Bias Analysis in Human Resource System

-for Blacksaber Software in 2021

Report prepared for Black Saber Software by Data Over Flow

2021-04-21

Contents


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Executive summary

We (Data Over Flow Co.Ltd.) have examined the structure of human resource system of the company (the Black Saber Software) by analyzing data on the company's hiring, promotion and salary process and found there to be no bias.

In our opinion, the system is fair during each of the three process, in accordance with Ontario's Human Rights Code and Black Saber's policies. Specifically, neither hiring nor promition process shows sign of gender/racial discrimination; the individual salary level is fairly evaluated based non-personal and work-related parameters only.

Technical report

Introduction

Research questions

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-
-

Does there exist bias in current employee enumeration?

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: salary ~ gender + role_seniority + financial_q + (1 | team) +
##     (1 | leadership_for_level) + (1 | productivity)
##    Data: current
##
## REML criterion at convergence: 131099.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.2023 -0.7420  0.0259  0.7217  2.8209
##
## Random effects:
##  Groups               Name        Variance Std.Dev.
##  productivity         (Intercept)   175447  418.9
##  team                 (Intercept)  4728844 2174.6
##  leadership_for_level (Intercept)        0    0.0
##  Residual                         11012729 3318.5
## Number of obs: 6906, groups:
## productivity, 99; team, 8; leadership_for_level, 3
##
## Fixed effects:
##                              Estimate Std. Error  t value
## (Intercept)                 119786.22    3429.18   34.931
## genderPrefer not to say      -1370.63     316.28   -4.334
## genderWoman                  -1762.75      85.71  -20.566
```

```
## role_seniorityEntry-level    -91052.82     241.44 -377.120
## role_seniorityJunior I       -85669.12     236.80 -361.779
## role_seniorityJunior II      -83173.38     237.55 -350.128
## role_seniorityManager        -50779.17     277.90 -182.728
## role_senioritySenior I       -77882.04     241.05 -323.101
## role_senioritySenior II      -72455.57     243.13 -298.016
## role_senioritySenior III     -66868.66     248.75 -268.819
## role_seniorityVice president  28600.83     431.48   66.285
## financial_q2013 Q3              127.56    4706.39    0.027
## financial_q2013 Q4             1437.04    3721.55    0.386
## financial_q2014 Q1             2341.89    3471.22    0.675
## financial_q2014 Q2             2620.15    3450.62    0.759
## financial_q2014 Q3             2604.31    3409.62    0.764
## financial_q2014 Q4             2575.17    3395.82    0.758
## financial_q2015 Q1             3169.85    3374.06    0.939
## financial_q2015 Q2             3258.91    3362.35    0.969
## financial_q2015 Q3             3319.39    3353.31    0.990
## financial_q2015 Q4             2985.28    3350.28    0.891
## financial_q2016 Q1             3046.45    3348.70    0.910
## financial_q2016 Q2             2917.87    3346.72    0.872
## financial_q2016 Q3             2916.36    3345.68    0.872
## financial_q2016 Q4             2817.11    3344.86    0.842
## financial_q2017 Q1             2602.41    3343.91    0.778
## financial_q2017 Q2             2704.95    3342.78    0.809
## financial_q2017 Q3             2760.15    3341.78    0.826
## financial_q2017 Q4             2795.63    3341.90    0.837
## financial_q2018 Q1             2829.87    3340.91    0.847
## financial_q2018 Q2             2859.78    3340.39    0.856
## financial_q2018 Q3             2888.66    3339.90    0.865
## financial_q2018 Q4             2802.67    3339.66    0.839
## financial_q2019 Q1             2813.87    3339.18    0.843
## financial_q2019 Q2             2784.68    3339.20    0.834
## financial_q2019 Q3             2924.55    3338.78    0.876
## financial_q2019 Q4             2958.60    3338.67    0.886
## financial_q2020 Q1             3018.52    3338.20    0.904
## financial_q2020 Q2             3033.13    3338.16    0.909
## financial_q2020 Q3             3060.49    3337.88    0.917
## financial_q2020 Q4             3029.47    3337.77    0.908
```

```
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular

## Linear mixed model fit by REML ['lmerMod']
## Formula: salary ~ gender + role_seniority + financial_q + (1 | team) +
##     (1 | leadership_for_level)
##    Data: current
##
## REML criterion at convergence: 131126.3
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.1863 -0.7558  0.0129  0.7257  2.8045
##
## Random effects:
##  Groups               Name        Variance Std.Dev.
##  team                 (Intercept)  4730675 2175.01
##  leadership_for_level (Intercept)     6499   80.61
##  Residual                         11154062 3339.77
## Number of obs: 6906, groups:  team, 8; leadership_for_level, 3
##
## Fixed effects:
##                               Estimate Std. Error  t value
## (Intercept)                  1.200e+05  3.440e+03   34.886
## genderPrefer not to say     -1.289e+03  3.170e+02   -4.067
## genderWoman                 -1.786e+03  8.593e+01  -20.783
## role_seniorityEntry-level   -9.110e+04  2.403e+02 -379.117
## role_seniorityJunior I      -8.572e+04  2.355e+02 -363.925
## role_seniorityJunior II     -8.321e+04  2.367e+02 -351.495
## role_seniorityManager       -5.075e+04  2.756e+02 -184.170
## role_senioritySenior I      -7.793e+04  2.398e+02 -325.036
## role_senioritySenior II     -7.245e+04  2.427e+02 -298.581
## role_senioritySenior III    -6.690e+04  2.475e+02 -270.267
## role_seniorityVice president  2.851e+04  4.313e+02   66.106
## financial_q2013 Q3          -1.149e-08  4.723e+03    0.000
## financial_q2013 Q4           1.355e+03  3.738e+03    0.362
## financial_q2014 Q1           2.142e+03  3.482e+03    0.615
## financial_q2014 Q2           2.449e+03  3.463e+03    0.707
```

```
## financial_q2014 Q3            2.462e+03  3.420e+03    0.720
## financial_q2014 Q4            2.415e+03  3.407e+03    0.709
## financial_q2015 Q1            3.048e+03  3.385e+03    0.901
## financial_q2015 Q2            3.177e+03  3.373e+03    0.942
## financial_q2015 Q3            3.170e+03  3.364e+03    0.942
## financial_q2015 Q4            2.834e+03  3.361e+03    0.843
## financial_q2016 Q1            2.894e+03  3.360e+03    0.862
## financial_q2016 Q2            2.741e+03  3.358e+03    0.816
## financial_q2016 Q3            2.747e+03  3.356e+03    0.818
## financial_q2016 Q4            2.674e+03  3.356e+03    0.797
## financial_q2017 Q1            2.463e+03  3.355e+03    0.734
## financial_q2017 Q2            2.593e+03  3.354e+03    0.773
## financial_q2017 Q3            2.643e+03  3.353e+03    0.788
## financial_q2017 Q4            2.671e+03  3.353e+03    0.797
## financial_q2018 Q1            2.718e+03  3.352e+03    0.811
## financial_q2018 Q2            2.743e+03  3.351e+03    0.818
## financial_q2018 Q3            2.728e+03  3.351e+03    0.814
## financial_q2018 Q4            2.660e+03  3.350e+03    0.794
## financial_q2019 Q1            2.700e+03  3.350e+03    0.806
## financial_q2019 Q2            2.694e+03  3.350e+03    0.804
## financial_q2019 Q3            2.798e+03  3.349e+03    0.835
## financial_q2019 Q4            2.840e+03  3.349e+03    0.848
## financial_q2020 Q1            2.880e+03  3.349e+03    0.860
## financial_q2020 Q2            2.915e+03  3.349e+03    0.870
## financial_q2020 Q3            2.928e+03  3.349e+03    0.875
## financial_q2020 Q4            2.896e+03  3.348e+03    0.865
```

```
## Likelihood ratio test
##
## Model 1: salary ~ gender + role_seniority + financial_q + (1 | team) +
##     (1 | leadership_for_level) + (1 | productivity)
## Model 2: salary ~ gender + role_seniority + financial_q + (1 | team) +
##     (1 | leadership_for_level)
##   #Df LogLik Df  Chisq Pr(>Chisq)
## 1  45 -65550
## 2  44 -65563 -1 26.917  2.124e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
## Likelihood ratio test
##
## Model 1: salary ~ gender + role_seniority + financial_q + (1 | team) +
##     (1 | leadership_for_level)
## Model 2: salary ~ gender + role_seniority + financial_q + (1 | leadership_for_level)
##   #Df LogLik Df  Chisq Pr(>Chisq)
## 1  44 -65563
## 2  43 -66528 -1 1930.2  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
## Likelihood ratio test
##
## Model 1: salary ~ gender + role_seniority + financial_q + (1 | leadership_for_level)
## Model 2: salary ~ gender + role_seniority + financial_q + (1 | team)
##   #Df LogLik Df  Chisq Pr(>Chisq)
## 1  43 -66528
## 2  43 -65563  0 1930.1  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

For each research question, you will want to briefly describe any data manipulation, show some exploratory plots/summary tables, report on any methods you use (i.e. models you fit) and the conclusions you draw from these

Does there exist bias in the hiring process?

```
##
## Call:
## glm(formula = pass_phase1 ~ gender + gpa + extracurriculars +
##     cv + work_experience, family = binomial(link = "logit"),
##     data = phase1_new_applicants)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.60450  -0.64746  -0.00004   0.68146   1.96684
##
## Coefficients:
```

```
##                           Estimate Std. Error z value Pr(>|z|)
## (Intercept)              -25.16292  648.71016  -0.039  0.96906
## genderPrefer not to say    0.16339    0.85121   0.192  0.84778
## genderWoman               -0.05912    0.22001  -0.269  0.78815
## gpa                        2.09045    0.23547   8.878  < 2e-16 ***
## extracurriculars           0.28921    0.21330   1.356  0.17514
## cv                        18.68461  648.70981   0.029  0.97702
## work_experience            0.76135    0.27647   2.754  0.00589 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 849.52  on 612  degrees of freedom
## Residual deviance: 516.92  on 606  degrees of freedom
## AIC: 530.92
##
## Number of Fisher Scoring iterations: 17
```

```
##
## Call:
## glm(formula = pass_phase2 ~ gender + team_applied_for + cover_letter +
##     extracurriculars + work_experience + technical_skills + writing_skills +
##     leadership_presence + speaking_skills, family = binomial(link = "logit"),
##     data = phase2_new_applicants)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.7705  -0.1309  -0.0242  -0.0045   3.2873
##
## Coefficients: (1 not defined because of singularities)
##                             Estimate Std. Error z value Pr(>|z|)
## (Intercept)               -24.15050    4.79613  -5.035 4.77e-07 ***
## genderPrefer not to say   -16.20043 1974.74800  -0.008   0.9935
## genderWoman                -0.63266    0.79481  -0.796   0.4260
## team_applied_forSoftware    1.40910    0.76203   1.849   0.0644 .
## cover_letter                     NA         NA      NA       NA
## extracurriculars           -0.63485    0.71598  -0.887   0.3752
```

```
## work_experience           -0.10831    0.73646  -0.147   0.8831
## technical_skills           0.09897    0.02490   3.974 7.06e-05 ***
## writing_skills             0.10690    0.02747   3.892 9.93e-05 ***
## leadership_presence        1.00449    0.22639   4.437 9.13e-06 ***
## speaking_skills            0.90524    0.21952   4.124 3.73e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 157.306  on 299  degrees of freedom
## Residual deviance:  64.515  on 290  degrees of freedom
## AIC: 84.515
##
## Number of Fisher Scoring iterations: 16
```

```
##
## Call:
## glm(formula = final_hired ~ gender, family = binomial(link = "logit"),
##     data = phase3_new_applicants)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.2346  -1.2346  -0.8203   1.1213   1.5829
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.1335     0.5175   0.258    0.796
## genderWoman  -1.0498     0.9838  -1.067    0.286
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 30.316  on 21  degrees of freedom
## Residual deviance: 29.103  on 20  degrees of freedom
## AIC: 33.103
##
## Number of Fisher Scoring iterations: 4
```

```
##
##   61 61.5   66   68 70.5   72 72.5   74 74.5 75.5 76.5   77 77.5   78   80 81.5
##    1    1    1    1    1    1    1    1    1    2    2    1    1    2    1    1
## 83.5 84.5 90.5
##    1    1    1
```

For each research question, you will want to briefly describe any data manipulation, show some exploratory plots/summary tables, report on any methods you use (i.e. models you fit) and the conclusions you draw from these

Informative title for section addressing a research question

For each research question, you will want to briefly describe any data manipulation, show some exploratory plots/summary tables, report on any methods you use (i.e. models you fit) and the conclusions you draw from these

Data Visualization

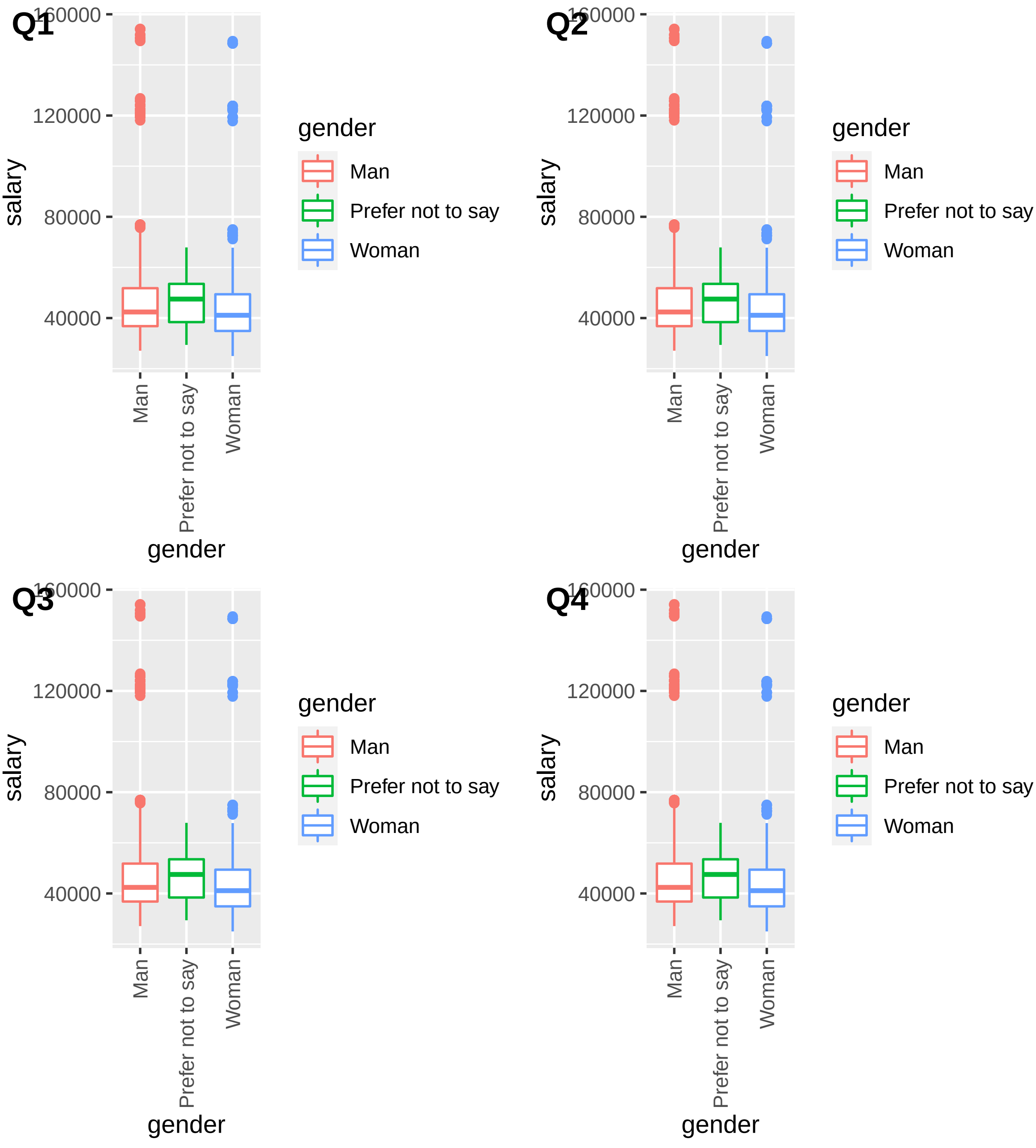


Figure 1: Salary Distribution for Men and Women in Each Quarter

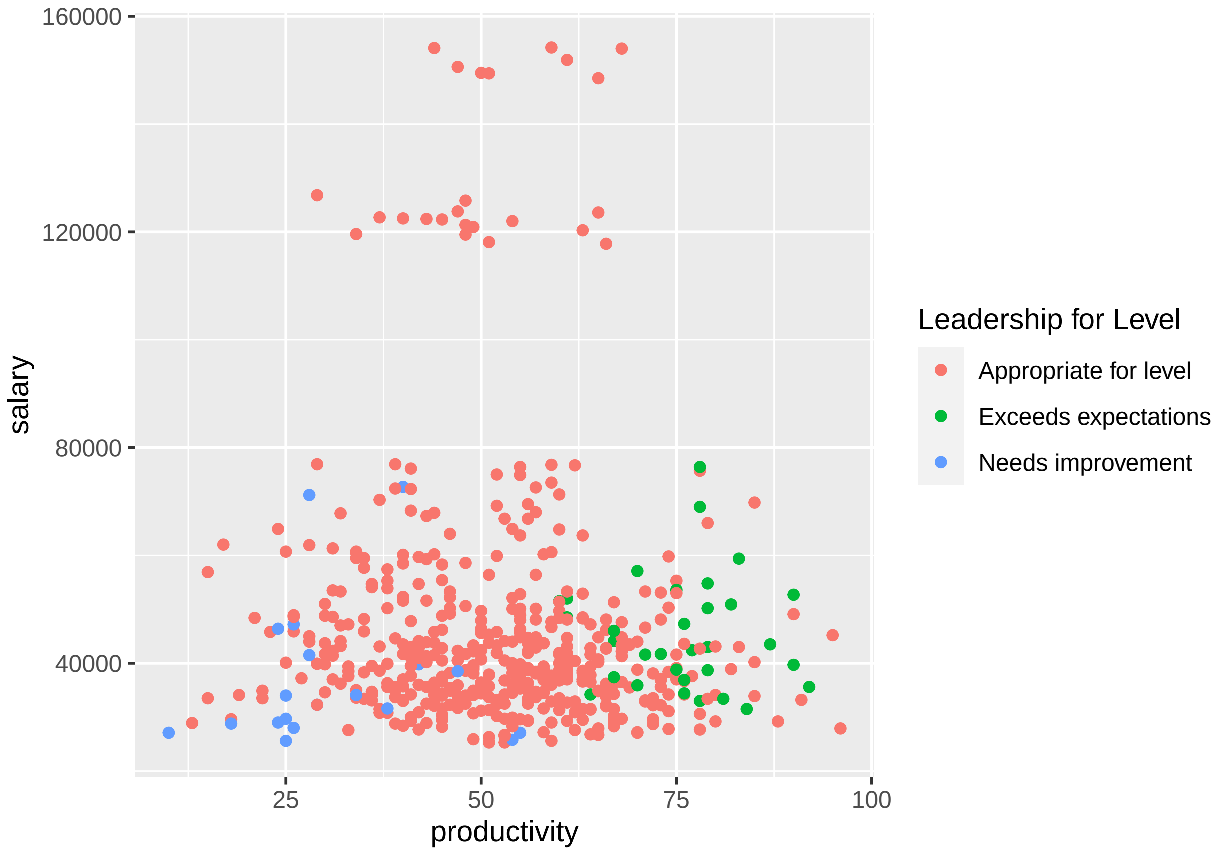


Figure 2: Salary Difference Across Leadership for Level Fixing Productivity

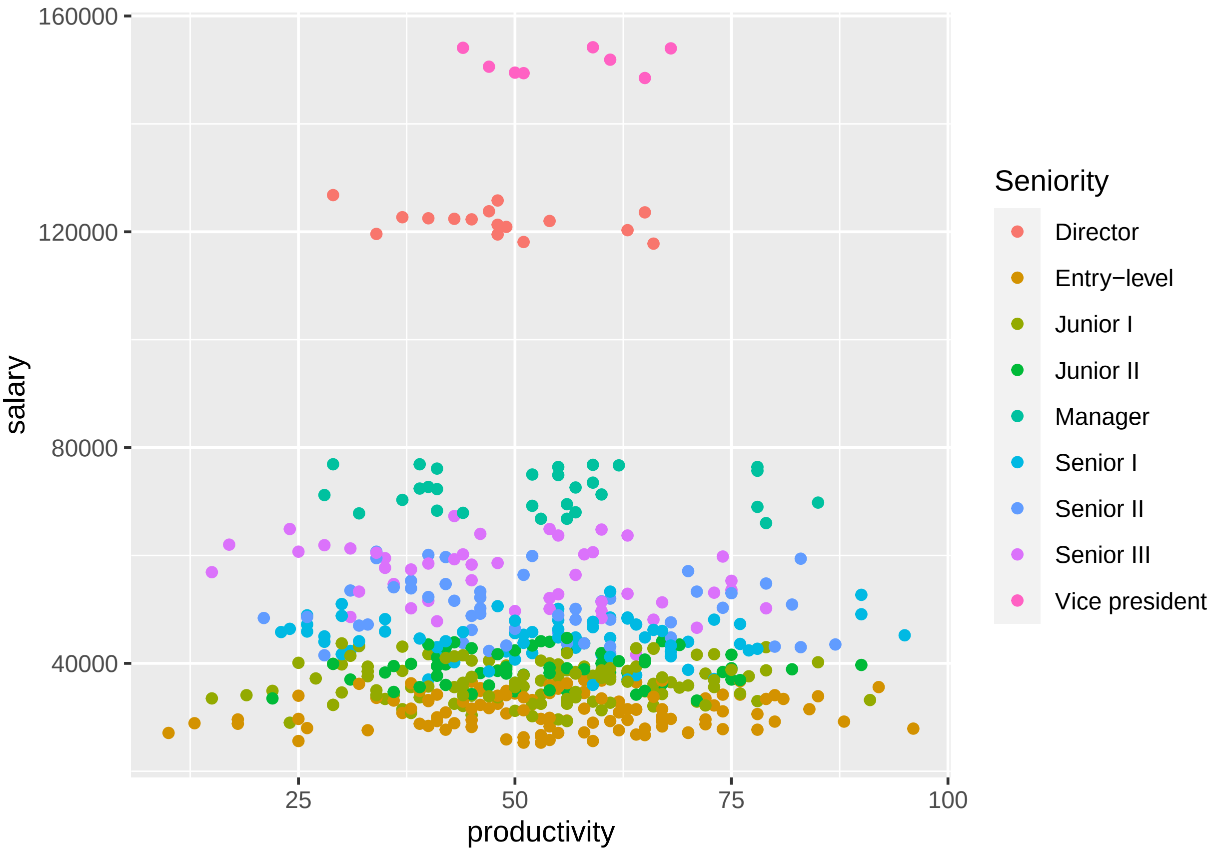


Figure 3: Salary Difference Across Role Seniority

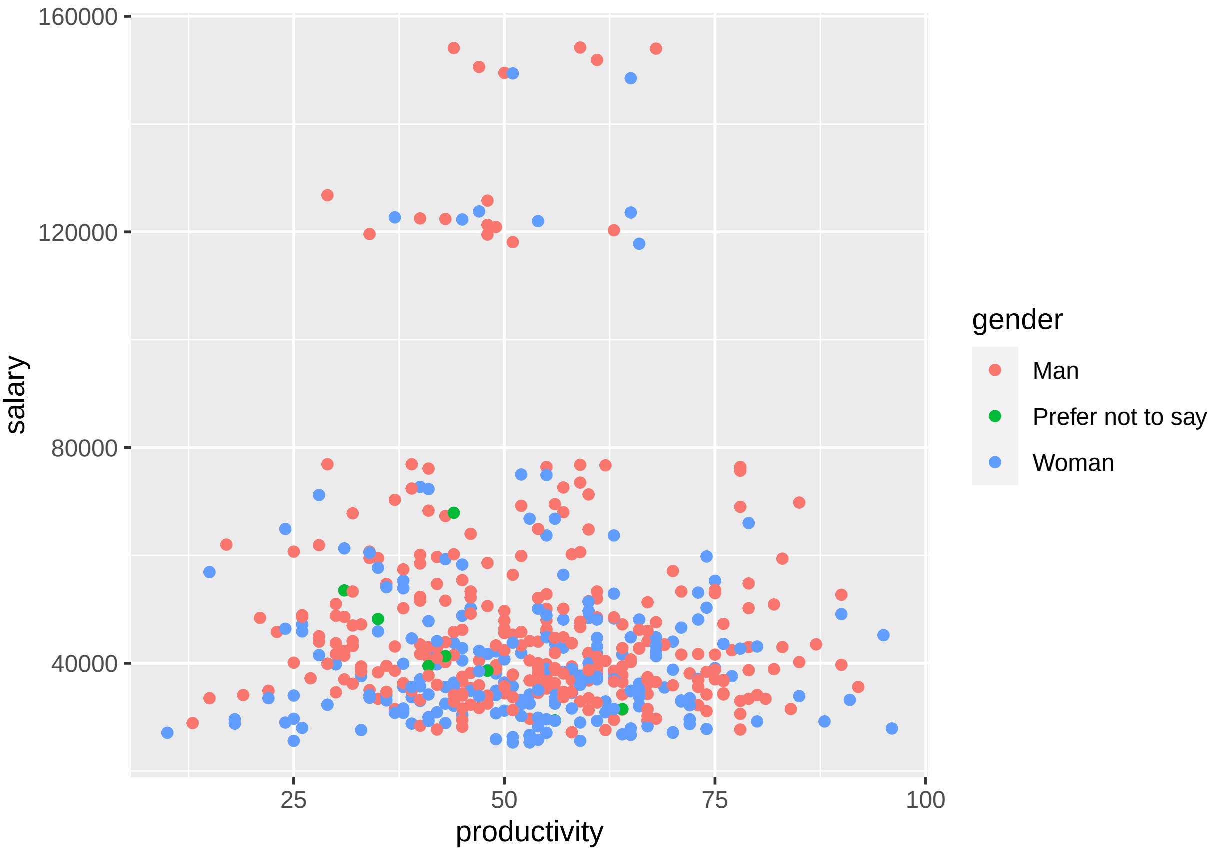


Figure 4: Salary Difference Across Leadership Levels

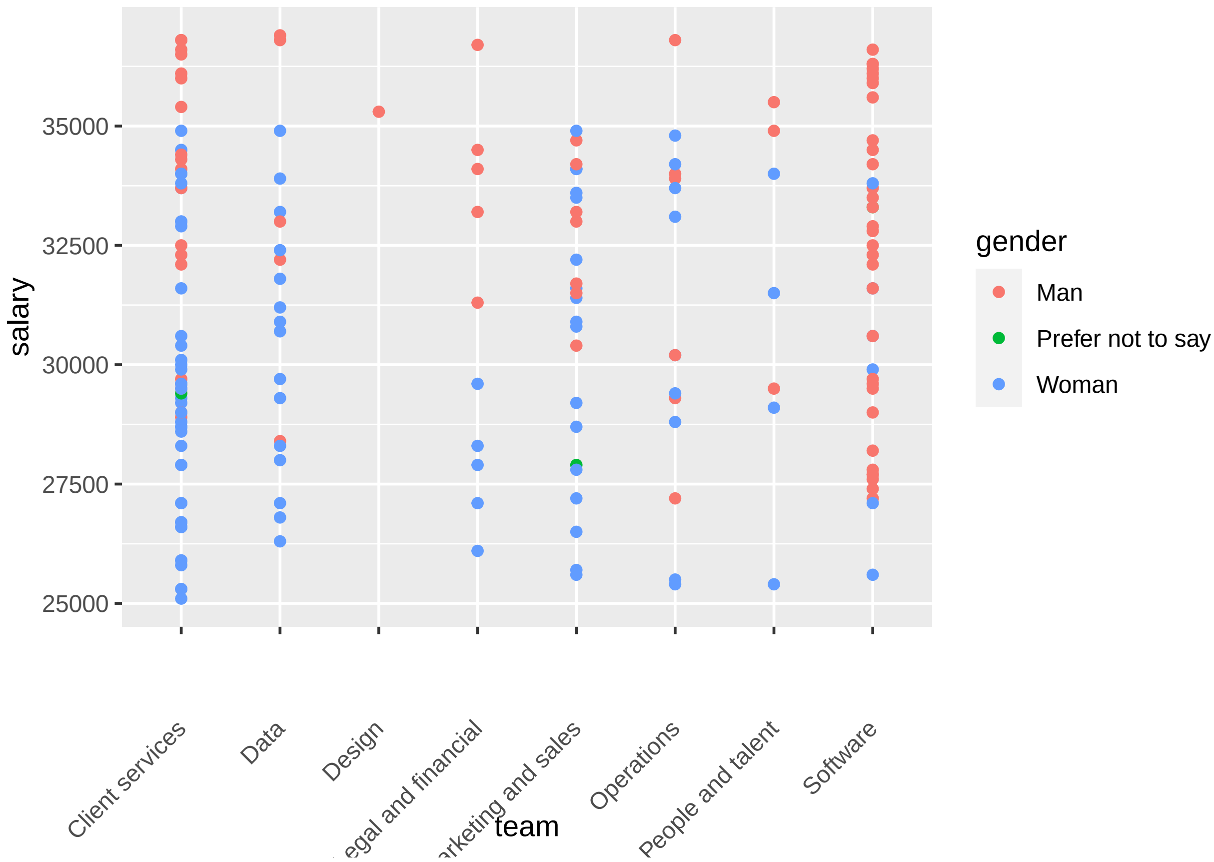


Figure 5: Salary Difference in Gender Across Teams, Fixing Quater and Seniority(Entry Level)

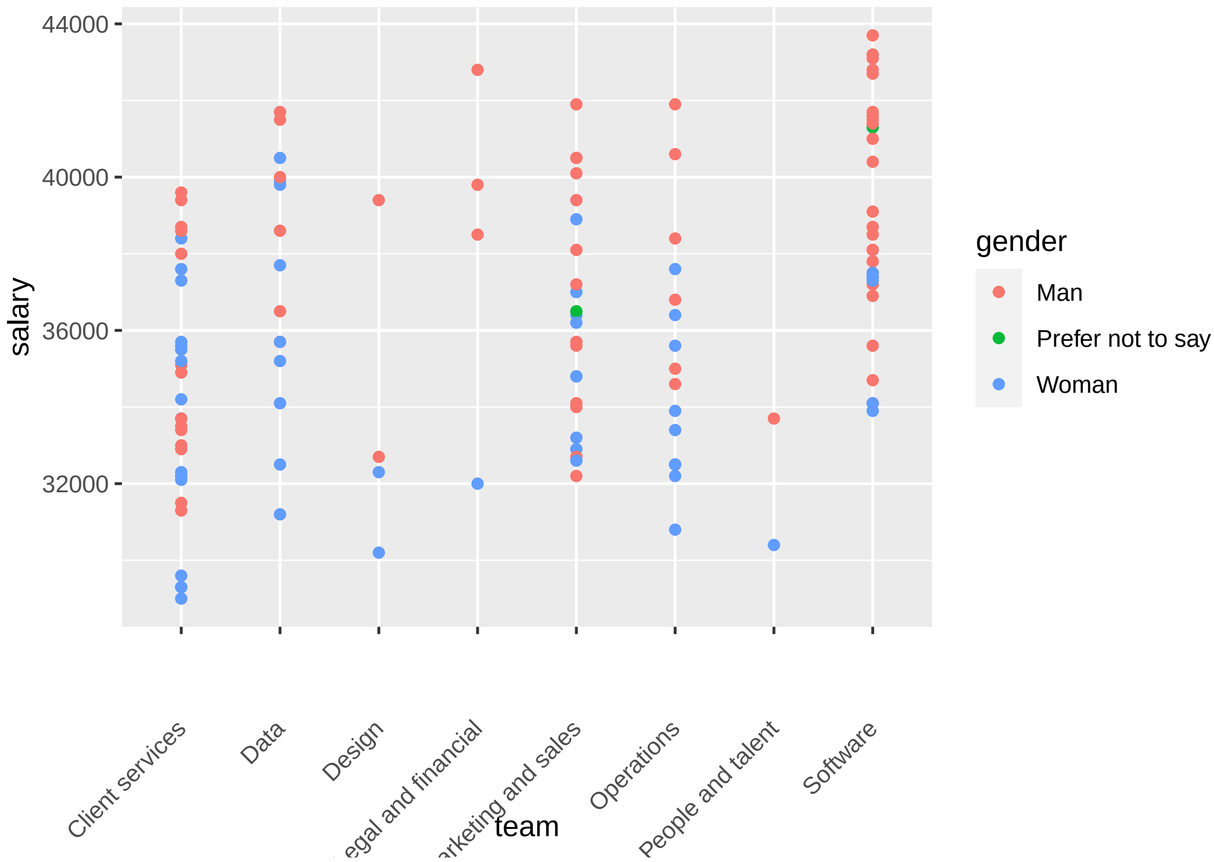


Figure 6: Salary Difference in Gender Across Teams, Fixing Quater and Seniority(Junior I)

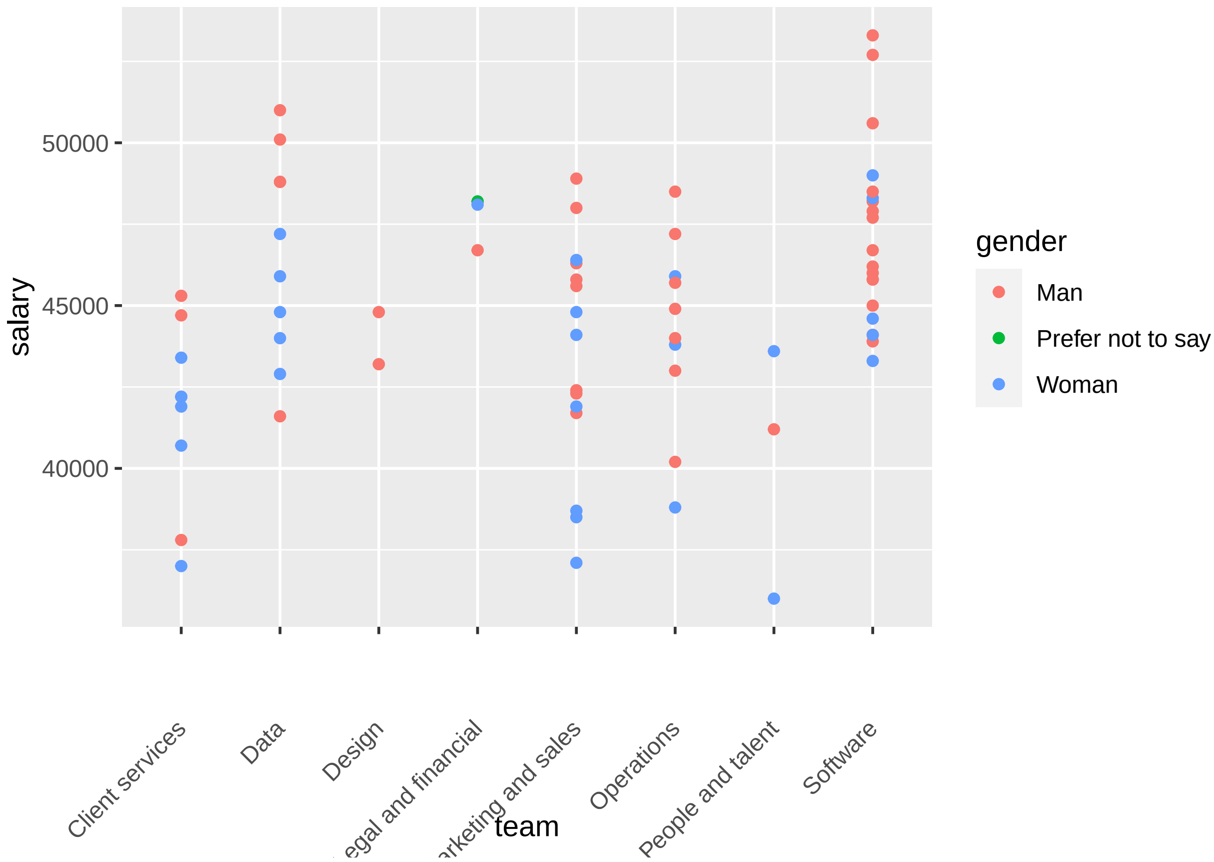


Figure 7: Salary Difference in Gender Across Teams, Fixing Quater and Seniority(Junior II)

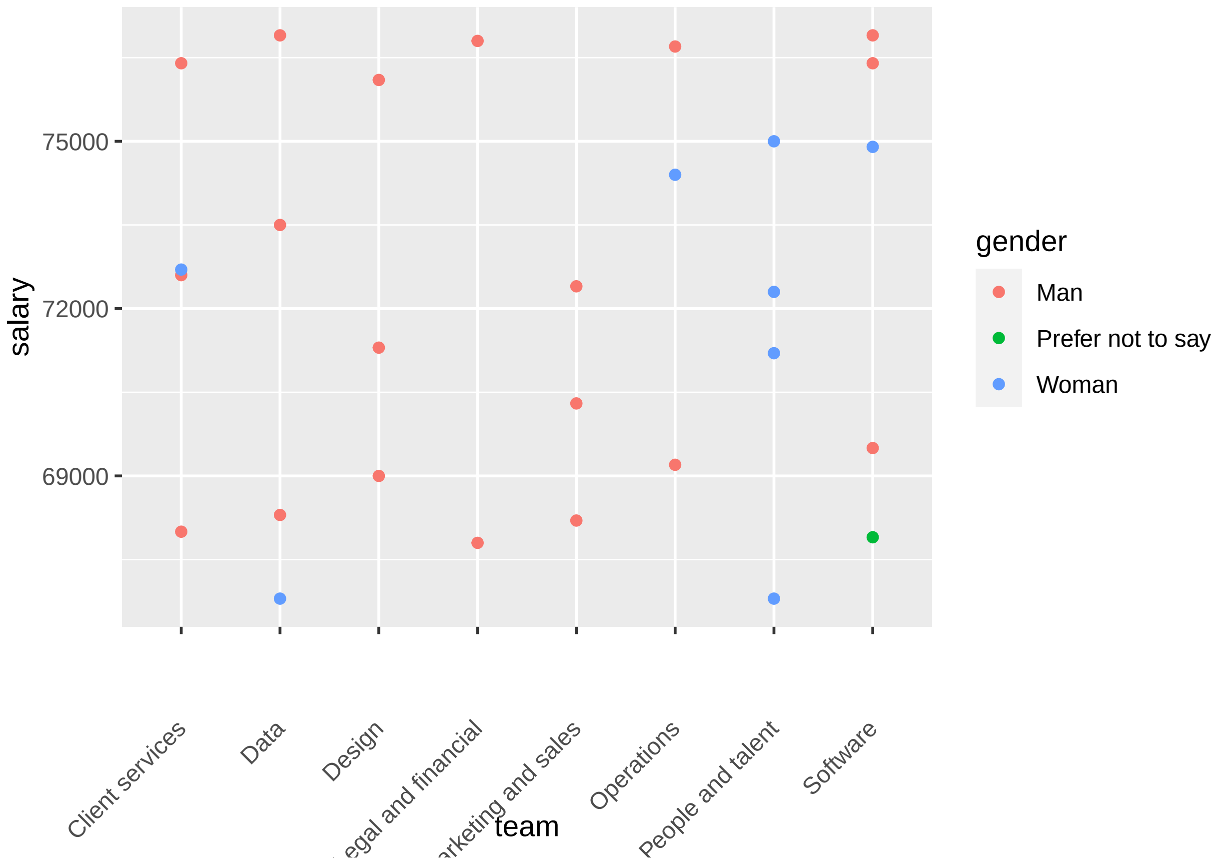


Figure 8: Salary Difference in Gender Across Teams, Fixing Quater and Seniority(Manager)

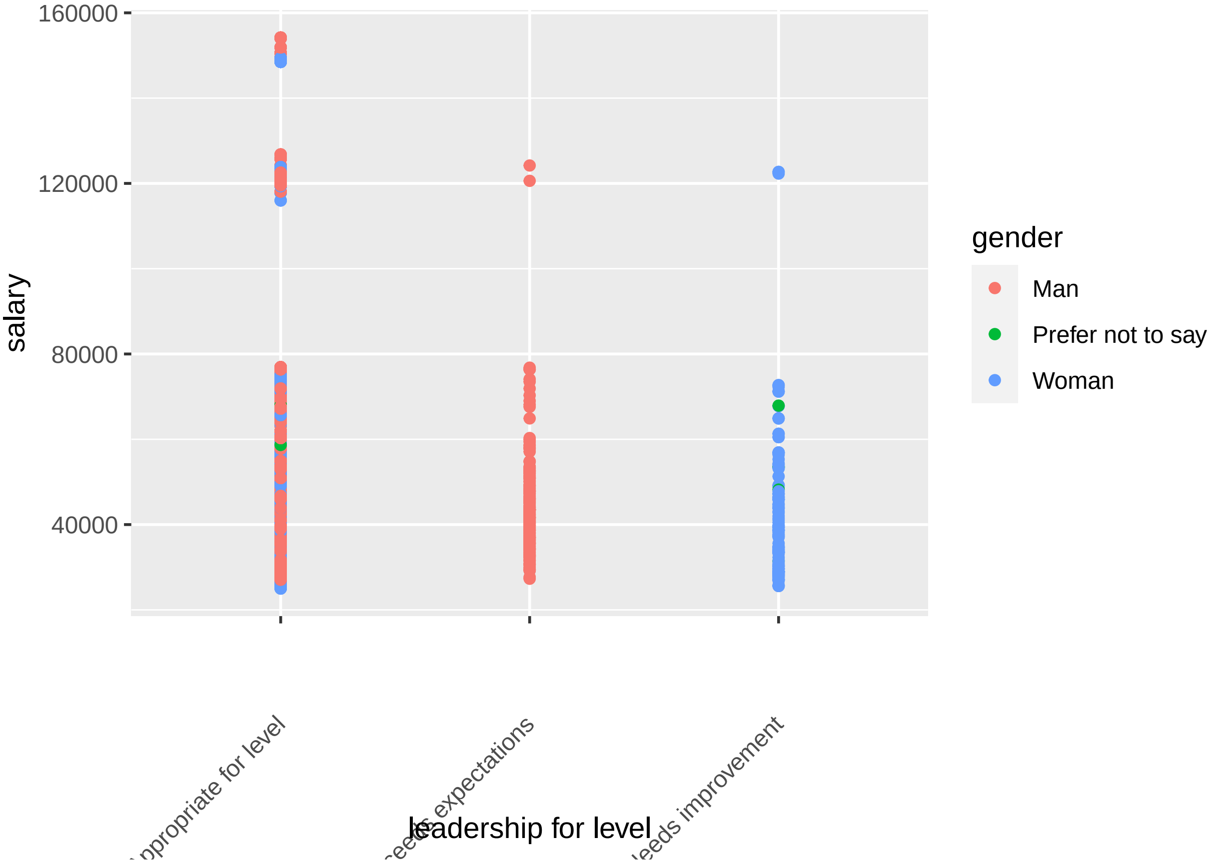


Figure 9: Salary Difference in Gender Across Leadership for Level

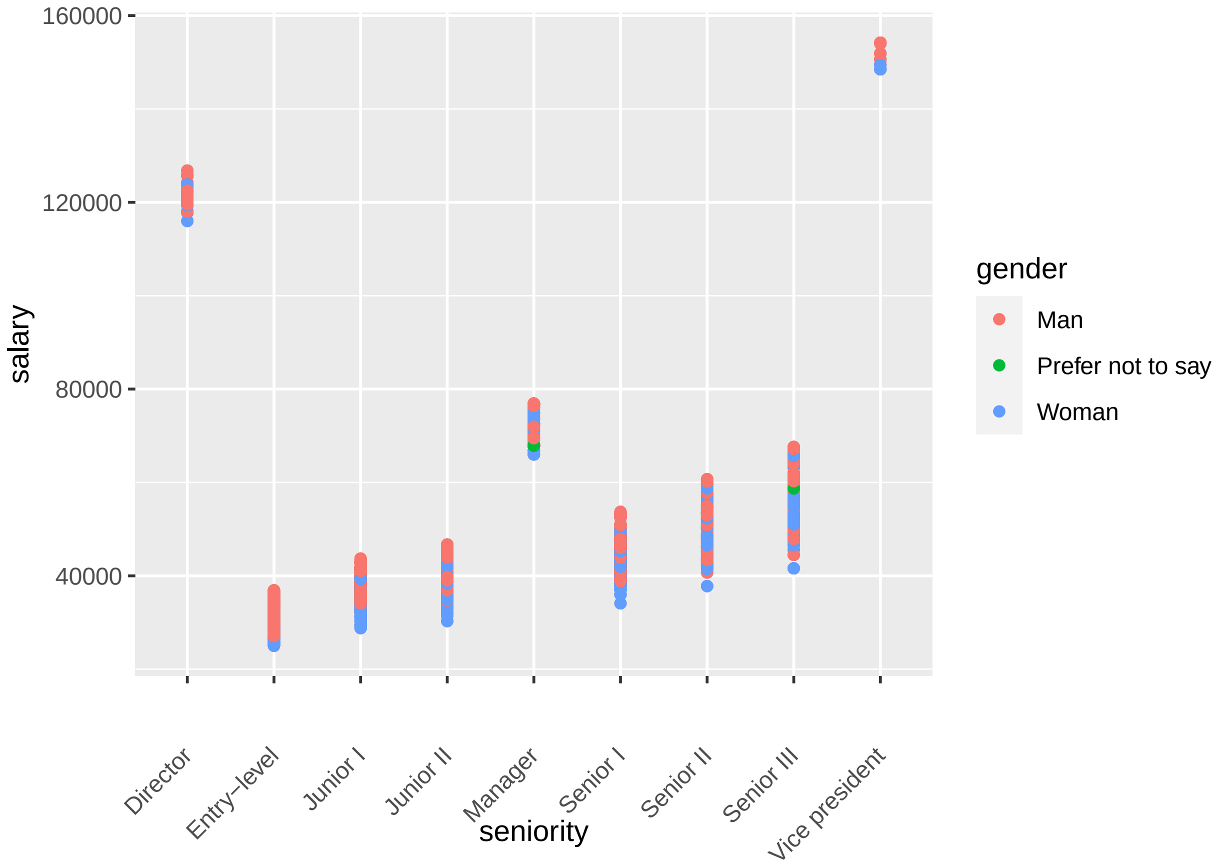


Figure 10: Salary Difference in Gender Across Seniority

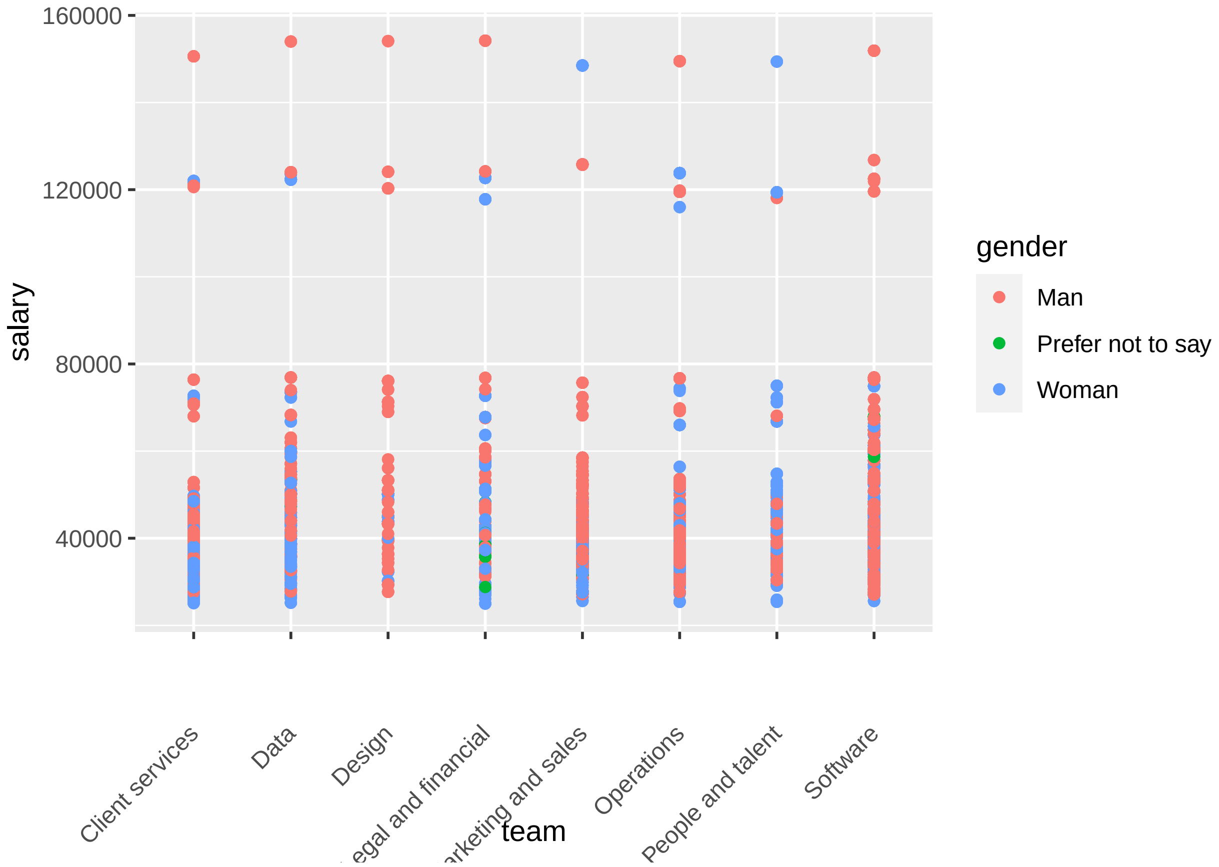


Figure 11: Salary Difference in Gender Across Teams

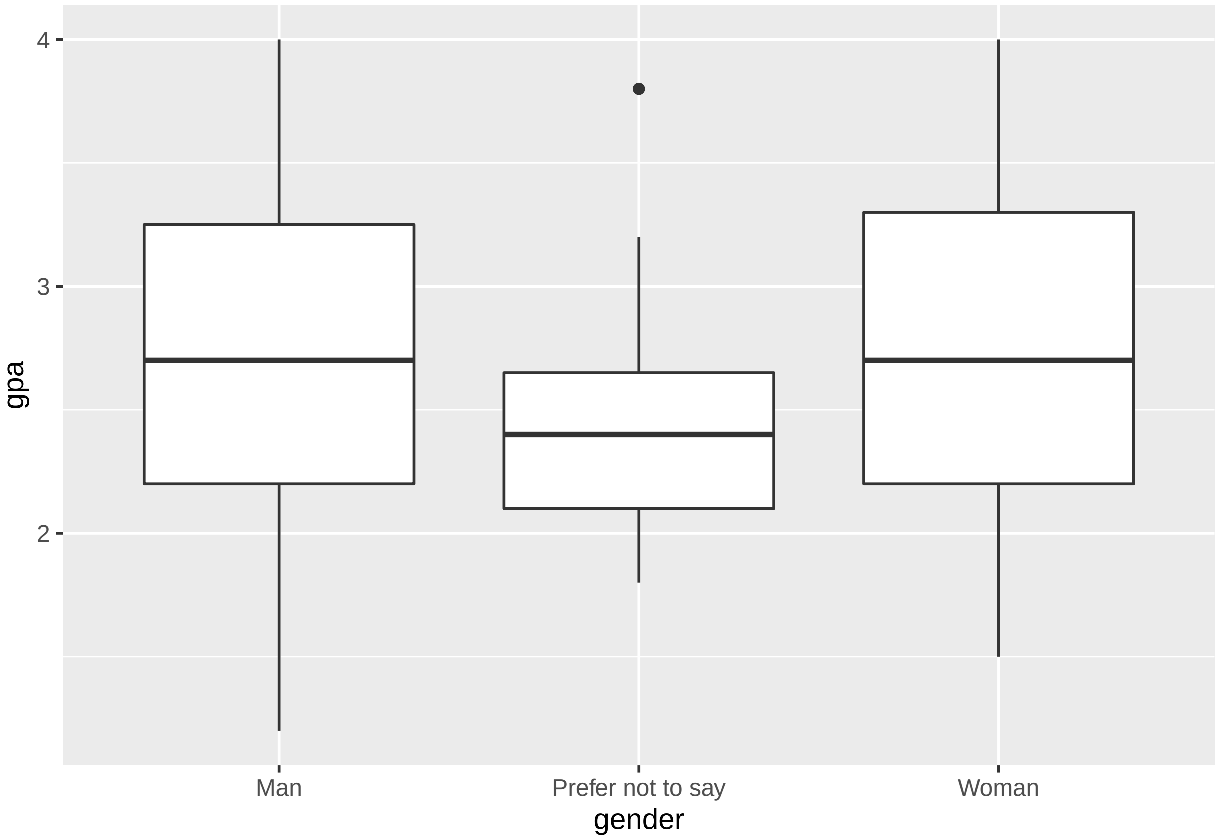


Figure 12: GPA Distribution Across Phase1 Applicants

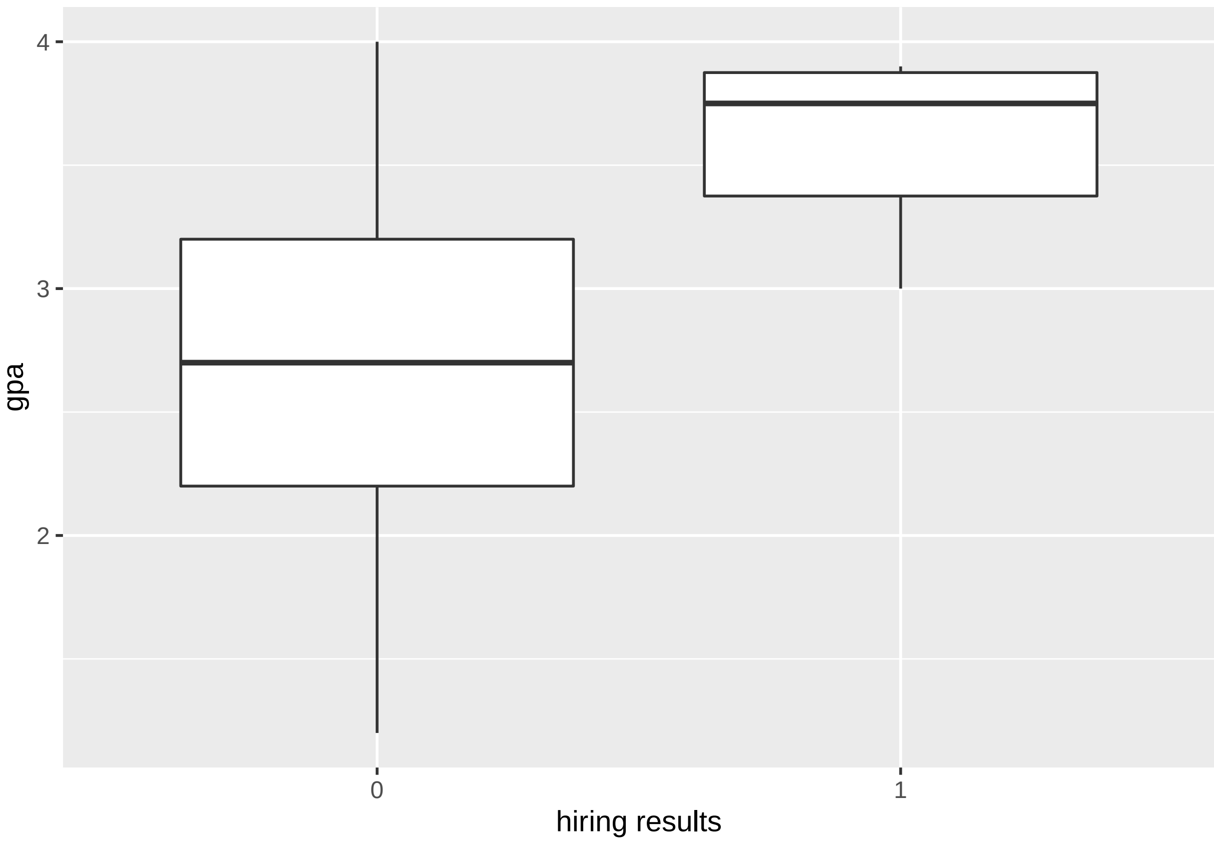


Figure 13: GPA Distribtion Across Hiring Results

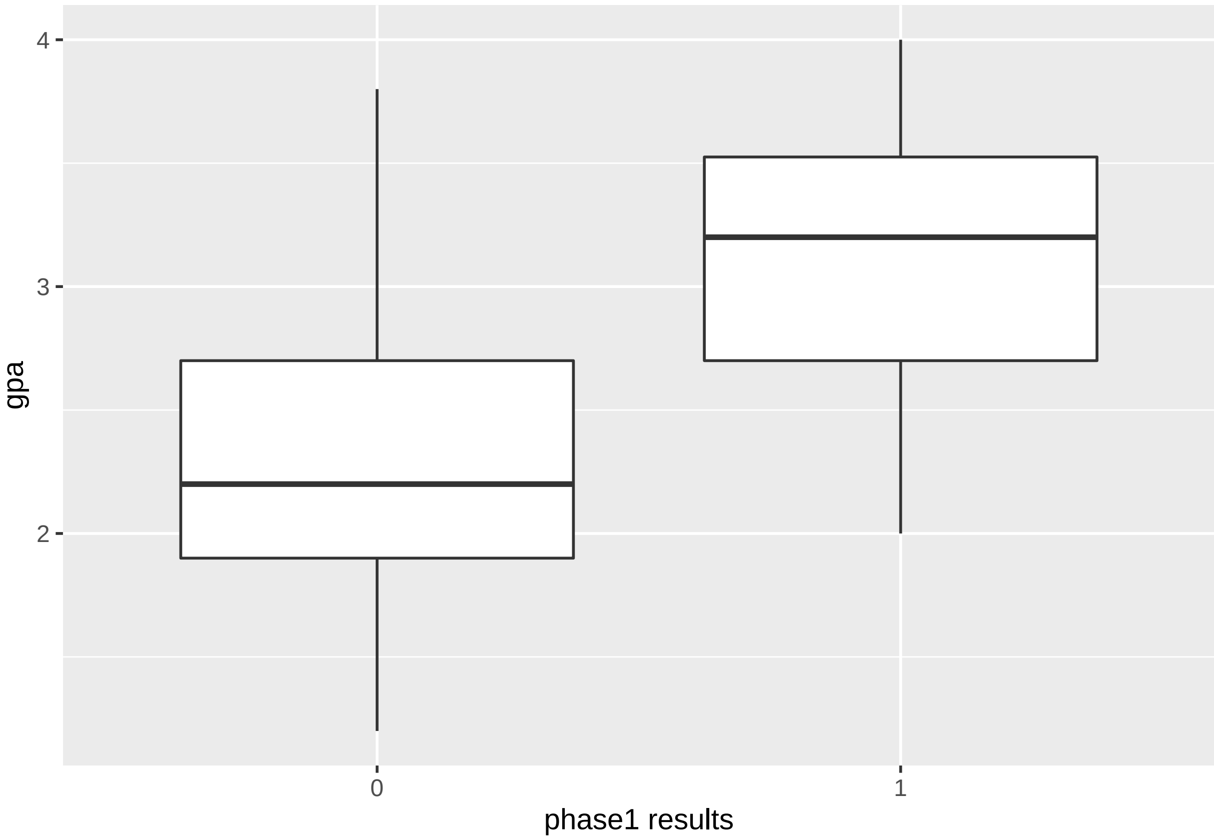


Figure 14: GPA Distribution Across Phase1 Results

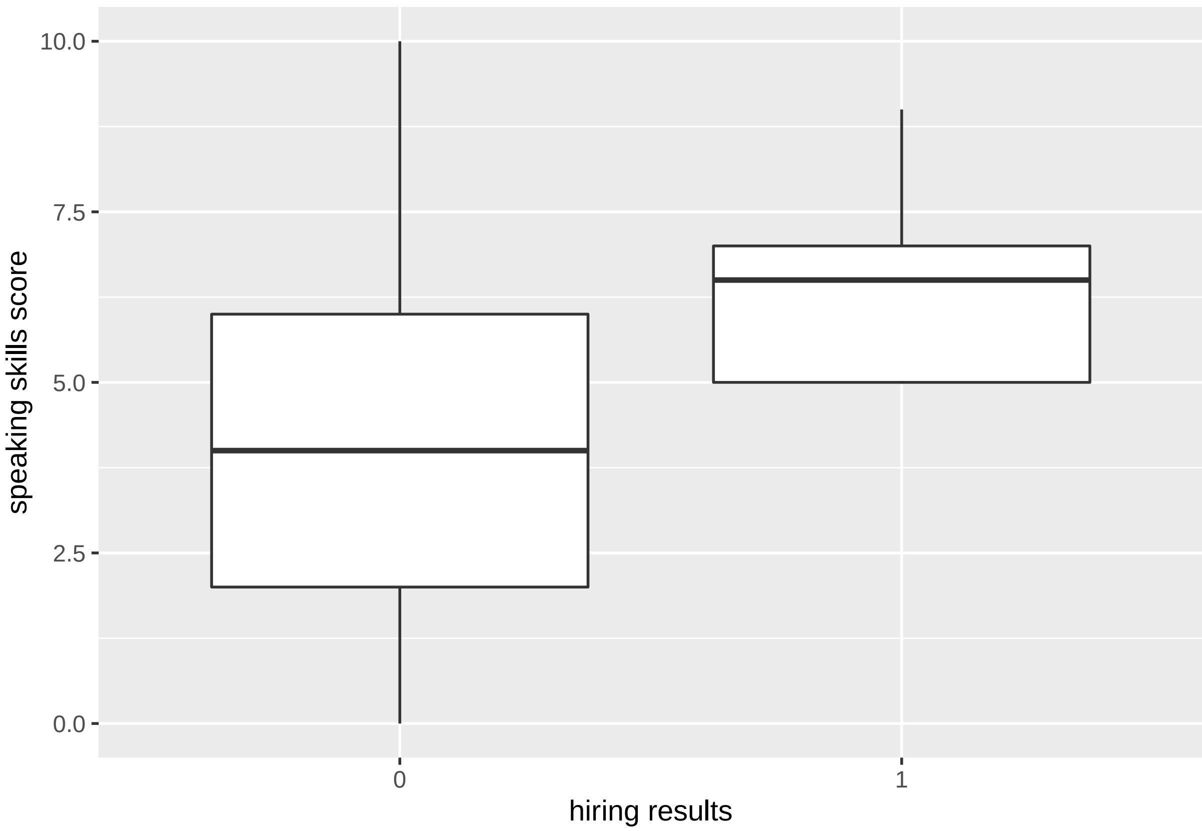


Figure 15: Speaking Skills Score Across Hiring Results

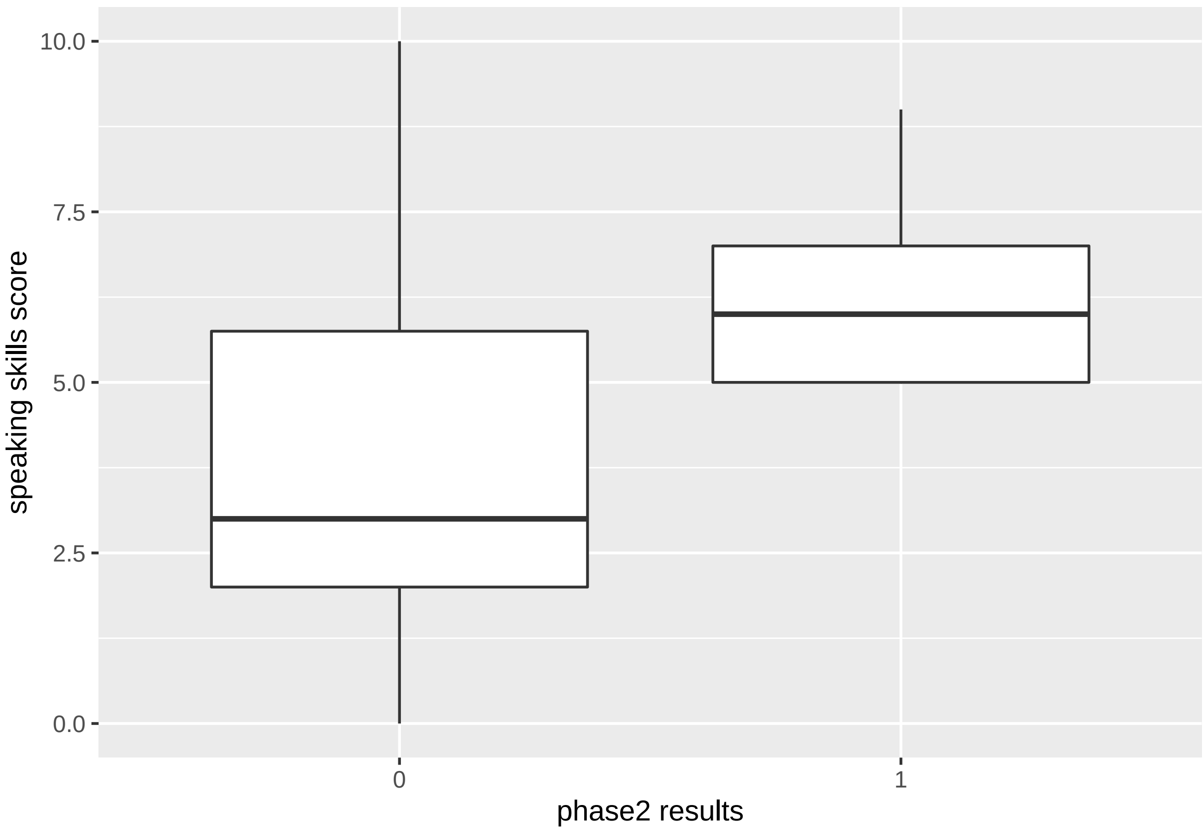
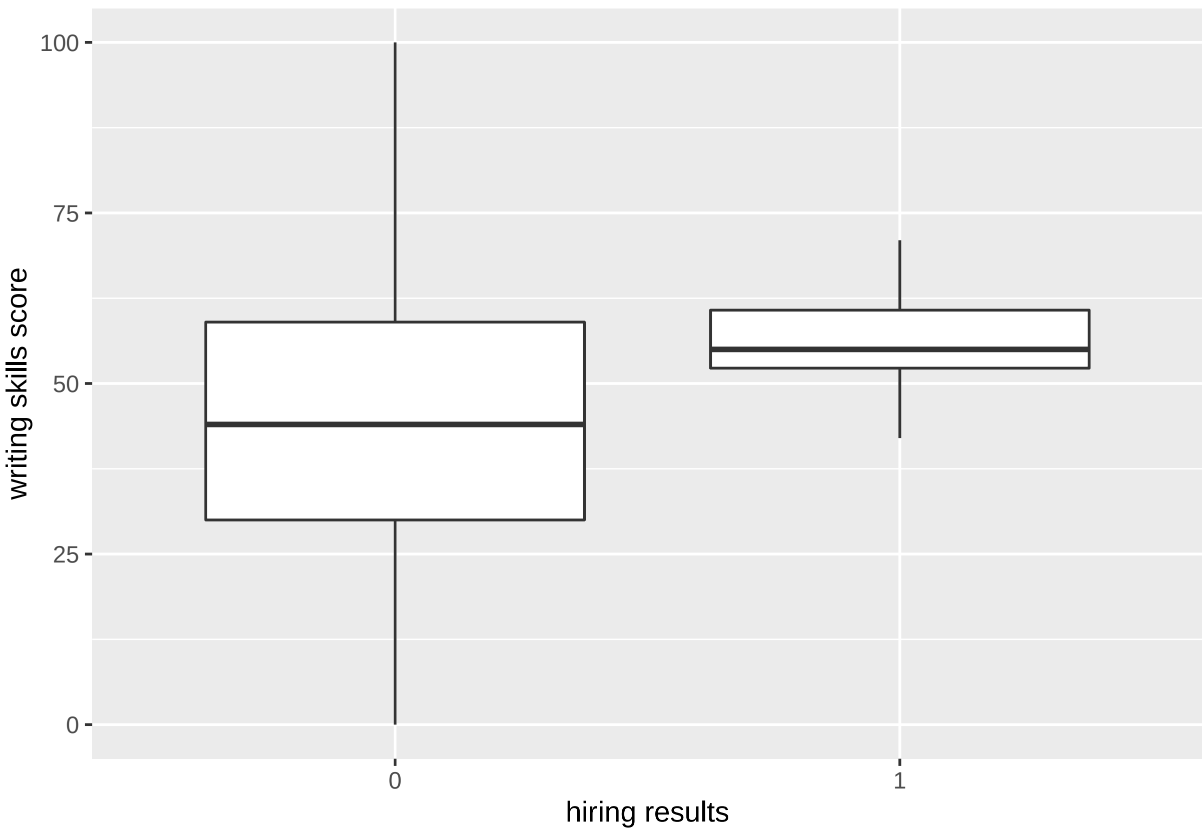
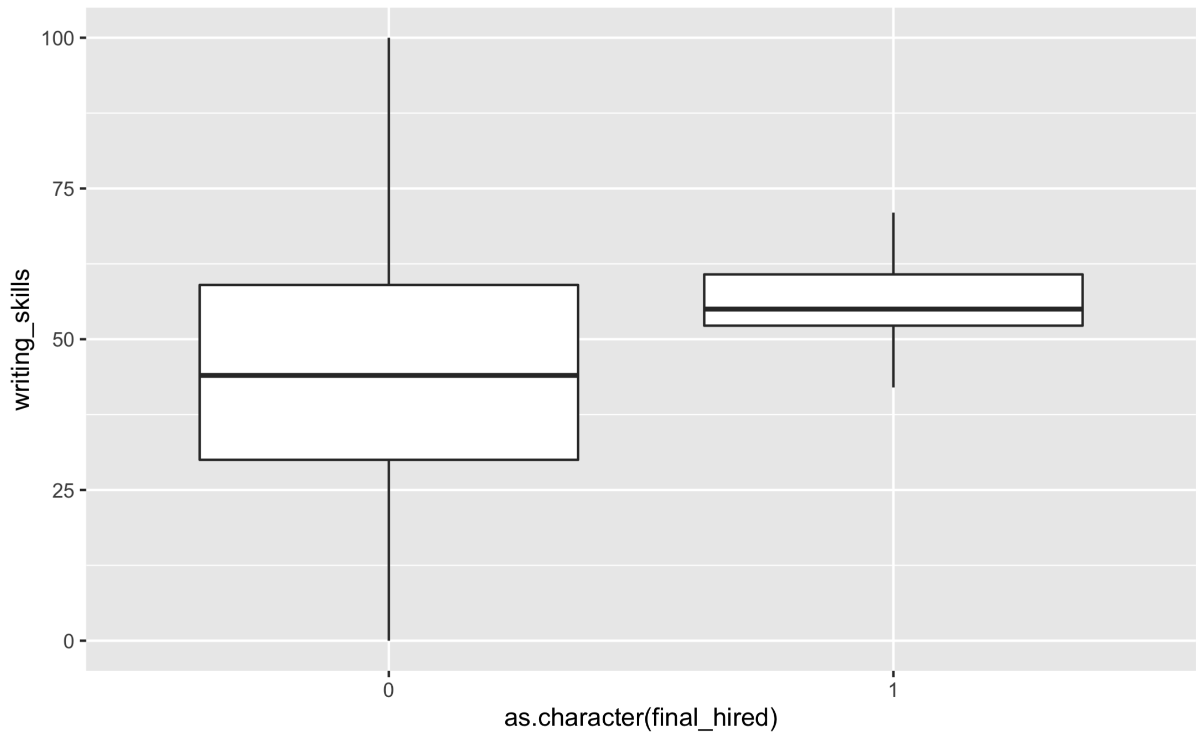
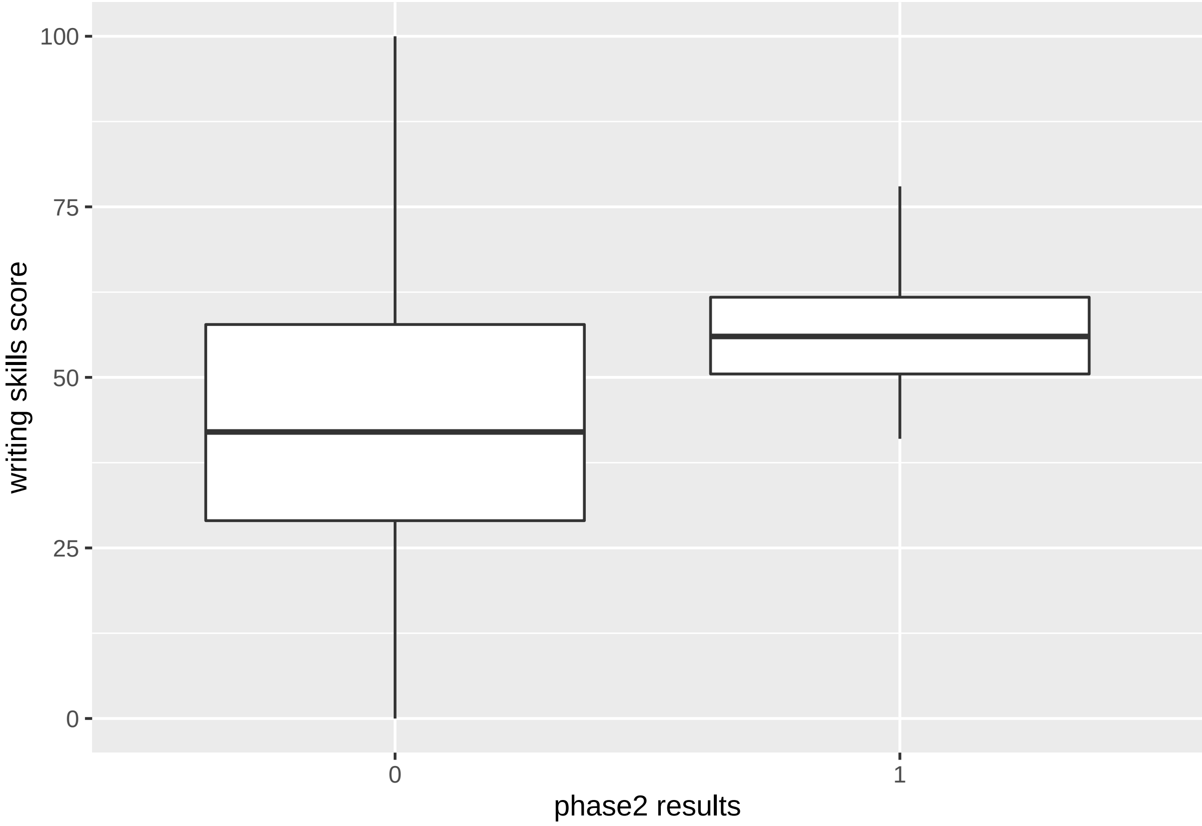


Figure 16: Speaking Skills Score Across Phase2 Results

Writing Skills VS if hired






writing skills score
100
75
50
25
0
0
1
phase2 results

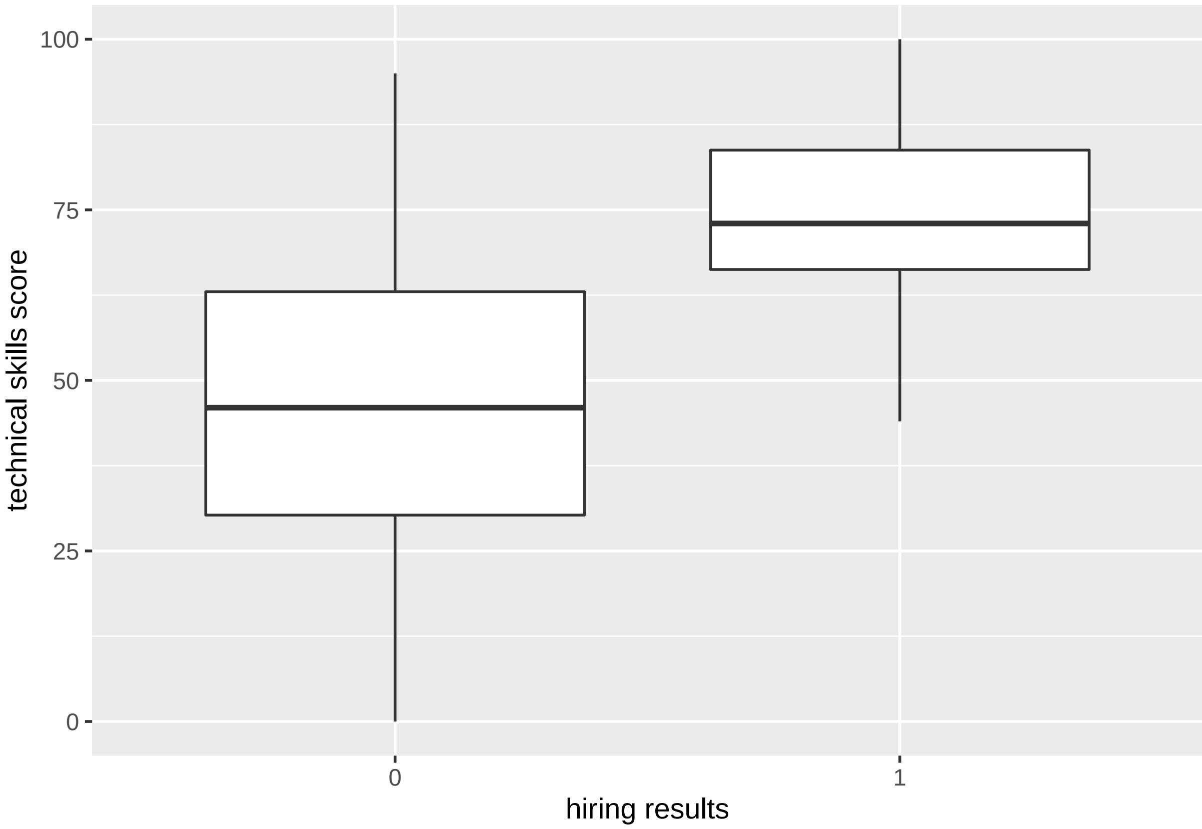
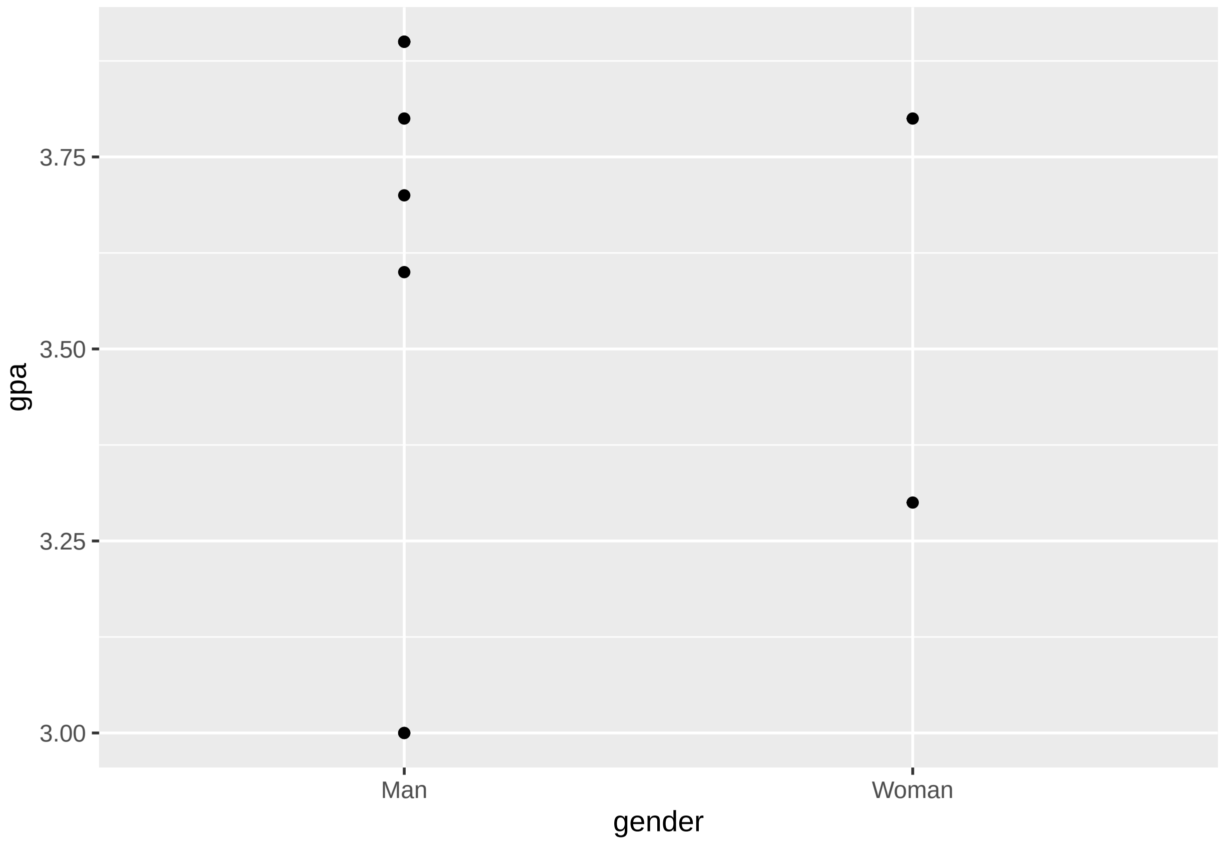
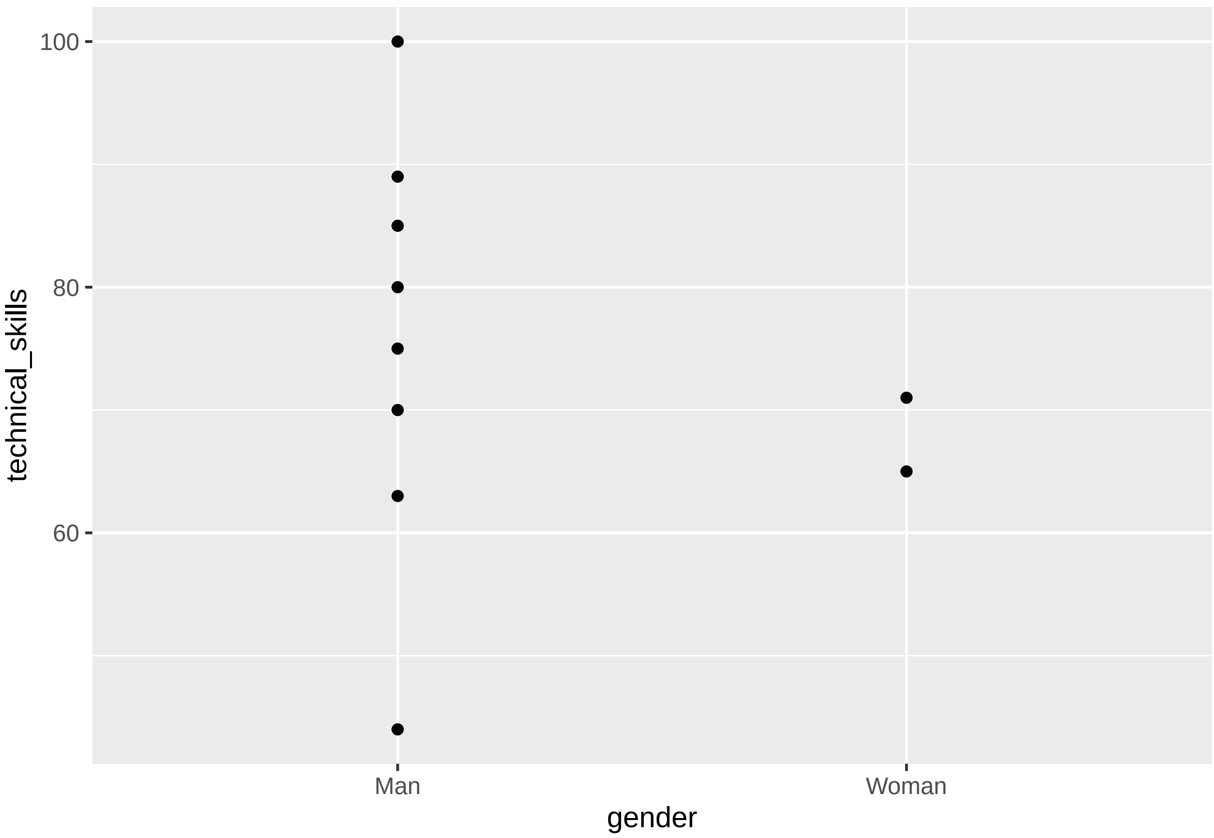
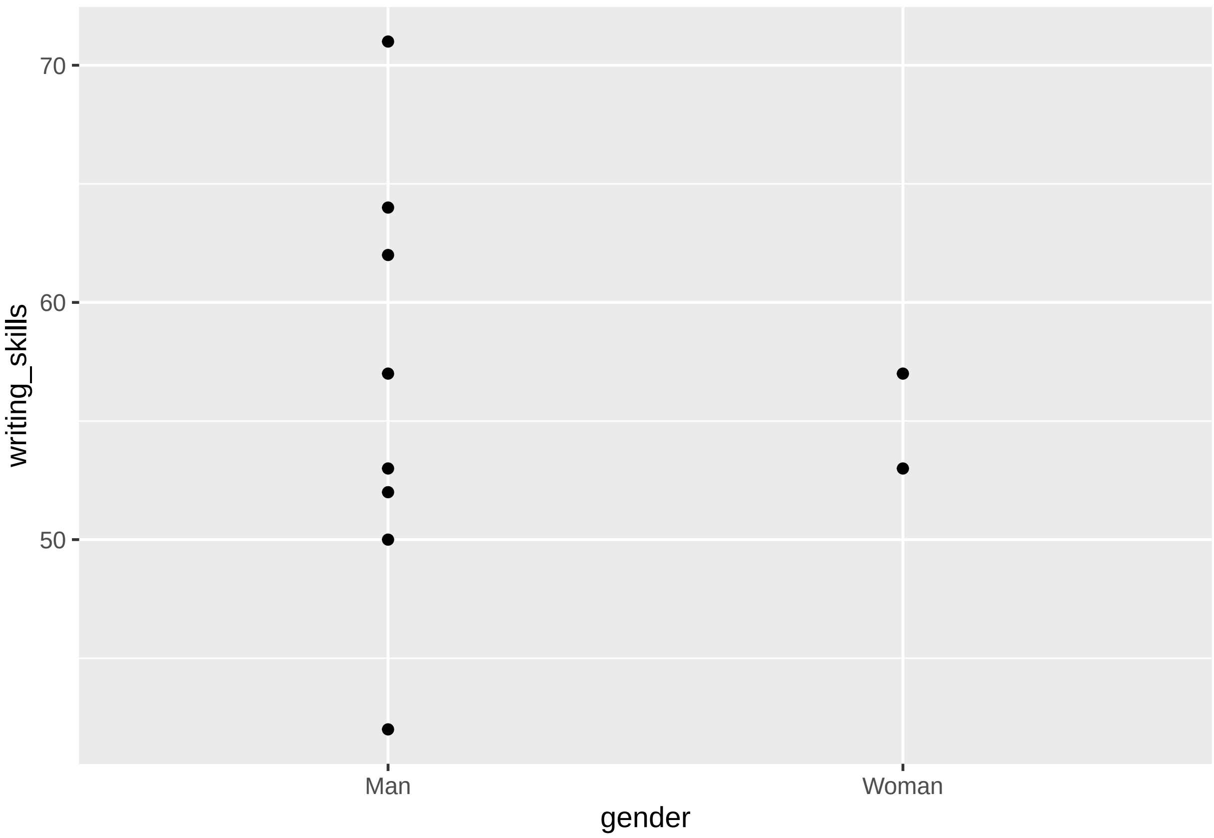
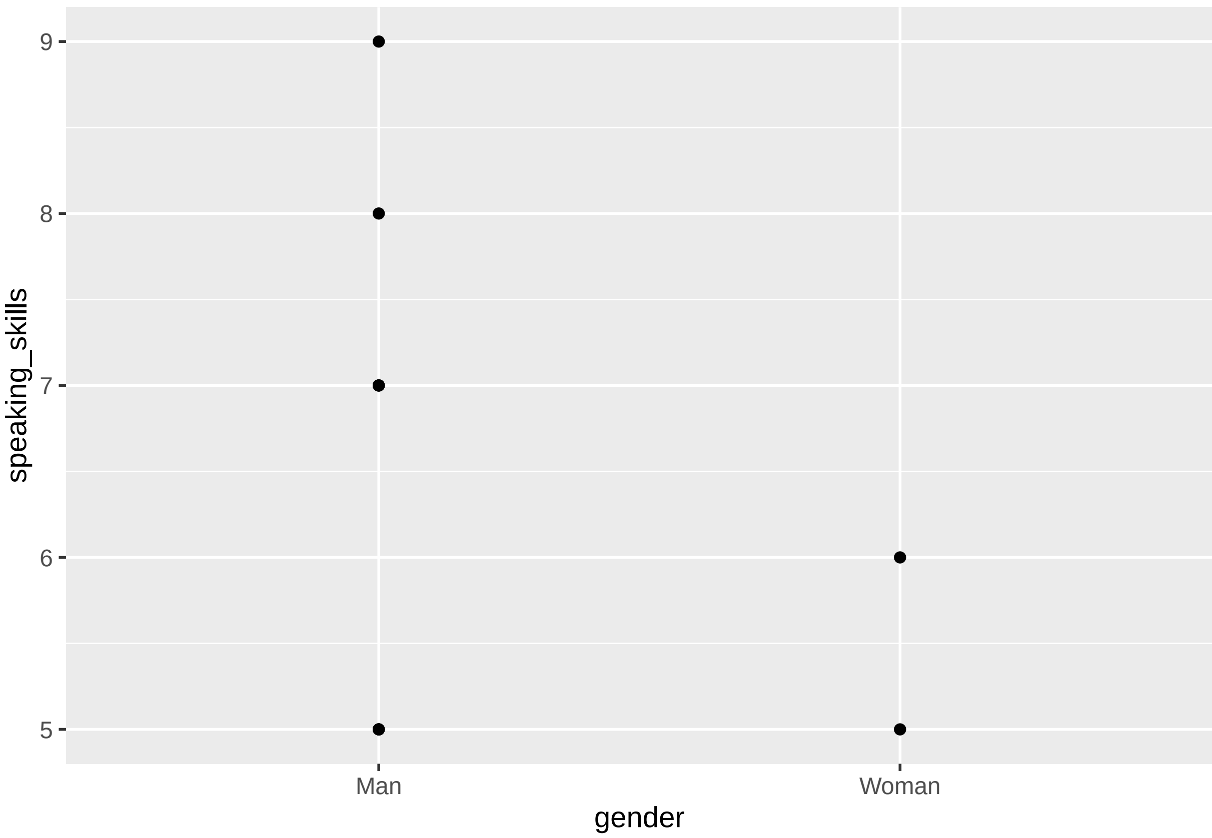


Figure 17: Technical Skills Score Across Hiring Results


3.75
3.50
3.25
3.00
gpa
Man
Woman
gender


100
80
60
technical_skills
Man
Woman
gender


70
60
50
writing_skills
Man
Woman
gender



Discussion

In this section you will summarize your findings across all the research questions and discuss the strengths and limitations of your work. It doesn't have to be long, but keep in mind that often people will just skim the intro and the discussion of a document like this, so make sure it is useful as a semi-standalone section (doesn't have to be completely standalone like the executive summary).

Strengths and limitations

- Dataset size tooooo small!! especially the final hired data and the phase 3 data (22 observations)

Consultant information

Consultant profiles

Rain Wu. Rain is a senior consultant with DataOverFlow. She specializes in data visualization. Rain earned her Bachelor of Science, Specialist in Statistics Methods and Practice, from the University of Toronto in 2022. Before joining DataOverFlow, Rain has 3 year of working experience as a data engineer at Aviva in Markham, Toronto.

Tina Wang. Tina is a junior consultant with DataOverFlow. She specializes in reproducible analysis. Tina earned her Bachelor of Science, Majoring in Computer Science and Statistics from the University of Toronto in 2022. Tina earned her master degree in financial insurance from the University of Toronto in 2024.

Yiqu Ding. Yiqu is a junior consultant with DataOverFlow. She specializes in statistical communication. Yiqu earned her Bachelor of Science, Majoring in Statistics and mathmatical application in finance and economics from the University of Toronto in 2022. Yiqu earned her master degree in financial insurance from the University of Toronto in 2024.

Code of ethical conduct

- We respect and protect confidential data obtained from, or relating to, clients and third parties, as well as personal data and information about about employees from Data Over Flow. We only share information when there is a business purpose, and then do so in accordance with applicable laws and professional standards.
- We take proactive measures to safeguard our archives, computers and other data-storage devices containing confidential information or personal data. We promptly report any loss, damage or inapproprita disclosure of confidential information or personal data.
- We use social media and technology in a responsible way and respect everyone we work with. We obtain, develop and protect intellectual capital in an appropriate manner. We respect the resrtictions on its use and reproduction.