Milestone 4 - R vs. Python Preference Analysis through the RStudio Community Survey

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1. Goal

The objective of this project is to utilize the information collected from the RStudio community survey to understand the factors influencing the preference for R or Python among people like data scientists. And predict the possible trend of preference of using R or Python in the future.

2. Data Source

The primary source of data is the annual R Community Survey conducted by RStudio, which is hosted on GitHub. Accessing this data requires cloning the GitHub repository where the survey results are stored. Initially, I intended to use the `use_git_clone()` function from the `usethis` package to get the contents of the repository, but after reading the package description, I found that this function has been removed in the latest version. So instead I used the `clone()` function from the `git2r` package. The data files are all in TSV format and provide comprehensive demographic information about the survey respondents and R usage patterns. However, the data set is not suitable for all types of analyses; for example, respondents' answers may be self-selected or biased towards more engaged community members, which is not always representative of the entire R user community.

Given the nature of the data, I chose to focus on specific aspects such as demographics, professional background, and specific R usage details across years. I pulled from multiple annual surveys and brought them together to create a comprehensive data set. Also, in order to process the multilingual results, I translated all Spanish-language questionnaires and their results so that they could be processed in English. The processed data set contains responses from several years and provides a solid basis for trend analysis within the R community. Additionally, because the survey questions varied from year to year, I had to assign different codes to process each year's results before they could be integrated. To columns that have not appeared in other data sets, I use NA values to fill them. Detailed data extraction and initial processing scripts can be found in Appendix 2.1.

To analyze survey data effectively, a function has been designed that offers various features to handle responses with considerable flexibility. This function includes the rm.na parameter, which dictates the treatment of NA values in the data set: setting rm.na = TRUE excludes NA values from the calculation, ensuring that percentages are based on non-missing responses only, whereas rm.na = FALSE includes them, reflecting the total number of responses including missing ones. Furthermore, the sort parameter controls the ordering of results; setting sort = TRUE will arrange the outcomes by their frequency, while sort = FALSE returns them in the order they appear in the data set.

Additionally, there's another function can split multiple answers separated by commas within a single response and aggregate these into a nested list format, facilitating detailed analysis of each individual component of the responses. This split-and-summarize approach is particularly useful for handling multiple-choice questions or questions allowing multiple responses. Moreover, the function provides a feature to extract the most frequently occurring responses, enabling users to focus on the top 'N' results, which can be particularly insightful for prioritizing key areas in data interpretation. This approach and its functionalities are detailed in Appendix 2.2 of the report.

3. Data Processing

As shown through the code below, there are a total of 75 attributes in the data set. Due to the specificity of the data being the result of a questionnaire, we can't be sure which columns are important at the beginning, so even though there are a lot of columns, we have to keep them instead of deleting them.

```
length(names(survey_combined))
```

```
## [1] 75
```

However, for the information collected in the data set, we have to do some processing. The first is the time information in the questionnaire, we need to convert the `Qtime` column in the `survey`, the purpose of which is to convert the original datetime string to a datetime object (of type `POSIXct` or `POSIXlt`) in R, so that it can be analysed at a later time, in particular, here we have specified that the time zone is the one of Auckland, New Zealand, and the before and after cases are as follows:

```
est <- locale(tz = "Pacific/Auckland")
survey_combined$Qtime <-
  parse_datetime(as.character(survey1$Qtime),
                 format = "%Y/%m/%d %H:%M:%S",
                 locale = est)
```

Before:

```
## [1] "2020-12-11 09:07:39 UTC" "2020-12-11 09:08:00 UTC"
## [3] "2020-12-11 09:08:55 UTC" "2020-12-11 09:11:57 UTC"
## [5] "2020-12-11 09:12:13 UTC" "2020-12-11 09:12:18 UTC"
```

After:

```
## [1] "2020-12-11 09:07:39 NZDT" "2020-12-11 09:08:00 NZDT"
## [3] "2020-12-11 09:08:55 NZDT" "2020-12-11 09:11:57 NZDT"
## [5] "2020-12-11 09:12:13 NZDT" "2020-12-11 09:12:18 NZDT"
```

In particular, in the 2019 survey data, the time data is formatted as MM-DD-YYYY, so it needs to be treated separately and specially so that the time format can be harmonised in the merger.

```
est <- locale(tz = "Pacific/Auckland")
survey_combined$Qtime <-
  parse_datetime(as.character(survey2$Qtime),
                 format = "%m/%d/%Y %H:%M:%S",
                 locale = est)
```

Before:

```
## [1] "12/13/2019 9:50:30"  "12/13/2019 9:50:38"  "12/13/2019 9:51:19"
## [4] "12/13/2019 9:53:51"  "12/13/2019 10:01:03" "12/13/2019 10:04:42"
```

After:

```
## [1] "2019-12-13 09:50:30 NZDT" "2019-12-13 09:50:38 NZDT"
## [3] "2019-12-13 09:51:19 NZDT" "2019-12-13 09:53:51 NZDT"
## [5] "2019-12-13 10:01:03 NZDT" "2019-12-13 10:04:42 NZDT"
```

Secondly, for the open text answers to the gender question in the questionnaire, we have to convert all the text to lower case to ensure that all the data can be processed in a consistent format. We also remove the whitespace before and after the strings to eliminate any extra spaces that may occur before and after the strings due to irregularities in typing. Finally, a regular expression `[[:punct:]]` is used to match any punctuation and replace it with an empty string to remove any punctuation that may affect subsequent text processing or analysis.

```
survey_combined$Qgender <-
  survey_combined$Qgender %>% tolower() %>% str_trim() %>%
  str_replace_all("[[:punct:]]", "")
opentext_gender_dictionary <-
  read_csv("dictionary/opentext_gender_dictionary.csv")
gender_dictionary <-
  opentext_gender_dictionary %>%
  mutate(Input = str_replace_all(Input, "[[:punct:]]", ""))
```

Before:

```
## [1] "Female"     "Non-binary" "Male"       "Male"       "male"
## [6] "Female"
```

After:

```
## [1] Female     Non-binary Male       Male       male       Female
## 202 Levels: "Gender" is sex stereotypes. "Identifying" with a gender reinforces regressive, sexist s
```

We do the same for race-related issues.

```
opentext_ethnicity_dictionary <-
  read_csv("dictionary/opentext_ethnicity_dictionary.csv")
ethnicity_dictionary <- opentext_ethnicity_dictionary %>%
  mutate(Input = str_replace_all(Input, "[[:punct:]]", ""))
```

Before:

```
## [1] "Asian"     "White"     "White"     "White"     "White"     "Ashkenazi"
```

After:

```
## [1] "Asian"     "White"     "White"     "White"     "White"     "Ashkenazi"
```

In addition, we are going to categorise each row in the survey according to the year in the Qr_year column and add or modify the learner_type column to reflect the type of learner. Depending on the year, learners will be categorised as Early Learners (between 1900 and 2016), Recent Learners (2017 and later) or Unknown (NA) at very old years (less than 1900).

```r
survey <- survey %>%
  mutate(learner_type = ifelse(
    Qr_year < 1900,
    NA,
    ifelse(Qr_year <= 2016, "Early Learner", "Recent Learner")
  ))
```

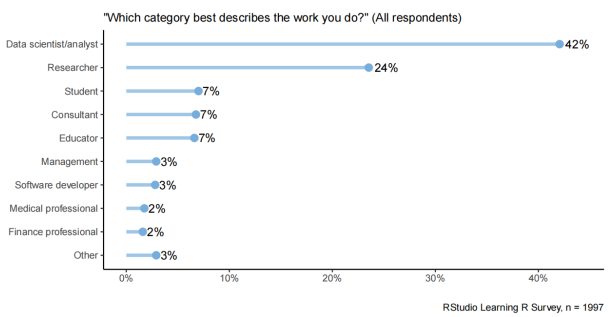
Sample:

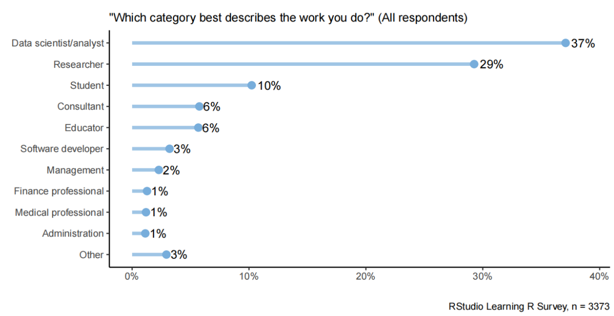
```
## [1] "Early Learner"  "Early Learner"  "Recent Learner" "Early Learner"
## [5] "Early Learner"  "Early Learner"
```

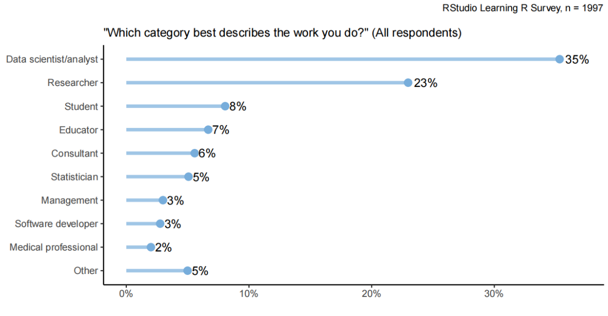
The full data processing code will be appended to 3.1.

4. Data Exploration

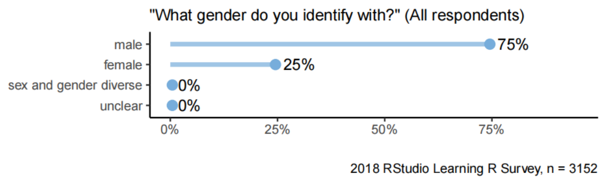
Since our main objective is to analyse and predict the preferences of a specific population for R or Python. Like analysing which groups of people prefer R, or which relevant factors play a bigger role in preferring R, based on survey data obtained in the last three years. So I'm going to start by looking at the types of work people do, and see which groups of people use R the most, so that I can see which groups of people are likely to have a larger share of influence on preferences. Therefore, in this section I will choose to look at the proportional relationship between the number of people using R and the occupations they are in, in the form of generating graphs for the three years from 2018 to 2020. The code of this part will be included in Appendix 4.1.

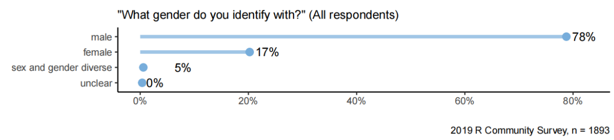


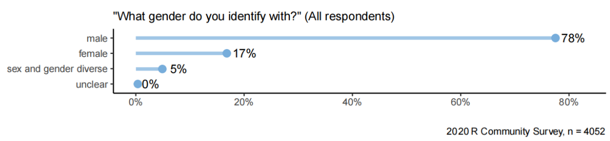




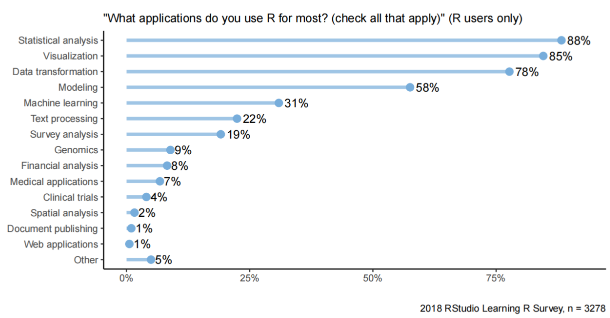
We can see that from 2018 to 2020 (listed from left to right), Data Scientists/Analysts are consistently the largest occupational group, with a percentage of 37% of the 3,373 respondents in the first chart, increasing to 42% of the 1,997 respondents in the second chart. Researchers had the second highest percentage in the first chart at 29 per cent, but dropped to 24 per cent in the second chart. The percentage of students, counsellors, and educators all declined as well. The percentage of management and software developers remained stable, while the percentage of healthcare professionals and financial professionals increased slightly. Overall, the increase in the percentage of data scientists/analysts suggests that their interest in learning about R may be on the rise, despite the decrease in the number of participants in the survey. Also, whether the preference is affected by gender differences is also a part that I find more valuable to explore, as gender differences may cause people to have different values and ways of thinking. Below are the charts of the preferences for R by gender.

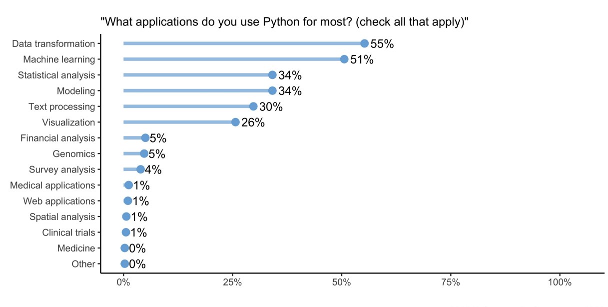


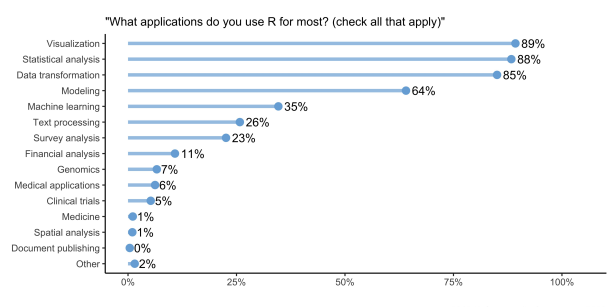


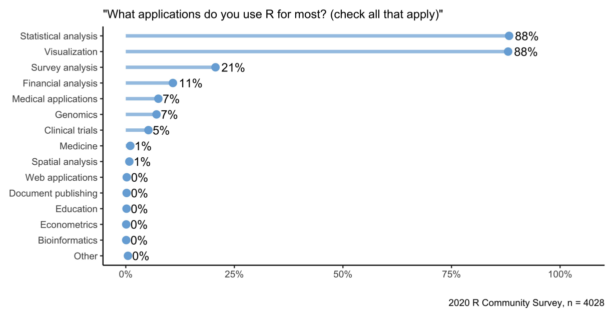


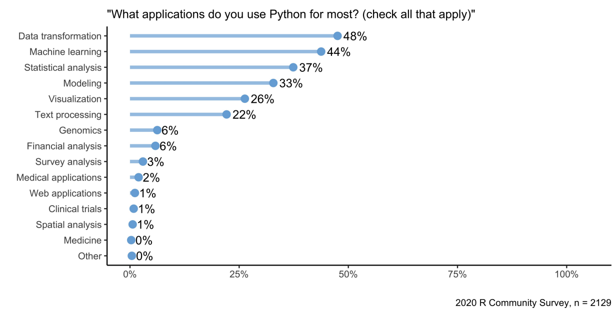
The R Community Survey, conducted between 2018 and 2020, showed that respondents who self-identified as male were in the majority in all years, increasing slightly from 75 per cent in 2018 to 78 per cent in 2019 and 2020. The proportion of female respondents decreased from 25 per cent in 2018 to 17 per cent in the latter two years. The gender and sexual diversity category begins to appear in 2019, accounting for 5 per cent in both that year and 2020, and was not listed in the 2018 survey. The number of respondents increased from 1,893 in 2019 to 4,052 in 2020, indicating a larger survey sample and a better understanding of gender diversity. The most critical, and I think the factor that determines whether or not people will use R over Python, is the degree of their preference for R to be used under a particular domain. If there is a higher preference for Python over R for a particular application (like data visualisation), then I think that means that people will favour Python in that domain.











Across the 2018 to 2020 surveys, R is most frequently used for statistical analysis and visualization, consistently scoring the highest among other applications. Machine learning shows a higher prevalence in Python usage compared to R. Data transformation is also common in both R and Python, but it ranks slightly higher in Python applications. Over the years, R maintains its stronghold in statistical analysis and visualization while Python is preferred for machine learning tasks. There's an observed drop in the percentage of users applying R for data transformation from 2018 to 2020, while Python's use for data transformation has also declined slightly in 2020.

5. Analytical Plan

(Implementation is shown in the results section - 6.)

The next phase of the analysis is to extend our examination of RStudio community survey data to better understand the evolving preferences for R and Python. This involves detailed statistical modeling and predictive analytics to ascertain how demographic factors, industry participation, and programming experience influence language preference. The predictors includes responses from a diverse set of participants, varying across industry(`Qindustry`), gender(`Qgender`), experience with R(`Qr_experience`), their title as well as work title(`Qtitle`, `Qwork_title`) and the year they started learning R(`Qr_year`).

First, we will create a new binary outcome, `Prefer`, based on a weighted evaluation of respondents' enjoyment and recommendation of R compared to Python. This nuanced view will provide insights beyond mere usage metrics.

Secondly, to address the analytical challenges, we will build a random forest model using the `ranger` package, which is robust to categorical data and capable of modeling complex interactions and nonlinear relationships.

Next, to make comparisons in the performance of different models. I'll use the `rpart` package to build a decision tree model and use the `tensorflow` package to build a model based on the neural network based on the same predictors. After that, we can find out which model performs the best.

Finally, a logistic regression model will be used to analyze the effect of time on language preferences. By converting the `Qtime` variable into a numeric format representing the year, this model will help reveal trends in preference over time.

6. Results

Each of these predictors has been transformed into factors to ensure they are appropriately treated in the modeling process. Missing values within key categorical variables were replaced with randomly selected non-missing values from the same column to maintain the integrity of the model results. The random seed was set to ensure reproducibility of the random replacements. The code for doing this is attached to Appendix 6.1.

One significant enhancement in our approach is the creation of a new binary outcome, `Prefer`. This outcome is based on a weighted evaluation of respondents' enjoyment, recommendation, and usage frequency of R compared to Python, giving us a nuanced view of preference beyond mere usage metrics. The weightage formula used leverages enjoyment and usage frequency more than recommendation, reflecting a more experiential bias towards language preference. `Enjoyment`, which assesses how much users enjoy using R or Python, is considered highly influential in determining overall preference. It is weighted at 50% (0.5). This higher weighting reflects the hypothesis that personal satisfaction and pleasure derived from using a language can significantly influence one's preference. `Usage frequency` measures how often respondents use R or Python, and it is weighted at 30% (0.3). This reflects the idea that frequent usage indicates a higher comfort level and preference for the language. I encode the data from `Q_r_how_often_used` and `Qpython_use` to get the frequency. The coding for usage frequency is as follows: "More than once a day": 1.0, "Between once a day and once a week": 0.75, "Between once a week and once a month": 0.5, "Less than once a month": 0.25, "I don't use R/Python any more": 0, For any situation else: randomly pick one from [0, 0.25, 0.5, 0.75, 1]. `Recommendation`, which measures the likelihood of respondents recommending R or Python to others, is given a slightly lower weight of 20% (0.2), under the assumption that while recommendation is important, it might be more influenced by external factors such as community support or industry trends, rather than personal preference. If the weighted sum for R is greater than or equal to the weighted sum for Python, then `Prefer` is set to 1. This indicates a preference for R over Python. Conversely, if the weighted sum for R is less than the weighted sum for Python, `Prefer` is set to -1, indicating a preference for Python. The code for this calculation is attached to Appendix 6.2.

Here I split the data into train and test sets, and implement a random forest model below. The code of generating this model will be attached to Appendix 6.3.

```
colnames(survey_combined) <- make.names(colnames(survey_combined))
train_idx <- sample(nrow(survey_combined), 0.8*nrow(survey_combined))
train_data <- survey_combined[train_idx, ]
test_data <- survey_combined[-train_idx, ]
```

Random Forest

```
## Ranger result
##
## Call:
##  ranger(Prefer ~ Qr_experience + Qindustry + Qr_year + Qgender +      Qtitle + Qwork_title, data = t
##
## Type:                             Classification
## Number of trees:                  500
## Sample size:                      6812
## Number of independent variables:  6
## Mtry:                             2
## Target node size:                 1
## Variable importance mode:         impurity
## Splitrule:                        gini
## OOB prediction error:             3.88 %
```

```
## Qr_experience     Qindustry       Qr_year       Qgender        Qtitle
##      29.89356      67.82344      62.20107      35.38974     152.28526
##   Qwork_title
##      51.16764
```

```
##       pred
## actual   -1    1
##     -1    1   71
##     1     1 1631
```

```
## [1] "Random Forest Accuracy: 0.957746478873239"
```

The Random Forest model performed very well in classifying the Prefer variable with high accuracy (95.60%). In all the predictions, only a few negative categories (-1) were misclassified as positive (1) and similarly a few positive categories (1) were misclassified as negative (-1). `Qtitle` variable contributed the most to the model, followed by `Qindustry` and `Qr_year`, which played a key role in the prediction of Prefer. `Qgender` had a lesser impact on the results. The next is Tree model. The code of generating this model will be attached to Appendix 6.4.

Tree

```
##        Qtitle     Qindustry       Qr_year       Qgender    Qwork_title
##   153.7614522    16.0630106    15.3639997    11.3385077     10.7336860
## Qr_experience
##     0.7913386
```

```
##       pred
## actual   -1    1
##     -1    2   70
##     1    14 1618
```

```
## [1] "Tree Accuracy: 0.950704225352113"
```

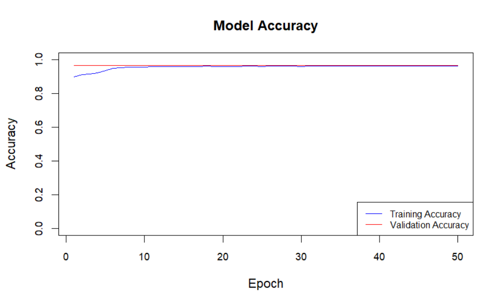
The decision tree model also showed `Qtitle` as the most important variable compared to the random forest model. However, the Random Forest model performed better in terms of variable importance scores and classification accuracy, especially in terms of higher variable importance scores and lower misclassification rates. `Qgender` still does not play a significant role in it. The next is a neural network model. The code of generating this model will be attached to Appendix 6.5.

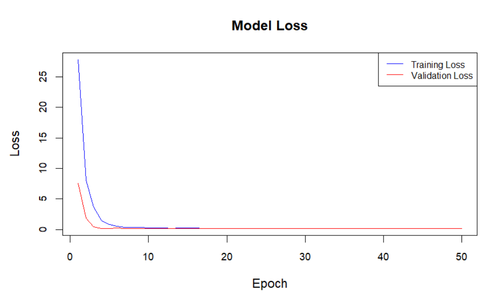
Neural Network

In the data preprocessing stage, use `mutate_if` to convert factor and character variables to numeric types to suit the input requirements of the neural network. The neural network model consists of the following components: Input layer: has the same number of nodes as the number of input features. Hidden layer: the first layer has 64 nodes, the activation function is relu and a dropout of 40% is used to prevent overfitting. The second layer has 32 nodes with an activation function of relu and a dropout of 30%. Output layer: 3 nodes, corresponding to the triple classification task, with a softmax activation function. When compiling the model, sparse_categorical_crossentropy is used as the loss function, since the target variable is a category label in integer form. The optimiser is chosen as adam, which is an adaptive learning rate optimisation algorithm for dealing with complex neural network models. The evaluation metric is chosen as accuracy. When training the model, the number of training rounds (epochs) is set to 50, the batch size is set to 32, and the validation split is set to 20%.

```
## 54/54 - 0s - 465us/step - accuracy: 0.9577 - loss: 0.1778
```

```
## [1] "Neural Network Accuracy: 0.957746505737305"
```





The result is better than the Random Forest model and the decision tree model, and the fitting is fast in no more than 15 epochs.

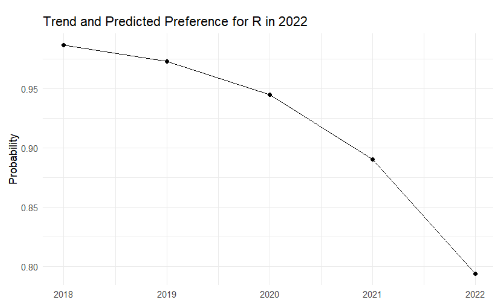
Logistic Regression

Further, a logistic regression model was used to analyze the effect of time on language preferences. By converting the `Qtime` variable into a numeric format that represents the year, we incorporated this as a predictor in our logistic regression model. This model revealed a strong negative trend in the preference for R over time, suggesting a potential shift towards Python as years progress. The code of the model will be in Appendix 6.6.

```
##
## Call:
## glm(formula = Prefer ~ YearFromTime, family = binomial(), data = survey_combined)
##
## Coefficients:
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)  1509.01854  126.01086   11.97   <2e-16 ***
## YearFromTime   -0.74563    0.06239  -11.95   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2805.3  on 8515  degrees of freedom
## Residual deviance: 2642.0  on 8514  degrees of freedom
## AIC: 2646
##
## Number of Fisher Scoring iterations: 6

## [1] "Predicted probability of preferring R in 2022: 0.793943991117411"
```

Predictive analytics were then employed to forecast preferences for 2022. The logistic model's results indicated a notable decline in preference for R, projecting a significant likelihood of preferring R in 2022 at around 79.3%. This suggests a stabilization or slight rebound in preference for R despite previous declines, potentially due to evolving features or community dynamics. The plot code will be in Appendix 6.7.



Visualization of these trends was performed using ggplot2, highlighting the decline and the predicted stabilization in R preference. This visual representation not only confirms the numerical findings but also provides an easily interpretable view of how preferences might shift in the near future.

7. Disscussion

In our analysis of the RStudio community survey data to discern preferences for R versus Python, several strengths and limitations are evident, each influencing our ability to effectively meet the project goals.

Strengths:

Comprehensive Demographic and Professional Data: The dataset includes a wide range of demographic and professional background information, which enables a detailed cohort analysis across different industry sectors and experience levels. This richness in data allows us to identify nuanced patterns and preferences among various subgroups.

Weighted Preference Calculations: By incorporating a weighted evaluation of respondents' enjoyment, recommendation, and usage frequency of R compared to Python, our approach provides a more nuanced view of preference. This method goes beyond mere usage metrics, enabling a more refined understanding of language favorability.

Temporal Dimension: The dataset spans several years, allowing for a robust analysis of trends over time. This temporal aspect helps us understand how preferences have evolved and can provide insights into future trends.

Variety of Analytical Methods: We employed various analytical methods, including random forest, decision tree, and neural network models. Each method offers unique strengths in handling the data, providing different perspectives on the factors influencing language preference.

Limitations:

Self-Selection Bias: The dataset is derived from a self-selected group of survey respondents, potentially introducing a bias toward those more engaged in the RStudio community or more passionate about programming languages. This may not be representative of the broader population of users, skewing the preference data towards more experienced users or those with specific professional inclinations.

Data Imputation and Translation: The translation of responses from Spanish and the handling of open-ended responses introduce complexities in data consistency and interpretation. Missing data, particularly in key variables like Qr_enjoyment and Qrecommend, needed to be imputed, which can affect the accuracy of the derived preference indicator.

Binary Outcome Simplification: The binary outcome created for logistic regression (prefer R over Python) simplifies the complex continuum of preference and may not capture subtler shifts in attitudes. This reduction can lead to an oversimplified understanding of preferences, missing out on more granular insights.

Survey Design Changes: Annual changes in survey design and question phrasing can impact the comparability of data year-over-year. Such changes can complicate trend analyses and longitudinal studies, as differences in survey design may introduce variability that is not related to actual changes in preferences.

Potential Overfitting: The high accuracy of models like the random forest and neural network may indicate potential overfitting, particularly if the models are not sufficiently validated. Overfitting can lead to models that perform well on training data but poorly on unseen data.

In summary, while the RStudio community survey data provides a rich and detailed source of information for analyzing preferences for R versus Python, careful consideration of its limitations is essential. Addressing these limitations through robust data handling and validation techniques is crucial for deriving accurate and generalizable insights from the analysis.

8. Conclusion

Overall, my project successfully analyzed preferences for R versus Python using the RStudio community survey data. The detailed cohort analysis and weighted preference calculations provided nuanced insights into language favorability, revealing interesting trends over time.

However, prediction models, while showing high accuracy, faced limitations like potential overfitting and simplification of preferences into a binary outcome. In the future, using penalized regression models or advanced neural network architectures could improve prediction accuracy and robustness.

This project lays a strong foundation for further research into programming language preferences, offering valuable insights for more sophisticated analyses with larger datasets.

Appendices

2.1 Acquisition and integration of survey data:

```
library(choroplethr)
library(choroplethrMaps)
data(country.map)
library(tidyverse)
library(RColorBrewer)
library(gendercodeR)
library(ggrepel)
library(git2r)

#obtaining the GitHUb repository
path <- file.path("r-community-survey")
dir.create(path, recursive = TRUE)
repo <-
  clone("https://github.com/rstudio/r-community-survey.git", path)

#data of Year 2020
survey1_name <- "2020 R Community Survey"
column_formats1 <- cols(
  Qtime1 = col_datetime(),
  Qr_experience1 = col_character(),
  Qhow_to_learn_r1 = col_character(),
  Qreason_to_learn1 = col_character(),
  Qr_use1 = col_character(),
  Qtools1 = col_character(),
  Qobstacles_to_starting1 = col_character(),
  Qr_year1 = col_double(),
  Qr_learning_path1 = col_character(),
  Qr_reason_experienced1 = col_character(),
  Qmost_difficult_aspect1 = col_character(),
  Qr_how_often_used1 = col_character(),
  Qr_OS1 = col_character(),
  Qused_for1 = col_character(),
  Qr_enjoyment1 = col_double(),
  Qrecommend1 = col_double(),
  Qtools_with_r1 = col_character(),
  Qtidyverse_learning1 = col_character(),
  Qtidyverse_today1 = col_character(),
  Qlike_best1 = col_character(),
  Qlike_least1 = col_character(),
  Qr_problems1 = col_character(),
  Qr_discover_packages1 = col_character(),
  Qr_share1 = col_character(),
  Qr_change1 = col_character(),
  Qrobot_test1 = col_character(),
  Qrmarkdown1 = col_character(),
  Qrmarkdown_apps1 = col_character(),
  Qrmarkdown_change1 = col_character(),
  Qshiny1 = col_character(),
  Qshiny_use1 = col_character(),
  Qshiny_change1 = col_character(),
```

```
  Qpython_use1 = col_character(),
  Qpython_apps1 = col_character(),
  Qpython_tools1 = col_character(),
  Qpython_enjoy1 = col_double(),
  Qpython_recommend1 = col_double(),
  Qpython_change1 = col_character(),
  Qcoding_languages1 = col_character(),
  Qfirst_language1 = col_character(),
  Qyear_born1 = col_double(),
  Qgender1 = col_character(),
  Qethnicity1 = col_character(),
  Qdegree1 = col_character(),
  Qcountry1 = col_character(),
  Qindustry1 = col_character(),
  Qtitle1 = col_character(),
  Qwork_title1 = col_character(),
  Qteam_r_users1 = col_character(),
  Qr_community1 = col_character(),
  Qevents1 = col_character(),
  Qhear1 = col_character(),
  language1 = col_character()
)
survey_raw1 <- read_tsv("./data/2020-combined-survey-final.tsv",
                        col_types = column_formats1)
survey_questions1 <-
  read_tsv(("./data/2020-combined-survey-names.tsv")) %>%
  select("Question_name" = english_name, "Question_text" = english)
respondents_raw1 <- nrow(survey_raw1)
survey_non_robot1 <- survey_raw1 %>%
  mutate(robot_test1 = ifelse(!is.na(Qrobot_test), tolower(Qrobot_test), NA))
survey1 <- survey_non_robot1 %>%
  filter(!is.na(robot_test1)) %>%
  filter(
    robot_test1 == "5" |
      str_detect(robot_test1, "five") |
      robot_test1 == "cinco" | robot_test1 == "fife"
  )
respondents1 <- nrow(survey1)
survey_save1 <- survey1


#data of Year 2019
survey_name2 <- "2019 R Community Survey"
column_formats2 = cols(
  Qtime = col_character(),
  Qr_experience = col_character(),
  Qr_difficulty = col_double(),
  Qr_length_to_success = col_character(),
  Qhow_to_learn_r = col_character(),
  Qreason_to_learn = col_character(),
  Qr_use = col_character(),
  Qtools = col_character(),
  Qobstacles_to_starting = col_character(),
```

```
  Qr_year = col_double(),
  Qr_learning_path = col_character(),
  Qr_difficulty = col_double(),
  Qtime_to_proficiency = col_character(),
  Qreason_to_learn = col_character(),
  Qmost_difficult_aspect = col_character(),
  Qr_how_often_used = col_character(),
  Qused_for = col_character(),
  Qr_enjoyment = col_double(),
  Qrecommend = col_double(),
  Qtools_with_r = col_character(),
  Qtidyverse_learning = col_character(),
  Qtidyverse_today = col_character(),
  Qlike_best = col_character(),
  Qlike_least = col_character(),
  Qr_problems = col_character(),
  Qr_discover_packages = col_character(),
  Qr_share = col_character(),
  Qr_change = col_character(),
  Qrobot_test = col_character(),
  Qrmarkdown = col_character(),
  Qrmarkdown_apps = col_character(),
  Qrmarkdown_change = col_character(),
  Qshiny = col_character(),
  Qshiny_change  = col_character(),
  Qpython_use = col_character(),
  Qpython_apps = col_character(),
  Qpython_enjoy = col_double(),
  Qpython_recommend = col_double(),
  Qpython_change = col_character(),
  Qlanguages  = col_character(),
  Qfirst_language = col_character(),
  Qyear_born = col_double(),
  Qgender  = col_character(),
  Qethnicity  = col_character(),
  Qdegree  = col_character(),
  Qcountry  = col_character(),
  Qindustry  = col_character(),
  Qtitle  = col_character(),
  Qwork_title  = col_character(),
  Qteam_r_users = col_character(),
  Qevents  = col_character(),
  Qhear  = col_character()
)
english_column_names <-
  read_tsv("./data/survey-questions-2019-en.tsv")
english_survey <-
  read_tsv(
    file = "./data/2019 English R Community Survey Responses.tsv",
    col_types = column_formats2,
    col_names = english_column_names$Question_name,
    skip = 1
  )
```

```
names(english_survey) <- english_column_names$Question_name
english_survey$language <- "English"
spanish_survey <-
  read_tsv(
    "./data/2019 Spanish R Community Survey Responses.tsv",
    col_types = column_formats2,
    col_names = english_column_names$Question_name,
    skip = 1
  )
names(spanish_survey) <- english_column_names$Question_name
spanish_survey$language <- "Spanish"
survey_raw2 <- rbind(english_survey, spanish_survey)
survey_questions2 <-
  read_tsv("./data/survey-questions-2019-en.tsv")
respondents_raw2 <- nrow(survey_raw2)
survey2 <- survey_raw2 %>%
  mutate(robot_test = str_to_lower(Qrobot_test)) %>%
  filter(!is.na(robot_test)) %>%
  filter(robot_test == "8" |
           robot_test == "eight" | robot_test == "ocho")
respondents2 <- nrow(survey2)
survey_save2 <- survey2

#data of Year 2018
survey_name3 <- "2018 RStudio Learning R Survey"
column_formats3 = cols(
  Qtime = col_datetime(format = ""),
  Qindustry = col_character(),
  Qtitle = col_character(),
  Qwork_title = col_character(),
  Qlanguages = col_character(),
  Qfirst_language = col_character(),
  Qr_experience = col_character(),
  Qr_year = col_double(),
  Qtime_to_proficiency = col_character(),
  Qr_learning_path = col_character(),
  Qreason_to_learn = col_character(),
  Qr_use = col_character(),
  Qr_length_to_success = col_character(),
  Qr_difficulty = col_double(),
  Qr_reason_experienced = col_character(),
  Qr_how_often_used = col_character(),
  Qr_enjoyment = col_double(),
  Qr_difficulty_experienced = col_double(),
  Qtidyverse_learning = col_character(),
  Qtidyverse_today = col_character(),
  Qshiny = col_character(),
  Qunit_tests = col_character(),
  Qlike_best = col_character(),
  Qlike_least = col_character(),
  Qrecommend = col_double(),
  Qused_for = col_character(),
  Qmost_difficult_aspect = col_character(),
```

```
  blank_question = col_character(),
  Qnot_live_without = col_character(),
  Qcapability_missing = col_character(),
  Qtools = col_character(),
  Qchange_one_thing = col_character(),
  Qyear_born = col_double(),
  Qgender = col_character(),
  Qcountry = col_character(),
  Qethnicity = col_character(),
  Qdegree = col_character(),
  Qteam_r_users = col_double(),
  Qversion_control = col_character(),
  Qtools_with_r = col_character(),
  Qobstacles_to_starting = col_character(),
  Qbiggest_difficulty = col_character(),
  Qhow_to_learn_r = col_character(),
  learner_type = col_character(),
  Qgender_coded = col_character(),
  Qethnicity_processed = col_character(),
  Qethnicity_coded = col_character(),
  number_responses = col_double()
)
english_survey <- read_tsv("data/survey_English.tsv",
                           col_types = column_formats3)
english_survey$language <- "English"
spanish_survey <- read_tsv("data/survey_Spanish.tsv",
                           col_types = column_formats3)
spanish_survey <- spanish_survey %>% select(-blank2_question)
spanish_survey$language <- "Spanish"
survey3 <- rbind(english_survey, spanish_survey)
survey_questions3 <- read_csv("data/survey_questions.csv")
respondents3 <- nrow(survey3)

#data set merge
library(plyr)
survey_combined <- rbind.fill(survey1, survey2, survey3)
```

2.2 Multiple functions used to pre-process survey data:

```
# This tallies up the results for a question
# rm.na = TRUE to calculate percentages based on non-NA results; set to FALSE
# to include NAs
# set sort = TRUE sorts the result by count; set to FALSE to return in whatever
# order they occur
tally_question <-
  function(df,
           question_name,
           rm.na = TRUE,
           sort = TRUE) {
    quoted_question <- enquo(question_name)
    filtered_df <- df
    if (rm.na) {
      filtered_df <- filtered_df %>%
```

```r
        filter(!is.na(!!quoted_question))
    }
    results_df <- filtered_df %>%
      count(!!quoted_question, sort = sort) %>%
      add_tally(n, name = "nn") %>%
      mutate(percent = round(n / nn * 100, 1),
             prop_responses = n / nn)
    return(results_df)
  }
# This tallies up the results for a question
# rm.na = TRUE to calculate percentages based on non-NA results; set to
# FALSE to include NAs
# set sort = TRUE sorts the result by count; set to FALSE to return in whatever
# order they occur
tally_question_by_question <-
  function(df,
           question_name,
           by_question_name,
           # column name to group by
           rm.na = TRUE,
           sort = TRUE) {
    quoted_question <- enquo(question_name)
    quoted_by_question <- enquo(by_question_name)
    filtered_df <- df
    if (rm.na) {
      filtered_df <- filtered_df %>%
        filter(!is.na(!!quoted_question))
    }
    results_df <- filtered_df %>%
      count(!!quoted_question, sort = sort) %>%
      add_tally(n, name = "nn") %>%
      mutate(percent = round(n / nn * 100, 1),
             prop_responses = n / nn)
    return(results_df)
  }
# Split and aggregate: derives multiple answers to a single question
# by separating on commas and returning
# the results as an embedded list in the dataframe.
split_and_aggregate <- function(df, question_name) {
  quoted_question <- enquo(question_name)
  responses_df <- df %>%
    summarize(responses = sum(!is.na(!!quoted_question)))
  splits <- df %>%
    mutate(items = purrr::map(!!quoted_question, str_split, ", ")) %>%
    unnest(items)
  aggregated_items <- splits %>%
    unnest(items) %>%
    group_by(items) %>%
    count(sort = TRUE)
  aggregated_items <- aggregated_items %>%
    mutate(num_responses = responses_df$responses)
  return(aggregated_items)
}
```

```r
# Top N choices: function to distill many possible results
# to a question to the top N
# responses, with the rest aggregated into an "Other" answer.
top_n_choices <-
  function(df, column_name, total_responses, num = 10) {
    quoted_column_name <- enquo(column_name)
    summarized_responses <- df %>%
      mutate(
        percent = round(n / total_responses * 100, 1),
        prop_responses = n / total_responses
      ) %>%
      arrange(desc(percent))
    # Now take these responses and only show the top N, aggregating the rest
    # into an Other category
    literals <- head(summarized_responses, num) %>%
      ungroup()
    other <- tail(summarized_responses, -num) %>%
      ungroup() %>%
      summarize(
        !!quoted_column_name := "Other",
        n = sum(n),
        percent = round(n / first(total_responses) * 100, 1),
        prop_responses = n / first(total_responses)
      )
    top_n <- rbind(literals, other) %>% drop_na()
    return(top_n)
  }
question_text <-
  function(question_name_string,
           respondents_note = "",
           wrap_length = 55)
  {
    qtext <-
      survey_questions %>% filter(Question_name == question_name_string) %>%
      select(Question_text)
    if (str_length(qtext$Question_text) >= wrap_length) {
      return_text <-
        qtext$Question_text %>% str_wrap(width = wrap_length - 5)
    } else {
      return_text <- qtext$Question_text
    }
    return(paste0('"', return_text, '" ', respondents_note))
  }
```

3.1 Processing the survey:

```r
survey1 <- survey_save1
est <- locale(tz = "Pacific/Auckland")
survey1$Qtime <-
  parse_datetime(as.character(survey1$Qtime),
                 format = "%m/%d/%Y %H:%M:%S",
                 locale = est)
survey1 <- survey1 %>%
  mutate(learner_type = ifelse(
```

```r
    Qr_year < 1900,
    NA,
    ifelse(Qr_year <= 2016, "Early Learner", "Recent Learner")
  ))
survey1$Qgender <-
  survey1$Qgender %>% tolower() %>% str_trim() %>%
  str_replace_all("[[:punct:]]", "")
opentext_gender_dictionary <-
  read_csv("dictionary/opentext_gender_dictionary.csv")
gender_dictionary <-
  opentext_gender_dictionary %>%
  mutate(Input = str_replace_all(Input, "[[:punct:]]", ""))
source("gendercoder/R/genderCode.R")
survey1 <-
  genderRecode(
    survey,
    method = "narrow",
    genderColName = "Qgender",
    outputColName = "Qgender_coded",
    customDictionary = gender_dictionary
  )
survey1 <-
  survey1 %>%
  mutate(Qgender_coded = ifelse(Qgender_coded == "", NA, Qgender_coded))
uncoded_genders <-
  survey1 %>% group_by(Qgender_coded) %>% count(sort = TRUE)
write_csv(uncoded_genders, "dictionary/uncoded_genders_language.csv")
opentext_ethnicity_dictionary <-
  read_csv("dictionary/opentext_ethnicity_dictionary.csv")
ethnicity_dictionary <- opentext_ethnicity_dictionary %>%
  mutate(Input = str_replace_all(Input, "[[:punct:]]", ""))
survey1 <- survey1 %>%
  mutate(Qethnicity_processed = ifelse(
    str_detect(Qethnicity, ","),
    "Multiple Ethnicities",
    Qethnicity
  ))
survey$Qethnicity_processed <-
  survey$Qethnicity_processed %>% tolower() %>% str_trim() %>%
  str_replace_all("[[:punct:]]", "")
survey1 <- survey1 %>%
  left_join(ethnicity_dictionary, by = c("Qethnicity_processed" = "Input"))
uncoded_ethnicities <- survey %>%
  anti_join(ethnicity_dictionary, by = c("Qethnicity_processed" = "Input")) %>%
  count(Qethnicity_processed, sort = TRUE)
write_csv(uncoded_ethnicities,
          "dictionary/uncoded_ethnicities_language.csv")
survey <- survey1 %>%
  mutate(Qethnicity_coded = ifelse(Qethnicity_coded == "Prefer not to answer",
                                   NA,
                                   Qethnicity_coded))
collected_ethnicities <-
  survey %>% group_by(Qethnicity_coded) %>% count(sort = TRUE)
```

4.1 Plot and data analysis:

```
#lollipop chart
lollipop_chart <- function(df,
                           column_name,
                           fill_color,
                           title_string = NULL,
                           subtitle_string = "",
                           caption_string = survey_name,
                           pct_accuracy = 1) {
  quoted_column <- enquo(column_name)
  nudge_amount <- max(df$prop_responses, na.rm = TRUE) * 0.05
  df <- df %>%
    mutate(xaxis_factor = suppressWarnings(fct_relevel(
      fct_reorder(!!quoted_column, prop_responses), "Other"
    )))
  p <- ggplot(df, aes(x = xaxis_factor,
                      y = prop_responses)) +
    geom_point(color = fill_color, size = 3) +
    geom_segment(
      aes(xend = fct_rev(!!quoted_column), yend = 0),
      color = fill_color,
      size = 1.5,
      alpha = .7
    ) +
    geom_text(aes(label = scales::percent(prop_responses,
                                          accuracy = pct_accuracy)),
              hjust = -.25,
              color = "black") +
    labs(
      title = title_string,
      subtitle = subtitle_string,
      caption = caption_string,
      x = "",
      y = ""
    ) +
    coord_flip() +
    scale_y_continuous(limits = c(0, max(df$n) * 1.05)) +
    scale_y_continuous(labels = scales::percent_format(accuracy = 1),
                       limits = c(0, max(df$prop_responses) * 1.05)) +
    theme(
      panel.grid.major = element_blank(),
      panel.grid.minor = element_blank(),
      panel.background = element_rect(fill = "transparent", colour = NA),
      plot.background = element_rect(fill = "transparent", colour = NA)
    )
  lollipop_chart_100pc <- function(df,
                                   column_name,
                                   fill_color,
                                   title_string = NULL,
                                   subtitle_string = "",
                                   caption_string = survey_name,
                                   pct_accuracy = 1) {
    quoted_column <- enquo(column_name)
```

```
nudge_amount <- max(df$prop_responses, na.rm = TRUE) * 0.05
df <- df %>%
  mutate(xaxis_factor = suppressWarnings(fct_relevel(
    fct_reorder(!!quoted_column, prop_responses), "Other"
  )))
p <- ggplot(df, aes(x = xaxis_factor,
                    y = prop_responses)) +
  geom_point(color = fill_color, size = 3) +
  geom_segment(
    aes(xend = fct_rev(!!quoted_column), yend = 0),
    color = fill_color,
    size = 1.5,
    alpha = .7
  ) +
  geom_text(aes(label = scales::percent(prop_responses,
                                        accuracy = pct_accuracy)),
            hjust = -.25,
            color = "black") +
  labs(
    title = title_string,
    subtitle = subtitle_string,
    caption = caption_string,
    x = "",
    y = ""
  ) +
  coord_flip() +
  scale_y_continuous(labels = scales::percent_format(accuracy = 1),
                     limits = c(0, 1.05)) +
  theme(
    panel.grid.major = element_blank(),
    panel.grid.minor = element_blank(),
    panel.background = element_rect(fill = "transparent", colour = NA),
    plot.background = element_rect(fill = "transparent", colour = NA)
  )

#Respondent Job
job_title_dictionary <-
  read_delim(
    "dictionary/work-title-dictionary.tsv",
    delim = "\t",
    col_types = "cc"
  )
job_titles <- survey %>% select(Qwork_title) %>%
  drop_na() %>%
  left_join(job_title_dictionary, c("Qwork_title" = "Input"))
job_title_exceptions <- survey %>% select(Qwork_title) %>%
  drop_na() %>%
  anti_join(job_title_dictionary, c("Qwork_title" = "Input"))
job_title_totals <- job_titles %>% count(Output, sort = TRUE)
job_title_responses <- sum(!is.na(survey$Qwork_title))
job_titles <-
  job_title_totals %>% mutate(percent = round(n /
                                              job_title_responses * 100,
```

```
                                                  0))
top_10_titles <-
  top_n_choices(job_titles, Output, job_title_responses, 10)
top_10_titles <- top_10_titles %>%
  mutate(
    JobTitle = factor(Output, levels = rev(Output)),
    position = cumsum(percent) - percent / 2,
    label = ifelse(percent >= 5, paste0(JobTitle, "\n", round(percent),
                                        "%"), "")
  )
lollipop_chart (
  df = top_10_titles,
  column_name = JobTitle,
  fill_color = params$bar_colors,
  subtitle_string = question_text("Qwork_title", "(All respondents)"),
  caption_string = paste0("RStudio Learning R Survey, n = ",
                          job_title_responses)
)
plot_save("Respondent Job Titles (All Respondents).pdf")

#Respondent Gender
genders <- survey_combined %>%
  group_by(Qgender) %>%
  count(sort = TRUE) %>%
  mutate(unit = 1) %>%
  drop_na()
gender_responses <- sum(genders$n, na.rm = TRUE)
genders <- genders %>%
  group_by(unit) %>%
  mutate(
    percent = round(n / gender_responses * 100),
    prop_responses = n / gender_responses,
    position = cumsum(percent) - percent / 2,
    label = ifelse(percent >= 10, paste0(
      Qgender_coded, "\n", round(percent), "%"
    ), "")
  ) %>%
  arrange(desc(percent))
genders <- genders %>%
  mutate(Qgender_coded = factor(as.character(Qgender_coded), levels = rev(
    c("male", "female", "sex and gender diverse", "unclear")
  ))) %>%
  drop_na()
lollipop_chart(
  df                   = genders,
  column_name          = Qgender_coded,
  subtitle_string      = question_text("Qgender", "(All respondents)"),
  title_string         = "",
  fill_color           = params$bar_colors,
  caption_string       = paste0(survey_name, ", n = ", gender_responses)
)
plot_save("Respondent Identified Genders (All Respondents).pdf",
          height = 2)
```

```r
#What do Python used for
python_use_dictionary <-
  read_delim("dictionary/use_dictionary.tsv",
             delim = "\t",
             col_types = "cc")
uses <-
  survey %>% mutate(application = purrr::map(Qpython_apps, str_split, ", "))
%>% unnest(cols = c(application))
apps_used <-
  uses %>% unnest(cols = c(application)) %>% select(application)
parsed_use_used <- apps_used %>%
  left_join(python_use_dictionary, c("application" = "Input"))
parsed_use_exceptions <- apps_used %>%
  anti_join(python_use_dictionary, c("application" = "Input"))
use_responses <- sum(!is.na(survey$Qpython_apps))
parsed_use_tally <- parsed_use_used %>% count(Output, sort = TRUE)
parsed_use_tally <- parsed_use_tally %>%
  mutate(
    percent = round(n / use_responses * 100),
    prop_responses = n / use_responses
  ) %>%
  arrange(desc(percent))
app_plot <- head(parsed_use_tally, 15) %>%
  ungroup() %>%
  arrange(prop_responses)
other <- tail(parsed_use_tally,-15) %>%
  ungroup() %>%
  summarize(
    Output = "Other",
    n = sum(n),
    percent = round(n / use_responses * 100),
    prop_responses = n / use_responses
  )
app_plot <- rbind(other, app_plot) %>% drop_na()
app_plot <- app_plot %>%
  mutate(Output = factor(as.character(Output), levels = Output))
lollipop_chart_100pc(
  app_plot,
  Output,
  fill_color = params$bar_colors,
  subtitle_string =  question_text("Qpython_apps", "", 75),
  caption = paste0(survey_name, ", n = ", use_responses)
)
plot_save("What Do You Use Python For.pdf")
plot_save("What Do You Use Python For.jpg")

#What do R used for
r_use_dictionary <-
  read_delim("dictionary/use_dictionary.tsv",
             delim = "\t",
             col_types = "cc")
uses <-
  survey %>% mutate(application = purrr::map(Qused_for, str_split, ", "))
```

```
    %>% unnest()
    apps_used <- uses %>% unnest() %>% select(application)
    parsed_use_used <- apps_used %>%
      left_join(r_use_dictionary, c("application" = "Input"))
    parsed_use_exceptions <- apps_used %>%
      anti_join(r_use_dictionary, c("application" = "Input"))
    use_responses <- sum(!is.na(survey$Qused_for))
    parsed_use_tally <- parsed_use_used %>% count(Output, sort = TRUE)
    parsed_use_tally <- parsed_use_tally %>%
      mutate(
        percent = round(n / use_responses * 100),
        prop_responses = n / use_responses
      ) %>%
      arrange(desc(percent))
    app_plot <- head(parsed_use_tally, 15) %>%
      ungroup() %>%
      arrange(prop_responses)
    other <- tail(parsed_use_tally,-15) %>%
      ungroup() %>%
      summarize(
        Output = "Other",
        n = sum(n),
        percent = round(n / use_responses * 100),
        prop_responses = n / use_responses
      )

    app_plot <- rbind(other, app_plot) %>% drop_na()
    app_plot <- app_plot %>%
      mutate(Output = factor(as.character(Output), levels = Output))
    lollipop_chart_100pc(
      app_plot,
      Output,
      fill_color = params$bar_colors,
      subtitle_string =  question_text("Qused_for", "", 75),
      caption = paste0(survey_name, ", n = ", use_responses)
    )
    plot_save("What Do You Use R For.pdf")
    plot_save("What Do You Use R For.jpg")
```

6.1 Data Cleaning:

```
set.seed(251172095)
replace_na_with_random <- function(column) {
  non_na_values <- column[!is.na(column)]
  column[is.na(column)] <- sample(non_na_values, sum(is.na(column)),
                                  replace = TRUE)
  return(column)
}

survey_combined <- survey_combined %>%
  mutate(
    Qindustry = replace_na_with_random(Qindustry),
    Qr_experience = replace_na_with_random(Qr_experience),
```

```r
    Qgender = replace_na_with_random(Qgender),
    Qr_year = replace_na_with_random(Qr_year),
    Qtitle = replace_na_with_random(Qtitle),
    Qwork_title = replace_na_with_random(Qwork_title)
  )

survey_combined$Qr_year <- as.factor(survey_combined$Qr_year)
survey_combined$Qgender <- as.factor(survey_combined$Qgender)
survey_combined$Qindustry <- as.factor(survey_combined$Qindustry)
survey_combined$Qr_experience <- as.factor(survey_combined$Qr_experience)
survey_combined$Qtitle <- as.factor(survey_combined$Qtitle)
survey_combined$Qwork_title <- as.factor(survey_combined$Qwork_title)
```

6.2 Prefer Calculation:

```r
survey_combined <- survey_combined %>%
  mutate(
    Qr_how_often_used = replace_na_with_random(Qr_how_often_used),
    Qpython_use = replace_na_with_random(Qpython_use),
    Qr_enjoyment = replace_na_with_random(Qr_enjoyment),
    Qrecommend = replace_na_with_random(Qrecommend),
    Qpython_enjoy = replace_na_with_random(Qpython_enjoy),
    Qpython_recommend = replace_na_with_random(Qpython_recommend)
  )

survey_combined$Qr_how_often_used <- case_when(
  survey_combined$Qr_how_often_used == "More than once a day" ~ 1.0,
  survey_combined$Qr_how_often_used == "Between once a day and once a week" ~
    0.75,
  survey_combined$Qr_how_often_used == "Between once a week and once a month" ~
    0.5,
  survey_combined$Qr_how_often_used == "Less than once a month" ~ 0.25,
  survey_combined$Qr_how_often_used == "I don't use R any more" ~ 0,
  TRUE ~ sample(c(0, 0.25, 0.5, 0.75, 1.0), 1)
)

survey_combined$Qpython_use <- case_when(
  survey_combined$Qpython_use == "I don't use Python" ~ 0,
  survey_combined$Qpython_use == "Occasionally -- less than once a month"
  ~ 0.25,
  survey_combined$Qpython_use ==
    "Monthly -- between once a week and once a month" ~ 0.5,
  survey_combined$Qpython_use == "Weekly -- Between once a day and once a week"
  ~ 0.75,
  survey_combined$Qpython_use == "Daily -- Once or more per day" ~ 1.0,
  TRUE ~ sample(c(0, 0.25, 0.5, 0.75, 1.0), 1)
)

survey_combined$Prefer <- case_when(
  survey_combined$Qr_enjoyment * 0.5 + survey_combined$Qrecommend * 0.2 +
    survey_combined$Qr_how_often_used * 0.3 >=
    survey_combined$Qpython_enjoy * 0.5 + survey_combined$Qpython_recommend *
    0.2 + survey_combined$Qpython_use * 0.3 ~ 1,
```

```
  survey_combined$Qr_enjoyment * 0.5 + survey_combined$Qrecommend * 0.2 +
    survey_combined$Qr_how_often_used * 0.3 <
    survey_combined$Qpython_enjoy * 0.5 + survey_combined$Qpython_recommend *
    0.2 + survey_combined$Qpython_use * 0.3 ~ -1
)

survey_combined$Prefer <- as.factor(survey_combined$Prefer)
```

6.3 Random Forest Model:

```
library(ranger)

fit.rf <- ranger(
  Prefer ~ Qr_experience + Qindustry + Qr_year + Qgender + Qtitle + Qwork_title,
  data = train_data,
  importance = 'impurity',
  classification = TRUE,
  verbose = FALSE
)

fit.rf
importance(fit.rf)

rf_predictions <- predict(fit.rf, data = test_data)
conf_matrix_rf <- table(actual = test_data$Prefer,
                        pred = rf_predictions$predictions)
conf_matrix_rf
rf_accuracy <- sum(rf_predictions$predictions == test_data$Prefer) /
  nrow(test_data)
print(paste("Random Forest Accuracy:", rf_accuracy))
```

6.4 Decision Tree Model:

```
library(rpart)

fit.tree <- rpart(
  Prefer ~ Qr_experience + Qindustry + Qr_year + Qgender + Qtitle + Qwork_title,
  data = train_data,
  method = "class",
)

fit.tree$variable.importance

tree_predictions <- predict(fit.tree, test_data, type = "class")
conf_matrix_tree <- table(actual = test_data$Prefer, pred = tree_predictions)
conf_matrix_tree
tree_accuracy <- sum(tree_predictions == test_data$Prefer) / nrow(test_data)
print(paste("Tree Accuracy:", tree_accuracy))
```

6.5 Neural Network Model:

```r
# Preprocess the data for neural network
train_data_nn <- train_data %>%
  mutate_if(is.factor, as.numeric) %>%
  mutate_if(is.character, as.numeric)

test_data_nn <- test_data %>%
  mutate_if(is.factor, as.numeric) %>%
  mutate_if(is.character, as.numeric)

# Define the input and output
x_train <- as.matrix(train_data_nn %>% select(Qr_experience, Qindustry,
                                              Qr_year, Qgender,
                                              Qtitle, Qwork_title))
y_train <- as.numeric(train_data_nn$Prefer)
x_test <- as.matrix(test_data_nn %>% select(Qr_experience, Qindustry, Qr_year,
                                            Qgender, Qtitle, Qwork_title))
y_test <- as.numeric(test_data_nn$Prefer)

# Define the neural network model
model <- keras_model_sequential() %>%
  layer_dense(units = 64, activation = 'relu', input_shape = ncol(x_train)) %>%
  layer_dropout(rate = 0.4) %>%
  layer_dense(units = 32, activation = 'relu') %>%
  layer_dropout(rate = 0.3) %>%
  layer_dense(units = 3, activation = 'softmax')

# Compile the model
model %>% compile(
  loss = 'sparse_categorical_crossentropy',
  optimizer = optimizer_adam(),
  metrics = c('accuracy')
)

# Fit the model
history <- model %>% fit(
  x_train, y_train,
  epochs = 50,
  batch_size = 32,
  validation_split = 0.2,
  verbose = 0
)

# Evaluate the model
nn_accuracy <- model %>% evaluate(x_test, y_test)
print(paste("Neural Network Accuracy:", nn_accuracy$accuracy))
plot(
  history$metrics$accuracy,
  type = "l",
  col = "blue",
  ylim = c(0, 1),
  xlab = "Epoch",
  ylab = "Accuracy",
  main = "Model Accuracy",
```

```
  cex.main = 1.2,
  cex.lab = 1.1,
  cex.axis = 0.9
)
lines(history$metrics$val_accuracy, col = "red")
legend(
  "bottomright",
  legend = c("Training Accuracy", "Validation Accuracy"),
  col = c("blue", "red"),
  lty = 1,
  cex = 0.8
)
plot(
  history$metrics$loss,
  type = "l",
  col = "blue",
  ylim = range(c(
    history$metrics$loss, history$metrics$val_loss
  )),
  xlab = "Epoch",
  ylab = "Loss",
  main = "Model Loss",
  cex.main = 1.2,
  cex.lab = 1.1,
  cex.axis = 0.9
)
lines(history$metrics$val_loss, col = "red")
legend(
  "topright",
  legend = c("Training Loss", "Validation Loss"),
  col = c("blue", "red"),
  lty = 1,
  cex = 0.8
)
```

6.6 Logistic Regression Model:

```
survey_combined$YearFromTime <- as.numeric(format(survey_combined$Qtime, "%Y"))
survey_combined$YearFromTime <- as.numeric(survey_combined$YearFromTime)
model_time <- glm(Prefer ~ YearFromTime, family = binomial(),
                  data = survey_combined)
summary(model_time)

future_year <- data.frame(YearFromTime = 2022)
future_prediction <- predict(model_time, newdata = future_year,
                             type = "response")
predicted_probability <- as.numeric(future_prediction)
print(paste(
  "Predicted probability of preferring R in 2022:",
  predicted_probability
))
```

6.7 Plot:

```
plot_data <- data.frame(
  Year = c(2018, 2019, 2020, 2021, 2022),
  Probability = c(
    predict(
      model_time,
      newdata = data.frame(YearFromTime = c(2018, 2019, 2020, 2021)),
      type = "response"
    ),
    predicted_probability
  )
)

library(ggplot2)
ggplot(plot_data, aes(x = Year, y = Probability)) +
  geom_line() +
  geom_point() +
  labs(title = "Trend and Predicted Preference for R in 2022", x = "Year",
       y = "Probability") +
  theme_minimal()
```

EOF