

exploration (7 variables selection)

2025-11-06

```
install.packages("haven")

##
## The downloaded binary packages are in
## /var/folders/g_/_1jm_0wb9519gm4d8zgwd_s300000gn/T//RtmpW8RZzp downloaded_packages
library(haven)

gss <- read_dta("/Users/joyqu/Desktop/PLSC/GSS2024.dta")

head(gss)

## # A tibble: 6 x 813
##   year      id wrkstat hrs1      hrs2      evwork      wrkslf    occ10
##   <dbl+lbl> <dbl> <dbl+lbl> <dbl+lbl> <dbl+lbl> <dbl+lbl> <dbl+lbl>
## 1 2024      1 1 [wor~     43      NA(i) [iap]  NA(i) [iap]  2 [som~  230 [edu~
## 2 2024      2 5 [ret~ NA(i) [iap]  NA(i) [iap]      1 [yes]  2 [som~  800 [acc~
## 3 2024      3 5 [ret~ NA(i) [iap]  NA(i) [iap]      1 [yes]  2 [som~  430 [man~
## 4 2024      4 2 [wor~     20      NA(i) [iap]  NA(i) [iap]  2 [som~ 4760 [ret~
## 5 2024      5 5 [ret~ NA(i) [iap]  NA(i) [iap]      1 [yes]  2 [som~ 5860 [off~
## 6 2024      6 4 [une~ NA(i) [iap]  NA(i) [iap]  NA(i) [iap]  1 [sel~ 4000 [che~
## # i 805 more variables: prestg10 <dbl+lbl>, prestg105plus <dbl+lbl>,
## #   indus10 <dbl+lbl>, marital <dbl+lbl>, martype <dbl+lbl>, divorce <dbl+lbl>,
## #   widowed <dbl+lbl>, spwrksta <dbl+lbl>, sphrs1 <dbl+lbl>, sphrs2 <dbl+lbl>,
## #   spevwork <dbl+lbl>, cowrksta <dbl+lbl>, cowrkslf <dbl+lbl>,
## #   coevwork <dbl+lbl>, cohhrs1 <dbl+lbl>, cohhrs2 <dbl+lbl>, spwrkslf <dbl+lbl>,
## #   spocc10 <dbl+lbl>, sppres10 <dbl+lbl>, sppres105plus <dbl+lbl>,
## #   spind10 <dbl+lbl>, coocc10 <dbl+lbl>, coind10 <dbl+lbl>, ...
dim(gss)

## [1] 3309 813
library(dplyr)

##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
## 
##   filter, lag
## The following objects are masked from 'package:base':
## 
##   intersect, setdiff, setequal, union
library(tidyr)
head(gss)
```

```

## # A tibble: 6 x 813
##   year      id wrkstat hrs1      hrs2      evwork      wrkslf    occ10
##   <dbl+lbl> <dbl> <dbl+lbl> <dbl+lbl> <dbl+lbl> <dbl+lbl> <dbl+lbl>
## 1 2024      1 1 [wor~ 43      NA(i) [iap] NA(i) [iap] 2 [som~ 230 [edu~
## 2 2024      2 5 [ret~ NA(i) [iap] NA(i) [iap]      1 [yes] 2 [som~ 800 [acc~
## 3 2024      3 5 [ret~ NA(i) [iap] NA(i) [iap]      1 [yes] 2 [som~ 430 [man~
## 4 2024      4 2 [wor~ 20      NA(i) [iap] NA(i) [iap] 2 [som~ 4760 [ret~
## 5 2024      5 5 [ret~ NA(i) [iap] NA(i) [iap]      1 [yes] 2 [som~ 5860 [off~
## 6 2024      6 4 [une~ NA(i) [iap] NA(i) [iap] NA(i) [iap] 1 [sel~ 4000 [che~
## # i 805 more variables: prestg10 <dbl+lbl>, prestg105plus <dbl+lbl>,
## #   indus10 <dbl+lbl>, marital <dbl+lbl>, martype <dbl+lbl>, divorce <dbl+lbl>,
## #   widowed <dbl+lbl>, spwrksta <dbl+lbl>, sphrs1 <dbl+lbl>, sphrs2 <dbl+lbl>,
## #   spevwork <dbl+lbl>, cowrksta <dbl+lbl>, cowrkslf <dbl+lbl>,
## #   coevwork <dbl+lbl>, cohhrs1 <dbl+lbl>, cohhrs2 <dbl+lbl>, spwrkslf <dbl+lbl>,
## #   spocc10 <dbl+lbl>, sppres10 <dbl+lbl>, sppres105plus <dbl+lbl>,
## #   spind10 <dbl+lbl>, coocc10 <dbl+lbl>, coind10 <dbl+lbl>, ...
## # Keep only needed variables
gss_clean <- gss %>%
  select(polviews, age, educ, race, sex, occ10, region, marital) %>%
  # remove "Don't Know / NA / Refused / No answer"
  filter(!polviews %in% c(8, 9),      # GSS missing codes for polviews
         !is.na(polviews)) %>%
  # Convert categorical vars to factors
  mutate(
    polviews = as.integer(polviews),           # 1=ext lib ... 7=ext cons
    race = factor(race),
    sex = factor(sex),
    occ10 = factor(occ10),
    region = factor(region),
    marital = factor(marital)
  )
head(gss_clean)

## # A tibble: 6 x 8
##   polviews age      educ          race  sex  occ10 region marital
##   <int> <dbl> <dbl+lbl>       <fct> <fct> <fct> <fct> <fct>
## 1 4 33     16 [4 years of college] 2     1     230  1     5
## 2 3 64     16 [4 years of college] 1     1     800  1     5
## 3 1 69     14 [2 years of college] 1     2     430  1     1
## 4 4 70     13 [1 year of college]  1     2     5860 1     3
## 5 2 48     13 [1 year of college]  1     2     9640 1     1
## 6 4 30     14 [2 years of college] 1     2     3600 1     3

set.seed(123)  # makes the sample reproducible

sample100 <- gss_clean %>%
  drop_na() %>%          # removes any row with ANY missing value
  sample_n(100)

head(sample100)

## # A tibble: 6 x 8
##   polviews age      educ          race  sex  occ10 region marital
##   <int> <dbl> <dbl+lbl>       <fct> <fct> <fct> <fct> <fct>

```

```

## 1      4 67      16 [4 years of college] 1      1    1740  4      5
## 2      5 56      14 [2 years of college] 3      2     50   4      3
## 3      6 33      14 [2 years of college] 1      2    7750  2      5
## 4      3 24      16 [4 years of college] 1      2    2550  1      5
## 5      3 46      14 [2 years of college] 1      2    5610  4      1
## 6      4 25      12 [12th grade]           1      1    6440  3      5

sample100_nolabel <- sample100 %>%
  select(-polviews)      # remove the numeric ideology variable
head(sample100_nolabel)

## # A tibble: 6 x 7
##   age     educ             race   sex   occ10 region marital
##   <dbl>   <dbl>          <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 67      16 [4 years of college] 1      1    1740  4      5
## 2 56      14 [2 years of college] 3      2     50   4      3
## 3 33      14 [2 years of college] 1      2    7750  2      5
## 4 24      16 [4 years of college] 1      2    2550  1      5
## 5 46      14 [2 years of college] 1      2    5610  4      1
## 6 25      12 [12th grade]         1      1    6440  3      5

write.csv(sample100_nolabel, "gss_sample_100_unlabeled.csv", row.names = FALSE)

var <- read.csv("/Users/joyqu/Desktop/PLSC/gss_gpt5_var_predictions.csv")
head(var)

##   age educ race sex occ10 region marital pred_polview
##   1   67   16   1   1   1740     4     5       5
##   2   56   14   3   2    50     4     3       4
##   3   33   14   1   2   7750     2     5       4
##   4   24   16   1   2   2550     1     5       2
##   5   46   14   1   2   5610     4     1       5
##   6   25   12   1   1   6440     3     5       5

# Extract variables
y_true <- as.numeric(sample100$polviews)
y_pred <- as.numeric(var$pred_polview)

# Compute metrics
MAE <- mean(abs(y_true - y_pred))
MSE <- mean((y_true - y_pred)^2)
Accuracy <- mean(y_true == y_pred)
Within1 <- mean(abs(y_true - y_pred) <= 1)

cat("Mean Absolute Error:", MAE, "\n")

## Mean Absolute Error: 1.4
cat("Mean Squared Error:", MSE, "\n")

## Mean Squared Error: 3.04
cat("Exact Match Accuracy:", round(Accuracy*100, 1), "%\n")

## Exact Match Accuracy: 15 %
cat("Within ±1 Accuracy:", round(Within1*100, 1), "%\n")

## Within ±1 Accuracy: 66 %

```

```

narrative <- read.csv("/Users/joyqu/Desktop/PLSC/gss_gpt5_narrative_predictions.csv")
head(narrative)

##    id
## 1  1
## 2  2
## 3  3
## 4  4
## 5  5
## 6  6
##
## 1                               He is 67, a man in the West who values ...
## 2 She is 56 years old, she has settled into a steady rhythm in the West, where routines give structure ...
## 3                                     At 33, this woman in the Midwest balances work, personal commi...
## 4           She is 24, a woman living in the Northeast, still shaping her path in work and life. ...
## 5           She is 46 years old, she has settled into a steady rhythm in the West, where routines give ...
## 6                               He is 25, a man living in the South, still shaping ...

##    pred_polview_narr
## 1              5
## 2              4
## 3              5
## 4              3
## 5              5
## 6              5

# Extract variables
y_true <- as.numeric(sample100$polviews)
y_pred <- as.numeric(narrative$pred_polview_narr)

# Compute metrics
MAE <- mean(abs(y_true - y_pred))
MSE <- mean((y_true - y_pred)^2)
Accuracy <- mean(y_true == y_pred)
Within1 <- mean(abs(y_true - y_pred) <= 1)

cat("Mean Absolute Error:", MAE, "\n")

## Mean Absolute Error: 1.32
cat("Mean Squared Error:", MSE, "\n")

## Mean Squared Error: 2.72
cat("Exact Match Accuracy:", round(Accuracy*100, 1), "%\n")

## Exact Match Accuracy: 18 %
cat("Within ±1 Accuracy:", round(Within1*100, 1), "%\n")

## Within ±1 Accuracy: 67 %

library(dplyr)
library(readr)
library(caret)      # for confusionMatrix

## Loading required package: ggplot2
## Loading required package: lattice

```

```

library(MLmetrics) # for f1

##
## Attaching package: 'MLmetrics'

## The following objects are masked from 'package:caret':
##
##     MAE, RMSE

## The following object is masked from 'package:base':
##
##     Recall

library(purrr)

##
## Attaching package: 'purrr'

## The following object is masked from 'package:caret':
##
##     lift

library(dplyr)

df <- sample100 %>%
  mutate(row_id = row_number()) %>%
  select(
    row_id,
    POLVIEWS_TRUE = polviews,
    age, sex, race, educ, marital, occ10, region # <- keep whatever predictors you want
  ) %>%
  inner_join(
    var %>%
      mutate(row_id = row_number()) %>%
      select(row_id, pred_var = pred_polview),
    by = "row_id"
  ) %>%
  inner_join(
    narrative %>%
      mutate(row_id = row_number()) %>%
      select(row_id, pred_narr = pred_polview_narr),
    by = "row_id"
  )

library(dplyr)
f1_macro <- function(true, pred) {
  true <- as.character(true)
  pred <- as.character(pred)

  f1_scores <- sapply(unique(true), function(cls) {
    MLmetrics::F1_Score(
      y_pred = pred == cls,
      y_true = true == cls
    )
  })
  mean(f1_scores, na.rm = TRUE)
}

```

```

f1_weighted <- function(true, pred) {
  true <- as.character(true)
  pred <- as.character(pred)

  classes <- unique(true)
  weights <- prop.table(table(true))

  f1_scores <- sapply(classes, function(cls) {
    MLmetrics::F1_Score(
      y_pred = pred == cls,
      y_true = true == cls
    )
  })
}

sum(f1_scores * weights[names(f1_scores)], na.rm = TRUE)
}

# 1. Build df and KEEP ALL predictors from sample100
df <- sample100 %>%
  mutate(row_id = row_number()) %>%
  select(
    row_id,
    POLVIEWS_TRUE = polviews,
    # keep ALL predictors here:
    age,
    sex,
    race,
    educ,
    marital,
    occ10,
    region
  ) %>%
  inner_join(
    var %>%
      mutate(row_id = row_number()) %>%
      select(row_id, pred_var = pred_polview),
    by = "row_id"
  ) %>%
  inner_join(
    narrative %>%
      mutate(row_id = row_number()) %>%
      select(row_id, pred_narr = pred_polview_narr),
    by = "row_id"
  )

df <- df %>%
  mutate(
    # Factor version for F1
    POLVIEWS_TRUE_fac = factor(POLVIEWS_TRUE),
    pred_var_fac      = factor(pred_var, levels = levels(POLVIEWS_TRUE_fac)),
    pred_narr_fac     = factor(pred_narr, levels = levels(POLVIEWS_TRUE_fac)),

    # Numeric version for bias / error
  )

```

```

polviews_num = as.numeric(as.character(POLVIEWS_TRUE)),
pred_var_num = as.numeric(as.character(pred_var)),
pred_narr_num = as.numeric(as.character(pred_narr)),

# Signed errors
error_var = pred_var_num - polviews_num,
error_narr = pred_narr_num - polviews_num
)
results <- tibble(
  Model = c("Variable Model", "Narrative Model"),
  Macro_F1 = c(
    f1_macro(df$POLVIEWS_TRUE_fac, df$pred_var_fac),
    f1_macro(df$POLVIEWS_TRUE_fac, df$pred_narr_fac)
  ),
  Weighted_F1 = c(
    f1_weighted(df$POLVIEWS_TRUE_fac, df$pred_var_fac),
    f1_weighted(df$POLVIEWS_TRUE_fac, df$pred_narr_fac)
  )
)

print(results)

## # A tibble: 2 x 3
##   Model           Macro_F1  Weighted_F1
##   <chr>          <dbl>      <dbl>
## 1 Variable Model     0.841     0.784
## 2 Narrative Model    0.831     0.749

mislabeled_comparison <- df %>%
  mutate(
    # Wrong / right flags
    var_wrong = pred_var != POLVIEWS_TRUE,
    narr_wrong = pred_narr != POLVIEWS_TRUE,

    # Case types with only two models
    case_type = case_when(
      var_wrong & !narr_wrong ~ "Only Variable Model Wrong",
      !var_wrong & narr_wrong ~ "Only Narrative Model Wrong",
      var_wrong & narr_wrong ~ "Both Wrong",
      TRUE ~ "Both Correct"
    ),

    # Differences vs true (numeric scale 1-7)
    diff_var = as.numeric(pred_var) - as.numeric(POLVIEWS_TRUE),
    diff_narr = as.numeric(pred_narr) - as.numeric(POLVIEWS_TRUE),

    # Bias direction for each model (only label as too lib/con if it's wrong)
    bias_var = dplyr::case_when(
      !var_wrong ~ "Correct",
      diff_var > 0 ~ "Too Conservative",
      diff_var < 0 ~ "Too Liberal",
      TRUE ~ NA_character_
    ),
    bias_narr = dplyr::case_when(

```

```

!narr_wrong      ~ "Correct",
diff_narr > 0    ~ "Too Conservative",
diff_narr < 0    ~ "Too Liberal",
TRUE            ~ NA_character_
)
) %>%
select(
  row_id, POLVIEWS_TRUE,
  pred_var, pred_narr,
  var_wrong, narr_wrong,
  case_type,
  bias_var, bias_narr
)

# Save to CSV
write.csv(mislabeled_comparison,
          "mislabeled_cases_comparison.csv",
          row.names = FALSE)

bias_table <- mislabeled_comparison %>%
  select(bias_var, bias_narr) %>%
  tidyr::pivot_longer(
    cols      = everything(),
    names_to  = "model",
    values_to = "bias"
  ) %>%
  dplyr::filter(bias != "Correct") %>%    # only mislabeled cases
  dplyr::group_by(model, bias) %>%
  dplyr::summarise(count = dplyr::n(), .groups = "drop_last") %>%
  dplyr::mutate(
    percent = count / sum(count) * 100
  ) %>%
  dplyr::ungroup() %>%
  dplyr::mutate(
    model = dplyr::recode(
      model,
      bias_var  = "Variable Model",
      bias_narr = "Narrative Model"
    )
  ) %>%
  dplyr::arrange(model, bias)
bias_table

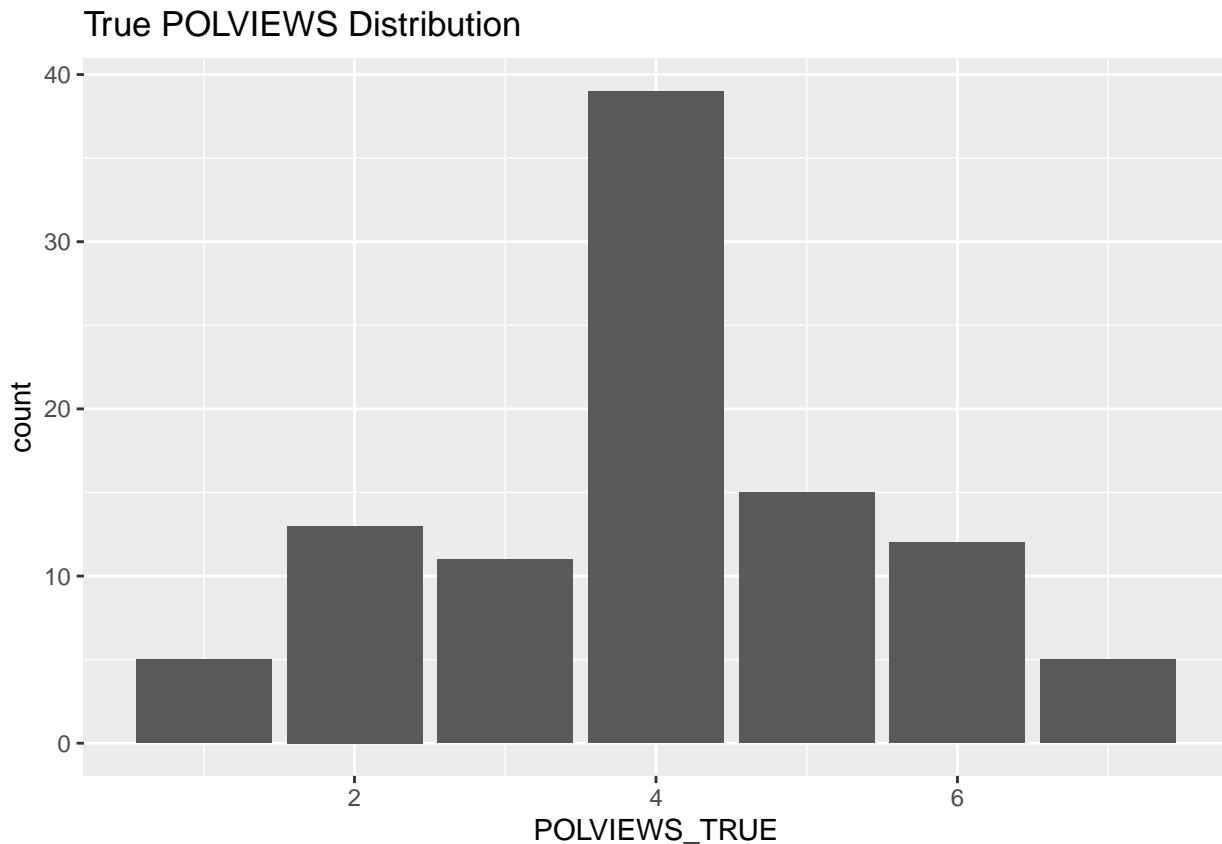
## # A tibble: 4 x 4
##   model           bias       count  percent
##   <chr>         <chr>     <int>    <dbl>
## 1 Narrative Model Too Conservative    57    69.5
## 2 Narrative Model Too Liberal        25    30.5
## 3 Variable Model  Too Conservative   58    68.2
## 4 Variable Model  Too Liberal       27    31.8

#true polviews distribution
library(ggplot2)

ggplot(df, aes(x = POLVIEWS_TRUE)) +

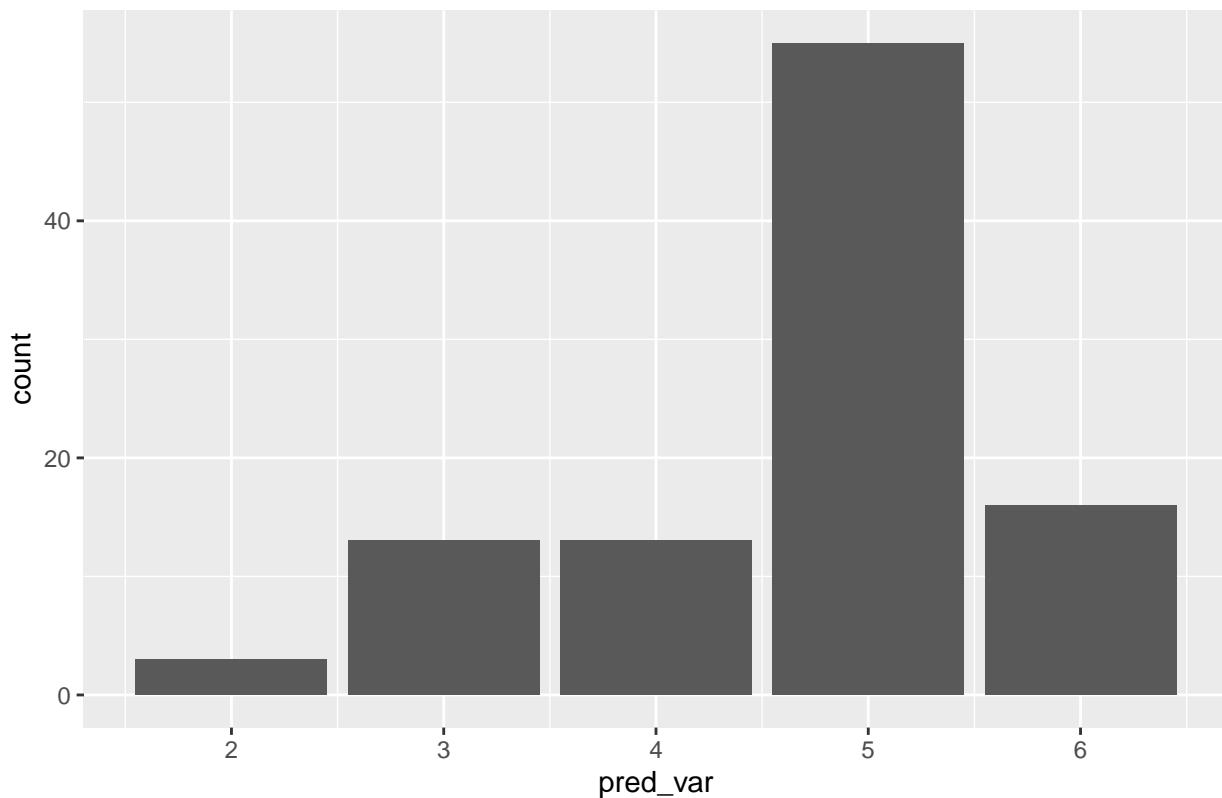
```

```
geom_bar() +
ggtitle("True POLVIEWS Distribution")
```



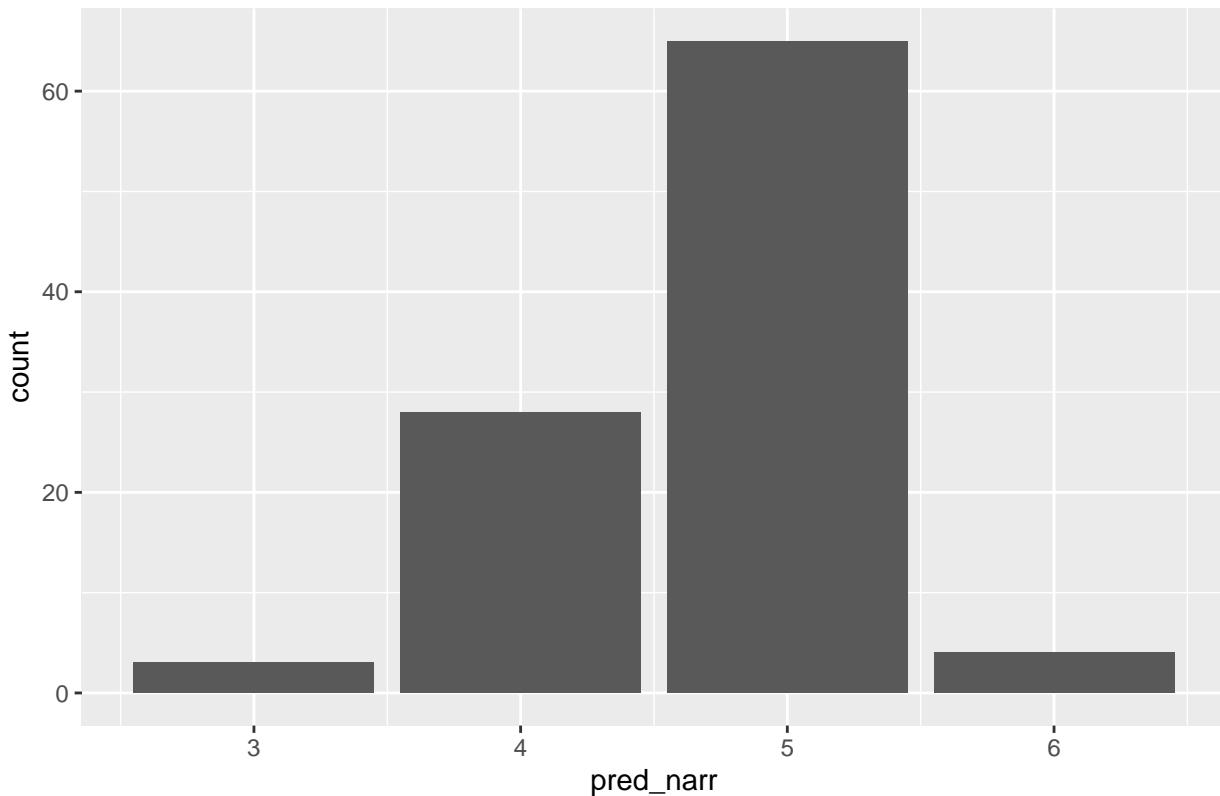
```
ggplot(df, aes(x = pred_var)) +
  geom_bar() +
  ggtitle("Variable Model Pred Distribution")
```

Variable Model Pred Distribution



```
ggplot(df, aes(x = pred_narr)) +  
  geom_bar() +  
  ggtitle("Narrative Model Pred Distribution")
```

Narrative Model Pred Distribution



```
library(dplyr)

df <- df %>%
  mutate(
    POLVIEWS_TRUE = as.numeric(as.character(POLVIEWS_TRUE)),
    pred_var      = as.numeric(as.character(pred_var)),
    pred_narr     = as.numeric(as.character(pred_narr))
  )
df <- df %>%
  mutate(
    error_var   = pred_var - POLVIEWS_TRUE,
    error_narr  = pred_narr - POLVIEWS_TRUE
  )

summary(df$error_var)

##      Min. 1st Qu. Median      Mean 3rd Qu.      Max.
##    -3.00   -1.00   1.00     0.66   2.00   5.00

summary(df$error_narr)

##      Min. 1st Qu. Median      Mean 3rd Qu.      Max.
##    -2.00   -0.25   1.00     0.68   2.00   4.00

mean(df$error_var, na.rm = TRUE) # > 0 => too conservative on average

## [1] 0.66
```

```

mean(df$error_narr, na.rm = TRUE)

## [1] 0.68

bias_by_predictor <- function(data, predictor) {
  data %>%
    group_by({{ predictor }}) %>%
    summarise(
      n = n(),
      mean_error_var = mean(error_var, na.rm = TRUE),
      mean_error_narr = mean(error_narr, na.rm = TRUE),

      prop_too_cons_var = mean(error_var > 0, na.rm = TRUE),
      prop_too_lib_var = mean(error_var < 0, na.rm = TRUE),

      prop_too_cons_narr = mean(error_narr > 0, na.rm = TRUE),
      prop_too_lib_narr = mean(error_narr < 0, na.rm = TRUE)
    ) %>%
    arrange(desc(mean_error_var))
}

bias_by_predictor(df, age)

## # A tibble: 50 x 8
##   age     n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <dbl> <int>       <dbl>        <dbl>          <dbl>          <dbl>
## 1 79     1         4           3             1             0
## 2 49     2         3           2.5            1             0
## 3 73     1         3           3             1             0
## 4 76     1         3           2             1             0
## 5 82     1         3           2             1             0
## 6 83     4         2.75        2             1             0
## 7 74     1         2           1             1             0
## 8 58     4         1.75        1.5            0.75          0
## 9 70     3         1.67        0.667          1             0
## 10 63    5         1.6          1.4            0.8            0.2
## # i 40 more rows
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
bias_by_predictor(df, sex)

## # A tibble: 2 x 8
##   sex     n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <fct> <int>       <dbl>        <dbl>          <dbl>          <dbl>
## 1 2      47         0.723       0.681          0.532          0.277
## 2 1      53         0.604       0.679          0.623          0.264
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
bias_by_predictor(df, race)

## # A tibble: 3 x 8
##   race     n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <fct> <int>       <dbl>        <dbl>          <dbl>          <dbl>
## 1 2      13         0.846       1.31           0.692          0.231
## 2 1      77         0.727       0.584           0.597          0.234
## 3 3      10         -0.1        0.6            0.3            0.6
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>

```

```

bias_by_predictor(df, educ)

## # A tibble: 14 x 8
##   educ          n mean_error_var mean_error_narr prop_too_cons_var
##   <dbl+lbl>    <int>      <dbl>        <dbl>            <dbl>
## 1 20 [8 or more years o~     2         4           3           1
## 2 19 [7 years of colleg~    1         3           3           1
## 3 13 [1 year of college]   6        1.5          1.33        0.667
## 4 15 [3 years of colleg~   29        1           1           1
## 5 16 [4 years of colleg~   26        0.923        0.577        0.654
## 6 12 [12th grade]          21        0.667        0.714        0.619
## 7 14 [2 years of colleg~   20        0.55          0.85        0.65
## 8 6 [6th grade]             1         0           1           0
## 9 11 [11th grade]          1         0           1           0
## 10 18 [6 years of colleg~  7          0           0           0.429
## 11 17 [5 years of colleg~  9        -0.111        0.222        0.333
## 12 10 [10th grade]          2        -0.5           0           0
## 13 9 [9th grade]            1        -1           -1           0
## 14 0 [no formal schooli~   1        -2           -1           0
## # i 3 more variables: prop_too_lib_var <dbl>, prop_too_cons_narr <dbl>,
## #   prop_too_lib_narr <dbl>

bias_by_predictor(df, marital)

## # A tibble: 4 x 8
##   marital          n mean_error_var mean_error_narr prop_too_cons_var
##   <fct>    <int>      <dbl>        <dbl>            <dbl>
## 1 2                 8       1.62          1           0.75
## 2 1                44       0.841         0.5          0.636
## 3 3                16       0.812         0.625        0.625
## 4 5                32       0.0938        0.875        0.438
## # i 3 more variables: prop_too_lib_var <dbl>, prop_too_cons_narr <dbl>,
## #   prop_too_lib_narr <dbl>

bias_by_predictor(df, occ10)

## # A tibble: 73 x 8
##   occ10          n mean_error_var mean_error_narr prop_too_cons_var prop_too_cons_narr
##   <fct>    <int>      <dbl>        <dbl>            <dbl>            <dbl>
## 1 2200          1       5           4           1           0
## 2 5120          1       4           3           1           0
## 3 9620          1       4           4           1           0
## 4 710           2       3           2.5          1           0
## 5 735           1       3           2           1           0
## 6 1460          1       3           3           1           0
## 7 3645          1       3           2           1           0
## 8 5600          1       3           3           1           0
## 9 5820          1       3           3           1           0
## 10 1050          1      2           1           1           0
## # i 63 more rows
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>

bias_by_predictor(df, region)

## # A tibble: 4 x 8
##   region          n mean_error_var mean_error_narr prop_too_cons_var prop_too_cons_narr
##   <fct>    <int>      <dbl>        <dbl>            <dbl>            <dbl>

```

```

##   <fct>  <int>      <dbl>      <dbl>      <dbl>      <dbl>
## 1 3       37       1.05      0.811     0.595     0.189
## 2 2       24       0.667     0.625     0.583     0.292
## 3 1       12       0.583     0.75      0.667     0.25
## 4 4       27       0.148     0.519     0.519     0.370
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
#when mean error > 0, this predictor is more conservative on average
#prop_too_cons_var: proportion of cases where variable model is too conservative

df$occ10 <- as.numeric(as.character(df$occ10))

label_maps <- list(
  # ---- Gender ----
  sex = c(
    "1" = "Male",
    "2" = "Female"
  ),
  # ---- Race ----
  race = c(
    "1" = "White",
    "2" = "Black",
    "3" = "Other"
  ),
  # ---- Marital Status ----
  marital = c(
    "1" = "Married",
    "2" = "Widowed",
    "3" = "Divorced",
    "4" = "Separated",
    "5" = "Never married"
  ),
  # ---- Region: your custom 1-4 mapping ----
  region = c(
    "1" = "Northeast",
    "2" = "Midwest",
    "3" = "South",
    "4" = "West"
  ),
  # ---- OCC10 major category mapping ----
  # We'll assign labels based on ranges inside the function
  occ10 = c(
    "0010-0950" = "Management/Professional",
    "1000-1240" = "Service",
    "1300-1965" = "Sales/Office",
    "2000-3955" = "Construction/Maintenance",
    "4000-5940" = "Production/Transportation",
    "5950-9750" = "Military"
  )
)

```

```

map_occ10 <- function(code) {
  if (is.na(code)) return(NA_character_)
  if (code >= 10 & code <= 950) return("Management/Professional")
  if (code >= 1000 & code <= 1240) return("Service")
  if (code >= 1300 & code <= 1965) return("Sales/Office")
  if (code >= 2000 & code <= 3955) return("Construction/Maintenance")
  if (code >= 4000 & code <= 5940) return("Production/Transportation")
  if (code >= 5950 & code <= 9830) return("Military")
  return(NA_character_)
}

bucket_age <- function(a) {
  dplyr::case_when(
    is.na(a) ~ NA_character_,
    a < 30 ~ "18-29",
    a >= 30 & a < 45 ~ "30-44",
    a >= 45 & a < 65 ~ "45-64",
    a >= 65 ~ "65+",
    TRUE ~ NA_character_
  )
}

plot_mean_error_by_predictor <- function(data, predictor) {

  pred_sym <- rlang::ensym(predictor)
  pred_name <- rlang::as_name(pred_sym)

  summary_df <- data %>%
    dplyr::group_by (!!pred_sym) %>%
    dplyr::summarise(
      n = dplyr::n(),
      mean_error_var = mean(error_var, na.rm = TRUE),
      mean_error_narr = mean(error_narr, na.rm = TRUE),
      .groups = "drop"
    ) %>%
    tidyr::pivot_longer(
      cols = c(mean_error_var, mean_error_narr),
      names_to = "model",
      values_to = "mean_error"
    ) %>%
    dplyr::mutate(
      model = dplyr::recode(
        model,
        mean_error_var = "Variable model",
        mean_error_narr = "Narrative model"
      )
    )

  # Now add human-readable labels
  if (pred_name == "occ10") {

    summary_df <- summary_df %>%
      dplyr::mutate(
        predictor_label = vapply(.data[[pred_name]], map_occ10, character(1))
  }
}

```

```

    )

} else if (pred_name == "age") {

  # use age buckets instead of raw ages
  summary_df <- summary_df %>%
    dplyr::mutate(
      predictor_label = bucket_age(.data[[pred_name]])
    )
} else if (pred_name == "educ") {

  summary_df <- summary_df %>%
    dplyr::mutate(
      predictor_label = factor(
        as.numeric(.data[[pred_name]]),
        levels = sort(unique(as.numeric(.data[[pred_name]])))
      )
    )
}

} else if (pred_name %in% names(label_maps)) {

  map_vec <- label_maps[[pred_name]]

  summary_df <- summary_df %>%
    dplyr::mutate(
      predictor_label = map_vec[as.character(.data[[pred_name]])]
    )
}

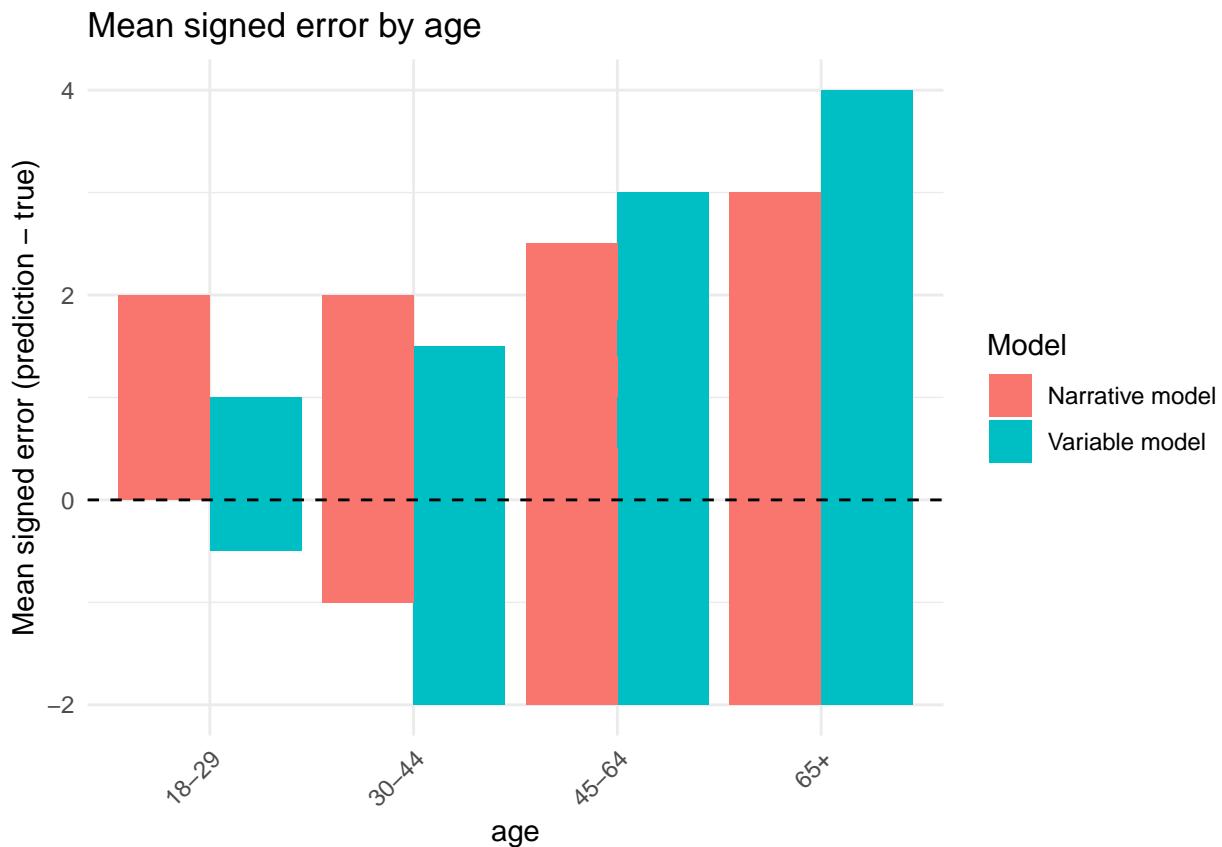
} else {

  summary_df <- summary_df %>%
    dplyr::mutate(
      predictor_label = as.character(.data[[pred_name]])
    )
}

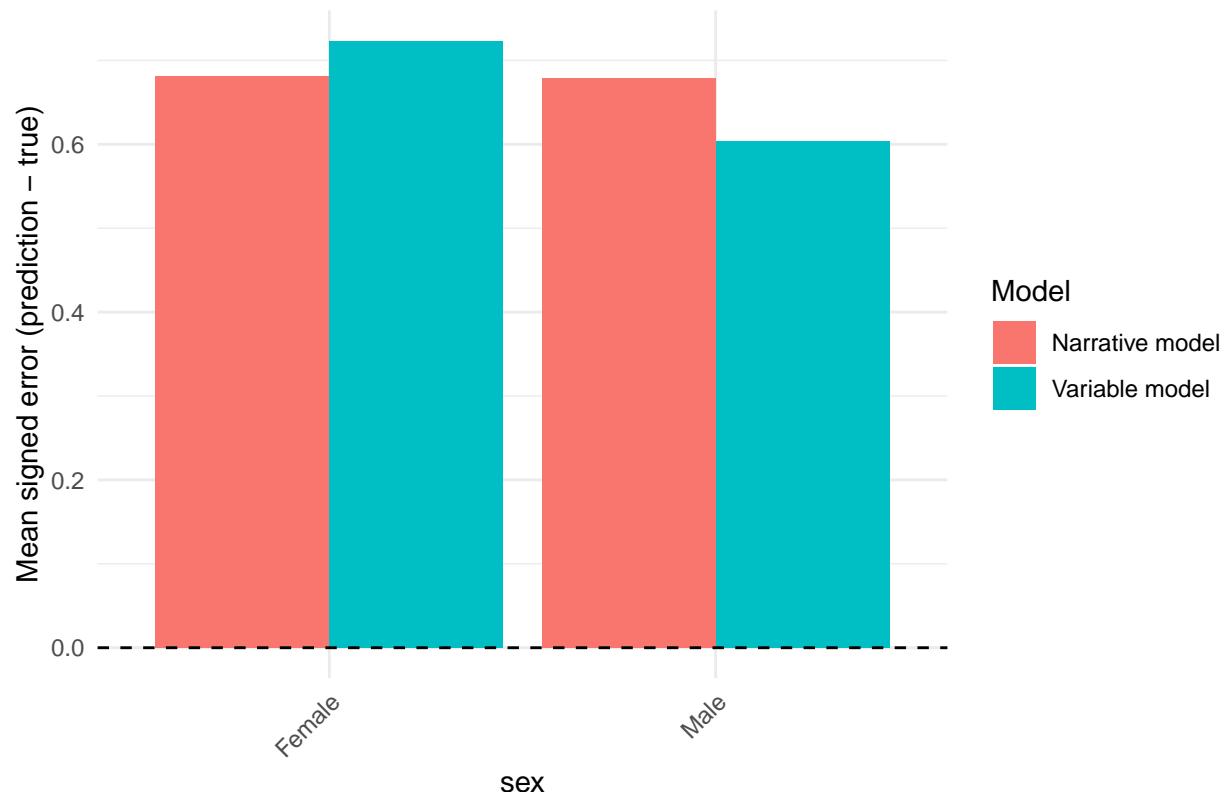
ggplot(summary_df,
       aes(x = predictor_label,
           y = mean_error,
           fill = model)) +
  geom_col(position = "dodge") +
  geom_hline(yintercept = 0, linetype = "dashed") +
  labs(
    title = paste("Mean signed error by", pred_name),
    x = pred_name,
    y = "Mean signed error (prediction - true)",
    fill = "Model"
  ) +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
}

plot_mean_error_by_predictor(df, age)

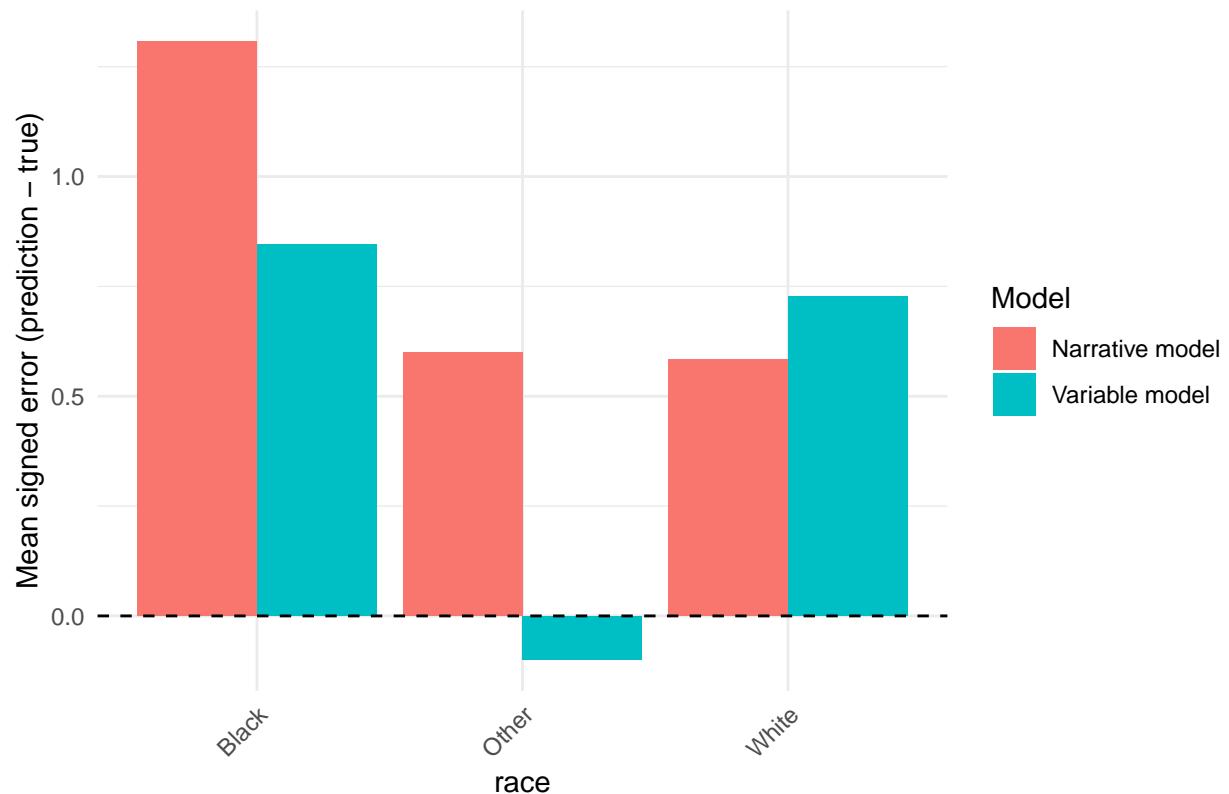
```



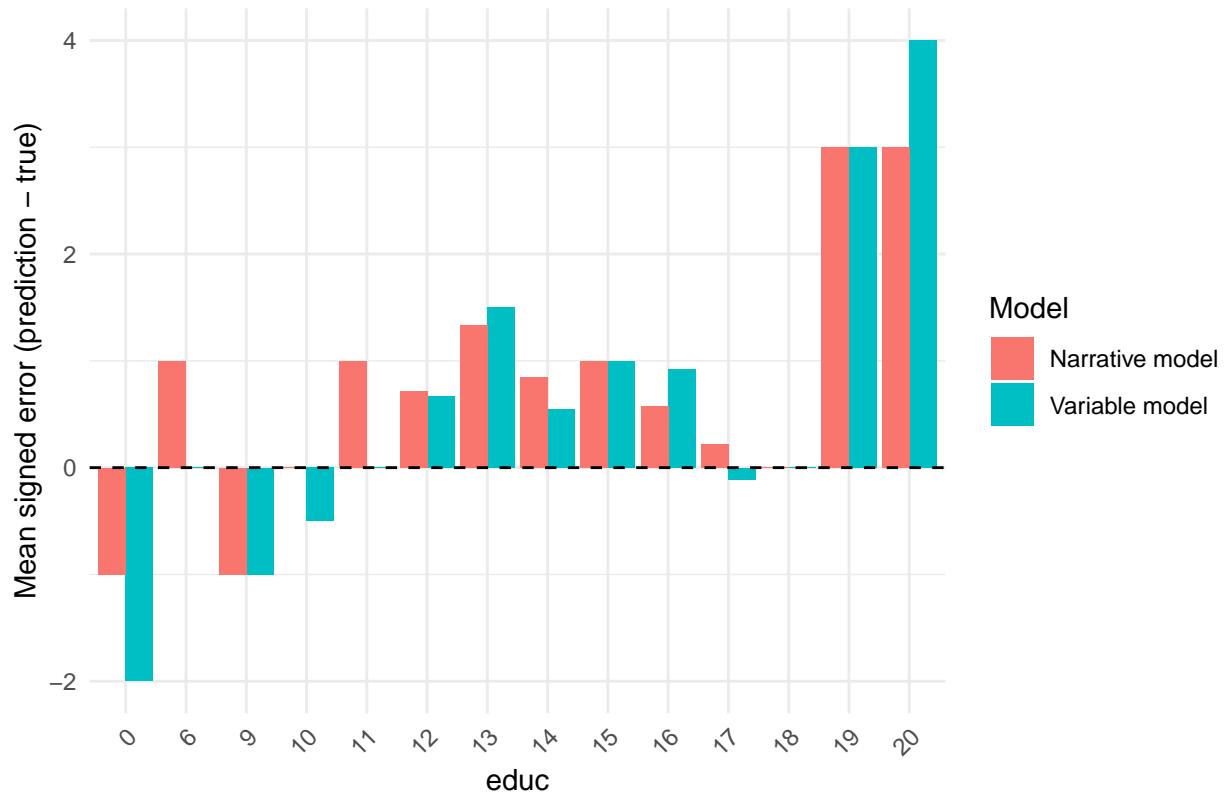
Mean signed error by sex



Mean signed error by race

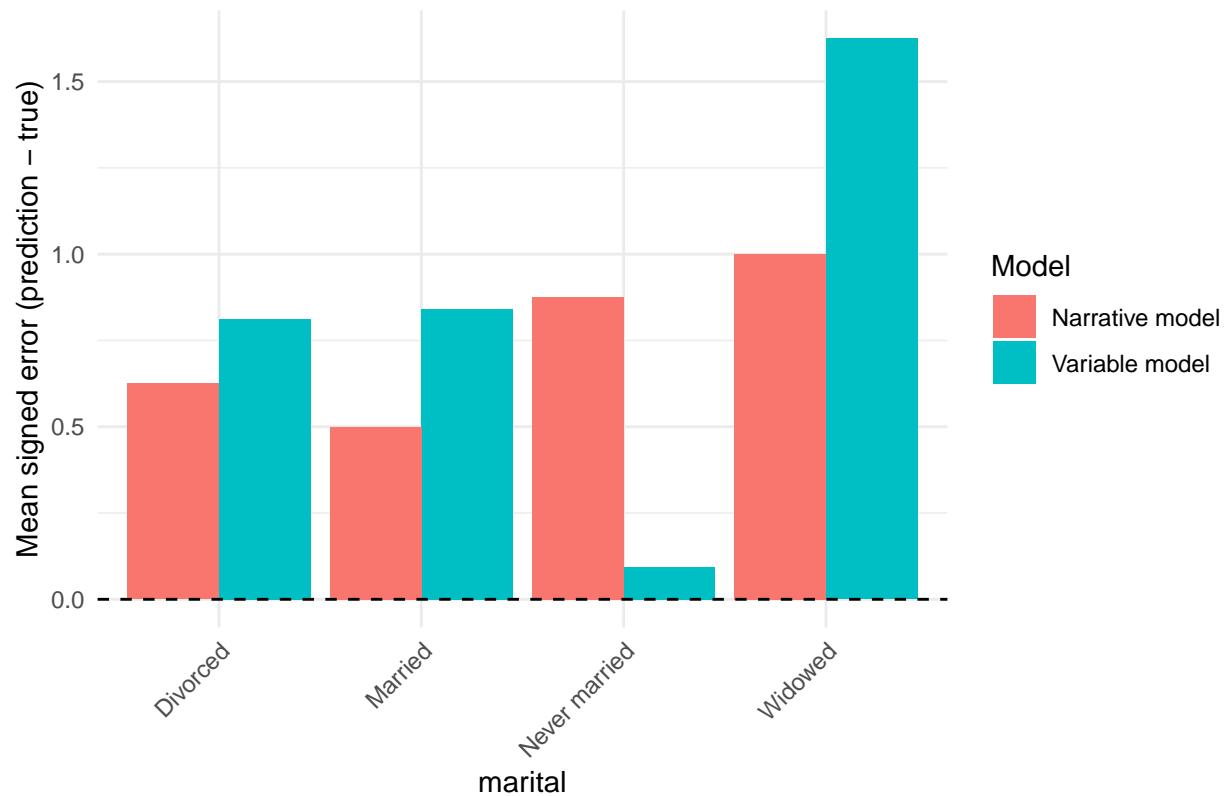


Mean signed error by educ



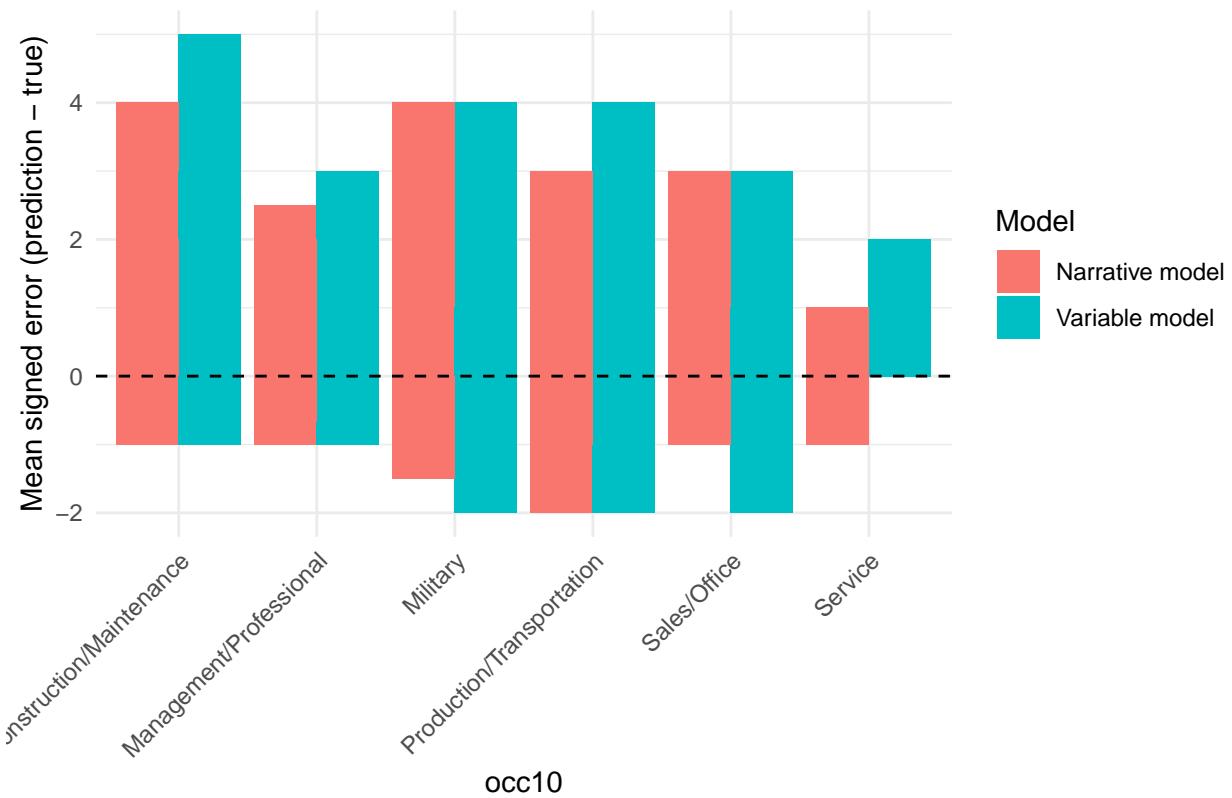
```
plot_mean_error_by_predictor(df, marital)
```

Mean signed error by marital



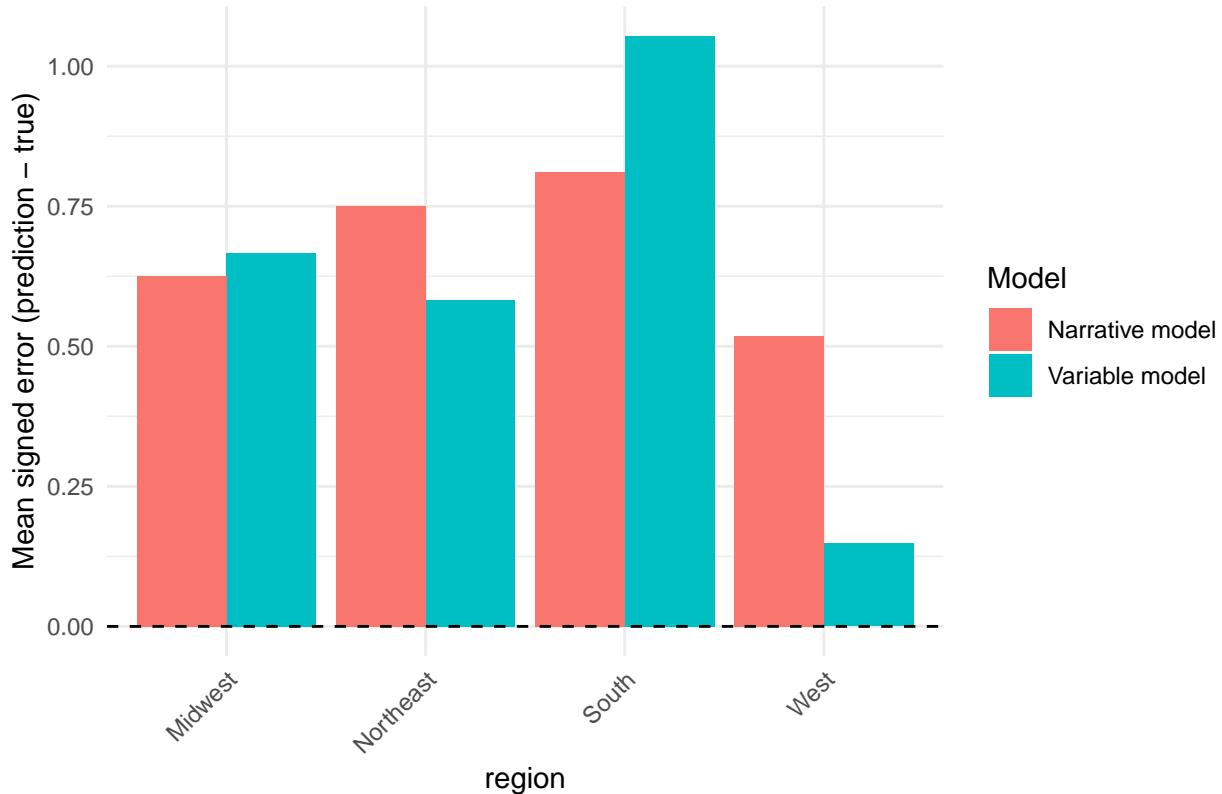
```
plot_mean_error_by_predictor(df, occ10)
```

Mean signed error by occ10



```
plot_mean_error_by_predictor(df, region)
```

Mean signed error by region



```
#collapse POLVIEWS into two categories: conservative or not conservative
```

```
sample100_binary <- sample100 %>%
  mutate(
    polviews_binary = case_when(
      polviews %in% c(1, 2, 3, 4) ~ 0,    # Not conservative
      polviews %in% c(5, 6, 7) ~ 1,      # Conservative
    )
  ) %>%
  filter(!is.na(polviews_binary))
head(sample100_binary)
```

```
## # A tibble: 6 x 9
##   polviews age       educ      race sex   occ10 region marital polviews_binary
##   <int> <dbl> <dbl+lbl> <dbl+lbl> <fct> <fct> <fct> <fct> <dbl>
## 1      4 67        16 [4 yea~ 1     1    1740  4     5             0
## 2      5 56        14 [2 yea~ 3     2     50    4     3             1
## 3      6 33        14 [2 yea~ 1     2    7750  2     5             1
## 4      3 24        16 [4 yea~ 1     2    2550  1     5             0
## 5      3 46        14 [2 yea~ 1     2    5610  4     1             0
## 6      4 25        12 [12th ~ 1     1    6440  3     5             0
```

```
sample100_nolabel_bin <- sample100_binary %>%
  select(-polviews_binary) %>% # remove the binary ideology variable
  select(-polviews) # remove the numeric ideology variable
```

```
head(sample100_nolabel_bin)
```

```

## # A tibble: 6 x 7
##   age      educ          race  sex  occ10 region marital
##   <dbl> <dbl+lbl> <fct> <fct> <fct> <fct> <fct>
## 1 67      16 [4 years of college] 1     1    1740  4     5
## 2 56      14 [2 years of college] 3     2     50   4     3
## 3 33      14 [2 years of college] 1     2    7750  2     5
## 4 24      16 [4 years of college] 1     2    2550  1     5
## 5 46      14 [2 years of college] 1     2    5610  4     1
## 6 25      12 [12th grade]        1     1    6440  3     5
write.csv(sample100_nolabel_bin, "gss_sample_100_unlabeled_bin.csv", row.names = FALSE)

var_bin <- read.csv("/Users/joyqu/Desktop/PLSC/gss_gpt5_var_predictions_bin.csv")
head(var_bin)

##   age educ race sex occ10 region marital pred_polview
##   1   67   16   1   1   1740     4     5         1
##   2   56   14   3   2    50     4     3         0
##   3   33   14   1   2   7750     2     5         0
##   4   24   16   1   2   2550     1     5         0
##   5   46   14   1   2   5610     4     1         0
##   6   25   12   1   1   6440     3     5         1

# Extract variables
y_true_bin <- as.numeric(sample100_binary$polviews_binary)
y_pred_bin <- as.numeric(var_bin$pred_polview)

# Compute metrics
MAE <- mean(abs(y_true_bin - y_pred_bin))
MSE <- mean((y_true_bin - y_pred_bin)^2)
Accuracy <- mean(y_true_bin == y_pred_bin)
Within1 <- mean(abs(y_true_bin - y_pred_bin) <= 1)

cat("Mean Absolute Error:", MAE, "\n")

## Mean Absolute Error: 0.53
cat("Mean Squared Error:", MSE, "\n")

## Mean Squared Error: 0.53
cat("Exact Match Accuracy:", round(Accuracy*100, 1), "%\n")

## Exact Match Accuracy: 47 %
cat("Within ±1 Accuracy:", round(Within1*100, 1), "%\n")

## Within ±1 Accuracy: 100 %

narrative_bin <- read.csv("/Users/joyqu/Desktop/PLSC/gss_gpt5_narrative_predictions_bin.csv")
head(narrative_bin)

##   id
## 1 1
## 2 2
## 3 3
## 4 4
## 5 5
## 6 6

```

```

##                                     He is 67, a man in the West who values ...
## 1
## 2 She is 56 years old, she has settled into a steady rhythm in the West, where routines give structure ...
## 3                                     At 33, this woman in the Midwest balances work, personal commitments ...
## 4 She is 24, a woman living in the Northeast, still shaping her path in work and life. ...
## 5 She is 46 years old, she has settled into a steady rhythm in the West, where routines give ...
## 6                                     He is 25, a man living in the South, still shaping ...

##   pred_polview_narr
## 1           1
## 2           1
## 3           1
## 4           0
## 5           1
## 6           1

# Extract variables
y_true_bin <- as.numeric(sample100_binary$polviews_binary)
y_pred_bin <- as.numeric(narrative_bin$pred_polview_narr)

# Compute metrics
MAE <- mean(abs(y_true_bin - y_pred_bin))
MSE <- mean((y_true_bin - y_pred_bin)^2)
Accuracy <- mean(y_true_bin == y_pred_bin)
Within1 <- mean(abs(y_true_bin - y_pred_bin) <= 1)

cat("Mean Absolute Error:", MAE, "\n")

## Mean Absolute Error: 0.61
cat("Mean Squared Error:", MSE, "\n")

## Mean Squared Error: 0.61
cat("Exact Match Accuracy:", round(Accuracy*100, 1), "%\n")

## Exact Match Accuracy: 39 %
cat("Within ±1 Accuracy:", round(Within1*100, 1), "%\n")

## Within ±1 Accuracy: 100 %

df_bin <- sample100_binary %>%
  mutate(row_id = row_number()) %>%
  select(
    row_id,
    POLVIEWS_TRUE = polviews_binary,
    age, sex, race, educ, marital, occ10, region    # <- keep whatever predictors you want
  ) %>%
  inner_join(
    var_bin %>%
      mutate(row_id = row_number()) %>%
      select(row_id, pred_var = pred_polview),
    by = "row_id"
  ) %>%
  inner_join(
    narrative_bin %>%
      mutate(row_id = row_number())
  )

```

```

    select(row_id, pred_narr = pred_polview_narr),
    by = "row_id"
)
head(df_bin)

## # A tibble: 6 x 11
##   row_id POLVIEWS_TRUE age   sex   race   educ   marital occ10 region pred_var
##   <int>      <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1     1        0.67    1     1     16 [4 y~ 5       1740   4     1
## 2     2        1.56    2     3     14 [2 y~ 3       50     4     0
## 3     3        1.33    2     1     14 [2 y~ 5       7750   2     0
## 4     4        0.24    2     1     16 [4 y~ 5       2550   1     0
## 5     5        0.46    2     1     14 [2 y~ 1       5610   4     0
## 6     6        0.25    1     1     12 [12t~ 5       6440   3     1
## # i 1 more variable: pred_narr <int>

df_bin <- df_bin %>%
  mutate(
    # Factor version for F1
    POLVIEWS_TRUE_fac = factor(POLVIEWS_TRUE),
    pred_var_fac      = factor(pred_var, levels = levels(POLVIEWS_TRUE_fac)),
    pred_narr_fac     = factor(pred_narr, levels = levels(POLVIEWS_TRUE_fac)),

    # Numeric version for bias / error
    polviews_num = as.numeric(as.character(POLVIEWS_TRUE)),
    pred_var_num = as.numeric(as.character(pred_var)),
    pred_narr_num = as.numeric(as.character(pred_narr)),

    # Signed errors
    error_var  = pred_var_num - polviews_num,
    error_narr = pred_narr_num - polviews_num
  )
results <- tibble(
  Model = c("Variable Model", "Narrative Model"),
  Macro_F1 = c(
    f1_macro(df_bin$POLVIEWS_TRUE_fac, df_bin$pred_var_fac),
    f1_macro(df_bin$POLVIEWS_TRUE_fac, df_bin$pred_narr_fac)
  ),
  Weighted_F1 = c(
    f1_weighted(df_bin$POLVIEWS_TRUE_fac, df_bin$pred_var_fac),
    f1_weighted(df_bin$POLVIEWS_TRUE_fac, df_bin$pred_narr_fac)
  )
)

print(results)

## # A tibble: 2 x 3
##   Model           Macro_F1 Weighted_F1
##   <chr>          <dbl>     <dbl>
## 1 Variable Model  0.467     0.454
## 2 Narrative Model 0.385     0.405

mislabeled_comparison <- df_bin %>%
  mutate(
    # Wrong / right flags

```

```

var_wrong = pred_var != POLVIEWS_TRUE,
narr_wrong = pred_narr != POLVIEWS_TRUE,

# Case types with only two models
case_type = case_when(
  var_wrong & !narr_wrong ~ "Only Variable Model Wrong",
  !var_wrong & narr_wrong ~ "Only Narrative Model Wrong",
  var_wrong & narr_wrong ~ "Both Wrong",
  TRUE                 ~ "Both Correct"
),

# Differences vs true (numeric scale 1-7)
diff_var = as.numeric(pred_var) - as.numeric(POLVIEWS_TRUE),
diff_narr = as.numeric(pred_narr) - as.numeric(POLVIEWS_TRUE),

# Bias direction for each model (only label as too lib/con if it's wrong)
bias_var = dplyr:::case_when(
  !var_wrong           ~ "Correct",
  diff_var > 0        ~ "Too Conservative",
  diff_var < 0        ~ "Too Liberal",
  TRUE                ~ NA_character_
),
bias_narr = dplyr:::case_when(
  !narr_wrong          ~ "Correct",
  diff_narr > 0        ~ "Too Conservative",
  diff_narr < 0        ~ "Too Liberal",
  TRUE                ~ NA_character_
)
) %>%
select(
  row_id, POLVIEWS_TRUE,
  pred_var, pred_narr,
  var_wrong, narr_wrong,
  case_type,
  bias_var, bias_narr
)

# Save to CSV
write.csv(mislabeled_comparison,
          "mislabeled_cases_comparison_bin.csv",
          row.names = FALSE)

bias_table <- mislabeled_comparison %>%
  select(bias_var, bias_narr) %>%
  tidyr::pivot_longer(
    cols      = everything(),
    names_to  = "model",
    values_to = "bias"
) %>%
  dplyr::filter(bias != "Correct") %>%    # only mislabeled cases
  dplyr::group_by(model, bias) %>%
  dplyr::summarise(count = dplyr::n(), .groups = "drop_last") %>%
  dplyr::mutate(

```

```

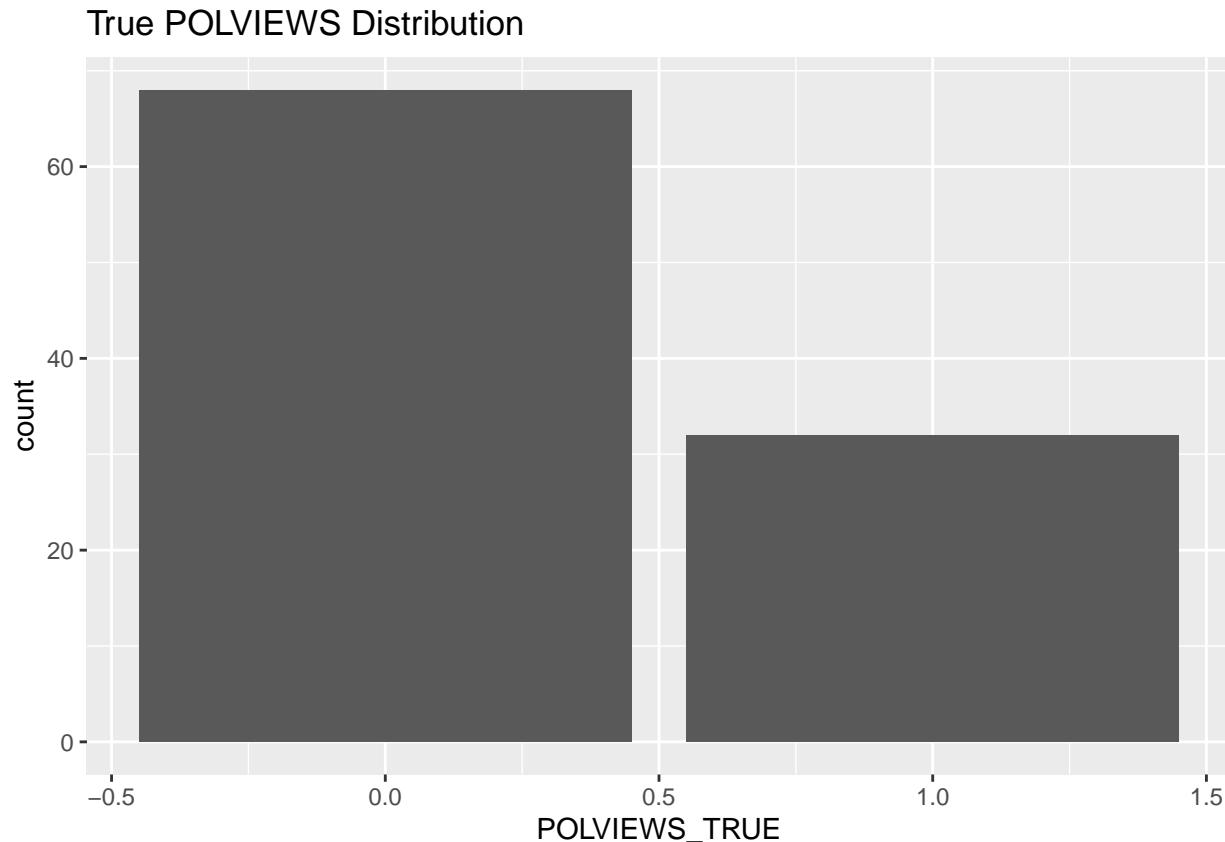
percent = count / sum(count) * 100
) %>%
dplyr::ungroup() %>%
dplyr::mutate(
  model = dplyr::recode(
    model,
    bias_var = "Variable Model",
    bias_narr = "Narrative Model"
  )
) %>%
dplyr::arrange(model, bias)
bias_table

## # A tibble: 4 x 4
##   model      bias     count percent
##   <chr>     <chr>     <int>   <dbl>
## 1 Narrative Model Too Conservative  53    86.9
## 2 Narrative Model Too Liberal      8     13.1
## 3 Variable Model Too Conservative  41    77.4
## 4 Variable Model Too Liberal      12    22.6

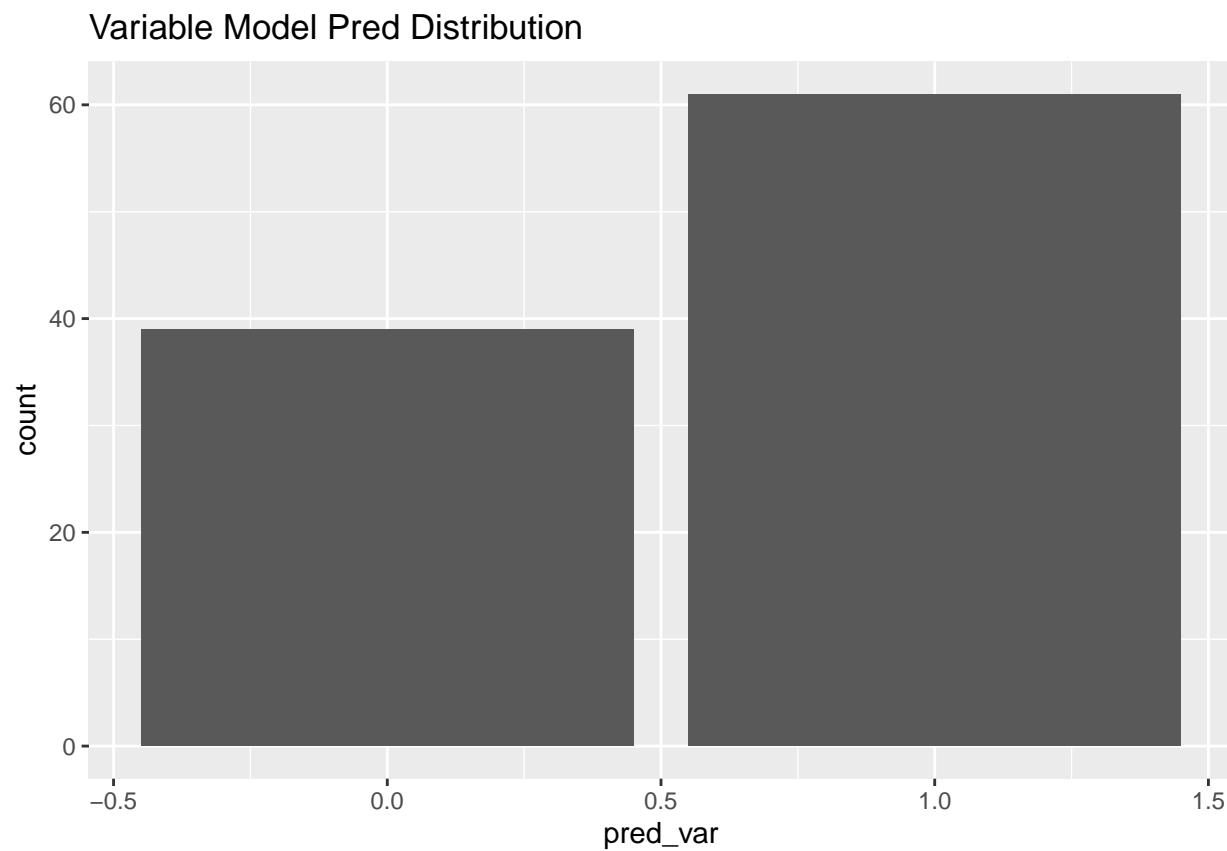
#true polviews distribution

ggplot(df_bin, aes(x = POLVIEWS_TRUE)) +
  geom_bar() +
  ggtitle("True POLVIEWS Distribution")

```

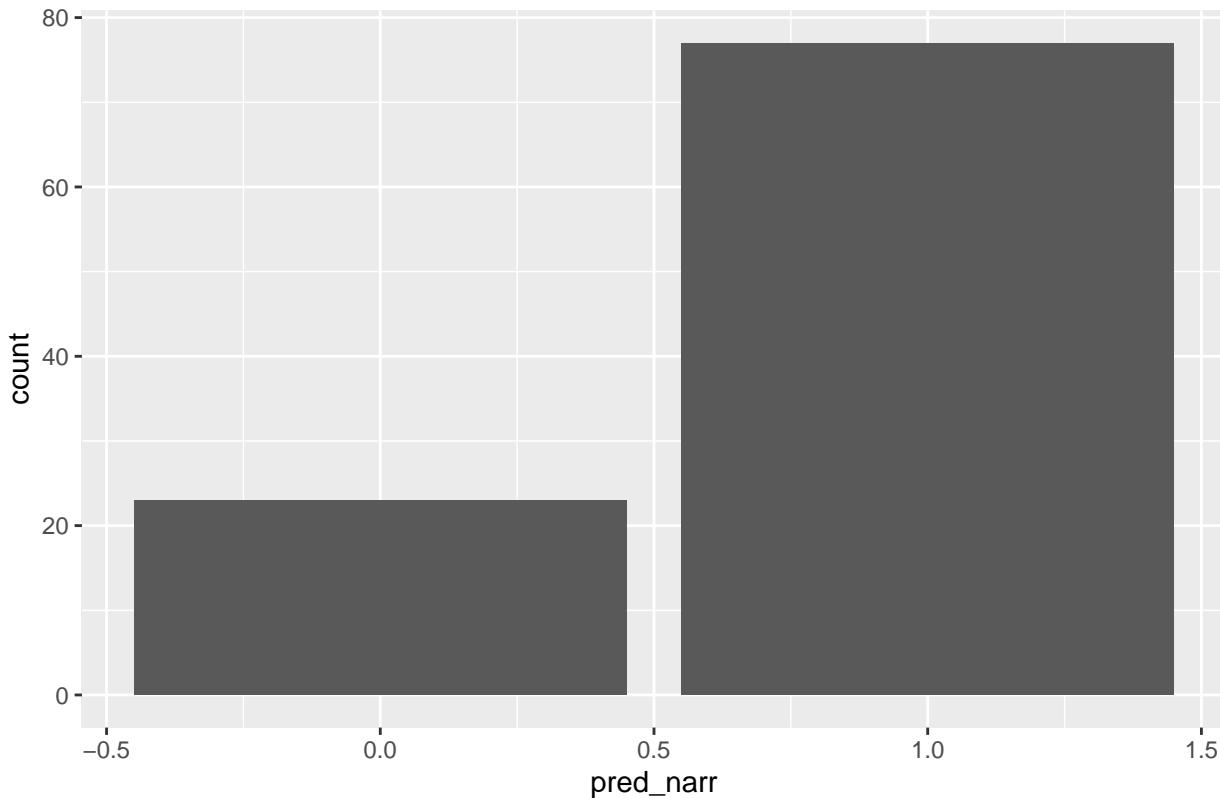


```
ggplot(df_bin, aes(x = pred_var)) +  
  geom_bar() +  
  ggtitle("Variable Model Pred Distribution")
```



```
ggplot(df_bin, aes(x = pred_narr)) +  
  geom_bar() +  
  ggtitle("Narrative Model Pred Distribution")
```

Narrative Model Pred Distribution



```
df_bin$occ10 <- as.numeric(as.character(df_bin$occ10))
bias_by_predictor(df_bin, age)

## # A tibble: 50 x 8
##   age      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <dbl> <int>      <dbl>          <dbl>            <dbl>            <dbl>
## 1 21      1        1           1              1               1               0
## 2 25      2        1           1              1               1               0
## 3 31      1        1           1              1               1               0
## 4 39      1        1           1              1               1               0
## 5 55      1        1           1              1               1               0
## 6 61      1        1           1              1               1               0
## 7 67      2        1           1              1               1               0
## 8 73      1        1           1              1               1               0
## 9 74      1        1           1              1               1               0
## 10 76     1        1           1              1               1               0
## # i 40 more rows
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
bias_by_predictor(df_bin, sex)

## # A tibble: 2 x 8
##   sex      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <fct> <int>      <dbl>          <dbl>            <dbl>            <dbl>
## 1 1       53        0.302         0.491          0.396          0.0943
## 2 2       47        0.277         0.404          0.426          0.149
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
```

```

bias_by_predictor(df_bin, race)

## # A tibble: 3 x 8
##   race      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <fct> <int>     <dbl>        <dbl>          <dbl>          <dbl>
## 1 1       77     0.364       0.442       0.468       0.104
## 2 2       13     0.231       0.615       0.231         0
## 3 3       10     -0.2        0.3        0.2        0.4
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>

bias_by_predictor(df_bin, educ)

## # A tibble: 14 x 8
##   educ                  n mean_error_var mean_error_narr prop_too_cons_var
##   <dbl+lbl> <int>     <dbl>        <dbl>          <dbl>
## 1 15 [3 years of colleg~    2     1           1           1
## 2 19 [7 years of colleg~    1     1           1           1
## 3 20 [8 or more years o~    2     1           1           1
## 4 13 [1 year of college]  6     0.667       0.833       0.667
## 5 12 [12th grade]        21    0.571       0.762       0.571
## 6 16 [4 years of colleg~  26    0.346       0.269       0.423
## 7 14 [2 years of colleg~  20    0.2          0.65        0.35
## 8 6  [6th grade]          1     0           1           0
## 9 9  [9th grade]          1     0           0           0
## 10 10 [10th grade]        2     0           0.5         0
## 11 11 [11th grade]        1     0           1           0
## 12 17 [5 years of colleg~  9    -0.222      -0.111       0.222
## 13 18 [6 years of colleg~  7    -0.286      -0.429         0
## 14 0  [no formal schooli~  1    -1           0           0
## # i 3 more variables: prop_too_lib_var <dbl>, prop_too_cons_narr <dbl>,
## #   prop_too_lib_narr <dbl>

bias_by_predictor(df_bin, marital)

## # A tibble: 4 x 8
##   marital      n mean_error_var mean_error_narr prop_too_cons_var
##   <fct> <int>     <dbl>        <dbl>          <dbl>
## 1 2       8     0.625       0.5          0.75
## 2 3      16     0.375       0.5          0.5
## 3 1      44     0.341       0.364       0.432
## 4 5      32     0.0938      0.531       0.25
## # i 3 more variables: prop_too_lib_var <dbl>, prop_too_cons_narr <dbl>,
## #   prop_too_lib_narr <dbl>

bias_by_predictor(df_bin, occ10)

## # A tibble: 73 x 8
##   occ10      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <dbl> <int>     <dbl>        <dbl>          <dbl>          <dbl>
## 1 20      1     1           1           1           0
## 2 120     1     1           0           1           0
## 3 710     2     1           1           1           0
## 4 1106    1     1           1           1           0
## 5 1460    1     1           1           1           0
## 6 1740    1     1           1           1           0
## 7 2145    1     1           1           1           0

```

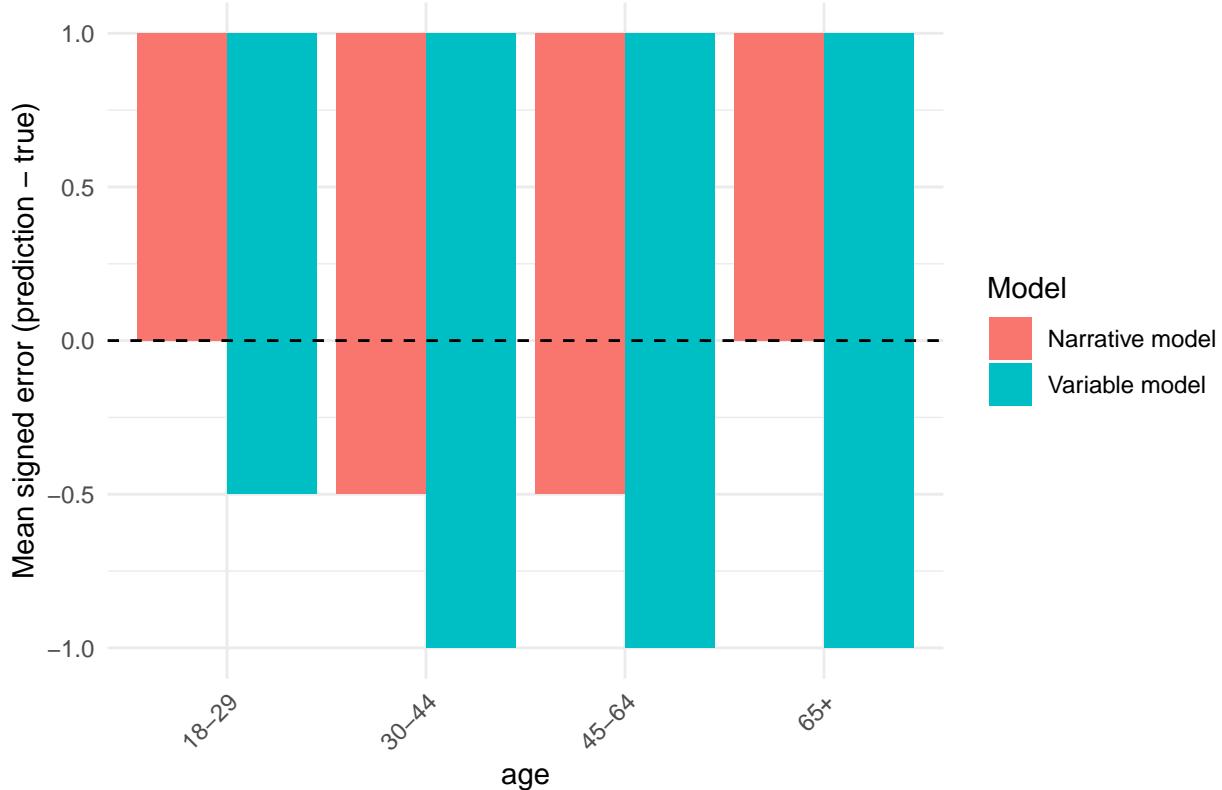
```

##   8 2200     1          1          1          1          0
##   9 3600     2          1          1          1          0
## 10 3850     3          1          1          1          0
## # i 63 more rows
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
bias_by_predictor(df_bin, region)

## # A tibble: 4 x 8
##   region      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <fct>    <int>       <dbl>        <dbl>        <dbl>        <dbl>
## 1 3            37      0.486      0.486      0.541      0.0541
## 2 2            24      0.333      0.458      0.417      0.0833
## 3 1            12      0.25       0.333      0.333      0.0833
## 4 4            27       0          0.444      0.259      0.259
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
plot_mean_error_by_predictor(df_bin, age)

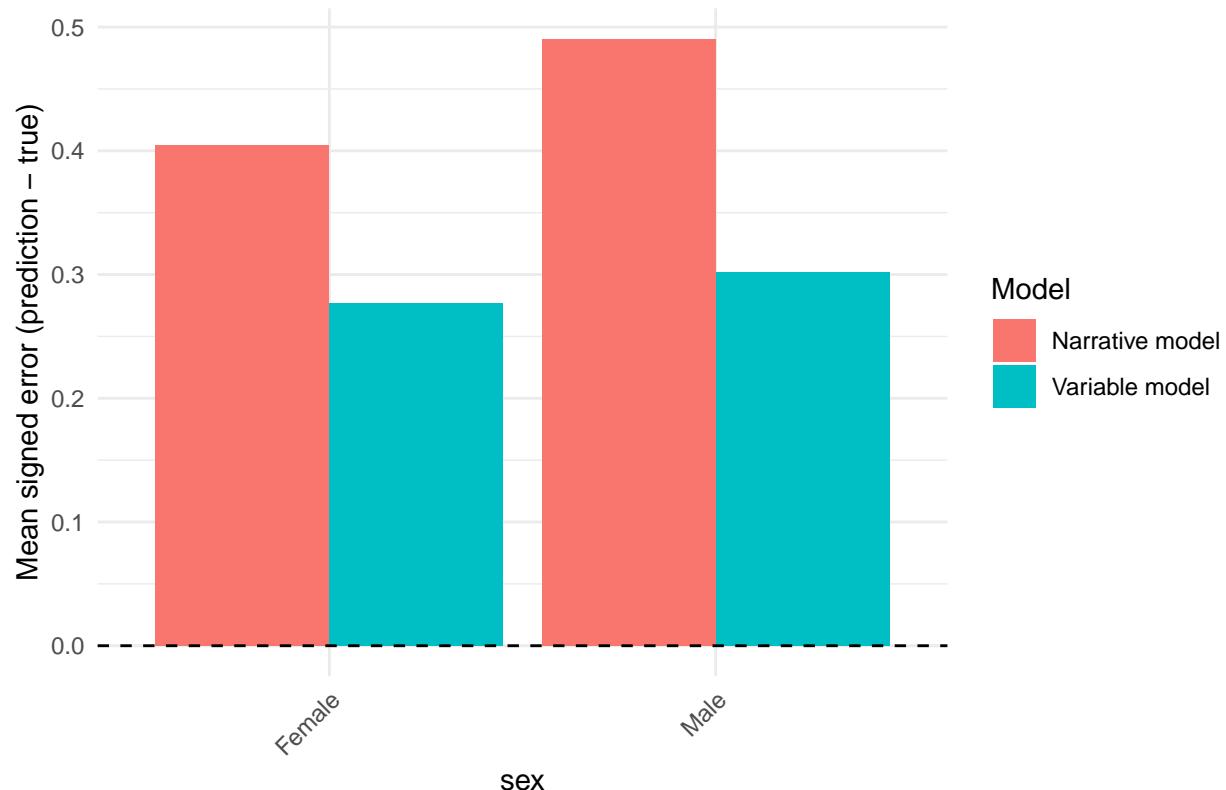
```

Mean signed error by age



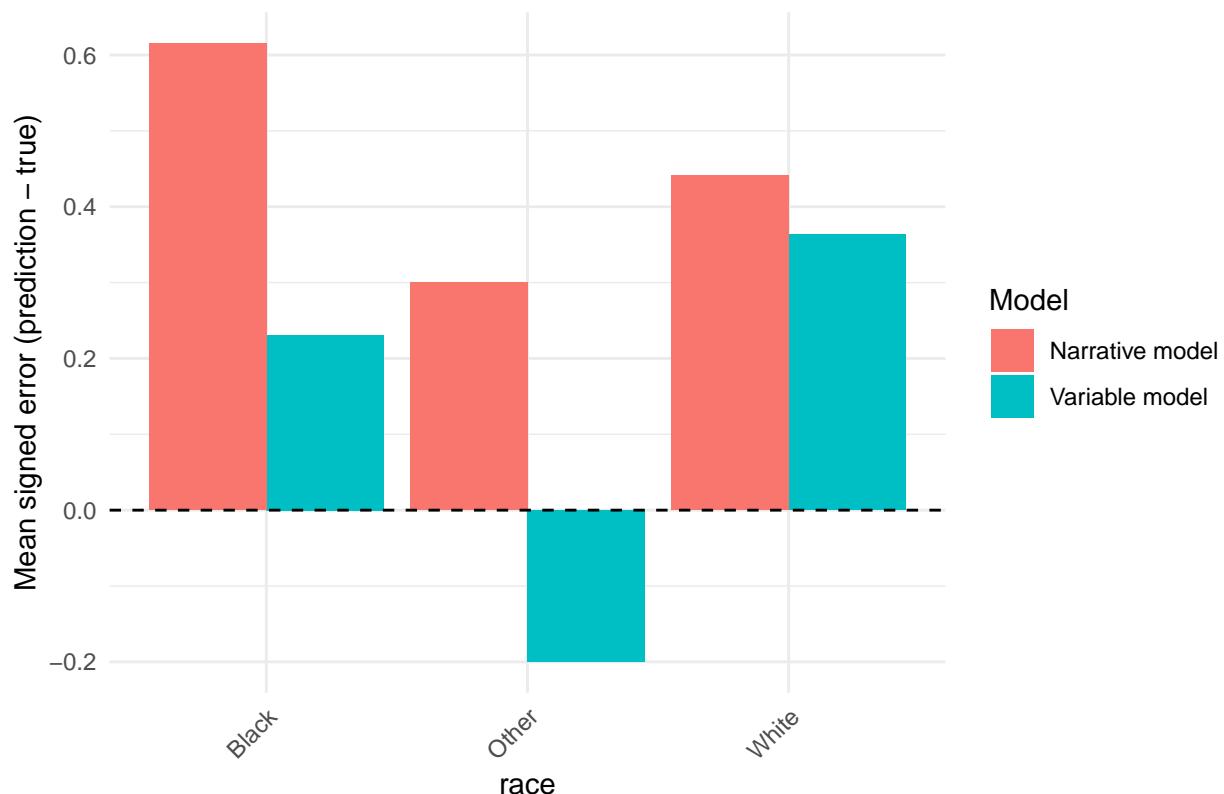
```
plot_mean_error_by_predictor(df_bin, sex)
```

Mean signed error by sex

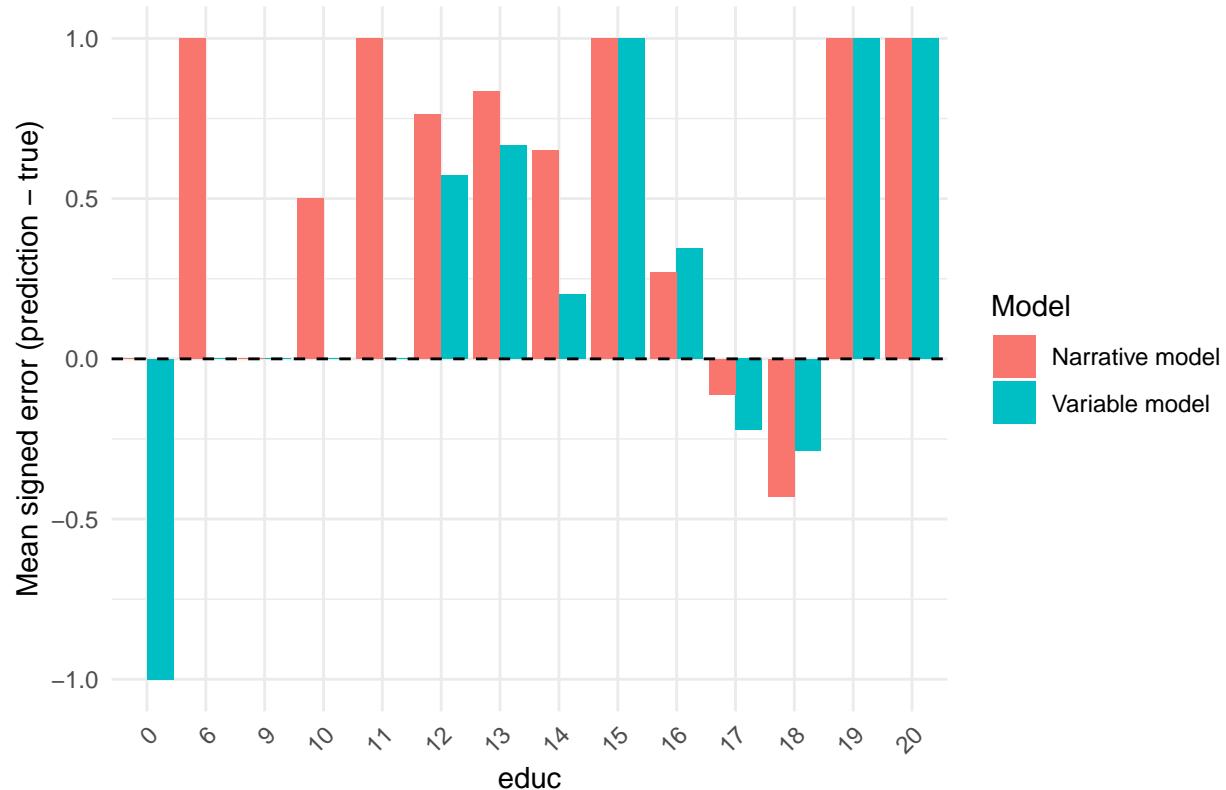


```
plot_mean_error_by_predictor(df_bin, race)
```

Mean signed error by race

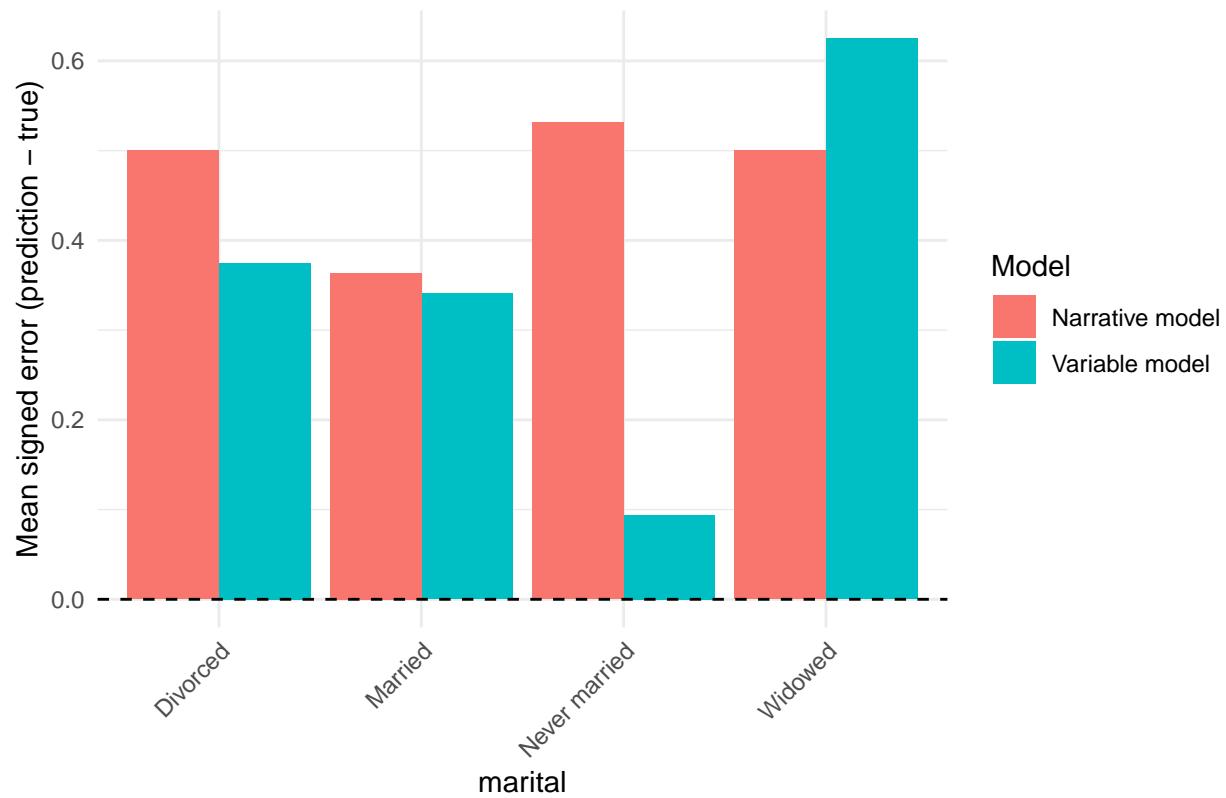


Mean signed error by educ

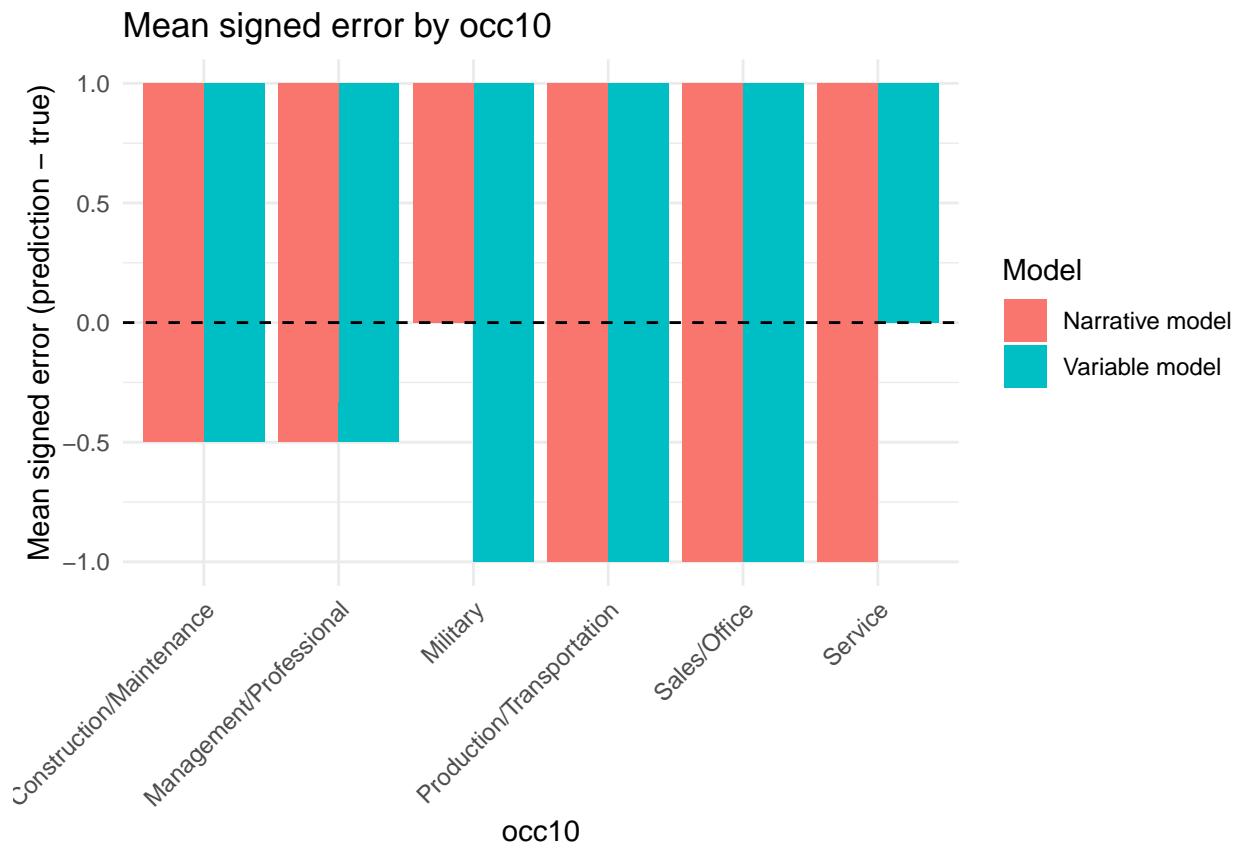


```
plot_mean_error_by_predictor(df_bin, marital)
```

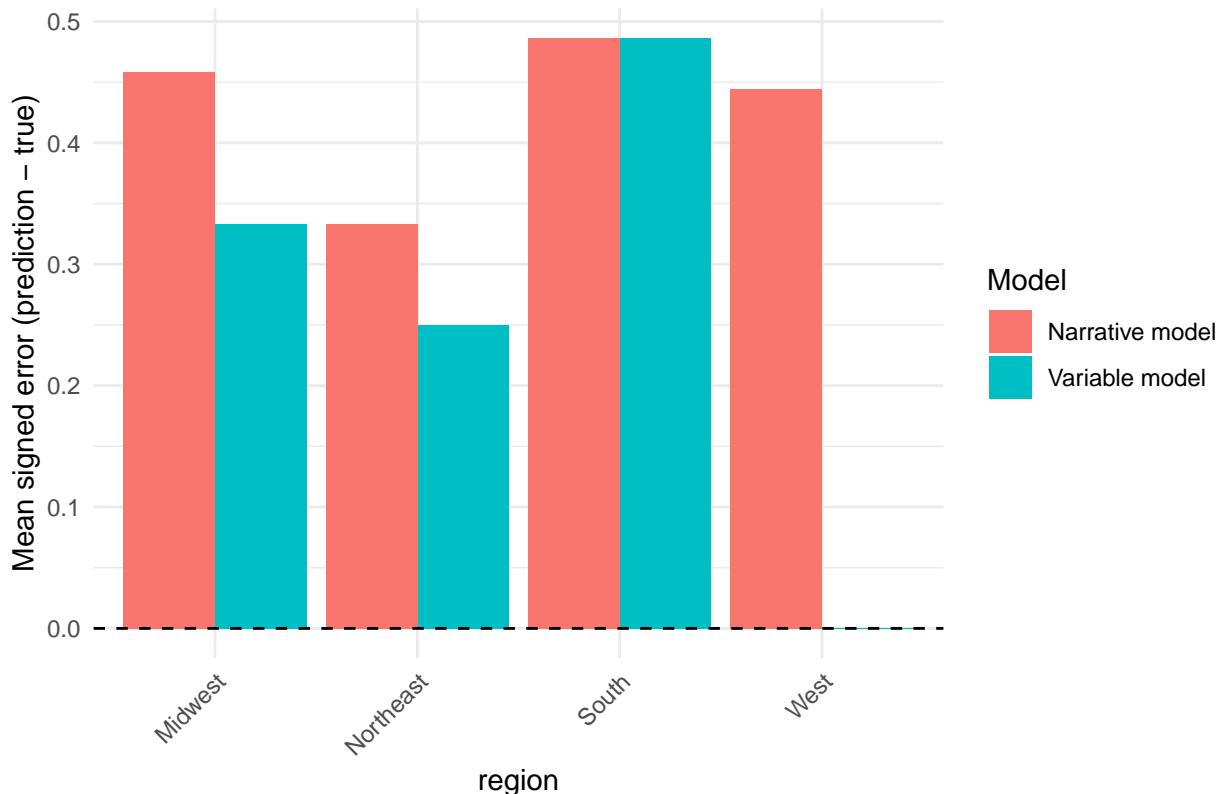
Mean signed error by marital



```
plot_mean_error_by_predictor(df_bin, occ10)
```



Mean signed error by region



```
#collapse POLVIEWS into three categories: 1 = Liberal, 2 = Moderate, 3 = Conservative
sample100_3 <- sample100 %>%
  mutate(
    polviews_3 = case_when(
      polviews %in% c(1, 2, 3) ~ 1, # liberal
      polviews %in% c(4) ~ 2, # moderate
      polviews %in% c(5, 6, 7) ~ 3 # conservative
    )
  ) %>%
  filter(!is.na(polviews_3))
head(sample100_3)
```

```
## # A tibble: 6 x 9
##   polviews age       educ          race  sex   occ10 region marital polviews_3
##   <dbl> <dbl> <dbl+lbl> <dbl+lbl> <fct> <fct> <dbl> <dbl> <dbl>
## 1       4 67        16 [4 years of~ 1     1    1740  4     5           2
## 2       5 56        14 [2 years of~ 3     2     50    4     3           3
## 3       6 33        14 [2 years of~ 1     2    7750  2     5           3
## 4       3 24        16 [4 years of~ 1     2    2550  1     5           1
## 5       3 46        14 [2 years of~ 1     2    5610  4     1           1
## 6       4 25        12 [12th grade] 1     1    6440  3     5           2
```

```
sample100_nolabel_3 <- sample100_3 %>%
  select(-polviews_3) %>% # remove the binary ideology variable
  select(-polviews) # remove the numeric ideology variable
```

```
head(sample100_nolabel_3)
```

```

## # A tibble: 6 x 7
##   age      educ          race  sex  occ10 region marital
##   <dbl>    <dbl>        <fct> <fct> <fct> <fct>
## 1 67      16 [4 years of college] 1     1    1740  4     5
## 2 56      14 [2 years of college] 3     2     50    4     3
## 3 33      14 [2 years of college] 1     2    7750  2     5
## 4 24      16 [4 years of college] 1     2    2550  1     5
## 5 46      14 [2 years of college] 1     2    5610  4     1
## 6 25      12 [12th grade]       1     1    6440  3     5
write.csv(sample100_nolabel_3, "gss_sample_100_unlabeled_3.csv", row.names = FALSE)

var_3 <- read.csv("/Users/joyqu/Desktop/PLSC/gss_gpt5_var_predictions_3.csv")
head(var_3)

##   age  educ race  sex  occ10 region marital pred_polview
##   1   67   16   1   1   1740    4   5       2
##   2   56   14   3   2   50     4   3       2
##   3   33   14   1   2   7750    2   5       2
##   4   24   16   1   2   2550    1   5       1
##   5   46   14   1   2   5610    4   1       2
##   6   25   12   1   1   6440    3   5       2

# Extract variables
y_true_3 <- as.numeric(sample100_3$polviews_3)
y_pred_3 <- as.numeric(var_3$pred_polview)

# Compute metrics
MAE <- mean(abs(y_true_3 - y_pred_3))
MSE <- mean((y_true_3 - y_pred_3)^2)
Accuracy <- mean(y_true_3 == y_pred_3)
Within1 <- mean(abs(y_true_3 - y_pred_3) <= 1)

cat("Mean Absolute Error:", MAE, "\n")

## Mean Absolute Error: 0.75
cat("Mean Squared Error:", MSE, "\n")

## Mean Squared Error: 1.03
cat("Exact Match Accuracy:", round(Accuracy*100, 1), "%\n")

## Exact Match Accuracy: 39 %
cat("Within ±1 Accuracy:", round(Within1*100, 1), "%\n")

## Within ±1 Accuracy: 86 %

narrative_3 <- read.csv("/Users/joyqu/Desktop/PLSC/gss_gpt5_narrative_predictions_3.csv")
head(narrative_3)

##   id
## 1 1
## 2 2
## 3 3
## 4 4

```

```

## 5 5
## 6 6
##
## 1 He is 67, a man in the West who values ...
## 2 She is 56 years old, she has settled into a steady rhythm in the West, where routines give structure ...
## 3 At 33, this woman in the Midwest balances work, personal commitments, and leisure ...
## 4 She is 24, a woman living in the Northeast, still shaping her path in work and life. ...
## 5 She is 46 years old, she has settled into a steady rhythm in the West, where routines give ...
## 6 He is 25, a man living in the South, still shaping ...
## pred_polview_narr
## 1 2
## 2 2
## 3 2
## 4 2
## 5 2
## 6 3

# Extract variables
y_true_3 <- as.numeric(sample100_3$polviews_3)
y_pred_3 <- as.numeric(narrative_3$pred_polview_narr)

# Compute metrics
MAE <- mean(abs(y_true_3 - y_pred_3))
MSE <- mean((y_true_3 - y_pred_3)^2)
Accuracy <- mean(y_true_3 == y_pred_3)
Within1 <- mean(abs(y_true_3 - y_pred_3) <= 1)

cat("Mean Absolute Error:", MAE, "\n")

## Mean Absolute Error: 0.58
cat("Mean Squared Error:", MSE, "\n")

## Mean Squared Error: 0.66
cat("Exact Match Accuracy:", round(Accuracy*100, 1), "%\n")

## Exact Match Accuracy: 46 %
cat("Within ±1 Accuracy:", round(Within1*100, 1), "%\n")

## Within ±1 Accuracy: 96 %

df_3 <- sample100_3 %>%
  mutate(row_id = row_number()) %>%
  select(
    row_id,
    POLVIEWS_TRUE = polviews_3,
    age, sex, race, educ, marital, occ10, region    # <- keep whatever predictors you want
  ) %>%
  inner_join(
    var_3 %>%
      mutate(row_id = row_number()) %>%
      select(row_id, pred_var = pred_polview),
    by = "row_id"
  ) %>%
  inner_join(

```

```

narrative_3 %>%
  mutate(row_id = row_number()) %>%
  select(-row_id, pred_narr = pred_polview_narr),
  by = "row_id"
)
head(df_3)

## # A tibble: 6 x 11
##   row_id POLVIEWS_TRUE age     sex   race   educ   marital occ10 region pred_var
##   <int>      <dbl> <dbl+> <fct> <fct> <dbl+lb> <fct>  <fct> <fct>  <int>
## 1     1         2.67    1     1     16 [4 y~ 5     1740    4     2
## 2     2         3.56    2     3     14 [2 y~ 3     50      4     2
## 3     3         3.33    2     1     14 [2 y~ 5     7750    2     2
## 4     4         1.24    2     1     16 [4 y~ 5     2550    1     1
## 5     5         1.46    2     1     14 [2 y~ 1     5610    4     2
## 6     6         2.25    1     1     12 [12t~ 5     6440    3     2
## # i 1 more variable: pred_narr <int>

df_3 <- df_3 %>%
  mutate(
    # Factor version for F1
    POLVIEWS_TRUE_fac = factor(POLVIEWS_TRUE),
    pred_var_fac      = factor(pred_var, levels = levels(POLVIEWS_TRUE_fac)),
    pred_narr_fac     = factor(pred_narr, levels = levels(POLVIEWS_TRUE_fac)),

    # Numeric version for bias / error
    polviews_num = as.numeric(as.character(POLVIEWS_TRUE)),
    pred_var_num = as.numeric(as.character(pred_var)),
    pred_narr_num = as.numeric(as.character(pred_narr)),

    # Signed errors
    error_var  = pred_var_num - polviews_num,
    error_narr = pred_narr_num - polviews_num
  )
results <- tibble(
  Model = c("Variable Model", "Narrative Model"),
  Macro_F1 = c(
    f1_macro(df_3$POLVIEWS_TRUE_fac, df_3$pred_var_fac),
    f1_macro(df_3$POLVIEWS_TRUE_fac, df_3$pred_narr_fac)
  ),
  Weighted_F1 = c(
    f1_weighted(df_3$POLVIEWS_TRUE_fac, df_3$pred_var_fac),
    f1_weighted(df_3$POLVIEWS_TRUE_fac, df_3$pred_narr_fac)
  )
)

print(results)

## # A tibble: 2 x 3
##   Model           Macro_F1  Weighted_F1
##   <chr>          <dbl>       <dbl>
## 1 Variable Model  0.689      0.682
## 2 Narrative Model 0.678      0.654

```

```

mislabeled_comparison <- df_3 %>%
  mutate(
    # Wrong / right flags
    var_wrong = pred_var != POLVIEWS_TRUE,
    narr_wrong = pred_narr != POLVIEWS_TRUE,

    # Case types with only two models
    case_type = case_when(
      var_wrong & !narr_wrong ~ "Only Variable Model Wrong",
      !var_wrong & narr_wrong ~ "Only Narrative Model Wrong",
      var_wrong & narr_wrong ~ "Both Wrong",
      TRUE                 ~ "Both Correct"
    ),

    # Differences vs true (numeric scale 1-7)
    diff_var = as.numeric(pred_var) - as.numeric(POLVIEWS_TRUE),
    diff_narr = as.numeric(pred_narr) - as.numeric(POLVIEWS_TRUE),

    # Bias direction for each model (only label as too lib/con if it's wrong)
    bias_var = dplyr:::case_when(
      !var_wrong           ~ "Correct",
      diff_var > 0        ~ "Too Conservative",
      diff_var < 0        ~ "Too Liberal",
      TRUE                ~ NA_character_
    ),
    bias_narr = dplyr:::case_when(
      !narr_wrong          ~ "Correct",
      diff_narr > 0        ~ "Too Conservative",
      diff_narr < 0        ~ "Too Liberal",
      TRUE                ~ NA_character_
    )
  ) %>%
  select(
    row_id, POLVIEWS_TRUE,
    pred_var, pred_narr,
    var_wrong, narr_wrong,
    case_type,
    bias_var, bias_narr
  )

# Save to CSV
write.csv(mislabeled_comparison,
          "mislabeled_cases_comparison_3.csv",
          row.names = FALSE)

bias_table <- mislabeled_comparison %>%
  select(bias_var, bias_narr) %>%
  tidyr:::pivot_longer(
    cols      = everything(),
    names_to = "model",
    values_to = "bias"
  ) %>%
  dplyr:::filter(bias != "Correct") %>%    # only mislabeled cases

```

```

dplyr::group_by(model, bias) %>%
dplyr::summarise(count = dplyr::n(), .groups = "drop_last") %>%
dplyr::mutate(
  percent = count / sum(count) * 100
) %>%
dplyr::ungroup() %>%
dplyr::mutate(
  model = dplyr::recode(
    model,
    bias_var = "Variable Model",
    bias_narr = "Narrative Model"
  )
) %>%
dplyr::arrange(model, bias)
bias_table

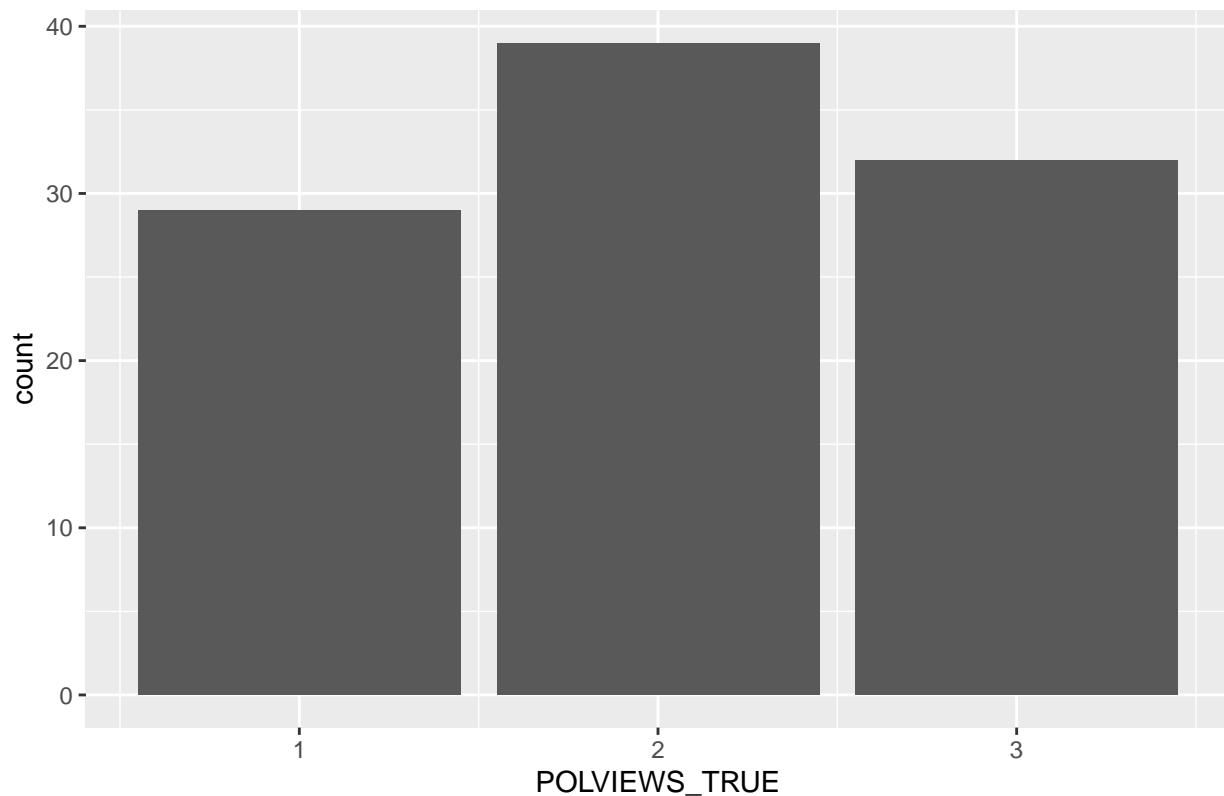
## # A tibble: 4 x 4
##   model           bias       count  percent
##   <chr>          <chr>     <int>    <dbl>
## 1 Narrative Model Too Conservative    33    61.1
## 2 Narrative Model Too Liberal        21    38.9
## 3 Variable Model  Too Conservative   37    60.7
## 4 Variable Model  Too Liberal       24    39.3

#true polviews distribution

ggplot(df_3, aes(x = POLVIEWS_TRUE)) +
  geom_bar() +
  ggtitle("True POLVIEWS Distribution")

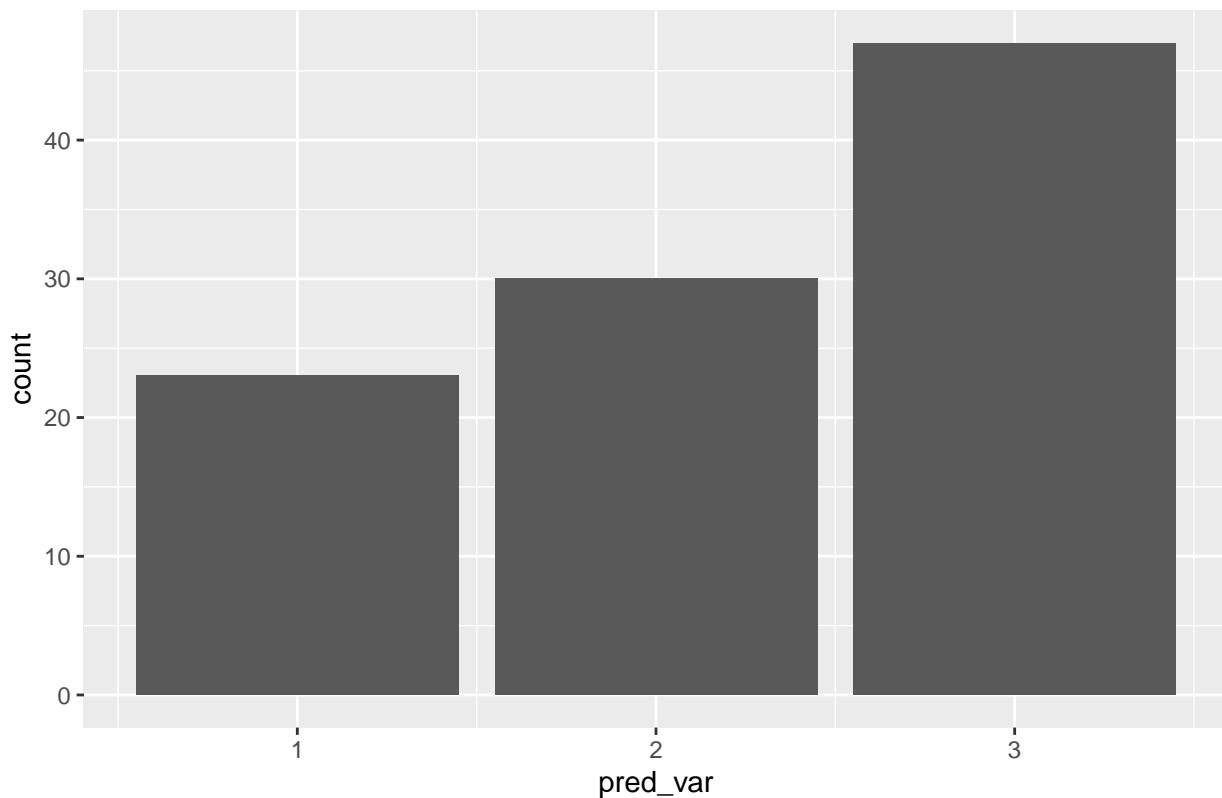
```

True POLVIEWS Distribution



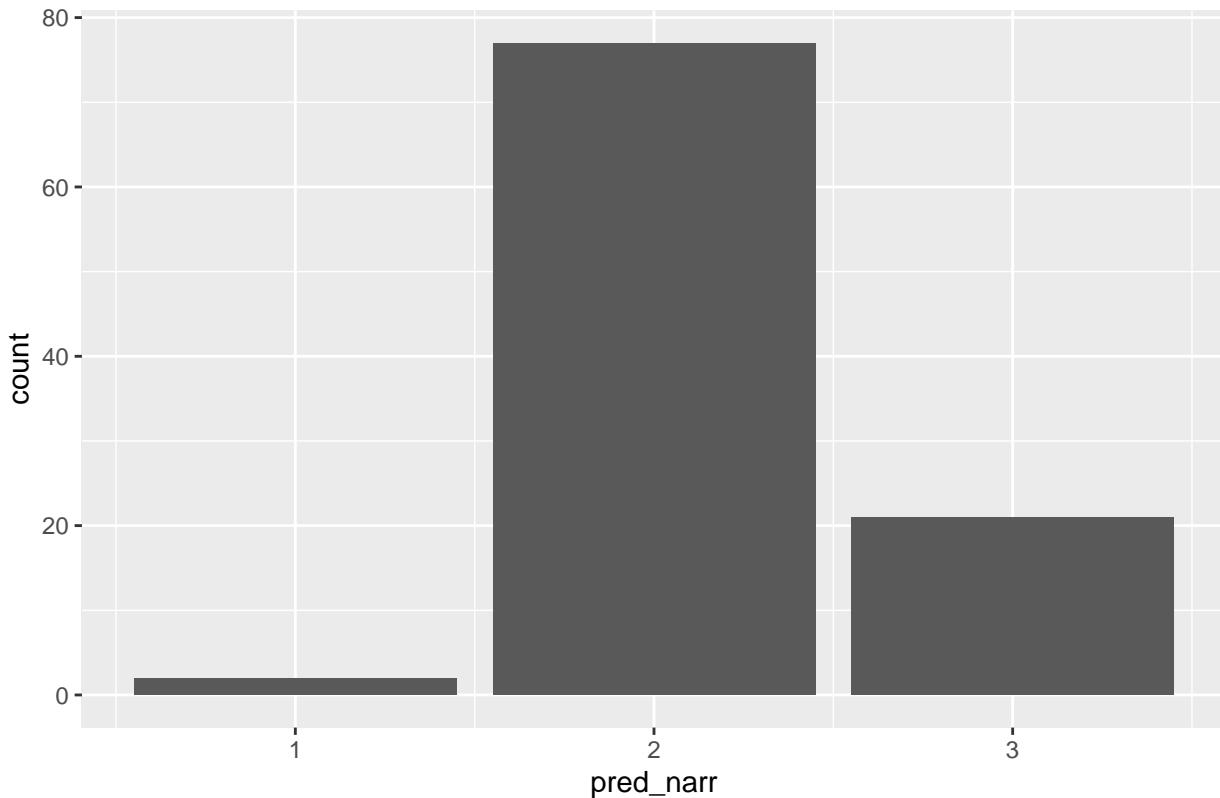
```
ggplot(df_3, aes(x = pred_var)) +  
  geom_bar() +  
  ggtitle("Variable Model Pred Distribution")
```

Variable Model Pred Distribution



```
ggplot(df_3, aes(x = pred_narr)) +  
  geom_bar() +  
  ggtitle("Narrative Model Pred Distribution")
```

Narrative Model Pred Distribution



```

df_3$occ10 <- as.numeric(as.character(df_3$occ10))
bias_by_predictor(df_3, age)

## # A tibble: 50 x 8
##   age      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <dbl> <int>      <dbl>           <dbl>            <dbl>            <dbl>
## 1 73       1        2             1              1              0
## 2 76       1        2             1              1              0
## 3 79       1        2             1              1              0
## 4 82       1        2             1              1              0
## 5 49       2        1.5            1              1              0
## 6 83       4        1.5            0.75            1              0
## 7 39       1        1              0              1              0
## 8 46       2        1              0.5             1              0
## 9 47       1        1              1              1              0
## 10 55      1        1              0              1              0
## # i 40 more rows
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
bias_by_predictor(df_3, sex)

## # A tibble: 2 x 8
##   sex      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <fct> <int>      <dbl>           <dbl>            <dbl>            <dbl>
## 1 2       47        0.234          0.0851          0.383          0.234
## 2 1       53        0.189          0.226           0.358          0.245
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
```

```

bias_by_predictor(df_3, race)

## # A tibble: 3 x 8
##   race      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <fct> <int>       <dbl>        <dbl>        <dbl>        <dbl>
## 1 1       77       0.351       0.117       0.416       0.182
## 2 2       13      -0.0769      0.615       0.231       0.308
## 3 3       10       -0.5        -0.1        0.2         0.6
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>

bias_by_predictor(df_3, educ)

## # A tibble: 14 x 8
##   educ                  n mean_error_var mean_error_narr prop_too_cons_var
##   <dbl+lbl> <int>       <dbl>        <dbl>        <dbl>
## 1 19 [7 years of colleg~    1       2           1           1
## 2 20 [8 or more years o~    2       2           1           1
## 3 15 [3 years of colleg~    2       0.5          0           0.5
## 4 16 [4 years of colleg~   26      0.385       0.115       0.423
## 5 13 [1 year of college]  6       0.333       0.667       0.5
## 6 12 [12th grade]         21      0.286       0.238       0.429
## 7 14 [2 years of colleg~  20       0.2          0.15        0.4
## 8 9 [9th grade]           1       0           0           0
## 9 10 [10th grade]         2       0           0           0
## 10 17 [5 years of colleg~  9       -0.111      -0.111      0.222
## 11 18 [6 years of colleg~  7       -0.571      -0.143        0
## 12 0 [no formal schooli~   1       -1           0           0
## 13 6 [6th grade]          1       -1           0           0
## 14 11 [11th grade]        1       -1           0           0
## # i 3 more variables: prop_too_lib_var <dbl>, prop_too_cons_narr <dbl>,
## #   prop_too_lib_narr <dbl>

bias_by_predictor(df_3, marital)

## # A tibble: 4 x 8
##   marital     n mean_error_var mean_error_narr prop_too_cons_var
##   <fct> <int>       <dbl>        <dbl>        <dbl>
## 1 2        8       0.875       0.375       0.75
## 2 3       16       0.5          0.125       0.5
## 3 1       44       0.409       0.0227      0.455
## 4 5       32      -0.375       0.312       0.0938
## # i 3 more variables: prop_too_lib_var <dbl>, prop_too_cons_narr <dbl>,
## #   prop_too_lib_narr <dbl>

bias_by_predictor(df_3, occ10)

## # A tibble: 73 x 8
##   occ10      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <dbl> <int>       <dbl>        <dbl>        <dbl>        <dbl>
## 1 710       2       2           1           1           0
## 2 1460      1       2           1           1           0
## 3 2200      1       2           1           1           0
## 4 5120      1       2           1           1           0
## 5 5600      1       2           1           1           0
## 6 5820      1       2           1           1           0
## 7 8750      1       2           2           1           0

```

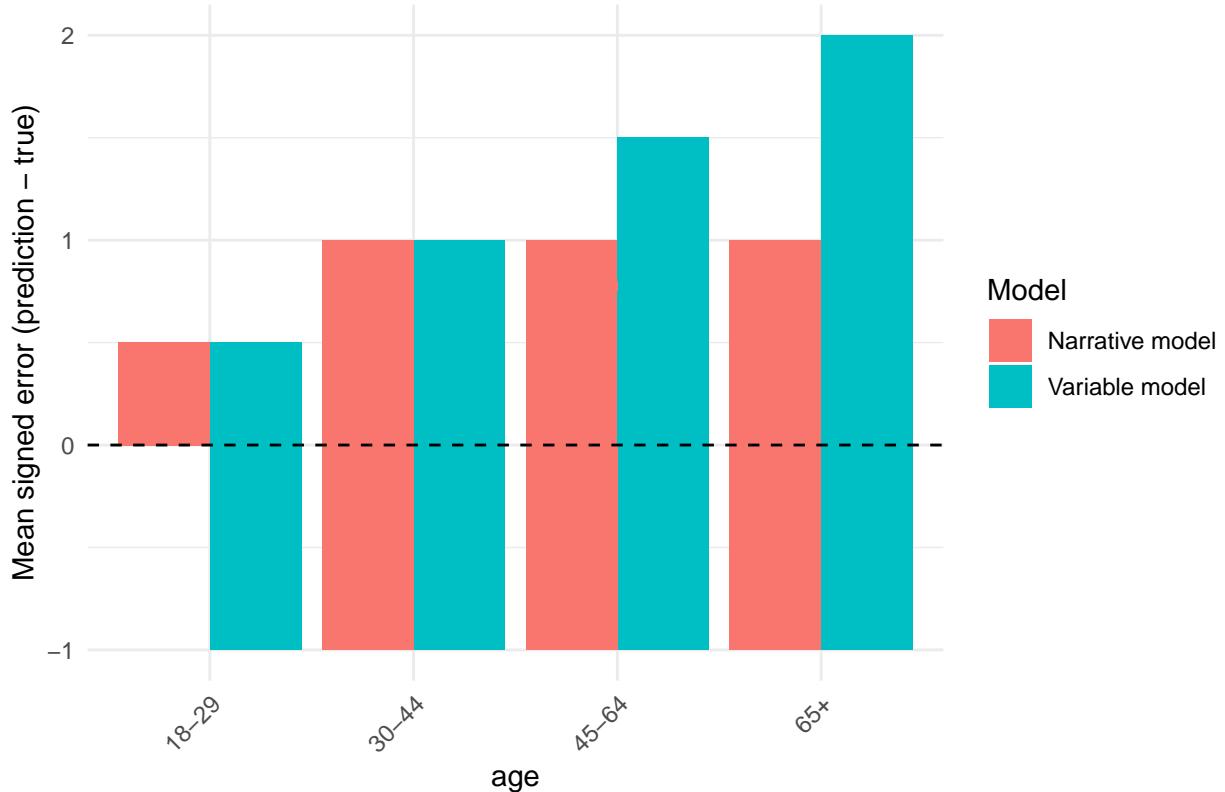
```

##   8 9620    1          2          2          1          0
##   9    20    1          1          0          1          0
## 10   735    1          1          1          1          0
## # i 63 more rows
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
bias_by_predictor(df_3, region)

## # A tibble: 4 x 8
##   region     n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <fct>   <int>        <dbl>        <dbl>        <dbl>        <dbl>
## 1 2         24       0.417       0.167       0.417       0.125
## 2 3         37       0.324       0.189       0.378       0.216
## 3 1         12       0.25        0.25        0.333       0.167
## 4 4         27      -0.148       0.0741      0.333       0.407
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
plot_mean_error_by_predictor(df_3, age)

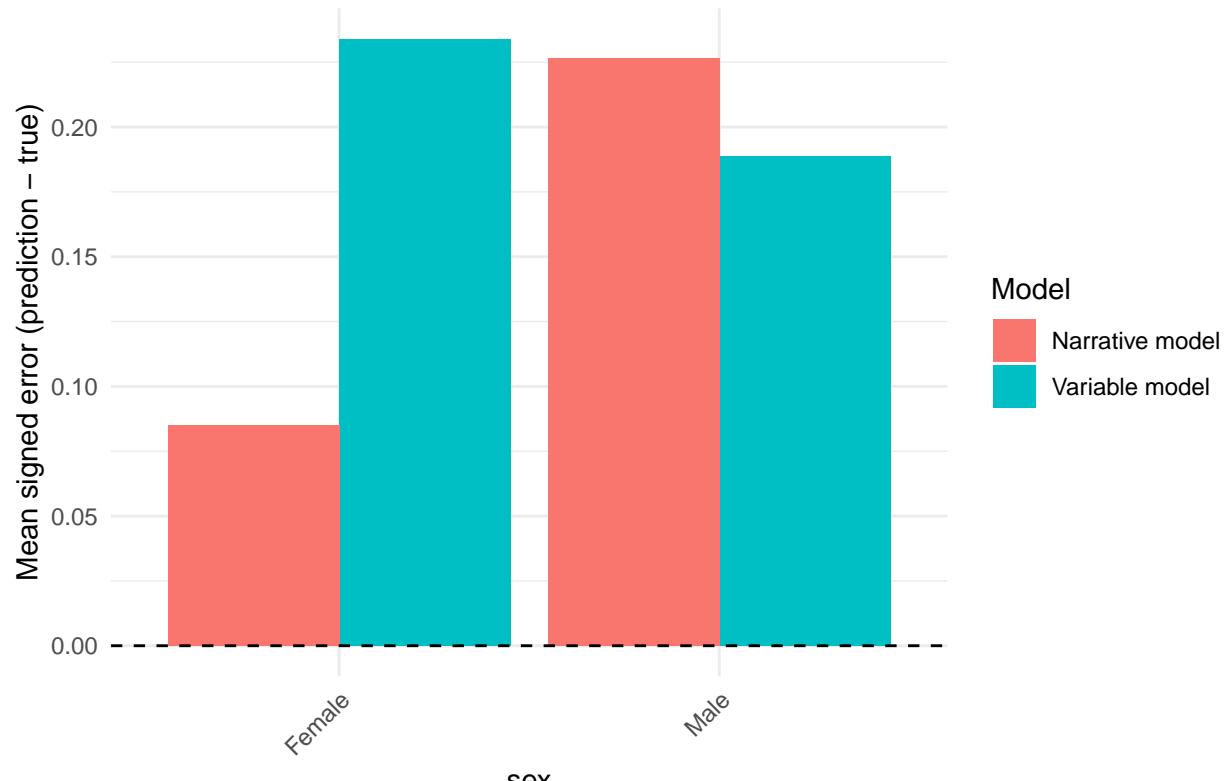
```

Mean signed error by age

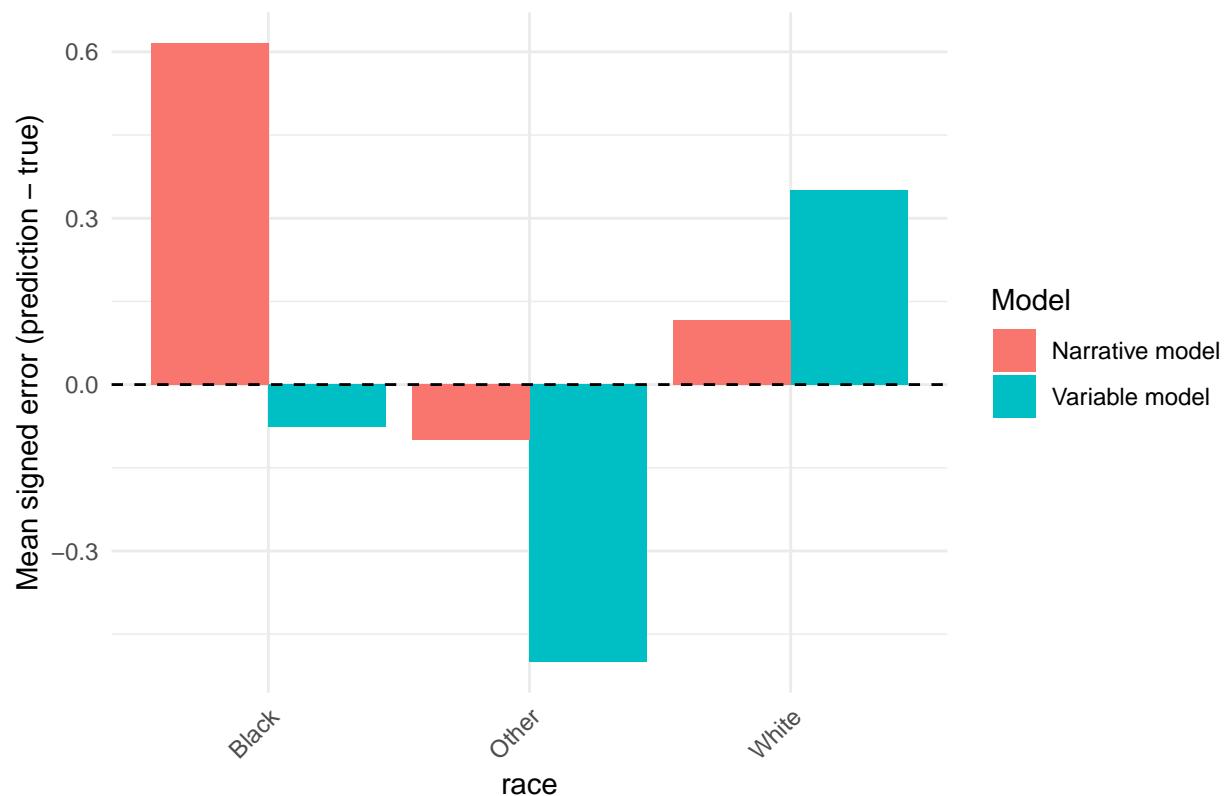


```
plot_mean_error_by_predictor(df_3, sex)
```

Mean signed error by sex

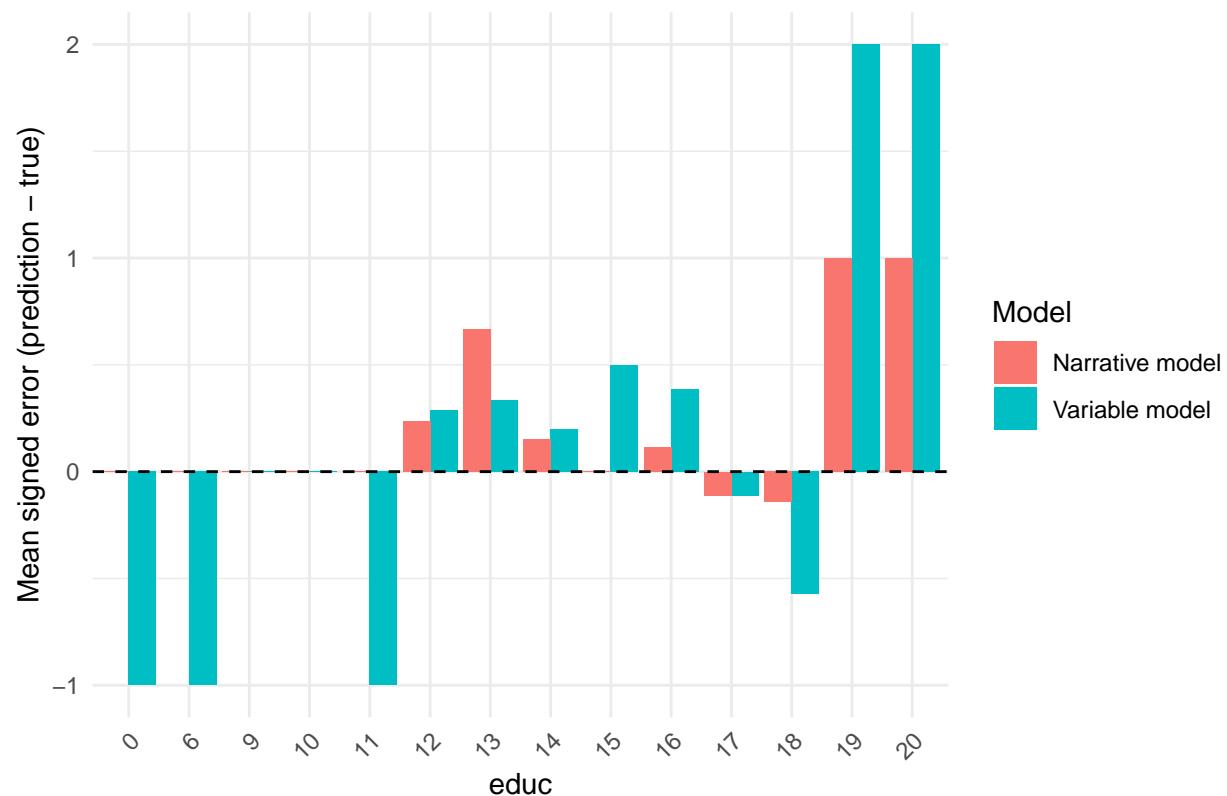


Mean signed error by race

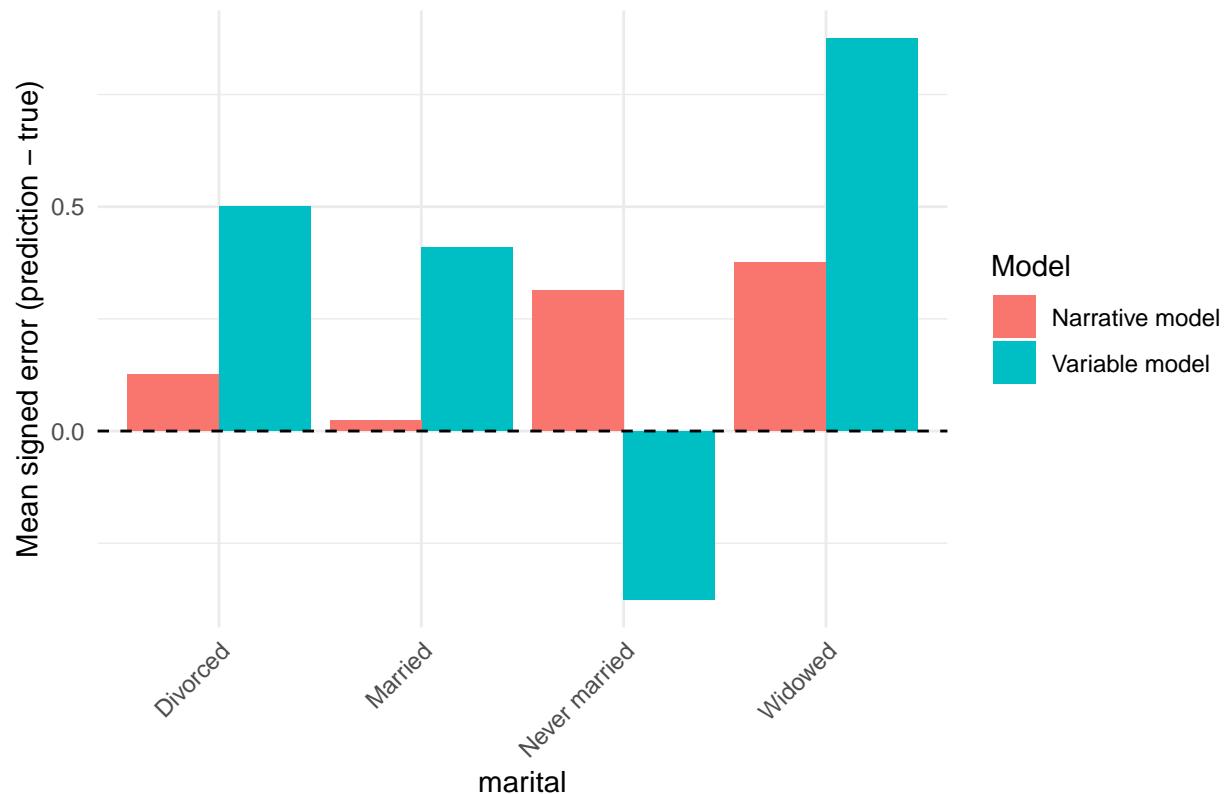


```
plot_mean_error_by_predictor(df_3, educ)
```

Mean signed error by educ

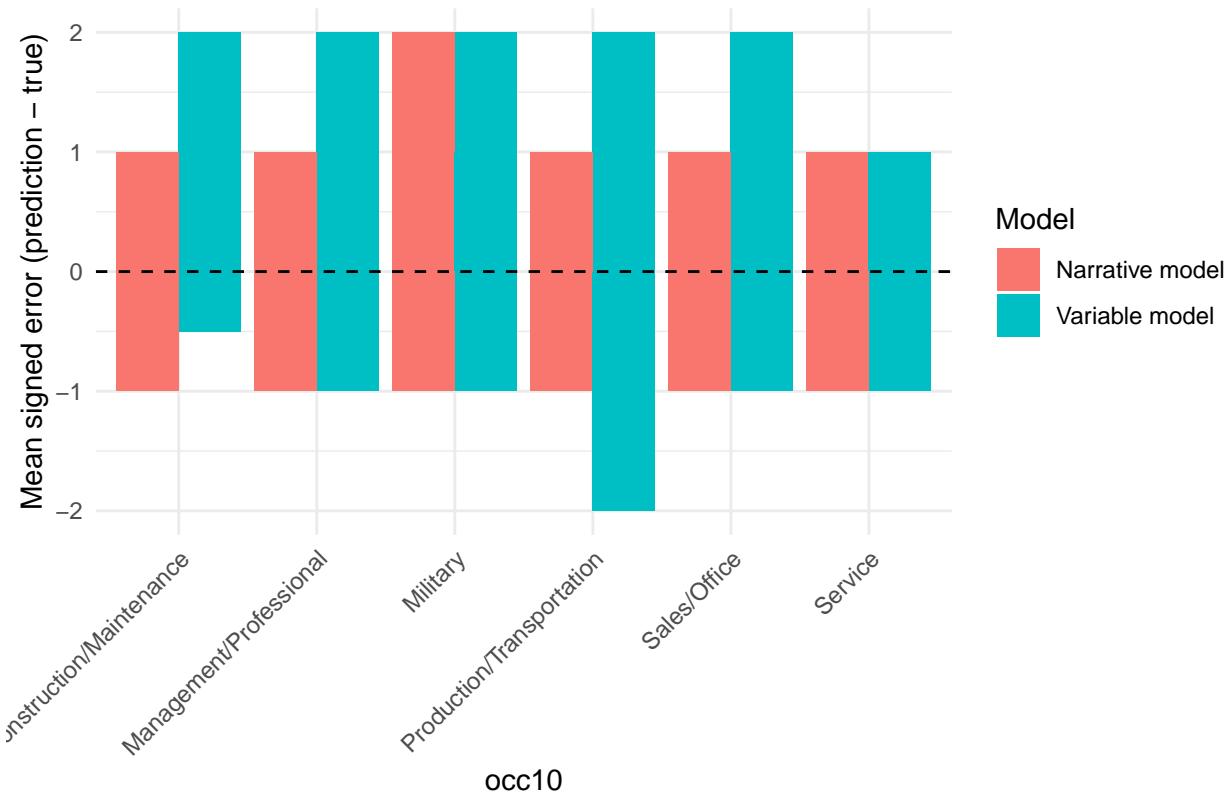


Mean signed error by marital



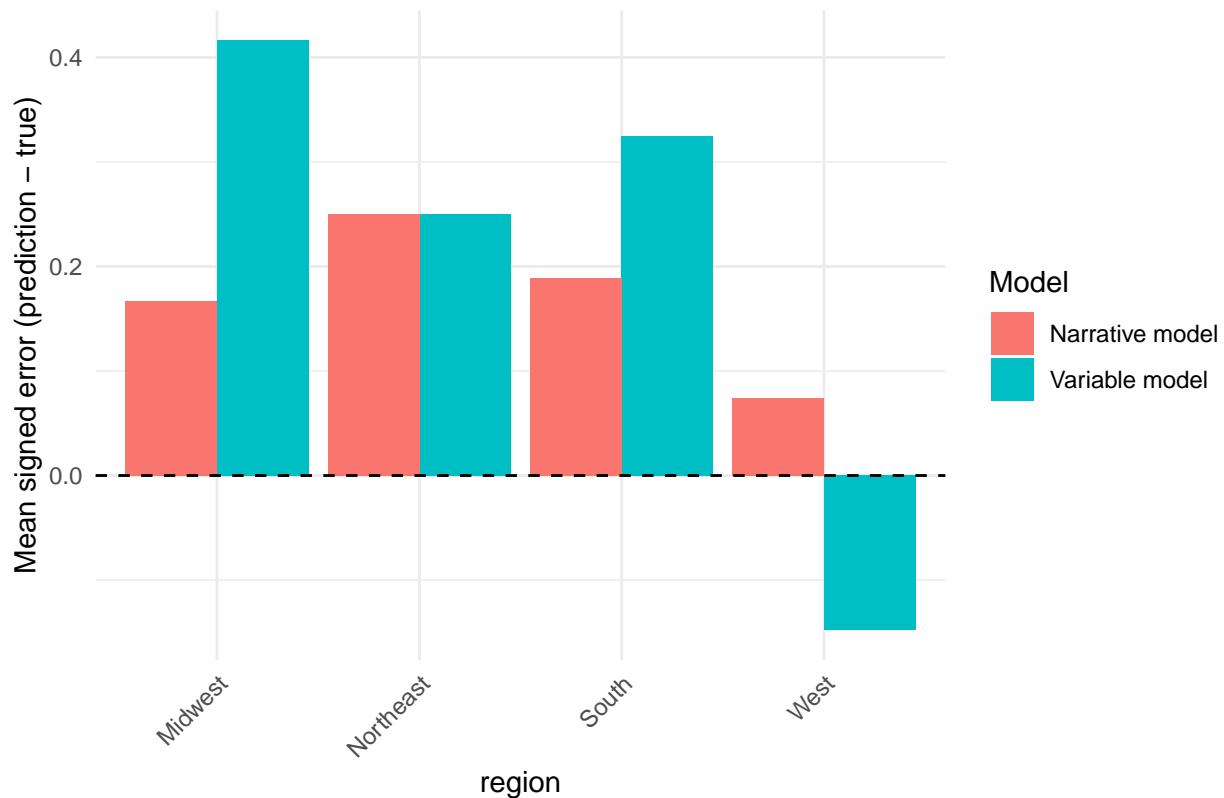
```
plot_mean_error_by_predictor(df_3, occ10)
```

Mean signed error by occ10



```
plot_mean_error_by_predictor(df_3, region)
```

Mean signed error by region



```
#collapse POLVIEWS into four categories:
sample100_4 <- sample100 %>%
  mutate(
    polviews_4= case_when(
      polviews %in% c(1, 2) ~ 1,    # extremely liberal
      polviews %in% c(3) ~ 2,      # slightly liberal
      polviews %in% c(4) ~ 3,      # moderate
      polviews %in% c(5, 6, 7) ~ 4    # conservative
    )
  ) %>%
  filter(!is.na(polviews_4))
head(sample100_4)

## # A tibble: 6 x 9
##   polviews age      educ          race  sex  occ10 region marital polviews_4
##   <dbl>   <dbl> <dbl+lbl>       <fct> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1        4 67      16 [4 years of~ 1     1    1740    4      5            3
## 2        5 56      14 [2 years of~ 3     2     50     4      3            4
## 3        6 33      14 [2 years of~ 1     2    7750    2      5            4
## 4        3 24      16 [4 years of~ 1     2    2550    1      5            2
## 5        3 46      14 [2 years of~ 1     2    5610    4      1            2
## 6        4 25      12 [12th grade] 1     1    6440    3      5            3

sample100_nolabel_4 <- sample100_4 %>%
  select(-polviews_4) %>% # remove the ideology variable
  select(-polviews) # remove the numeric ideology variable
```

```

head(sample100_nolabel_4)

## # A tibble: 6 x 7
##   age      educ          race  sex  occ10 region marital
##   <dbl>    <dbl>        <fct> <fct> <fct> <fct> <fct>
## 1 67      16 [4 years of college] 1     1    1740  4     5
## 2 56      14 [2 years of college] 3     2     50   4     3
## 3 33      14 [2 years of college] 1     2    7750  2     5
## 4 24      16 [4 years of college] 1     2    2550  1     5
## 5 46      14 [2 years of college] 1     2    5610  4     1
## 6 25      12 [12th grade]       1     1    6440  3     5
write.csv(sample100_nolabel_4, "gss_sample_100_unlabeled_4.csv", row.names = FALSE)

var_4 <- read.csv("/Users/joyqu/Desktop/PLSC/gss_gpt5_var_predictions_4.csv")
head(var_4)

##   age educ race sex occ10 region marital pred_polview
##   1   67   16   1   1   1740     4     5         3
##   2   56   14   3   2   50       4     3         3
##   3   33   14   1   2   7750     2     5         3
##   4   24   16   1   2   2550     1     5         2
##   5   46   14   1   2   5610     4     1         3
##   6   25   12   1   1   6440     3     5         3

# Extract variables
y_true_4 <- as.numeric(sample100_4$polviews_4)
y_pred_4 <- as.numeric(var_4$pred_polview)

# Compute metrics
MAE <- mean(abs(y_true_4 - y_pred_4))
MSE <- mean((y_true_4 - y_pred_4)^2)
Accuracy <- mean(y_true_4 == y_pred_4)
Within1 <- mean(abs(y_true_4 - y_pred_4) <= 1)

cat("Mean Absolute Error:", MAE, "\n")

## Mean Absolute Error: 0.95
cat("Mean Squared Error:", MSE, "\n")

## Mean Squared Error: 1.71
cat("Exact Match Accuracy:", round(Accuracy*100, 1), "%\n")

## Exact Match Accuracy: 35 %
cat("Within ±1 Accuracy:", round(Within1*100, 1), "%\n")

## Within ±1 Accuracy: 78 %

narrative_4 <- read.csv("/Users/joyqu/Desktop/PLSC/gss_gpt5_narrative_predictions_4.csv")
head(narrative_4)

##   id
## 1  1
## 2  2
## 3  3

```

```

## 4 4
## 5 5
## 6 6
##
## 1 He is 67, a man in the West who values ...
## 2 She is 56 years old, she has settled into a steady rhythm in the West, where routines give structure ...
## 3 At 33, this woman in the Midwest balances work, personal commitments, and leisure ...
## 4 She is 24, a woman living in the Northeast, still shaping her path in work and life. ...
## 5 She is 46 years old, she has settled into a steady rhythm in the West, where routines give ...
## 6 He is 25, a man living in the South, still shaping ...
## pred_polview_narr
## 1 3
## 2 3
## 3 4
## 4 2
## 5 3
## 6 4

# Extract variables
y_true_4 <- as.numeric(sample100_4$polviews_4)
y_pred_4 <- as.numeric(narrative_4$pred_polview_narr)

# Compute metrics
MAE <- mean(abs(y_true_4 - y_pred_4))
MSE <- mean((y_true_4 - y_pred_4)^2)
Accuracy <- mean(y_true_4 == y_pred_4)
Within1 <- mean(abs(y_true_4 - y_pred_4) <= 1)

cat("Mean Absolute Error:", MAE, "\n")

## Mean Absolute Error: 0.83
cat("Mean Squared Error:", MSE, "\n")

## Mean Squared Error: 1.47
cat("Exact Match Accuracy:", round(Accuracy*100, 1), "%\n")

## Exact Match Accuracy: 44 %
cat("Within ±1 Accuracy:", round(Within1*100, 1), "%\n")

## Within ±1 Accuracy: 78 %

df_4 <- sample100_4 %>%
  mutate(row_id = row_number()) %>%
  select(
    row_id,
    POLVIEWS_TRUE = polviews_4,
    age, sex, race, educ, marital, occ10, region    # <- keep whatever predictors you want
  ) %>%
  inner_join(
    var_4 %>%
      mutate(row_id = row_number()) %>%
      select(row_id, pred_var = pred_polview),
    by = "row_id"
  ) %>%

```

```

inner_join(
  narrative_4 %>%
    mutate(row_id = row_number()) %>%
    select(row_id, pred_narr = pred_polview_narr),
  by = "row_id"
)
head(df_4)

## # A tibble: 6 x 11
##   row_id POLVIEWS_TRUE age   sex   race   educ   marital occ10 region pred_var
##   <int>      <dbl> <dbl> <fct> <fct> <dbl+lb> <fct>   <fct> <fct>   <int>
## 1     1         3.67    1     1     16 [4 y~ 5       1740    4       3
## 2     2         4.56    2     3     14 [2 y~ 3       50      4       3
## 3     3         4.33    2     1     14 [2 y~ 5       7750    2       3
## 4     4         2.24    2     1     16 [4 y~ 5       2550    1       2
## 5     5         2.46    2     1     14 [2 y~ 1       5610    4       3
## 6     6         3.25    1     1     12 [12t~ 5       6440    3       3
## # i 1 more variable: pred_narr <int>

df_4 <- df_4 %>%
  mutate(
    # Factor version for F1
    POLVIEWS_TRUE_fac = factor(POLVIEWS_TRUE),
    pred_var_fac      = factor(pred_var, levels = levels(POLVIEWS_TRUE_fac)),
    pred_narr_fac     = factor(pred_narr, levels = levels(POLVIEWS_TRUE_fac)),

    # Numeric version for bias / error
    polviews_num = as.numeric(as.character(POLVIEWS_TRUE)),
    pred_var_num = as.numeric(as.character(pred_var)),
    pred_narr_num = as.numeric(as.character(pred_narr)),

    # Signed errors
    error_var  = pred_var_num - polviews_num,
    error_narr = pred_narr_num - polviews_num
  )
results <- tibble(
  Model = c("Variable Model", "Narrative Model"),
  Macro_F1 = c(
    f1_macro(df_4$POLVIEWS_TRUE_fac, df_4$pred_var_fac),
    f1_macro(df_4$POLVIEWS_TRUE_fac, df_4$pred_narr_fac)
  ),
  Weighted_F1 = c(
    f1_weighted(df_4$POLVIEWS_TRUE_fac, df_4$pred_var_fac),
    f1_weighted(df_4$POLVIEWS_TRUE_fac, df_4$pred_narr_fac)
  )
)

print(results)

## # A tibble: 2 x 3
##   Model           Macro_F1  Weighted_F1
##   <chr>          <dbl>        <dbl>
## 1 Variable Model  0.765       0.726
## 2 Narrative Model 0.778       0.711

```

```

mislabeled_comparison <- df_4 %>%
  mutate(
    # Wrong / right flags
    var_wrong = pred_var != POLVIEWS_TRUE,
    narr_wrong = pred_narr != POLVIEWS_TRUE,

    # Case types with only two models
    case_type = case_when(
      var_wrong & !narr_wrong ~ "Only Variable Model Wrong",
      !var_wrong & narr_wrong ~ "Only Narrative Model Wrong",
      var_wrong & narr_wrong ~ "Both Wrong",
      TRUE                 ~ "Both Correct"
    ),

    # Differences vs true (numeric scale 1-7)
    diff_var = as.numeric(pred_var) - as.numeric(POLVIEWS_TRUE),
    diff_narr = as.numeric(pred_narr) - as.numeric(POLVIEWS_TRUE),

    # Bias direction for each model (only label as too lib/con if it's wrong)
    bias_var = dplyr:::case_when(
      !var_wrong           ~ "Correct",
      diff_var > 0        ~ "Too Conservative",
      diff_var < 0        ~ "Too Liberal",
      TRUE                ~ NA_character_
    ),
    bias_narr = dplyr:::case_when(
      !narr_wrong          ~ "Correct",
      diff_narr > 0        ~ "Too Conservative",
      diff_narr < 0        ~ "Too Liberal",
      TRUE                ~ NA_character_
    )
  ) %>%
  select(
    row_id, POLVIEWS_TRUE,
    pred_var, pred_narr,
    var_wrong, narr_wrong,
    case_type,
    bias_var, bias_narr
  )

# Save to CSV
write.csv(mislabeled_comparison,
          "mislabeled_cases_comparison_4.csv",
          row.names = FALSE)

bias_table <- mislabeled_comparison %>%
  select(bias_var, bias_narr) %>%
  tidyr::pivot_longer(
    cols      = everything(),
    names_to = "model",
    values_to = "bias"
  ) %>%
  dplyr::filter(bias != "Correct") %>%    # only mislabeled cases

```

```

dplyr::group_by(model, bias) %>%
dplyr::summarise(count = dplyr::n(), .groups = "drop_last") %>%
dplyr::mutate(
  percent = count / sum(count) * 100
) %>%
dplyr::ungroup() %>%
dplyr::mutate(
  model = dplyr::recode(
    model,
    bias_var = "Variable Model",
    bias_narr = "Narrative Model"
  )
) %>%
dplyr::arrange(model, bias)
bias_table

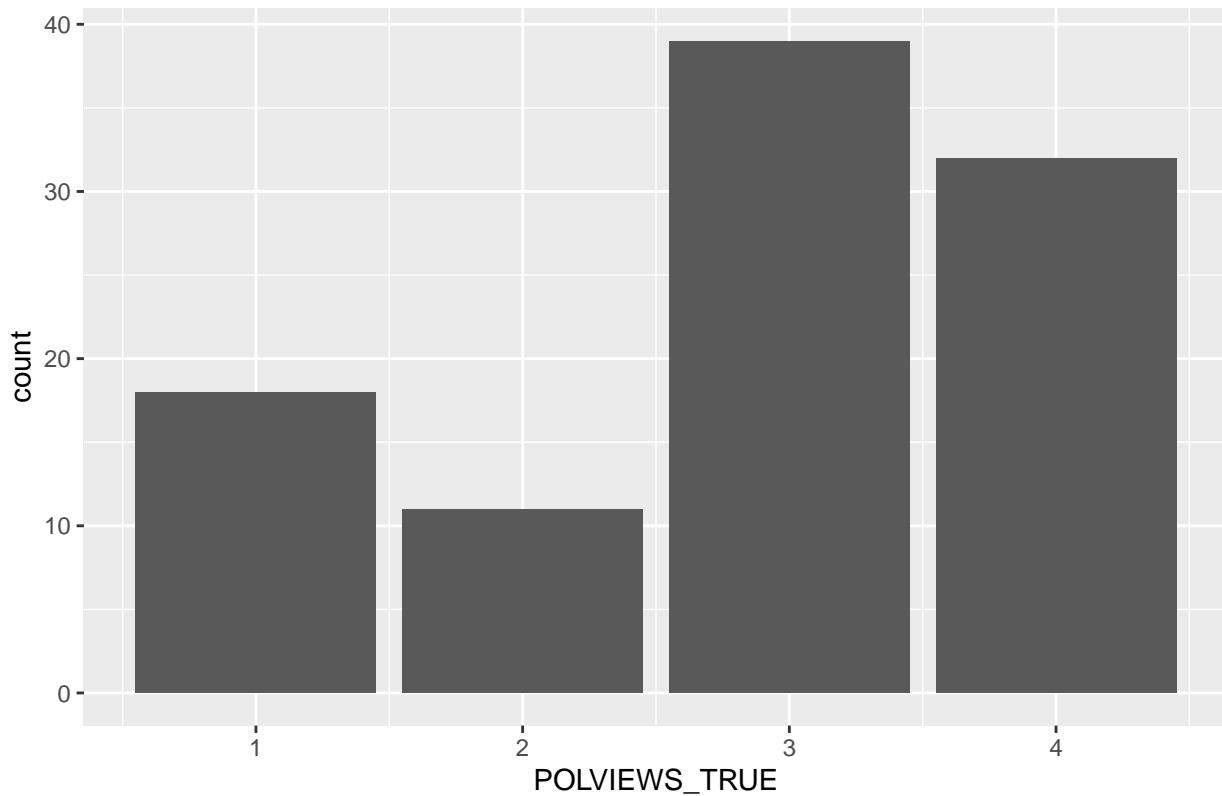
## # A tibble: 4 x 4
##   model           bias       count  percent
##   <chr>          <chr>     <int>    <dbl>
## 1 Narrative Model Too Conservative    41    73.2
## 2 Narrative Model Too Liberal        15    26.8
## 3 Variable Model  Too Conservative   44    67.7
## 4 Variable Model  Too Liberal       21    32.3

#true polviews distribution

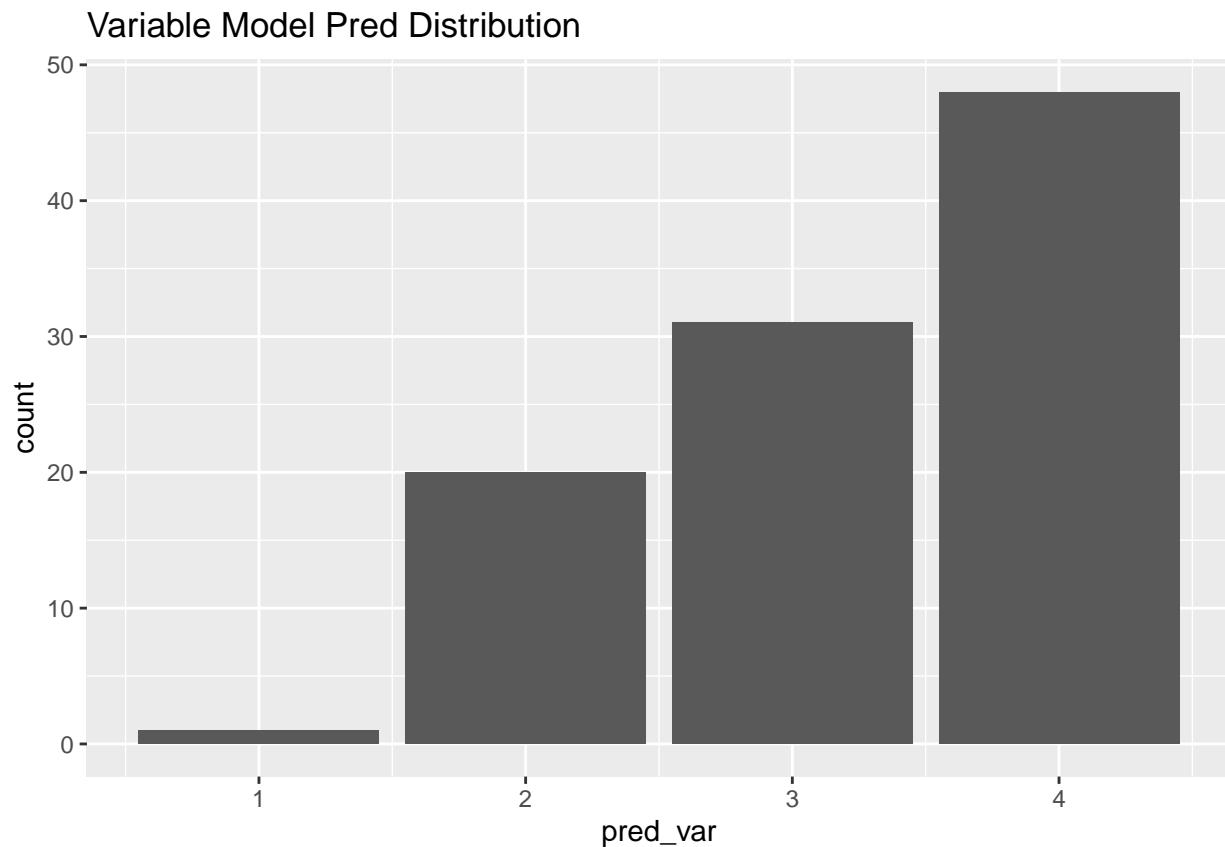
ggplot(df_4, aes(x = POLVIEWS_TRUE)) +
  geom_bar() +
  ggtitle("True POLVIEWS Distribution")

```

True POLVIEWS Distribution

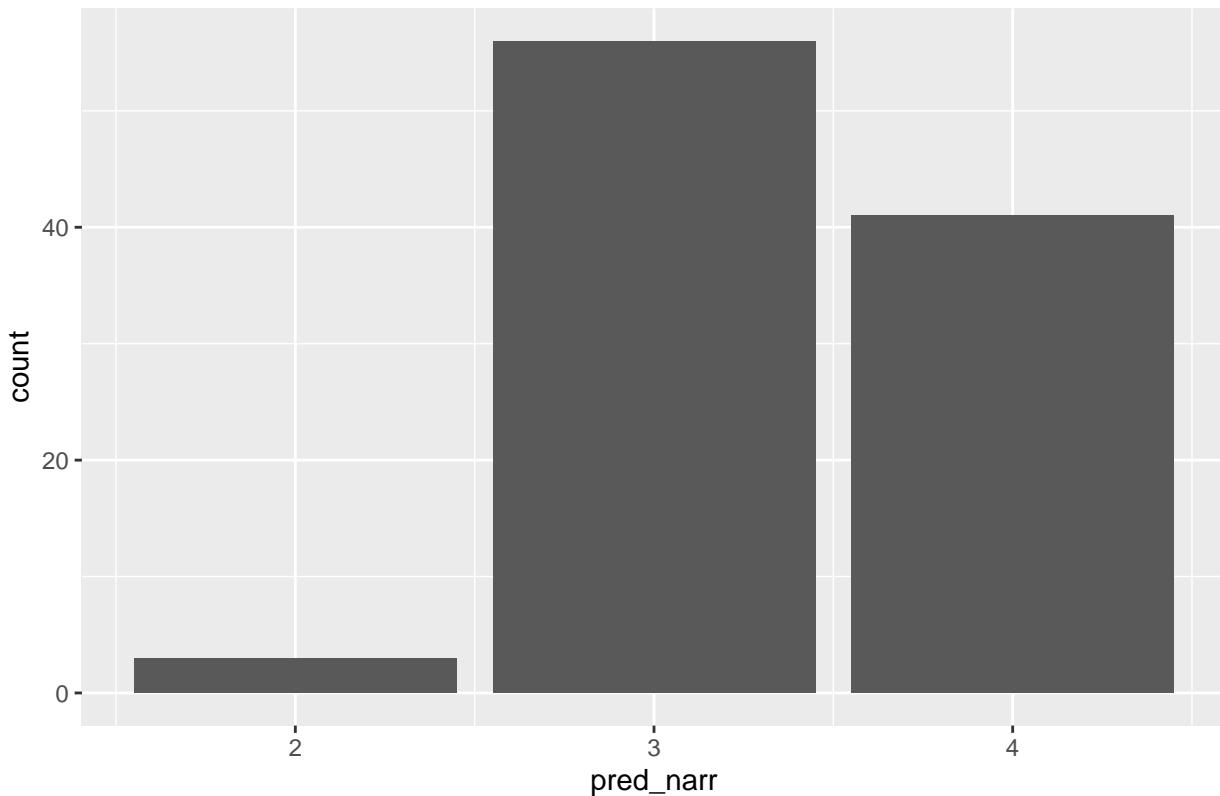


```
ggplot(df_4, aes(x = pred_var)) +  
  geom_bar() +  
  ggtitle("Variable Model Pred Distribution")
```



```
ggplot(df_4, aes(x = pred_narr)) +  
  geom_bar() +  
  ggtitle("Narrative Model Pred Distribution")
```

Narrative Model Pred Distribution



```

df_4$occ10 <- as.numeric(as.character(df_4$occ10))
bias_by_predictor(df_4, age)

## # A tibble: 50 x 8
##   age      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <dbl> <int>      <dbl>           <dbl>            <dbl>            <dbl>
## 1 73      1        3             2              1              0
## 2 79      1        3             3              1              0
## 3 49      2        2.5           2.5            1              0
## 4 76      1        2             1              1              0
## 5 82      1        2             2              1              0
## 6 83      4        2             1.25           1              0
## 7 58      4        1.5            0.75          0.75            0.25
## 8 63      5        1.4            1.4            0.8             0
## 9 39      1        1             0              1              0
## 10 40     2        1             2              1              0
## # i 40 more rows
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
bias_by_predictor(df_4, sex)

## # A tibble: 2 x 8
##   sex      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <fct> <int>      <dbl>           <dbl>            <dbl>            <dbl>
## 1 2       47        0.468          0.574          0.447          0.191
## 2 1       53        0.358          0.491          0.434          0.226
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
```

```

bias_by_predictor(df_4, race)

## # A tibble: 3 x 8
##   race      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <fct> <int>      <dbl>        <dbl>          <dbl>          <dbl>
## 1 1       77      0.506       0.468        0.442        0.156
## 2 2       13      0.385       1            0.538        0.231
## 3 3       10      -0.3        0.4           0.3          0.6
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>

bias_by_predictor(df_4, educ)

## # A tibble: 14 x 8
##   educ                  n mean_error_var mean_error_narr prop_too_cons_var
##   <dbl+lbl> <int>      <dbl>        <dbl>          <dbl>
## 1 19 [7 years of colleg~    1      3            2            1
## 2 20 [8 or more years o~    2      2.5           2            1
## 3 13 [1 year of college]  6      1            1.33          0.667
## 4 16 [4 years of colleg~  26     0.615         0.423          0.5
## 5 15 [3 years of colleg~  2      0.5           0.5           0.5
## 6 12 [12th grade]        21     0.476         0.571          0.429
## 7 14 [2 years of colleg~  20     0.25          0.55          0.4
## 8 6  [6th grade]          1      0             0             0
## 9 9  [9th grade]          1      0             0             0
## 10 10 [10th grade]        2      0             0.5           0
## 11 18 [6 years of colleg~  7     -0.143         0.286          0.429
## 12 17 [5 years of colleg~  9     -0.222         0.111          0.333
## 13 0  [no formal schooli~  1     -1             0             0
## 14 11 [11th grade]        1     -1             0             0
## # i 3 more variables: prop_too_lib_var <dbl>, prop_too_cons_narr <dbl>,
## #   prop_too_lib_narr <dbl>

bias_by_predictor(df_4, marital)

## # A tibble: 4 x 8
##   marital      n mean_error_var mean_error_narr prop_too_cons_var
##   <fct> <int>      <dbl>        <dbl>          <dbl>
## 1 2       8      1.25         0.875        0.75
## 2 3      16      0.688        0.688        0.5
## 3 1      44      0.523        0.386        0.477
## 4 5      32     -0.0938       0.562        0.281
## # i 3 more variables: prop_too_lib_var <dbl>, prop_too_cons_narr <dbl>,
## #   prop_too_lib_narr <dbl>

bias_by_predictor(df_4, occ10)

## # A tibble: 73 x 8
##   occ10      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <dbl> <int>      <dbl>        <dbl>          <dbl>          <dbl>
## 1 1460     1      3            2            1            0
## 2 2200     1      3            2            1            0
## 3 5120     1      3            3            1            0
## 4 5600     1      3            2            1            0
## 5 5820     1      3            2            1            0
## 6 9620     1      3            3            1            0
## 7 710      2      2.5          1.5           1            0

```

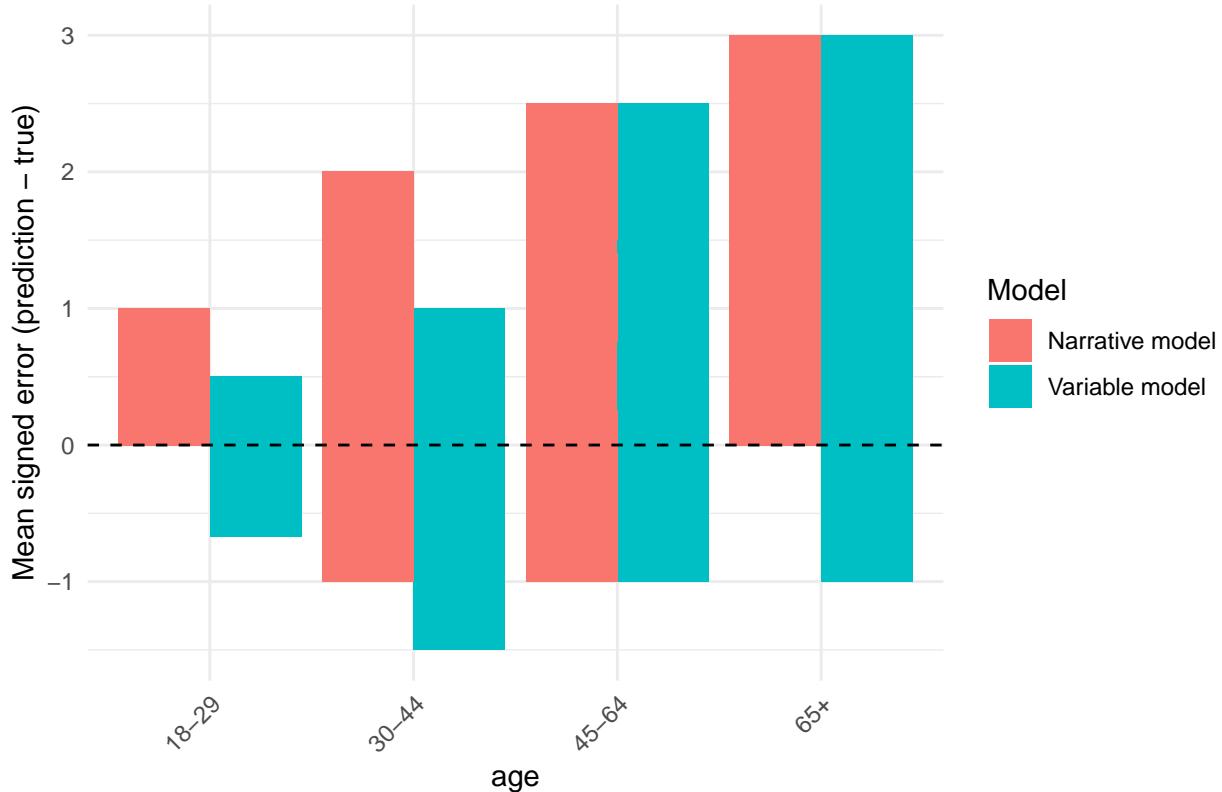
```

##   8    735     1      2      2      1      0
##   9   3320     1      2      2      1      0
## 10   3645     1      2      2      1      0
## # i 63 more rows
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
bias_by_predictor(df_4, region)

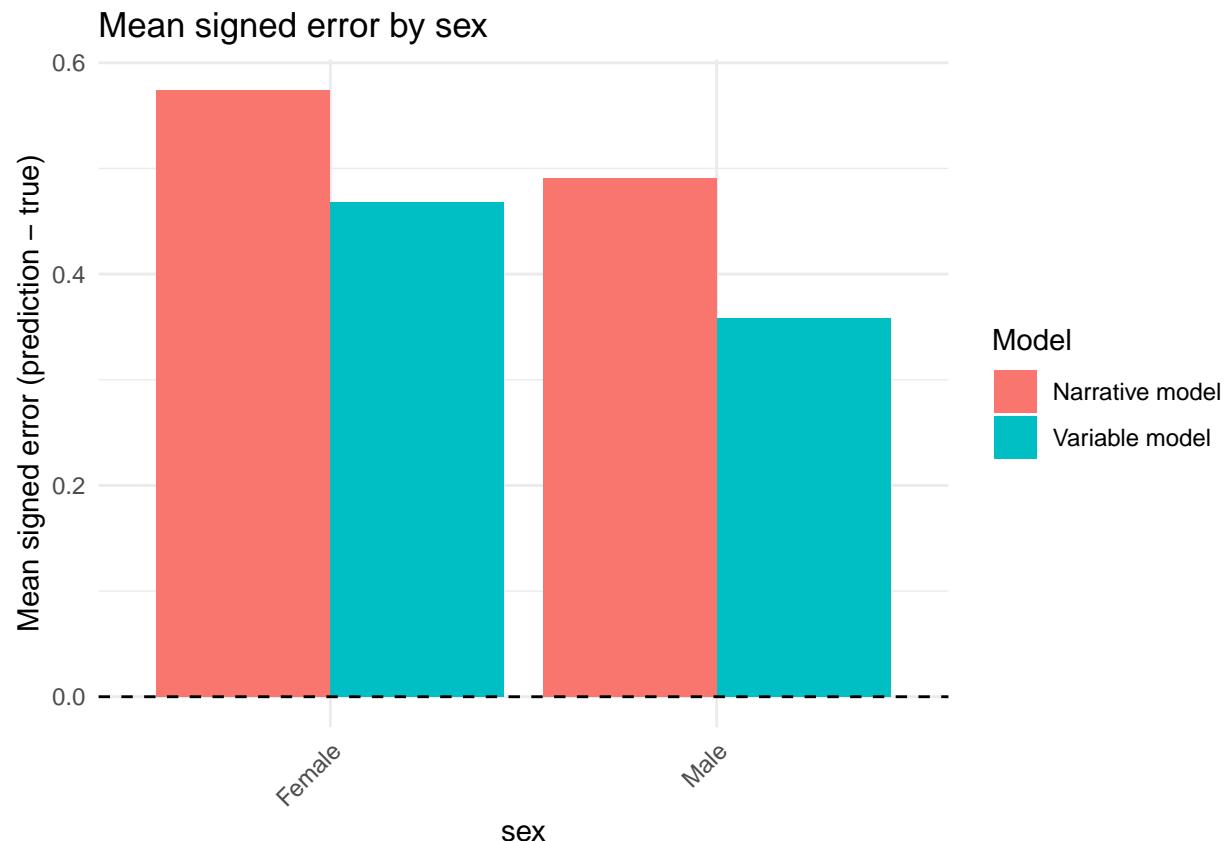
## # A tibble: 4 x 8
##   region     n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <fct>   <int>        <dbl>        <dbl>        <dbl>        <dbl>
## 1 1         12       0.667       0.5       0.583       0.0833
## 2 2         24       0.625       0.667       0.417       0.125
## 3 3         37       0.541       0.595       0.432       0.135
## 4 4         27      -0.0741      0.333       0.407       0.444
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
plot_mean_error_by_predictor(df_4, age)

```

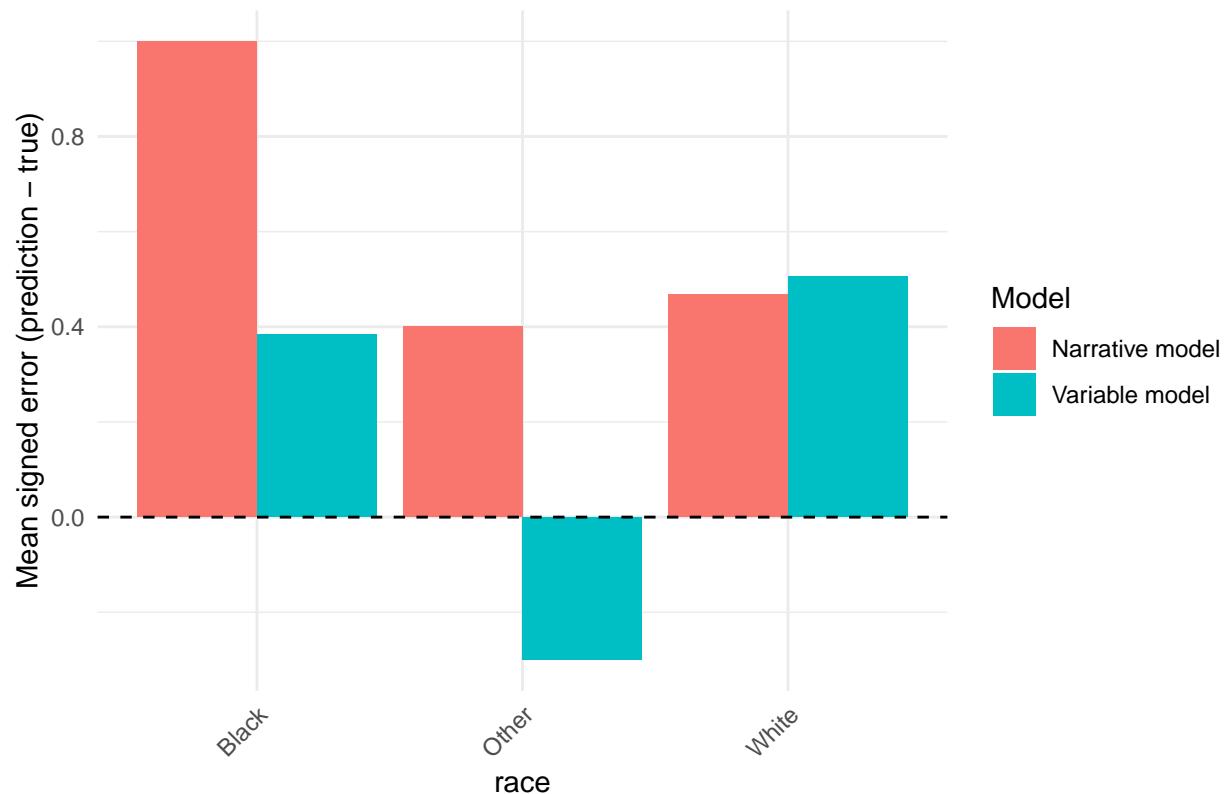
Mean signed error by age



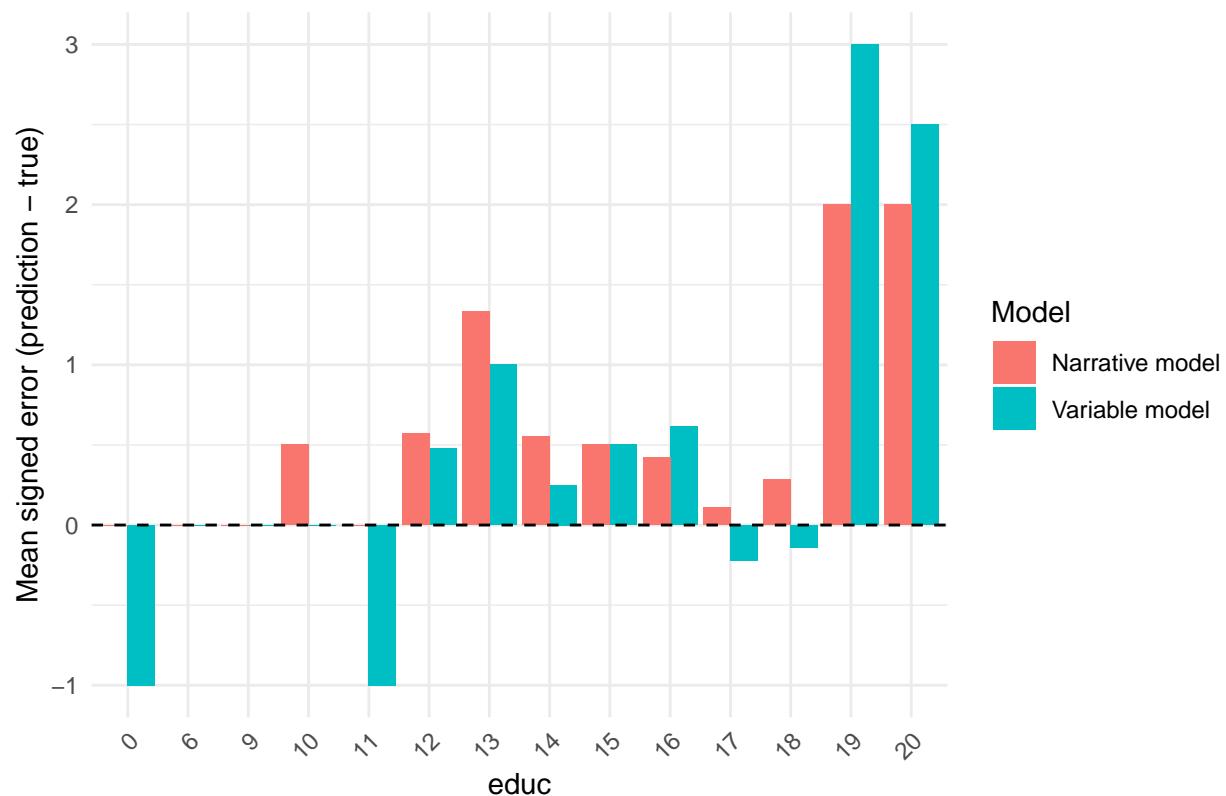
```
plot_mean_error_by_predictor(df_4, sex)
```



Mean signed error by race

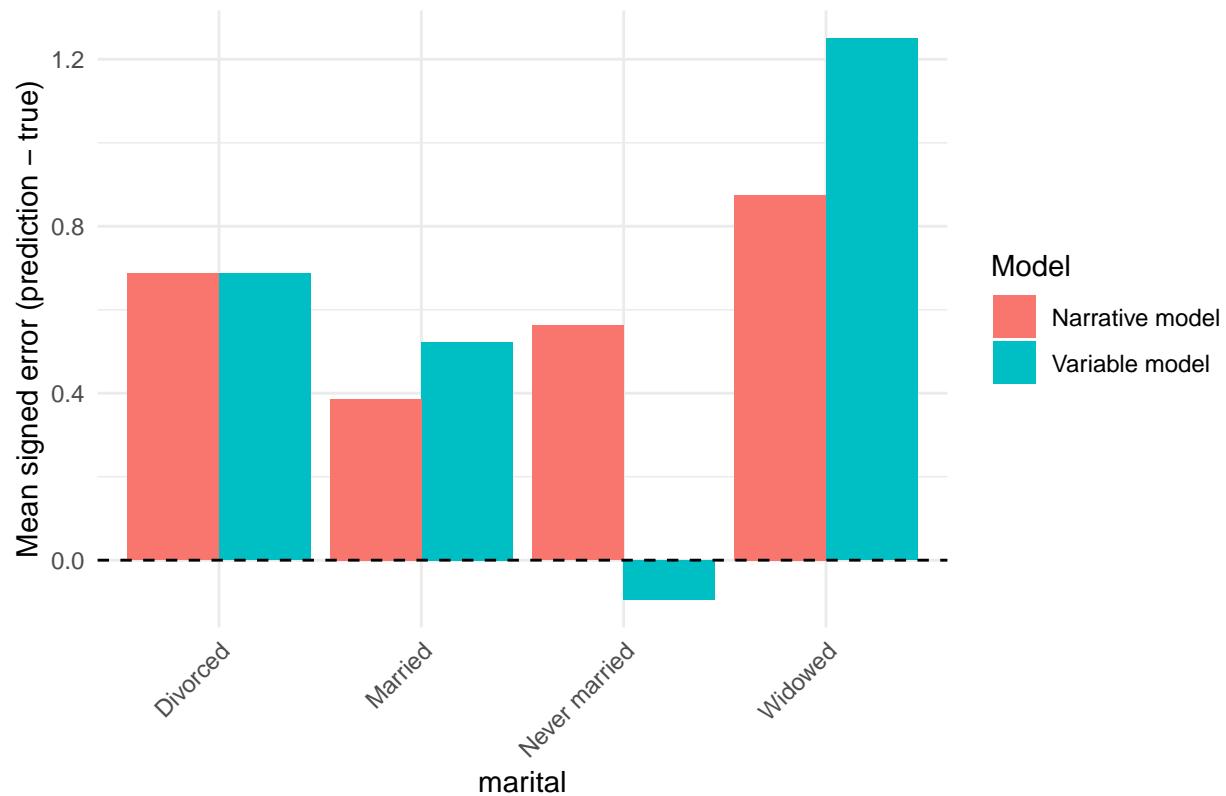


Mean signed error by educ



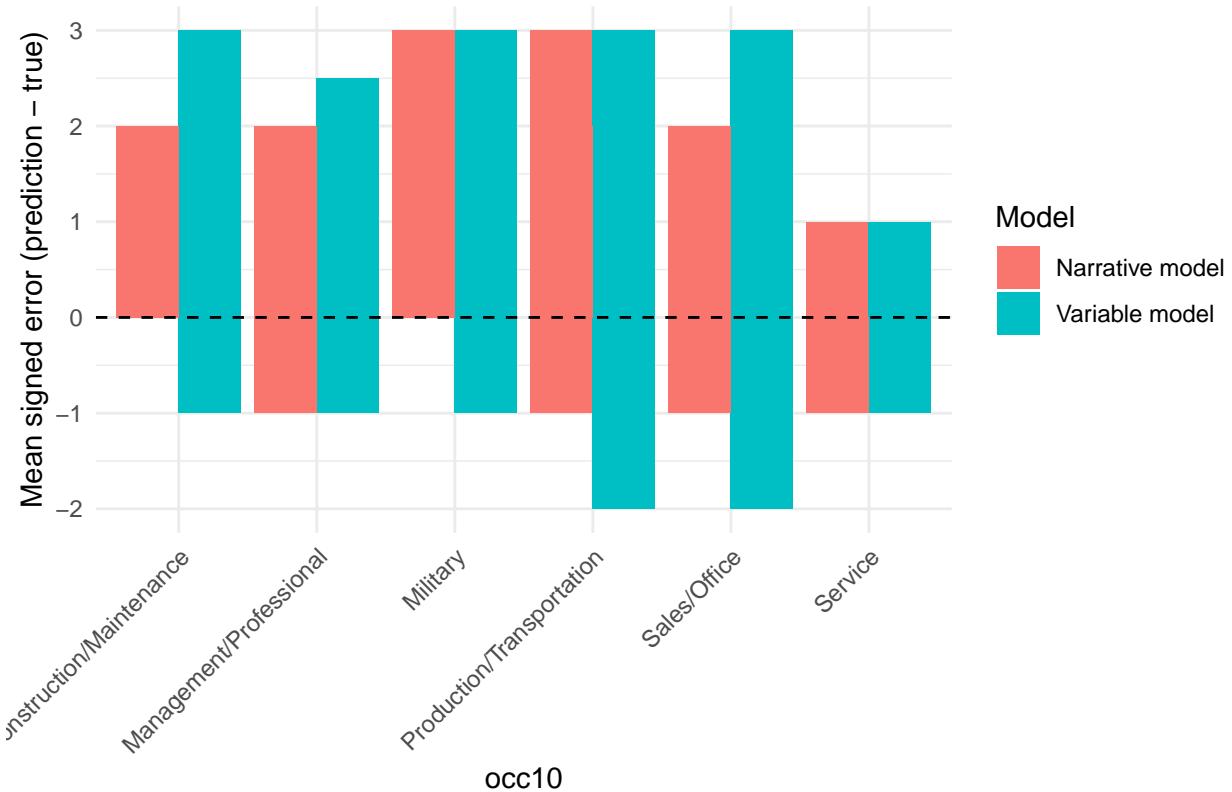
```
plot_mean_error_by_predictor(df_4, marital)
```

Mean signed error by marital



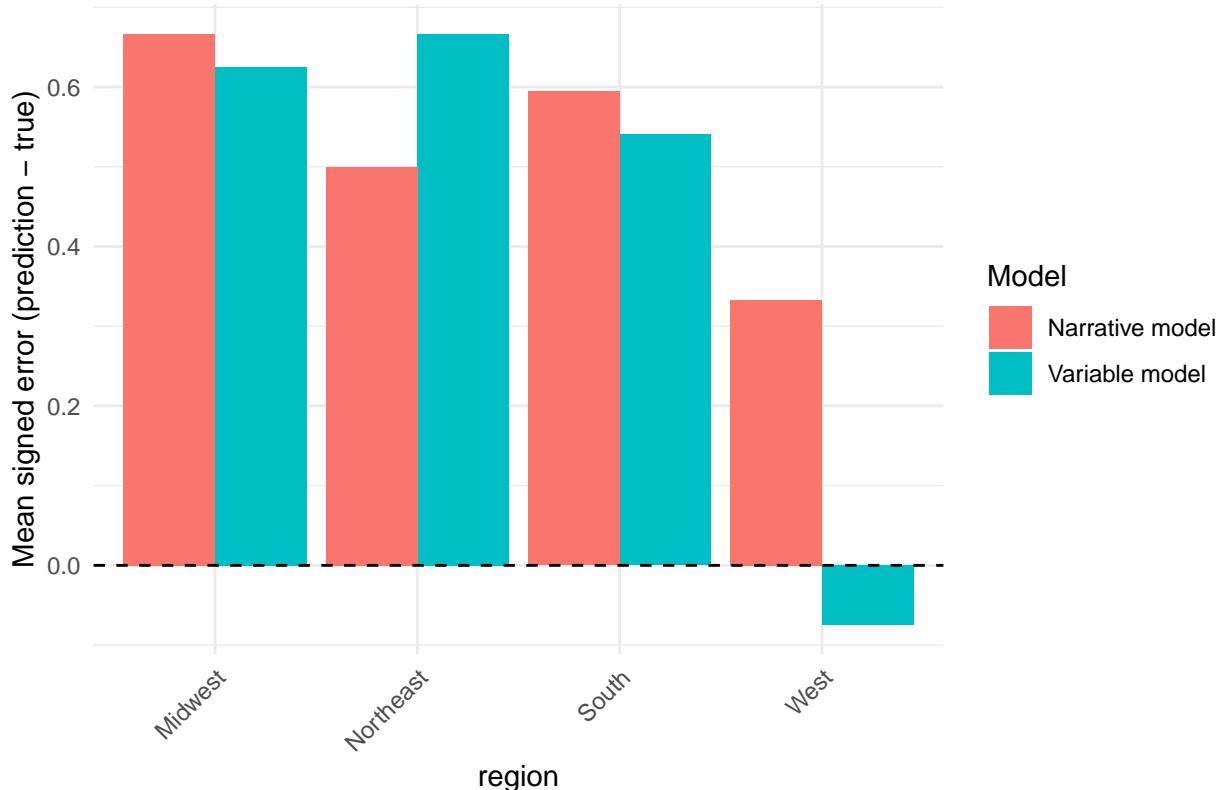
```
plot_mean_error_by_predictor(df_4, occ10)
```

Mean signed error by occ10



```
plot_mean_error_by_predictor(df_4, region)
```

Mean signed error by region



```
#collapse POLVIEWS into five categories
sample100_5 <- sample100 %>%
  mutate(
    polviews_5= case_when(
      polviews %in% c(1) ~ 1,    # extremely liberal
      polviews %in% c(2,3) ~ 2,   # liberal
      polviews %in% c(4) ~ 3,    # moderate
      polviews %in% c(5,6) ~ 4,   # conservative
      polviews %in% c(7) ~ 5     # extremely conservative
    )
  ) %>%
  filter(!is.na(polviews_5))
head(sample100_5)

## # A tibble: 6 x 9
##   polviews age      educ          race sex  occ10 region marital polviews_5
##   <dbl>   <dbl> <dbl+lbl> <dbl+lbl> <fct> <fct> <fct> <fct> <dbl>
## 1       1  67      16 [4 years of~ 1    1    1740  4     5           3
## 2       2  56      14 [2 years of~ 3    2     50    4     3           4
## 3       3  33      14 [2 years of~ 1    2    7750  2     5           4
## 4       4  24      16 [4 years of~ 1    2    2550   1     5           2
## 5       5  46      14 [2 years of~ 1    2    5610   4     1           2
## 6       6  25      12 [12th grade] 1    1    6440   3     5           3

sample100_nolabel_5 <- sample100_5 %>%
  select(-polviews_5) %>% # remove the ideology variable
  select(-polviews) # remove the numeric ideology variable
```

```

head(sample100_nolabel_5)

## # A tibble: 6 x 7
##   age      educ          race  sex  occ10 region marital
##   <dbl> <dbl+lbl> <fct> <fct> <fct> <fct> <fct>
## 1 67      16 [4 years of college] 1     1    1740  4     5
## 2 56      14 [2 years of college] 3     2     50   4     3
## 3 33      14 [2 years of college] 1     2    7750  2     5
## 4 24      16 [4 years of college] 1     2    2550  1     5
## 5 46      14 [2 years of college] 1     2    5610  4     1
## 6 25      12 [12th grade]        1     1    6440  3     5
write.csv(sample100_nolabel_5, "gss_sample_100_unlabeled_5.csv", row.names = FALSE)

var_5 <- read.csv("/Users/joyqu/Desktop/PLSC/gss_gpt5_var_predictions_5.csv")
head(var_5)

##   age educ race sex occ10 region marital pred_polview
##   1   67   16   1   1   1740     4     5       3
##   2   56   14   3   2   50      4     3       3
##   3   33   14   1   2   7750     2     5       3
##   4   24   16   1   2   2550     1     5       2
##   5   46   14   1   2   5610     4     1       3
##   6   25   12   1   1   6440     3     5       4

# Extract variables
y_true_5 <- as.numeric(sample100_5$polviews_5)
y_pred_5 <- as.numeric(var_5$pred_polview)

# Compute metrics
MAE <- mean(abs(y_true_5 - y_pred_5))
MSE <- mean((y_true_5 - y_pred_5)^2)
Accuracy <- mean(y_true_5 == y_pred_5)
Within1 <- mean(abs(y_true_5 - y_pred_5) <= 1)

cat("Mean Absolute Error:", MAE, "\n")

## Mean Absolute Error: 0.89

cat("Mean Squared Error:", MSE, "\n")

## Mean Squared Error: 1.43

cat("Exact Match Accuracy:", round(Accuracy*100, 1), "%\n")

## Exact Match Accuracy: 35 %

cat("Within ±1 Accuracy:", round(Within1*100, 1), "%\n")

## Within ±1 Accuracy: 79 %

narrative_5 <- read.csv("/Users/joyqu/Desktop/PLSC/gss_gpt5_narrative_predictions_5.csv")
head(narrative_5)

##   id
## 1  1
## 2  2
## 3  3

```

```

## 4 4
## 5 5
## 6 6
##
## 1 He is 67, a man in the West who values ...
## 2 She is 56 years old, she has settled into a steady rhythm in the West, where routines give structure ...
## 3 At 33, this woman in the Midwest balances work, personal commitments, and leisure ...
## 4 She is 24, a woman living in the Northeast, still shaping her path in work and life. ...
## 5 She is 46 years old, she has settled into a steady rhythm in the West, where routines give ...
## 6 He is 25, a man living in the South, still shaping ...
## pred_polview_narr
## 1 3
## 2 3
## 3 4
## 4 2
## 5 3
## 6 4

# Extract variables
y_true_5 <- as.numeric(sample100_5$polviews_5)
y_pred_5 <- as.numeric(narrative_5$pred_polview_narr)

# Compute metrics
MAE <- mean(abs(y_true_5 - y_pred_5))
MSE <- mean((y_true_5 - y_pred_5)^2)
Accuracy <- mean(y_true_5 == y_pred_5)
Within1 <- mean(abs(y_true_5 - y_pred_5) <= 1)

cat("Mean Absolute Error:", MAE, "\n")

## Mean Absolute Error: 0.81
cat("Mean Squared Error:", MSE, "\n")

## Mean Squared Error: 1.23
cat("Exact Match Accuracy:", round(Accuracy*100, 1), "%\n")

## Exact Match Accuracy: 38 %
cat("Within ±1 Accuracy:", round(Within1*100, 1), "%\n")

## Within ±1 Accuracy: 83 %

df_5 <- sample100_5 %>%
  mutate(row_id = row_number()) %>%
  select(
    row_id,
    POLVIEWS_TRUE = polviews_5,
    age, sex, race, educ, marital, occ10, region    # <- keep whatever predictors you want
  ) %>%
  inner_join(
    var_5 %>%
      mutate(row_id = row_number()) %>%
      select(row_id, pred_var = pred_polview),
    by = "row_id"
  ) %>%

```

```

inner_join(
  narrative_5 %>%
    mutate(row_id = row_number()) %>%
    select(row_id, pred_narr = pred_polview_narr),
  by = "row_id"
)
head(df_5)

## # A tibble: 6 x 11
##   row_id POLVIEWS_TRUE age   sex   race   educ   marital occ10 region pred_var
##   <int>      <dbl> <dbl> <fct> <fct> <dbl+lb> <fct>   <fct> <fct>   <int>
## 1     1         3.67    1     1     16 [4 y~ 5     1740    4     3
## 2     2         4.56    2     3     14 [2 y~ 3     50     4     3
## 3     3         4.33    2     1     14 [2 y~ 5     7750    2     3
## 4     4         2.24    2     1     16 [4 y~ 5     2550    1     2
## 5     5         2.46    2     1     14 [2 y~ 1     5610    4     3
## 6     6         3.25    1     1     12 [12t~ 5     6440    3     4
## # i 1 more variable: pred_narr <int>

df_5 <- df_5 %>%
  mutate(
    # Factor version for F1
    POLVIEWS_TRUE_fac = factor(POLVIEWS_TRUE),
    pred_var_fac      = factor(pred_var, levels = levels(POLVIEWS_TRUE_fac)),
    pred_narr_fac     = factor(pred_narr, levels = levels(POLVIEWS_TRUE_fac)),

    # Numeric version for bias / error
    polviews_num = as.numeric(as.character(POLVIEWS_TRUE)),
    pred_var_num = as.numeric(as.character(pred_var)),
    pred_narr_num = as.numeric(as.character(pred_narr)),

    # Signed errors
    error_var  = pred_var_num - polviews_num,
    error_narr = pred_narr_num - polviews_num
  )
results <- tibble(
  Model = c("Variable Model", "Narrative Model"),
  Macro_F1 = c(
    f1_macro(df_5$POLVIEWS_TRUE_fac, df_5$pred_var_fac),
    f1_macro(df_5$POLVIEWS_TRUE_fac, df_5$pred_narr_fac)
  ),
  Weighted_F1 = c(
    f1_weighted(df_5$POLVIEWS_TRUE_fac, df_5$pred_var_fac),
    f1_weighted(df_5$POLVIEWS_TRUE_fac, df_5$pred_narr_fac)
  )
)

print(results)

## # A tibble: 2 x 3
##   Model           Macro_F1  Weighted_F1
##   <chr>          <dbl>       <dbl>
## 1 Variable Model  0.805      0.712
## 2 Narrative Model 0.810      0.713

```

```

mislabeled_comparison <- df_5 %>%
  mutate(
    # Wrong / right flags
    var_wrong = pred_var != POLVIEWS_TRUE,
    narr_wrong = pred_narr != POLVIEWS_TRUE,

    # Case types with only two models
    case_type = case_when(
      var_wrong & !narr_wrong ~ "Only Variable Model Wrong",
      !var_wrong & narr_wrong ~ "Only Narrative Model Wrong",
      var_wrong & narr_wrong ~ "Both Wrong",
      TRUE                 ~ "Both Correct"
    ),

    # Differences vs true (numeric scale 1-7)
    diff_var = as.numeric(pred_var) - as.numeric(POLVIEWS_TRUE),
    diff_narr = as.numeric(pred_narr) - as.numeric(POLVIEWS_TRUE),

    # Bias direction for each model (only label as too lib/con if it's wrong)
    bias_var = dplyr:::case_when(
      !var_wrong           ~ "Correct",
      diff_var > 0        ~ "Too Conservative",
      diff_var < 0        ~ "Too Liberal",
      TRUE                ~ NA_character_
    ),
    bias_narr = dplyr:::case_when(
      !narr_wrong          ~ "Correct",
      diff_narr > 0        ~ "Too Conservative",
      diff_narr < 0        ~ "Too Liberal",
      TRUE                ~ NA_character_
    )
  ) %>%
  select(
    row_id, POLVIEWS_TRUE,
    pred_var, pred_narr,
    var_wrong, narr_wrong,
    case_type,
    bias_var, bias_narr
  )

# Save to CSV
write.csv(mislabeled_comparison,
          "mislabeled_cases_comparison_5.csv",
          row.names = FALSE)

bias_table <- mislabeled_comparison %>%
  select(bias_var, bias_narr) %>%
  tidyr:::pivot_longer(
    cols      = everything(),
    names_to = "model",
    values_to = "bias"
  ) %>%
  dplyr:::filter(bias != "Correct") %>%    # only mislabeled cases

```

```

dplyr::group_by(model, bias) %>%
dplyr::summarise(count = dplyr::n(), .groups = "drop_last") %>%
dplyr::mutate(
  percent = count / sum(count) * 100
) %>%
dplyr::ungroup() %>%
dplyr::mutate(
  model = dplyr::recode(
    model,
    bias_var = "Variable Model",
    bias_narr = "Narrative Model"
  )
) %>%
dplyr::arrange(model, bias)
bias_table

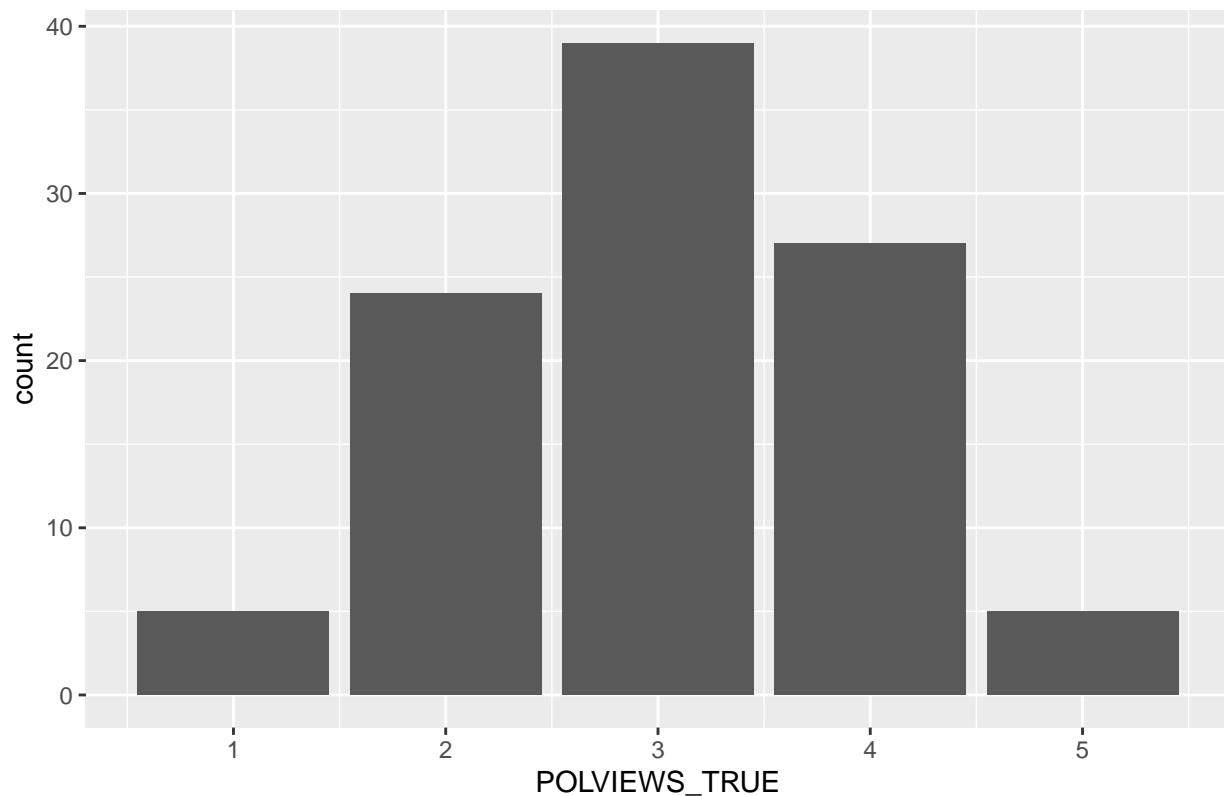
## # A tibble: 4 x 4
##   model           bias       count  percent
##   <chr>          <chr>     <int>    <dbl>
## 1 Narrative Model Too Conservative    45    72.6
## 2 Narrative Model Too Liberal        17    27.4
## 3 Variable Model  Too Conservative   47    72.3
## 4 Variable Model  Too Liberal       18    27.7

#true polviews distribution

ggplot(df_5, aes(x = POLVIEWS_TRUE)) +
  geom_bar() +
  ggtitle("True POLVIEWS Distribution")

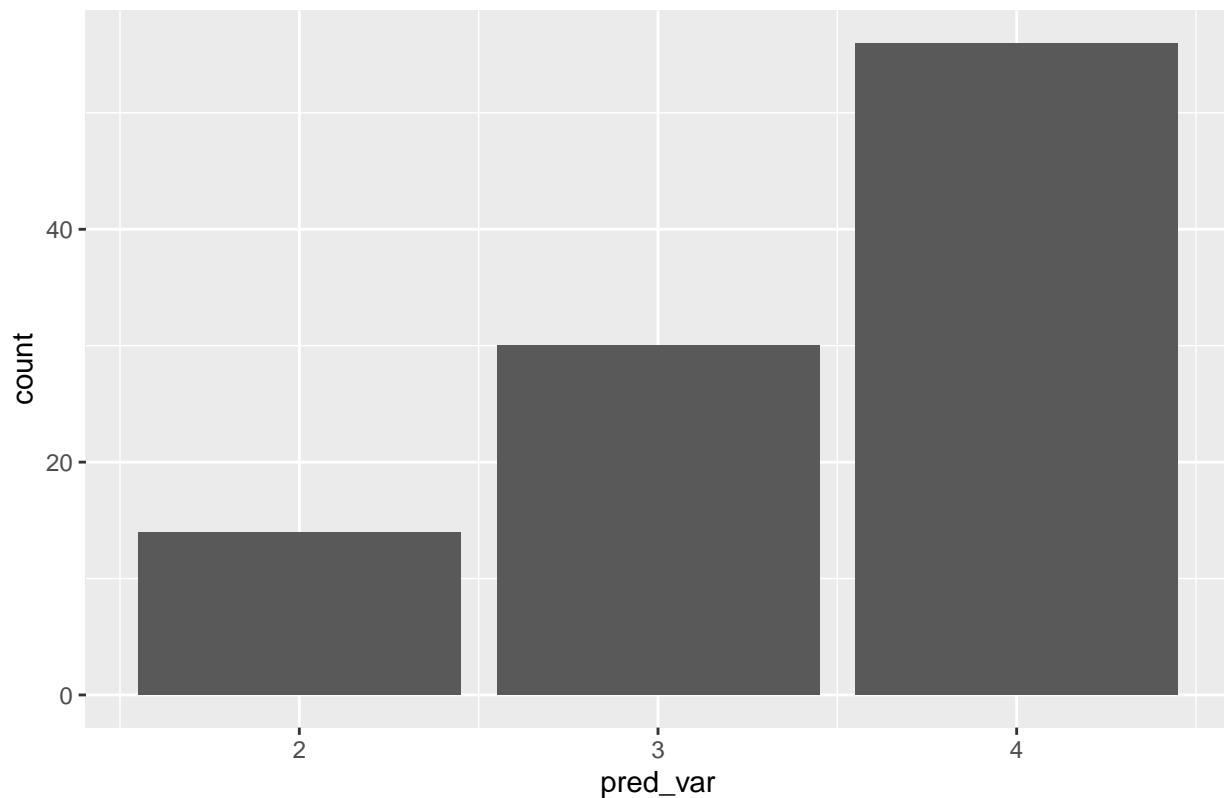
```

True POLVIEWS Distribution



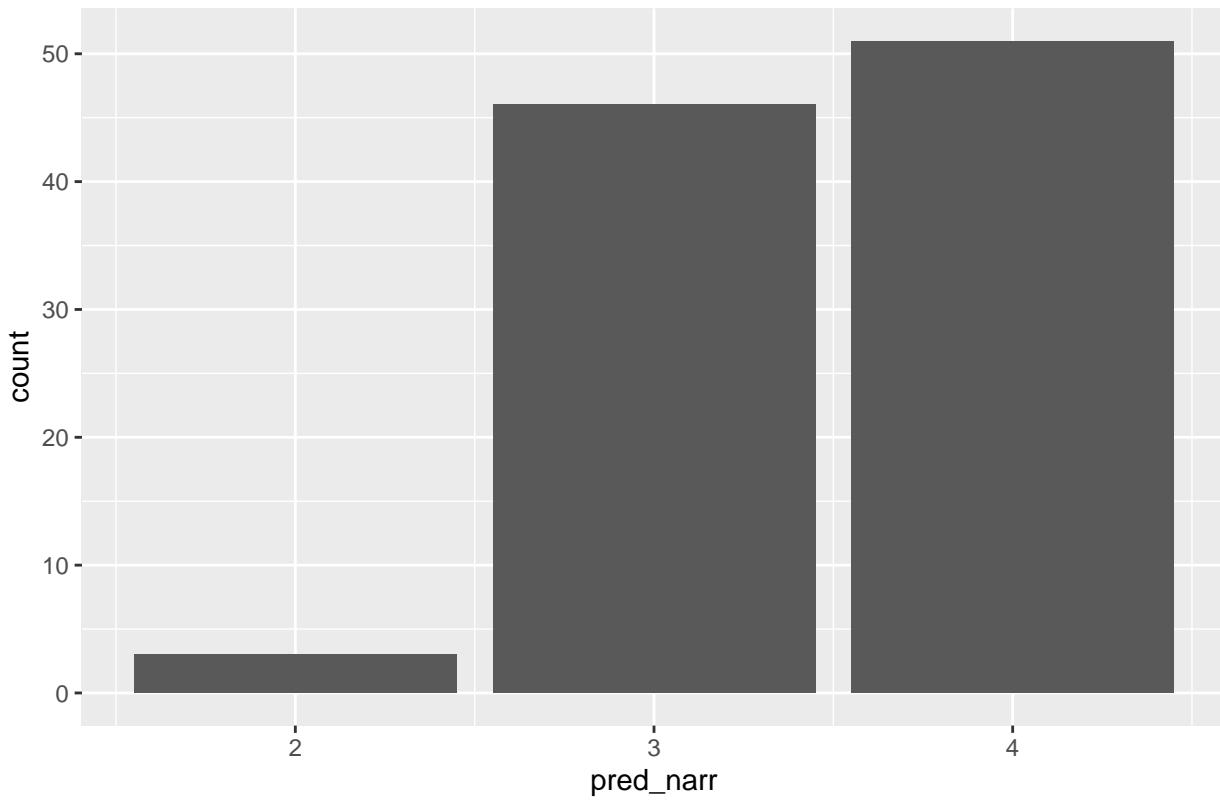
```
ggplot(df_5, aes(x = pred_var)) +  
  geom_bar() +  
  ggtitle("Variable Model Pred Distribution")
```

Variable Model Pred Distribution



```
ggplot(df_5, aes(x = pred_narr)) +  
  geom_bar() +  
  ggtitle("Narrative Model Pred Distribution")
```

Narrative Model Pred Distribution



```

df_5$occ10 <- as.numeric(as.character(df_5$occ10))
bias_by_predictor(df_5, age)

## # A tibble: 50 x 8
##   age      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <dbl> <int>      <dbl>          <dbl>            <dbl>            <dbl>
## 1 73       1        2             2              1               0
## 2 76       1        2             2              1               0
## 3 79       1        2             2              1               0
## 4 82       1        2             2              1               0
## 5 83       4       1.75           1              1               0
## 6 29       2        1.5            1              1               0
## 7 49       2        1.5            1.5             1               0
## 8 63       5        1.2            1.4             0.8             0
## 9 25       2        1             0.5             1               0
## 10 31      1        1             1               1               0
## # i 40 more rows
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
bias_by_predictor(df_5, sex)

## # A tibble: 2 x 8
##   sex      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <fct> <int>      <dbl>          <dbl>            <dbl>            <dbl>
## 1 2       47        0.426         0.426          0.468          0.170
## 2 1       53        0.358         0.472          0.472          0.189
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
```

```

bias_by_predictor(df_5, race)

## # A tibble: 3 x 8
##   race      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <fct> <int>      <dbl>        <dbl>          <dbl>          <dbl>
## 1 1       77      0.506       0.403         0.519         0.143
## 2 2       13      0.308       0.846         0.385         0.154
## 3 3       10      -0.4        0.3           0.2           0.5
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>

bias_by_predictor(df_5, educ)

## # A tibble: 14 x 8
##   educ                  n mean_error_var mean_error_narr prop_too_cons_var
##   <dbl+lbl> <int>      <dbl>        <dbl>          <dbl>
## 1 20 [8 or more years o~    2      2.5        2            1
## 2 19 [7 years of colleg~   1      2           1            1
## 3 6 [6th grade]           1      1           0            1
## 4 15 [3 years of colleg~  2      1           0.5          1
## 5 13 [1 year of college]  6      0.667       1            0.667
## 6 12 [12th grade]         21     0.524       0.619        0.524
## 7 16 [4 years of colleg~  26     0.462       0.269        0.462
## 8 14 [2 years of colleg~  20     0.35        0.55         0.5
## 9 9 [9th grade]           1      0           0            0
## 10 10 [10th grade]        2      0           0.5          0
## 11 11 [11th grade]        1      0           0            0
## 12 18 [6 years of colleg~  7      0           0.143        0.286
## 13 17 [5 years of colleg~  9      -0.333      0.111        0.222
## 14 0 [no formal schooli~   1      -2           -1           0
## # i 3 more variables: prop_too_lib_var <dbl>, prop_too_cons_narr <dbl>,
## #   prop_too_lib_narr <dbl>

bias_by_predictor(df_5, marital)

## # A tibble: 4 x 8
##   marital      n mean_error_var mean_error_narr prop_too_cons_var
##   <fct> <int>      <dbl>        <dbl>          <dbl>
## 1 2        8      1           0.875        0.75
## 2 3       16      0.625       0.625        0.625
## 3 1       44      0.432       0.295        0.5
## 4 5       32      0.0625      0.469        0.281
## # i 3 more variables: prop_too_lib_var <dbl>, prop_too_cons_narr <dbl>,
## #   prop_too_lib_narr <dbl>

bias_by_predictor(df_5, occ10)

## # A tibble: 73 x 8
##   occ10      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <dbl> <int>      <dbl>        <dbl>          <dbl>          <dbl>
## 1 2200     1      3           2             1             0
## 2 9620     1      3           3             1             0
## 3 710      2      2           1.5           1             0
## 4 735      1      2           1             1             0
## 5 1460     1      2           1             1             0
## 6 5120     1      2           2             1             0
## 7 5600     1      2           2             1             0

```

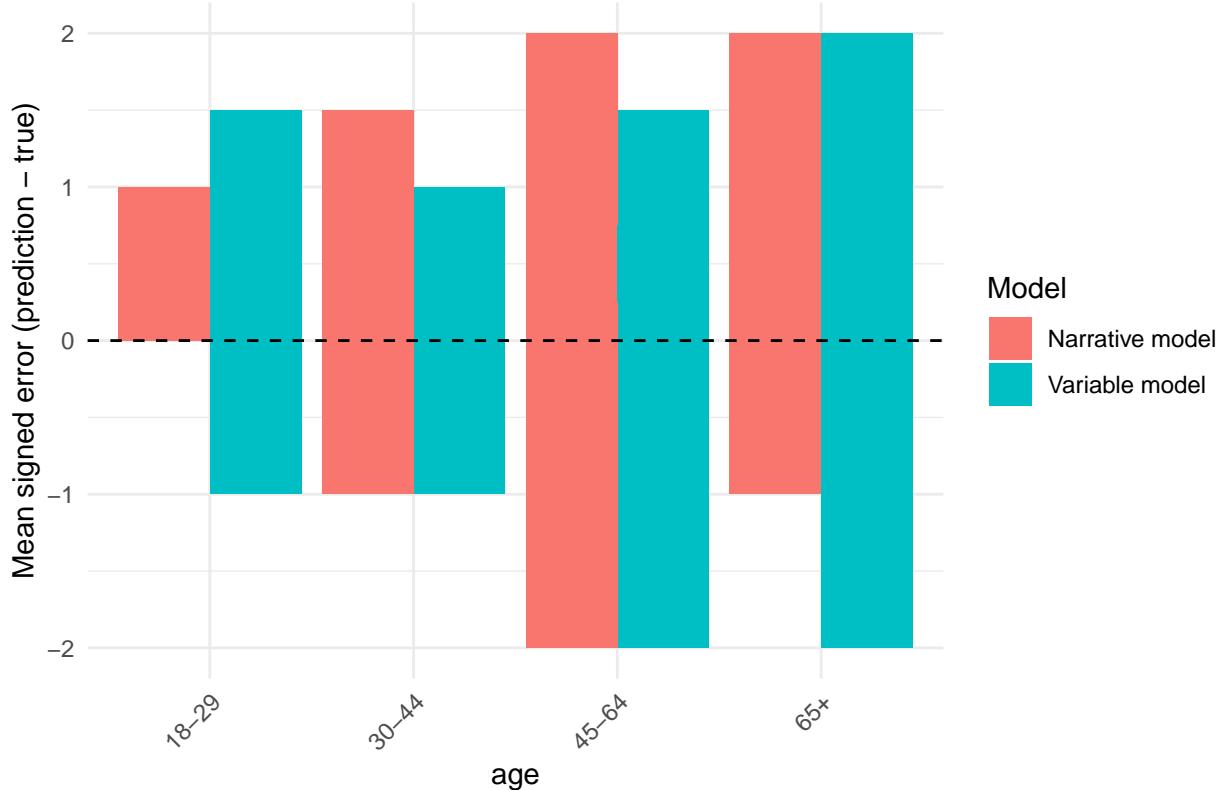
```

##   8 5820     1          2          2          1          0
##   9 8750     1          2          2          1          0
## 10 9350     1          2          2          1          0
## # i 63 more rows
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
bias_by_predictor(df_5, region)

## # A tibble: 4 x 8
##   region      n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var
##   <fct>    <int>        <dbl>        <dbl>        <dbl>        <dbl>
## 1 2         24       0.625       0.5       0.5       0.125
## 2 3         37       0.595       0.595       0.486       0.135
## 3 1         12       0.5         0.25       0.583       0.0833
## 4 4         27      -0.148       0.296       0.370       0.333
## # i 2 more variables: prop_too_cons_narr <dbl>, prop_too_lib_narr <dbl>
plot_mean_error_by_predictor(df_5, age)

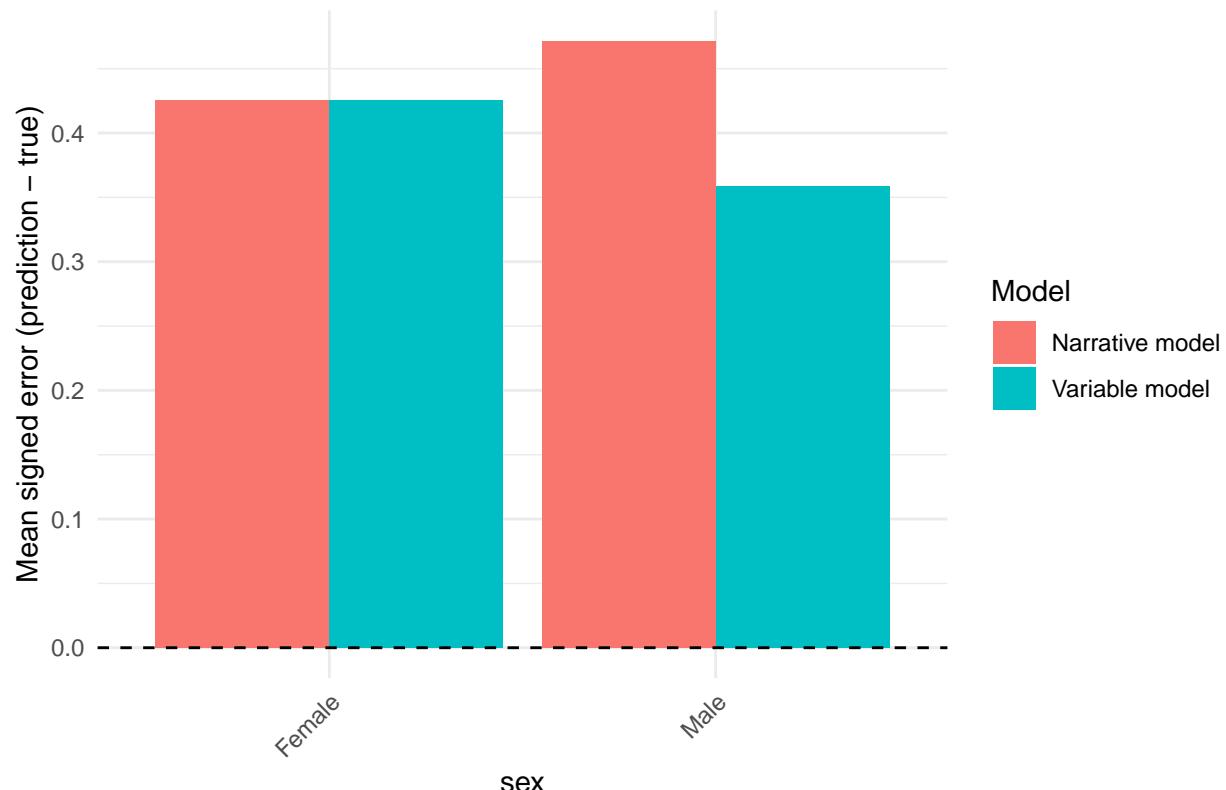
```

Mean signed error by age



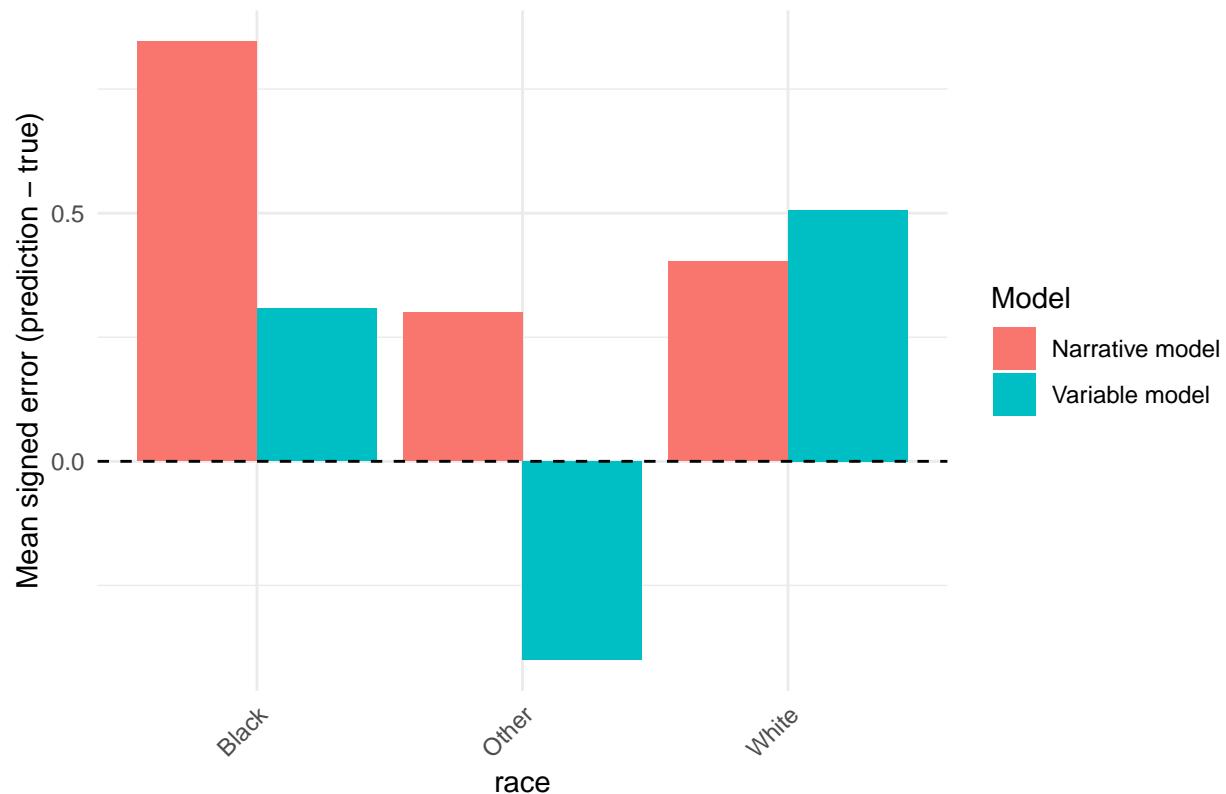
```
plot_mean_error_by_predictor(df_5, sex)
```

Mean signed error by sex

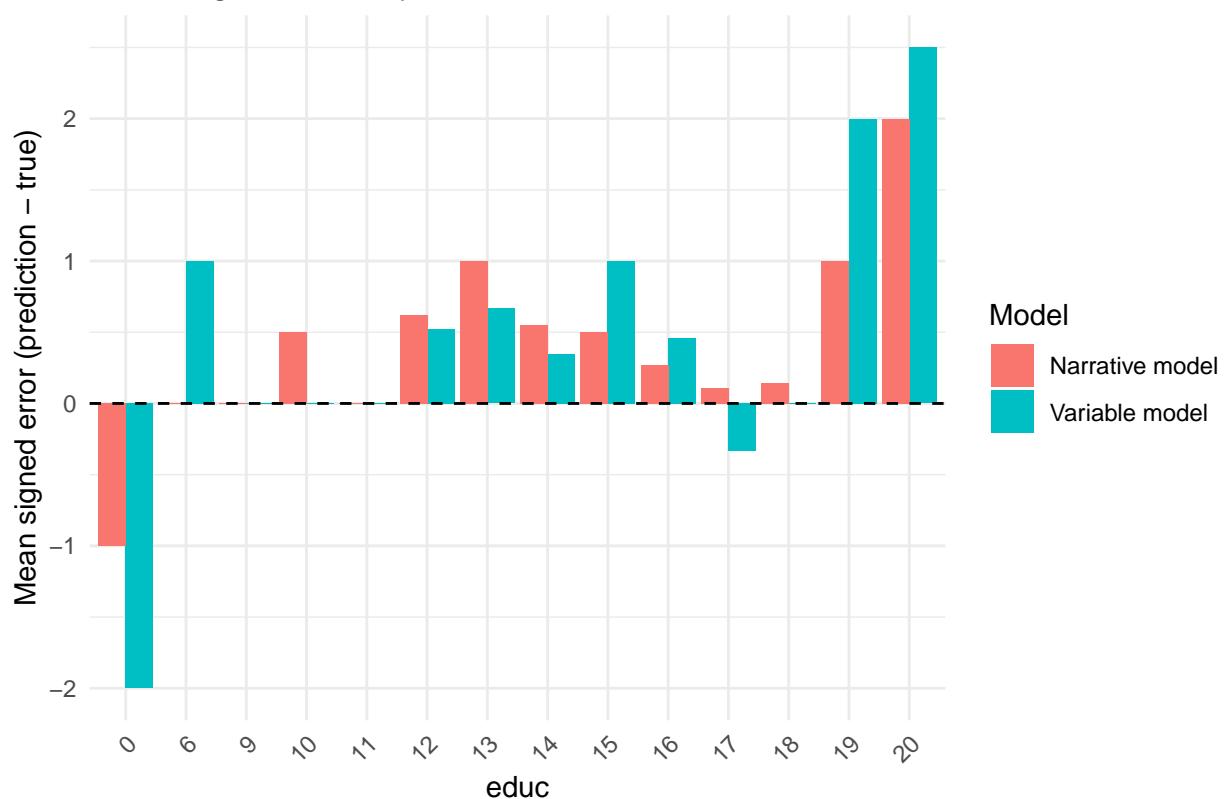


```
plot_mean_error_by_predictor(df_5, race)
```

Mean signed error by race

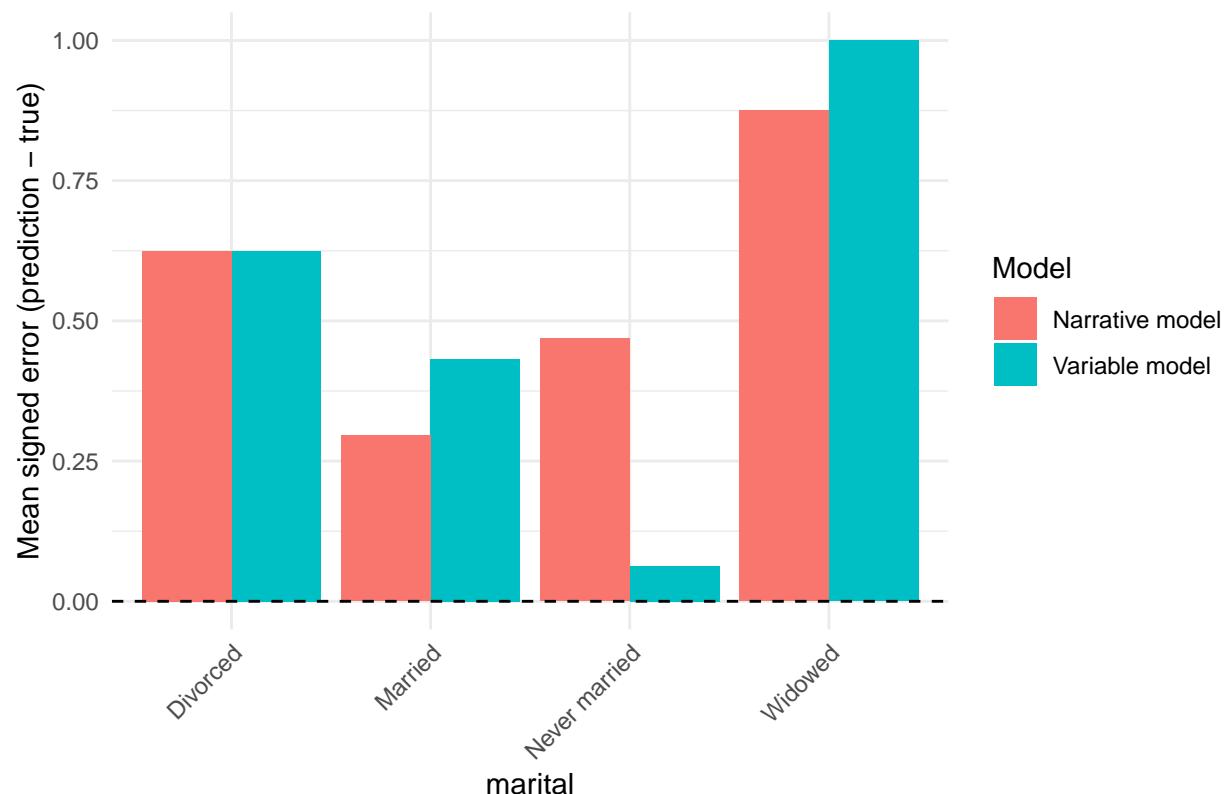


Mean signed error by educ



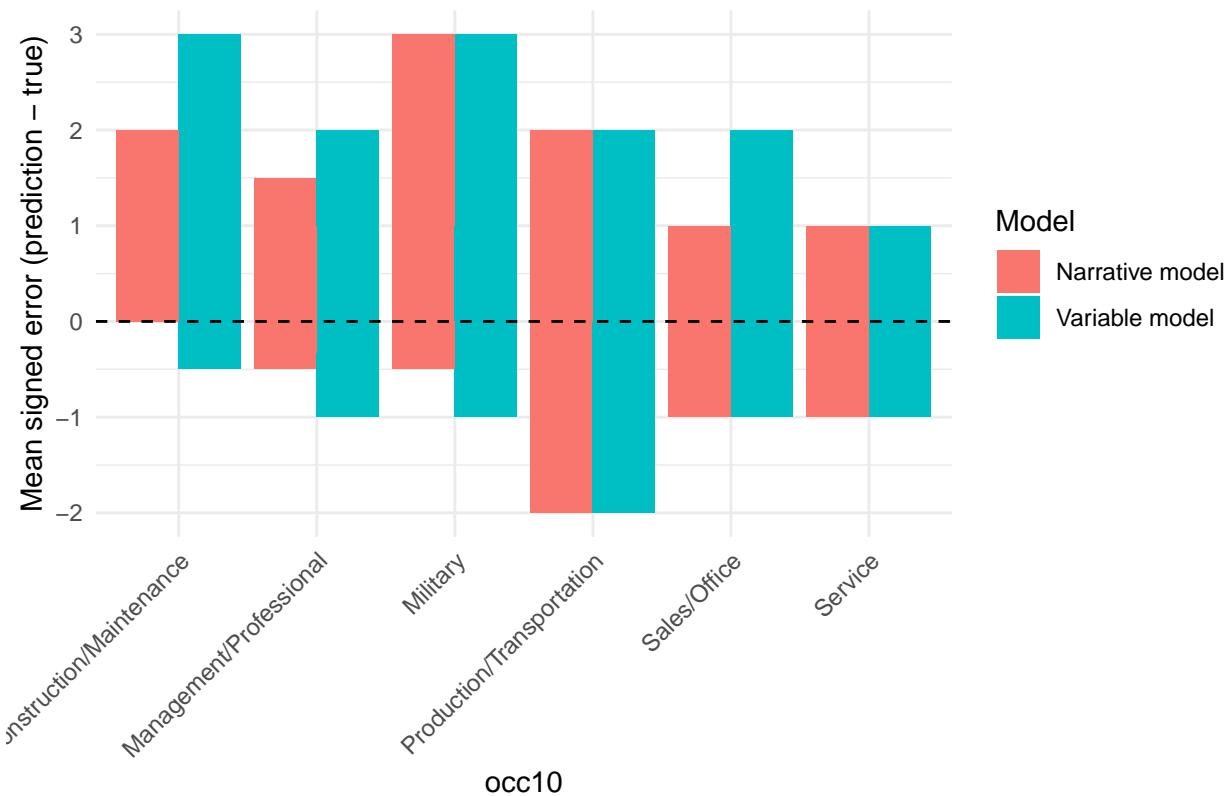
```
plot_mean_error_by_predictor(df_5, marital)
```

Mean signed error by marital



```
plot_mean_error_by_predictor(df_5, occ10)
```

Mean signed error by occ10



```
plot_mean_error_by_predictor(df_5, region)
```

Mean signed error by region

