Analyzing Nuances within the Machine Learning Community

Author 1 and Author 2

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Header

Author Contributions

Author 1: Contributed to questions 1 and 3 and did the formatting for the pdf

Author 2: Contributed to questions 2 and 4 along with doing the advanced analysis.

Use of GPT

ChatGPT was used as a substitute for documentation for R. Since we were unfamiliar with R, we asked ChatGPT how to use R in certain methods in order to find and filter out conditions in the dataset. We additionally used GPT to analyze reasoning and to confirm what we thought was correct about the dataset, as well as to identify extra questions that could be answered for our advanced analysis.

Introduction

The data used in this analysis is from the 2020 Kaggle "Most Popular & Widely Used Machine Learning" Survey. It details questions about Kaggle's users, as well as their most used machine learning languages, platforms, education levels, and more. Our analysis today focuses on identifying key relationships within the data and to notice if there are any interesting patterns that we can find within it.

Main Research Questions

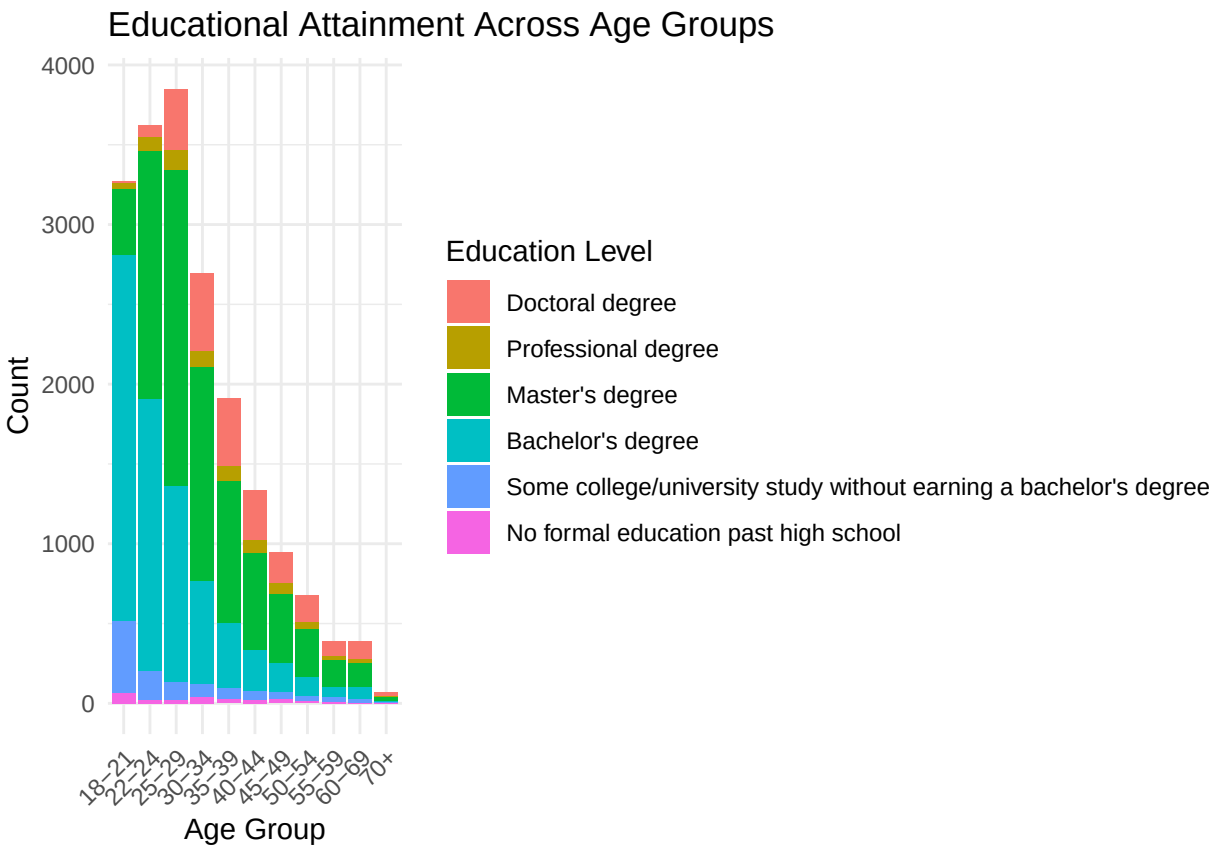
1) Analyze the relationship between age groups and highest education levels amongst the survey respondents. How does educational attainment vary across those in different age brackets. (can use chi-square test)
2) Investigate how programming languages and skillsets change between groups of different experience levels. Do more experienced users tend to use a wider variety of programming languages, or specific programming languages. (can use the release date of certain languages as a spearhead)
3) Examine the global distribution of survey participants and their professional jobs, extrapolating this to the general population of the world. Are certain jobs more popular in certain countries?
4) Do larger companies hire older, more experienced employees for data roles compared to smaller companies? Conduct hypothesis tests to find differences in both age and salary between companies, and then check for confounding.

Question 1) Age-Education Relationship

One thing we want to test in regards to the age-education relationship in this graph is that we want to compare it to the education attainment for adults 25 and older in the United States. This has the following distribution:

- 30.5% have no formal education
- 26.8% have some college/university experience
- 25.8% have a bachelor's degree
- 10.9% have a master's degree
- 3.7% have a professional degree
- 2.3% have a doctoral degree

Methods




```
##
##  Chi-squared test for given probabilities
##
## data:  observed_counts
## X-squared = 33177, df = 5, p-value < 2.2e-16
```

Analysis

Looking through this graph, we can notice a lot of things. For instance, it can be noticed that there is an obvious trend of younger users who took this survey, with the peak of the users falling from the 18-21

range to the 25-29 range. This slowly falls off, with each age range slowly losing ground on the majority of users. Other patterns to notice include the influx of people with a bachelor's degree, with the visible majority being placed at the age range of 18-21, and slowly lowering down percent wise as age increases. On the other hand, degrees like masters, professional, and doctoral are very low in the 18-21 age range, which makes sense intuitively, because these degrees typically require the previous ones to acquire. This means that those in the 18-21 and 22-24 age ranges very rarely have these advanced degrees, and the age range of 25-29 is the first age range we actually see a significant amount of these education levels. Otherwise, other education levels to note include the fact that master's degrees are found often at the 22-24 age range and beyond, comprising the most of all the education levels after this age. Additionally, when comparing the given probabilities to the true distribution of education levels in the United States for ages 25 and above, we can notice that the Chi-Square Test has a p-value of 2.2e-16, which means that our data is significantly different than the actual distribution of education levels amongst adults in the United States.

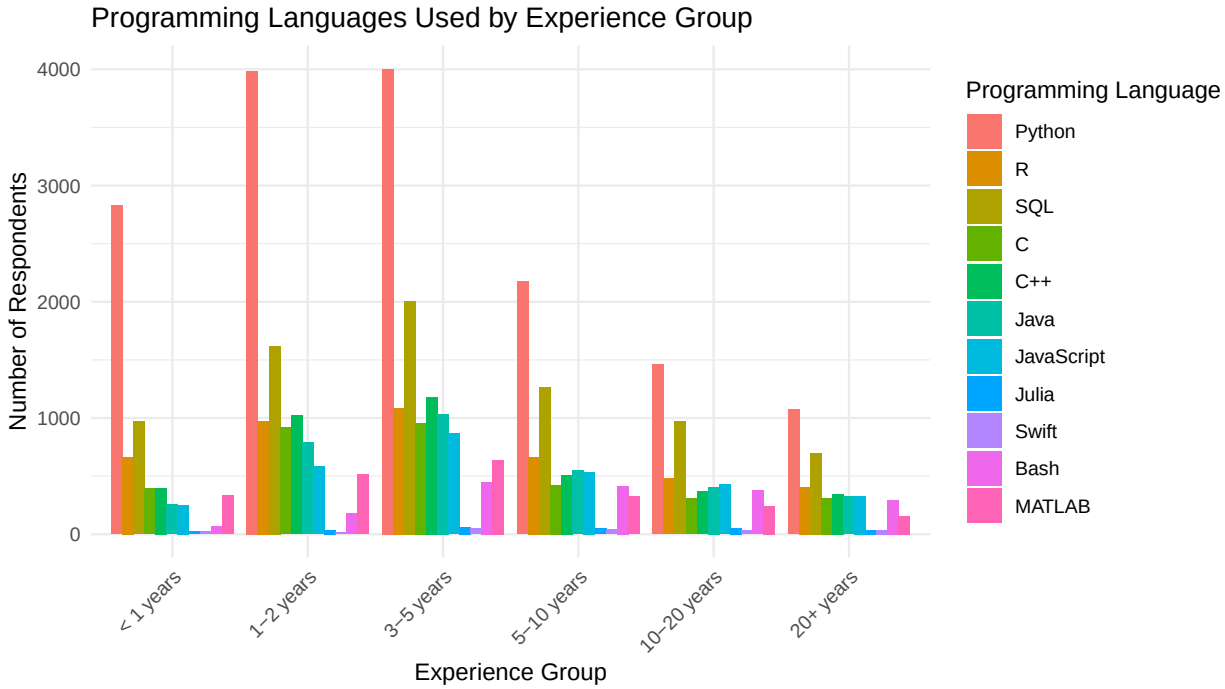
Conclusion

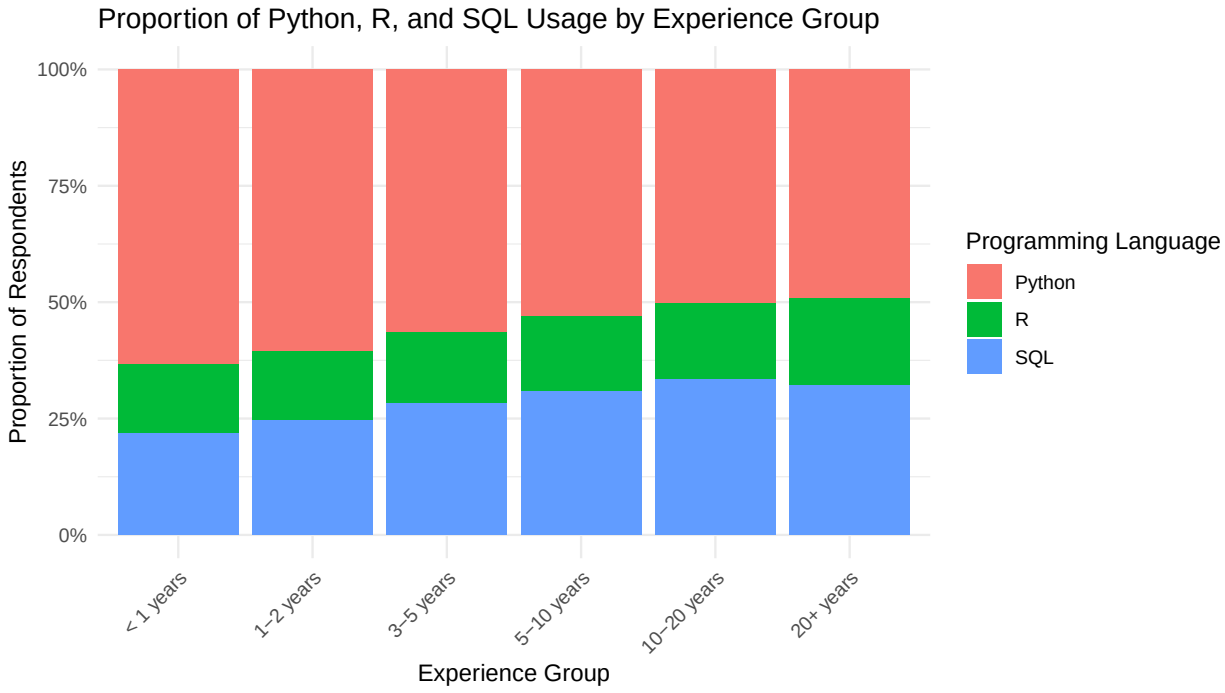
Further analysis of the data and the graph created above shows that the educational attainment for those who took this survey, and by connotation, are interested in Machine Learning, is very different than the actual educational attainment in the United States. This somewhat makes sense; machine learning is a typically much more education-based topic that people have to learn, so those who want to learn it and apply it in their lives typically go to college and even higher education to achieve their goals. The other things we noticed also make sense; younger people rarely have degrees above a bachelor's, because they don't have the necessary amount of time to get those degrees. Additionally, most of the ages in the graph tend to be younger, skewing right, which makes sense, because machine learning has only become an especially popular topic recently, which maybe be reflected in our data.

Question 2) Correlation Between Experience and Programming Languages Used

To examine how programming language usage changes between people with different levels of experience in data-related fields, we first cleaned the data by removing rows with null values. Then, we cleaned the columns corresponding to different programming languages by changing the data types from strings to binary values where 1 represents usage of that programming language and 0 means it isn't used. Finally, we count usage of each programming language for each experience level and create a grouped bar plot. From that grouped bar plot, the most impactful languages are further examined in a stacked bar chart.

Methods





Analysis

Looking at the grouped bar plot reveals that the 3 most relevant languages (Python, SQL, R) stay relatively consistent within all experience levels. This means that Python is always the most common language by far across all levels of experience, followed by SQL, and then by R. This pattern is never broken in the visualization. One surprising takeaway from the plot is that C and C++ are relatively more popular among

lower levels of experience whereas they drop below languages like Java and JavaScript in the higher levels of experience.

In the stacked bar chart, we more closely inspect the three most relevant programming languages and how their relative usages change as experience level grows. A clear trend can be seen in Python's usage. As people become more experienced, the proportion of respondents using Python decreases, which could be due to less adoption of Python in earlier years. SQL and R both show a trend of increasing presence among people with greater programming experience. SQL's trend of increasing with experienced users is even more obvious than that of R.

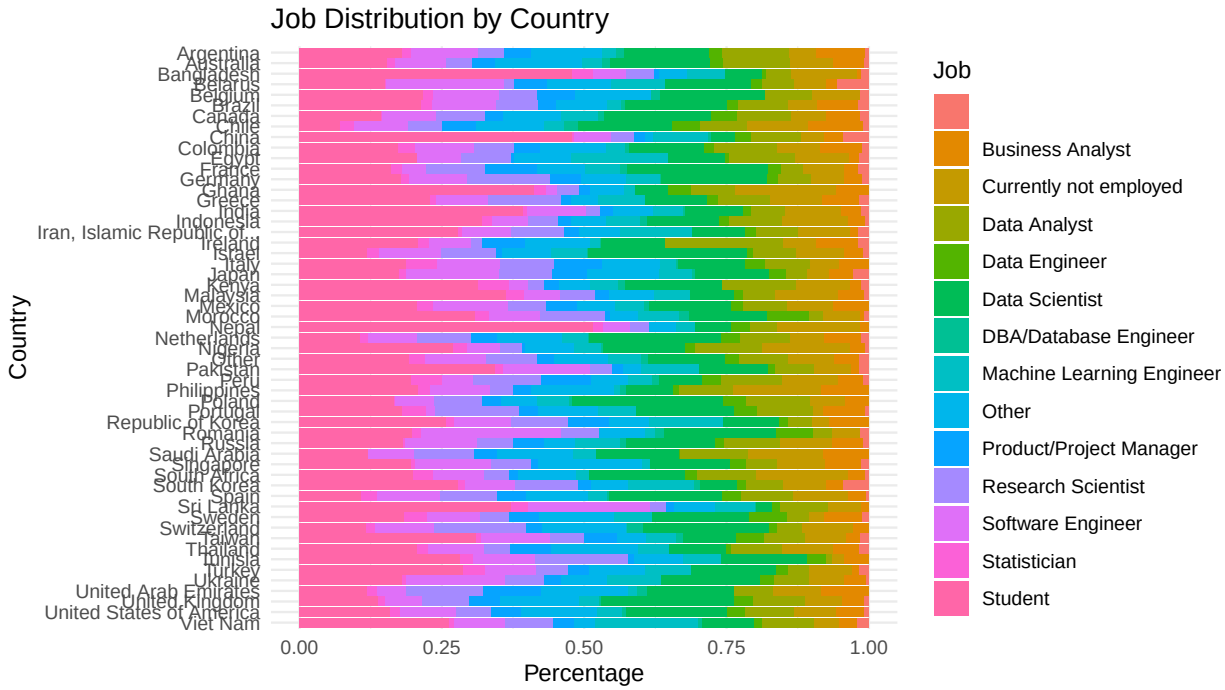
Conclusion

Python, SQL, and R have all stayed massively relevant to programmers of all experience levels in data-related fields. Python has been significantly more popular among less experienced programmers while SQL sees a significant increase of usage among more experienced programmers.

Question 3) Distribution of Jobs and general Population

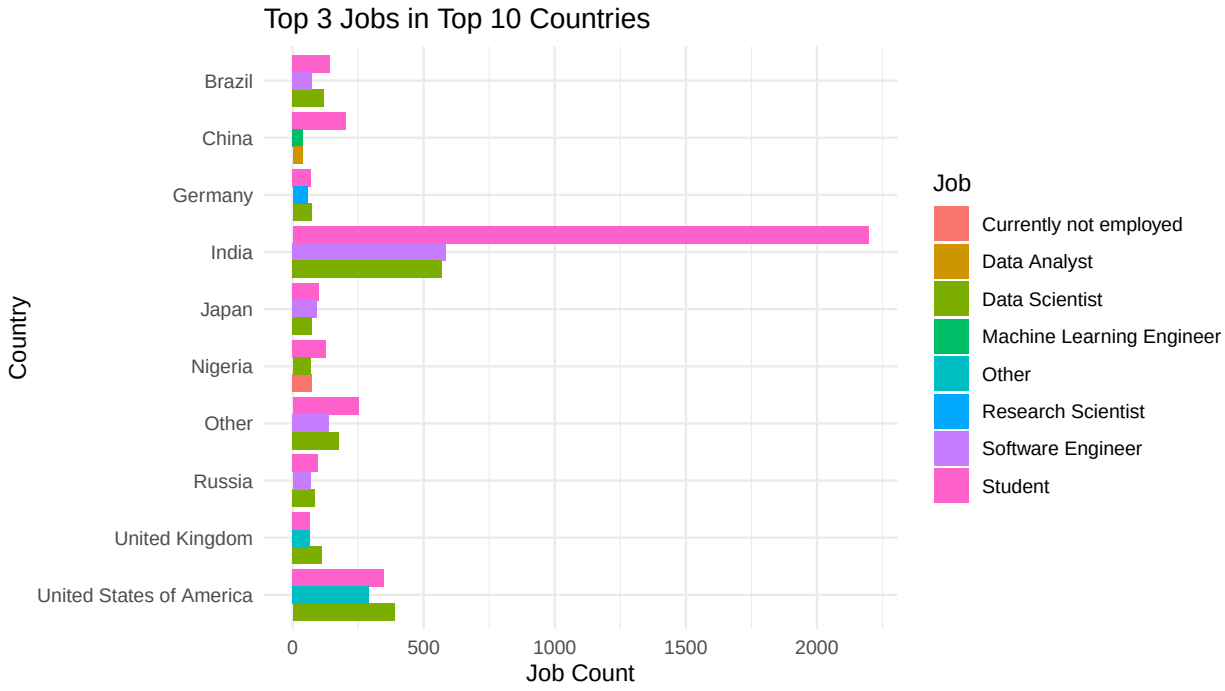
For this question, we want to investigate how the general population of the data and their relationships with their jobs is like. For instance, for each country, what is the most typical job, and what does this say about the population using Kaggle? Additionally, we want to take into account the top 3 jobs in each country, while also maintaining a global job distribution of which people from different countries use Kaggle the most.

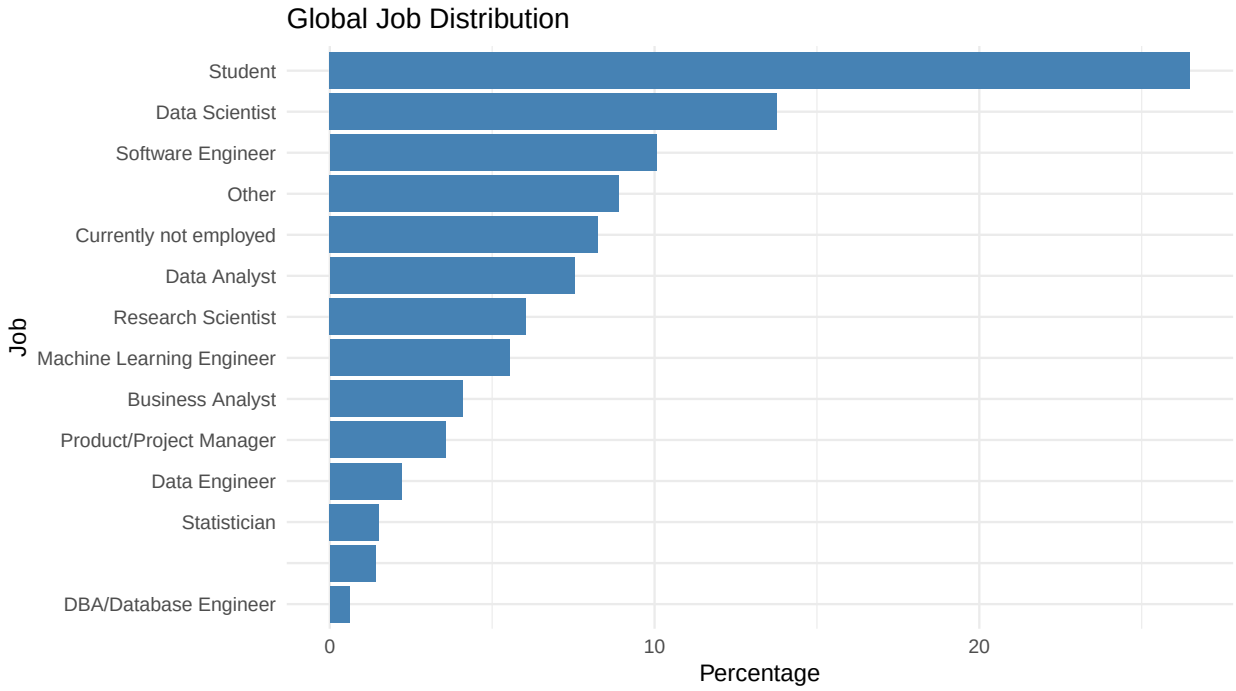
Methods




```
##
##  Pearson's Chi-squared test with simulated p-value (based on 2000
##  replicates)
##
```

```
## data:  job_country_table_grouped
## X-squared = 3084.8, df = NA, p-value = 0.0004998
```





Analysis

Looking through our graphs, there are a few things to note. For instance, the most popular "job" that people have that took the survey was Student. According to our earlier graph, this is mostly due to countries like India, the United States, and China, whose top 3 jobs all contain "Student". This is a trend that is seen

throughout most countries as well, as even when we center the data on each individual country, we can see that significant number of users are still students. Although the global job distribution includes student, data scientist, software engineer, and more, student significantly dwarfs all the other jobs, with users that are "Students" being ~2x more populous than the second most worked job, "Data Scientist". This means that some jobs are significantly more popular than others, as shown by our Chi-Square Test. The p-value of a ~0.0005 demonstrates that our job distribution is significantly different than a uniform distribution of all of the jobs.

Conclusion

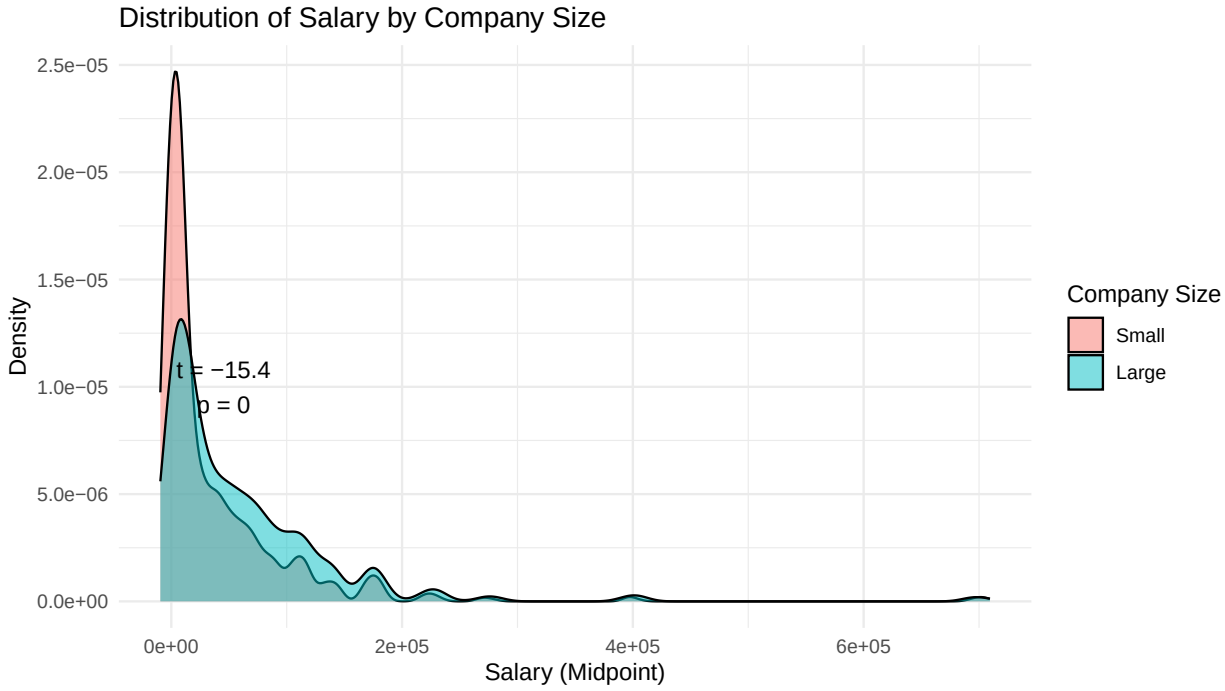
To conclude, we can notice a few significant trends within our data. India and the United States are the primary countries of the users who took this survey, and the jobs most associated with these users included "Student", "Software Engineer", "Data Scientist", and "Other". These show within the overall global distribution of jobs, whose top 4 jobs were identical. This same distribution is similar within all the individual countries, showing that a lot of the people who use Kaggle and filled out this survey about machine learning were typically students, engineers, or data scientists, which fits into Kaggle's overall use of being a place to store data and have competitions with it.

Question 4) Hiring Preferences of Larger vs. Smaller Companies

o investigate age and salary differences between employees of large and small companies, we began by removing rows with missing salary or company size data from the dataset. In order to have numeric values for variables such as age and salary instead of strings, the midpoints of given ranges were used as data points instead of the entire range.

Next, two two-sample t-tests were conducted. The first two-sample t-test compared average age of employees at large vs. small companies. The second test compared average salary of employees at large vs. small companies. Both tests were two-tailed, meaning we are looking for a difference in either direction. Density plots were generated to visualize the two distributions for each metric right next to each other. Finally, a correlation analysis was conducted to find a confounding relationship between age and salary.

Methods




```
##
##  Pearson's product-moment correlation
##
## data:  salary_data$age_midpoint and salary_data$salary_midpoint
## t = 28.603, df = 10727, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
```

```
##  0.2485329 0.2836969
## sample estimates:
##       cor
## 0.2662035
```

Analysis

Before discussing the results of the two t-tests conducted, we had to check the assumptions of the two-sample t-test. For both tests, the variances of the two distributions were roughly equal. For the test comparing ages, the two distributions of age were found to be roughly normal, passing the normality assumption for that test. However, the salary distributions were found to deviate slightly from a normal distribution with a right skew. Because our sample size was deemed large (**20,000+**), we continued with both two-sample t-tests.

The two-sample t-test on ages resulted in a t-statistic of -5.15 and p-value of ~0, so we reject the null hypothesis meaning there is a significant difference in mean age between small and large companies. In this case, we observed larger companies having older employees. The two-sample t-test on salaries resulted in a t-statistic of -15.4 and p-value of ~0, so we reject the null hypothesis, meaning there is a significant difference in mean salary between large and small companies. In this case, the observed mean salary of large companies was higher.

The correlative analysis between age and salary resulted in a Pearson's correlation coefficient of **0.266**. This shows a relatively weak positive relationship between age and salary.

Conclusion

Large companies tend to higher older employees for higher salaries, meaning these employees are likely more experienced. The correlation between age and salary was found to be positive, but relatively weak.

Advanced Analysis) Predict Career Trajectory of Job-Seekers

To investigate the relationship between individual factors like experience and skill with someone's career path within data-related jobs, I conducted a multinomial logistic regression analysis. This model was chosen because we wanted interpretable results that were appropriate for multi-classification.

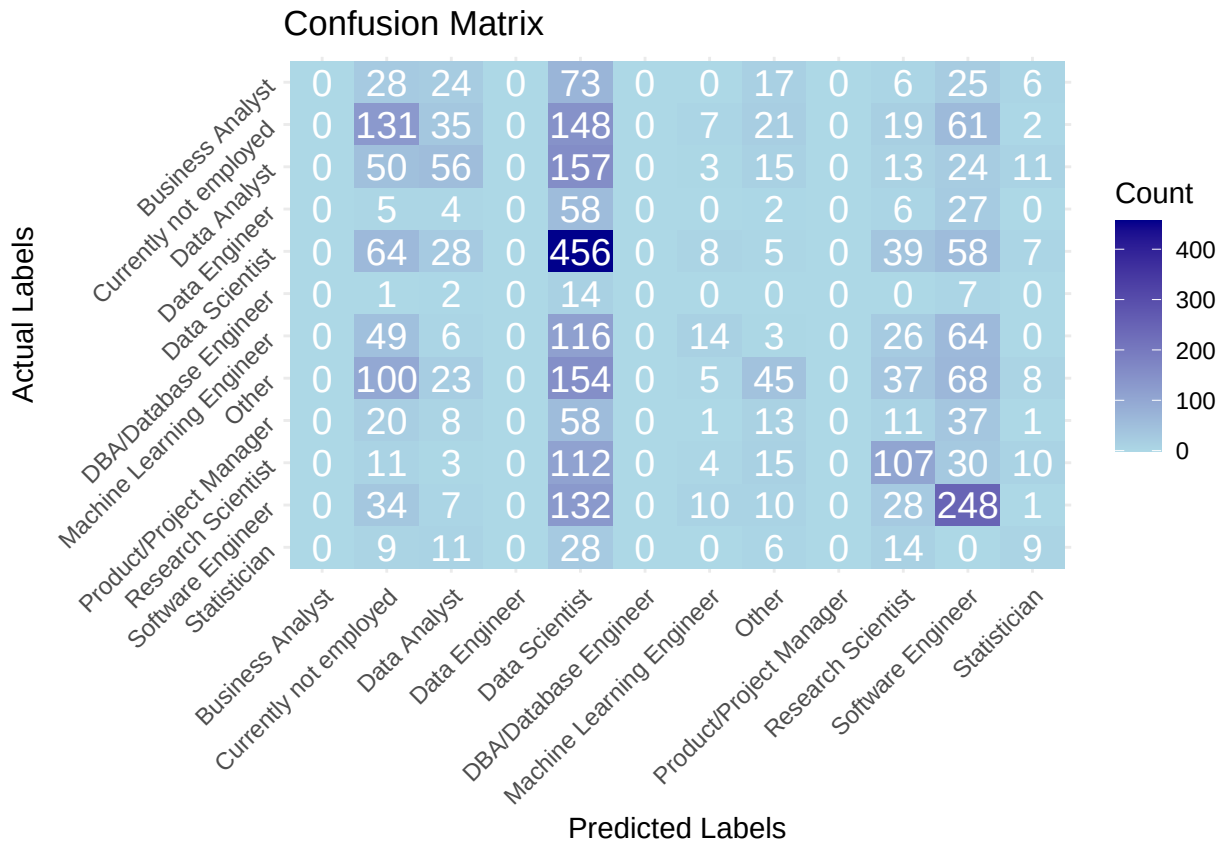
We had to first clean the data by removing rows where one of the explanatory or response variables were missing. We then converted the programming language columns into one-hot encoded numerical values where **1** means that language is used by the individual. Education and experience were encoded as ordinal numerical values with higher levels of education and experience having higher values. Finally, the model was tested on a train-test split with results plotted on a confusion matrix.

Methods

```
## # weights:  120 (99 variable)
## initial  value 25562.234706
## iter  10 value 22590.204459
## iter  20 value 21928.919274
## iter  30 value 21703.700713
## iter  40 value 21274.527005
## iter  50 value 21182.348170
## iter  60 value 21140.983871
## iter  70 value 21116.854172
```

```
## iter  80 value 21108.131055
## iter  90 value 21105.814120
## iter 100 value 21105.278022
## final  value 21105.278022
## stopped after 100 iterations

## Accuracy: 31.09 %
```



Analysis

After conducting the multinomial logistic regression, the model performed with an accuracy of **31.09%** on an unseen test set. Additionally, the confusion matrix above reveals that the model predicted "Data Scientist" **>1000** times even though it only appears in the test set about **650** times. Meanwhile, it only predicted "Data Analyst" **203** times even though it actually appears in the test set about **300** times. In fact, the confusion matrix reveals that a vast majority of incorrect predictions are when the model predicts "Data Scientist". This weakness in the model is likely due to the fact that the most common job title in the dataset is "Data Scientist", so the model optimized by predicting the most common class.

In the future, we could attempt to remedy the class imbalance issue by resampling from the under-represented classes. However, this is still flawed because without enough data in a class, the trend learned for that class likely won't be generalizeable.

P-values were calculated for each variable at each response level. While these p-values can not be directly interpreted because of a lack of normality in the explanatory variable distributions, they were used to rank the most significant explanatory variables for predicting certain classes. The smallest p-value corresponded to **Experience** as a strong predictor for **Software Engineer** with a coefficient of **0.534**. The second

smallest p-value corresponded to **SQL** as a strong predictor against **Research Scientist** with a coefficient of **-1.868**. This means that if an individual is skilled in SQL, their likelihood of being a Research Scientist significantly decreases.

Conclusion

Ultimately, this model is not effective at predicting what type of data-related job someone will hold based on factors like skills, experience, and education. This conclusion was reached because of the model's low accuracy on the test set as well as significant class imbalances apparent from the confusion matrix.

Conclusions and Discussion

Summary of Findings

The machine learning survey provided a lot of data about people and the ways they interact with machine learning, especially on Kaggle. One of the first things we noticed was the age-education relationship hidden within the data, which followed an interesting pattern that suggests machine learning is a higher education led field, as Master's degrees and PhDs typically became more and more popular as people aged, typically meaning that those who are involved in this field usually want higher education to be successful. Additionally, during our analysis of the experience-programming relationship, we noticed that Python, R, and SQL were the most widely used programming languages within coders, and surprisingly, maintains a very steady usage rate between all experience groups, even increasing as one gains more experience. This could potentially indicate the usefulness of Python even at the highest levels of data analysis and machine learning, which makes sense with the context we now know. In terms of the job distribution within countries, we noticed that the global job distribution tended to favor people from countries like India or the United States, which were especially skewed towards being students. This falls in line with most other countries, as the top 3 jobs in the top 10 countries typically were students, software engineers, data scientists, or analysts, which makes sense, as Kaggle is a platform that contains data primarily for these roles. Finally, during our analysis of hiring preferences for larger versus smaller companies, we noticed that while the distribution for age between large and small companies remained relatively similarly, the distribution of salary by company size was quite different. One thing that we noticed was that small companies tend to have most salaries peaking up in one area, while larger comapnies are able to afford a flatter curve with peaks at different places, indicating they have resources to pay higher skilled employees with higher wages.