ income06, data = gss_train_dfmin)

summary(polymod_best)
```

```
##
## Call:
## lm(formula = egalit_scale ~ income06, data = gss_train_dfmin)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -22.5484  -6.7059   0.4677   7.2394  18.7828
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 25.86350    0.72845  35.505   <2e-16 ***
## income06    -0.38585    0.04119  -9.368   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 9.351 on 1479 degrees of freedom
## Multiple R-squared:  0.05602,    Adjusted R-squared:  0.05538
## F-statistic: 87.76 on 1 and 1479 DF,  p-value: < 2.2e-16
```

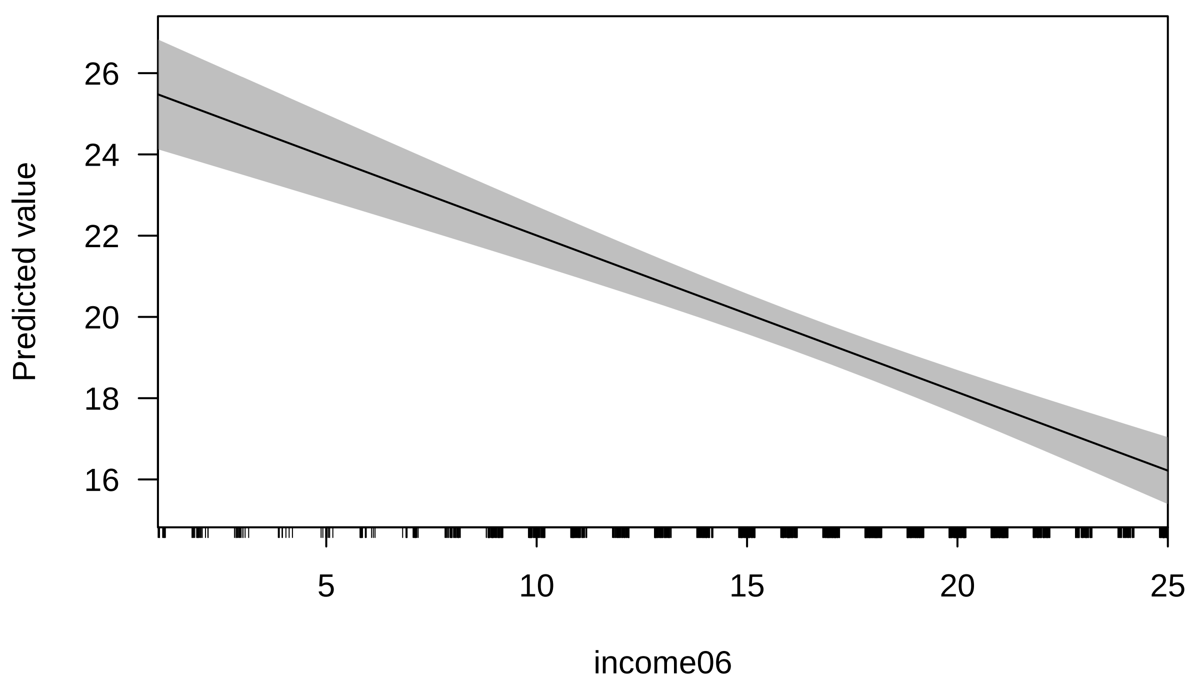
```
gss_test_dfmin_polyaug <- gss_test_dfmin %>%
  bind_cols(pred_egalit_scale = predict(polymod_best, newdata = gss_test_dfmin)) %>%
  pivot_longer(cols = c("egalit_scale", "pred_egalit_scale"), names_to = "val_type", values_to = "egali


gss_test_dfmin_polyaug %>% filter(str_detect(val_type, "pred")) %>%
  ggplot() +
  geom_line(aes(x = income06, y = egalit_scale, colour = val_type)) +
  geom_point(data = gss_test_dfmin_polyaug %>% filter(str_detect(val_type, "pred") == FALSE),
             aes(x = income06, y = egalit_scale, colour = val_type)) +
  theme_minimal() +
  ggtitle("Fit of Polynomial Regression against data",
          subtitle = "degree = 1")
```


```
margins::margins(polymod_best)
```

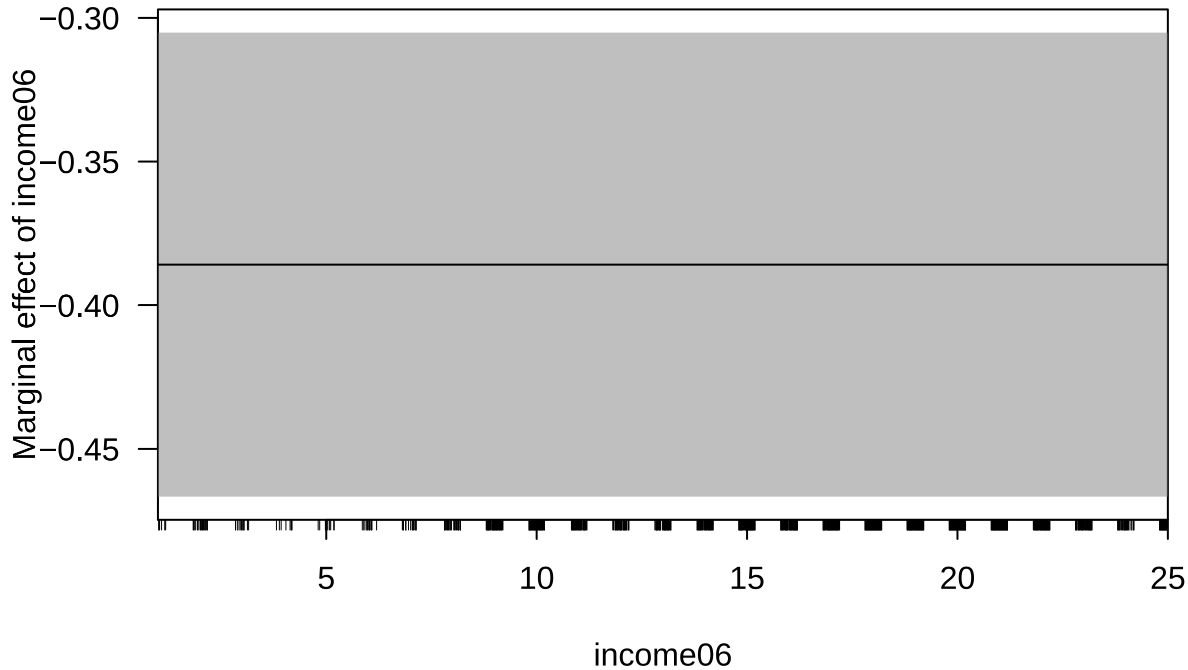
```
## Average marginal effects

## lm(formula = egalit_scale ~ income06, data = gss_train_dfmin)

##   income06
##    -0.3859
```

```
cplot(polymod_best, "income06")
```

```
##    xvals    yvals    upper    lower
## 1      1 25.47765 26.82954 24.12575
## 2      2 25.09179 26.36846 23.81513
## 3      3 24.70594 25.90809 23.50380
## 4      4 24.32009 25.44857 23.19161
## 5      5 23.93424 24.99008 22.87840
## 6      6 23.54839 24.53286 22.56392
## 7      7 23.16253 24.07719 22.24788
## 8      8 22.77668 23.62346 21.92991
## 9      9 22.39083 23.17218 21.60948
## 10    10 22.00498 22.72402 21.28594
## 11    11 21.61913 22.27985 20.95840
## 12    12 21.23328 21.84084 20.62571
## 13    13 20.84742 21.40844 20.28640
## 14    14 20.46157 20.98444 19.93871
## 15    15 20.07572 20.57076 19.58068
## 16    16 19.68987 20.16921 19.21052
## 17    17 19.30402 19.78100 18.82703
## 18    18 18.91816 19.40632 18.43001
## 19    19 18.53231 19.04427 18.02035
## 20    20 18.14646 18.69322 17.59970
```




```r
cplot(polymod_best, "income06", what = "effect")
```



Since the best-fit degree is 1, the final model is a linear one-variable fit. `income06` has a negative effect on `egalit_scale`, and the AME is constant at -0.386. As an individual moves into a higher income slab, their score on the constructed egalitarian scale decreases.

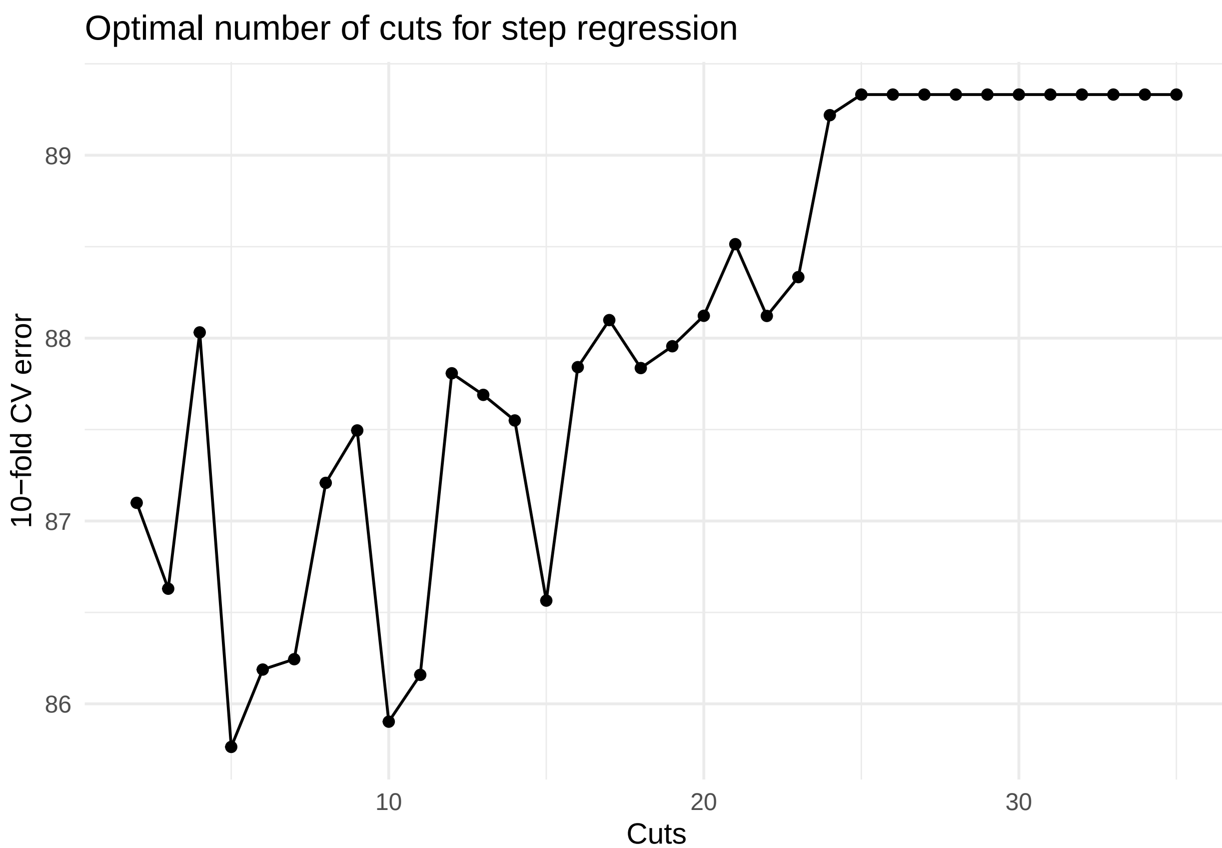
Q2: Step Regression

```
egalit_levels <- as.character(sort(unique(gss_train_dfmin$egalit_scale)))

stepreg2_mse <- function(splits, ncuts){
  # estimate the model on each fold
  model <- glm(egalit_scale ~ cut(income06, ncuts),
               data = analysis(splits))

  test_mse <- mean((predict(model, newdata = gss_test_dfmin) - gss_test_dfmin$egalit_scale)^2)

  return(test_mse)

  # model_acc <- broom::augment(model, newdata = assessment(splits)) %>%
  #   accuracy(truth = factor(egalit_scale, levels = egalit_levels), estimate = factor(round(.fitted),
  #
  # mean(model_acc$.estimate)
}


# estimate CV error for knots in 0:25
```

```r
results_step <- vfold_cv(gss_train_dfmin, v = 10)

stepreg_df <- expand(results_step, id, ncuts = 2:35) %>%
  left_join(results_step) %>%
  mutate(test_mse = map2_dbl(splits, ncuts, stepreg2_mse)) %>%
  group_by(ncuts) %>%
  summarize(mean_test_mse = mean(test_mse))
```

```
## Joining, by = "id"
```

```r
stepreg_df %>%
  ggplot(aes(ncuts, mean_test_mse)) +
  geom_point() +
  geom_line() +
  theme_minimal()+
  #scale_y_continuous(labels = scales::percent) +
  labs(title = "Optimal number of cuts for step regression",
       x = "Cuts",
       y = "10-fold CV error")
```



Optimal number of cuts: 5.

```r
stepreg_best <- glm(egalit_scale ~ cut(income06, 5),
                    data = gss_train_dfmin)

gss_test_dfmin_stepaug <- gss_test_dfmin %>%
  bind_cols(pred_egalit_scale = predict(stepreg_best, newdata = gss_test_dfmin)) %>%
```

```
  pivot_longer(cols = c("egalit_scale", "pred_egalit_scale"), names_to = "val_type", values_to = "egali


gss_test_dfmin_stepaug %>% filter(str_detect(val_type, "pred")) %>%
  ggplot() +
  geom_line(aes(x = income06, y = egalit_scale, colour = val_type)) +
  geom_point(data = gss_test_dfmin_stepaug %>% filter(str_detect(val_type, "pred") == FALSE),
             aes(x = income06, y = egalit_scale, colour = val_type)) +
  theme_minimal() +
  ggtitle("Fit of Step Regression against data",
          subtitle = "5 cuts")
```

This is a strange model to fit, given the categorical nature of the data, and the fit seems arbitrary.

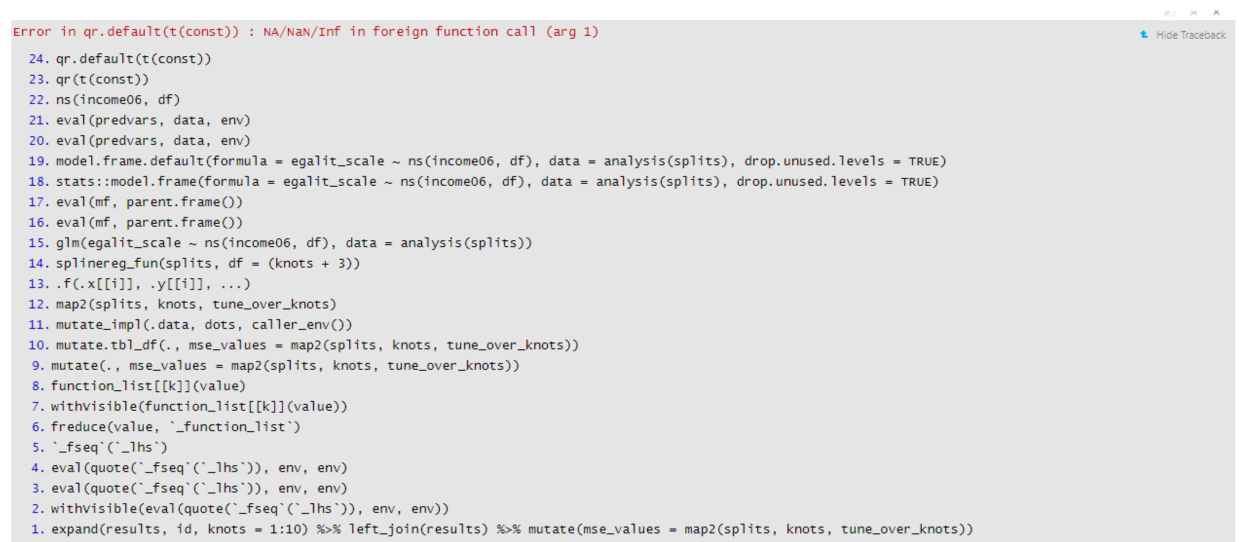
Q3: Natural Spline Regression

```
# ## Failed Method 1
#
# nsplinereg_mse <- function(degree_val, cut_val){
#   set.seed(02162020)
#
#   nspline_control <- trainControl(method = "cv", number = 10)
#
#   knots_len <- length(gss_train_dfmin$income06)
#   knots_val <- sort(gss_train_dfmin$income06)[2:(knots_len-1)]
```

```
#
#   nsplinereg_mod <- train(form = egalit_scale ~ ns(income06, df = (degree_val*(1+cut_val)), knots = k
#                           data = gss_train_dfmin %>% mutate(degree_val = degree_val,
#                                                             cut_val = cut_val),
#                           method = "glm",
#                           preProcess = c("center", "scale"),
#                           metric = "RMSE", trControl = nspline_control)
#
#   #summary(polyreg_mod)
#
#   train_mse <- mean((predict(nsplinereg_mod, newdata = gss_train_dfmin) - gss_train_dfmin$egalit_scal
#   test_mse <- mean((predict(nsplinereg_mod, newdata = gss_test_dfmin) - gss_test_dfmin$egalit_scale)^
#
#   out_tbl <- tibble(train_mse = train_mse,
#                     test_mse = test_mse)
#
#   return(out_tbl)
#   # if (mse_type == "train") return(train_mse) else return(test_mse)
# }
#
# nsplinereg_df <- expand_grid(poly_degree = seq(1, 15, by = 1),
#                              n_cuts = seq(1, 15, by = 1)) %>%
#   mutate(mse_values = map2(poly_degree, n_cuts, nsplinereg_mse)) %>%
#   unnest(mse_values)
#
# nsplinereg_df %>%
#   ggplot(aes(x = n_cuts, y = test_mse)) +
#   geom_line() +
#   geom_point() +
#   theme_minimal() +
#   ggtitle("Test MSE vs Number of Cuts", subtitle = "Natural Spline Regression")
```

```
# # FAILED METHOD 2 - Code from Lab
#
# # function to simplify things
# splinereg_fun <- function(splits, df = NULL){
#
#   # estimate the model on each fold
#   model <- glm(egalit_scale ~ ns(income06, df),
#                data = analysis(splits))
#
#   model_mse <- broom::augment(model, newdata = assessment(splits)) %>%
#     rcfss::mse(truth = egalit_scale, estimate = .fitted)
#
#
#
#   return(mean(model_mse$.estimate))
# }
#
# tune_over_knots <- function(splits, knots){
#   splinereg_fun(splits, df = (knots + 3))
# }
#
# # estimate CV error for knots in 0:25
```

```r
# results <- vfold_cv(gss_train_dfmin, v = 10)
#
# splinereg_df <- expand(results, id, knots = 1:10) %>%
#   left_join(results) %>%
#   mutate(mse_values = map2(splits, knots, tune_over_knots))
#
# splinereg_df %>%
#   group_by(knots) %>%
#   summarize(mean_test_mse = mean(mse_values, na.rm = T)) %>%
#   ggplot(aes(knots, mean_test_mse)) +
#   geom_point() +
#   geom_line() +
#   #scale_y_continuous(labels = scales::percent) +
#   labs(title = "Optimal number of knots for natural cubic spline regression",
#        x = "Knots",
#        y = "10-fold CV error")
```



```
Error in qr.default(t(const)) : NA/NaN/Inf in foreign function call (arg 1)
 24. qr.default(t(const))
 23. qr(t(const))
 22. ns(income06, df)
 21. eval(predvars, data, env)
 20. eval(predvars, data, env)
 19. model.frame.default(formula = egalit_scale ~ ns(income06, df), data = analysis(splits), drop.unused.levels = TRUE)
 18. stats::model.frame(formula = egalit_scale ~ ns(income06, df), data = analysis(splits), drop.unused.levels = TRUE)
 17. eval(mf, parent.frame())
 16. eval(mf, parent.frame())
 15. glm(egalit_scale ~ ns(income06, df), data = analysis(splits))
 14. splinereg_fun(splits, df = (knots + 3))
 13. .f(.x[[i]], .y[[i]], ...)
 12. map2(splits, knots, tune_over_knots)
 11. mutate_impl(.data, dots, caller_env())
 10. mutate.tbl_df(., mse_values = map2(splits, knots, tune_over_knots))
  9. mutate(., mse_values = map2(splits, knots, tune_over_knots))
  8. function_list[[k]](value)
  7. withVisible(function_list[[k]](value))
  6. freduce(value, `_function_list`)
  5. `_fseq`(`_lhs`)
  4. eval(quote(`_fseq`(`_lhs`)), env, env)
  3. eval(quote(`_fseq`(`_lhs`)), env, env)
  2. withVisible(eval(quote(`_fseq`(`_lhs`)), env, env))
  1. expand(results, id, knots = 1:10) %>% left_join(results) %>% mutate(mse_values = map2(splits, knots, tune_over_knots))
```


Figure 1: Error traceback for the above chunk

Q4: Estimating Egalitarianism with all Predictors

Reading and Cleaning Data

```
gss_train_df <- read_csv("../data/gss_train.csv") %>%
  mutate_if(is.numeric, ~as.integer(.x) ) %>%
  mutate_if(is.character, ~as.factor(.x))

gss_test_df <- read_csv("../data/gss_test.csv") %>%
  mutate_if(is.numeric, ~as.integer(.x) ) %>%
  mutate_if(is.character, ~as.factor(.x))
```

Helper Functions

```
model_gen <- function(model_type){
  set.seed(02142020)
  tr_control <- trainControl(method = "cv", number = 10)

  gss_model <- train(form = egalit_scale ~ ., data = gss_train_df,
                     method = model_type, preProcess = c("center", "scale"),
                    metric = "RMSE", trControl = tr_control)

  return(gss_model)
}
```

Implementing it in a `tibble` object:

```
result_df <- c("lm", "glmnet", "pcr", "pls") %>%
  enframe(name = NULL, value = "model_type") %>%
  mutate(model_obj = map(model_type, ~model_gen(.x)),
         predictor_obj = map(model_obj,
                             ~Predictor$new(model = .x,
                                            data = gss_train_df %>%
                                              select(-egalit_scale),
                                            y = gss_train_df$egalit_scale)),
         featureimp_obj = map(predictor_obj, ~FeatureImp$new(.x, loss = "mse")),
         interaction_obj = map(predictor_obj, ~Interaction$new(.x)),
         all_interaction_obj = map(predictor_obj, ~FeatureEffects$new(.x)))
```

Linear Regression

```
print("Training MSE for lm:")
```

```
## [1] "Training MSE for lm:"
```

```
mean((predict((result_df %>%
                filter(model_type == "lm") %>%
                dplyr::select(model_obj))$model_obj[[1]], newdata = gss_train_df) - gss_train_df$egalit_
```

```
## [1] 54.42554
```

```
print("Testing MSE for lm:")
```

```
## [1] "Testing MSE for lm:"
```

```r
mean((predict((result_df %>%
                filter(model_type == "lm") %>%
                select(model_obj))$model_obj[[1]], newdata = gss_test_df) - gss_test_df$egalit_scale)^2
```

```
## [1] 63.37644
```

```r
featureimp_plot_lm <- plot((result_df %>%
        filter(model_type == "lm") %>%
        select(featureimp_obj))$`featureimp_obj`[[1]]) +
  theme_minimal() +
  ggtitle("Linear Regression",
          subtitle = "Feature Importance")


interaction_plot_lm <- plot((result_df %>%
        filter(model_type == "lm") %>%
        select(interaction_obj))$`interaction_obj`[[1]]) +
  theme_minimal() +
  ggtitle("Linear Regression",
          subtitle = "Overall Interaction Strength")

all_interaction_plot_lm <- plot((result_df %>% filter(model_type == "lm") %>%
        select(all_interaction_obj))$all_interaction_obj[[1]])
```

Elastic Net

```r
print("Training MSE for Elastic Net:")
```

```
## [1] "Training MSE for Elastic Net:"
```

```r
mean((predict((result_df %>%
                filter(model_type == "glmnet") %>%
                dplyr::select(model_obj))$model_obj[[1]], newdata = gss_train_df) - gss_train_df$egalit_
```

```
## [1] 55.9775
```

```r
print("Testing MSE for Elastic Net:")
```

```
## [1] "Testing MSE for Elastic Net:"
```

```r
mean((predict((result_df %>%
                filter(model_type == "glmnet") %>%
                dplyr::select(model_obj))$model_obj[[1]], newdata = gss_test_df) - gss_test_df$egalit_s
```

```
## [1] 61.38986
```

```r
featureimp_plot_enet <- plot((result_df %>%
        filter(model_type == "glmnet") %>%
        select(featureimp_obj))$`featureimp_obj`[[1]]) +
  theme_minimal() +
  ggtitle("Elastic Net",
          subtitle = "Feature Importance")

interaction_plot_enet <- plot((result_df %>%
                                 filter(model_type == "glmnet") %>%
                                 select(interaction_obj))$interaction_obj[[1]]) +
```

```r
  theme_minimal() +
  ggtitle("Elastic Net",
          subtitle = "Overall Interaction Strength")

all_interaction_plot_enet <- plot((result_df %>%
                                    filter(model_type == "glmnet") %>%
                                    select(all_interaction_obj))$all_interaction_obj[[1]])
```

Principal Component Regression

```r
print("Training MSE for pcr:")
```

```
## [1] "Training MSE for pcr:"
```

```r
mean((predict((result_df %>%
                filter(model_type == "pcr") %>%
                dplyr::select(model_obj))$model_obj[[1]], newdata = gss_train_df) - gss_train_df$egalit_
```

```
## [1] 70.99323
```

```r
print("Testing MSE for pcr:")
```

```
## [1] "Testing MSE for pcr:"
```

```r
mean((predict((result_df %>%
                filter(model_type == "pcr") %>%
                dplyr::select(model_obj))$model_obj[[1]], newdata = gss_test_df) - gss_test_df$egalit_s
```

```
## [1] 69.07672
```

```r
featureimp_plot_pcr <- plot((result_df %>%
        filter(model_type == "pcr") %>%
        select(featureimp_obj))$`featureimp_obj`[[1]]) +
  theme_minimal() +
  ggtitle("Principal Component Regression",
          subtitle = "Feature Importance")

interaction_plot_pcr <- plot((result_df %>%
                                filter(model_type == "pcr") %>%
                                select(interaction_obj))$interaction_obj[[1]]) +
  theme_minimal() +
  ggtitle("Principal Component Regression",
          subtitle = "Overall Interaction Strength")

all_interaction_plot_pcr <- plot((result_df %>%
                                    filter(model_type == "pcr") %>%
                                    select(all_interaction_obj))$all_interaction_obj[[1]])
```

Partial Least Squares Regression

```r
print("Training MSE for pls:")
```

```
## [1] "Training MSE for pls:"
```

```r
mean((predict((result_df %>%
                filter(model_type == "pls") %>%
```

```
                dplyr::select(model_obj))$model_obj[[1]], newdata = gss_train_df) - gss_train_df$egalit_
```

```
## [1] 56.74024
```

```
print("Testing MSE for pls:")
```

```
## [1] "Testing MSE for pls:"
```

```
mean((predict((result_df %>%
                filter(model_type == "pls") %>%
                dplyr::select(model_obj))$model_obj[[1]], newdata = gss_test_df) - gss_test_df$egalit_sc
```

```
## [1] 62.17684
```

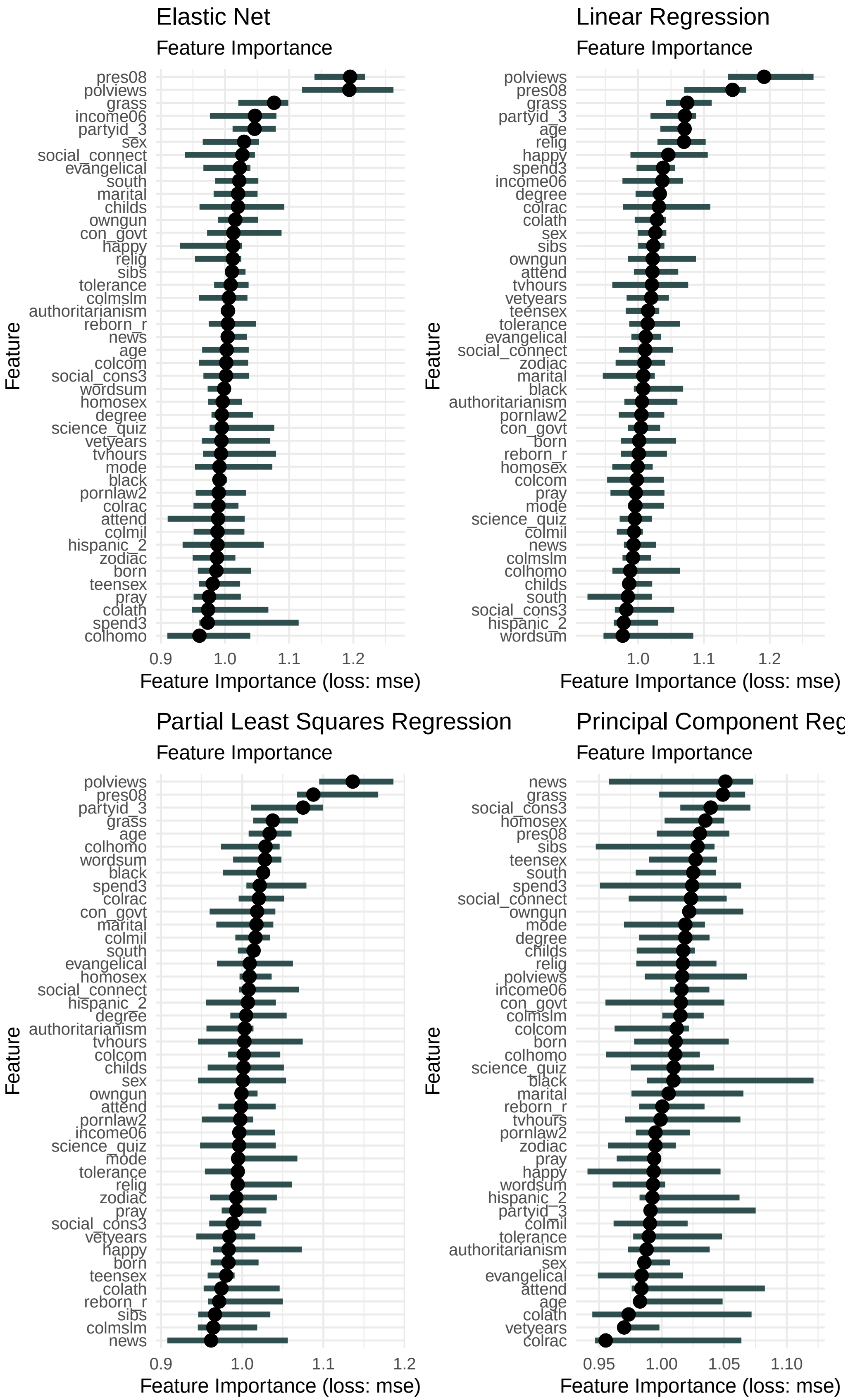
```
featureimp_plot_pls <- plot((result_df %>%
        filter(model_type == "pls") %>%
        select(featureimp_obj))$`featureimp_obj`[[1]]) +
  theme_minimal() +
  ggtitle("Partial Least Squares Regression",
          subtitle = "Feature Importance")

interaction_plot_pls <- plot((result_df %>%
                              filter(model_type == "pls") %>%
                              select(interaction_obj))$interaction_obj[[1]]) +
  theme_minimal() +
  ggtitle("Partial Least Squares Regression",
          subtitle = "Overall Interaction Strength")

all_interaction_plot_pls <- plot((result_df %>%
                                  filter(model_type == "pls") %>%
                                  select(all_interaction_obj))$all_interaction_obj[[1]])
```

Q5: Feature Importance & Interaction Effects

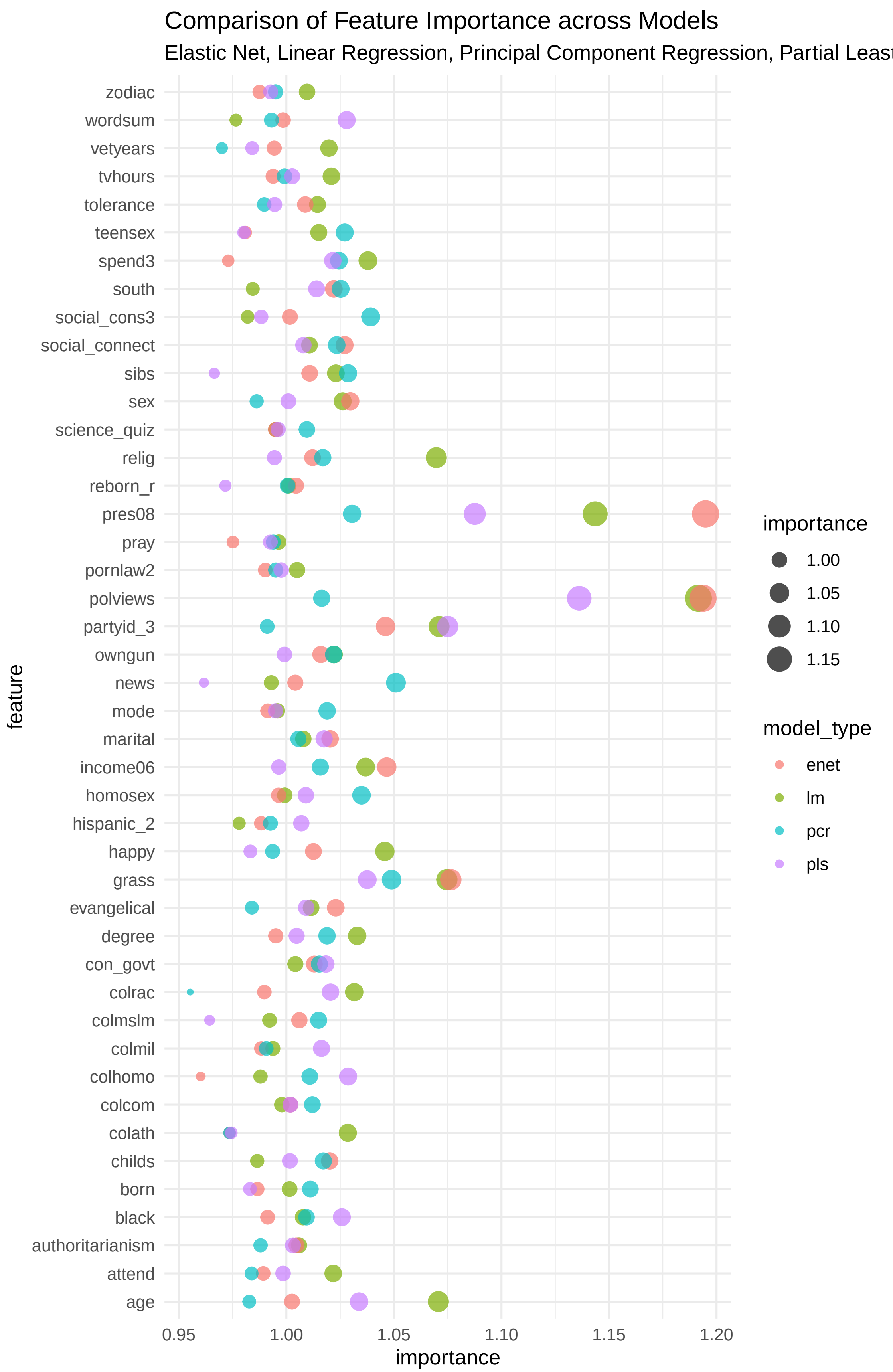
Feature Importance

`pres08`, `polviews`, `grass`, `partyid_3` seem to show up as the top features across models, which is in line with expectations – redistribution and opportunity play an important role in political narratives in the US. PCR seems to weight other variables as more important though, and much larger error-bars.

```
(featureimp_plot_enet + featureimp_plot_lm + featureimp_plot_pls + featureimp_plot_pcr)
```


Elastic Net
Feature Importance
pres08
polviews
grass
income06
partyid_3
sex
social_connect
evangelical
south
marital
childs
owngun
con_govt
happy
relig
sibs
tolerance
colmslm
authoritarianism
reborn_r
news
age
colcom
social_cons3
wordsum
homosex
degree
science_quiz
vetyears
tvhours
mode
black
pornlaw2
colrac
attend
colmil
hispanic_2
zodiac
born
teensex
pray
colath
spend3
colhomo
Feature
0.9
1.0
1.1
1.2
Feature Importance (loss: mse)
Linear Regression
Feature Importance
polviews
pres08
grass
partyid_3
age
relig
happy
spend3
income06
degree
colrac
colath
sex
sibs
owngun
attend
tvhours
vetyears
teensex
tolerance
evangelical
social_connect
zodiac
marital
black
authoritarianism
pornlaw2
con_govt
born
reborn_r
homosex
colcom
pray
mode
science_quiz
colmil
news
colmslm
colhomo
childs
south
social_cons3
hispanic_2
wordsum
Feature
1.0
1.1
1.2
Feature Importance (loss: mse)
Partial Least Squares Regression
Feature Importance
polviews
pres08
partyid_3
grass
age
colhomo
wordsum
black
spend3
colrac
con_govt
marital
colmil
south
evangelical
homosex
social_connect
hispanic_2
degree
authoritarianism
tvhours
colcom
childs
sex
owngun
attend
pornlaw2
income06
science_quiz
mode
tolerance
relig
zodiac
pray
social_cons3
vetyears
happy
born
teensex
colath
reborn_r
sibs
colmslm
news
Feature
0.9
1.0
1.1
1.2
Feature Importance (loss: mse)
Principal Component Reg
Feature Importance
news
grass
social_cons3
homosex
pres08
sibs
teensex
south
spend3
social_connect
owngun
mode
degree
childs
relig
polviews
income06
con_govt
colmslm
colcom
born
colhomo
science_quiz
black
marital
reborn_r
tvhours
pornlaw2
zodiac
pray
happy
wordsum
hispanic_2
partyid_3
colmil
tolerance
authoritarianism
sex
evangelical
attend
age
colath
vetyears
colrac
Feature
0.95
1.00
1.05
1.10
Feature Importance (loss: mse)

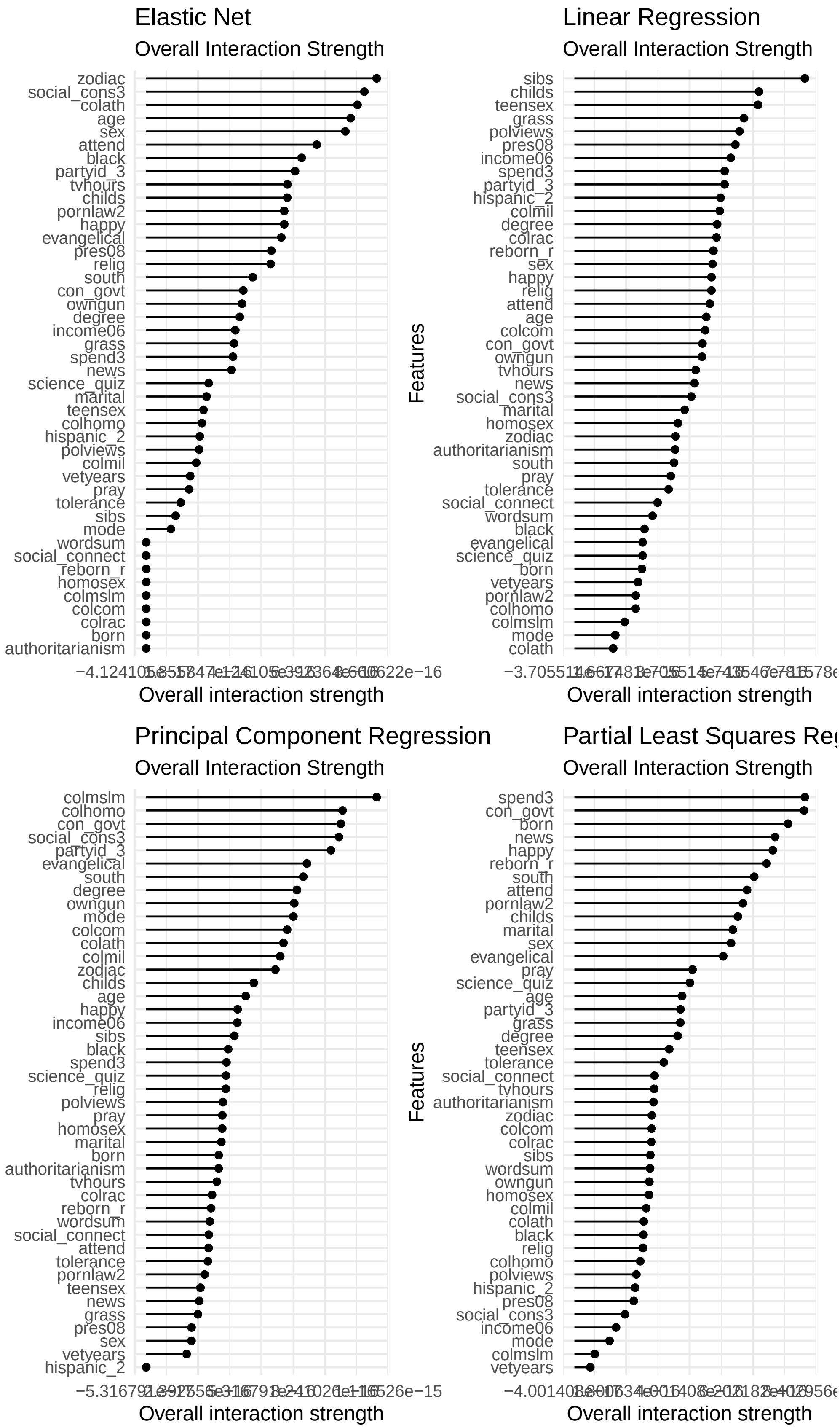
```
featureimp_values <- bind_rows((result_df %>%
             filter(model_type == "lm") %>%
             select(featureimp_obj))$featureimp_obj[[1]]$results %>%
            as_tibble() %>%
            mutate(model_type = "lm"),
          (result_df %>%
             filter(model_type == "glmnet") %>%
             select(featureimp_obj))$featureimp_obj[[1]]$results %>%
            as_tibble() %>%
            mutate(model_type = "enet"),
          (result_df %>%
             filter(model_type == "pcr") %>%
             select(featureimp_obj))$featureimp_obj[[1]]$results %>%
            as_tibble() %>%
            mutate(model_type = "pcr"),
          (result_df %>%
             filter(model_type == "pls") %>%
             select(featureimp_obj))$featureimp_obj[[1]]$results %>%
            as_tibble() %>%
            mutate(model_type = "pls"))

featureimp_values %>%
  ggplot(aes(x = feature, y = importance, colour = model_type, size = importance)) +
  geom_point(alpha = 0.7) +coord_flip() +
  theme_minimal() +
  ggtitle("Comparison of Feature Importance across Models",
          subtitle = "Elastic Net, Linear Regression, Principal Component Regression, Partial Least Squa
```


Comparison of Feature Importance across Models
Elastic Net, Linear Regression, Principal Component Regression, Partial Least
zodiac
wordsum
vetyears
tvhours
tolerance
teensex
spend3
south
social_cons3
social_connect
sibs
sex
science_quiz
relig
reborn_r
pres08
pray
pornlaw2
polviews
partyid_3
owngun
news
mode
marital
income06
homosex
hispanic_2
happy
grass
evangelical
degree
con_govt
colrac
colmslm
colmil
colhomo
colcom
colath
childs
born
black
authoritarianism
attend
age
feature
0.95
1.00
1.05
1.10
1.15
1.20
importance
importance
1.00
1.05
1.10
1.15
model_type
enet
lm
pcr
pls

Feature Interaction

All the interaction effects are extremely small, to the order of 10^{-15}. And as such, there is no consistency in the rank order of these interaction effects.

```
(interaction_plot_enet + interaction_plot_lm + interaction_plot_pcr + interaction_plot_pls)
```


Elastic Net
Overall Interaction Strength
zodiac
social_cons3
colath
age
sex
attend
black
partyid_3
tvhours
childs
pornlaw2
happy
evangelical
pres08
relig
south
con_govt
owngun
degree
income06
grass
spend3
news
science_quiz
marital
teensex
colhomo
hispanic_2
polviews
colmil
vetyears
pray
tolerance
sibs
mode
wordsum
social_connect
reborn_r
homosex
colmslm
colcom
colrac
born
authoritarianism
Features
Overall interaction strength
Linear Regression
Overall Interaction Strength
sibs
childs
teensex
grass
polviews
pres08
income06
spend3
partyid_3
hispanic_2
colmil
degree
colrac
reborn_r
sex
happy
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attend
age
colcom
con_govt
owngun
tvhours
news
social_cons3
marital
homosex
zodiac
authoritarianism
south
pray
tolerance
social_connect
wordsum
black
evangelical
science_quiz
born
vetyears
pornlaw2
colhomo
colmslm
mode
colath
Features
Overall interaction strength
Principal Component Regression
Overall Interaction Strength
colmslm
colhomo
con_govt
social_cons3
partyid_3
evangelical
south
degree
owngun
mode
colcom
colath
colmil
zodiac
childs
age
happy
income06
sibs
black
spend3
science_quiz
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polviews
pray
homosex
marital
born
authoritarianism
tvhours
colrac
reborn_r
wordsum
social_connect
attend
tolerance
pornlaw2
teensex
news
grass
pres08
sex
vetyears
hispanic_2
Features
Overall interaction strength
Partial Least Squares Re
Overall Interaction Strength
spend3
con_govt
born
news
happy
reborn_r
south
attend
pornlaw2
childs
marital
sex
evangelical
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science_quiz
age
partyid_3
grass
degree
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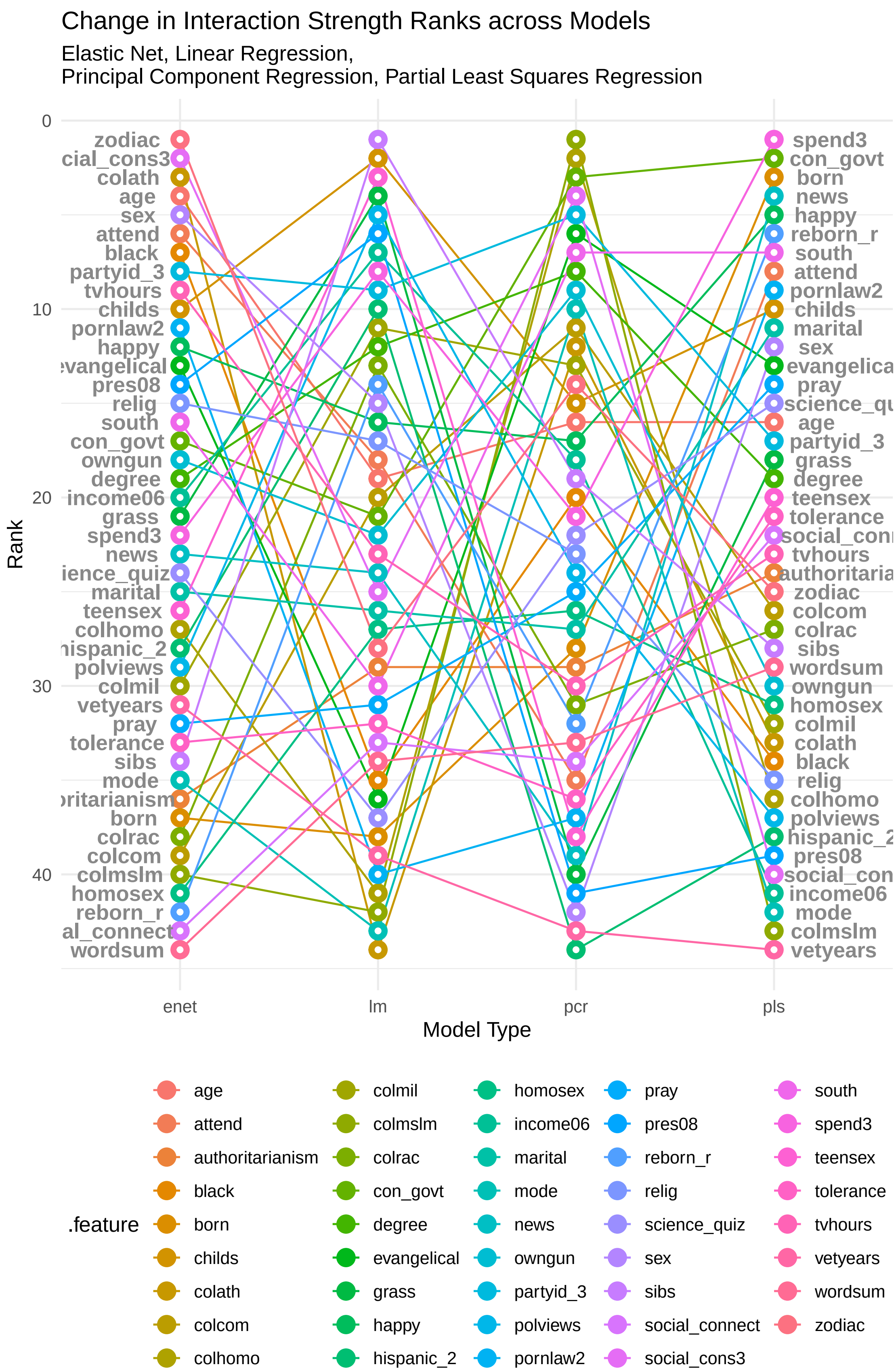
tolerance
social_connect
tvhours
authoritarianism
zodiac
colcom
colrac
sibs
wordsum
owngun
homosex
colmil
colath
black
relig
colhomo
polviews
hispanic_2
pres08
social_cons3
income06
mode
colmslm
vetyears
Features
Overall interaction strength

```r
interaction_ranks <- bind_rows((result_df %>%
             filter(model_type == "lm") %>%
             select(interaction_obj))$interaction_obj[[1]]$results %>%
            as_tibble() %>%
            mutate(rank = row_number(desc(.interaction)),
                   model_type = "lm"),
          (result_df %>%
             filter(model_type == "glmnet") %>%
             select(interaction_obj))$interaction_obj[[1]]$results %>%
            as_tibble() %>%
            mutate(rank = row_number(desc(.interaction)),
                   model_type = "enet"),
          (result_df %>%
             filter(model_type == "pcr") %>%
             select(interaction_obj))$interaction_obj[[1]]$results %>%
            as_tibble() %>%
            mutate(rank = row_number(desc(.interaction)),
                   model_type = "pcr"),
          (result_df %>%
             filter(model_type == "pls") %>%
             select(interaction_obj))$interaction_obj[[1]]$results %>%
            as_tibble() %>%
            mutate(rank = row_number(desc(.interaction)),
                   model_type = "pls"))
```

```r
ggplot(data = interaction_ranks, aes(x = model_type, y = rank, group = .feature)) +
  geom_line(aes(color = .feature), size = 0.5, alpha = 1) +
  geom_point(aes(color = .feature), size = 4, alpha = 1) +
  geom_point(color = "#FFFFFF", size = 1) +
  # scale_x_continuous(breaks = 1:16, minor_breaks = 1:16, expand = c(.05, .05)) +
  geom_text(data = interaction_ranks %>% filter(model_type == "enet"),
            aes(label = .feature, x = 0.85) , hjust = .85, fontface = "bold", color = "#888888", size =
  geom_text(data = interaction_ranks %>% filter(model_type == "pls"),
            aes(label = .feature, x = 4.15) , hjust = 0.15, fontface = "bold", color = "#888888", size =
  # coord_cartesian(ylim = c(1,show.top.n)) +
  theme_minimal() +
  scale_y_reverse()+
  labs(x = "Model Type",
       y = "Rank",
       title = "Change in Interaction Strength Ranks across Models",
       subtitle = "Elastic Net, Linear Regression, \nPrincipal Component Regression, Partial Least Squa
  theme(legend.position = "bottom")
```



Change in Interaction Strength Ranks across Models
Elastic Net, Linear Regression,
Principal Component Regression, Partial Least Squares Regression
Rank
Model Type
enet
lm
pcr
pls
.feature
age
attend
authoritarianism
black
born
childs
colath
colcom
colhomo
colmil
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con_govt
degree
evangelical
grass
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homosex
income06
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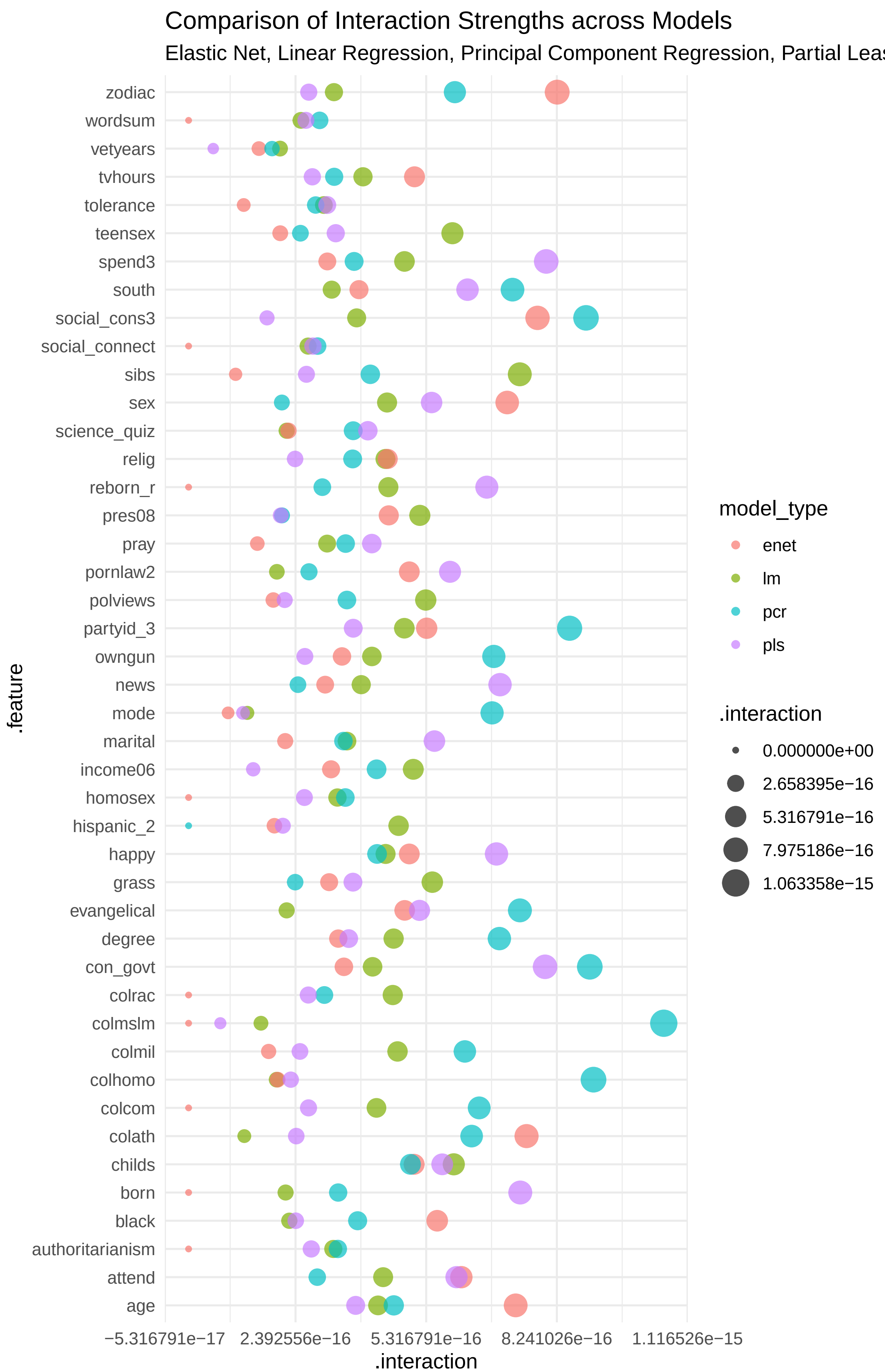
news
owngun
partyid_3
polviews
pornlaw2
pray
pres08
reborn_r
relig
science_quiz
sex
sibs
social_connect
social_cons3
south
spend3
teensex
tolerance
tvhours
vetyears
wordsum
zodiac

```
interaction_ranks %>%
  ggplot(aes(x = .feature, y = .interaction, colour = model_type, size = .interaction)) +
  geom_point(alpha = 0.7) +coord_flip() +
  theme_minimal() +
  ggtitle("Comparison of Interaction Strengths across Models",
          subtitle = "Elastic Net, Linear Regression, Principal Component Regression, Partial Least Squa
```


Comparison of Interaction Strengths across Models
Elastic Net, Linear Regression, Principal Component Regression, Partial Least
zodiac
wordsum
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south
social_cons3
social_connect
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black
authoritarianism
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−5.316791e−17
2.392556e−16
5.316791e−16
8.241026e−16
1.116526e−15
.interaction
model_type
enet
lm
pcr
pls
.interaction
0.000000e+00
2.658395e−16
5.316791e−16
7.975186e−16
1.063358e−15