LHR: Amsterdam Bias Analysis

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Load Libraries

```
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)
library(ggplot2)
library(openxlsx)
library(stringr)
library(friendlyeval)
```

Load Data

```
cms_raw <- read.xlsx('../input/Results_LHR/Output/20240308_CMs_LHR_SlimmeCheck.xlsx')
feature_counts_raw <- read.xlsx('../input/Results_LHR/Output/20240308_Important_Features_Counts.xlsx')
```

Preprocesing

```
### Confusion Matrices ###
summary(cms_raw)
```

```
##    Dataset             Model             Feature          Feature_Value
##  Length:480         Length:480         Length:480         Length:480
##  Class :character   Class :character   Class :character   Class :character
```

```
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##     Metric              Value
##  Length:480         Min.   :   0.0
##  Class :character   1st Qu.:  32.0
##  Mode  :character   Median :  83.0
##                     Mean   : 159.9
##                     3rd Qu.: 202.2
##                     Max.   :1024.0
```

```
print(unique(cms_raw$Dataset))
```

```
## [1] "Pilot"         "Prepilot"      "TrainingTrain" "TrainingTest"
```

```
print(unique(cms_raw$Model))
```

```
## [1] "BR" "AR"
```

```
print(unique(cms_raw$Feature))
```

```
## [1] "geslacht"         "Leeftijd&lt;30"   "Leeftijd&lt;40"   "Leeftijd&lt;50"
## [5] "IsNederlands"     "IsWesters"        "IsFulltimeParent" "IsParttimeParent"
```

```
cms_raw <- cms_raw %>%
  #0s indicate small sample sizes but are unlikely to be correct
  mutate(Value = ifelse(Value == 0, NA, Value))

#combine train and test since the original split is not actually recreated
#TODO: current approach results in NAs if either Train or Test is NA/0,
#I could just go with using data from the split that is sufficiently large in those cases
cms_train <- cms_raw %>%
  filter(Dataset == 'TrainingTrain') %>%
  rename(Value_Train = Value) %>%
  select(-Dataset)

cms_test <- cms_raw %>%
  filter(Dataset == 'TrainingTest') %>%
  rename(Value_Test = Value) %>%
  select(-Dataset)

cms_train_test <- cms_train %>%
  left_join(cms_test, by = c('Model', 'Feature', 'Feature_Value', 'Metric')) %>%
  mutate(Value = Value_Train + Value_Test,
         Dataset = 'TrainTest') %>%
  select(-Value_Train, -Value_Test)

cms_wide <- cms_raw %>%
  filter(!(Dataset %in% c('TrainingTrain', 'TrainingTest'))) %>%
  bind_rows(cms_train_test) %>%
```

```
  group_by(Feature, Feature_Value, Dataset, Model) %>%
  mutate(Share = (Value/sum(Value)) * 100,
         group_size = sum(Value)) %>%
  ungroup() %>%
  dplyr::select(-Value) %>%
  pivot_wider(names_from = Metric, values_from = Share) %>%
  mutate(TOTAL = TN+FP+TP+FN,
         ACT_N = FP + TN,
         ACT_P = FN + TP,
         PRED_P = FP + TP,
         PRED_N = FN + TN,
         FPR = (FP/ACT_N) * 100,
         PPV = (TP/PRED_P) * 100,
         FDR = (FP/PRED_P) * 100,
         TPR = (TP/ACT_P) * 100,
         STAT_PAR = PRED_P,
         ERROR = FP+FN) %>%
  mutate(Feature_EN = case_when(Feature == 'geslacht' ~ 'gender',
                                Feature == 'Leeftijd&lt;30' ~ 'Age < 30',
                                Feature == 'Leeftijd&lt;40' ~ 'Age < 40',
                                Feature == 'Leeftijd&lt;50' ~ 'Age < 50',
                                Feature == 'IsNederlands' ~ 'Dutch',
                                Feature == 'IsWesters' ~ 'Western',
                                .default = Feature),
         Feature_Value_EN = case_when(Feature_Value == 'V' ~ 'F',
                                      Feature == 'Leeftijd&lt;30' & Feature_Value == 1 ~ 'below 30',
                                      Feature == 'Leeftijd&lt;30' & Feature_Value == 0 ~ 'above 30',
                                      Feature == 'Leeftijd&lt;40' & Feature_Value == 1 ~ 'below 40',
                                      Feature == 'Leeftijd&lt;40' & Feature_Value == 0 ~ 'above 40',
                                      Feature == 'Leeftijd&lt;50' & Feature_Value == 1 ~ 'below 50',
                                      Feature == 'Leeftijd&lt;50' & Feature_Value == 0 ~ 'above 50',
                                      Feature == 'IsNederlands' & Feature_Value == 1 ~ 'Dutch',
                                      Feature == 'IsNederlands' & Feature_Value == 0 ~ 'Not Dutch',
                                      Feature == 'IsWesters' & Feature_Value == 1 ~ 'Western',
                                      Feature == 'IsWesters' & Feature_Value == 0 ~ 'Not Western',
                                      Feature == 'IsFulltimeParent' & Feature_Value == 1 ~ 'Full-time pa
                                      Feature == 'IsFulltimeParent' & Feature_Value == 0 ~ 'Not full-ti
                                      Feature == 'IsParttimeParent' & Feature_Value == 1 ~ 'Part-time pa
                                      Feature == 'IsParttimeParent' & Feature_Value == 0 ~ 'Not part-ti
                                      .default = Feature_Value),
         stage = paste0(Dataset, '/', Model),
         Model_EN = case_when(Model == 'BR' ~ 'Before Reweighing',
                              Model == 'AR' ~ 'After Reweighing'))

write.csv(cms_wide, '../output/cms_wide.csv')

cms_long <- cms_wide %>%
  pivot_longer(cols = c("TN", "FP", "FN", "TP", "TOTAL", "ACT_N", "ACT_P", "PRED_P", "PRED_N", "FPR", "
               names_to = 'Metric', values_to = 'Value')

write.csv(cms_long, '../output/cms_long.csv')
```

```
### Feature Importance ###
feature_counts <- feature_counts_raw %>%
  mutate(Count = ifelse(Count == 0, NA, Count),
         Feature_EN = case_when(Feature == 'geslacht' ~ 'gender',
                                Feature == 'Leeftijd&lt;30' ~ 'Age < 30',
                                Feature == 'Leeftijd&lt;40' ~ 'Age < 40',
                                Feature == 'Leeftijd&lt;50' ~ 'Age < 50',
                                Feature == 'IsNederlands' ~ 'Dutch',
                                Feature == 'IsWesters' ~ 'Western',
                                .default = Feature),
         Feature_Value_EN = case_when(Feature == 'geslacht' & Value == 1 ~ 'F', #not sure about gender
                                      Feature == 'geslacht' & Value == 0 ~ 'M',
                                      Feature == 'Leeftijd&lt;30' & Value == 1 ~ 'below 30',
                                      Feature == 'Leeftijd&lt;30' & Value == 0 ~ 'above 30',
                                      Feature == 'Leeftijd&lt;40' & Value == 1 ~ 'below 40',
                                      Feature == 'Leeftijd&lt;40' & Value == 0 ~ 'above 40',
                                      Feature == 'Leeftijd&lt;50' & Value == 1 ~ 'below 50',
                                      Feature == 'Leeftijd&lt;50' & Value == 0 ~ 'above 50',
                                      Feature == 'IsNederlands' & Value == 1 ~ 'Dutch',
                                      Feature == 'IsNederlands' & Value == 0 ~ 'Not Dutch',
                                      Feature == 'IsWesters' & Value == 1 ~ 'Western',
                                      Feature == 'IsWesters' & Value == 0 ~ 'Not Western',
                                      Feature == 'IsFulltimeParent' & Value == 1 ~ 'Full-time parent',
                                      Feature == 'IsFulltimeParent' & Value == 0 ~ 'Not full-time paren
                                      Feature == 'IsParttimeParent' & Value == 1 ~ 'Part-time parent',
                                      Feature == 'IsParttimeParent' & Value == 0 ~ 'Not part-time paren
                                      .default = as.character(Value))) %>%
  group_by(Feature_EN, Feature_Value_EN, dataset) %>%
  mutate(share = (Count/sum(Count, na.rm = T)) * 100) %>% #note that I remove NAs which are presumably
  ungroup()
```

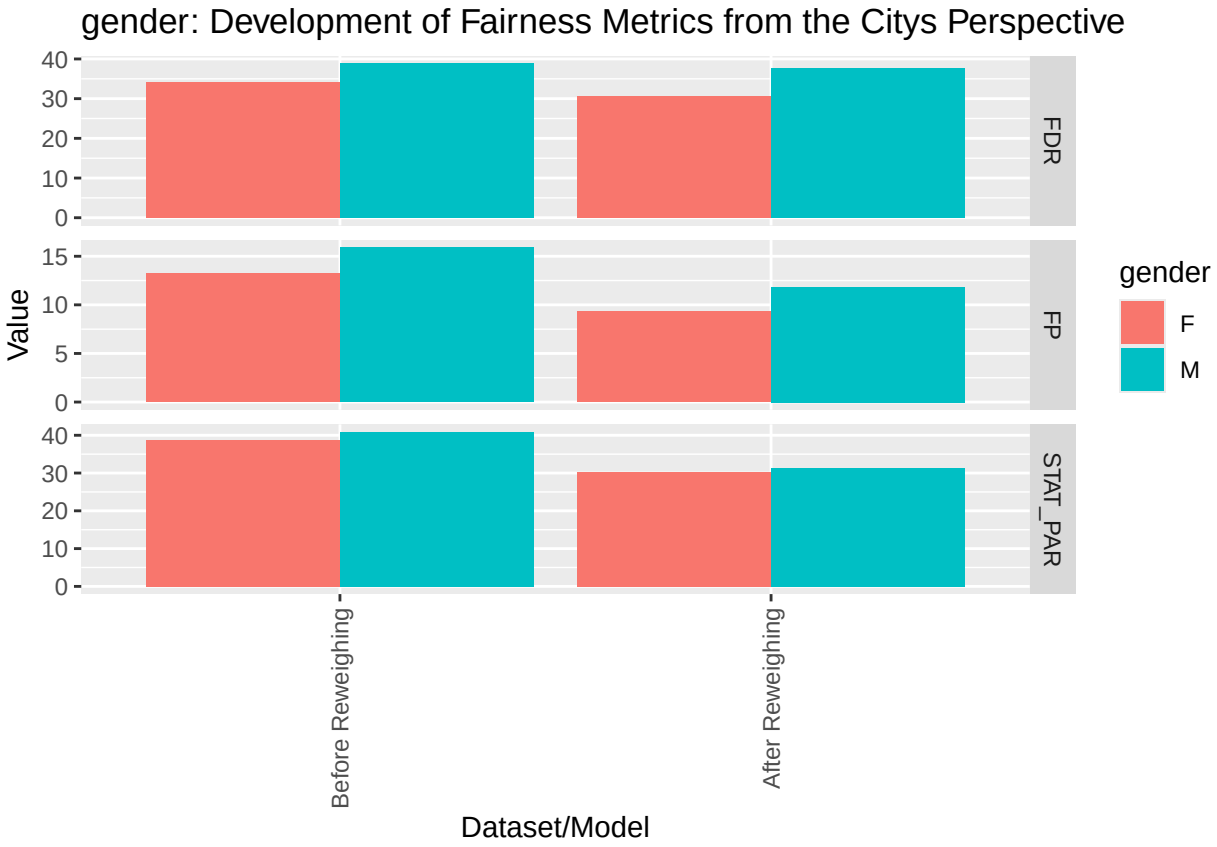
RQ 1 Results from the perspective of the city

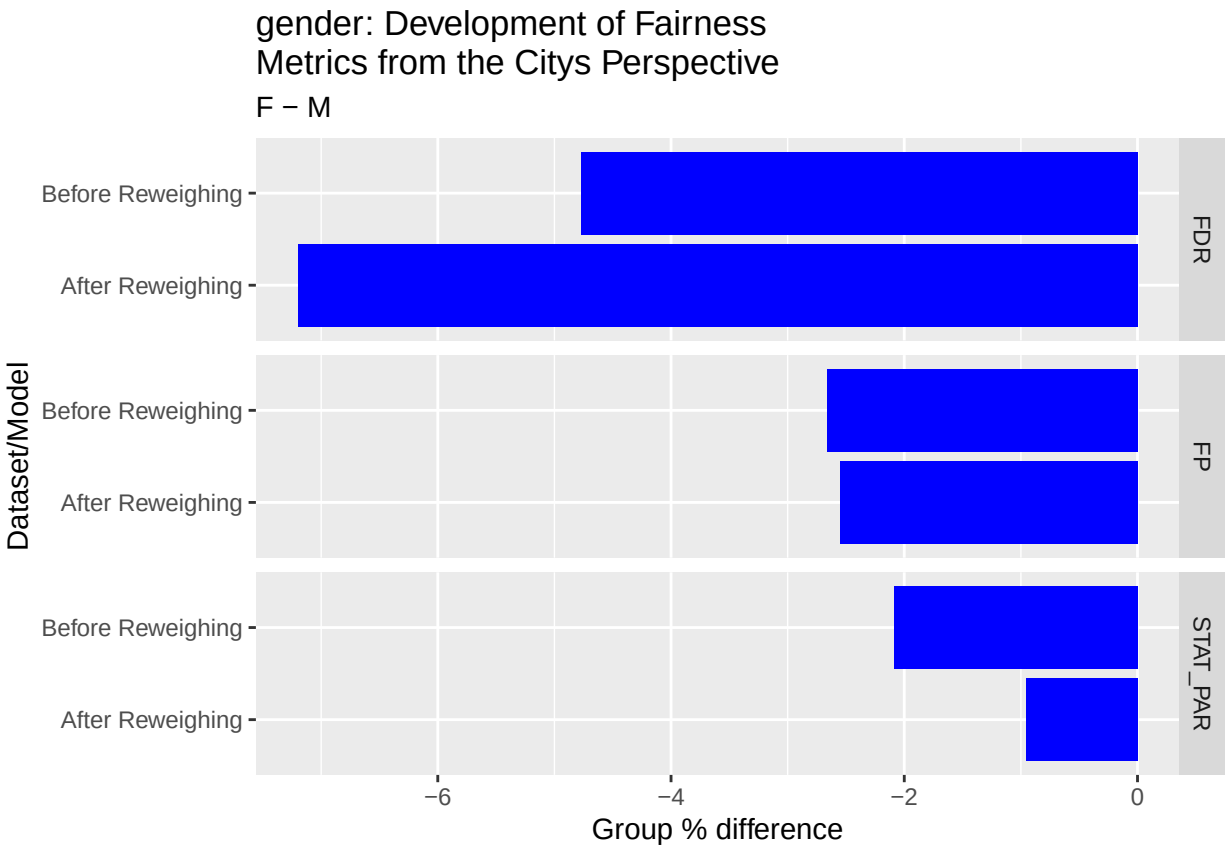
This set of graph is meant to illustrate how the city saw the development of its model: 1. First it evaluated its model before reweighing (BR) on the test data (TrainTest) 2. Then, it built the prepilot dataset and realized substantial bias when evaluating it against BR 3. Next, it reweighed the model, seeing improvements on the prepilot set. 4. Finally, it evaluated the model against the Pilot data.

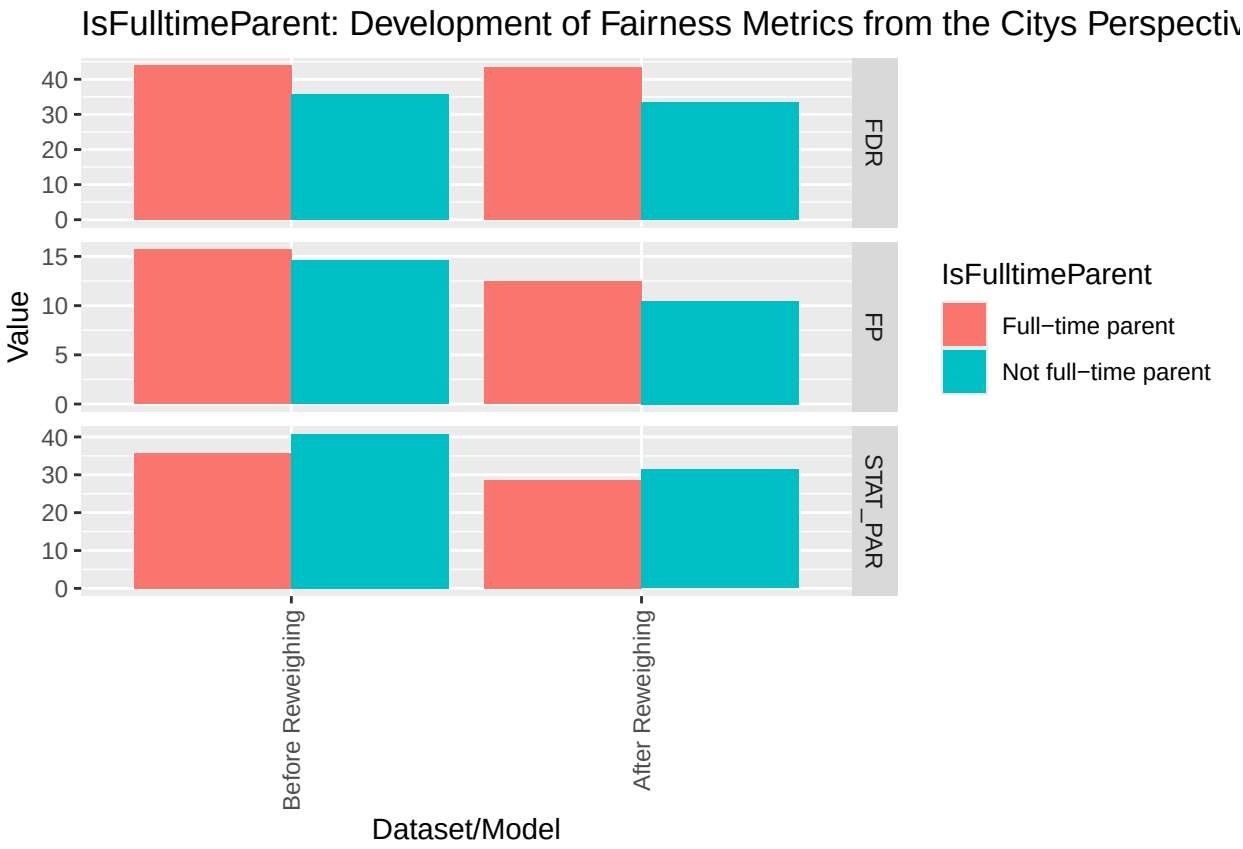
The city itself focused pretty exclusively on the share of FPs (FP widget in the graphs) (TODO: check that this is correct), but to show the tradeoffs involved in the process, I report several additional fairness metrics * FP: false positive share: FP/TOTAL -> intuition share of people who are wrongly flagged; goal is to get it as low as possible * FPR: false positive rate: FP/(FP+TN) -> intuition: share of people who haven't done anything wrong that are flagged; goal is to get it as low as possible * One_minus_PPV: positive predictive rate: TP/(TP+FP) -> intuition: share of people flagged who have done something wrong; goal is to get it as high as possible * PRED_P: predictive parity: TP+FP/TOTAL -> intuition: share of people flagged; goal is to get it as close as possible to the actual share of people who have done something wrong which is often an unknown quantity

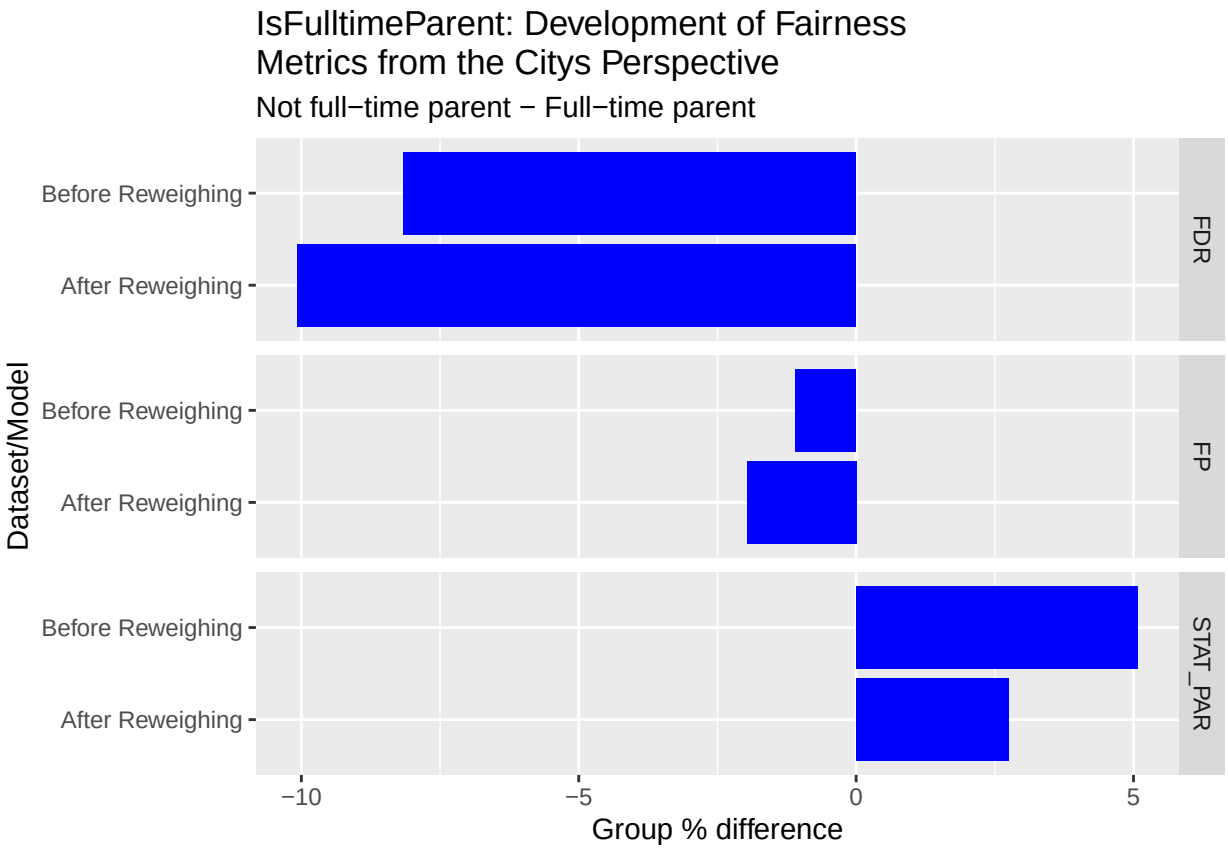
```
cms_city_perspective <- cms_long %>%
  filter(stage %in% c('Prepilot/BR', 'Prepilot/AR'),
         Metric %in% c('STAT_PAR', 'FDR', 'FP'),
         Feature_EN %in% c('gender', 'Age < 30', 'Age < 50', 'Dutch', 'IsFulltimeParent')) %>%
  mutate(order = case_when(stage == 'Prepilot/BR' ~ 1,
```

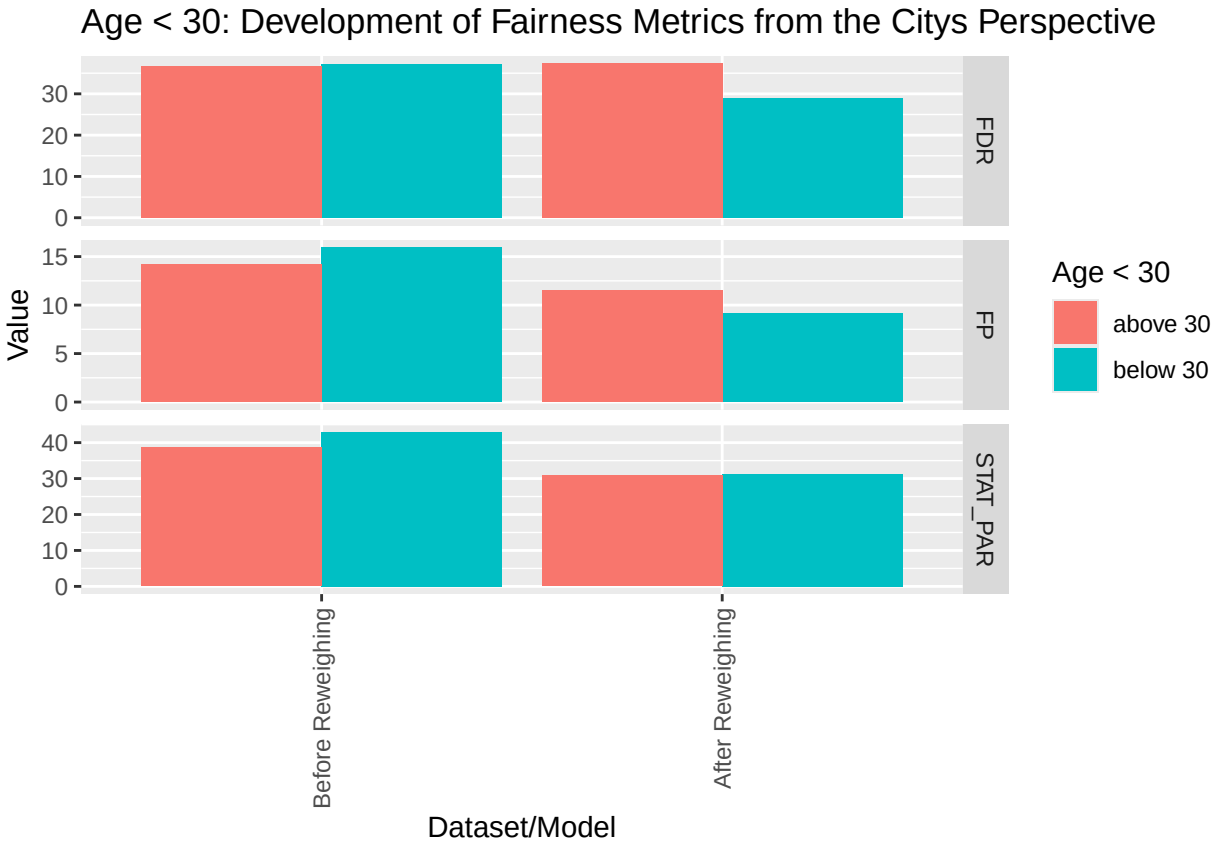
```
                            stage == 'Prepilot/AR' ~ 2,
                            .default = NA))


for(characteristic in unique(cms_city_perspective$Feature_EN)){
  cms_char <- cms_city_perspective %>%
    filter(Feature_EN == characteristic)

  p1 <- ggplot(cms_char, aes(x = reorder(Model_EN, order), y = Value, fill = Feature_Value_EN))+
    geom_bar(stat = 'identity', position = position_dodge())+
    facet_grid(Metric ~., scales = "free_y")+
    labs(x = 'Dataset/Model',
         title = paste0(characteristic, ': Development of Fairness Metrics from the Citys Perspective')
         fill = characteristic)+
    theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))

  print(p1)
  ggsave(paste0('../output/rq1_p1_', characteristic, '.png'), plot = p1, width = 10, height = 8)

  feature_vals <- unique(cms_char$Feature_Value_EN)

  cms_char_diff <- cms_char %>%
    dplyr::select(-Feature_Value, -group_size) %>%
    pivot_wider(names_from = 'Feature_Value_EN', values_from = 'Value') %>%
    #using Amsterdam's difference op here, though not sure the ref cat is always the same
    mutate(Diff = .data[[feature_vals[2]]] -  .data[[feature_vals[1]]])

  #TODO: add difference as operationalized by the city reports
  p2 <- ggplot(cms_char_diff, aes(x = reorder(Model_EN, -order), y = Diff))+
    geom_bar(stat = 'identity', position = position_dodge(), fill = 'blue') +
    facet_grid(Metric ~., scales = "free_y")+
    labs(x = 'Dataset/Model',
         y = 'Group % difference',
         title = paste0(characteristic, ': Development of Fairness \nMetrics from the Citys Perspective
         subtitle = paste0(feature_vals[2], ' - ', feature_vals[1]))+
    coord_flip()

  print(p2)
  ggsave(paste0('../output/rq1_p2_', characteristic, '.png'), plot = p2, width = 10, height = 8)
}
```

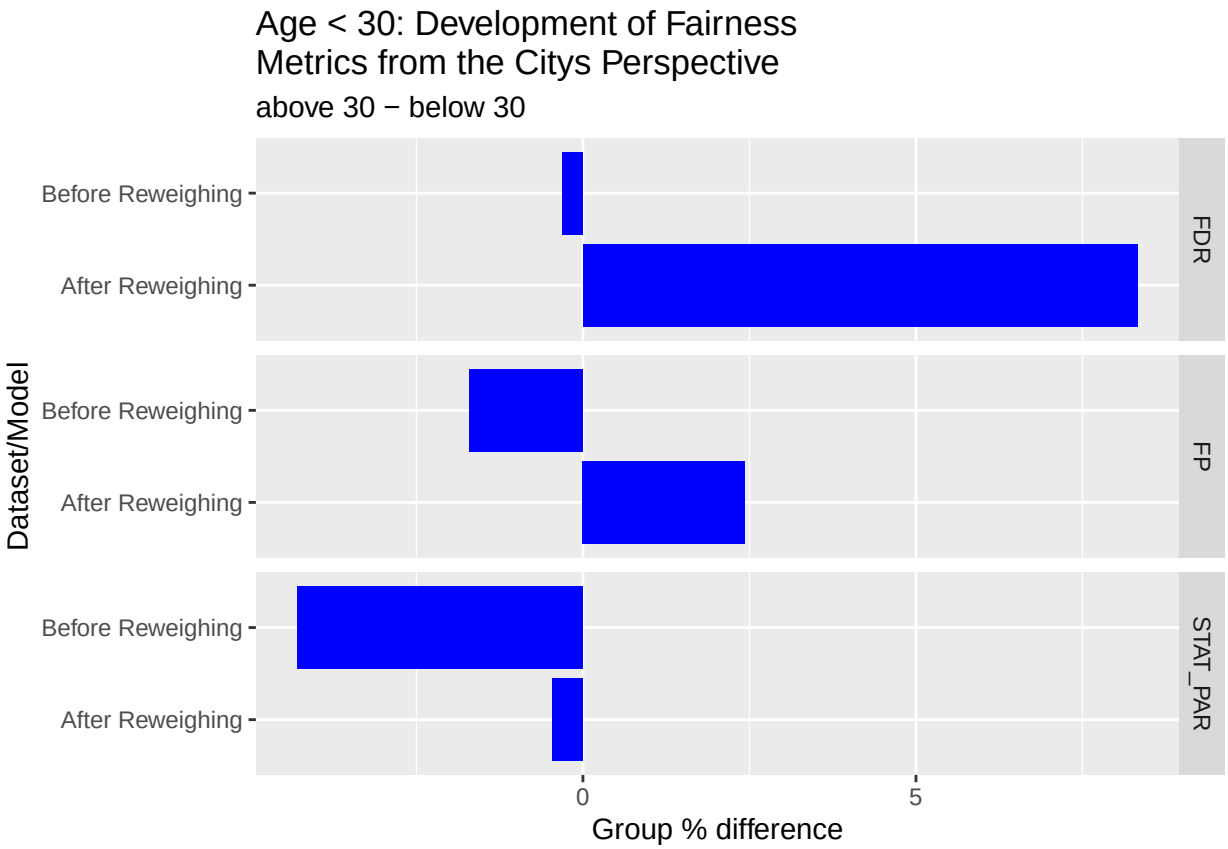

gender: Development of Fairness Metrics from the Citys Perspective
Value
FDR
FP
STAT_PAR
40
30
20
10
0
15
10
5
0
Before Reweighing
After Reweighing
Dataset/Model
gender
F
M

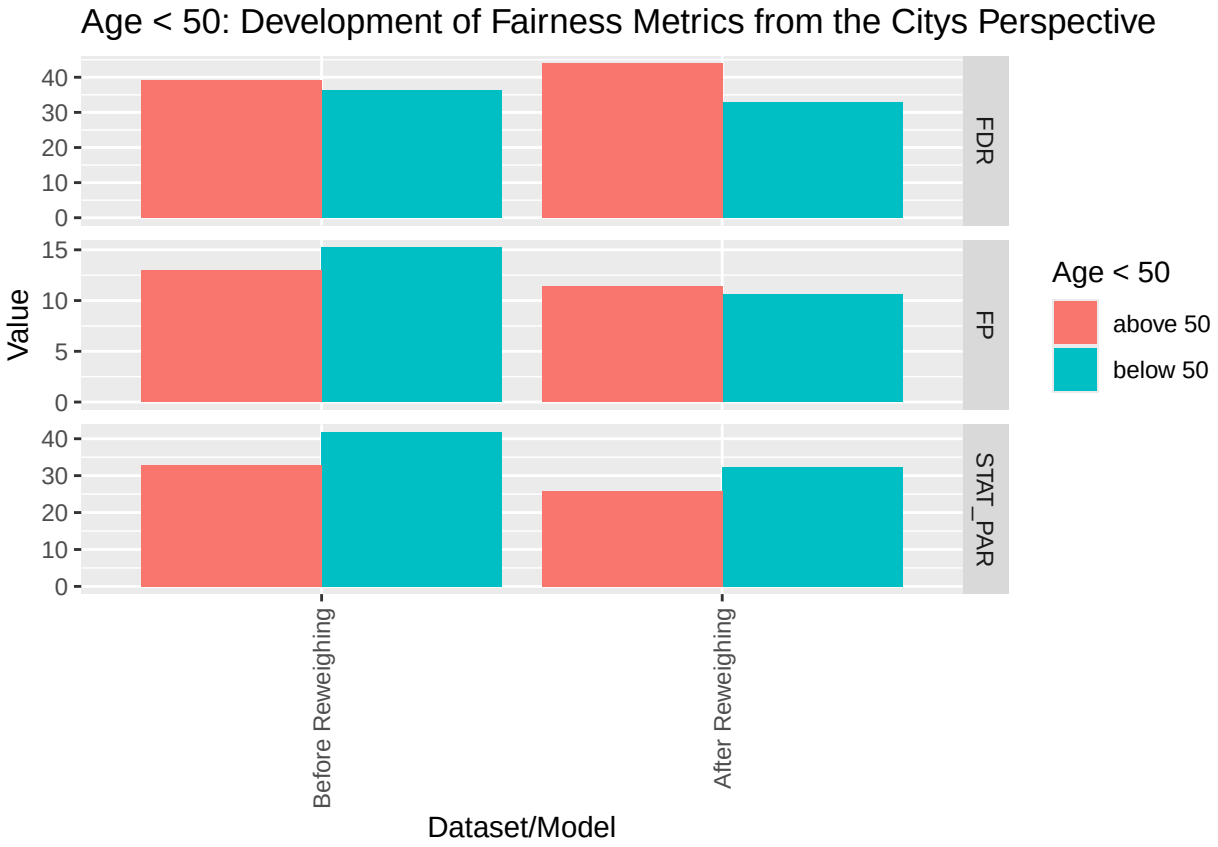

gender: Development of Fairness Metrics from the Citys Perspective
F − M
Dataset/Model
Before Reweighing
After Reweighing
Before Reweighing
After Reweighing
Before Reweighing
After Reweighing
FDR
FP
STAT_PAR
−6
−4
−2
0
Group % difference

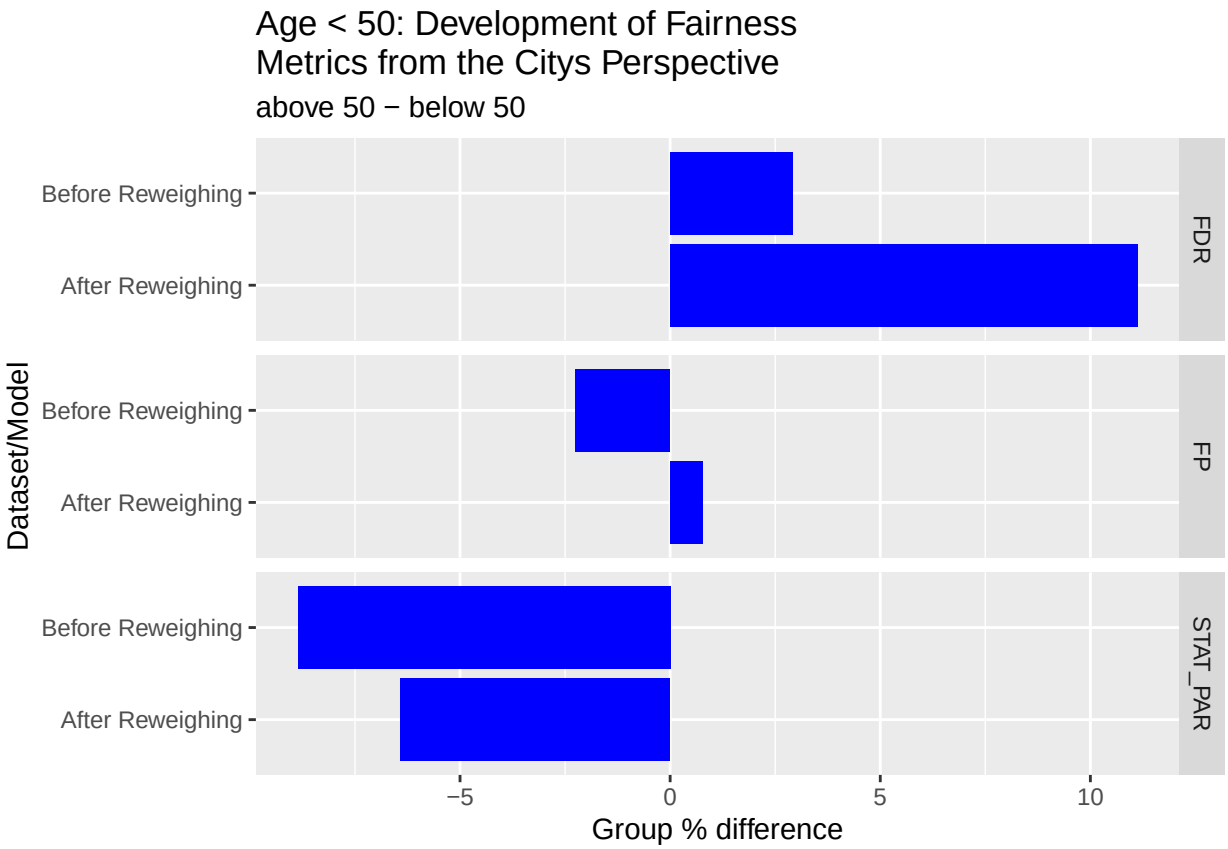

IsFulltimeParent: Development of Fairness Metrics from the Citys Perspectiv
Value
FDR
FP
STAT_PAR
40
30
20
10
0
15
10
5
0
Before Reweighing
After Reweighing
Dataset/Model
IsFulltimeParent
Full−time parent
Not full−time parent

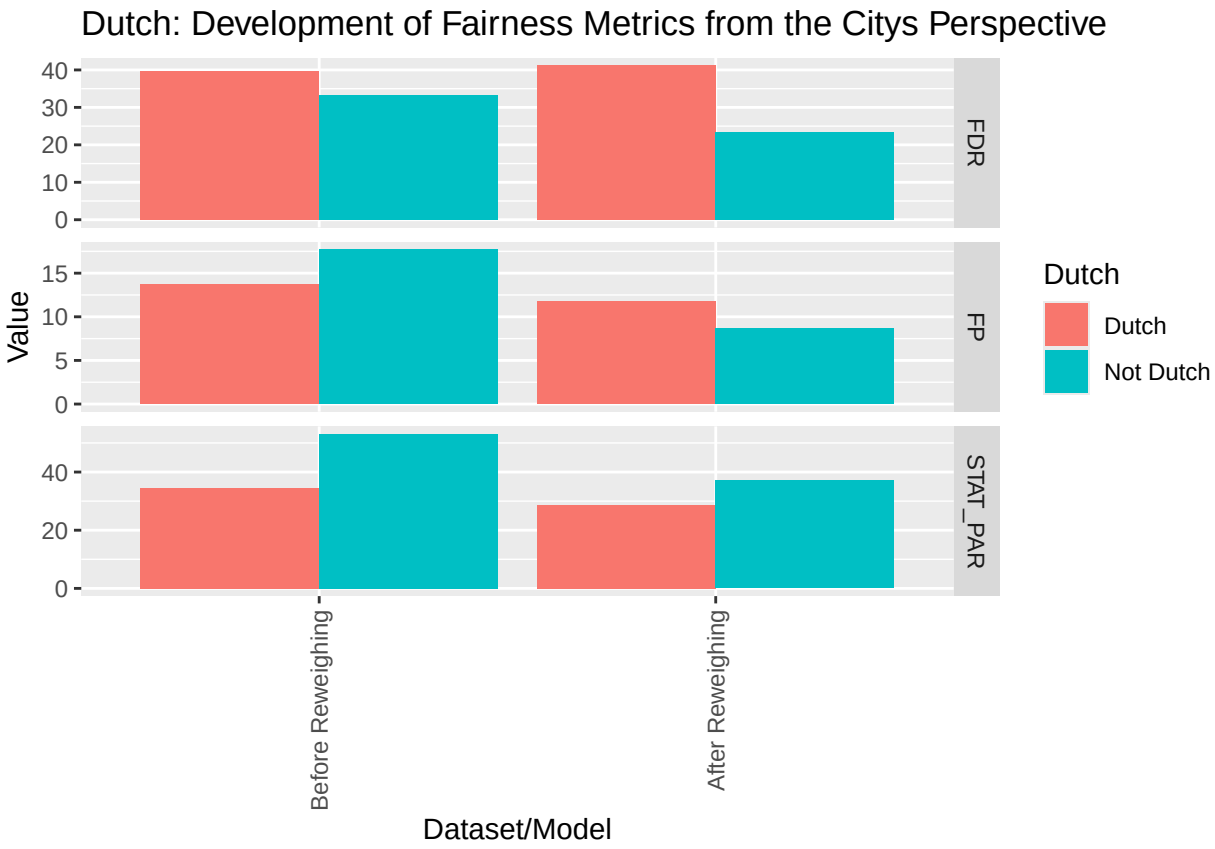

IsFulltimeParent: Development of Fairness Metrics from the Citys Perspective
Not full−time parent − Full−time parent
Dataset/Model
Before Reweighing
After Reweighing
Before Reweighing
After Reweighing
Before Reweighing
After Reweighing
FDR
FP
STAT_PAR
−10
−5
0
5
Group % difference

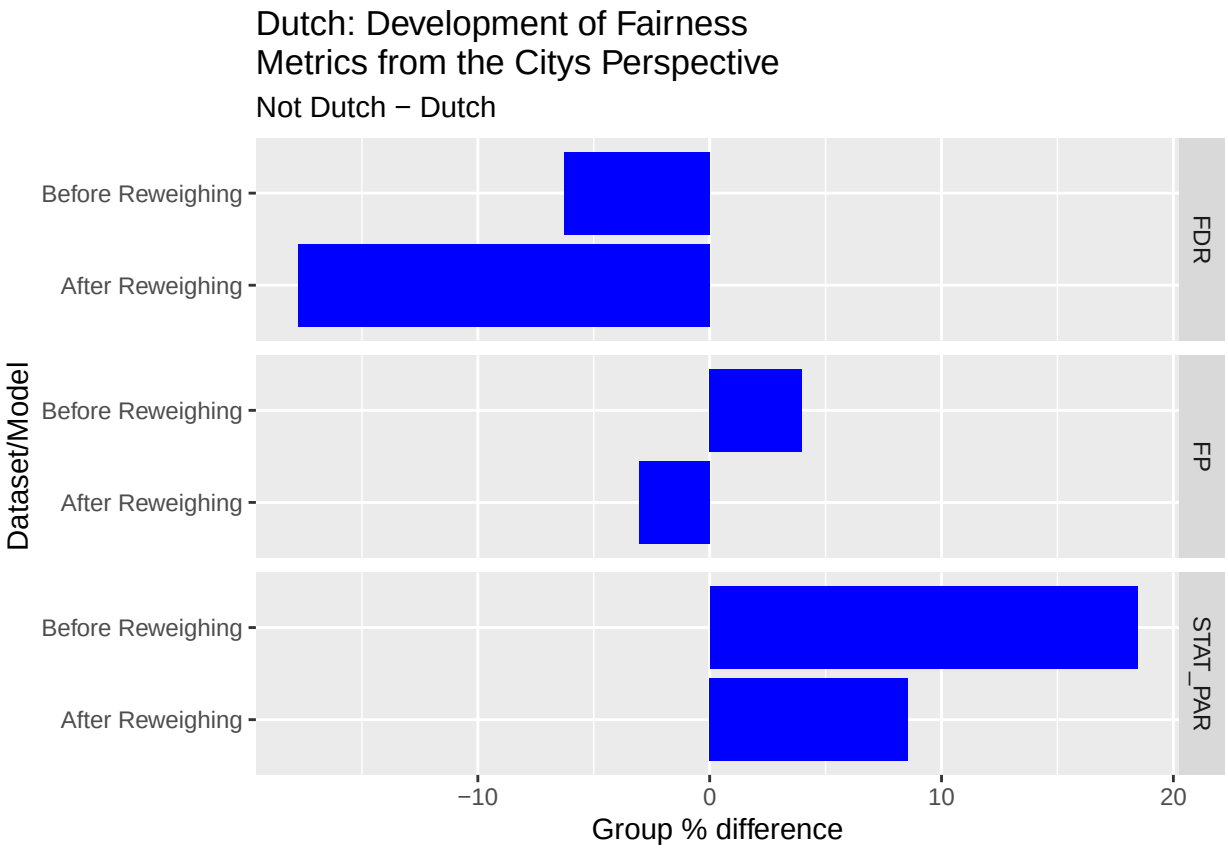

Age < 30: Development of Fairness Metrics from the Citys Perspective
Value
FDR
FP
STAT_PAR
30
20
10
0
15
10
5
0
40
30
20
10
0
Before Reweighing
After Reweighing
Dataset/Model
Age < 30
above 30
below 30


Age < 30: Development of Fairness Metrics from the Citys Perspective
above 30 − below 30
Dataset/Model
Before Reweighing
After Reweighing
Before Reweighing
After Reweighing
Before Reweighing
After Reweighing
FDR
FP
STAT_PAR
0
5
Group % difference


Age < 50: Development of Fairness Metrics from the Citys Perspective
Value
FDR
FP
STAT_PAR
40
30
20
10
0
15
10
5
0
Before Reweighing
After Reweighing
Dataset/Model
Age < 50
above 50
below 50


Age < 50: Development of Fairness Metrics from the Citys Perspective
above 50 − below 50
Dataset/Model
Before Reweighing
After Reweighing
Before Reweighing
After Reweighing
Before Reweighing
After Reweighing
FDR
FP
STAT_PAR
−5
0
5
10
Group % difference


Dutch: Development of Fairness Metrics from the Citys Perspective
Value
FDR
FP
STAT_PAR
40
30
20
10
0
15
10
5
0
40
20
0
Before Reweighing
After Reweighing
Dataset/Model
Dutch
Dutch
Not Dutch



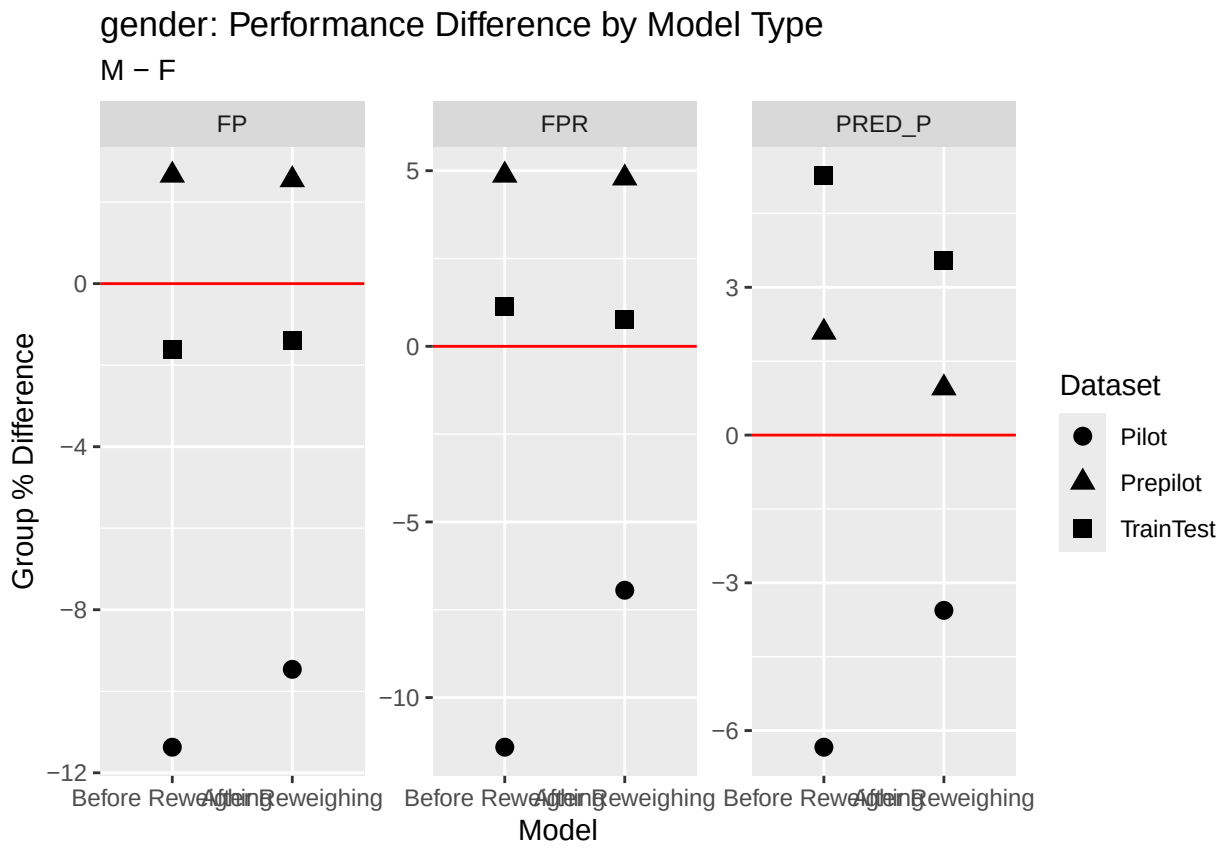
RQ2 Comparing before and after reweighing

Amsterdam realized that its model exhibited bias, according to its bias definition (FP), when it deployed it in a prepilot (which really was a virtual pilot). The city decided to reweigh the training data to decrease the impact of observations on the model that drove the bias. Let's have a look at how the two models faired when tested against a more complete set of fairness metrics and datasets.

```
cms_model_comp <- cms_long %>%
  filter(Metric %in% c('PRED_P', 'FP', 'One_minus_PPV', 'FPR'),
         Feature_EN %in% c('gender', 'Age < 30', 'Age < 50', 'Dutch', 'IsFulltimeParent')) %>%
  mutate(order = case_when(Model == 'BR' ~ 1,
                           Model == 'AR' ~ 2,
                           .default = NA),
         model_long = case_when(Model == 'BR' ~ 'Before reweighing',
                           Model == 'AR' ~ 'After reweighing',
                           .default = NA),)

for(characteristic in unique(cms_city_perspective$Feature_EN)){
  cms_char <- cms_model_comp %>%
    filter(Feature_EN == characteristic)

  feature_vals <- unique(cms_char$Feature_Value_EN)

  cms_char_diff <- cms_char %>%
    dplyr::select(-Feature_Value, -group_size) %>%
```

```
    pivot_wider(names_from = 'Feature_Value_EN', values_from = 'Value') %>%
    mutate(Diff = .data[[feature_vals[1]]] -  .data[[feature_vals[2]]])

  p3 <- ggplot(cms_char_diff, aes(x = reorder(Model_EN, order), y = Diff, shape = Dataset))+
    geom_point(size = 3)+
    facet_wrap(.~Metric, scales = 'free')+
    geom_hline(yintercept = 0, color = 'red', scales = 'free_y')+
    labs(x = 'Model', y = 'Group % Difference',
         title = paste0(characteristic, ': Performance Difference by Model Type'),
         subtitle = paste0(feature_vals[1], ' - ', feature_vals[2]))

  print(p3)

  ggsave(paste0('../output/rq2_p3_', characteristic, '.png'), plot = p3, width = 10, height = 8)
}
```

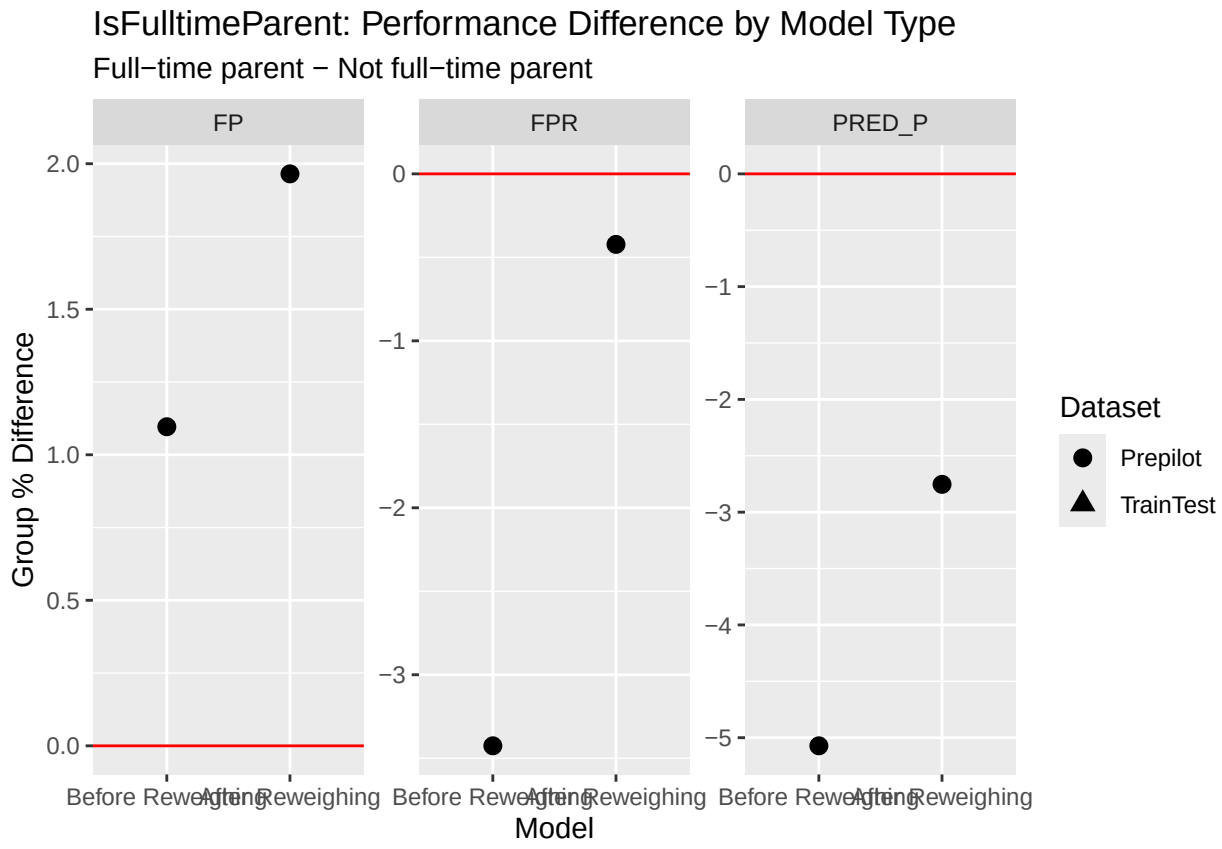
```
## Warning in geom_hline(yintercept = 0, color = "red", scales = "free_y"): Ignoring unknown parameters
## Ignoring unknown parameters: ‘scales‘
```




```
## Warning: Removed 6 rows containing missing values or values outside the scale range
## (‘geom_point()‘).
```

```
## Warning: Removed 6 rows containing missing values or values outside the scale range
## (‘geom_point()‘).
```

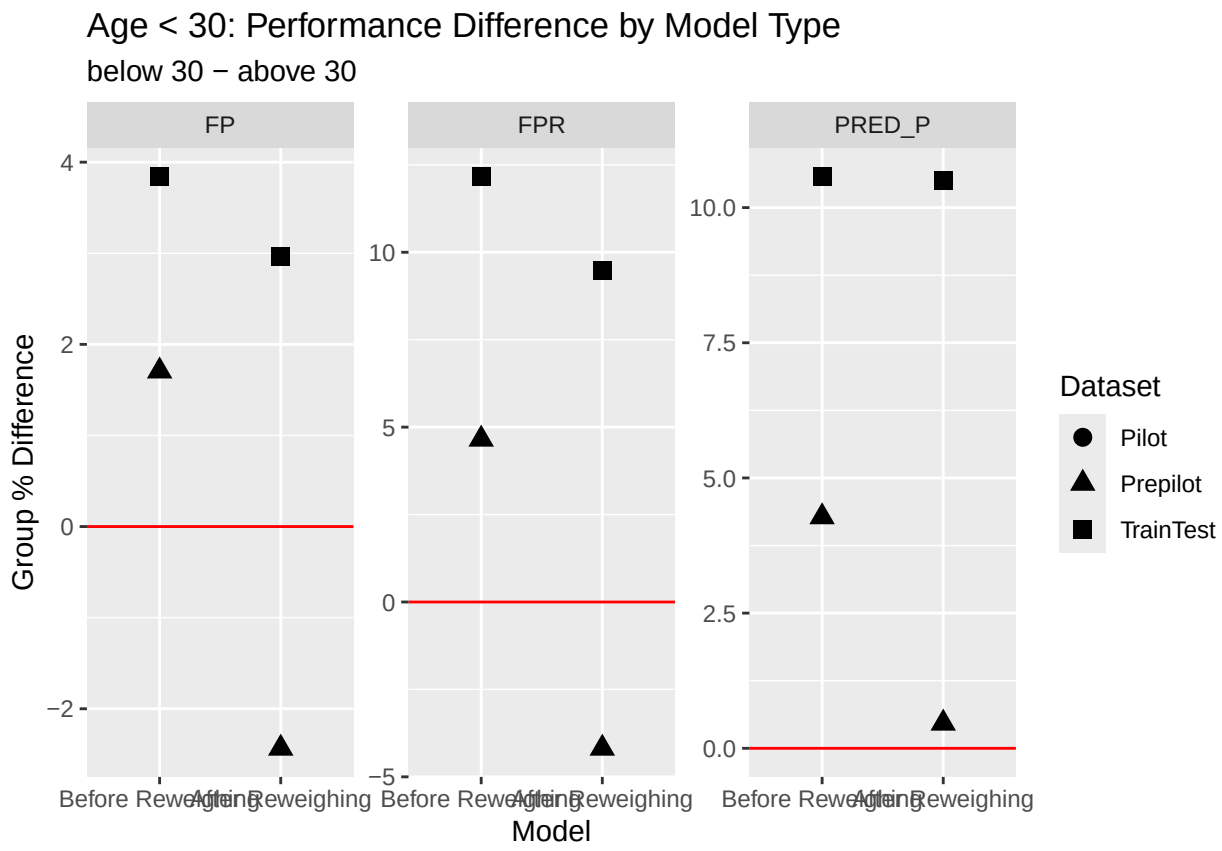
```
## Warning in geom_hline(yintercept = 0, color = "red", scales = "free_y"):
## Ignoring unknown parameters: ‘scales‘
```



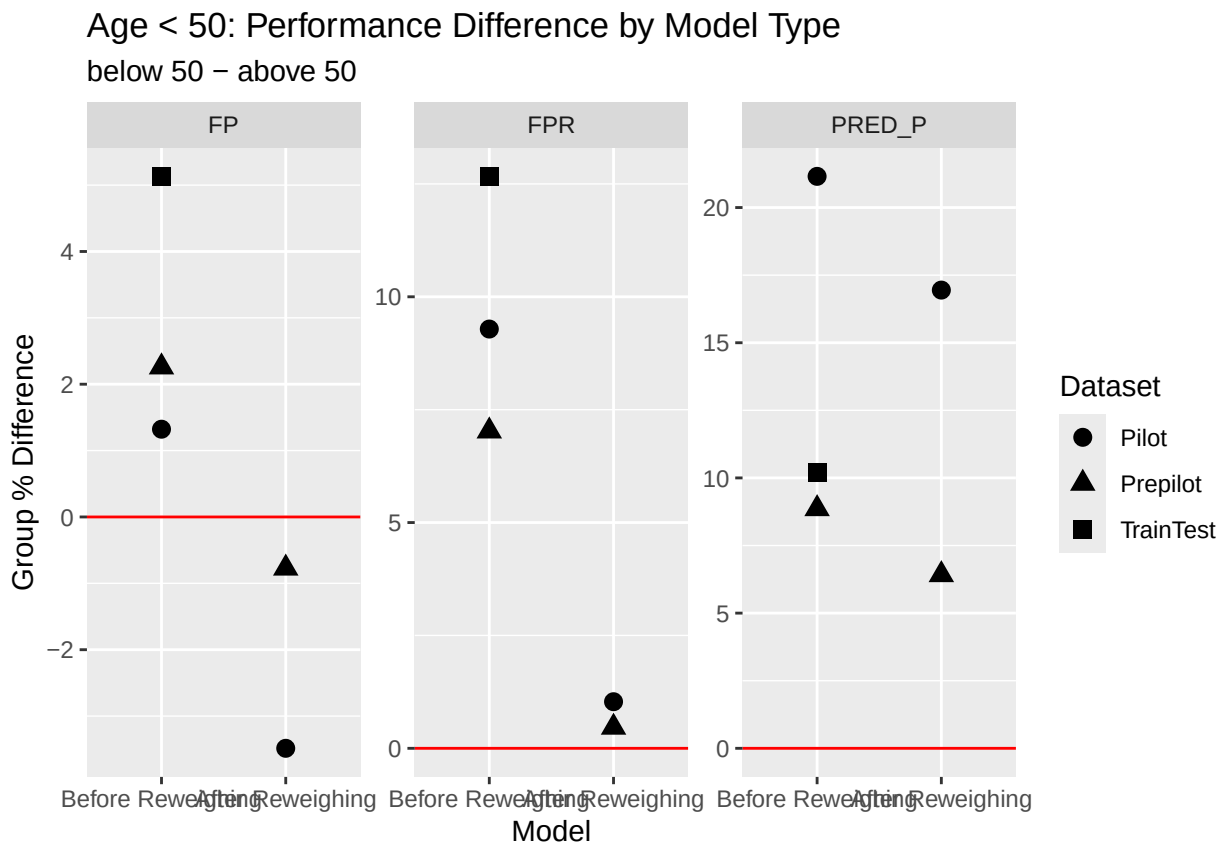

```
## Warning: Removed 6 rows containing missing values or values outside the scale range
## (‘geom_point()‘).
```

```
## Warning: Removed 6 rows containing missing values or values outside the scale range
## (‘geom_point()‘).
```

```
## Warning in geom_hline(yintercept = 0, color = "red", scales = "free_y"):
## Ignoring unknown parameters: ‘scales‘
```




```
## Warning: Removed 3 rows containing missing values or values outside the scale range
## (`geom_point()`).

## Warning: Removed 3 rows containing missing values or values outside the scale range
## (`geom_point()`).

## Warning in geom_hline(yintercept = 0, color = "red", scales = "free_y"):
## Ignoring unknown parameters: `scales`
```




```
## Warning: Removed 3 rows containing missing values or values outside the scale range
## (`geom_point()`).
```

```
## Warning: Removed 3 rows containing missing values or values outside the scale range
## (`geom_point()`).
```

RQ3 Error rate in Pilot

When looking at some of the graphs above, it stands stood out to me that the share of FPs jumped up substantially in the pilot. It seems useful to dig into that a bit more and find out if the rise in FP indicates a general deterioration of the model when confronted with pilot data and whether this potential deterioration is concentrated among particular groups.

```
cms_error <- cms_long %>%
  filter(stage %in% c('TrainTest/BR', 'Prepilot/BR', 'Prepilot/AR', 'Pilot/AR'),
         Metric %in% c('FP', 'FN', 'ERROR'),
         Feature_EN %in% c('gender', 'Age < 30', 'Age < 50', 'Dutch', 'IsFulltimeParent')) %>%
  mutate(order = case_when(stage == 'TrainTest/BR' ~ 1,
                           stage == 'Prepilot/BR' ~ 2,
                           stage == 'Prepilot/AR' ~ 3,
                           stage == 'Pilot/AR' ~ 4,
                           .default = NA))

for(characteristic in unique(cms_error$Feature_EN)){
  cms_char <- cms_error %>%
    filter(Feature_EN == characteristic)

  p4 <- ggplot(cms_char, aes(x = reorder(stage, order), y = Value, fill = Metric))+
    geom_bar(stat = 'identity', position = position_dodge())+
    facet_wrap(.~Feature_Value_EN)+
   labs(x = 'Dataset/Model', y = '% Error',
```

```
        title = paste0(characteristic, ': Development of Error rates across model development'),
        fill = 'Error Metric')+
    theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
  print(p4)

  ggsave(paste0('../output/rq3_p4_error_', characteristic, '.png'), plot = p4, width = 10, height = 8)
}
```


```
## Warning: Removed 3 rows containing missing values or values outside the scale range
## (`geom_bar()`).
## Removed 3 rows containing missing values or values outside the scale range
## (`geom_bar()`).
```


Age < 30: Development of Error rates across model development
above 30
below 30
% Error
0
20
40
TrainTest/BR
Prepilot/BR
Prepilot/AR
Pilot/AR
Dataset/Model
Error Metric
ERROR
FN
FP


Age < 50: Development of Error rates across model development
above 50
below 50
% Error
60
40
20
0
TrainTest/BR
Prepilot/BR
Prepilot/AR
Pilot/AR
Dataset/Model
Error Metric
ERROR
FN
FP

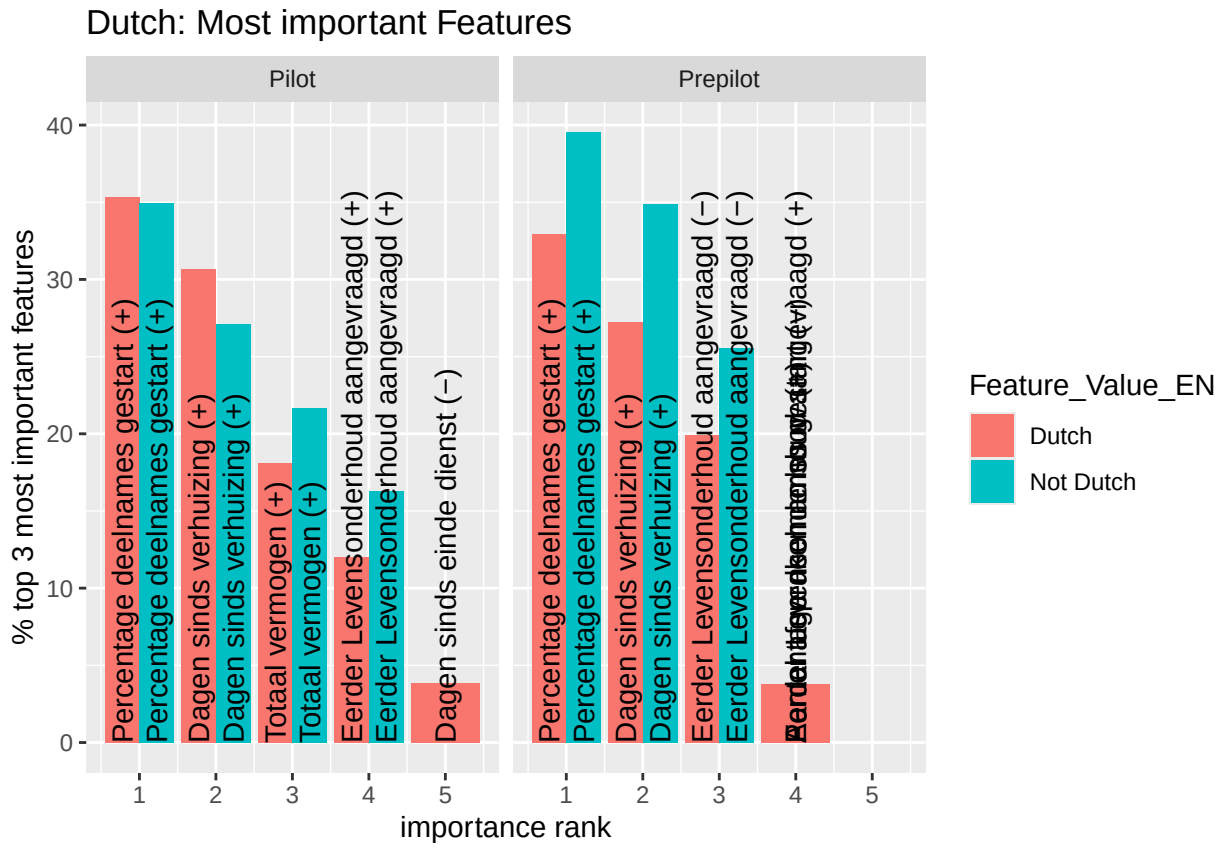

```
## Warning: Removed 3 rows containing missing values or values outside the scale range
## (`geom_bar()`).
## Removed 3 rows containing missing values or values outside the scale range
## (`geom_bar()`).
```

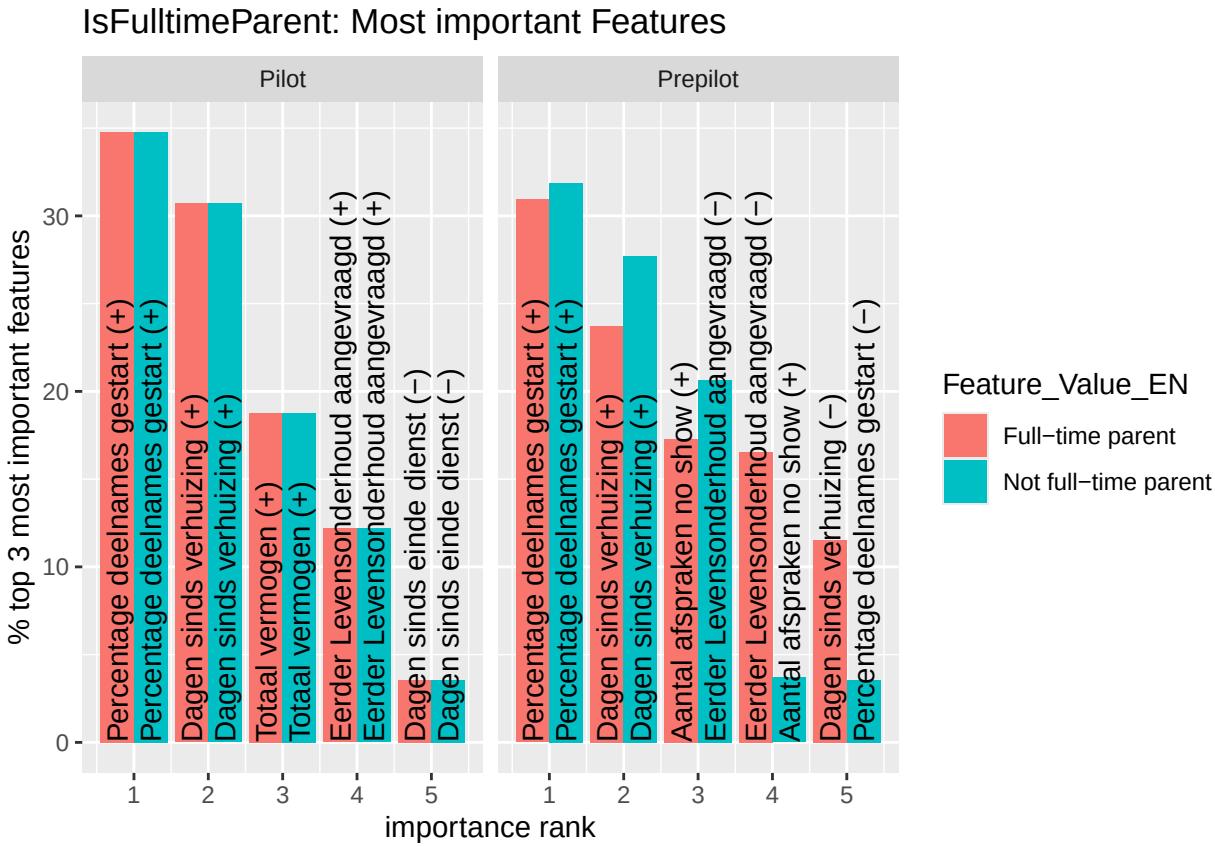
Feature importance

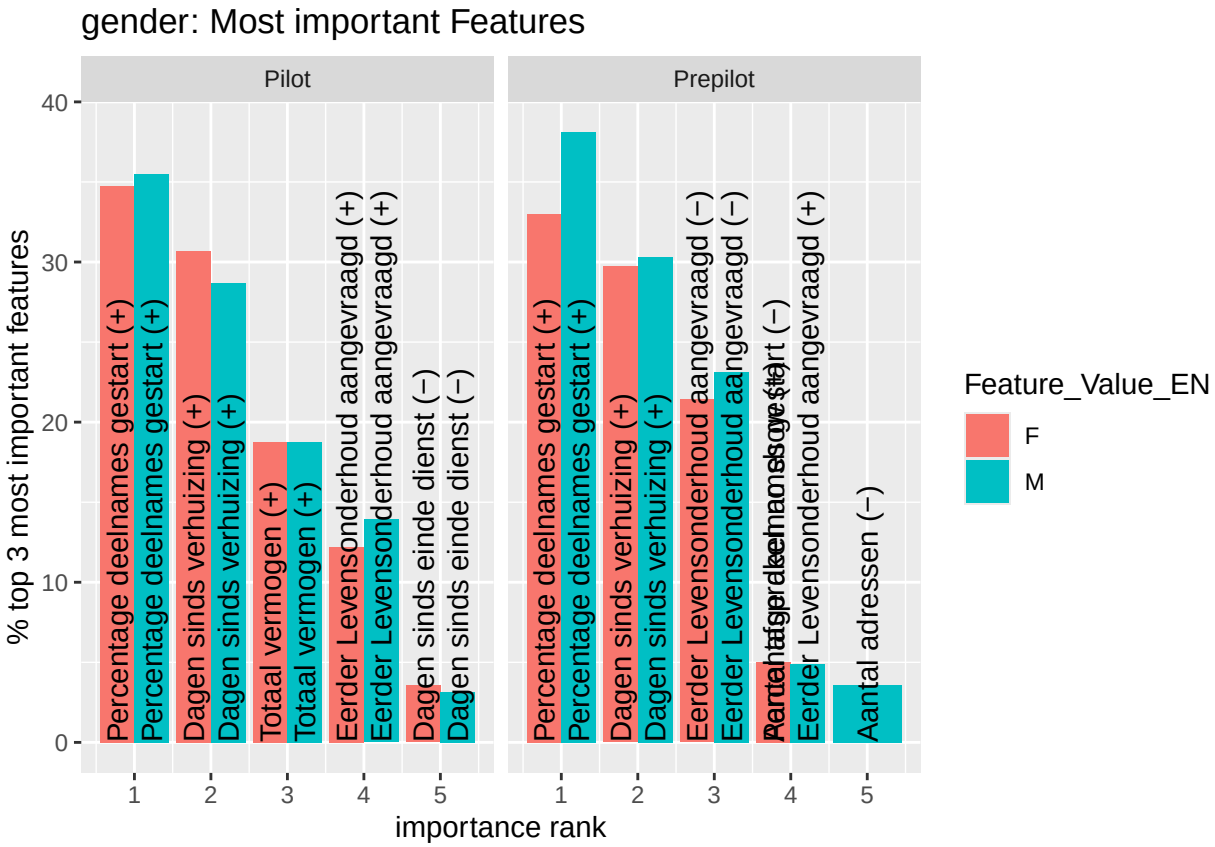
Along with the classification, the model provided caseworkers with the three most important features used by the model to come to its determination. Loek provided us access to the most important feature by demographic group. This allows us 1) to see if caseworkers could deduce beneficiary charactsitics from the highlighted features, potentially activating their biases, and 2) whether the model used different features for different demographic groups in coming to its determination. The latter could be concerning under due process considerations.

```
feature_counts_restricted <- feature_counts %>%
  filter(Feature_EN %in% c("gender", "IsFulltimeParent", "Dutch")) %>%
  group_by(Feature_EN, Feature_Value_EN, dataset) %>%
  arrange(desc(share)) %>%
  mutate(rank = dense_rank(desc(share))) %>%
  slice_max(n = 5, order_by = share) %>%
  ungroup() %>%
  filter(!is.na(share))

for(characteristic in unique(feature_counts_restricted$Feature_EN)){
  feature_counts_char <- feature_counts_restricted %>%
    filter(Feature_EN == characteristic)

  p5 <- ggplot(feature_counts_char, aes(x = rank, y = share, fill = Feature_Value_EN, label = Important
    geom_bar(stat = 'identity', position = position_dodge())+
    geom_text(aes(y = 0), hjust = 0, angle = 90, position = position_dodge(width = .9))+
```

```
    facet_grid(.~dataset)+
    labs(x = 'importance rank',
         y = '% top 3 most important features',
         title = paste0(characteristic, ': Most important Features'))

  print(p5)
  ggsave(paste0('../output/rq4_p5_feature_importance_', characteristic, '.png'), plot = p5, width = 10,

}
```




IsFulltimeParent: Most important Features
Pilot
Prepilot
% top 3 most important features
0
10
20
30
1
2
3
4
5
importance rank
Percentage deelnames gestart (+)
Percentage deelnames gestart (+)
Dagen sinds verhuizing (+)
Dagen sinds verhuizing (+)
Totaal vermogen (+)
Totaal vermogen (+)
Eerder Levensonderhoud aangevraagd (+)
Eerder Levensonderhoud aangevraagd (+)
Dagen sinds einde dienst (−)
Dagen sinds einde dienst (−)
Percentage deelnames gestart (+)
Percentage deelnames gestart (+)
Dagen sinds verhuizing (+)
Dagen sinds verhuizing (+)
Aantal afspraken no show (+)
Eerder Levensonderhoud aangevraagd (−)
Eerder Levensonderhoud aangevraagd (−)
Aantal afspraken no show (+)
Dagen sinds verhuizing (−)
Percentage deelnames gestart (−)
Feature_Value_EN
Full−time parent
Not full−time parent



Impossibility Theorem

TODO: placeholder to build graphs that illustrate the impossibility theorem. Incidentally, the data above illustrates that it's really a tradeoff between predictive parity, One_minus_PPV, and FPR (something i have embarrassingly often misstated).