Indeed.com Job Listings Analysis

1. Introduction

The job market is becoming ever more competitive, as a student nowadays it is harder and harder to land the job of your dreams. COVID-19 has even made it more challenging for recent graduates to find a fitting role after graduation. A lot of students complain about the gap between skills learned during their studies and the actual skills required in the workfield by companies. This motivates our investigation into Indeed job vacancy postings to find the skills that are actually required for different job types.

As Marketing Analytics students, we have both the marketing and analytical knowledge to succeed in a range of different job types in the field of marketing. We are interested in what the actual required skills are for jobs in fields related to our studies. Becoming a data scientist, data analist or maybe marketeer after our studies will require different skills and competencies and we would like to know to which degree we possess these skills and to which extent our study program effectively prepares us for the job market.

We aspire to find insights to help ourselves as well as our fellow students in making a choice relating to which skills to improve and perhaps which skills to forego in order to effectively land their first job. We aim to conduct our investigation in such a way that the methodology can be used by anyone for any location in the world and for any job type on Indeed.com. First of all, for our fellow students, the keyword and location analysis provide easily interpretable tables to see which skills are in demand for each roles, together with the best locations for jobs in the Netherlands. Our entire project is accessible and usable. The entire workflow can be tweaked to your needs by simply changing the search term in the scraper. This makes our project valuable for all job seekers in the world, as they can reproduce our data scraping and analysis for their specific job wishes.

For this project we decided to narrow down our investigation to the Netherlands. Three of our four members originate from the Netherlands and since we and our classmates are all studying at Tilburg University in the Netherlands right now, job options in the Netherlands are most relevant to us. Furthermore, we decided to investigate the 4 jobs most closely related to our master in Marketing Analytics program, being data scientist, marketeer, data-analist and marketing-analist. By narrowing down the project by not including too many locations and job searches, the project workflow will be much smoother and easier to reproduce for anyone interested in doing so.

2. Methodology

First, we built a web scraper that scrapes the vital information of each job posting associated with a specific job search. We used the BeautifulSoup package to collect job ids, job titles, salary, company name, dates, job summary and salaries if available. Afterwards, we scraped the job descriptions of the same search results to obtain the job descriptions of each job posting in a separate dataset by using a chrome webdriver with Python Selenium. Due to restrictions with captcha's, we collected multiple small batches of datasets per search term. In R we merged the data into one big file per search term by joining the datasets on the unique job id that serves as an identifier for each separate job advert on Indeed. After merging the files into one dataset per search term, we cleaned the data by removing duplicate entries and by cleaning up messy string location names. Location names such as Amsterdam-Zuid or Velsen-Noord were unwanted because they would appear as two distinct location in our analysis. Therefore, we wrote a function that removed all such extra unnecessary information in the location strings. We added a function that replaced certain unspecified locations such as Nederland or Randstad into Unknown, signifying that a job did not specify a specific location.

The final step in the cleaning process was cleaning the salary data. The salary data was quite sparse and also very messy. Roughly three-quarters of the data was missing, and for the data available, different measures were given. Some jobs gave hourly salary rates, whereas other jobs utilized monthly or yearly income as a salary measure. We made a function that removes unnecessary character strings in the salary data and converted all different salary measures into yearly income as a standard. We calculated yearly income for hourly rates based on 40 hour work week. We multiplied the hourly rate * 40 * 4 * 12 to get a yearly income rate based on the hourly wage. For the monthly income, we simply multiplied with 12 to arrive at a yearly income. Quite a few jobs gave a salary range instead of a fixed number. For those jobs, we decided to take the middle of the range. We kept the observations with missing values for salary in the dataset for the first part of the analysis because it would significantly reduce the number of observations otherwise.

3. Overview of the data After downloading and merging data we have 4 datasets in total. 1 dataset per search term for the following search terms: Data Scientist, Data Analist, Marketing Analist and Marketeer.The following section will provide a short overview of how the datasets look like. 3.1 This is how the data_scientist data set looks like: We can see that there are 706 job listings. It contains 13 columns.

```
##  [1] "X"                       "id"                      "title"
##  [4] "company"                 "location"                "postingdate"
##  [7] "today"                   "summary"                 "salary"
## [10] "url"                     "description"             "scrapetimesdescription"
## [13] "salary_good"
```

Here can be observed a summary of data_scientist.

```
##        X              id               title             company
##  Min.   :  1.0   Length:706         Length:706         Length:706
##  1st Qu.:177.2   Class :character   Class :character   Class :character
##  Median :353.5   Mode  :character   Mode  :character   Mode  :character
##  Mean   :353.5
##  3rd Qu.:529.8
##  Max.   :706.0
##
##    location         postingdate           today             summary
##  Length:706         Length:706         Length:706         Length:706
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##     salary              url            description
##  Length:706         Length:706         Length:706
##  Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##  scrapetimesdescription  salary_good
##  Length:706             Min.   :   4800
##  Class :character       1st Qu.:  36600
##  Mode  :character       Median :  49908
##                         Mean   :  78627
##                         3rd Qu.:  64800
##                         Max.   :2098560
```

```
##                          NA's   :557
```

3.2 This is how the data_analist data set looks like: We can see that there are 825 job listings. It contains 13 columns.

```
##  [1] "X"                     "id"                    "title"
##  [4] "company"               "location"              "postingdate"
##  [7] "today"                 "summary"               "salary"
## [10] "url"                   "description"           "scrapetimesdescription"
## [13] "salary_good"
```

Here can be observed a summary of data_analist.

```
##        X            id                 title              company
##  Min.   :  1   Length:825         Length:825         Length:825
##  1st Qu.:207   Class :character   Class :character   Class :character
##  Median :413   Mode  :character   Mode  :character   Mode  :character
##  Mean   :413
##  3rd Qu.:619
##  Max.   :825
##
##    location          postingdate           today             summary
##  Length:825         Length:825         Length:825         Length:825
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##     salary              url            description
##  Length:825         Length:825         Length:825
##  Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##  scrapetimesdescription  salary_good
##  Length:825             Min.   :   6000
##  Class :character       1st Qu.:  34506
##  Mode  :character       Median :  44412
##                         Mean   :  62025
##                         3rd Qu.:  54054
##                         Max.   :3432960
##                         NA's   :598
```

3.3 This is how the marketing_analist data set looks like: We can see that there are 409 job listings. It contains 13 columns.

```
##  [1] "X"                     "id"                    "title"
##  [4] "company"               "location"              "postingdate"
##  [7] "today"                 "summary"               "salary"
## [10] "url"                   "description"           "scrapetimesdescription"
## [13] "salary_good"
```

Here can be observed a summary of marketing_analist.

```
##        X            id                 title              company
```

```
##  Min.   :  1   Length:409         Length:409         Length:409
##  1st Qu.:103   Class :character   Class :character   Class :character
##  Median :205   Mode  :character   Mode  :character   Mode  :character
##  Mean   :205
##  3rd Qu.:307
##  Max.   :409
##
##    location         postingdate           today             summary
##  Length:409         Length:409         Length:409         Length:409
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##     salary              url            description
##  Length:409         Length:409         Length:409
##  Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##  scrapetimesdescription  salary_good
##  Length:409             Min.   : 4200
##  Class :character       1st Qu.:36525
##  Mode  :character       Median :47100
##                         Mean   :46376
##                         3rd Qu.:55392
##                         Max.   :96000
##                         NA's   :345
```

3.4 This is how the marketeer data set looks like:

We can see that there are 872 job listings. It contains 13 columns.

```
##  [1] "X"                      "id"                     "title"
##  [4] "company"                "location"               "postingdate"
##  [7] "today"                  "summary"                "salary"
## [10] "url"                    "description"            "scrapetimesdescription"
## [13] "salary_good"
```

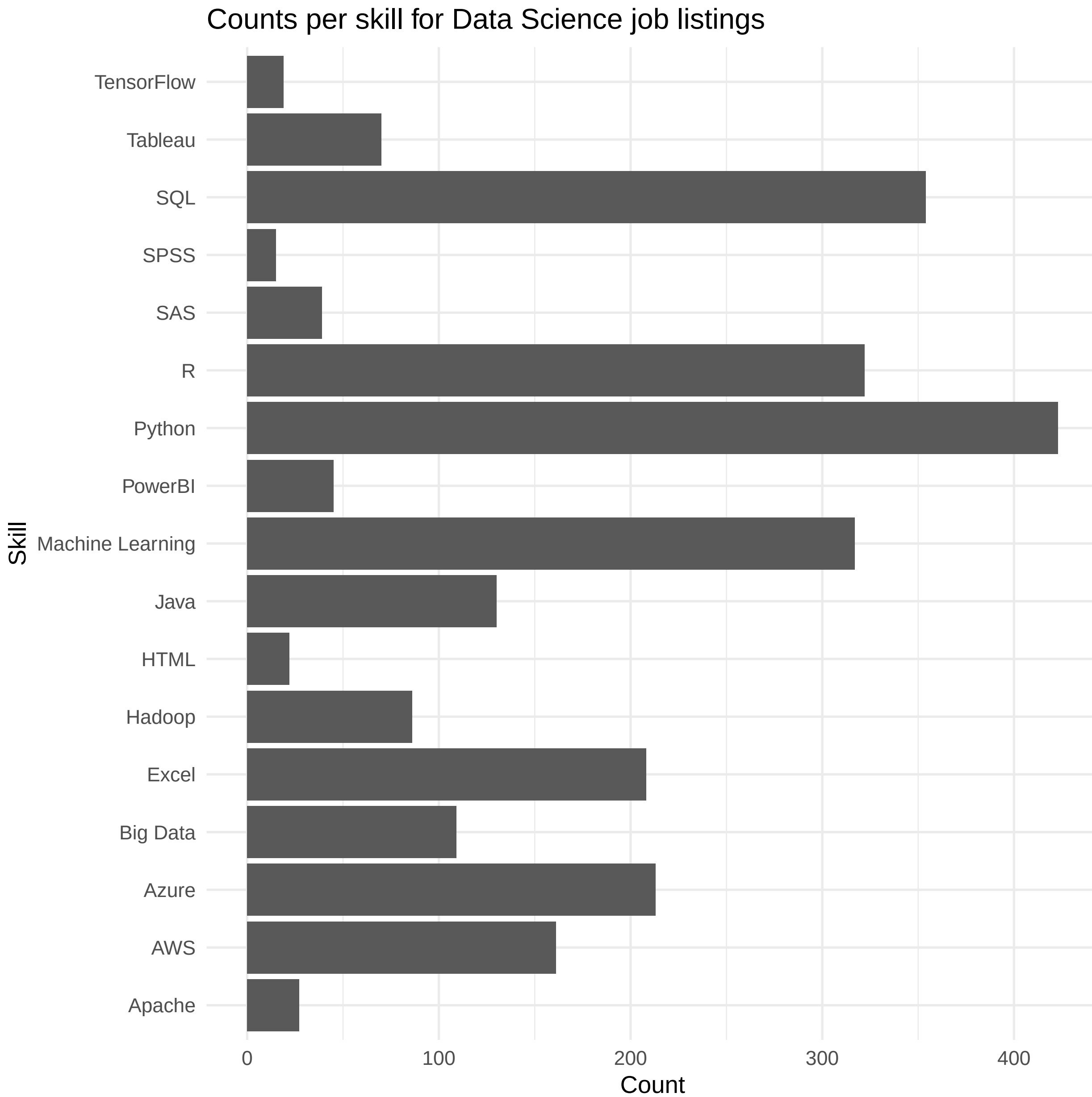
Here can be observed a summary of marketeer.

```
##        X              id               title             company
##  Min.   :  1.0   Length:872         Length:872         Length:872
##  1st Qu.:218.8   Class :character   Class :character   Class :character
##  Median :436.5   Mode  :character   Mode  :character   Mode  :character
##  Mean   :436.5
##  3rd Qu.:654.2
##  Max.   :872.0
##
##    location         postingdate           today             summary
##  Length:872         Length:872         Length:872         Length:872
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
```

```
##
##
##
##
##    salary             url            description
##  Length:872         Length:872         Length:872
##  Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##  scrapetimesdescription  salary_good
##  Length:872             Min.   :   8400
##  Class :character       1st Qu.:  30600
##  Mode  :character       Median :  36000
##                         Mean   :  58519
##                         3rd Qu.:  42000
##                         Max.   :2400000
##                         NA's   :653
```

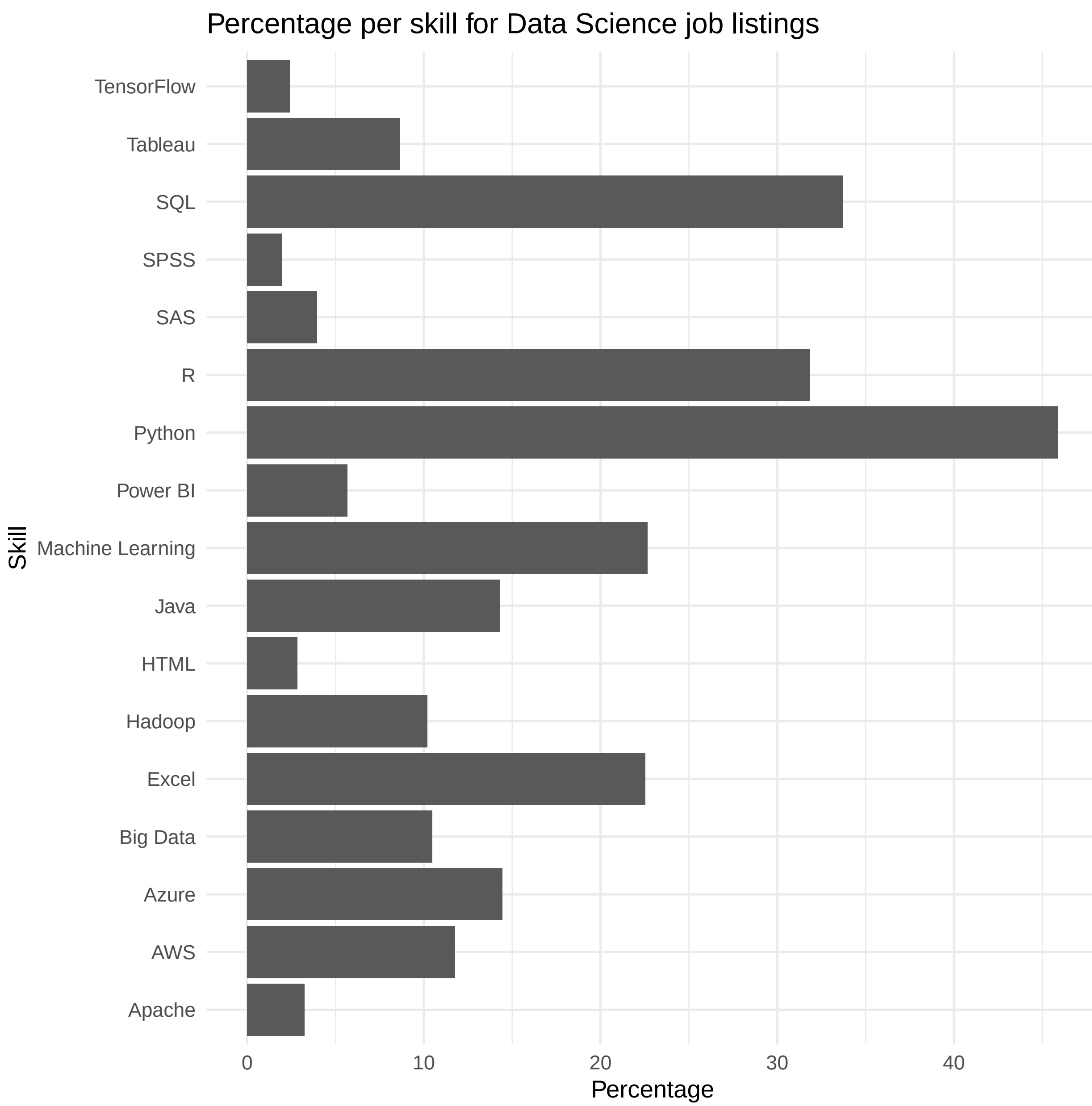
4. Keyword Analysis

In the following sections we provide the analysis for our research. We performed 3 types of analysises. 1: skill keyword analysis, in which we analyze the frequency of occurence for certain technical skills related to marketing analaytics. 2: location analysis, after knowing the right skills to pursue for the next job we provide a location analysis in which we investigate what the top locations for our 4 jobs. 3: salary analysis, we finish with a short analysis of average salaries for each job and the best locations salary wise for each job.

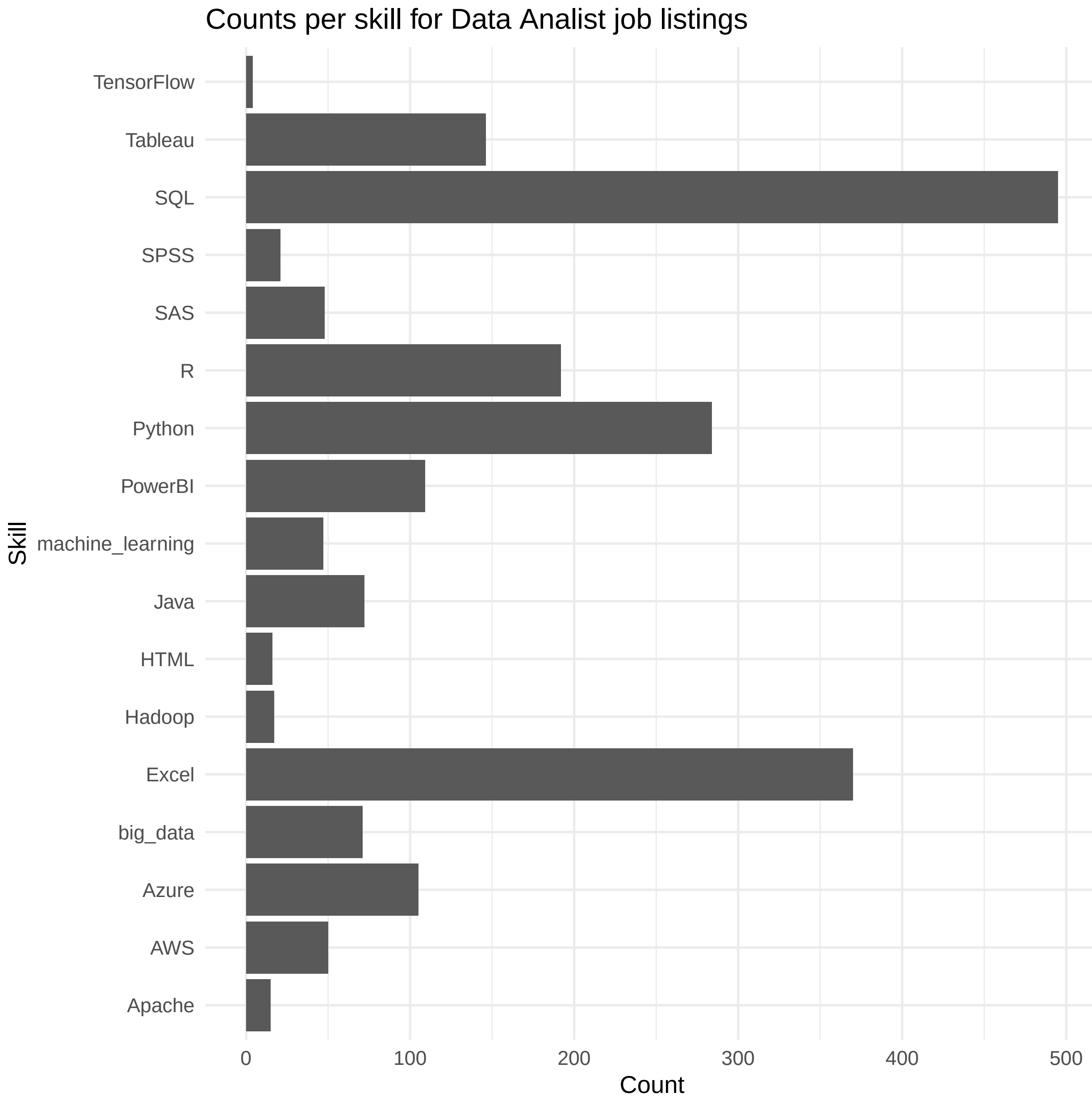


This is a plot of the core technical skills and their counts in the data scientist job ads. As we can see, there are 4 clear top skills to learn to become a data scientist. These include Python, SQL, R and machine learning, with each having counts over 300. Other important skills seem to be Java, Excel, Azure and AWS(amazon web services) with each having counts over 100.

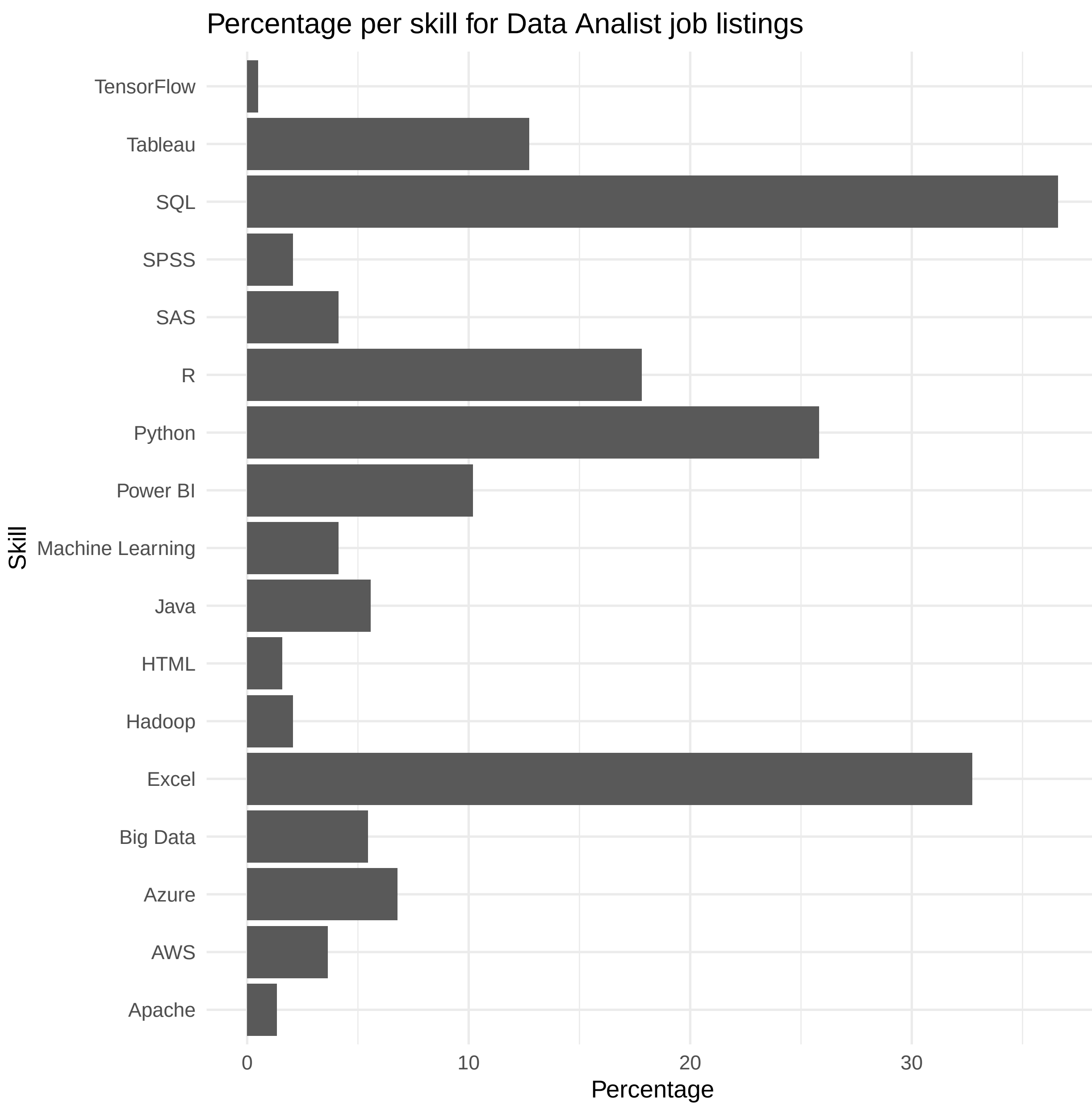
However, counts do not paint the entire picture. Some job ads have double or even more counts of the same skill within the same description. To control for this, we also calculate the percentage of job ads wherein each skill is featured in the description. For example, if in every second job ad, the skill R is mentioned, it will have a value of 0.5.



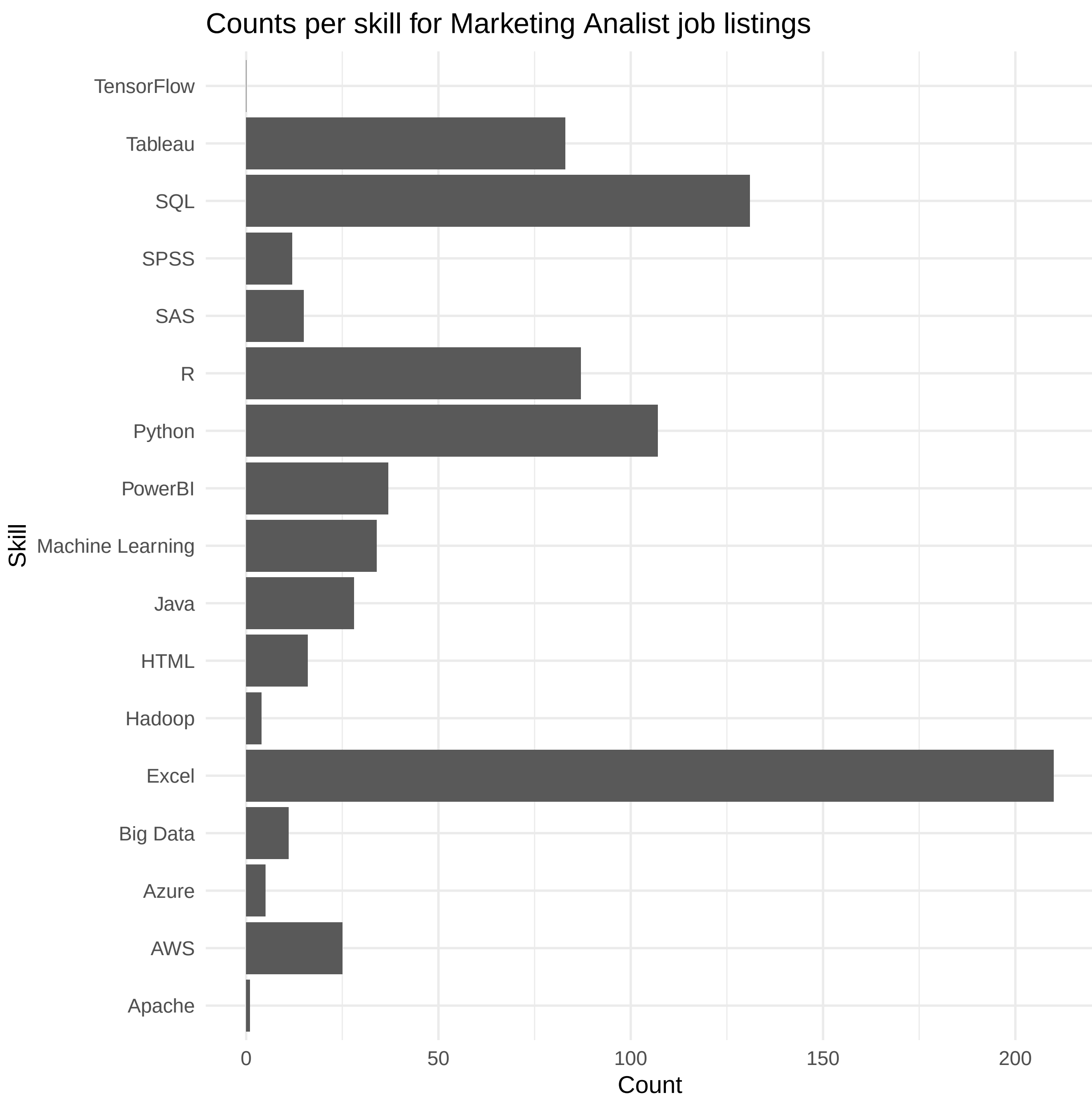
The percentage plot shows us that the percentage analysis bears quite similar results to the count analysis. Again Python, R, machine learning and SQL are the most important skills. However, the difference between Python and the other skills is bigger in terms of percentage occurrence than in count. Also in percentage terms, Excel is becoming more important, catching up with the top 4 skills and being almost equally important as machine learning.



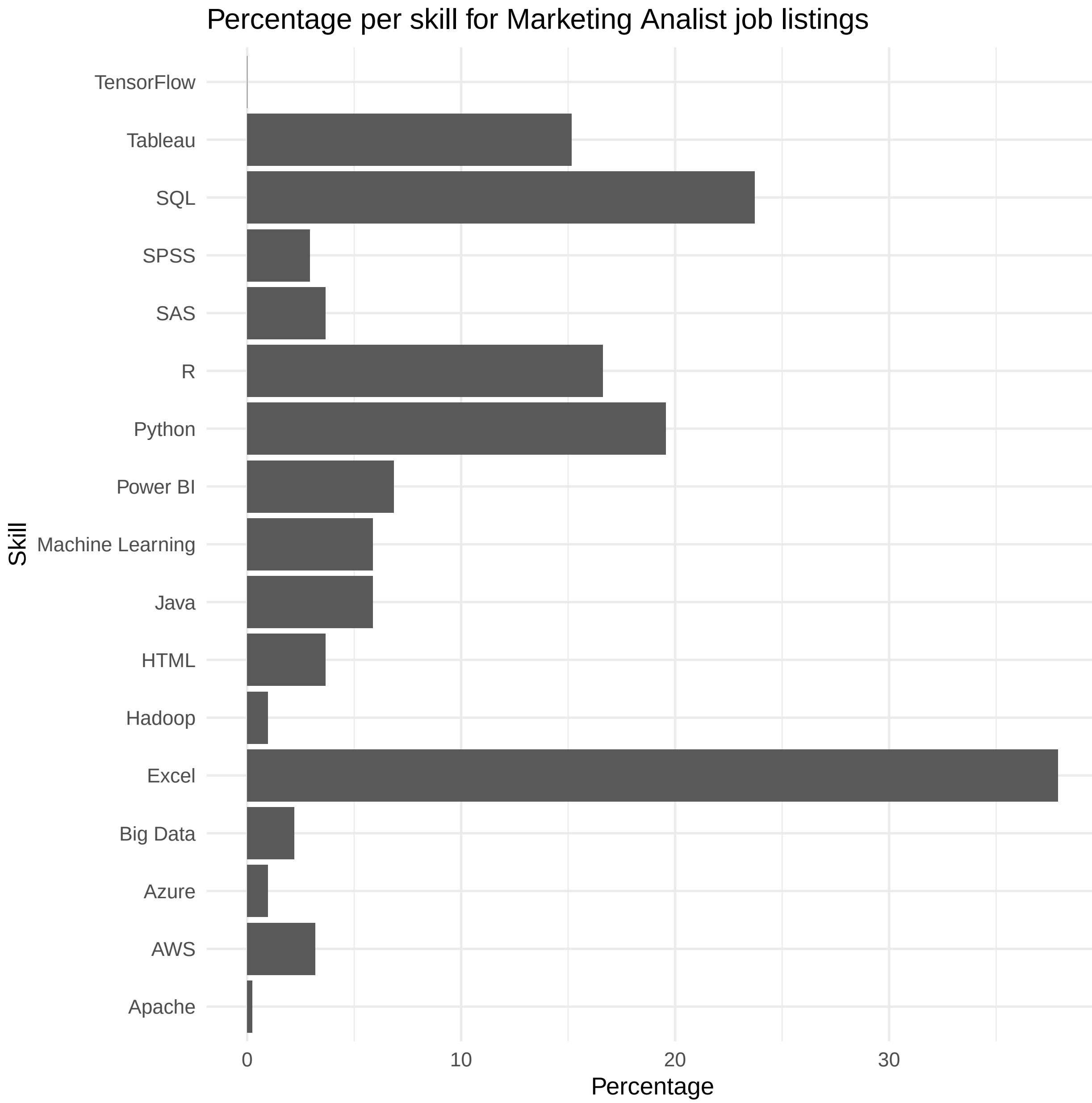
As we can see, quite a different picture for data analist jobs. The clear winner is SQL, which approaches the 500 count. After SQL, Excel is the second most sought after skill with over 350 counts. In 3rd and 4th come the 2 programming languages Python and R, with Python slightly edging R in terms of importance. Other important skills inclead Tableau, Power Bi and Azure.



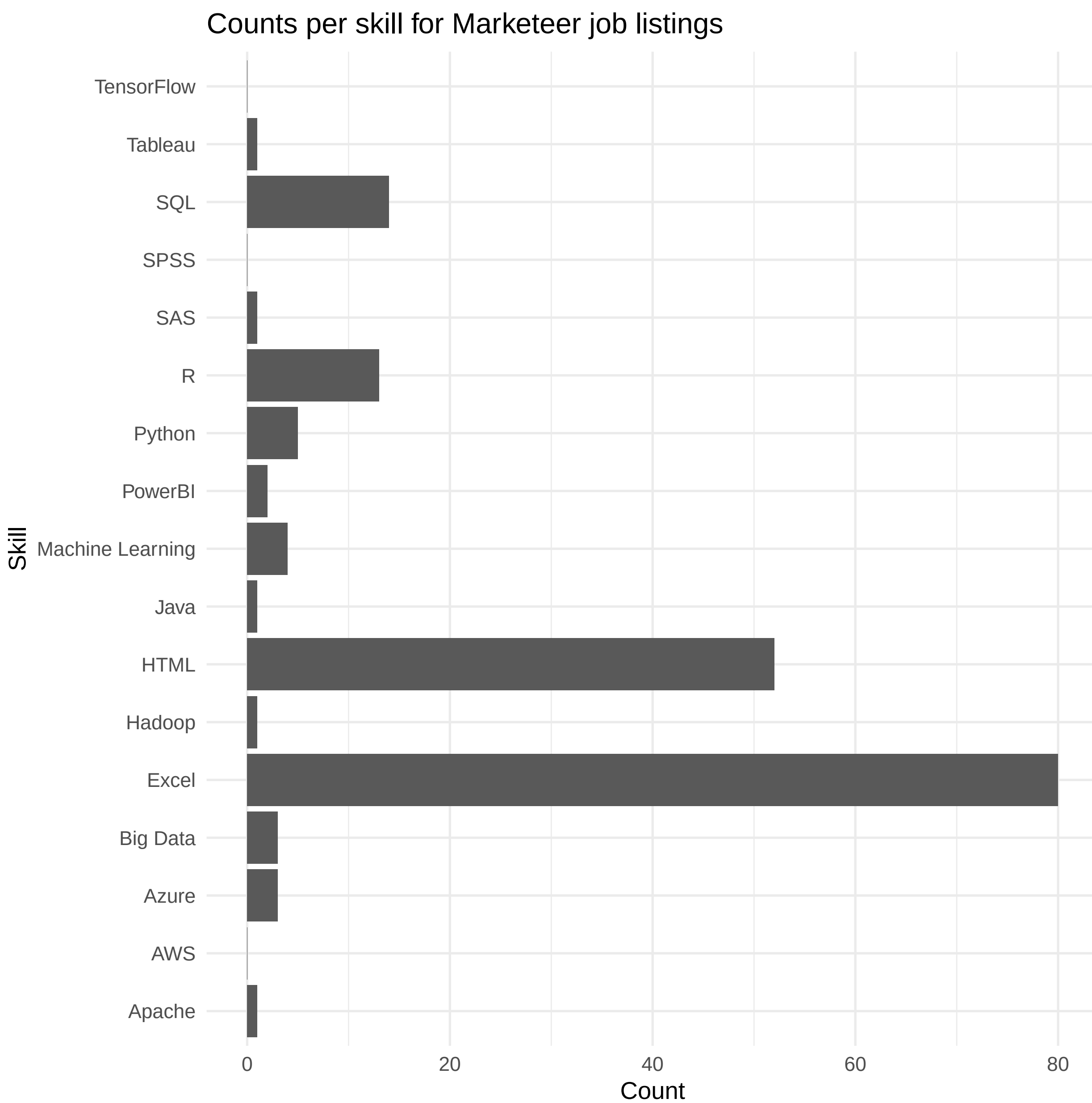
Again similar results for the percentage analysis. However, the difference between SQL and Excel is declining, with both being almost equally important. Also the difference with number 3 Python seems slightly smaller than in the count analysis. Again other important skills are R, Power BI and Tableau.



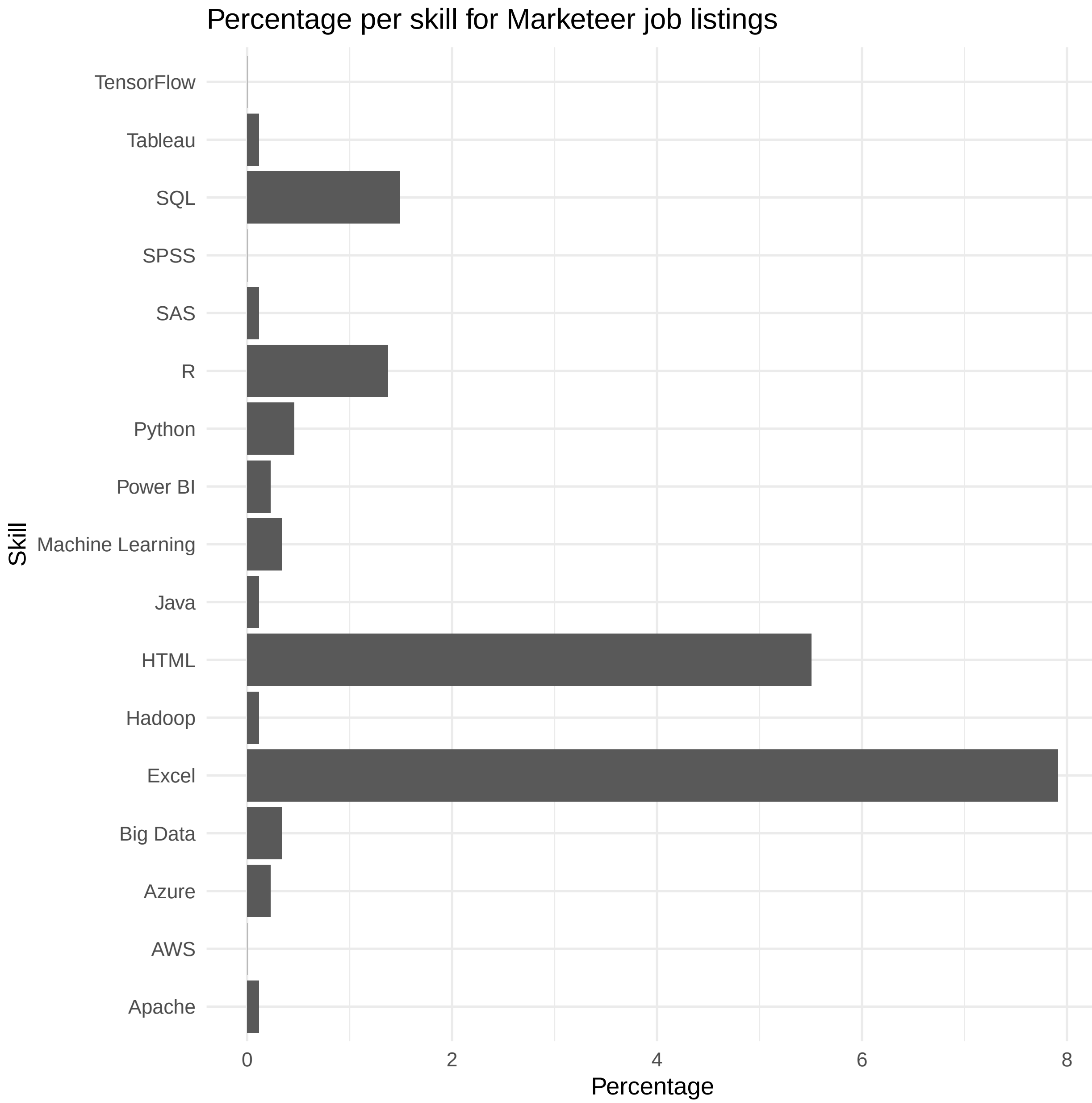
The clear winner for skills to learn for a marketing analyst is Excel, being the only skill reaching a count over 200. Other important skills are SQL, Tableau, R and Python, with all of them being very close to eachother in terms of relative importance. Then after quite a big gap, skills such as Power BI, AWS and Azure come, clearly seemingly not that meaningful to learn as a marketing analist.



The Percentage plot shows very similar results to the count plot. Again, Excel is the clear winner, with mentions in over 1/3 of the job descriptions. sQL, Python, R and Tableau follow on respected distance with all being roughly equally relevant for marketing analysts to learn.

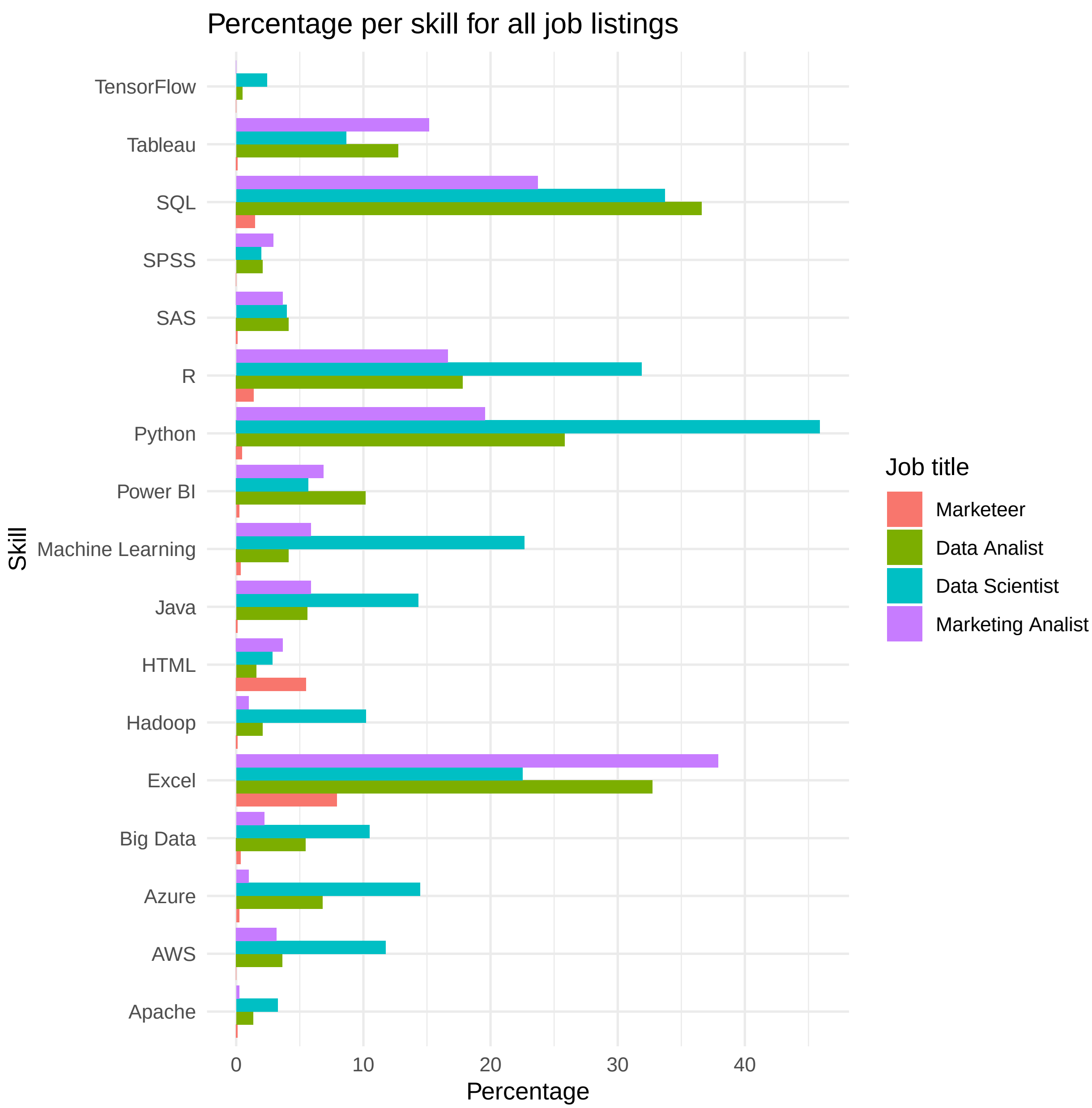


For Marketeers, it is clear that technical skills are less important than for the other jobs, which involve more data related tasks. Despite this fact, Excel is still valuable, being the clear winner for marketeers in terms of technical skills. 2nd spot is for HTML, which is seen as a valuable skill for marketeers to have. Other slightly important skills are R and SQL, with each of the other skills being almost equal to 0 in terms of occurrences in the job ads for marketeers.



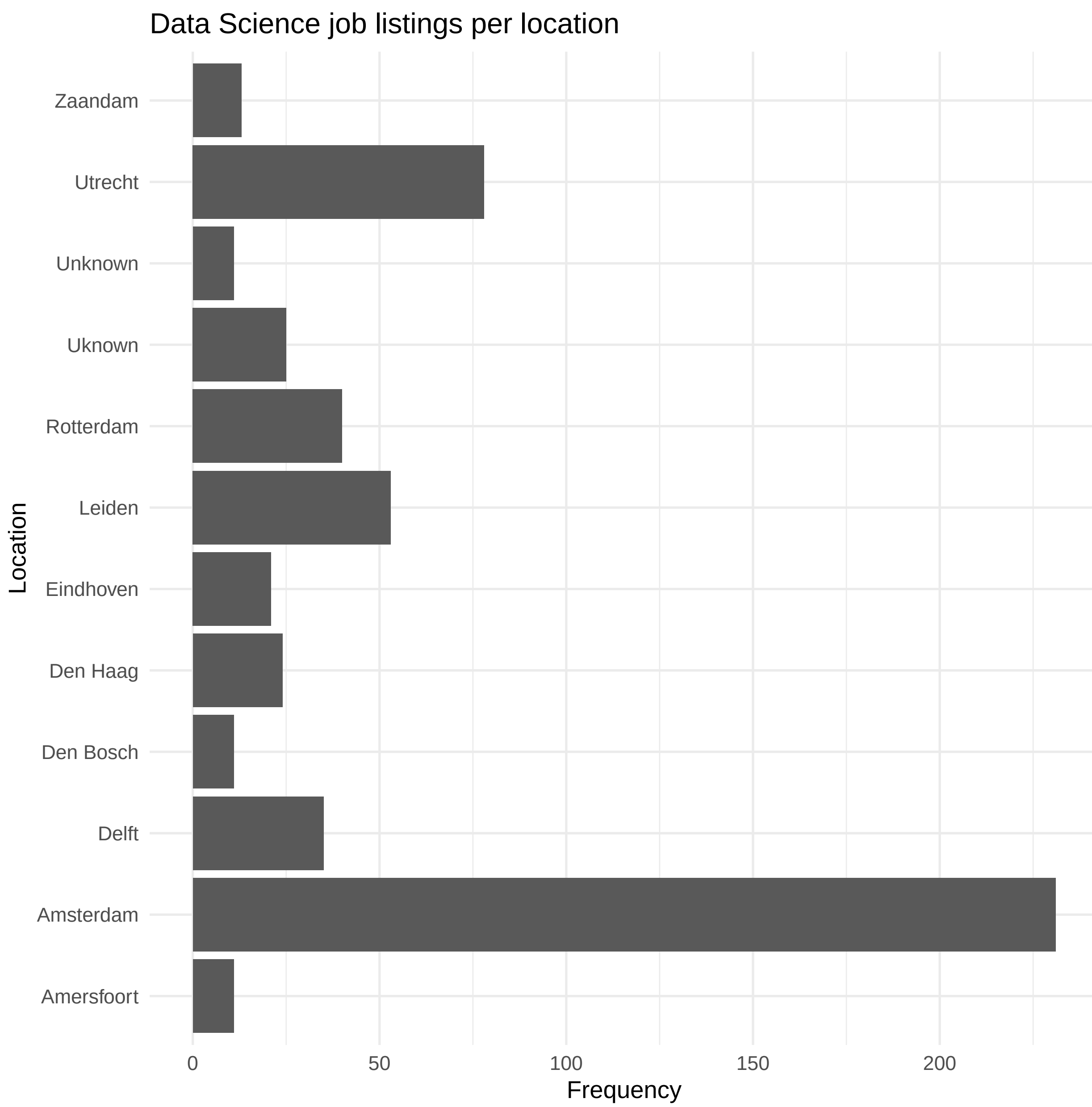
Similar results in percentage, which show that the technical skills get mentioned really infrequently in the job advertisements. Excel the winner in terms of technical skills gets mentioned in only 8 percent of job ads. Compared with winner skills for other job searches reaching over 30-40 %, there is a clear difference in the job requirements for marketeers.

Combining the seperate bar charts presented above into one bar graph, to conveniently compare the skills occurence for our 4 job searches. In the following section we will provide a comprehensive graph which shows each skill percentage occurrence for each job next to eachother. In order to facilitate direct comparison.

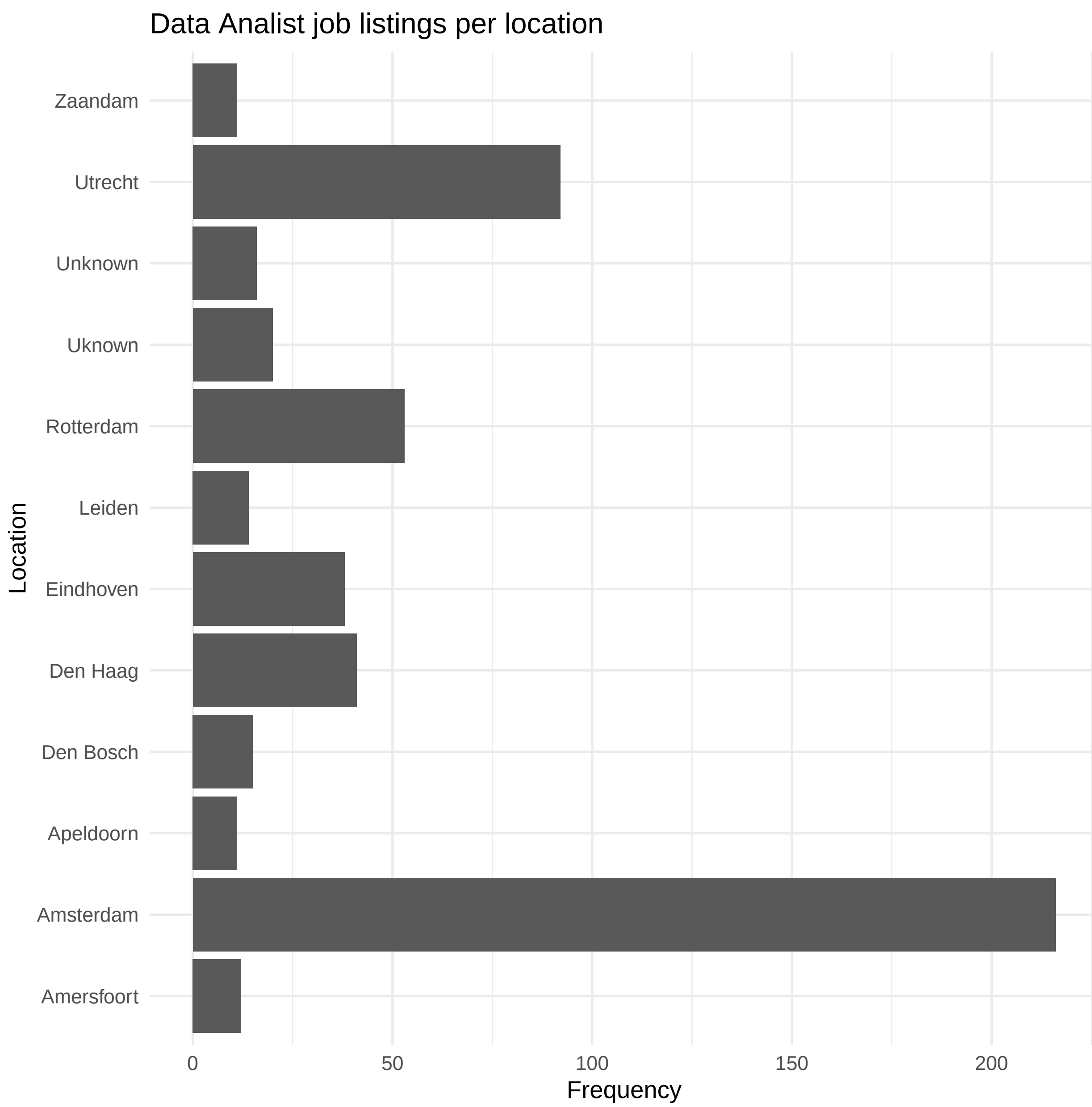


The top 4 skills in general are Python, R, SQL and Excel. With data scientist relying heavily on Python whereas fo marketing and data analysts it might be more fruitful to invest in your SQL skills. There seems a clear discrepancy between the R and SPSS heavy academic courses and the actual skills required by companies, more focused on SQL and Python to perform job tasks. Especially SQL is completely missing from the Master in Marketing analytics curriculum. Whereas Python is available in a few courses only.

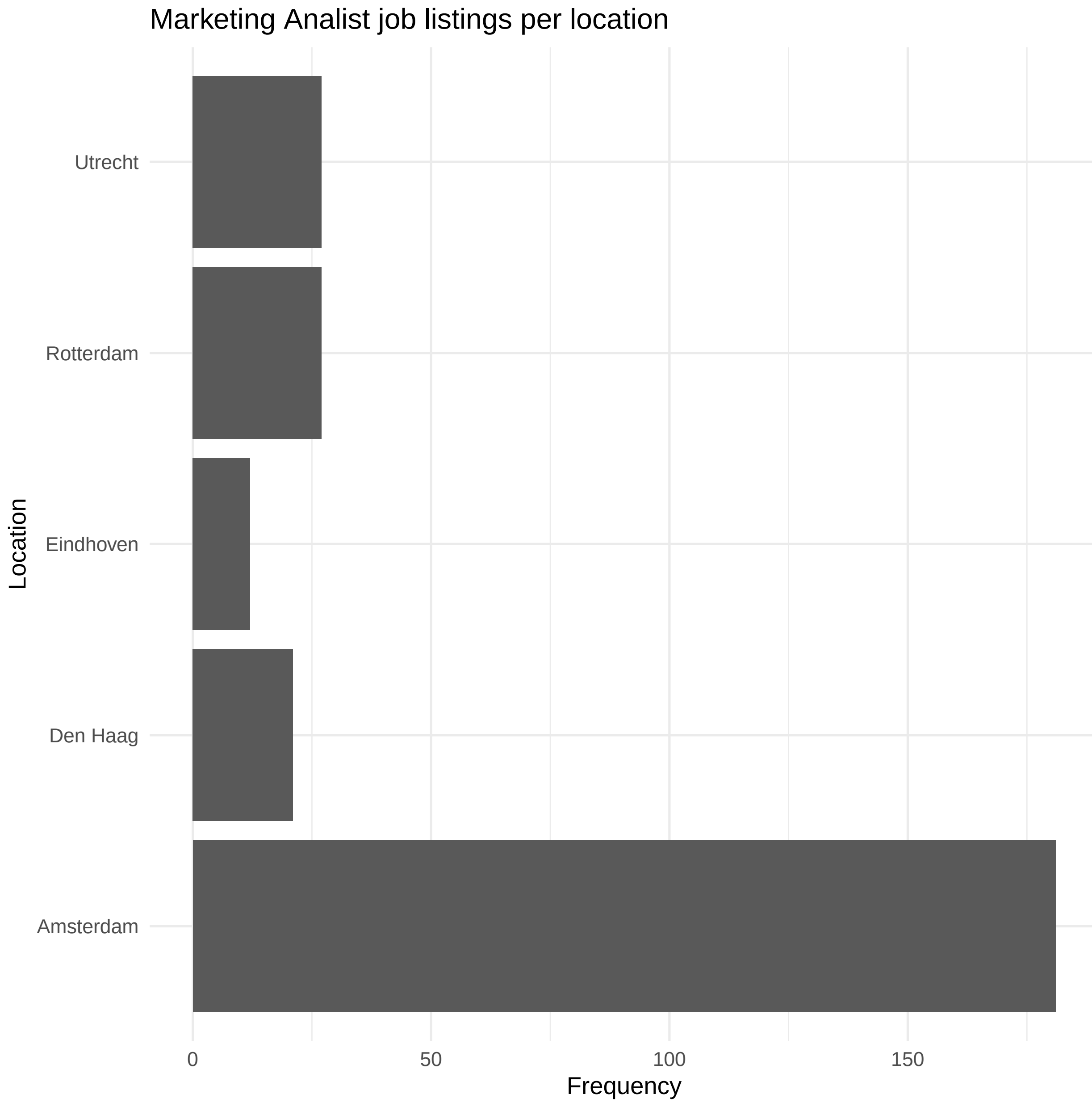
5. Location frequency analysis



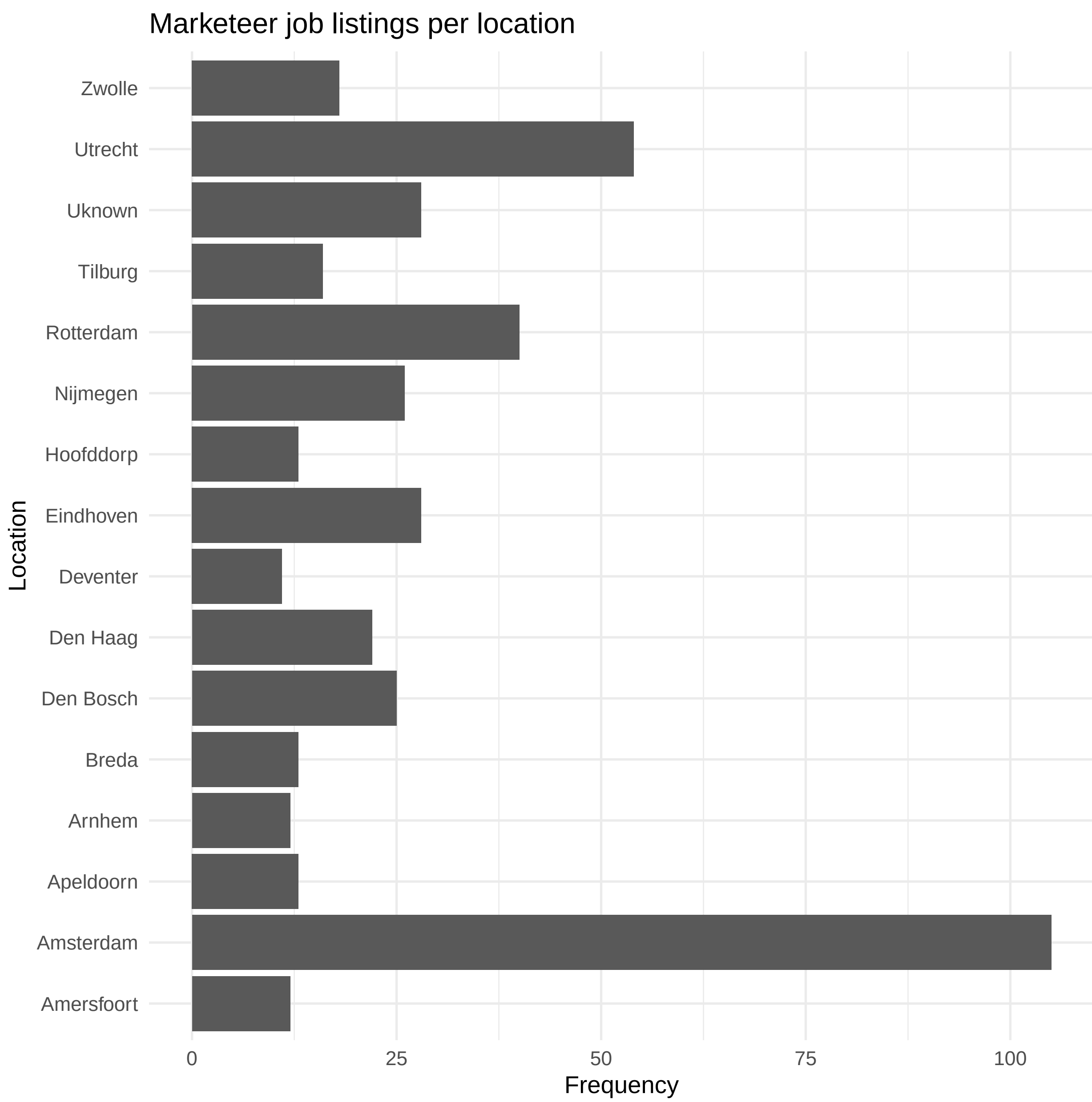
Amsterdam seems the place to be as a data scientist, with counts over 200, or roughly 1/3 of the entire number of jobs posted being in Amsterdam. Furthermore, as expected, the randstad features the most in job ads, with Utrecht, Rotterdam and Leiden coming in high as well. Outside of the randstad, Noord-Brabant in the form of Eindhoven and Den Bosch provide a decent number of job opportunities.



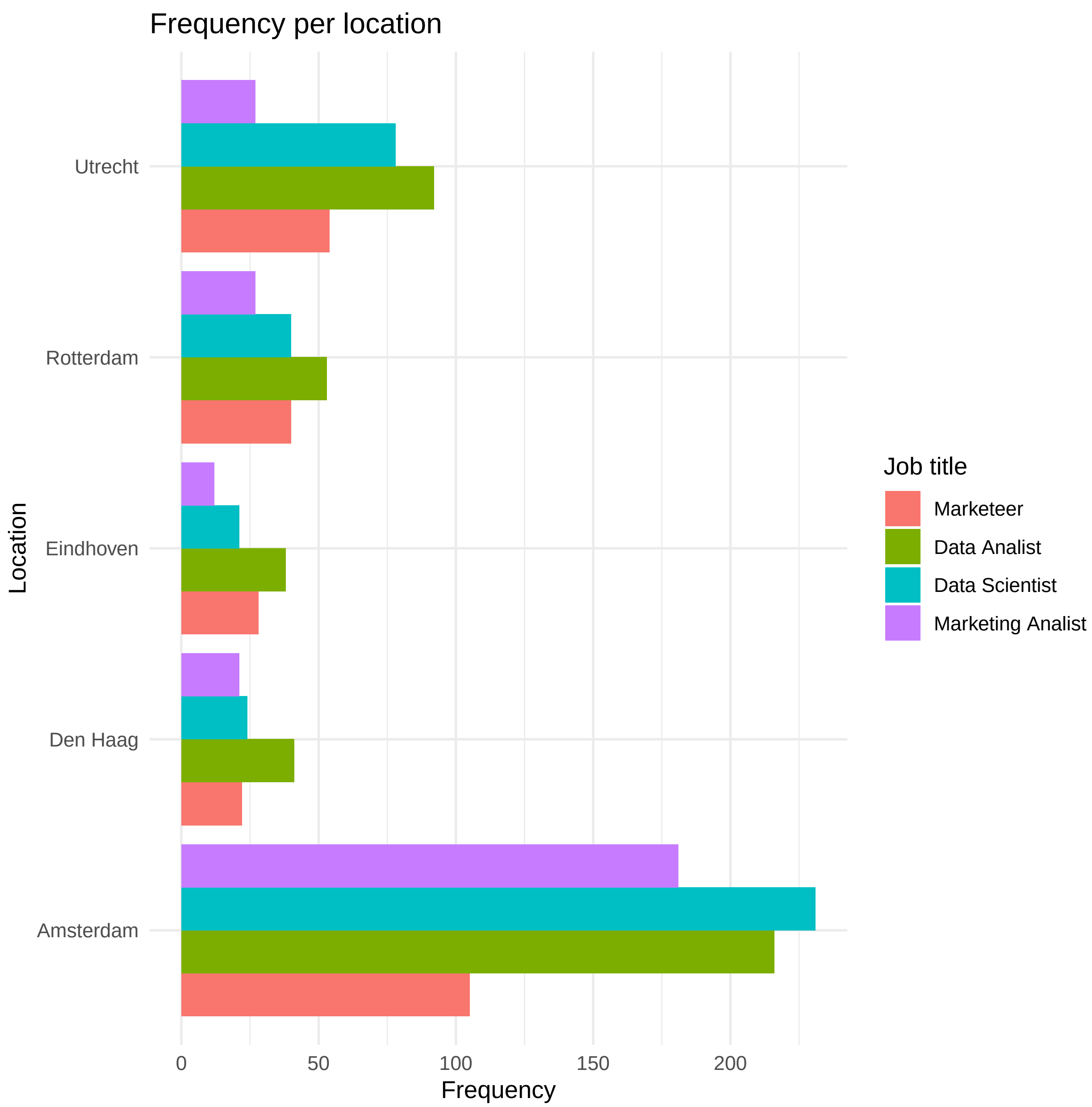
For data analysts, the picture is quite similar. Amsterdam again is the clear winner in terms of number of jobs offered, however, Utrecht seems relatively more important for data analysts compared to data scientists. Rotterdam again is number 3, with Den Haag and Eindhoven completing the top 5 in terms of locations.



For Marketing analysts we see the same top 5 as for data analysts. However, Utrecht, Rotterdam and Den Haag all have almost equal counts of Job offers and Amsterdam is a way more pronounced winner for Marketing analysts than for the other jobs scrutinized before.



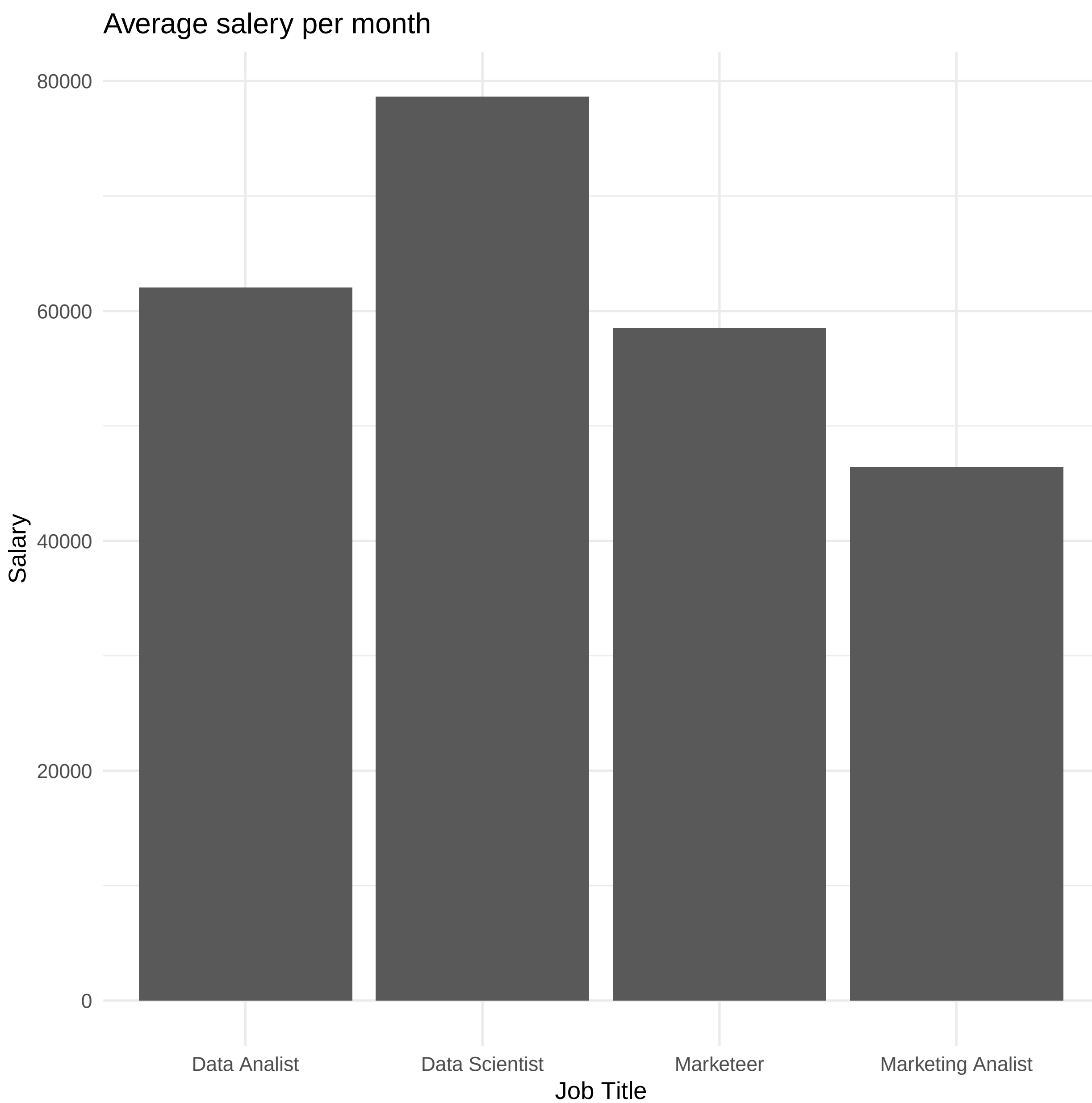
For Marketeers, it seems that there are more opportunities outside of the randstad available compared to the 3 data related jobs. Cities as Breda, Arnhem, Deventer and Nijmegen come in quite close to the randstad cities such as Rotterdam and Utrecht, suggesting that the job opportunities for marketeers are more evenly spread across the country.

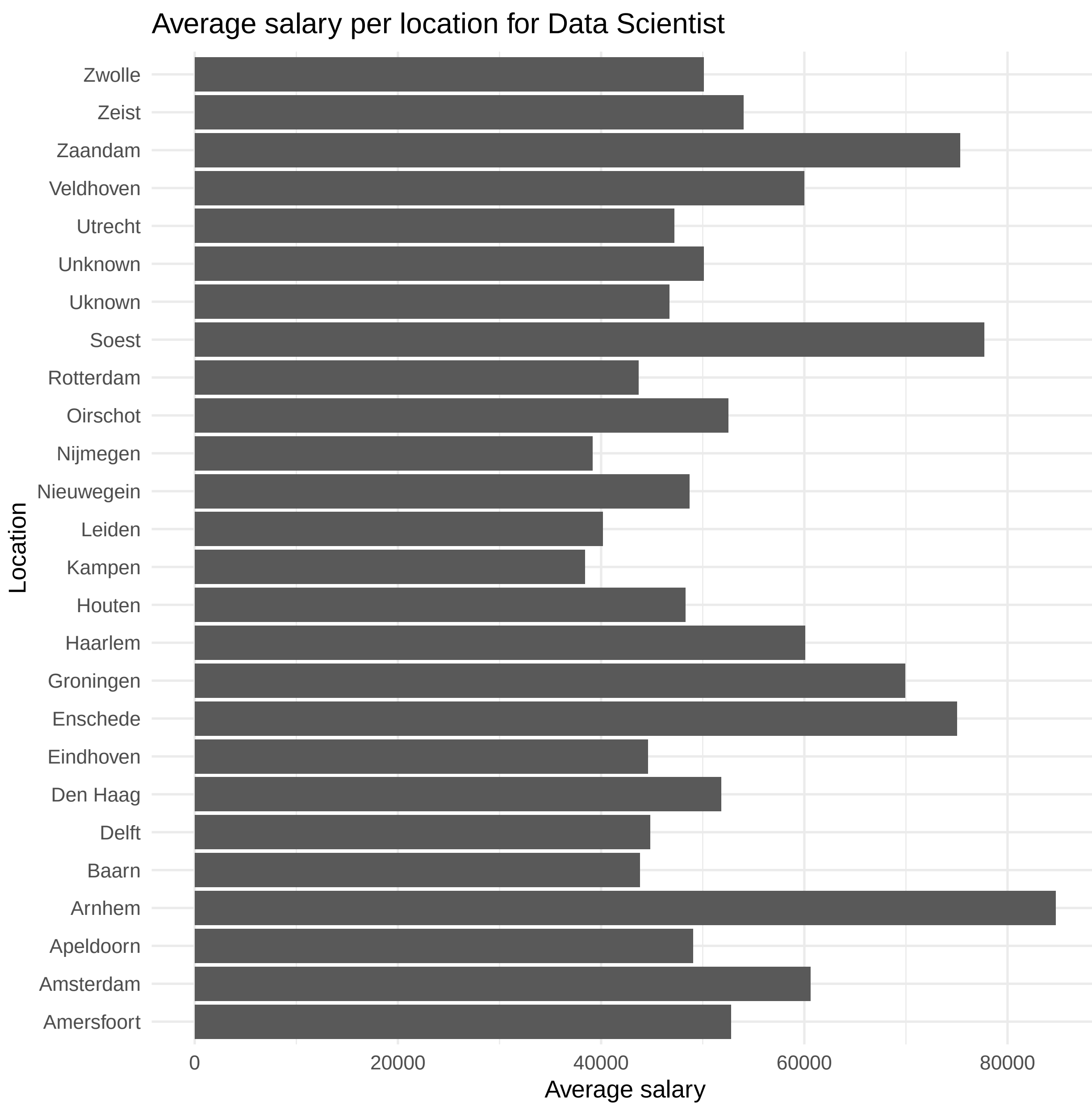


This graph show the top 5(plus remote) locations for job ads. As expected, Amsterdam is the clear winner for each job in terms of number of job offers, however the difference is less pronounced for marketeer related jobs than the other 3 jobs. Utrecht comes in 2nd in terms of number of job fofers whereas Rotterdam, Eindhoven and Den Haag are very equally ranked.

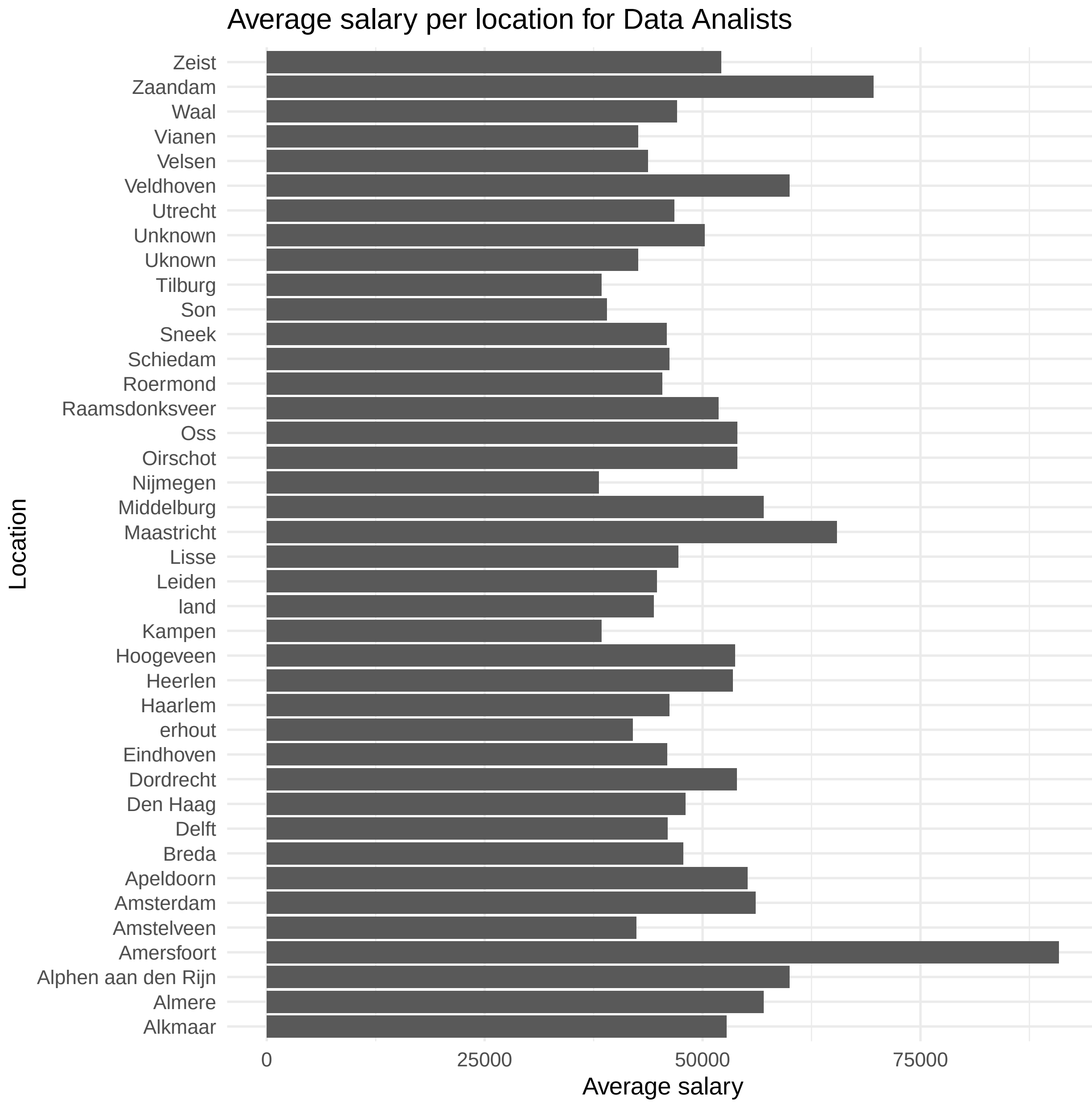
Now that we know what the most important skills are to learn for our 4 jobs and also what the best cities are to go to, to find a job quickly, we analyze the best jobs and locations in terms of pay.

6 Salary analysis

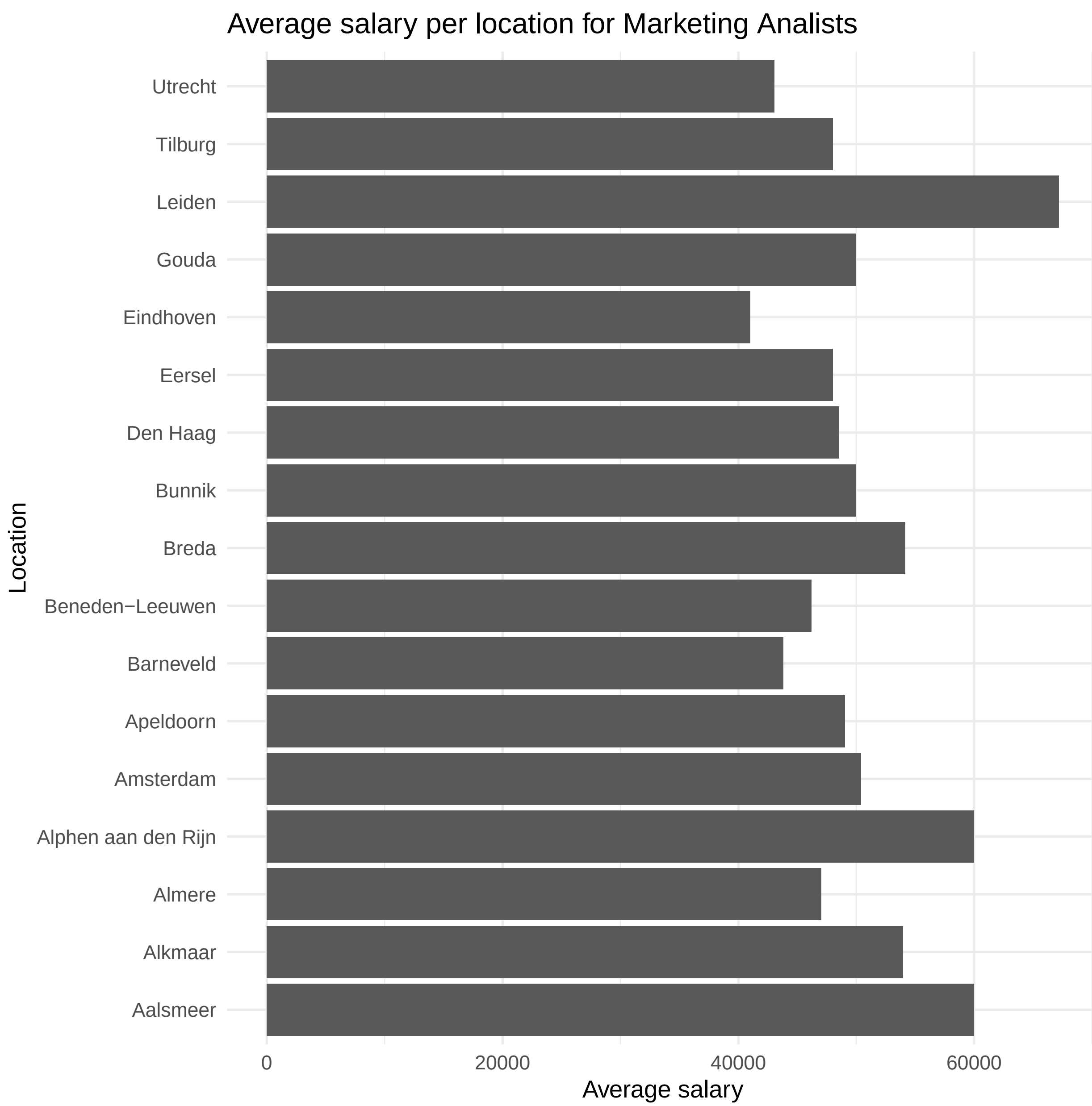

Average salery per month
80000
60000
40000
20000
0
Salary
Data Analist
Data Scientist
Marketeer
Marketing Analist
Job Title



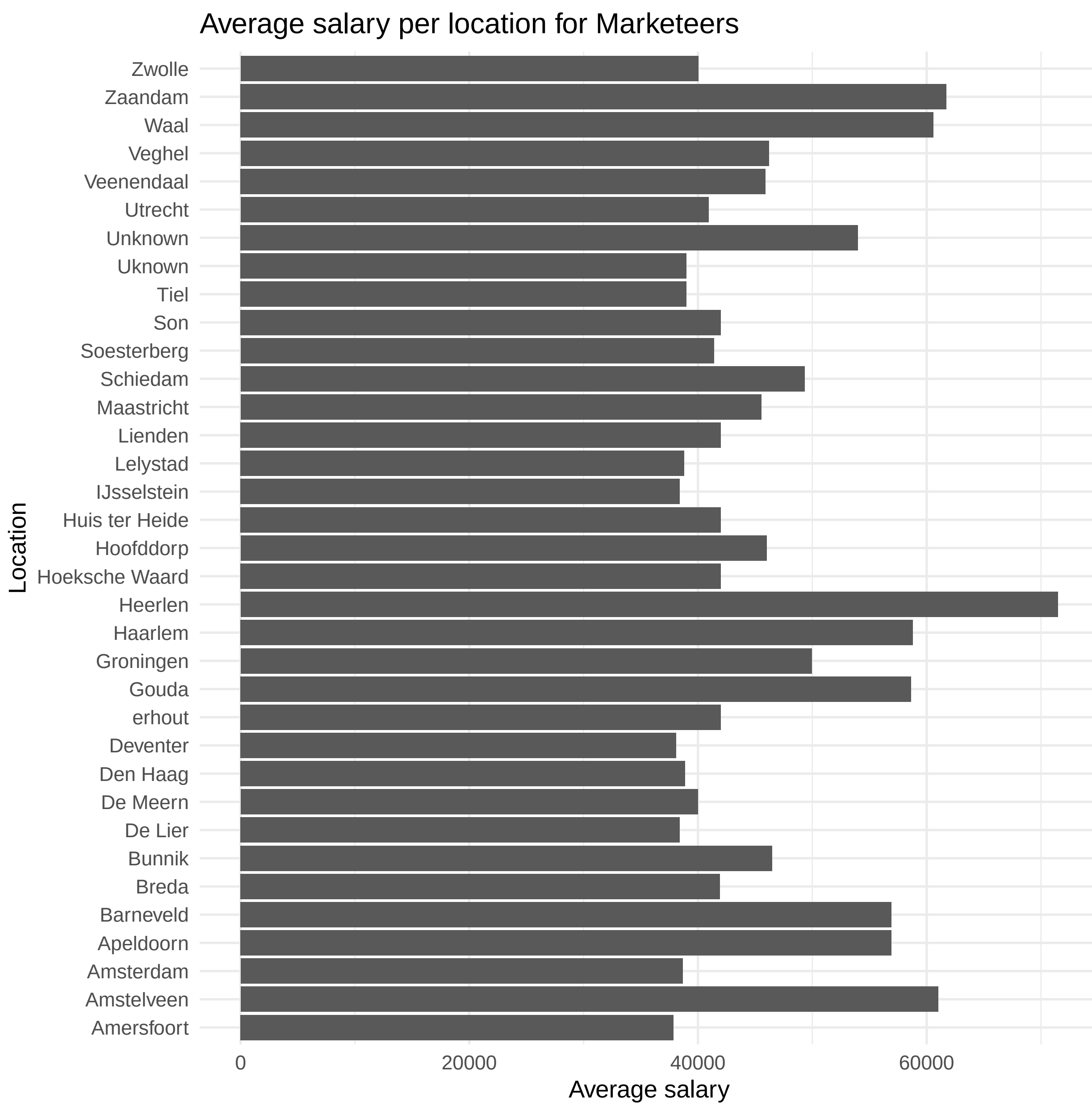
Amsterdam has over 200 job offers for data scientists. Number 2 Utrecht has 75 job postings so there is quite a big gap. Furthermore, Leiden takes in 3rd place quite surprisingly with 50 job offers.



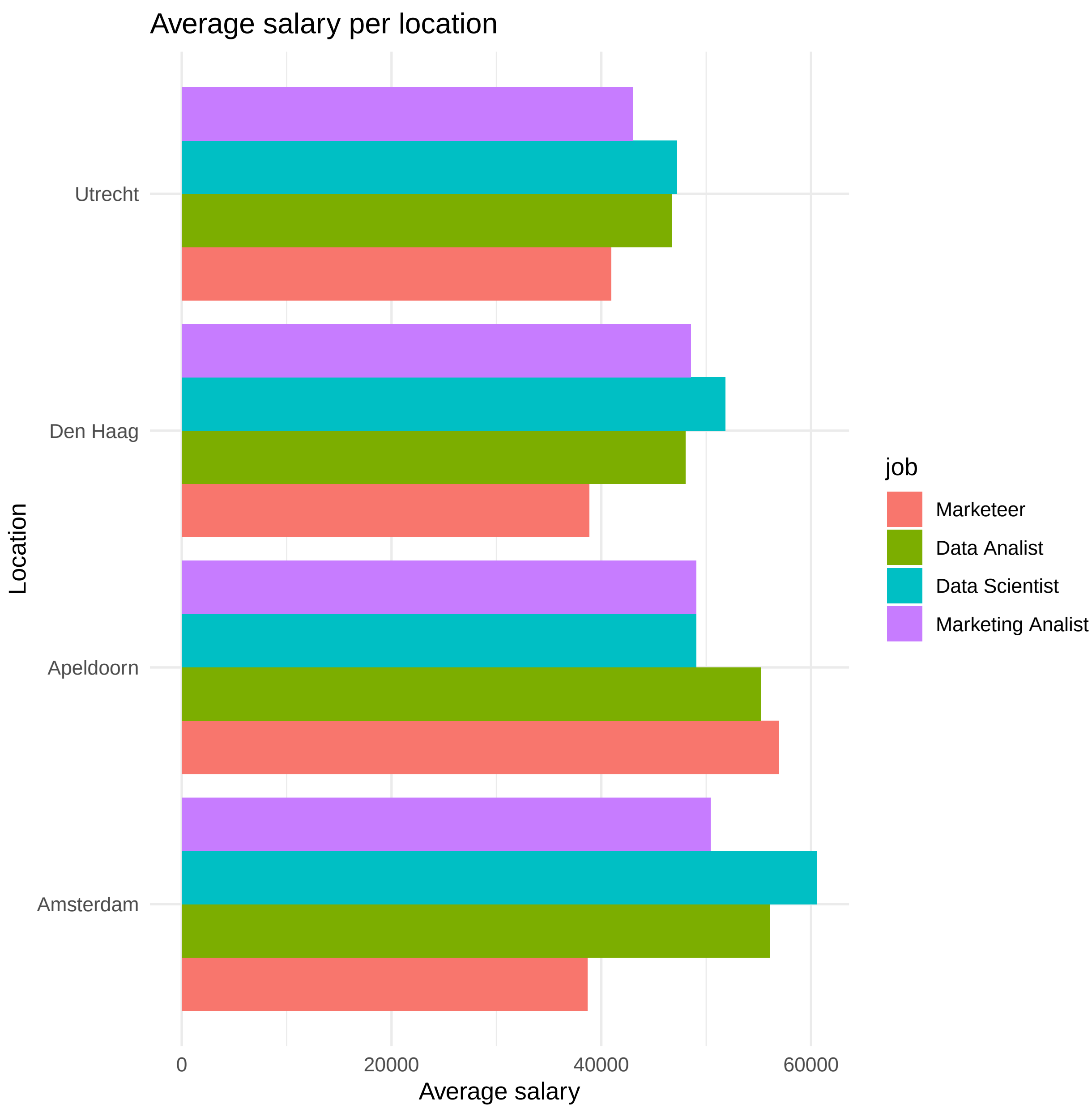
Apart from Amsterdam, Utrecht is quite an attractive spot for data analysts with almost 100 jobs being situated at Utrecht. The top 5 is Den Haag, Rotterdam and Eindhoven, with each around 50 job adverts.



For Marketing analysts, Amsterdam appears to be huge. Compared with other cities the amount of jobs offered is more than 5 times as high. Utrecht, Rotterdam, Eindhoven and Den Haag complete the top 5, but all at respective distance of Amsterdam.



For marketeers again, the same pattern can be viewed. Amsterdam by far the biggest for number of jobs, Utrecht takes 2nd spot and Rotterdam 3rd. However compared to other jobs, there appear quite a few cities outside of the randstad such as Nijmegen, Den Bosch, Breda and Arnhem.



This plot shows that data scientists in general dominate salaries in each location, shortly followed by data analist and marketing analist. However, in Leiden, there seems to be a particularly attractive marketing analist position opening up. 7 Conclusion and discussion

7.1 Conclusion

Our results show that the main skills required by jobs related to Data analysis, Data Science and Marketing are Excel, SQL, R and Python. The curriculum of Marketing Analytics is focused more on R and SPSS, and completely ignores SQL. We believe that students would benefit from the inclusion of courses which develop skills in SQL and Python.

For location, Amsterdam is the clear winner when it comes to number of job offers for any of our 4 search terms. Utrecht comes in 2nd and Rotterdam, Den Haag and Eindhoven make up the top 5. The results make sense since this are also the biggest cities in terms of population within the Netherlands. The results were pretty similar for the 3 data jobs but we saw a clear difference for marketeer jobs, where relatively more opportunities were situatied outside of the Randstad in cities such as Nijmegen, Breda and Arnhem.

For salary, data scientist seem to be in the best position, with on average the highest salaries compared to marketeers, data analysts and marketing analysts.

7.2 Discussion

Our research is limited due to limited sample size. Scraping indeed had its fair share of challenges and our focus on the Netherlands meant that we collected between 500 and 1100 observations per job search. However after cleaning out duplicates these numbers got adjusted downward. Especially for the salary analysis, there was a lot of missing data which meant datasets with a few hundred observations. This means that some of the location averages for salary could be very high or very low due to only one job being offered in that location with perhaps a very high or very low salary. THis suggests that the salary analysis is sensitive to outlier datapoints. This limited sample is however difficult to overcome, since most job ads do not show salary data.

7.3 Future research Our results can be reproduced for any job title and any location in the world. This makes it very interesting for future research to compare different countries with eachother in terms of salary and job skills for the 4 jobs researched in this analysis. However, it also opens up the opportunity to students and job seekers in general perform similar research in any kind of other field they are interested in. By tweaking the search term in the scraper and the skills being asked in the keyword analysis, it is possible to research for example what skills are important in a range of jobs and locations. Furthermore, we think that our analysis could be valuable over time by for example repeating the research on a monthly or yearly basis to observe possible developments over time in skills required, salaries offered and locations offering the most jobs.