## Bias correction in GLMs

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### Introduction

We intend to investigate our prediction based on known truth and any bias potentially introduced by non-linear averaging, conditioning or random effect. We'll start with a simple case of a only fixed effect model and then consider a mixed effect model.

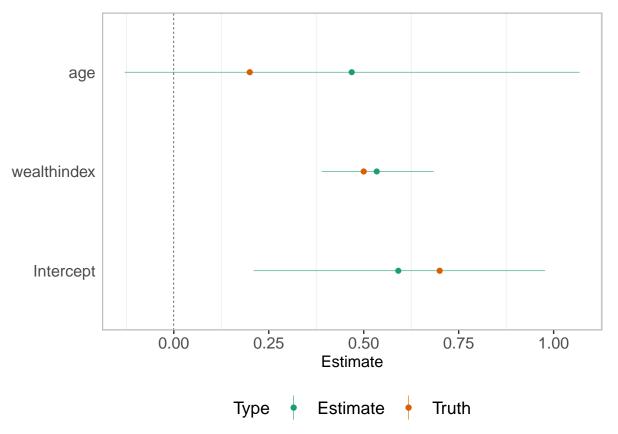
#### Simulation

We perform a simple simulation for a fixed effect model

```
\begin{split} \text{logit}(\text{status} = 1) &= \eta \\ \eta &= \beta_0 + \beta_A \text{Age} + \beta_W \text{Wealthindex} \\ \text{Age} &\sim \text{Uniform}(0.2, 1) \\ \text{Wealthindex} &\sim \text{Normal}(0, 1) \\ \beta_0 &= 0.7 \\ \beta_A &= 0.3 \\ \beta_W &= 0.6 \end{split}
```

## [1] 0.694

```
head(sim_df)
          age wealthindex status
## 1 0.8452918    1.5829806
## 2 0.2563395 -0.7920202
## 3 0.4192913 0.8592506
                               1
## 4 0.7882493    1.1605790
                               1
## 5 0.3893671 1.1220068
                               1
## 6 0.8806260 0.7425947
                               1
Simple logistic model
simple_mod <- glm(status ~ age + wealthindex, data = sim_df, family="binomial")</pre>
Coefficient plots
## True beta
true beta df <- data.frame(term=c("Intercept", "age", "wealthindex")
    , estimate=c(beta0, betaA, betaW)
## Tidy coef estimates
coef_df <- (broom::tidy(simple_mod, conf.int=TRUE)</pre>
# %>% dotwhisker::by_2sd(sim_df)
   %>% mutate(term = gsub("\\(|\\)", "", term))
print(coef_df)
## # A tibble: 3 x 7
## term
                estimate std.error statistic p.value conf.low conf.high
##
                   <dbl> <dbl> <dbl> <dbl>
    <chr>
                                                         <dbl>
                                                                   <dbl>
                   0.591
## 1 Intercept
                            0.196
                                       3.02 2.53e- 3
                                                         0.210
                                                                   0.978
                                                                   1.07
## 2 age
                   0.468
                            0.305
                                        1.53 1.25e- 1 -0.129
## 3 wealthindex
                            0.0752
                                       7.10 1.24e-12 0.389
                                                                   0.684
                   0.534
simple_coef_plot <- (plotEsize(coef_df)</pre>
   + geom_point(data=true_beta_df, aes(x=term, y=estimate, colour="Truth"))
   + labs(colour="Type")
   + scale_colour_brewer(palette="Dark2")
print(simple_coef_plot)
```



Variable effect plots – with and without bias adjustment

```
# Age
## Not bias adjusted
simple_vareff_age <- varpred(simple_mod, "age", isolate=TRUE, modelname="Not adjusted")</pre>
print(sigma(simple_mod))
## [1] 1.084869
## Bias adjusted
simple_vareff_age_adjust <- varpred(simple_mod, "age", isolate=TRUE, bias.adjust=TRUE, modelname="Bias
vareff_age <- simple_vareff_age</pre>
vareff_age$preds <- do.call("rbind", list(vareff_age$preds, simple_vareff_age_adjust$preds))</pre>
age_plot <- (plot(vareff_age)</pre>
           + labs(y="Prob. of improved \n service", colour="Model")
           + geom_hline(yintercept=true_prop, lty=2, colour="grey")
           + theme(legend.position="bottom")
)
# Wealth index
## Not bias adjusted
simple_vareff_wealthindex <- varpred(simple_mod, "wealthindex", isolate=TRUE, modelname="Not adjusted")
## Bias adjusted
simple_vareff_wealthindex_adjust <- varpred(simple_mod, "wealthindex", isolate=TRUE, bias.adjust=TRUE, simple_vareff_wealthindex_adjust=TRUE, simple_wareff_wealthindex_adjust=TRUE, simple_mod, "wealthindex", isolate=TRUE, bias.adjust=TRUE, simple_wareff_wealthindex_adjust=TRUE, simple_wareff_wareff_wealthindex_adjust=TRUE, simple_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_wareff_war
vareff_wealthindex <- simple_vareff_wealthindex</pre>
vareff_wealthindex$preds <- do.call("rbind", list(vareff_wealthindex$preds, simple_vareff_wealthindex_a
```

# Model — Bias adjusted — Not adjusted 0.75 0.75 Prob. of improved service 0.70 0.50 0.65 0.25 0.60 0.4 0.8 1.0 Ó 2 0.2 0.6 -2 wealthindex age

Figure 1: Variable prediction plots comparing bias unadjusted and adjusted predictions. The bias adjusted predictions are slighly lower but close to what we expect from effect size estimates (and their confidence intervals)?

Effect sizes on logit scale:

```
coef_df_logit <- (coef_df</pre>
    %>% select(term, estimate, conf.low, conf.high)
    %>% group_by(term)
    %>% summarise_all(plogis)
print(coef_df_logit)
## # A tibble: 3 x 4
##
                  estimate conf.low conf.high
     term
                              <dbl>
                                         <dbl>
##
     <chr>>
                     <dbl>
                     0.615
                              0.468
                                         0.744
## 1 age
## 2 Intercept
                     0.644
                              0.552
                                         0.727
## 3 wealthindex
                     0.630
                              0.596
                                         0.665
```

#### MRP approach

```
pred <- predict(simple_mod, type="link", se.fit=TRUE)</pre>
z.val <-qnorm(1 - (1 - 0.95)/2)
pred_df <- (data.frame(age=sim_df$age, wealthindex=sim_df$wealthindex, estimate=pred$fit, se=pred$se.fi
  %>% mutate(lwr = plogis(estimate-z.val*se)
     , upr = plogis(estimate+z.val*se)
     , estimate = plogis(estimate)
  )
head(pred_df)
       age wealthindex estimate
## 2 0.2563395 -0.7920202 0.5715182 0.1319246 0.5073696 0.6333501
## Age plot
age_mrp <- (pred_df
  %>% select(age, estimate, lwr, upr)
  %>% group by (age)
  %>% summarise_all(mean)
age_mrp_plot <- (ggplot(age_mrp, aes(x=age, y=estimate))</pre>
  + geom_line()
  + geom_line(aes(y=lwr), lty=2)
  + geom_line(aes(y=upr), lty=2)
   + geom_smooth(aes(ymin=lwr, ymax=upr), stat="identity")
print(age_mrp_plot)
```

