GSS Political Views Analysis - Refactored

1. Data Loading and Preparation

```r
# Load GSS data
gss <- read_dta("GSS2024.dta")
cat("Original dimensions:", dim(gss), "\n")
```

```
## Original dimensions: 3309 813
```

```r
# Clean and prepare data
gss_clean <- gss %>%
  select(polviews, age, educ, race, sex, occ10, region, marital) %>%
  filter(!polviews %in% c(8, 9), !is.na(polviews)) %>%
  mutate(
    polviews = as.integer(polviews),
    race = factor(race),
    sex = factor(sex),
    occ10 = factor(occ10),
    region = factor(region),
    marital = factor(marital)
  )

# Create reproducible sample
set.seed(123)
sample100 <- gss_clean %>%
  drop_na() %>%
  sample_n(100)

cat("Sample dimensions:", dim(sample100), "\n")
```

```
## Sample dimensions: 100 8
```

2. Helper Functions

```r
# F1 score calculation functions
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)
  })
```

```r
  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)
}

# Calculate performance metrics
calculate_metrics <- function(y_true, y_pred) {
  tibble(
    MAE = mean(abs(y_true - y_pred)),
    MSE = mean((y_true - y_pred)^2),
    Accuracy = mean(y_true == y_pred) * 100,
    Within1 = mean(abs(y_true - y_pred) <= 1) * 100
  )
}

# Print metrics nicely
print_metrics <- function(metrics, model_name) {
  cat("\n", model_name, ":\n", sep = "")
  cat("Mean Absolute Error:", round(metrics$MAE, 3), "\n")
  cat("Mean Squared Error:", round(metrics$MSE, 3), "\n")
  cat("Exact Match Accuracy:", round(metrics$Accuracy, 1), "%\n")
  cat("Within ±1 Accuracy:", round(metrics$Within1, 1), "%\n")
}

# Map occupation codes to categories
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 into groups
bucket_age <- function(a) {
  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+",
```

```r
    TRUE ~ NA_character_
  )
}

# Label mapping
label_maps <- list(
  sex = c("1" = "Male", "2" = "Female"),
  race = c("1" = "White", "2" = "Black", "3" = "Other"),
  marital = c("1" = "Married", "2" = "Widowed", "3" = "Divorced",
              "4" = "Separated", "5" = "Never married"),
  region = c("1" = "Northeast", "2" = "Midwest", "3" = "South", "4" = "West")
)

# Calculate bias by predictor
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),
      .groups = "drop"
    ) %>%
    arrange(desc(mean_error_var))
}

# Plot mean error by predictor
plot_mean_error_by_predictor <- function(data, predictor) {
  pred_sym <- rlang::ensym(predictor)
  pred_name <- rlang::as_name(pred_sym)

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

  # Add human-readable labels
```

```
  if (pred_name == "occ10") {
    summary_df <- summary_df %>%
      mutate(predictor_label = vapply(.data[[pred_name]], map_occ10, character(1)))
  } else if (pred_name == "age") {
    summary_df <- summary_df %>%
      mutate(predictor_label = bucket_age(.data[[pred_name]]))
  } else if (pred_name == "educ") {
    summary_df <- summary_df %>%
      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 %>%
      mutate(predictor_label = map_vec[as.character(.data[[pred_name]])])
  } else {
    summary_df <- summary_df %>%
      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))
}
```

3. Core Analysis Function

```
# Main analysis function for any classification scheme
analyze_classification <- function(sample_data, var_file, narr_file,
                                   class_var, class_suffix, save_prefix) {

  cat("\n", rep("=", 60), "\n", sep = "")
  cat("ANALYSIS:", class_suffix, "\n")
  cat(rep("=", 60), "\n\n")

  # Load predictions
  var_pred <- read.csv(var_file)
  narr_pred <- read.csv(narr_file)

  # Calculate and print metrics
  y_true <- as.numeric(sample_data[[class_var]])

  metrics_var <- calculate_metrics(y_true, as.numeric(var_pred$pred_polview))
  print_metrics(metrics_var, "Variable Model")

  metrics_narr <- calculate_metrics(y_true, as.numeric(narr_pred$pred_polview_narr))
```

```r
print_metrics(metrics_narr, "Narrative Model")

# Build comprehensive dataframe
df <- sample_data %>%
  mutate(row_id = row_number()) %>%
  select(row_id, POLVIEWS_TRUE = !!sym(class_var),
         age, sex, race, educ, marital, occ10, region) %>%
  inner_join(var_pred %>% mutate(row_id = row_number()) %>%
               select(row_id, pred_var = pred_polview), by = "row_id") %>%
  inner_join(narr_pred %>% mutate(row_id = row_number()) %>%
               select(row_id, pred_narr = pred_polview_narr), by = "row_id") %>%
  mutate(
    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)),
    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)),
    error_var = pred_var_num - polviews_num,
    error_narr = pred_narr_num - polviews_num
  )

# F1 Scores
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))
)

cat("\nF1 Scores:\n")
print(results)

# Bias analysis
cat("\nMean Errors:\n")
cat("Variable Model:", round(mean(df$error_var, na.rm = TRUE), 3), "\n")
cat("Narrative Model:", round(mean(df$error_narr, na.rm = TRUE), 3), "\n")

# Mislabeled cases comparison
mislabeled <- df %>%
  mutate(
    var_wrong = pred_var != POLVIEWS_TRUE,
    narr_wrong = pred_narr != POLVIEWS_TRUE,
    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"
    ),
    diff_var = as.numeric(pred_var) - as.numeric(POLVIEWS_TRUE),
    diff_narr = as.numeric(pred_narr) - as.numeric(POLVIEWS_TRUE),
    bias_var = case_when(
```

```r
      !var_wrong ~ "Correct",
      diff_var > 0 ~ "Too Conservative",
      diff_var < 0 ~ "Too Liberal",
      TRUE ~ NA_character_
    ),
    bias_narr = 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)

write.csv(mislabeled, paste0(save_prefix, "_mislabeled_cases_comparison.csv"),
          row.names = FALSE)

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

cat("\nBias Distribution:\n")
print(bias_table)

# Distribution plots
p1 <- ggplot(df, aes(x = POLVIEWS_TRUE)) +
  geom_bar() +
  ggtitle("True POLVIEWS Distribution") +
  theme_minimal()

p2 <- ggplot(df, aes(x = pred_var)) +
  geom_bar() +
  ggtitle("Variable Model Pred Distribution") +
  theme_minimal()

p3 <- ggplot(df, aes(x = pred_narr)) +
  geom_bar() +
  ggtitle("Narrative Model Pred Distribution") +
  theme_minimal()

print(p1)
print(p2)
```

```
  print(p3)

  # Bias by predictor
  df$occ10 <- as.numeric(as.character(df$occ10))

  cat("\nBias by Age:\n")
  print(bias_by_predictor(df, age))
  cat("\nBias by Sex:\n")
  print(bias_by_predictor(df, sex))
  cat("\nBias by Race:\n")
  print(bias_by_predictor(df, race))
  cat("\nBias by Education:\n")
  print(bias_by_predictor(df, educ))
  cat("\nBias by Marital Status:\n")
  print(bias_by_predictor(df, marital))
  cat("\nBias by Occupation:\n")
  print(bias_by_predictor(df, occ10))
  cat("\nBias by Region:\n")
  print(bias_by_predictor(df, region))

  # Plot error by predictors
  print(plot_mean_error_by_predictor(df, age))
  print(plot_mean_error_by_predictor(df, sex))
  print(plot_mean_error_by_predictor(df, race))
  print(plot_mean_error_by_predictor(df, educ))
  print(plot_mean_error_by_predictor(df, marital))
  print(plot_mean_error_by_predictor(df, occ10))
  print(plot_mean_error_by_predictor(df, region))

  return(df)
}
```

4. Classification Scheme Creation

```
# Original 7-point scale (already done in sample100)

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

# 3-category classification (1 = Liberal, 2 = Moderate, 3 = Conservative)
sample100_3 <- sample100 %>%
  mutate(polviews_3 = case_when(
    polviews %in% c(1, 2, 3) ~ 1,
    polviews %in% c(4) ~ 2,
    polviews %in% c(5, 6, 7) ~ 3
  )) %>%
```

```r
  filter(!is.na(polviews_3))

# 4-category classification
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))

# 5-category classification
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))
```

5. Run All Analyses

```r
# 7-point scale analysis
df_7 <- analyze_classification(
  sample100,
  "gss_gpt5_var_predictions.csv",
  "gss_gpt5_narrative_predictions.csv",
  "polviews",
  "7-Point Scale",
  "7point"
)
```

==
ANALYSIS: 7-Point Scale =

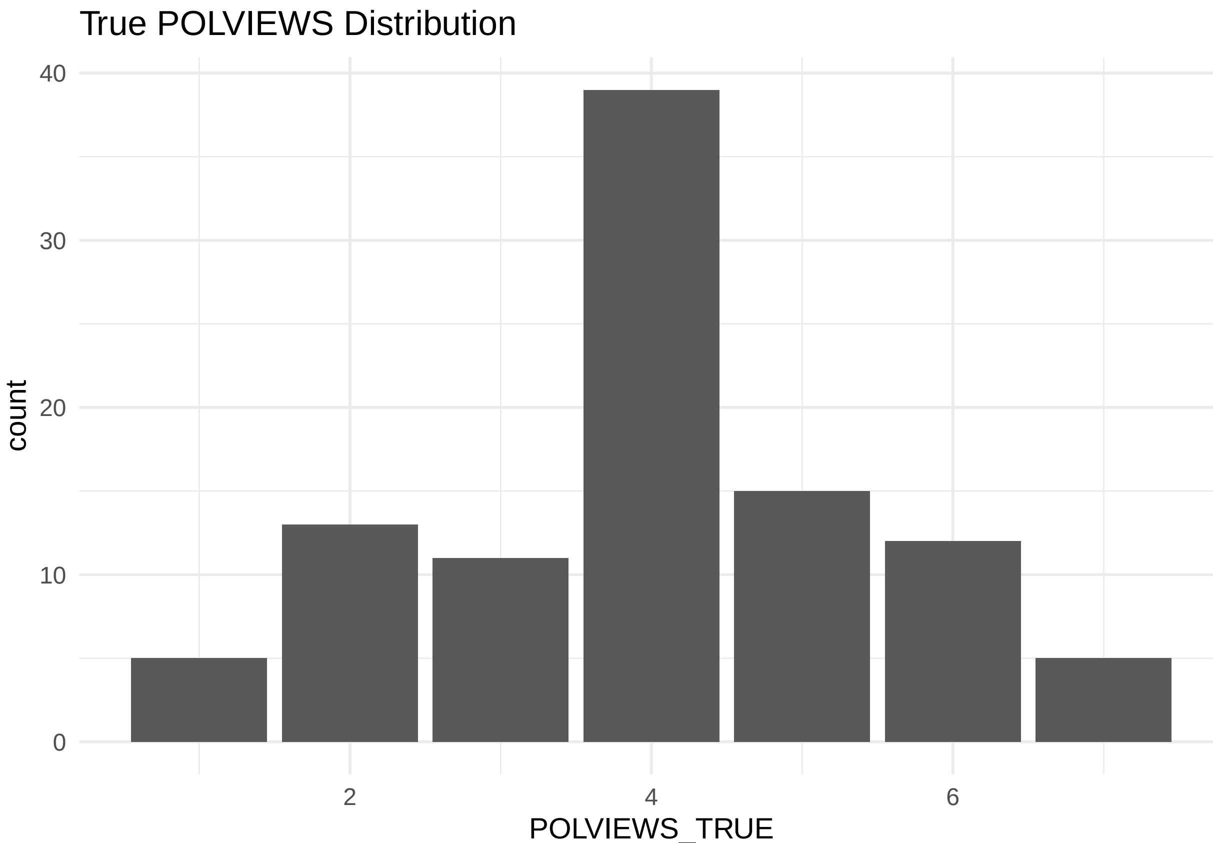
Variable Model: Mean Absolute Error: 1.4 Mean Squared Error: 3.04 Exact Match Accuracy: 15 % Within ±1 Accuracy: 66 %

Narrative Model: Mean Absolute Error: 1.32 Mean Squared Error: 2.72 Exact Match Accuracy: 18 % Within ±1 Accuracy: 67 %

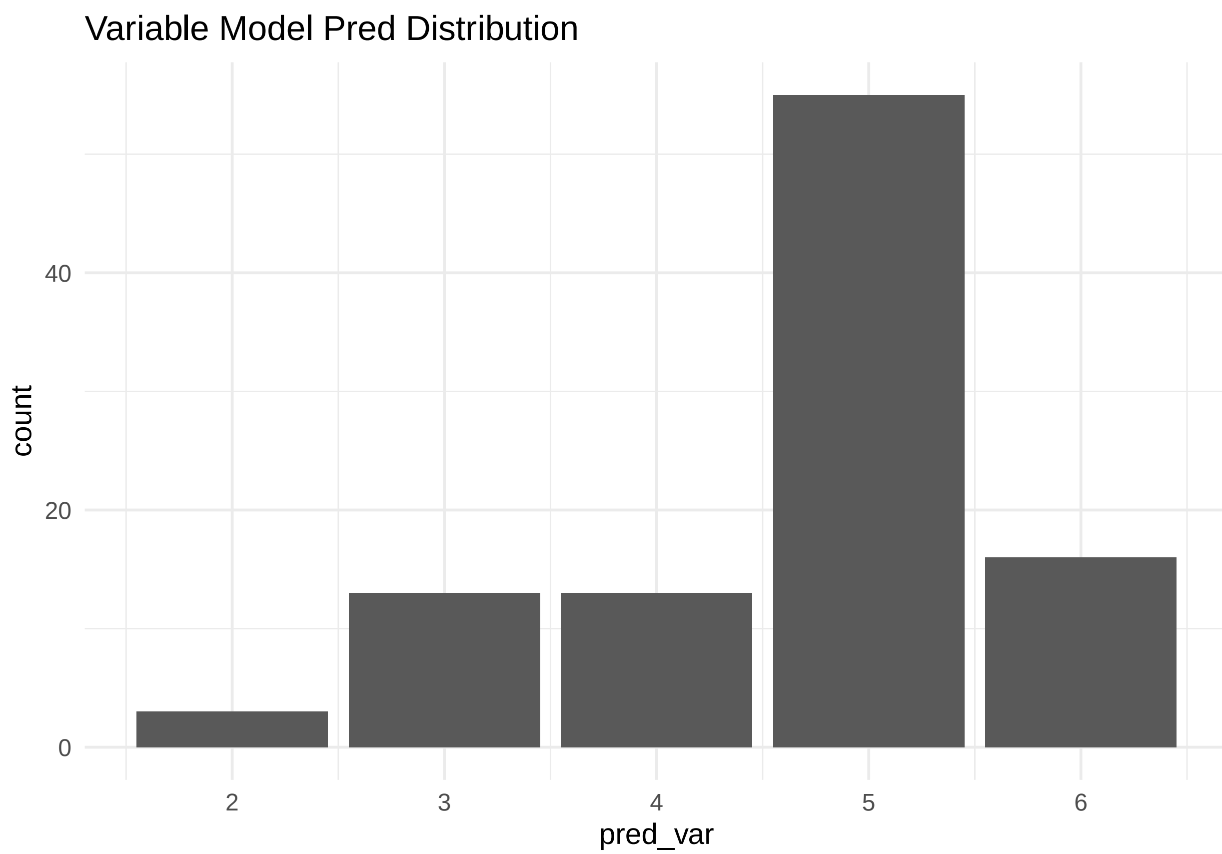
F1 Scores: # A tibble: 2 x 3 Model Macro_F1 Weighted_F1 1 Variable Model 0.841 0.784 2 Narrative Model 0.831 0.749

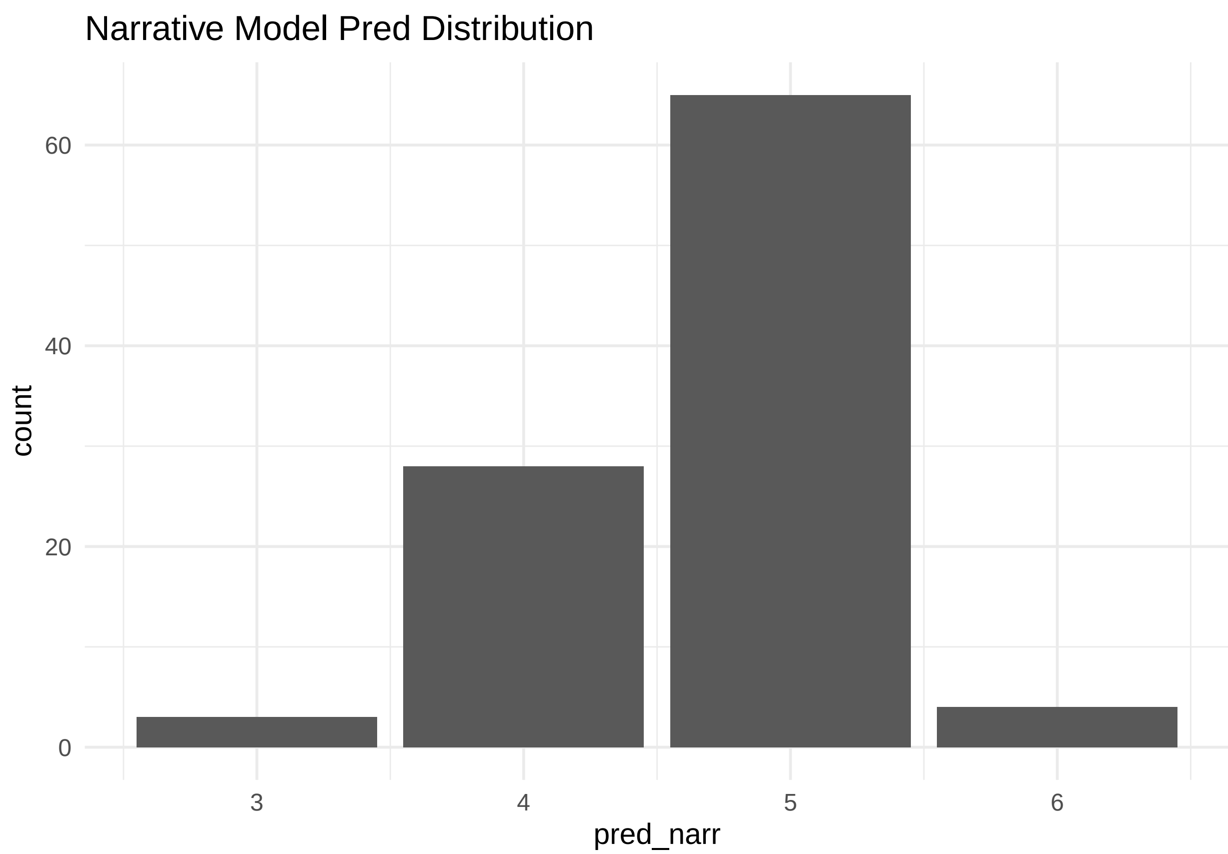
Mean Errors: Variable Model: 0.66 Narrative Model: 0.68

Bias Distribution: # A tibble: 4 x 4 model bias count percent 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


True POLVIEWS Distribution
40
30
20
10
0
count
2
4
6
POLVIEWS_TRUE

27 31.8


Variable Model Pred Distribution
count
40
20
0
2
3
4
5
6
pred_var



Bias by Age: # A tibble: 50 x 8 age n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 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 , prop_too_lib_narr

Bias by Sex: # A tibble: 2 x 8 sex n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 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 , prop_too_lib_narr

Bias by Race: # A tibble: 3 x 8 race n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 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 , prop_too_lib_narr

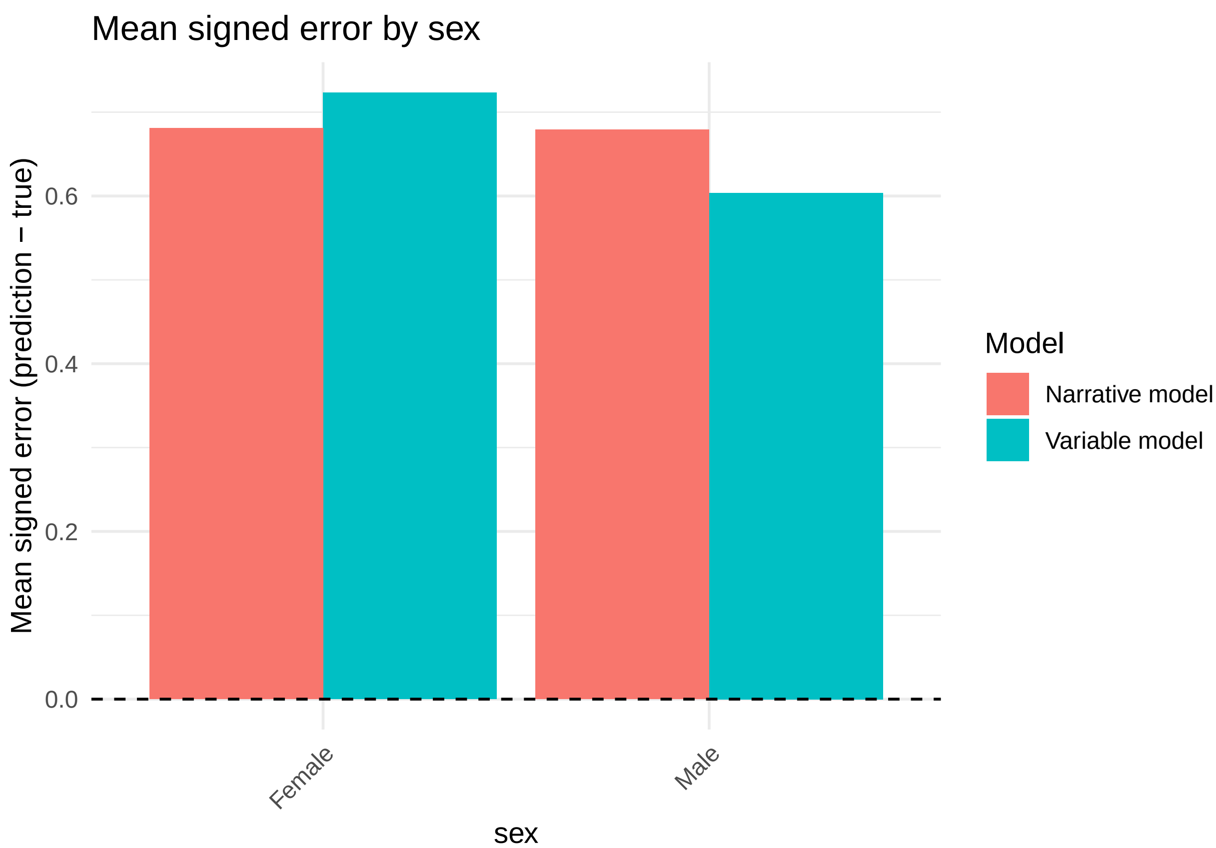
Bias by Education: # A tibble: 14 x 8 educ n mean_error_var mean_error_narr prop_too_cons_var <dbl+lbl> 1 20 [8 or more years o~ 2 4 3 1
2 19 [7 years of colleg~ 1 3 3 1
3 13 [1 year of college] 6 1.5 1.33 0.667 4 15 [3 years of colleg~ 2 1 1 1
5 16 [4 years of colleg~ 26 0.923 0.577 0.654 6 12 [12th 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 , prop_too_cons_narr , # prop_too_lib_narr

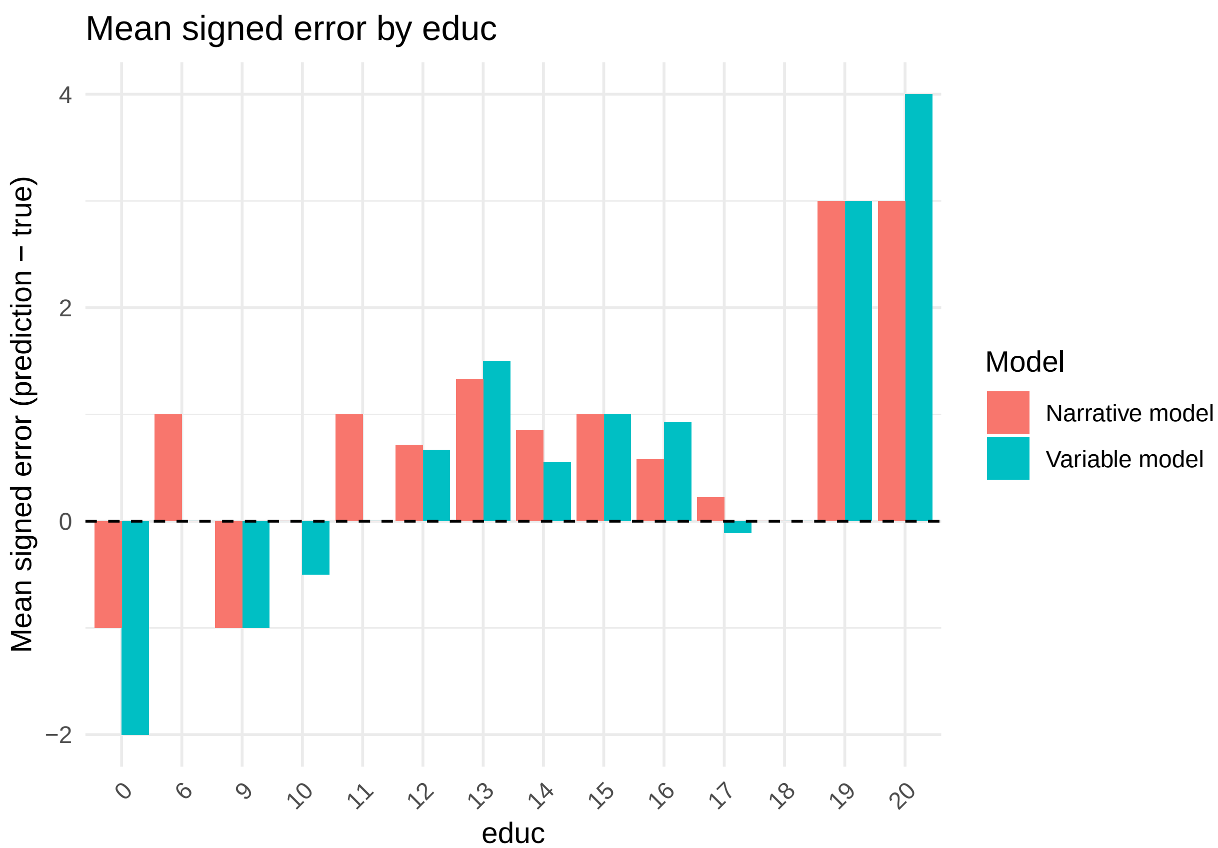
Bias by Marital Status: # A tibble: 4 x 8 marital n mean_error_var mean_error_narr prop_too_cons_var 1 2 8 1.62 1 0.75 2 1 44 0.841 0.5 0.636 3 3 16 0.812 0.625 0.625 4 5 32 0.0938 0.875 0.438 # i 3 more variables: prop_too_lib_var , prop_too_cons_narr , # prop_too_lib_narr

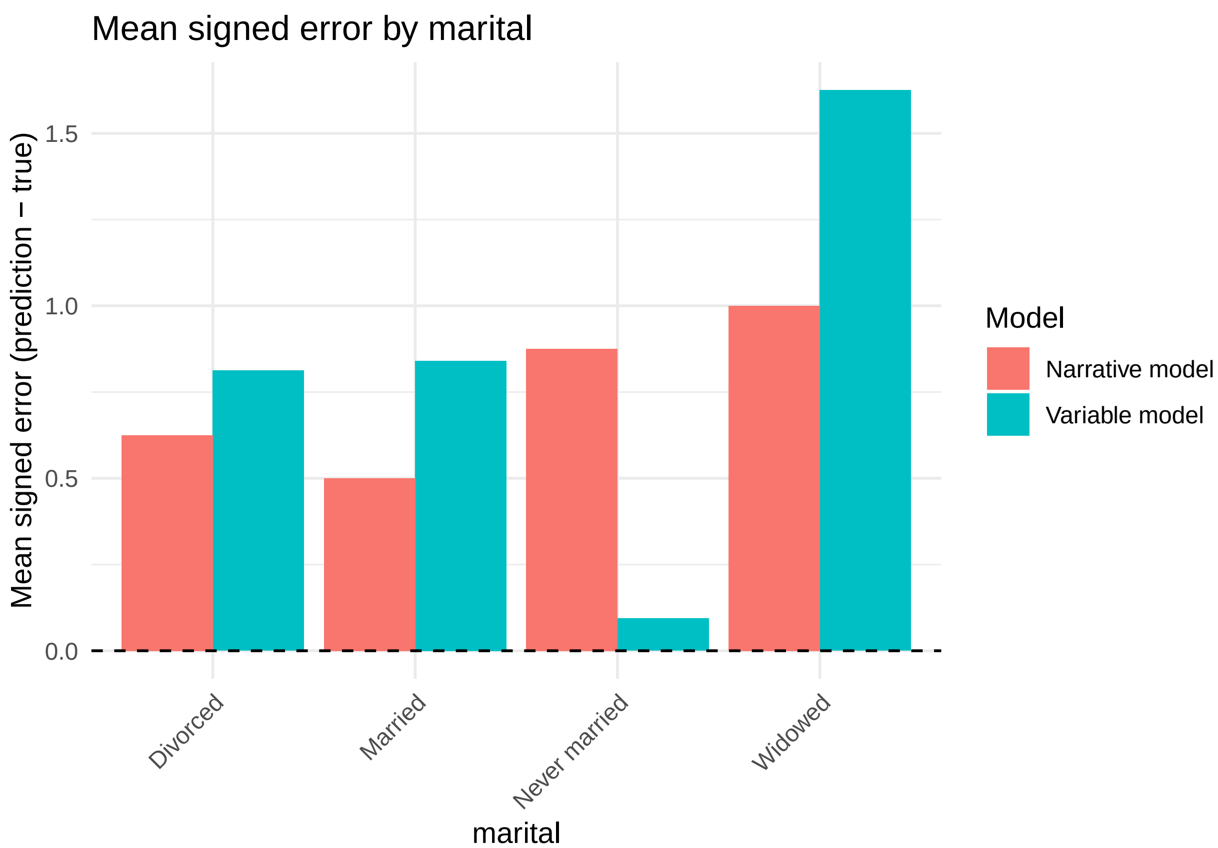
Bias by Occupation: # A tibble: 73 x 8 occ10 n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 1 2200 1 5 4 1 0 2 5120 1 4 3 1 0 3 9620 1 4 4 1 0 4 710 2 3 2.5 1 0 5 735 1 3 2 1 0 6 1460 1 3 3 1 0 7 3645 1 3 2 1 0 8 5600 1 3 3 1 0 9 5820 1 3 3 1 0 10 1050 1 2 1 1 0 # i 63 more rows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

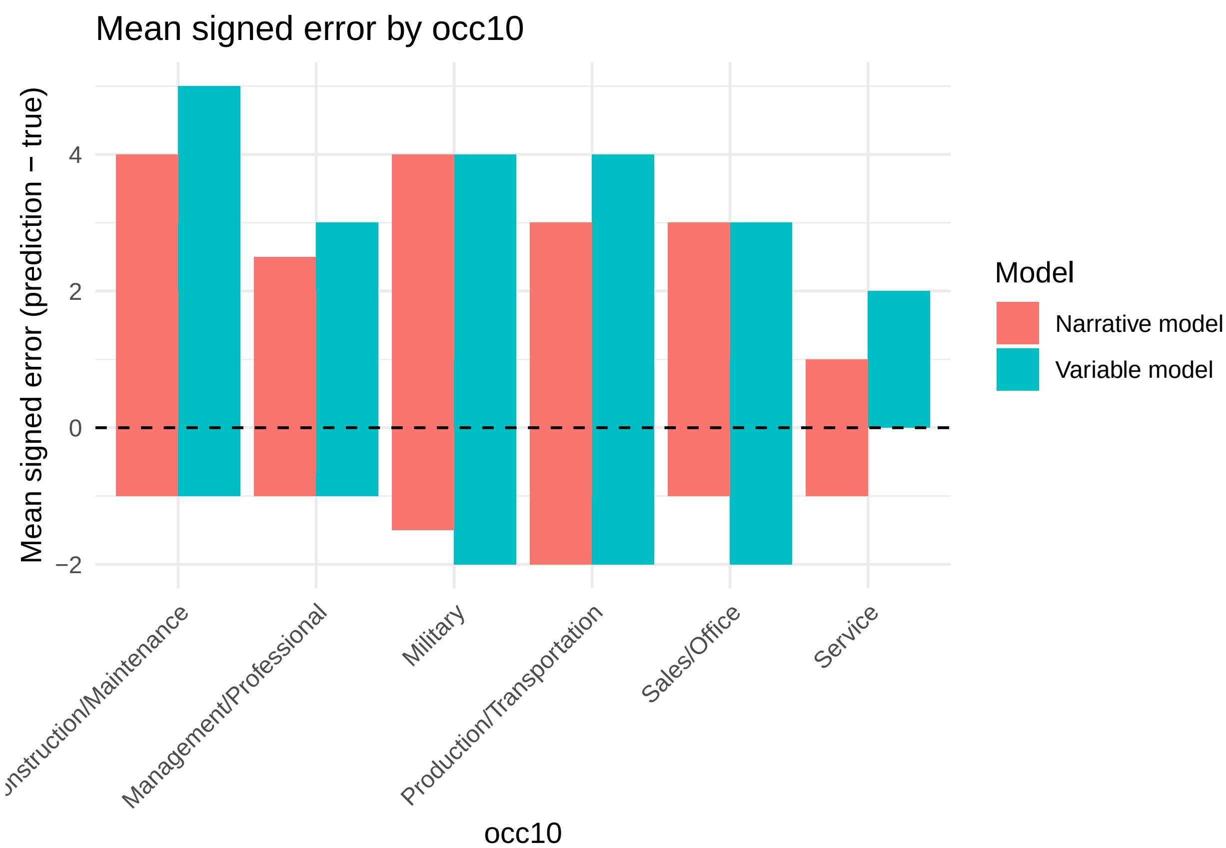
Bias by Region: # A tibble: 4 x 8 region n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 1 3 37 1.05 0.811 0.595 0.189 2 2 24 0.667 0.625 0.583 0.292 3 1 12 0.583 0.75 0.667 0.25 4 4 27 0.148 0.519 0.519 0.370 # i 2 more variables: prop_too_cons_narr , prop_too_lib_narr

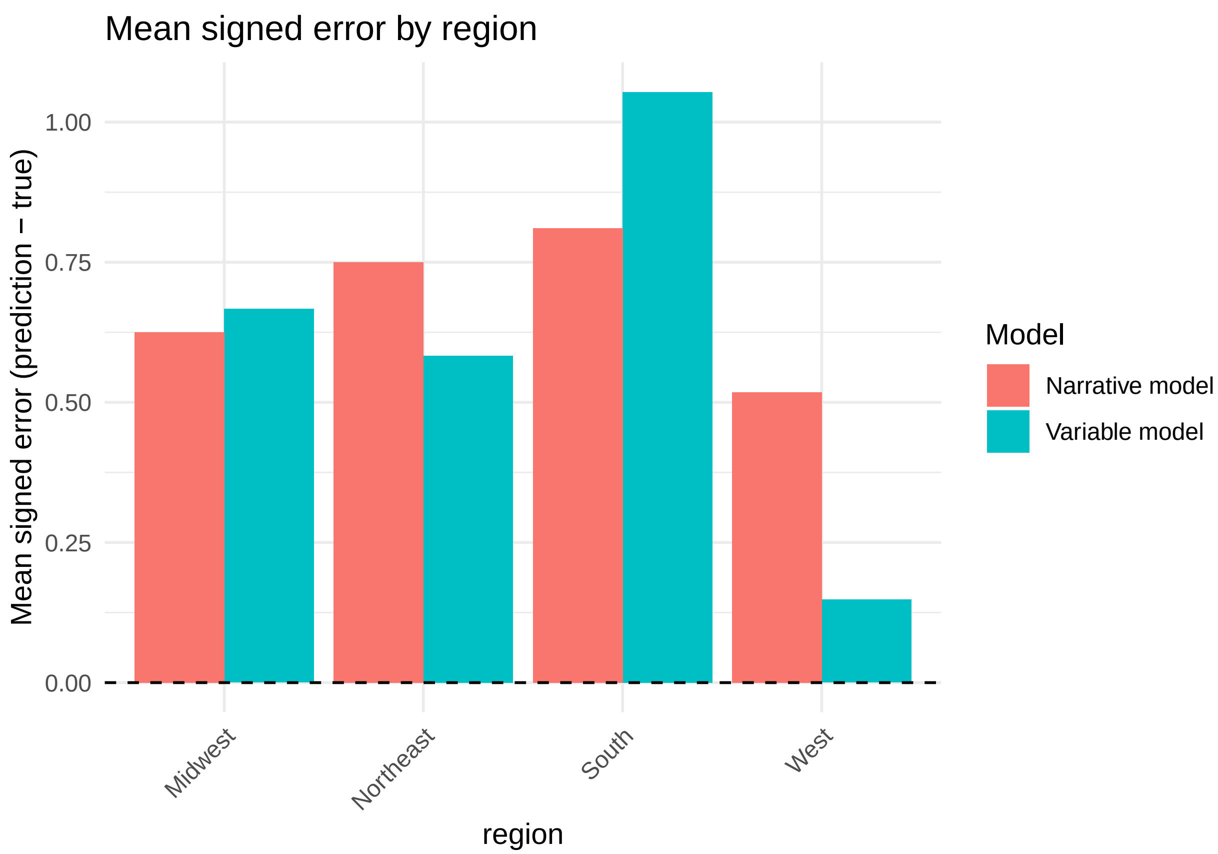

Mean signed error by sex
Mean signed error (prediction − true)
0.0
0.2
0.4
0.6
Female
Male
sex
Model
Narrative model
Variable model


Mean signed error by race
Mean signed error (prediction − true)
1.0
0.5
0.0
Black
Other
White
race
Model
Narrative model
Variable model


Mean signed error by educ
Mean signed error (prediction − true)
4
2
0
−2
0
6
9
10
11
12
13
14
15
16
17
18
19
20
educ
Model
Narrative model
Variable model


Mean signed error by marital
Mean signed error (prediction − true)
1.5
1.0
0.5
0.0
Divorced
Married
Never married
Widowed
marital
Model
Narrative model
Variable model


Mean signed error by occ10
Mean signed error (prediction − true)
4
2
0
−2
onstruction/Maintenance
Management/Professional
Military
Production/Transportation
Sales/Office
Service
occ10
Model
Narrative model
Variable model




```
# Binary analysis
df_bin <- analyze_classification(
  sample100_binary,
  "gss_gpt5_var_predictions_bin.csv",
  "gss_gpt5_narrative_predictions_bin.csv",
  "polviews_binary",
  "Binary Classification",
  "binary"
)
```

== ANALYSIS: Binary Classification =

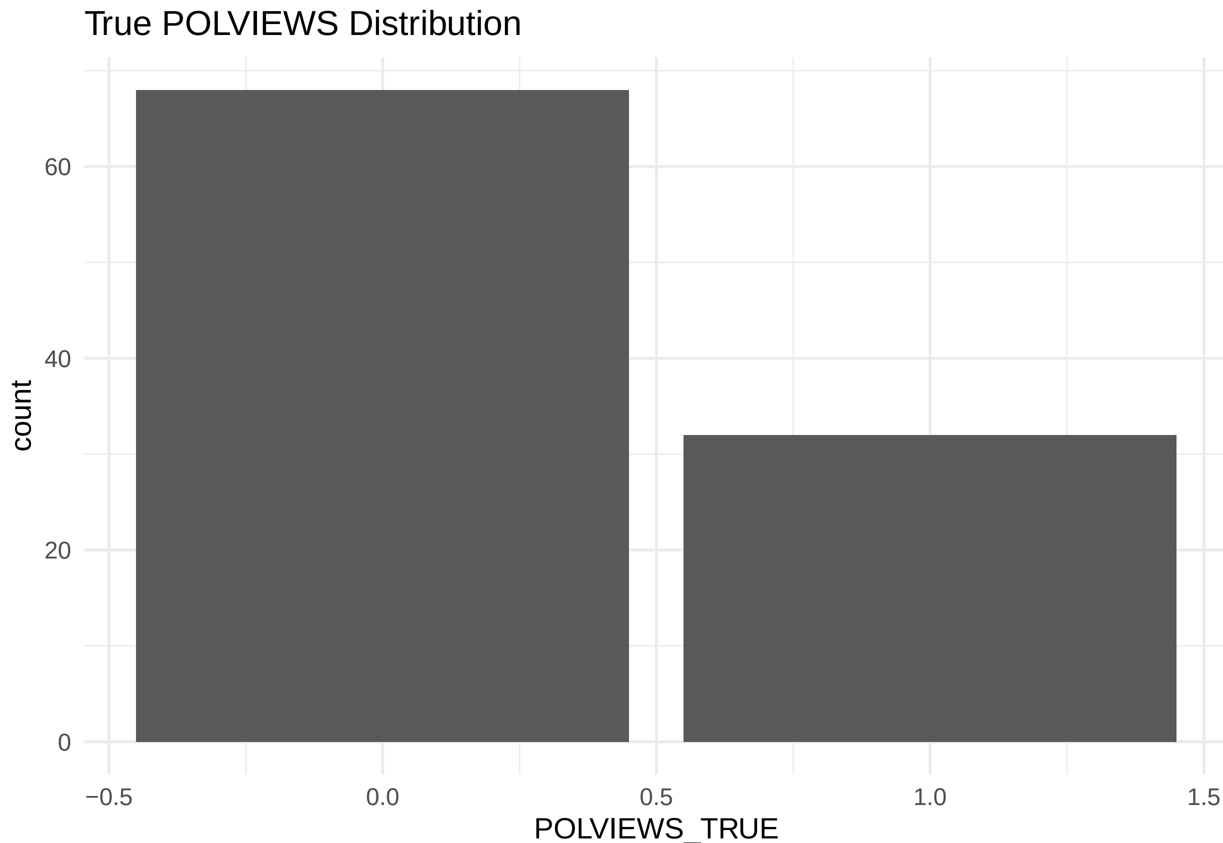
Variable Model: Mean Absolute Error: 0.53 Mean Squared Error: 0.53 Exact Match Accuracy: 47 % Within ±1 Accuracy: 100 %

Narrative Model: Mean Absolute Error: 0.61 Mean Squared Error: 0.61 Exact Match Accuracy: 39 % Within ±1 Accuracy: 100 %

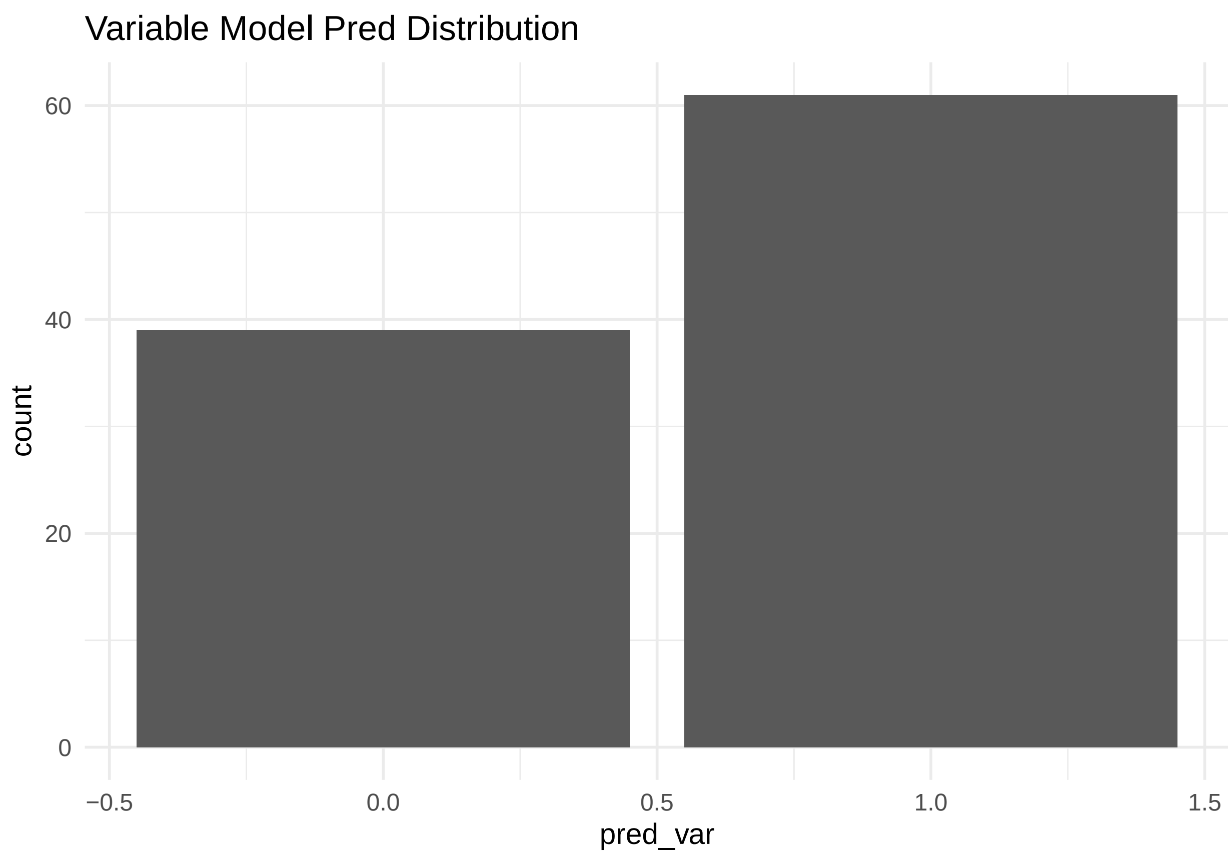
F1 Scores: # A tibble: 2 x 3 Model Macro_F1 Weighted_F1 1 Variable Model 0.467 0.454 2 Narrative Model 0.385 0.405

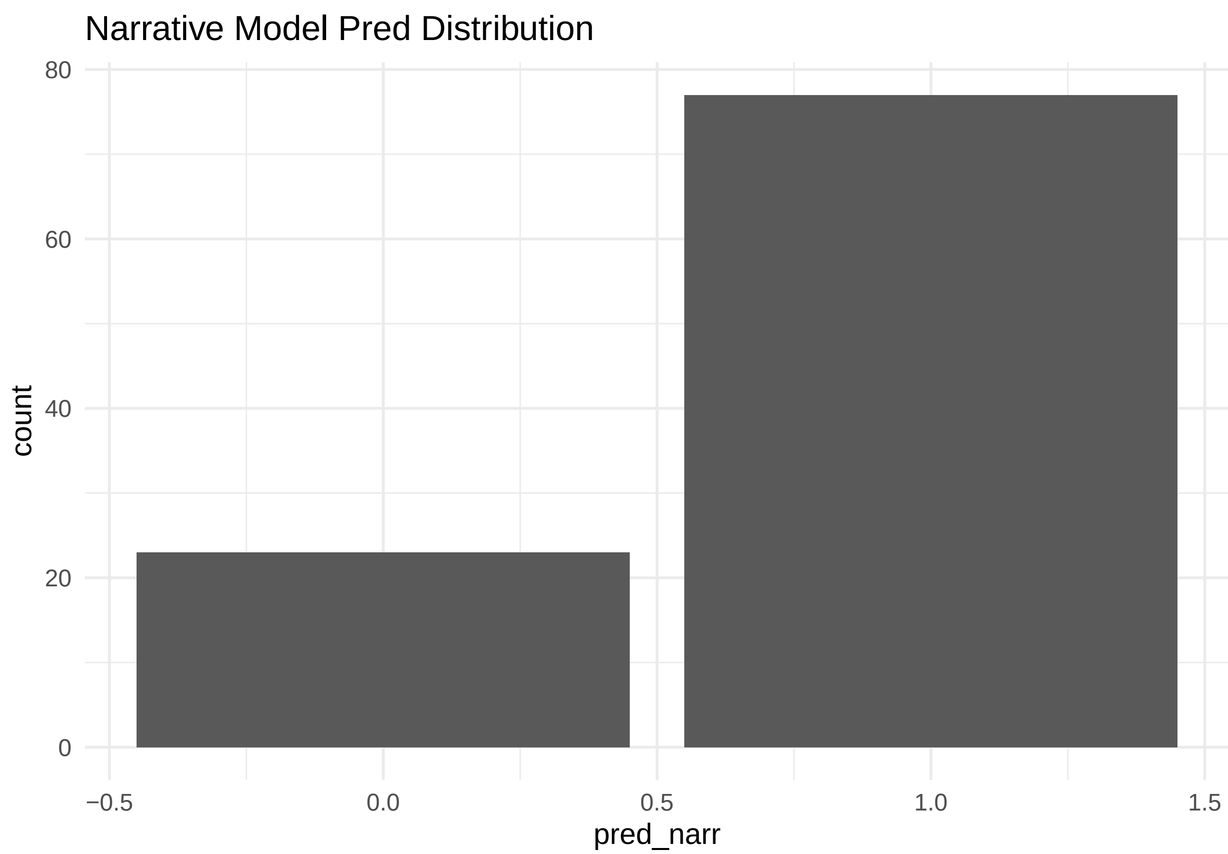
Mean Errors: Variable Model: 0.29 Narrative Model: 0.45

Bias Distribution: # A tibble: 4 x 4 model bias count percent 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


True POLVIEWS Distribution
count
60
40
20
0
−0.5
0.0
0.5
1.0
1.5
POLVIEWS_TRUE

12 22.6


Variable Model Pred Distribution
60
40
20
0
count
−0.5
0.0
0.5
1.0
1.5
pred_var



Bias by Age: # A tibble: 50 x 8 age n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 1 21 1 1 1 1 0 2 25 2 1 1 1 0 3 31 1 1 1 1 0 4 39 1 1 1 1 0 5 55 1 1 1 1 0 6 61 1 1 1 1 0 7 67 2 1 1 1 0 8 73 1 1 1 1 0 9 74 1 1 1 1 0 10 76 1 1 1 1 0 # i 40 more rows # i 2 more variables: prop_too_cons_narr , prop_too_lib_narr

Bias by Sex: # A tibble: 2 x 8 sex n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 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 , prop_too_lib_narr

Bias by Race: # A tibble: 3 x 8 race n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 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 , prop_too_lib_narr

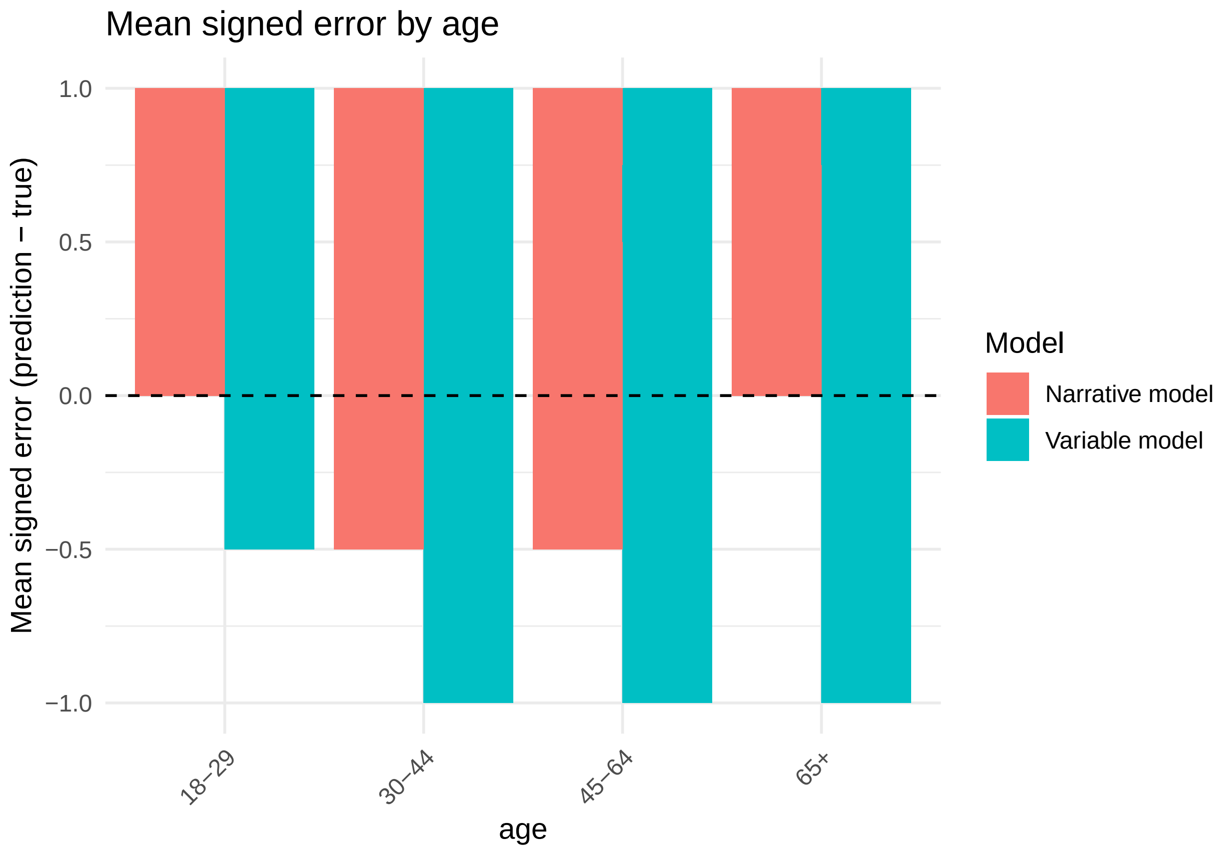
Bias by Education: # A tibble: 14 x 8 educ n mean_error_var mean_error_narr prop_too_cons_var <dbl+lbl> 1 15 [3 years of colleg~ 2 1 1 1
2 19 [7 years of colleg~ 1 1 1 1
3 20 [8 or more years o~ 2 1 1 1
4 13 [1 year of college] 6 0.667 0.833 0.667 5 12 [12th grade] 21 0.571 0.762 0.571 6 16 [4 years 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 , prop_too_cons_narr , # prop_too_lib_narr

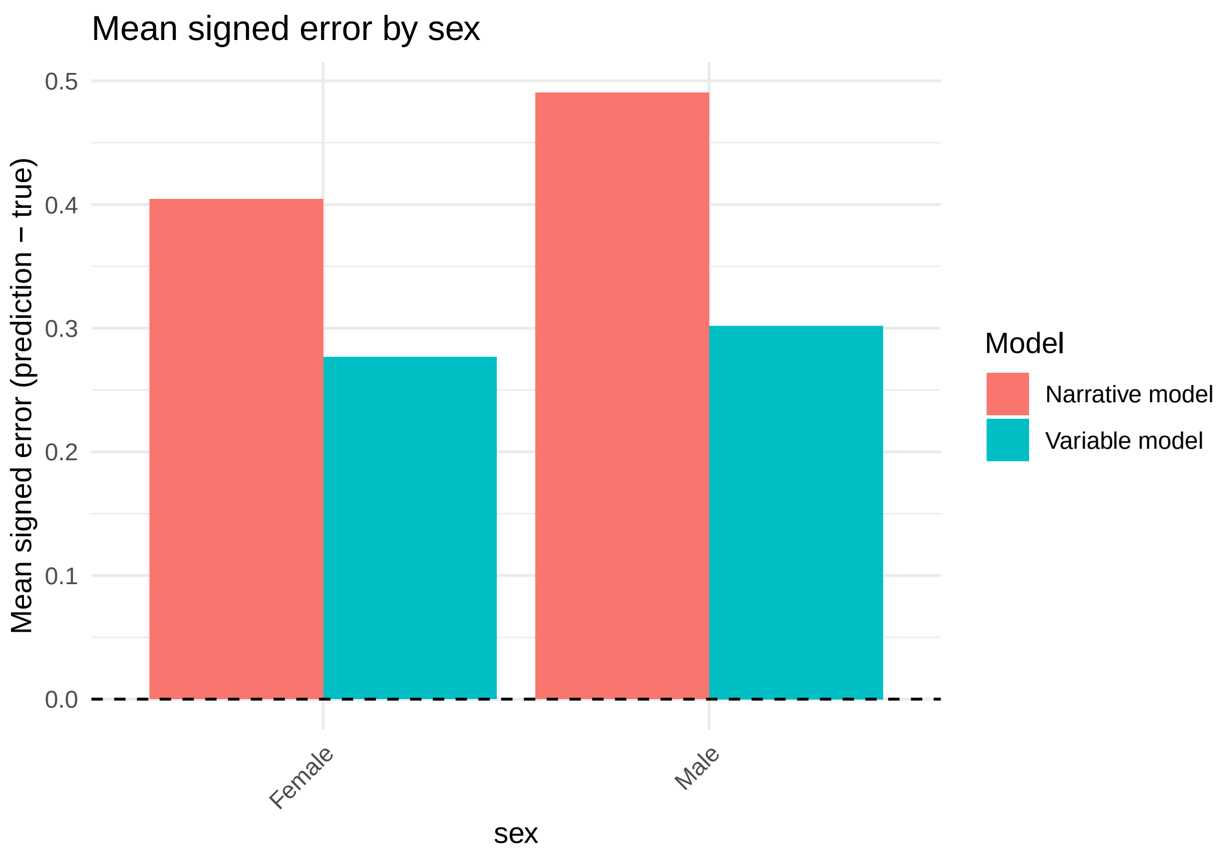
Bias by Marital Status: # A tibble: 4 x 8 marital n mean_error_var mean_error_narr prop_too_cons_var 1 2 8 0.625 0.5 0.75 2 3 16 0.375 0.5 0.5

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 , prop_too_cons_narr , # prop_too_lib_narr

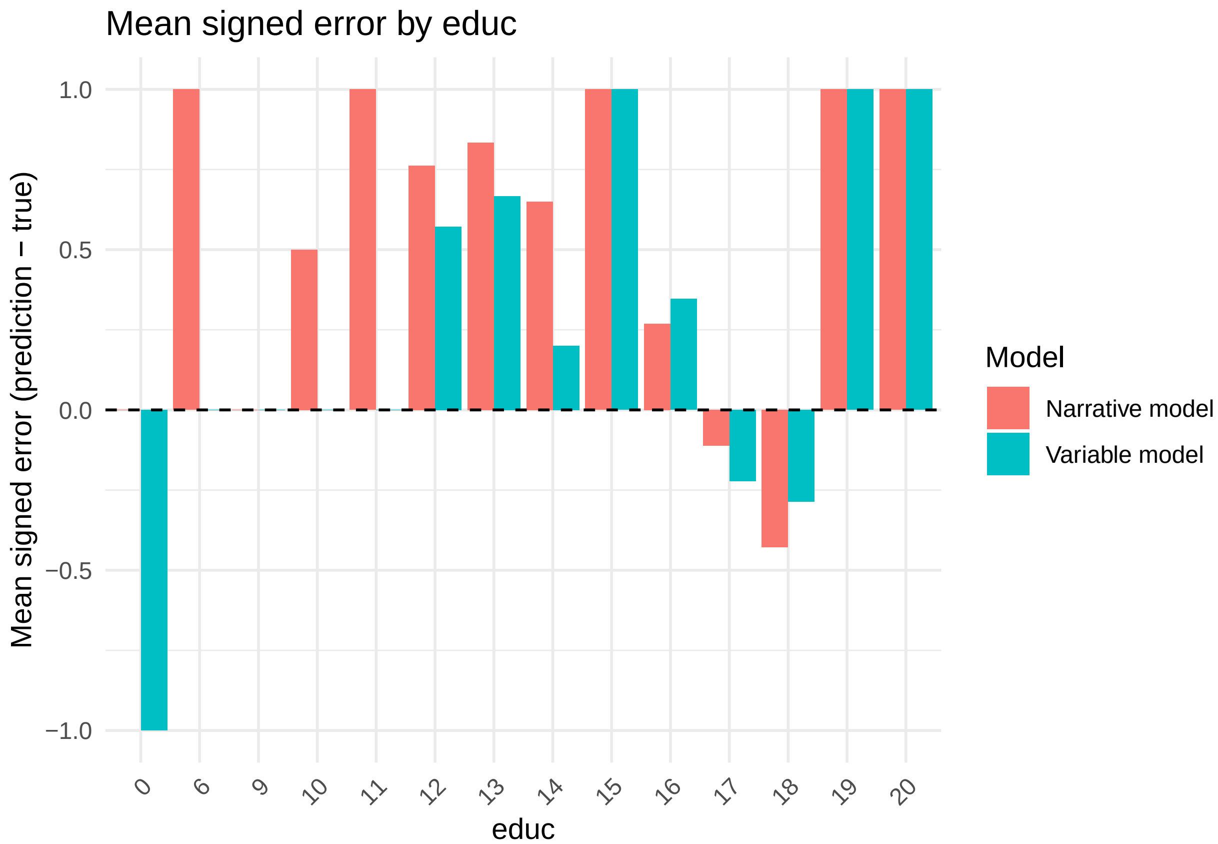
Bias by Occupation: # A tibble: 73 x 8 occ10 n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 1 20 1 1 1 1 0 2 120 1 1 0 1 0 3 710 2 1 1 1 0 4 1106 1 1 1 1 0 5 1460 1 1 1 1 0 6 1740 1 1 1 1 0 7 2145 1 1 1 1 0 8 2200 1 1 1 1 0 9 3600 2 1 1 1 0 10 3850 3 1 1 1 0 # i 63 more rows # i 2 more variables: prop_too_cons_narr , prop_too_lib_narr

Bias by Region: # A tibble: 4 x 8 region n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 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 , prop_too_lib_narr

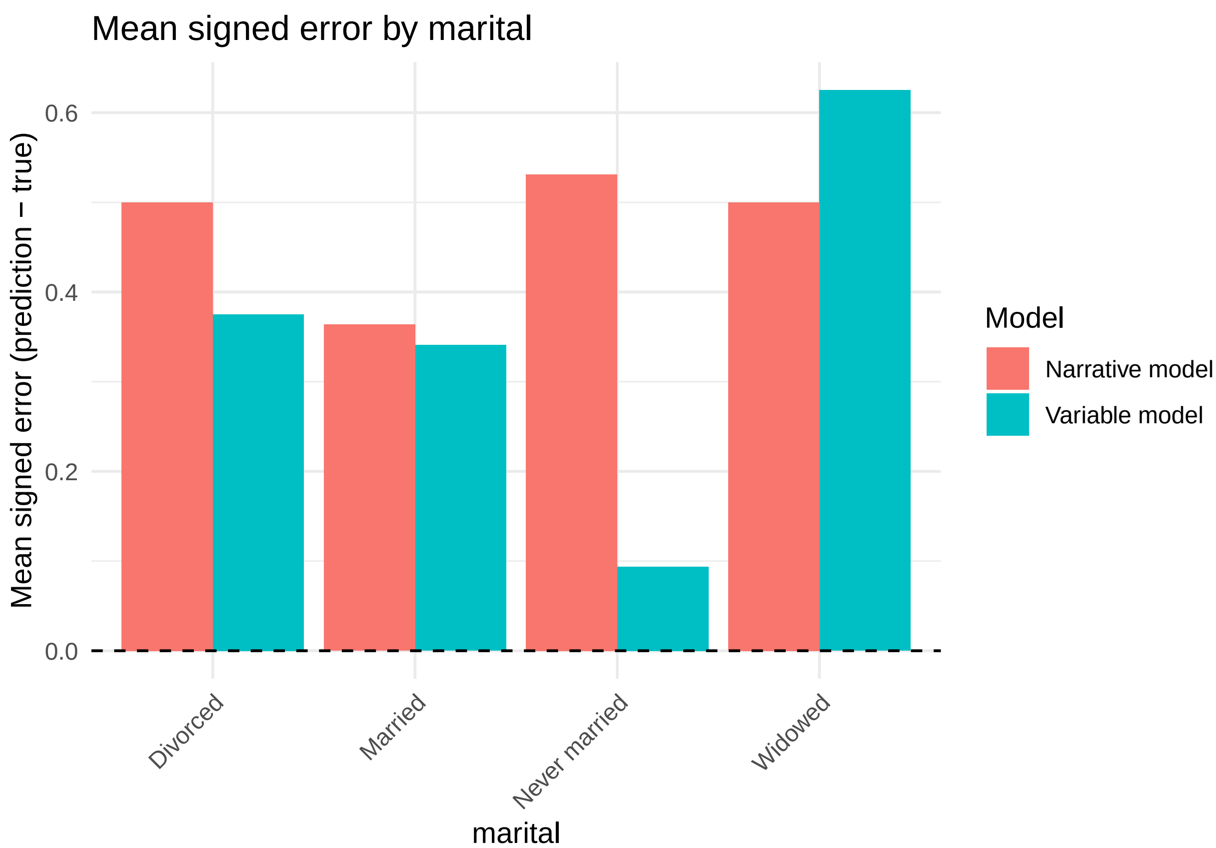


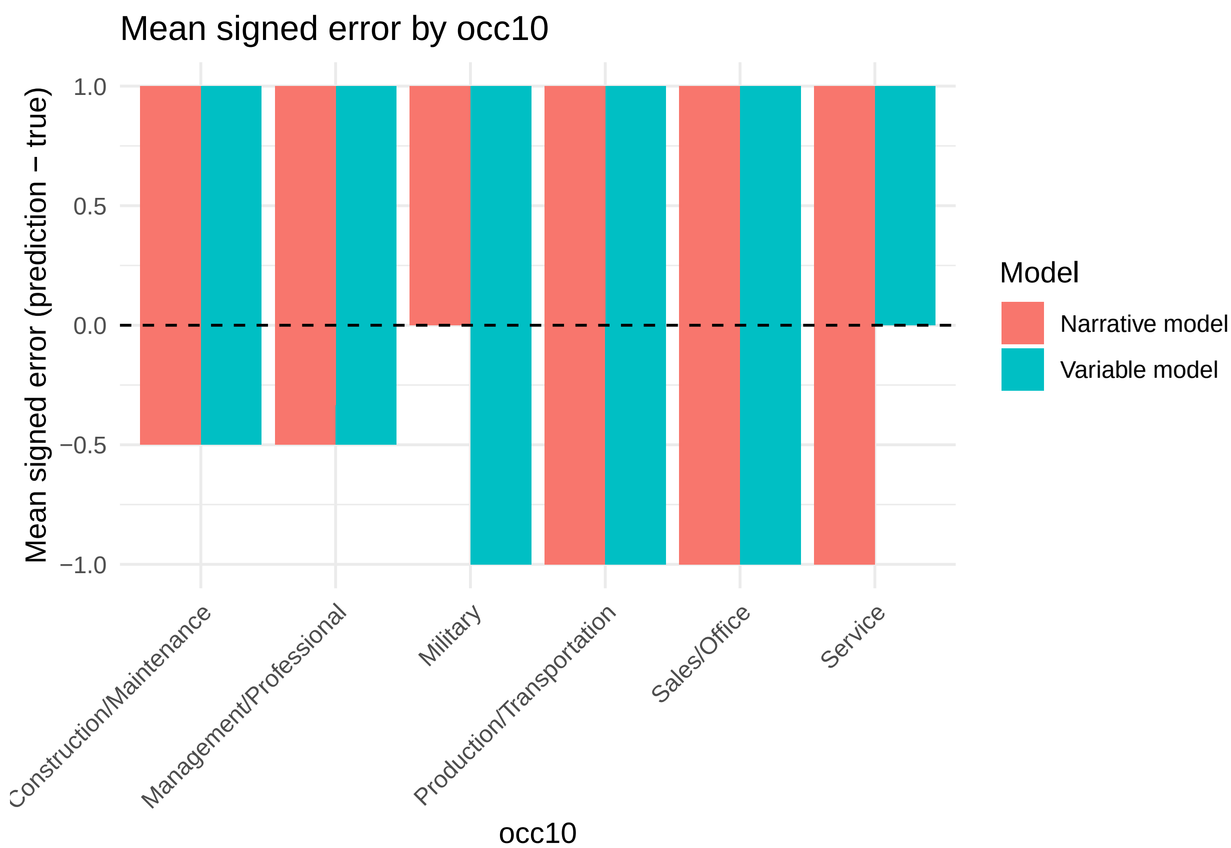

Mean signed error by sex
Mean signed error (prediction − true)
0.5
0.4
0.3
0.2
0.1
0.0
Female
Male
sex
Model
Narrative model
Variable model


Mean signed error by race
Mean signed error (prediction − true)
0.6
0.4
0.2
0.0
−0.2
Black
Other
White
race
Model
Narrative model
Variable model

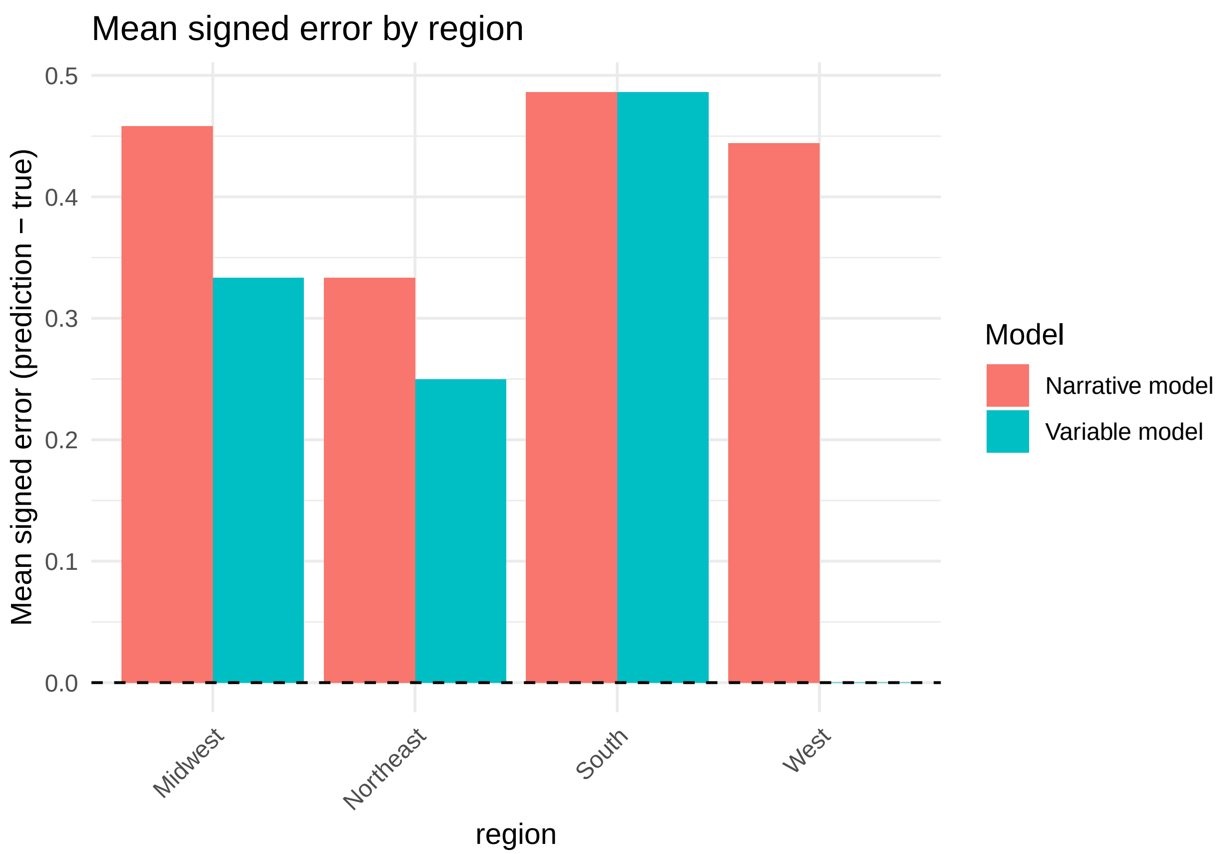


Mean signed error by educ
Mean signed error (prediction − true)
1.0
0.5
0.0
−0.5
−1.0
0
6
9
10
11
12
13
14
15
16
17
18
19
20
educ
Model
Narrative model
Variable model


Mean signed error by marital
Mean signed error (prediction − true)
0.6
0.4
0.2
0.0
Divorced
Married
Never married
Widowed
marital
Model
Narrative model
Variable model



Mean signed error by occ10
Mean signed error (prediction − true)
1.0
0.5
0.0
−0.5
−1.0
Construction/Maintenance
Management/Professional
Military
Production/Transportation
Sales/Office
Service
occ10
Model
Narrative model
Variable model




```r
# 3-category analysis
df_3 <- analyze_classification(
  sample100_3,
  "gss_gpt5_var_predictions_3.csv",
  "gss_gpt5_narrative_predictions_3.csv",
  "polviews_3",
  "3-Category Classification",
  "3cat"
)
```

== ANALYSIS: 3-Category Classification =

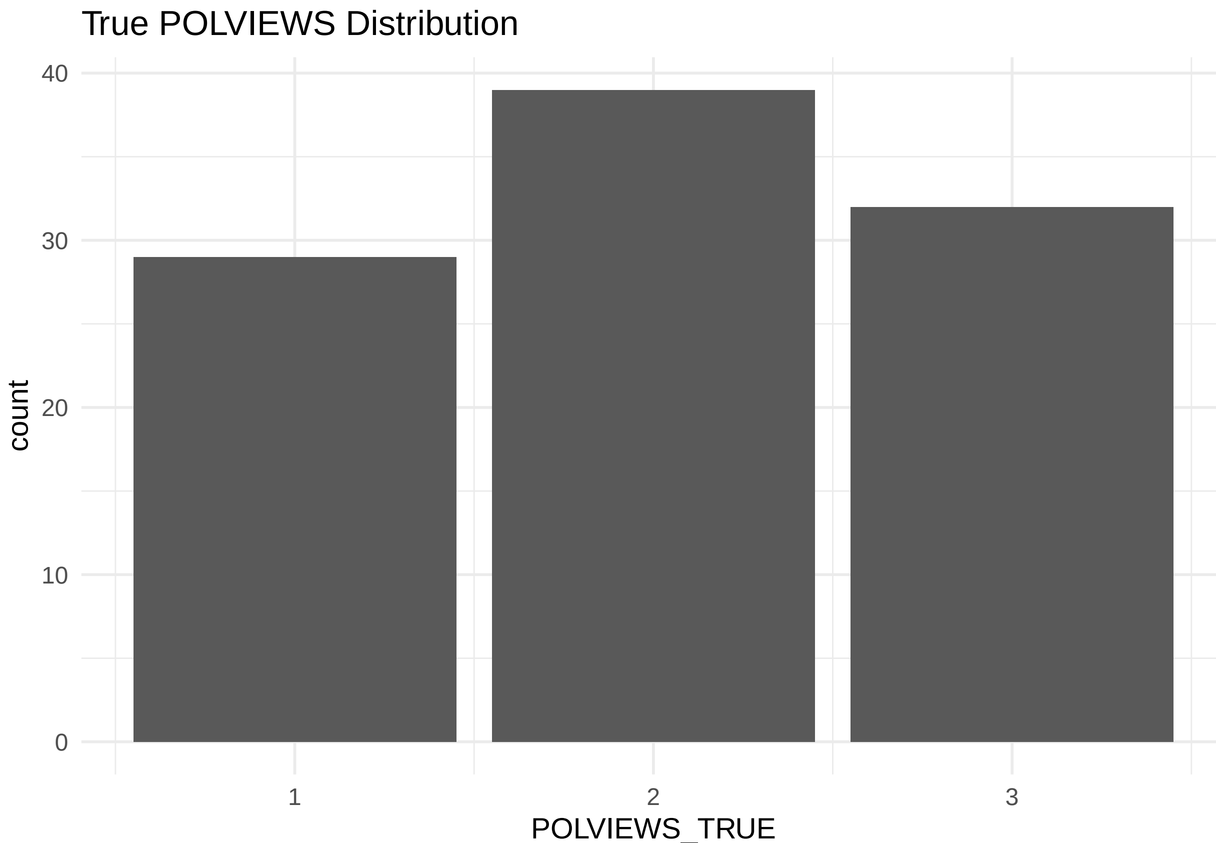
Variable Model: Mean Absolute Error: 0.75 Mean Squared Error: 1.03 Exact Match Accuracy: 39 % Within ±1 Accuracy: 86 %

Narrative Model: Mean Absolute Error: 0.58 Mean Squared Error: 0.66 Exact Match Accuracy: 46 % Within ±1 Accuracy: 96 %

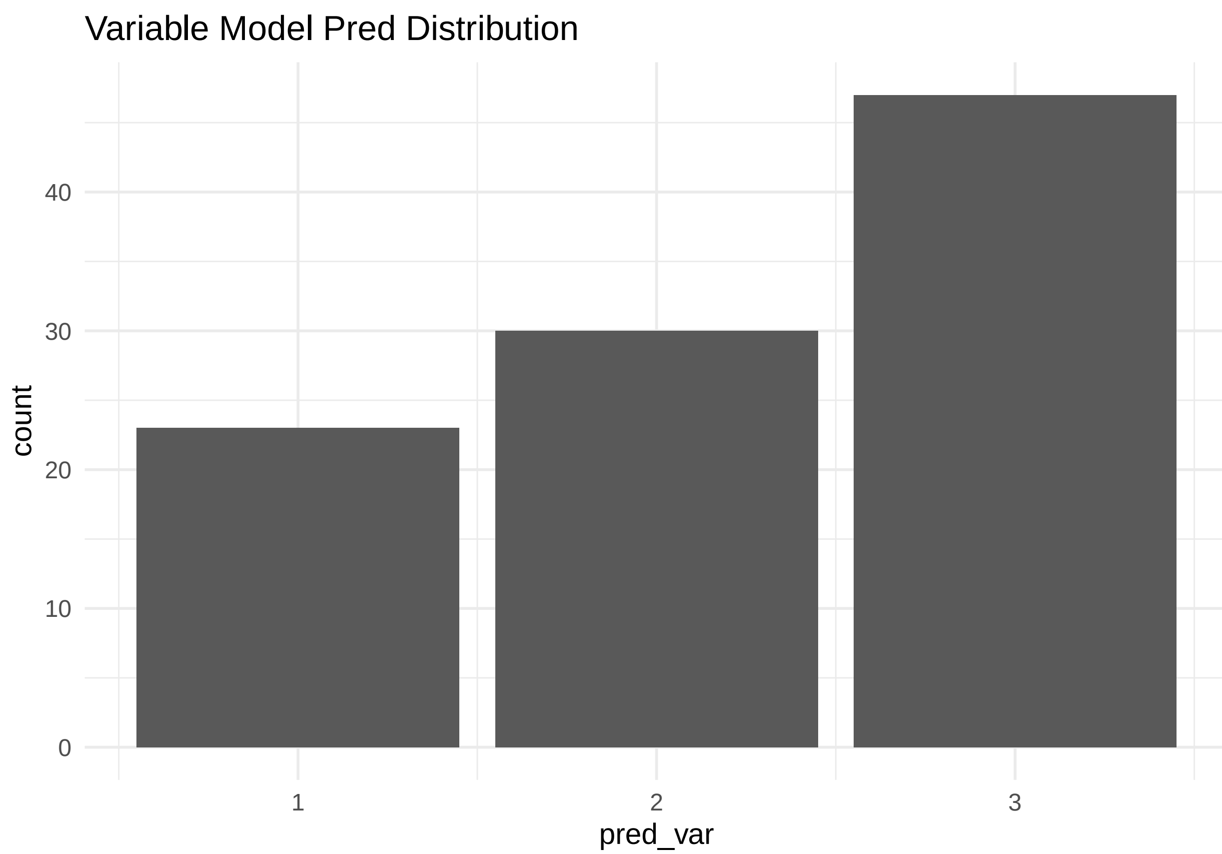
F1 Scores: # A tibble: 2 x 3 Model Macro_F1 Weighted_F1 1 Variable Model 0.689 0.682 2 Narrative Model 0.678 0.654

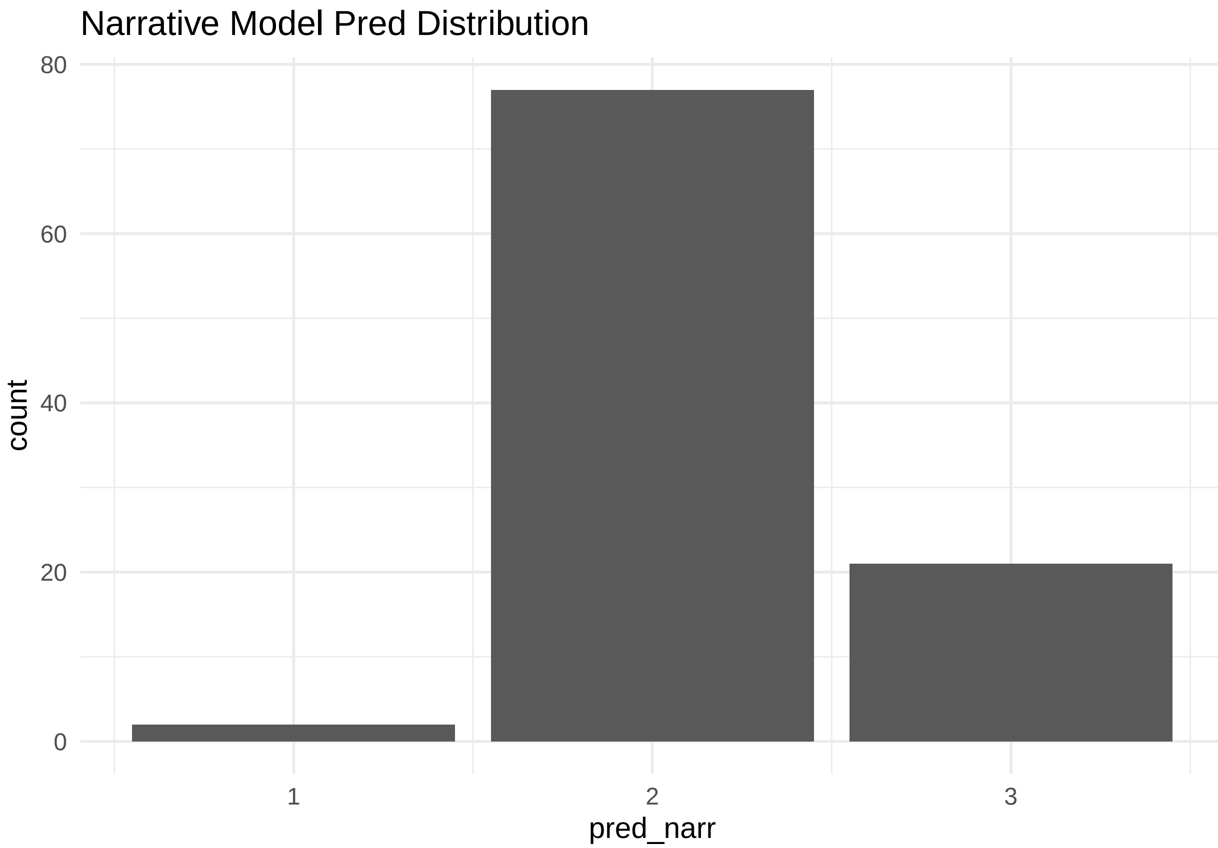
Mean Errors: Variable Model: 0.21 Narrative Model: 0.16

Bias Distribution: # A tibble: 4 x 4 model bias count percent 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


True POLVIEWS Distribution
count
40
30
20
10
0
1
2
3
POLVIEWS_TRUE

24 39.3


Variable Model Pred Distribution
count
40
30
20
10
0
1
2
3
pred_var



Bias by Age: # A tibble: 50 x 8 age n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 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 , prop_too_lib_narr

Bias by Sex: # A tibble: 2 x 8 sex n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 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 , prop_too_lib_narr

Bias by Race: # A tibble: 3 x 8 race n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 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 , prop_too_lib_narr

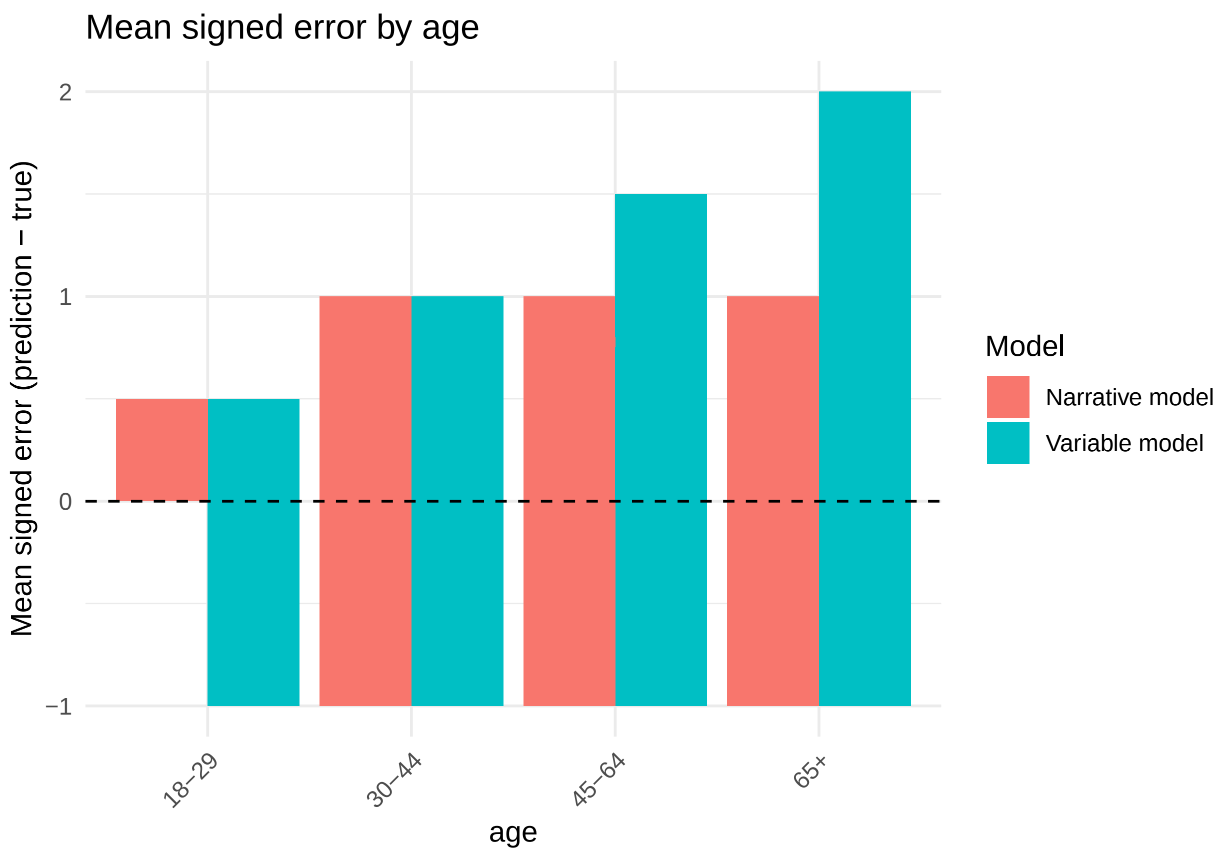
Bias by Education: # A tibble: 14 x 8 educ n mean_error_var mean_error_narr prop_too_cons_var <dbl+lbl> 1 19 [7 years of colleg~ 1 2 1 1
2 20 [8 or more years o~ 2 2 1 1
3 15 [3 years of colleg~ 2 0.5 0 0.5
4 16 [4 years of colleg~ 26 0.385 0.115 0.423 5 13 [1 year of college] 6 0.333 0.667 0.5
6 12 [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 , prop_too_cons_narr , # prop_too_lib_narr

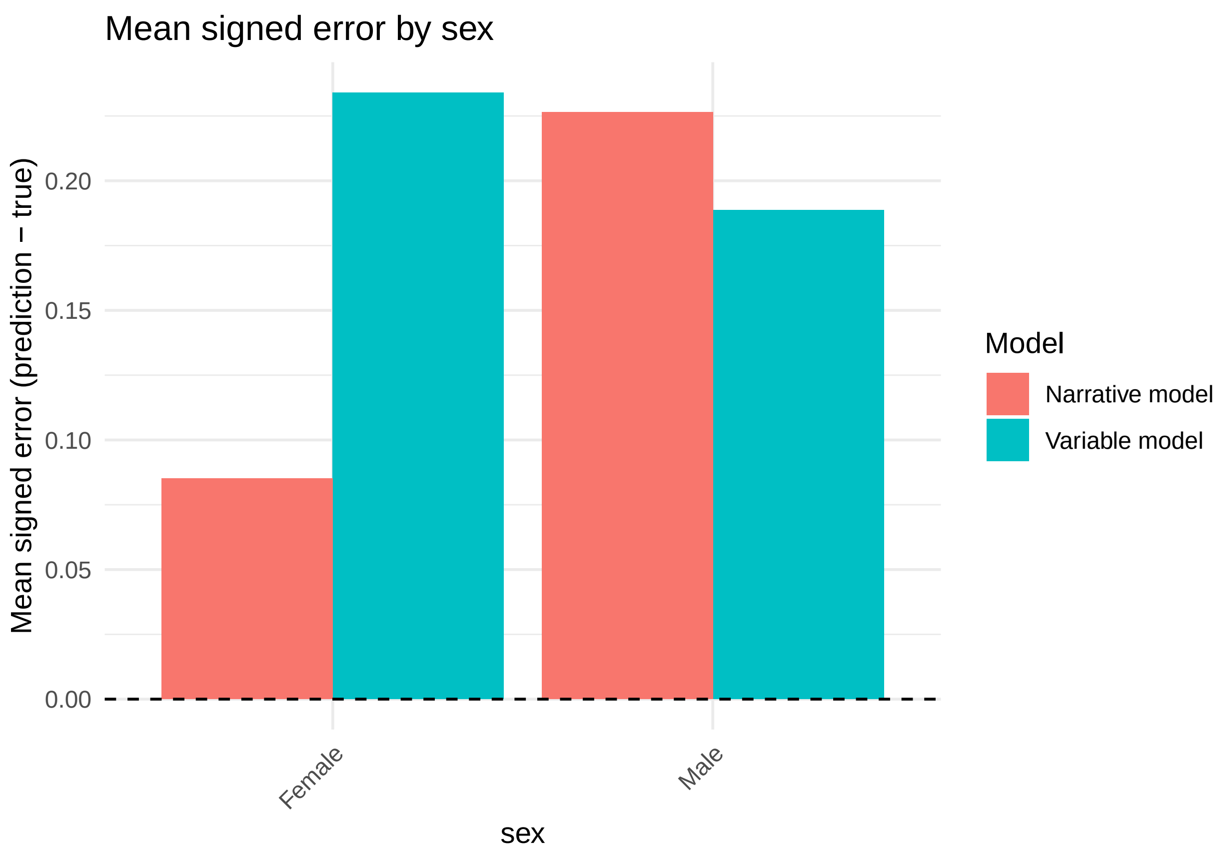
Bias by Marital Status: # A tibble: 4 x 8 marital n mean_error_var mean_error_narr prop_too_cons_var 1 2 8 0.875 0.375 0.75

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 , prop_too_cons_narr , # prop_too_lib_narr

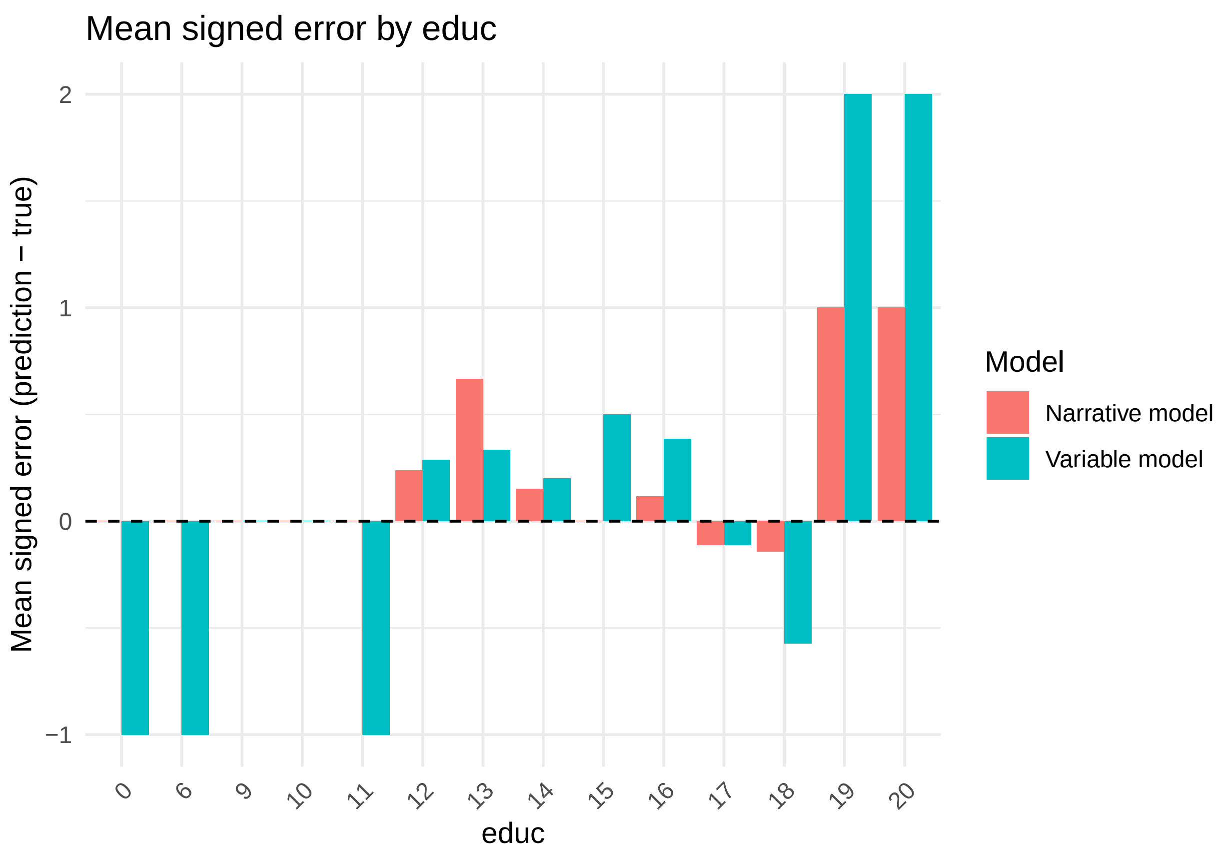
Bias by Occupation: # A tibble: 73 x 8 occ10 n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 1 710 2 2 1 1 0 2 1460 1 2 1 1 0 3 2200 1 2 1 1 0 4 5120 1 2 1 1 0 5 5600 1 2 1 1 0 6 5820 1 2 1 1 0 7 8750 1 2 2 1 0 8 9620 1 2 2 1 0 9 20 1 1 0 1 0 10 735 1 1 1 1 0 # i 63 more rows # i 2 more variables: prop_too_cons_narr , prop_too_lib_narr

Bias by Region: # A tibble: 4 x 8 region n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 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 , prop_too_lib_narr

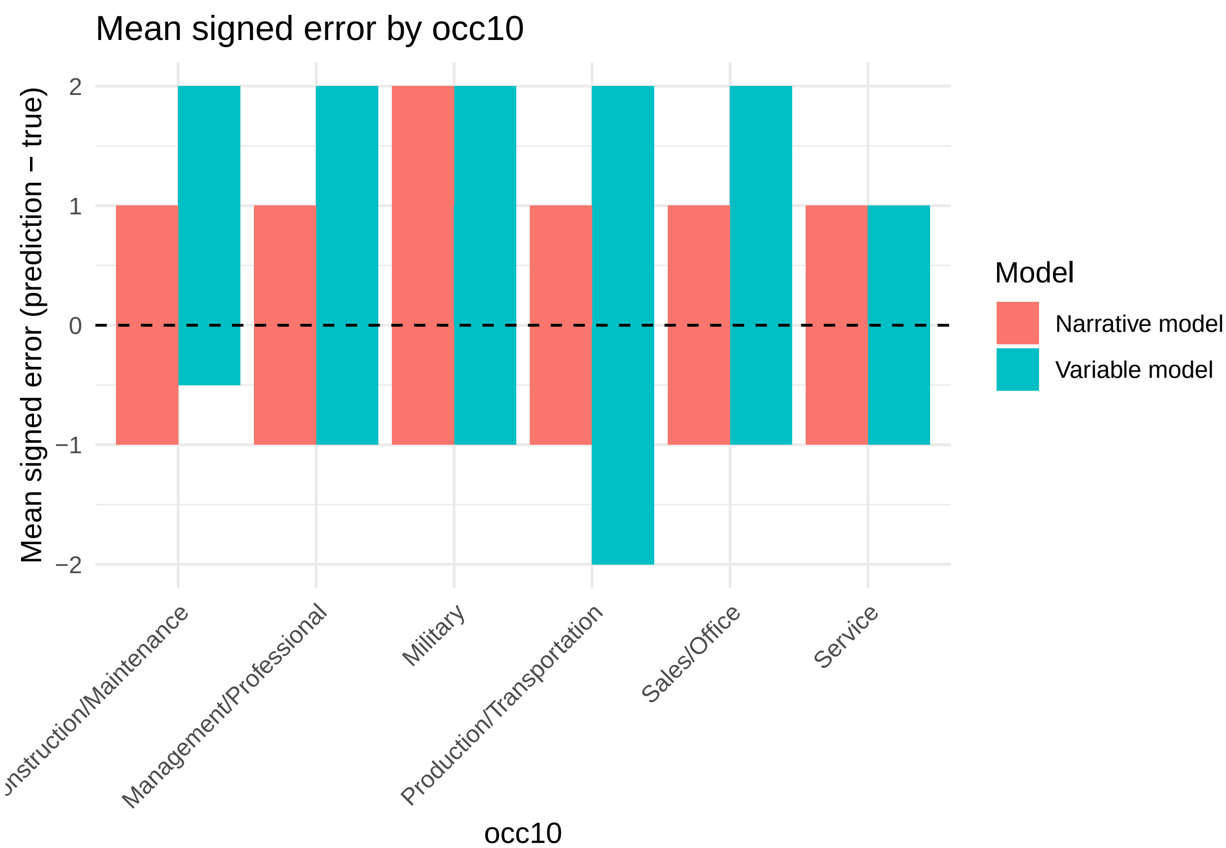



Mean signed error by sex
Mean signed error (prediction − true)
0.20
0.15
0.10
0.05
0.00
Female
Male
sex
Model
Narrative model
Variable model


Mean signed error by race
0.6
0.3
0.0
−0.3
Mean signed error (prediction − true)
Black
Other
White
race
Model
Narrative model
Variable model


Mean signed error by educ
Mean signed error (prediction − true)
2
1
0
−1
0
6
9
10
11
12
13
14
15
16
17
18
19
20
educ
Model
Narrative model
Variable model

Mean signed error by marital
Mean signed error (prediction − true)
0.5
0.0
Divorced
Married
Never married
Widowed
marital
Model
Narrative model
Variable model



Mean signed error by occ10
Mean signed error (prediction − true)
2
1
0
−1
−2
onstruction/Maintenance
Management/Professional
Military
Production/Transportation
Sales/Office
Service
occ10
Model
Narrative model
Variable model


```
# 4-category analysis
df_4 <- analyze_classification(
  sample100_4,
  "gss_gpt5_var_predictions_4.csv",
  "gss_gpt5_narrative_predictions_4.csv",
  "polviews_4",
  "4-Category Classification",
  "4cat"
)
```

== ANALYSIS: 4-Category Classification =

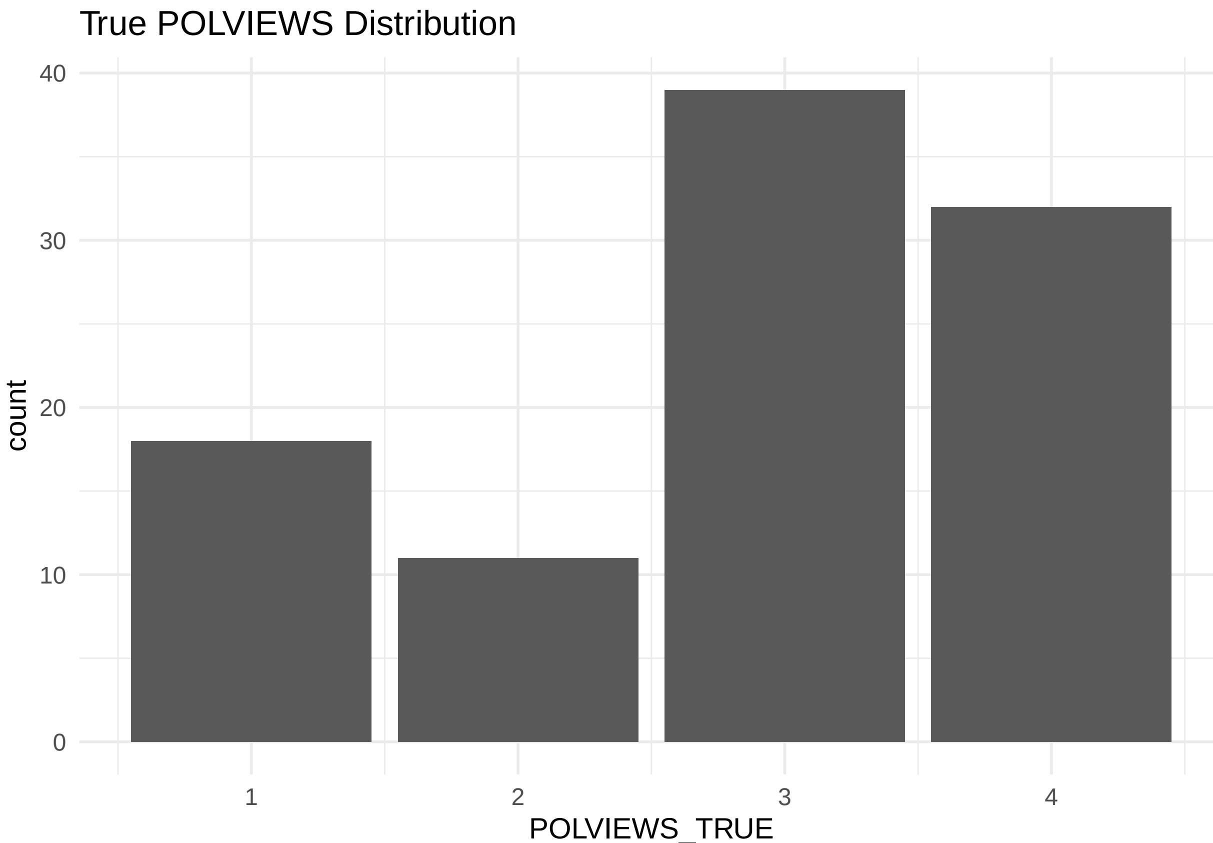
Variable Model: Mean Absolute Error: 0.95 Mean Squared Error: 1.71 Exact Match Accuracy: 35 % Within ±1 Accuracy: 78 %

Narrative Model: Mean Absolute Error: 0.83 Mean Squared Error: 1.47 Exact Match Accuracy: 44 % Within ±1 Accuracy: 78 %

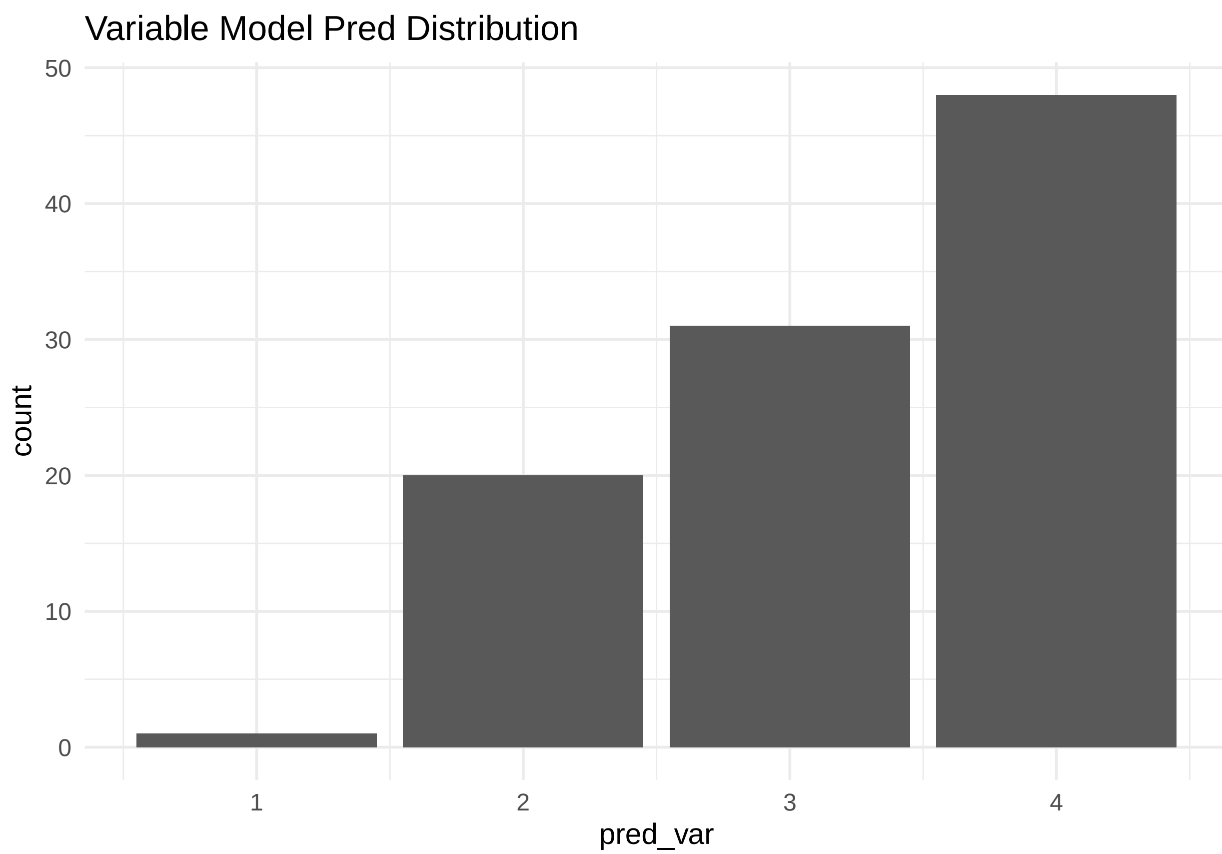
F1 Scores: # A tibble: 2 x 3 Model Macro_F1 Weighted_F1 1 Variable Model 0.765 0.726 2 Narrative Model 0.778 0.711

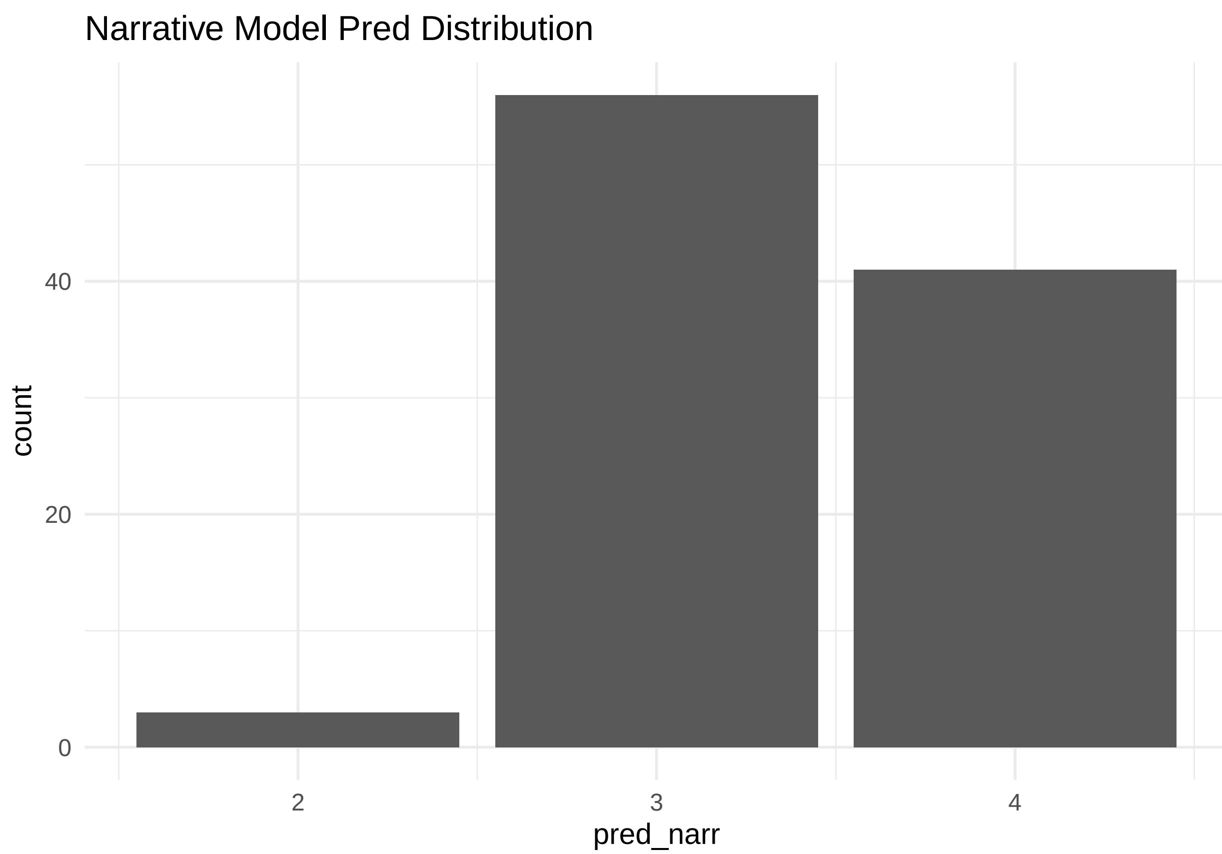
Mean Errors: Variable Model: 0.41 Narrative Model: 0.53

Bias Distribution: # A tibble: 4 x 4 model bias count percent 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


True POLVIEWS Distribution
count
40
30
20
10
0
1
2
3
4
POLVIEWS_TRUE

21 32.3


Variable Model Pred Distribution
count
pred_var
0
10
20
30
40
50
1
2
3
4



Bias by Age: # A tibble: 50 x 8 age n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 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 , prop_too_lib_narr

Bias by Sex: # A tibble: 2 x 8 sex n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 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 , prop_too_lib_narr

Bias by Race: # A tibble: 3 x 8 race n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 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 , prop_too_lib_narr

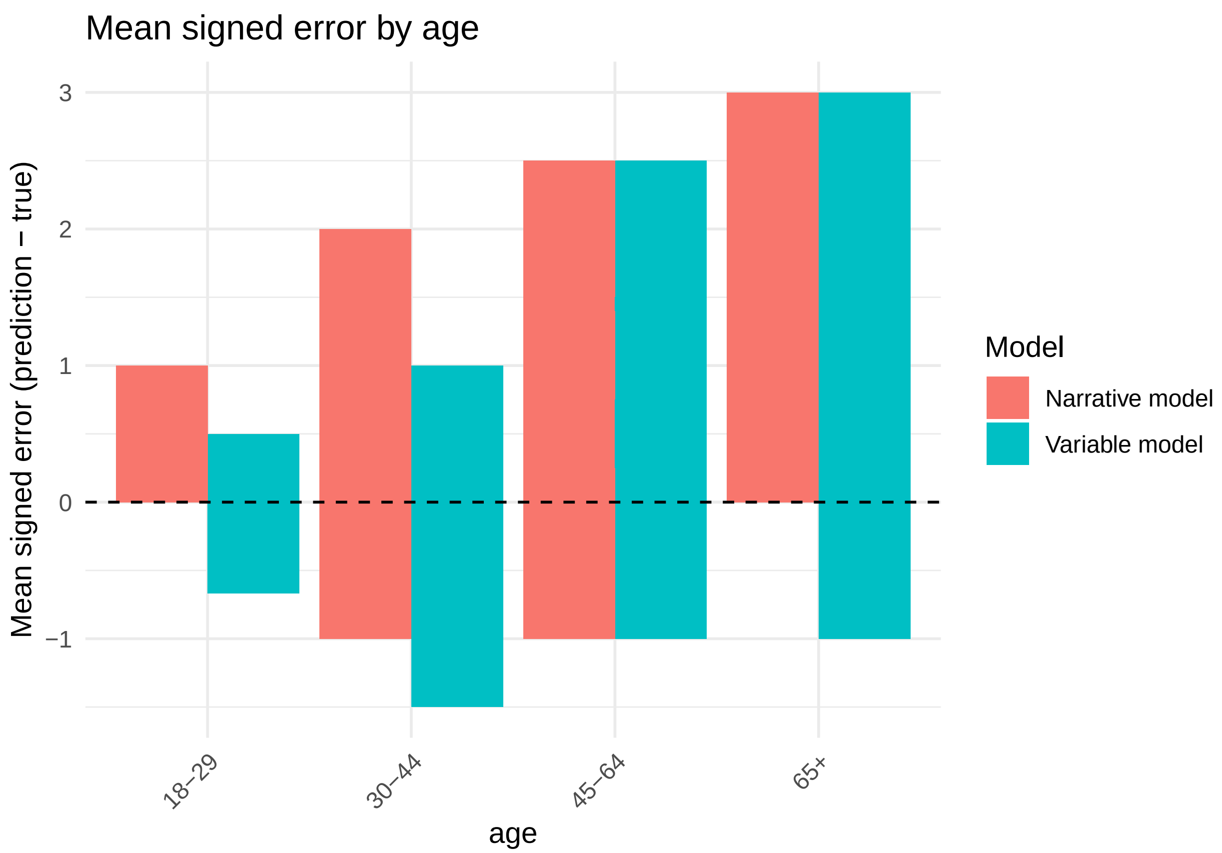
Bias by Education: # A tibble: 14 x 8 educ n mean_error_var mean_error_narr prop_too_cons_var <dbl+lbl> 1 19 [7 years of colleg~ 1 3 2 1
2 20 [8 or more years o~ 2 2.5 2 1
3 13 [1 year of college] 6 1 1.33 0.667 4 16 [4 years of colleg~ 26 0.615 0.423 0.5
5 15 [3 years of colleg~ 2 0.5 0.5 0.5
6 12 [12th 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

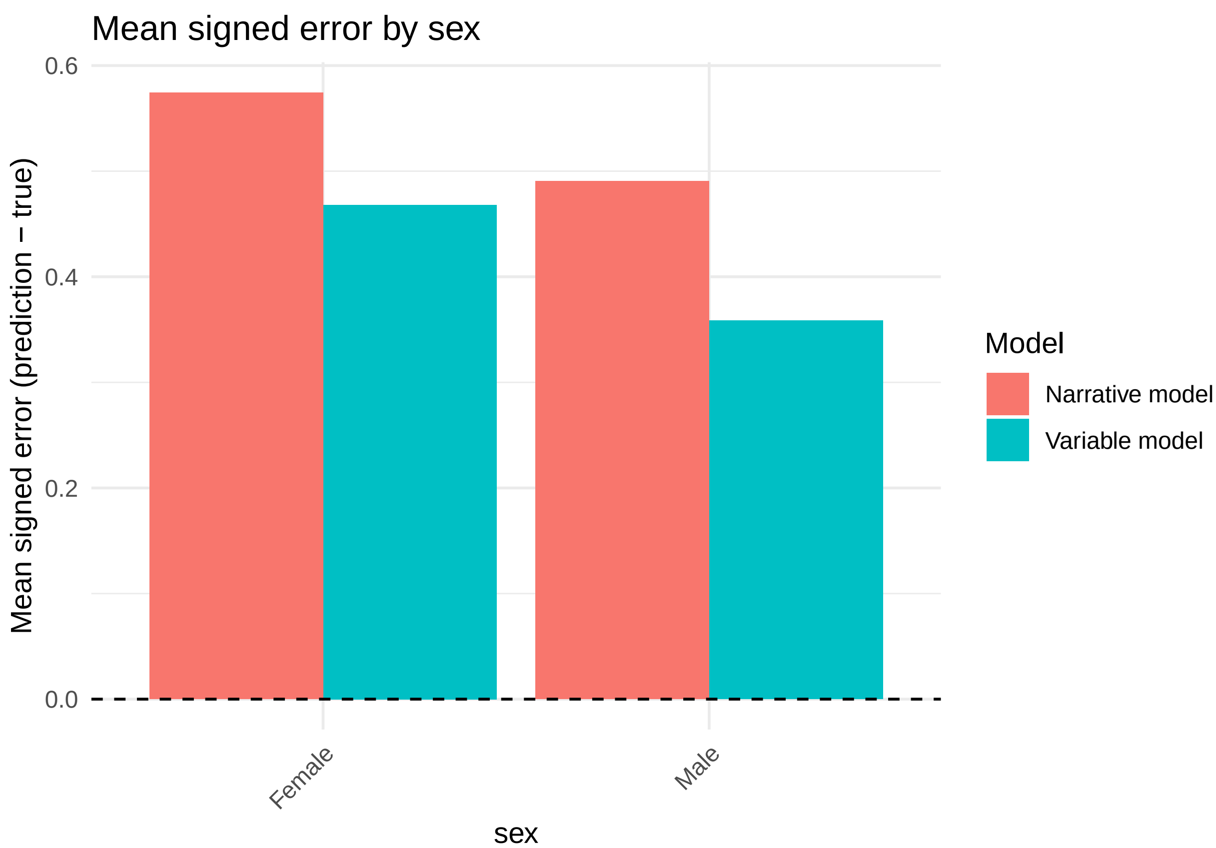
10 10 [10th grade] 2 0 0.5 0
11 18 [6 years of colleg~ 7 -0.143 0.286 0.429 12 17 [5 years of colleg~ 9 -0.222 0.111 0.333 13 0 [no formal schooli~ 1 -1 0 0
14 11 [11th grade] 1 -1 0 0
i 3 more variables: prop_too_lib_var , prop_too_cons_narr , # prop_too_lib_narr

Bias by Marital Status: # A tibble: 4 x 8 marital n mean_error_var mean_error_narr prop_too_cons_var 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 , prop_too_cons_narr , # prop_too_lib_narr

Bias by Occupation: # A tibble: 73 x 8 occ10 n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 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 , prop_too_lib_narr

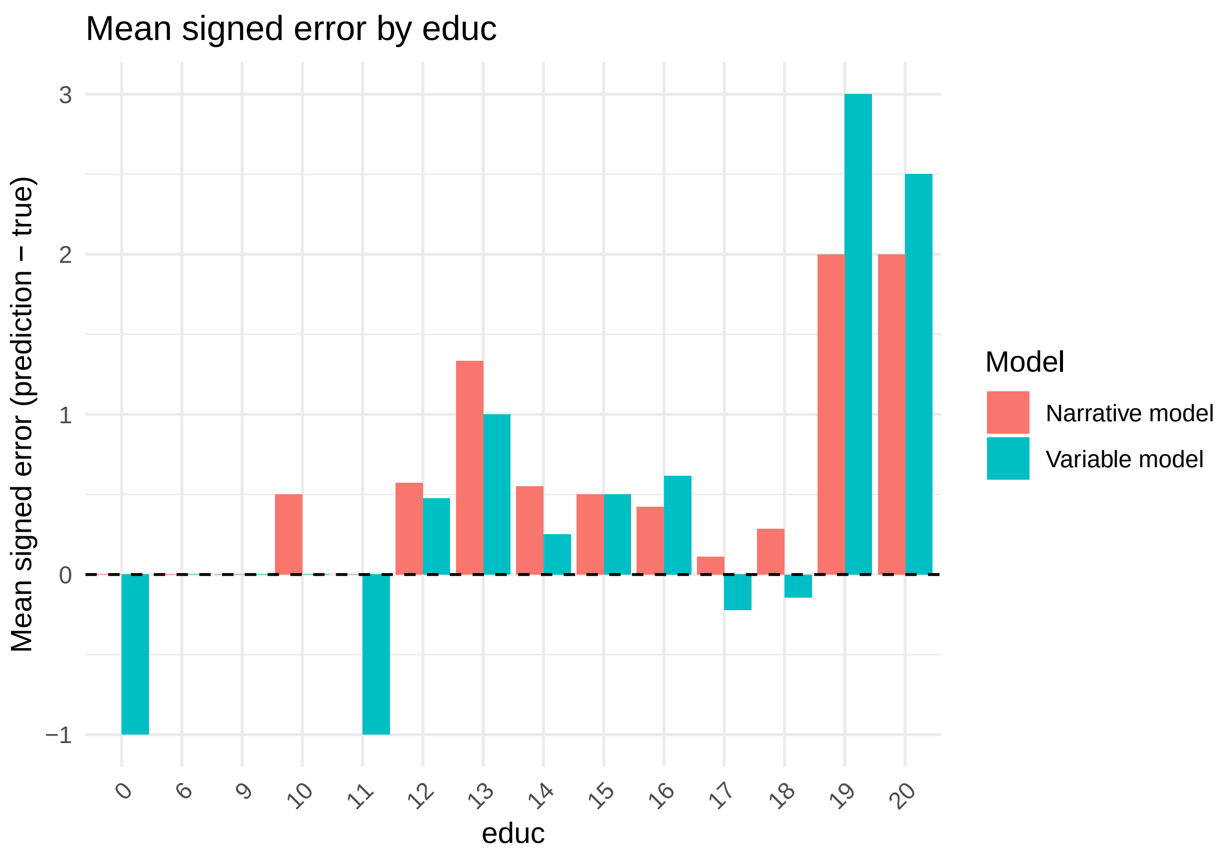
Bias by Region: # A tibble: 4 x 8 region n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 1 1 12 0.667 0.5 0.583 0.0833 2 2 24 0.625 0.667 0.417 0.125 3 3 37 0.541 0.595 0.432 0.135 4 4 27 -0.0741 0.333 0.407 0.444 # i 2 more variables: prop_too_cons_narr , prop_too_lib_narr

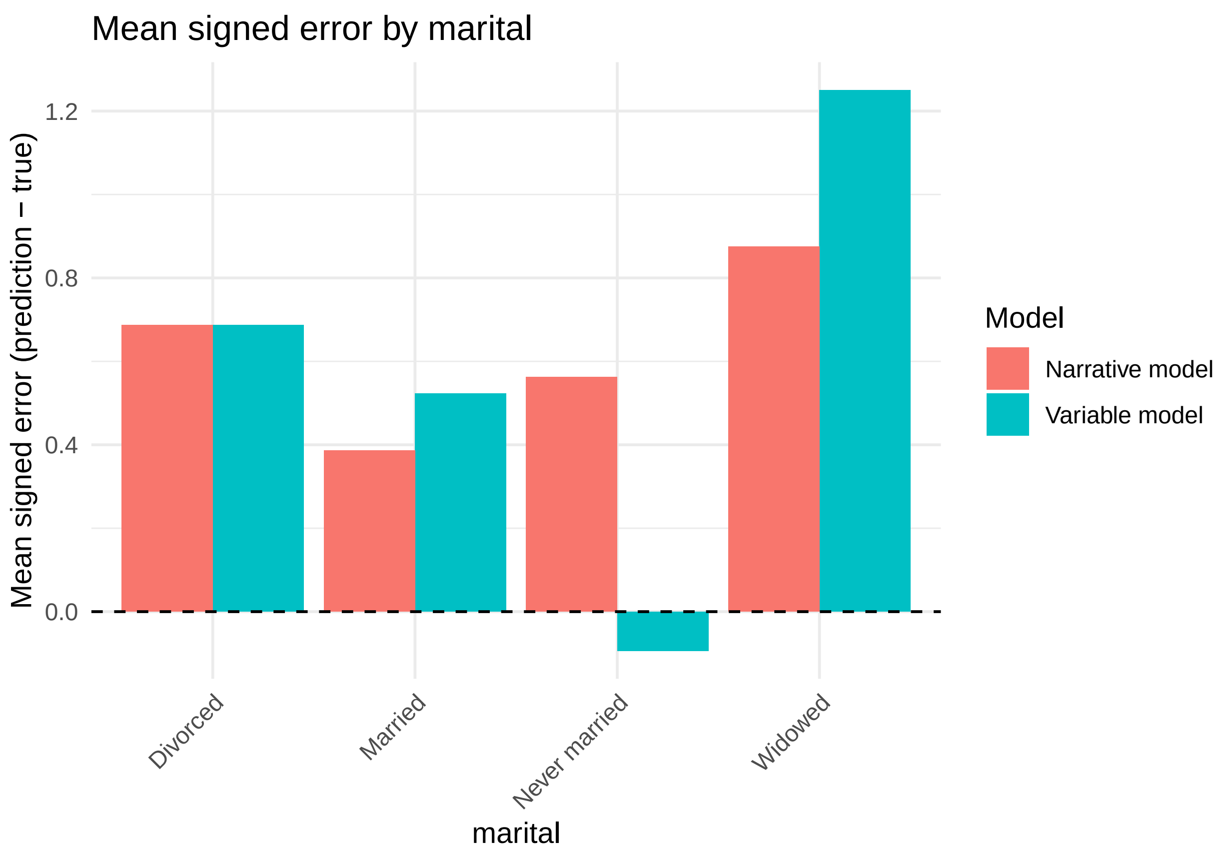


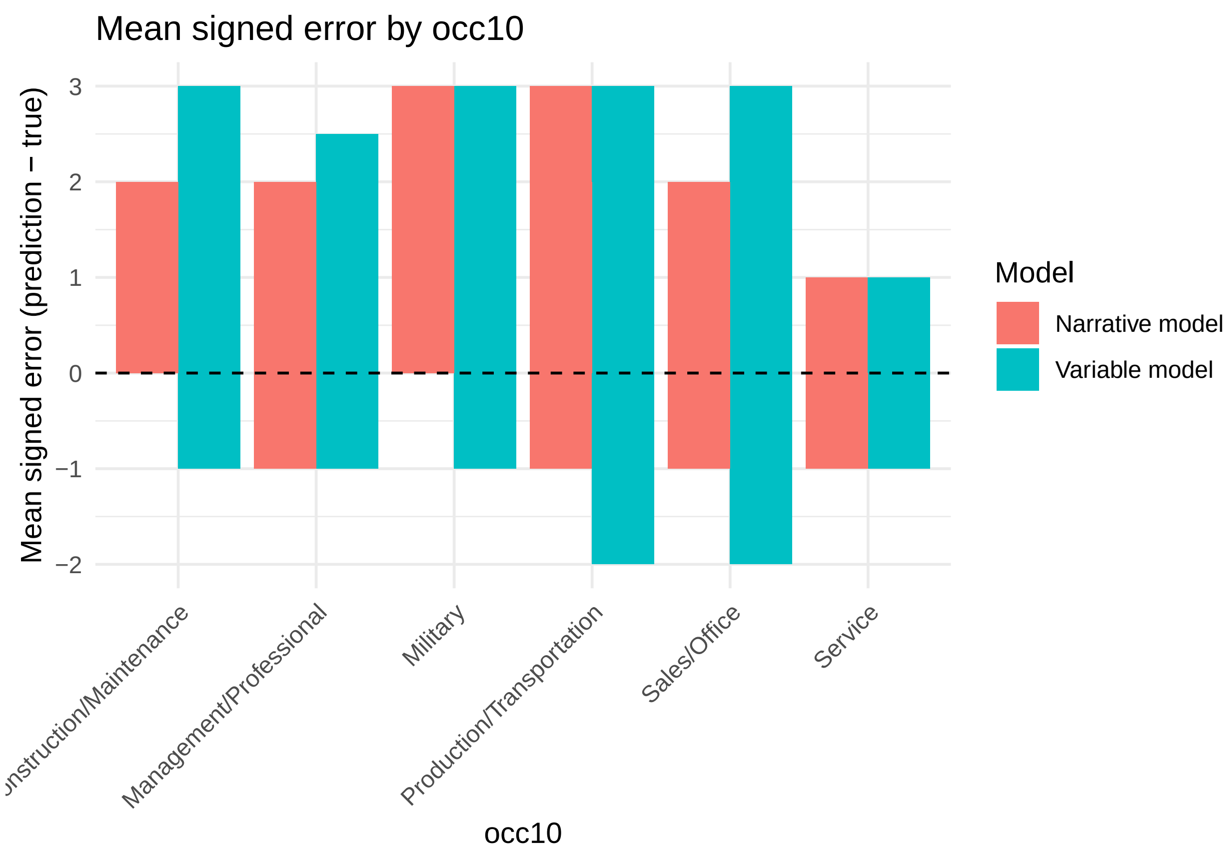


Mean signed error by sex
Mean signed error (prediction – true)
0.6
0.4
0.2
0.0
Female
Male
sex
Model
Narrative model
Variable model


Mean signed error by race
Mean signed error (prediction − true)
0.8
0.4
0.0
Black
Other
White
race
Model
Narrative model
Variable model


Mean signed error by educ
Mean signed error (prediction − true)
3
2
1
0
−1
0
6
9
10
11
12
13
14
15
16
17
18
19
20
educ
Model
Narrative model
Variable model


Mean signed error by marital
Mean signed error (prediction − true)
1.2
0.8
0.4
0.0
Divorced
Married
Never married
Widowed
marital
Model
Narrative model
Variable model


Mean signed error by occ10
Mean signed error (prediction − true)
3
2
1
0
−1
−2
onstruction/Maintenance
Management/Professional
Military
Production/Transportation
Sales/Office
Service
occ10
Model
Narrative model
Variable model


```
# 5-category analysis
df_5 <- analyze_classification(
  sample100_5,
  "gss_gpt5_var_predictions_5.csv",
  "gss_gpt5_narrative_predictions_5.csv",
  "polviews_5",
  "5-Category Classification",
  "5cat"
)
```

== ANALYSIS: 5-Category Classification =

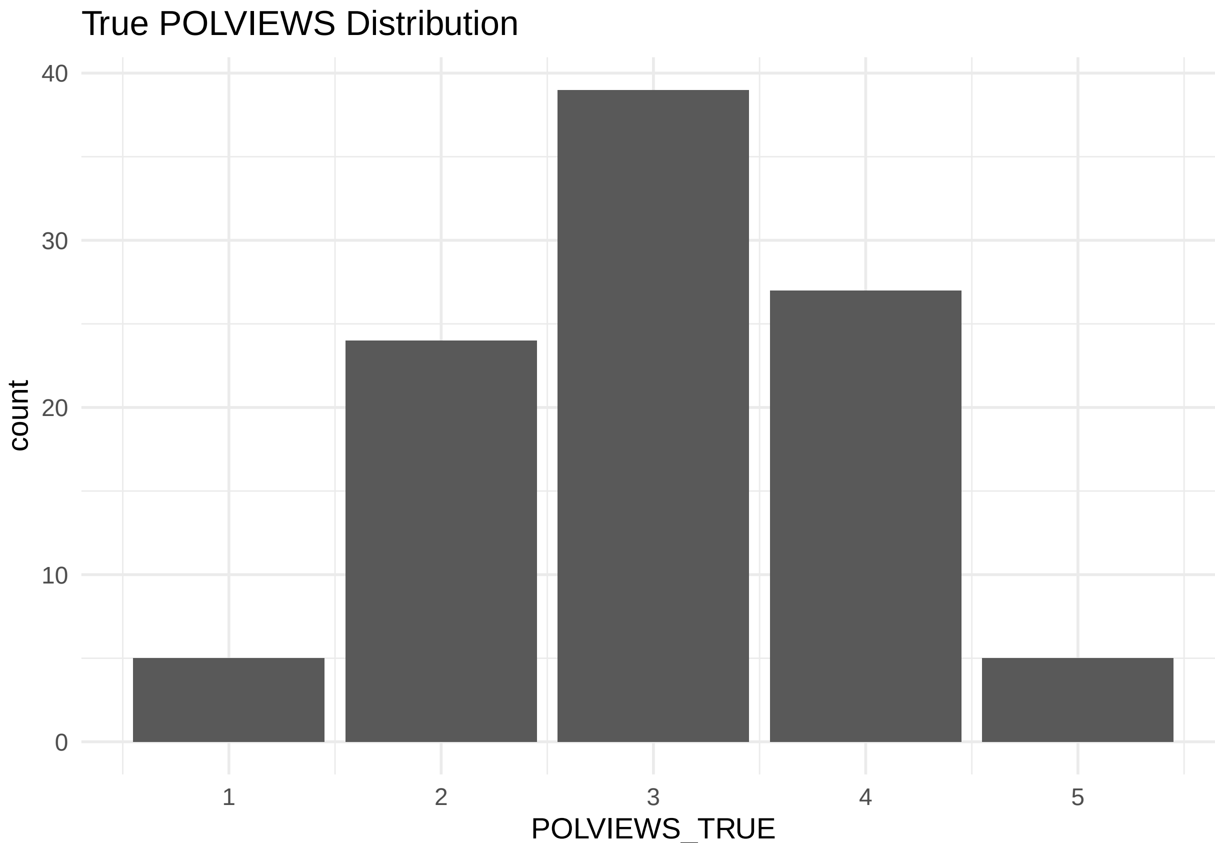
Variable Model: Mean Absolute Error: 0.89 Mean Squared Error: 1.43 Exact Match Accuracy: 35 % Within ±1 Accuracy: 79 %

Narrative Model: Mean Absolute Error: 0.81 Mean Squared Error: 1.23 Exact Match Accuracy: 38 % Within ±1 Accuracy: 83 %

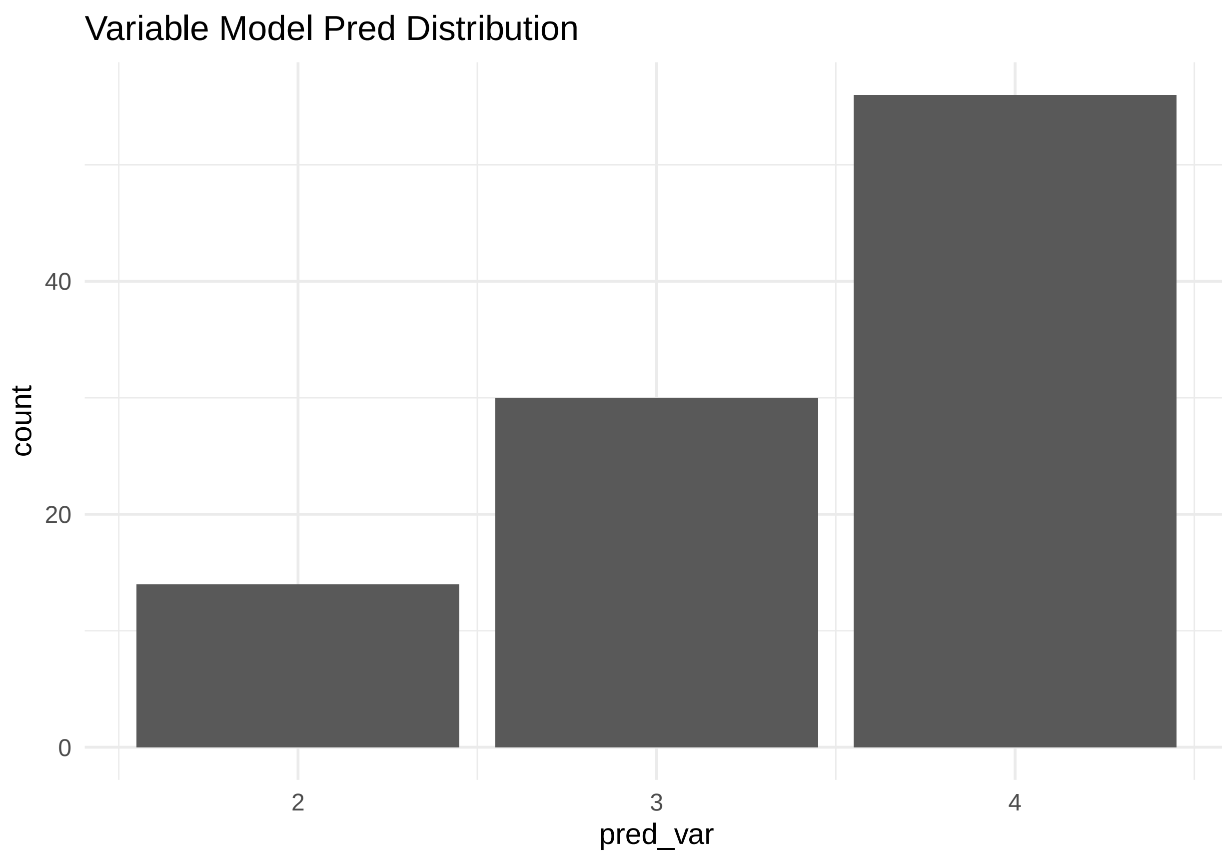
F1 Scores: # A tibble: 2 x 3 Model Macro_F1 Weighted_F1 1 Variable Model 0.805 0.712 2 Narrative Model 0.810 0.713

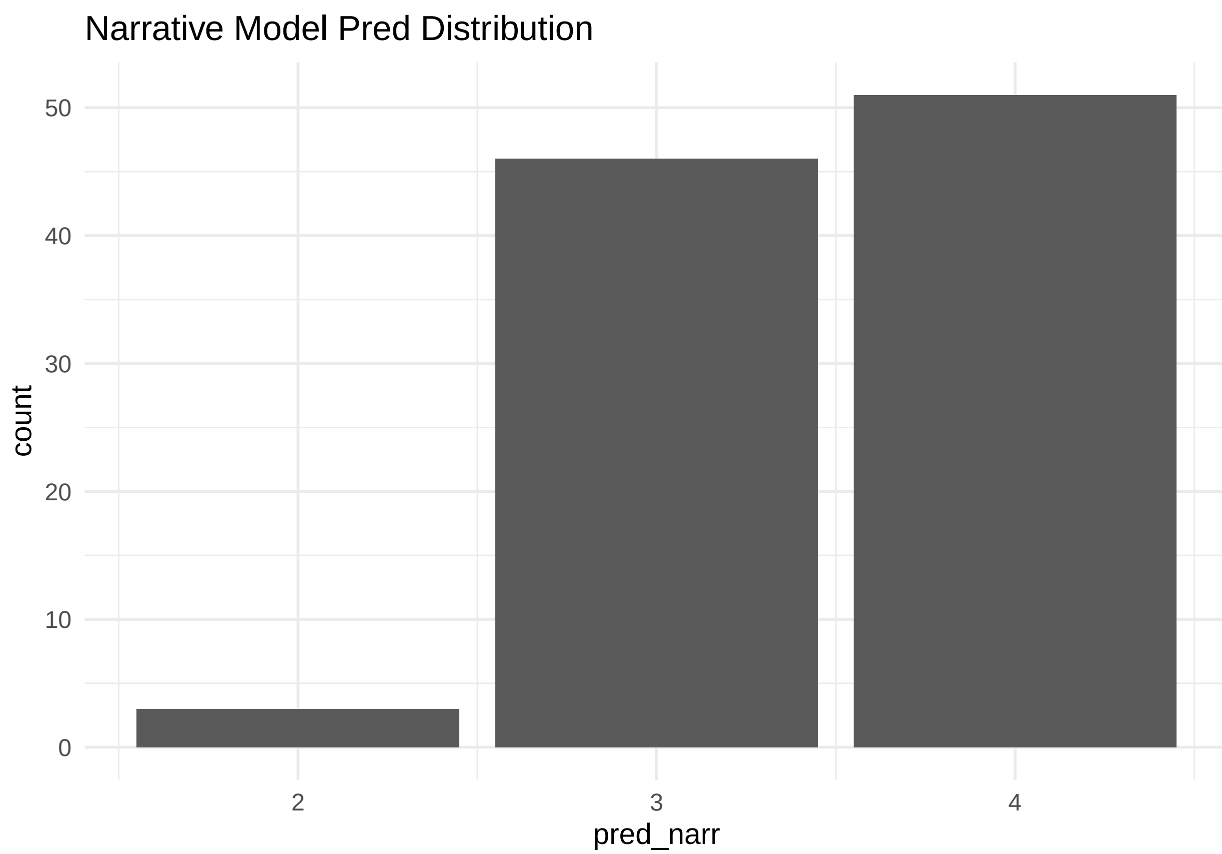
Mean Errors: Variable Model: 0.39 Narrative Model: 0.45

Bias Distribution: # A tibble: 4 x 4 model bias count percent 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


True POLVIEWS Distribution
count
POLVIEWS_TRUE
0
10
20
30
40
1
2
3
4
5

18 27.7


Variable Model Pred Distribution
count
40
20
0
2
3
4
pred_var



Bias by Age: # A tibble: 50 x 8 age n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 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 , prop_too_lib_narr

Bias by Sex: # A tibble: 2 x 8 sex n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 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 , prop_too_lib_narr

Bias by Race: # A tibble: 3 x 8 race n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 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 , prop_too_lib_narr

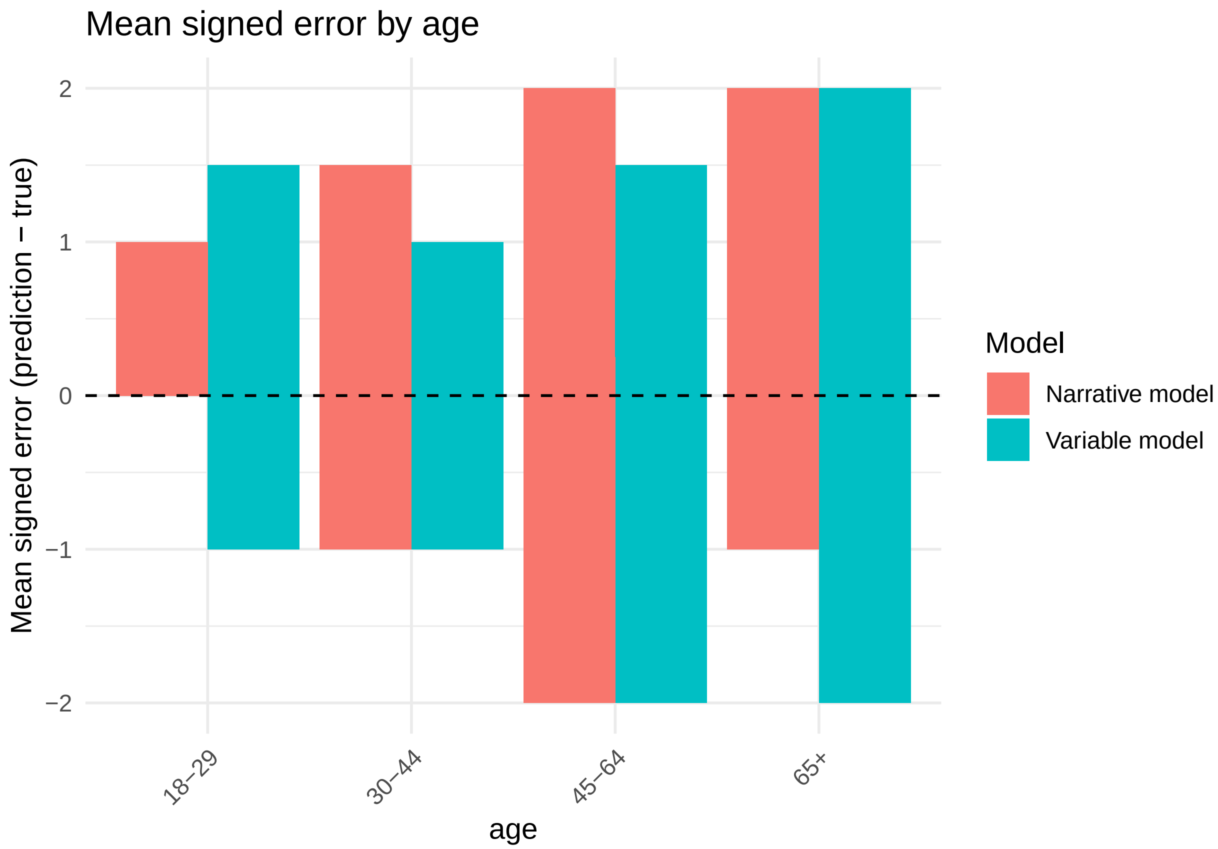
Bias by Education: # A tibble: 14 x 8 educ n mean_error_var mean_error_narr prop_too_cons_var <dbl+lbl> 1 20 [8 or more years o~ 2 2.5 2 1
2 19 [7 years of colleg~ 1 2 1 1
3 6 [6th grade] 1 1 0 1
4 15 [3 years of colleg~ 2 1 0.5 1
5 13 [1 year of college] 6 0.667 1 0.667 6 12 [12th grade] 21 0.524 0.619 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 , prop_too_cons_narr , # prop_too_lib_narr

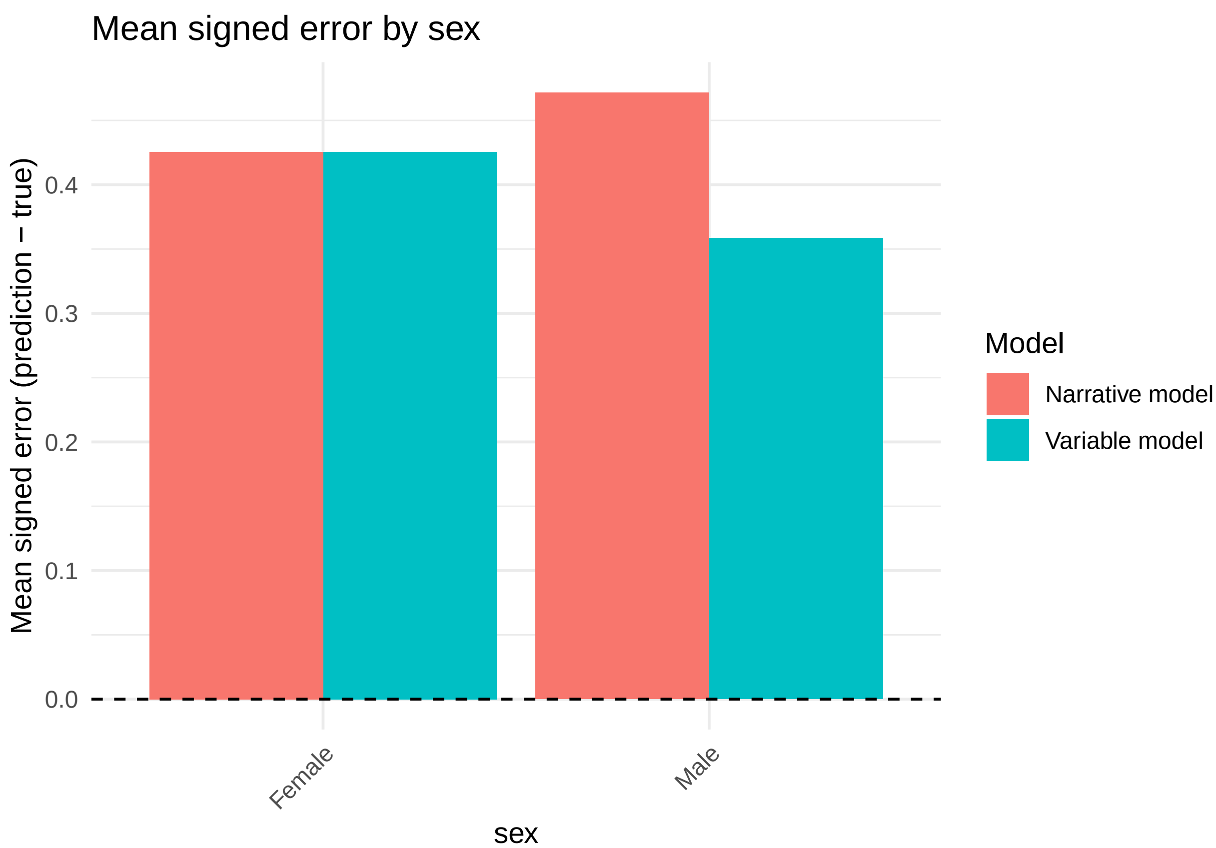
Bias by Marital Status: # A tibble: 4 x 8 marital n mean_error_var mean_error_narr prop_too_cons_var 1 2 8 1 0.875 0.75 2 3 16 0.625 0.625 0.625 3 1 44 0.432 0.295 0.5

4 5 32 0.0625 0.469 0.281 # i 3 more variables: prop_too_lib_var , prop_too_cons_narr , # prop_too_lib_narr

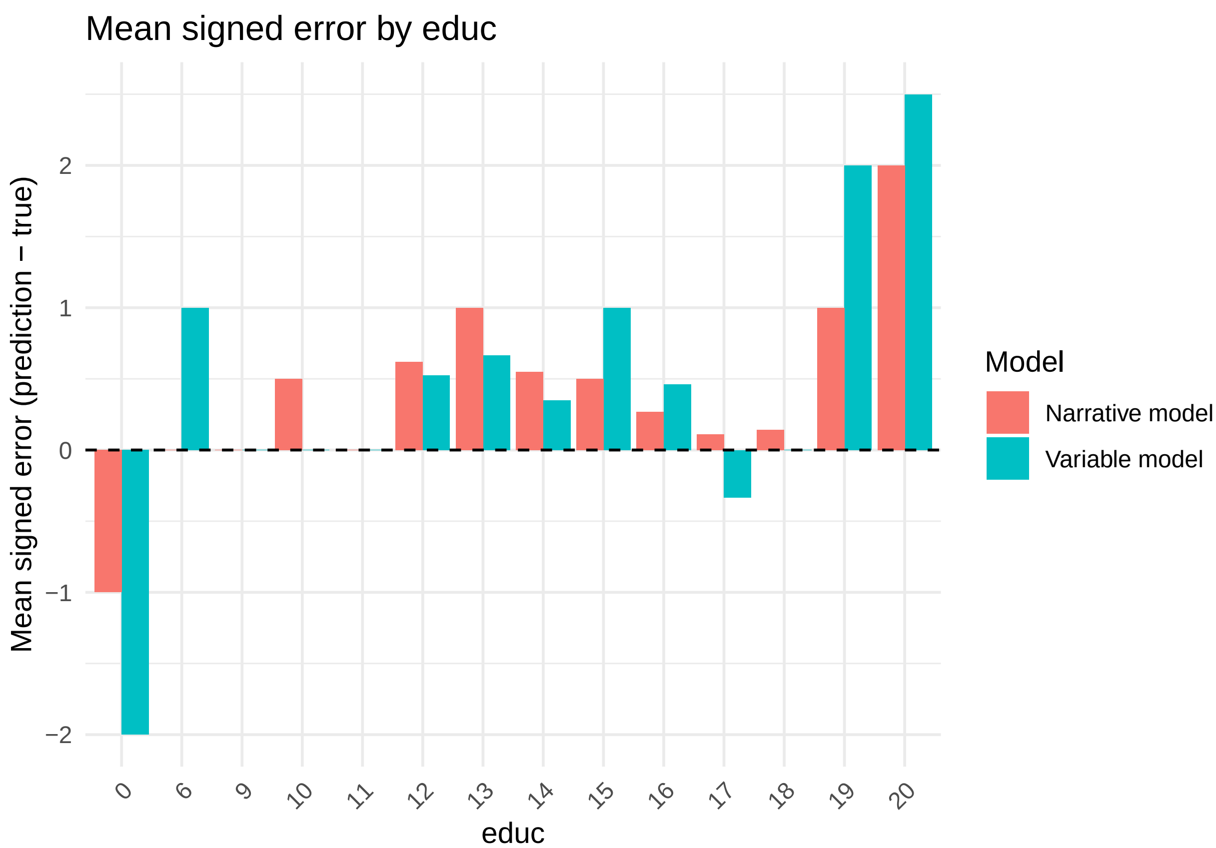
Bias by Occupation: # A tibble: 73 x 8 occ10 n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 1 2200 1 3 2 1 0 2 9620 1 3 3 1 0 3 710 2 2 1.5 1 0 4 735 1 2 1 1 0 5 1460 1 2 1 1 0 6 5120 1 2 2 1 0 7 5600 1 2 2 1 0 8 5820 1 2 2 1 0 9 8750 1 2 2 1 0 10 9350 1 2 2 1 0 # i 63 more rows # i 2 more variables: prop_too_cons_narr , prop_too_lib_narr

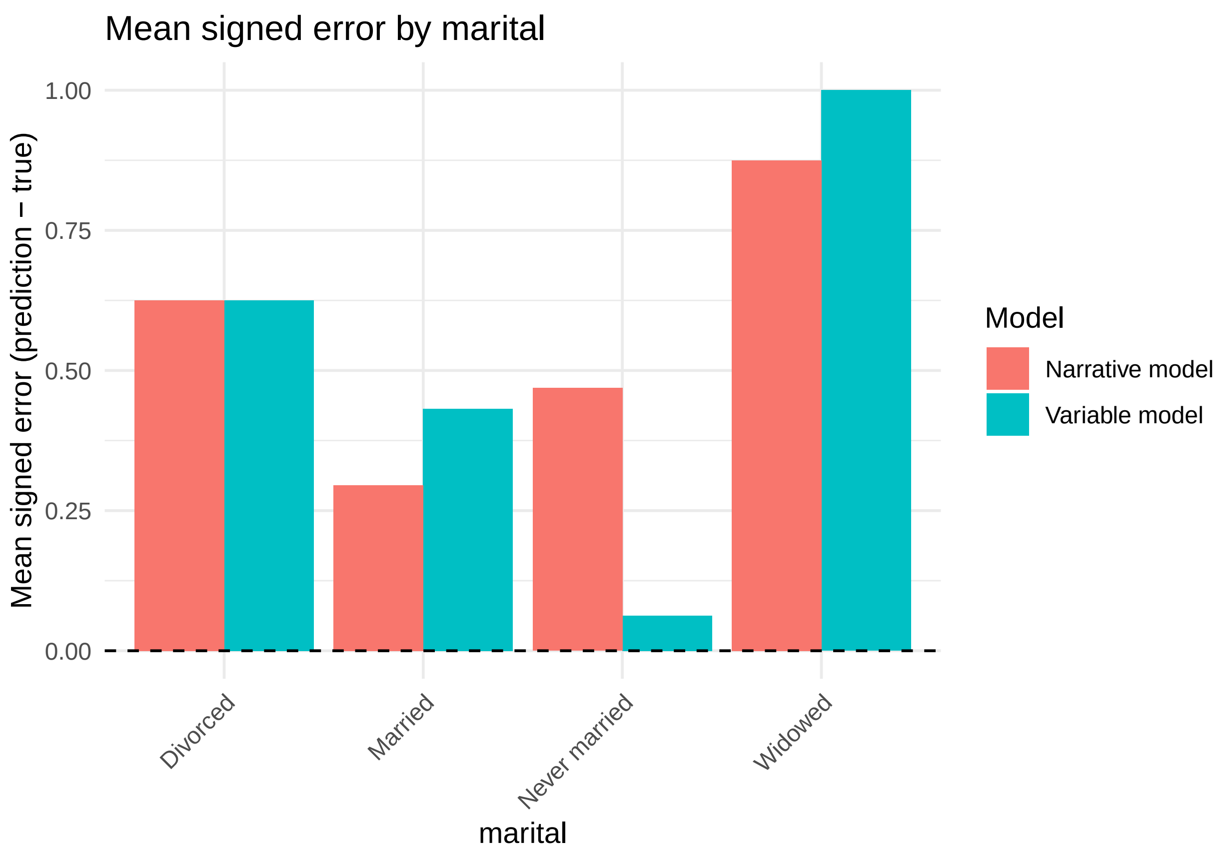
Bias by Region: # A tibble: 4 x 8 region n mean_error_var mean_error_narr prop_too_cons_var prop_too_lib_var 1 2 24 0.625 0.5 0.5 0.125 2 3 37 0.595 0.595 0.486 0.135 3 1 12 0.5 0.25 0.583 0.0833 4 4 27 -0.148 0.296 0.370 0.333 # i 2 more variables: prop_too_cons_narr , prop_too_lib_narr

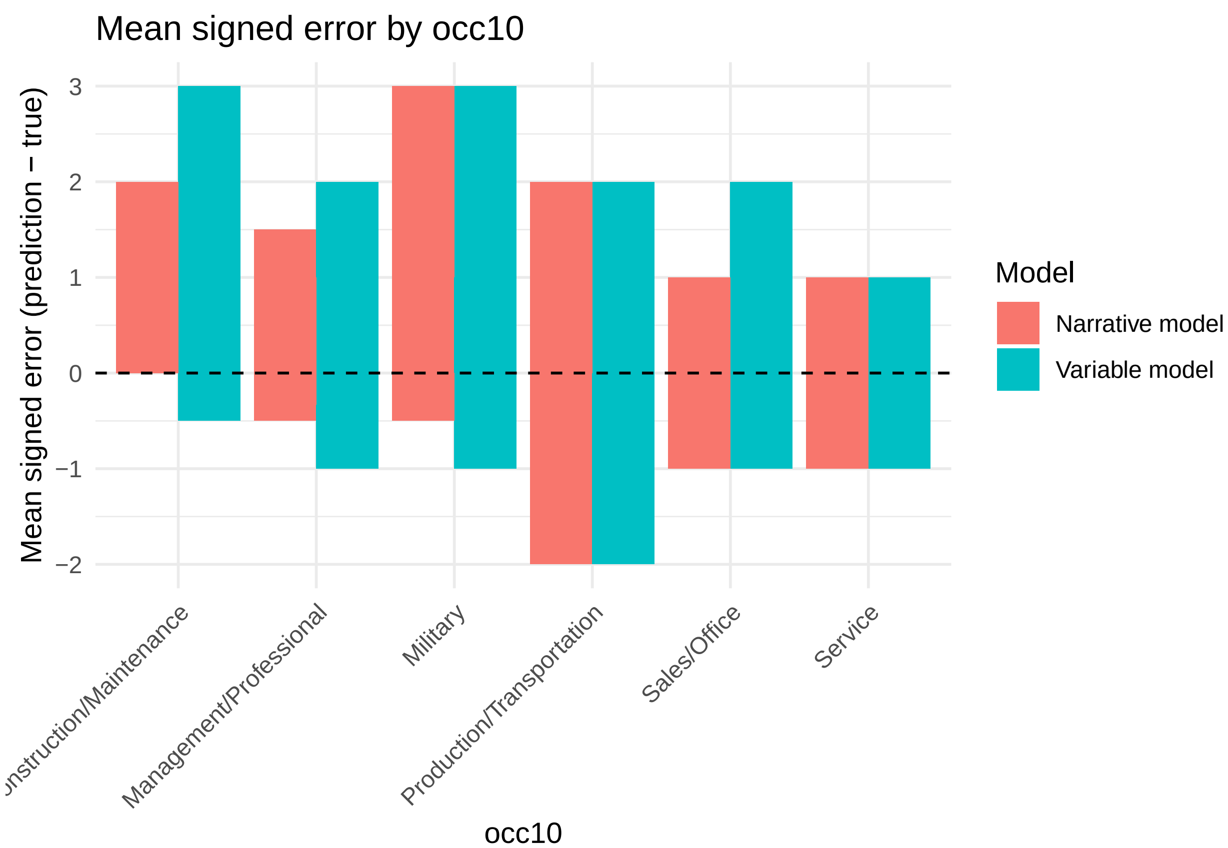


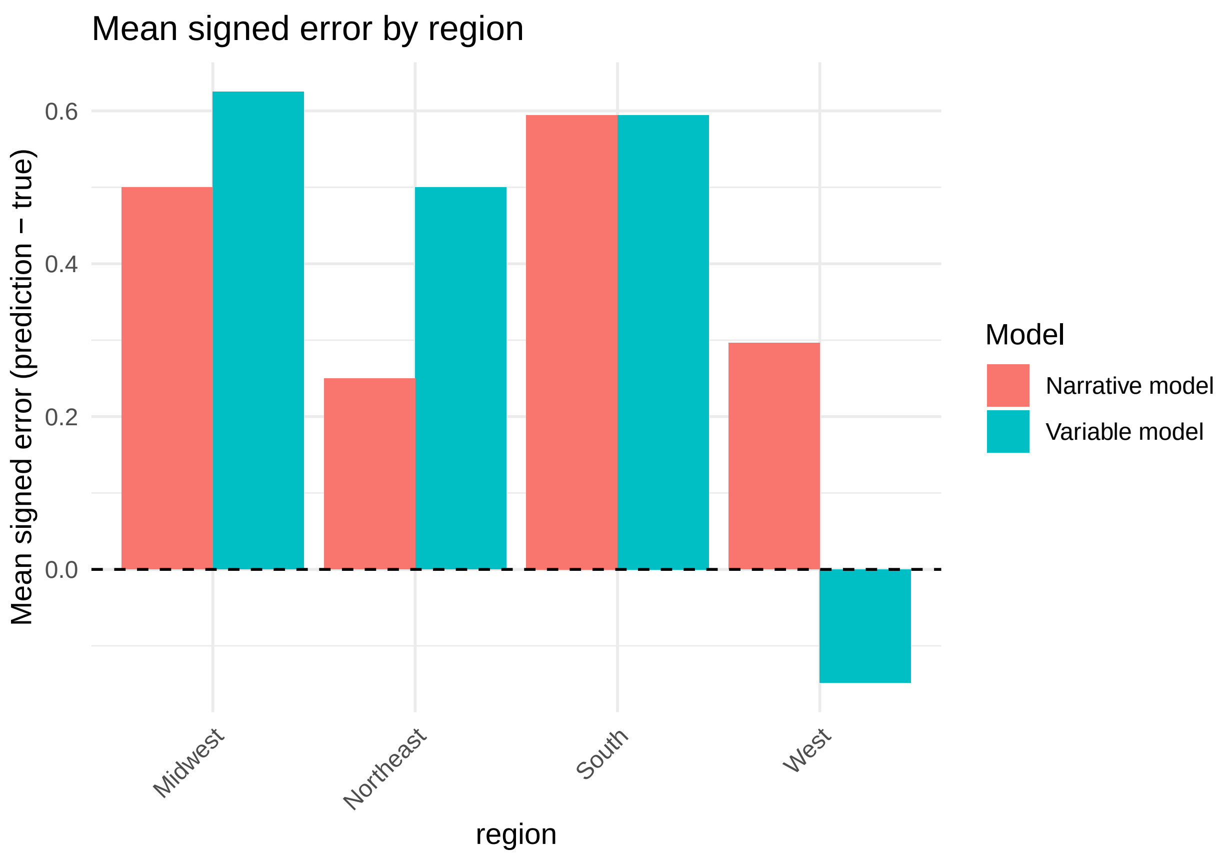

Mean signed error by sex
Mean signed error (prediction − true)
0.4
0.3
0.2
0.1
0.0
Female
Male
sex
Model
Narrative model
Variable model


Mean signed error by race
Mean signed error (prediction − true)
0.5
0.0
Black
Other
White
race
Model
Narrative model
Variable model


Mean signed error by educ
Mean signed error (prediction − true)
2
1
0
−1
−2
0
6
9
10
11
12
13
14
15
16
17
18
19
20
educ
Model
Narrative model
Variable model


Mean signed error by marital
Mean signed error (prediction − true)
1.00
0.75
0.50
0.25
0.00
Divorced
Married
Never married
Widowed
marital
Model
Narrative model
Variable model


Mean signed error by occ10
Mean signed error (prediction − true)
3
2
1
0
−1
−2
Model
Narrative model
Variable model
onstruction/Maintenance
Management/Professional
Military
Production/Transportation
Sales/Office
Service
occ10



6. Summary Comparison

```
# Create summary table across all classification schemes
summary_results <- tibble(
  Classification = c("7-Point", "Binary", "3-Category", "4-Category", "5-Category"),
  Var_MAE = c(
    mean(abs(df_7$error_var)),
    mean(abs(df_bin$error_var)),
    mean(abs(df_3$error_var)),
    mean(abs(df_4$error_var)),
    mean(abs(df_5$error_var))
  ),
  Narr_MAE = c(
    mean(abs(df_7$error_narr)),
    mean(abs(df_bin$error_narr)),
    mean(abs(df_3$error_narr)),
    mean(abs(df_4$error_narr)),
    mean(abs(df_5$error_narr))
  ),
  Var_Accuracy = c(
    mean(df_7$pred_var_num == df_7$polviews_num) * 100,
    mean(df_bin$pred_var_num == df_bin$polviews_num) * 100,
    mean(df_3$pred_var_num == df_3$polviews_num) * 100,
```

```r
    mean(df_4$pred_var_num == df_4$polviews_num) * 100,
    mean(df_5$pred_var_num == df_5$polviews_num) * 100
  ),
  Narr_Accuracy = c(
    mean(df_7$pred_narr_num == df_7$polviews_num) * 100,
    mean(df_bin$pred_narr_num == df_bin$polviews_num) * 100,
    mean(df_3$pred_narr_num == df_3$polviews_num) * 100,
    mean(df_4$pred_narr_num == df_4$polviews_num) * 100,
    mean(df_5$pred_narr_num == df_5$polviews_num) * 100
  )
)

cat("\nSummary Across All Classification Schemes:\n")
```

```
##
## Summary Across All Classification Schemes:
```

```r
print(summary_results, digits = 3)
```

```
## # A tibble: 5 x 5
##   Classification Var_MAE Narr_MAE Var_Accuracy Narr_Accuracy
##   <chr>            <dbl>    <dbl>        <dbl>         <dbl>
## 1 7-Point           1.4      1.32           15            18
## 2 Binary            0.53     0.61           47            39
## 3 3-Category        0.75     0.58           39            46
## 4 4-Category        0.95     0.83           35            44
## 5 5-Category        0.89     0.81           35            38
```