# MCristinaFernandez.module05RProject

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# The Situation

Your CEO has decided that the company needs a full-time data scientist, and possibly a team of them in the future. She thinks she needs someone who can help drive data science within then entire organization and could potentially lead a team in the future. She understands that data scientist salaries vary widely across the world and is unsure what to pay them. To complicate matters, salaries are going up due to the great recession and the market is highly competitive. Your CEO has asked you to prepare an analysis on data science salaries and provide them with a range to be competitive and get top talent. The position can work offshore, but the CEO would like to know what the difference is for a person working in the United States. Your company is currently a small company but is expanding rapidly.

```
require("tidyverse")
```

```
## Loading required package: tidyverse
```

```
## Warning: package 'dplyr' was built under R version 4.4.2
```

```
## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
## ✓ dplyr     1.1.4     ✓ readr     2.1.5
## ✓ forcats   1.0.0     ✓ stringr   1.5.1
## ✓ ggplot2   3.5.1     ✓ tibble    3.2.1
## ✓ lubridate 1.9.3     ✓ tidyr     1.3.1
## ✓ purrr     1.0.2
```

```
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
e errors
```

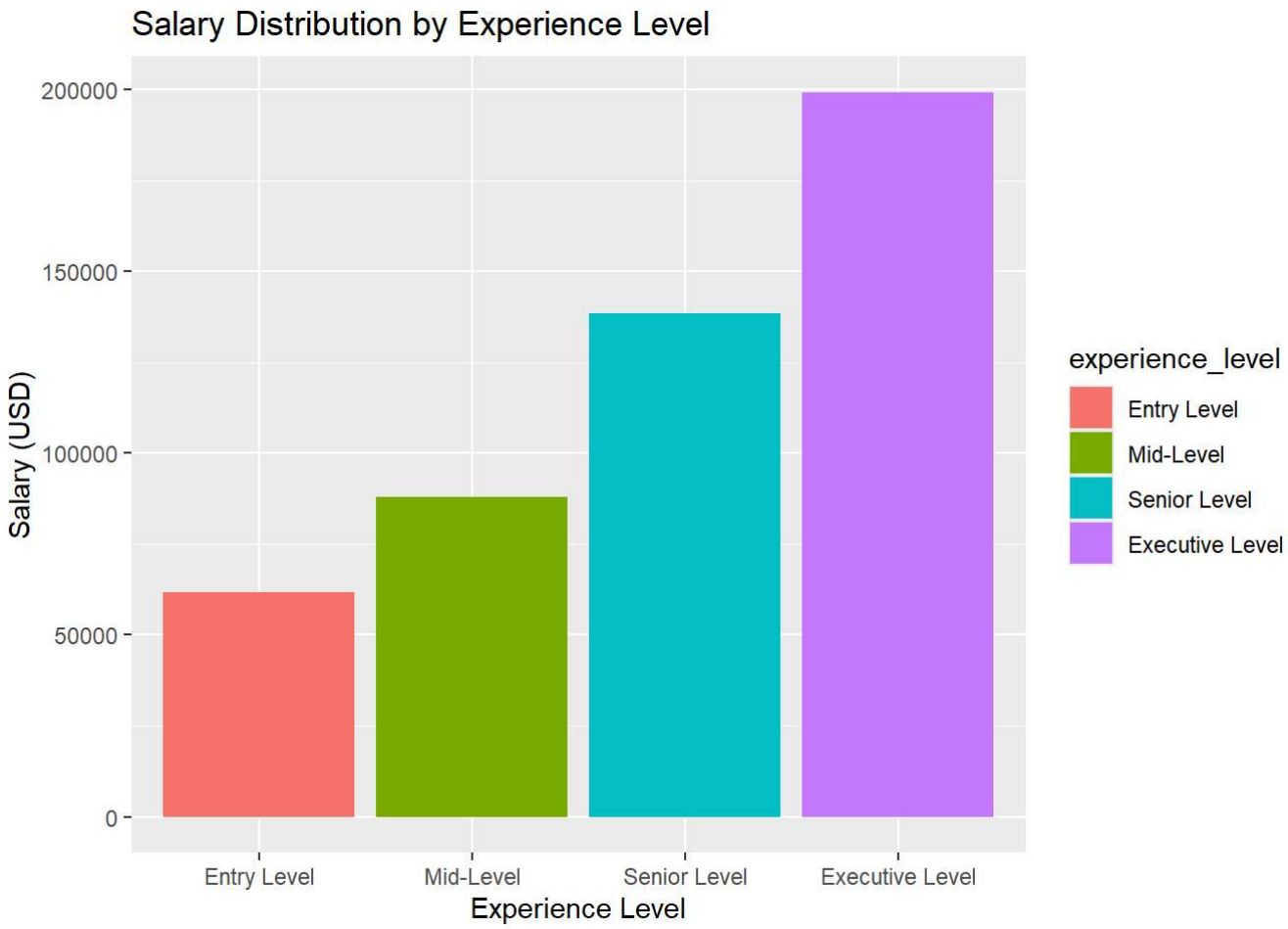
```
require("dplyr")
ds_salaries <- read.csv("C:/Users/crisf/OneDrive/Documents/DSE5002/project_1/r project data.cs
v")
view(ds_salaries)
```

I plan on looking up salaries by experience, employment type, company size, and remote ratio to see if/how these factors influence the salary ranges. I'm going to want to compare what the avg US-based salaries look like vs non-US based (the employee residence) I should see if I can determine any trends over time (perhaps look by year). Get ready for so, so many ggplot graphs.

```
# First, I want to look at the salaries in USD by experience
# Just so I remember: EN Entry-level / Junior MI Mid-level / Intermediate SE Senior-level / Expe
rt EX Executive-level

ds_salaries <- ds_salaries %>%
 mutate(experience_level = factor(recode(experience_level,
                                  EN = "Entry Level",     # I wanted to rename these codes so th
ey made sense to me
                                  MI = "Mid-Level",       # I also looked up how to make sure th
ey showed up in the right order
                                  SE = "Senior Level",
                                  EX = "Executive Level"),
                              levels = c("Entry Level", "Mid-Level", "Senior Level", "Executive
Level")))

salary_by_experience <- ds_salaries %>%
  group_by(experience_level) %>%
  summarize(
    avg_salary = mean(salary_in_usd),
    median_salary = median(salary_in_usd),
    min_salary = min(salary_in_usd),
    max_salary = max(salary_in_usd)
  )

print(salary_by_experience)
```

```
## # A tibble: 4 × 5
##   experience_level avg_salary median_salary min_salary max_salary
##   <fct>                 <dbl>         <dbl>      <int>      <int>
## 1 Entry Level          61643.        56500        4000     250000
## 2 Mid-Level            87996.        76940        2859     450000
## 3 Senior Level        138617.       135500       18907     412000
## 4 Executive Level     199392.       171438.      69741     600000
```

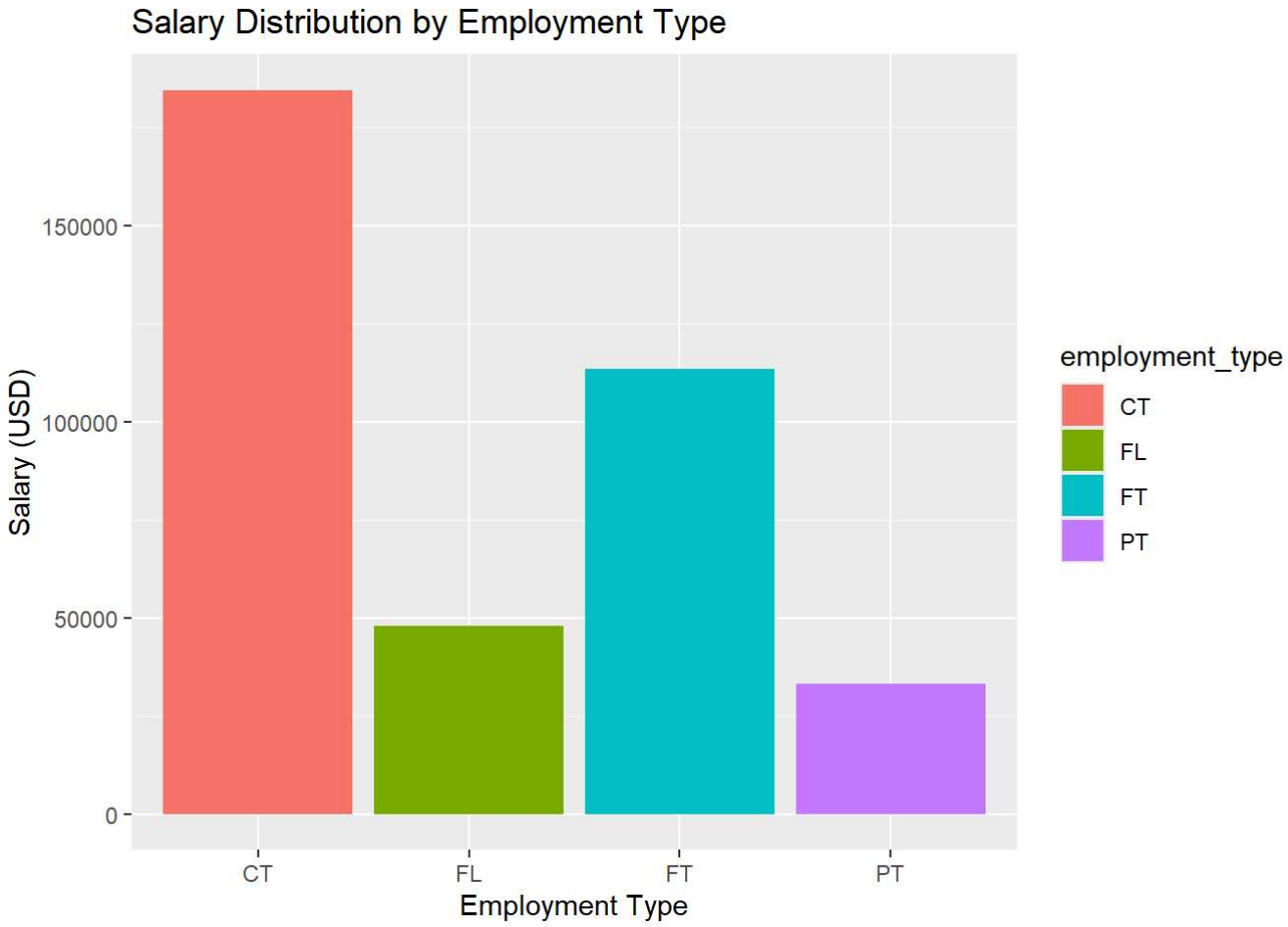
```
ggplot(salary_by_experience, aes(x = experience_level, y = avg_salary, fill = experience_level))
+
  geom_col() +
  labs(title = "Salary Distribution by Experience Level",
       x = "Experience Level",
       y = "Salary (USD)")
```




```
# Next, I want to see whether employment type influences salaries
# PT Part-time / FT Full-time / CT Contract / FL Freelance

salary_by_employment <- ds_salaries %>%
  group_by(employment_type) %>%
  summarize(
    avg_salary = mean(salary_in_usd),
    median_salary = median(salary_in_usd),
    min_salary = min(salary_in_usd),
    max_salary = max(salary_in_usd)
  )

print(salary_by_employment)
```

```
## # A tibble: 4 × 5
##   employment_type avg_salary median_salary min_salary max_salary
##   <chr>                <dbl>         <dbl>      <int>      <int>
## 1 CT                 184575        105000       31875     416000
## 2 FL                  48000         40000       12000     100000
## 3 FT                 113468.       104196.       2859     600000
## 4 PT                  33070.        18818.       5409     100000
```

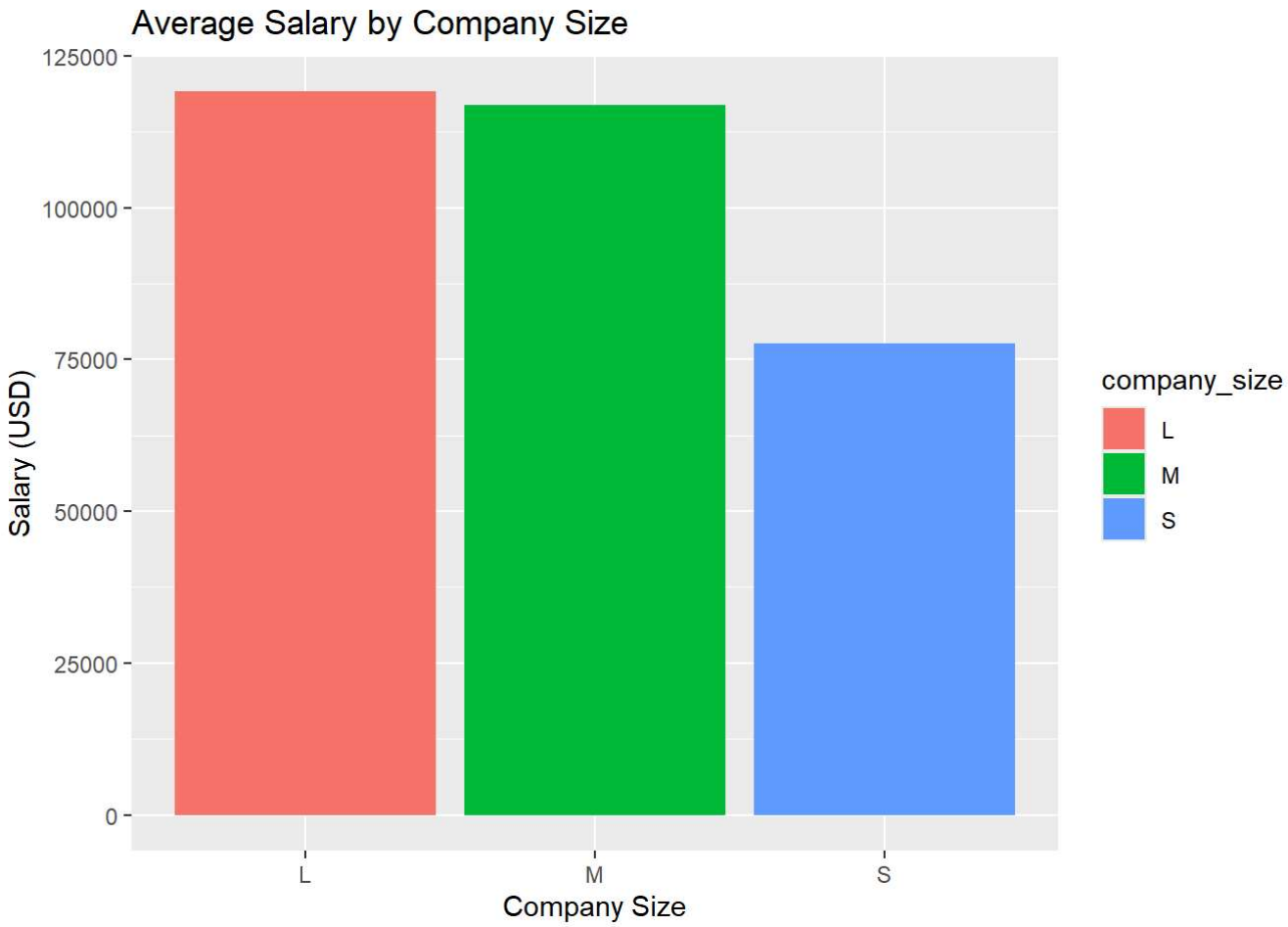
```
ggplot(salary_by_employment, aes(x = employment_type, y = avg_salary, fill = employment_type)) +
  geom_col() +
  labs(title = "Salary Distribution by Employment Type",
       x = "Employment Type",
       y = "Salary (USD)")
```




```
# How might the size of the company influence salaries?

salary_by_company_size <- ds_salaries %>%
  group_by(company_size) %>%
  summarize(
    avg_salary = mean(salary_in_usd),
    median_salary = median(salary_in_usd),
    min_salary = min(salary_in_usd),
    max_salary = max(salary_in_usd)
  )

print(salary_by_company_size)
```

```
## # A tibble: 3 × 5
##   company_size avg_salary median_salary min_salary max_salary
##   <chr>             <dbl>         <dbl>      <int>      <int>
## 1 L               119243.        100000       5882     600000
## 2 M               116905.        113188       4000     450000
## 3 S                77633.         65000       2859     416000
```

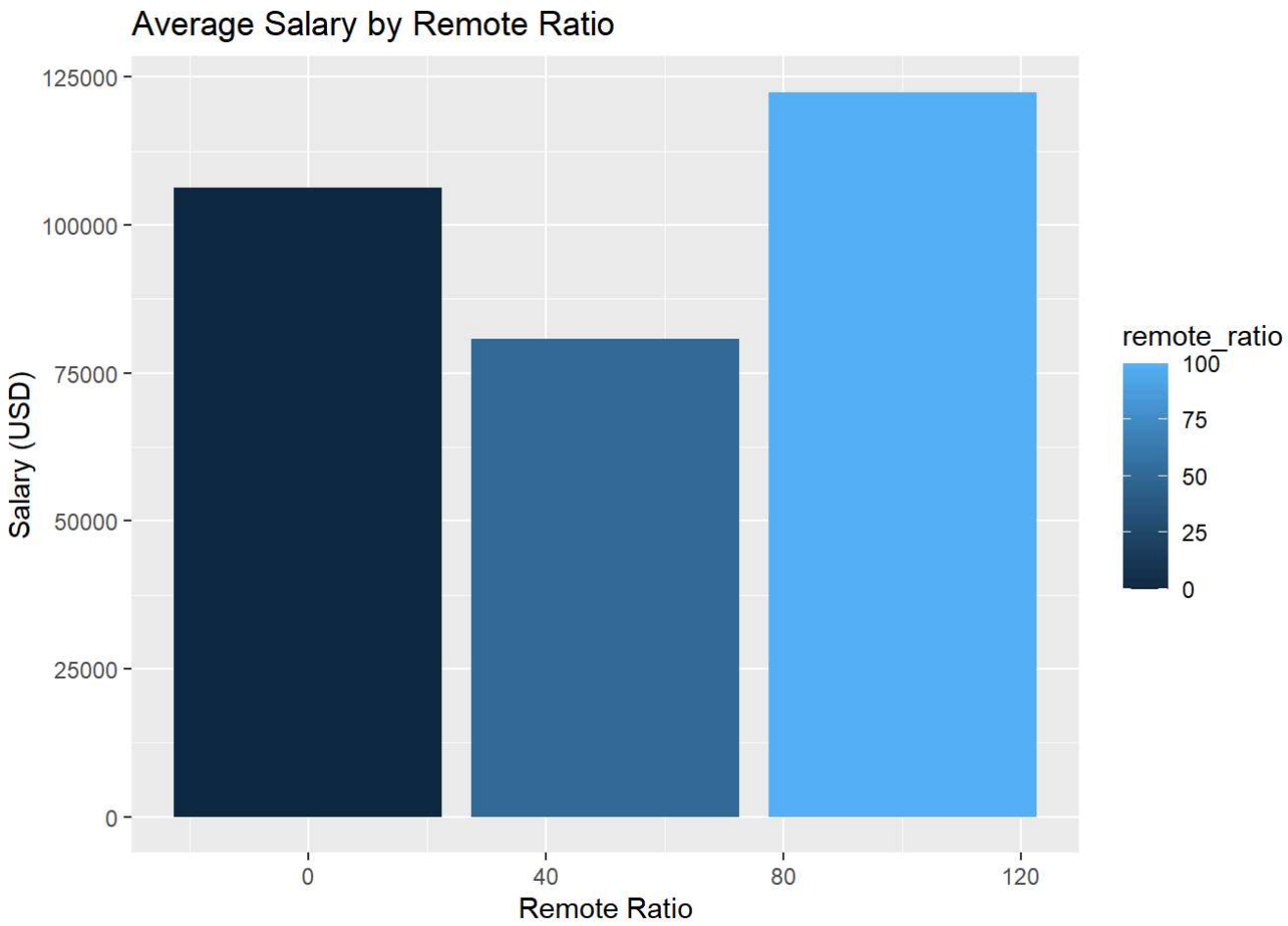
```
ggplot(salary_by_company_size, aes(x = company_size, y = avg_salary, fill = company_size)) +
  geom_col() +
  labs(title = "Average Salary by Company Size",
       x = "Company Size",
       y = "Salary (USD)")
```



```
# What about whether the person works in the office, remotely, or hybrid?

salary_by_remote_ratio <- ds_salaries %>%
  group_by(remote_ratio) %>%
  summarize(
    avg_salary = mean(salary_in_usd),
    median_salary = median(salary_in_usd),
    min_salary = min(salary_in_usd),
    max_salary = max(salary_in_usd)
  )

print(salary_by_remote_ratio)
```

```
## # A tibble: 3 × 5
##   remote_ratio avg_salary median_salary min_salary max_salary
##          <int>      <dbl>         <int>      <int>      <int>
## 1            0    106355.         99000       2859     450000
## 2           50     80823.         69999       5409     423000
## 3          100    122457.        115000       4000     600000
```

```
ggplot(salary_by_remote_ratio, aes(x = remote_ratio, y = avg_salary, fill = remote_ratio)) +
  geom_col() +
  labs(title = "Average Salary by Remote Ratio",
       x = "Remote Ratio",
       y = "Salary (USD)")
```

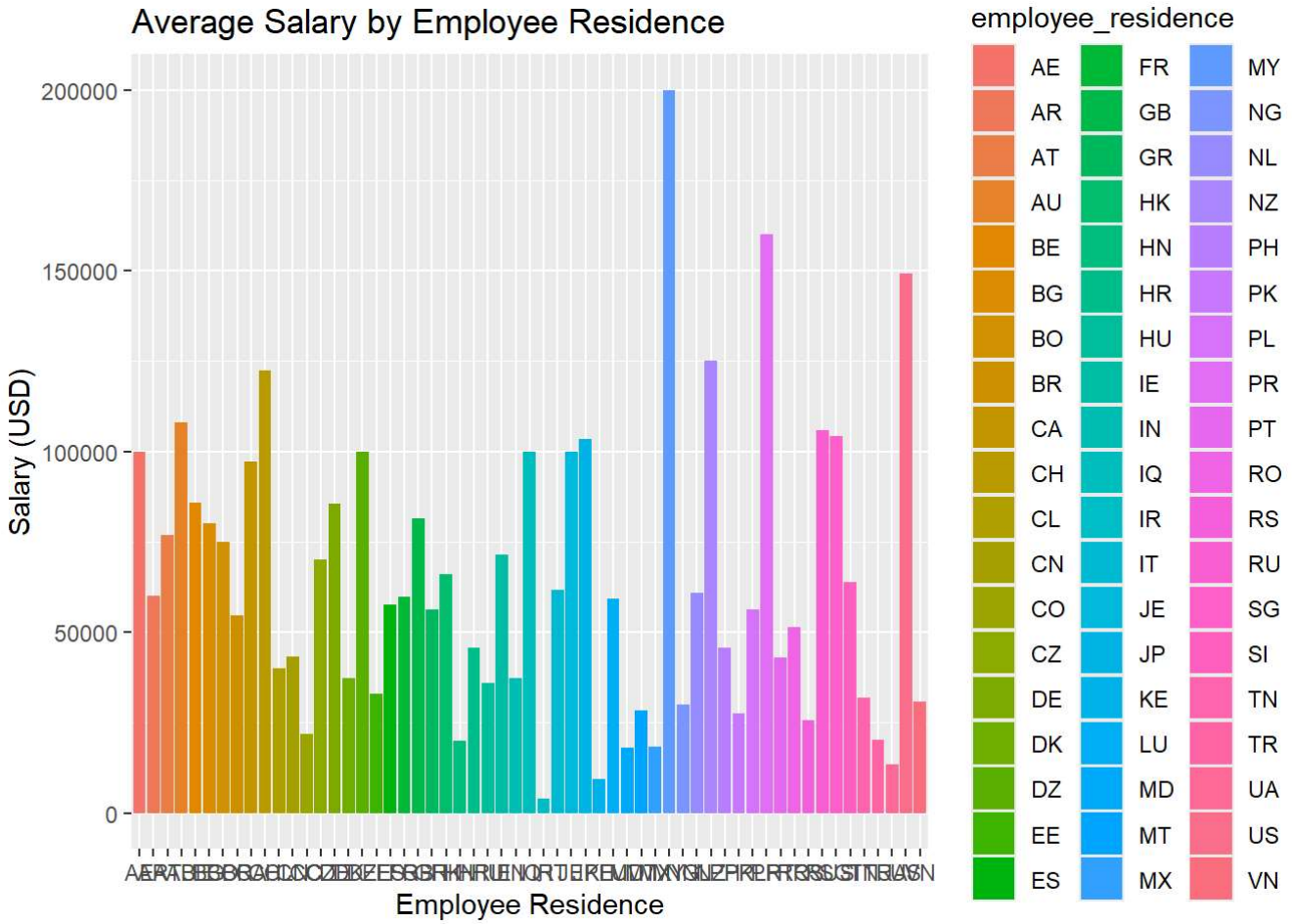



```
# That's not how I thought the salaries would trend!
```

```
# Does employee residence factor into salaries?
salary_by_residence <- ds_salaries %>%
  group_by(employee_residence) %>%
  summarize(
    avg_salary = mean(salary_in_usd),
    median_salary = median(salary_in_usd),
    min_salary = min(salary_in_usd),
    max_salary = max(salary_in_usd)
  )

print(salary_by_residence)
```

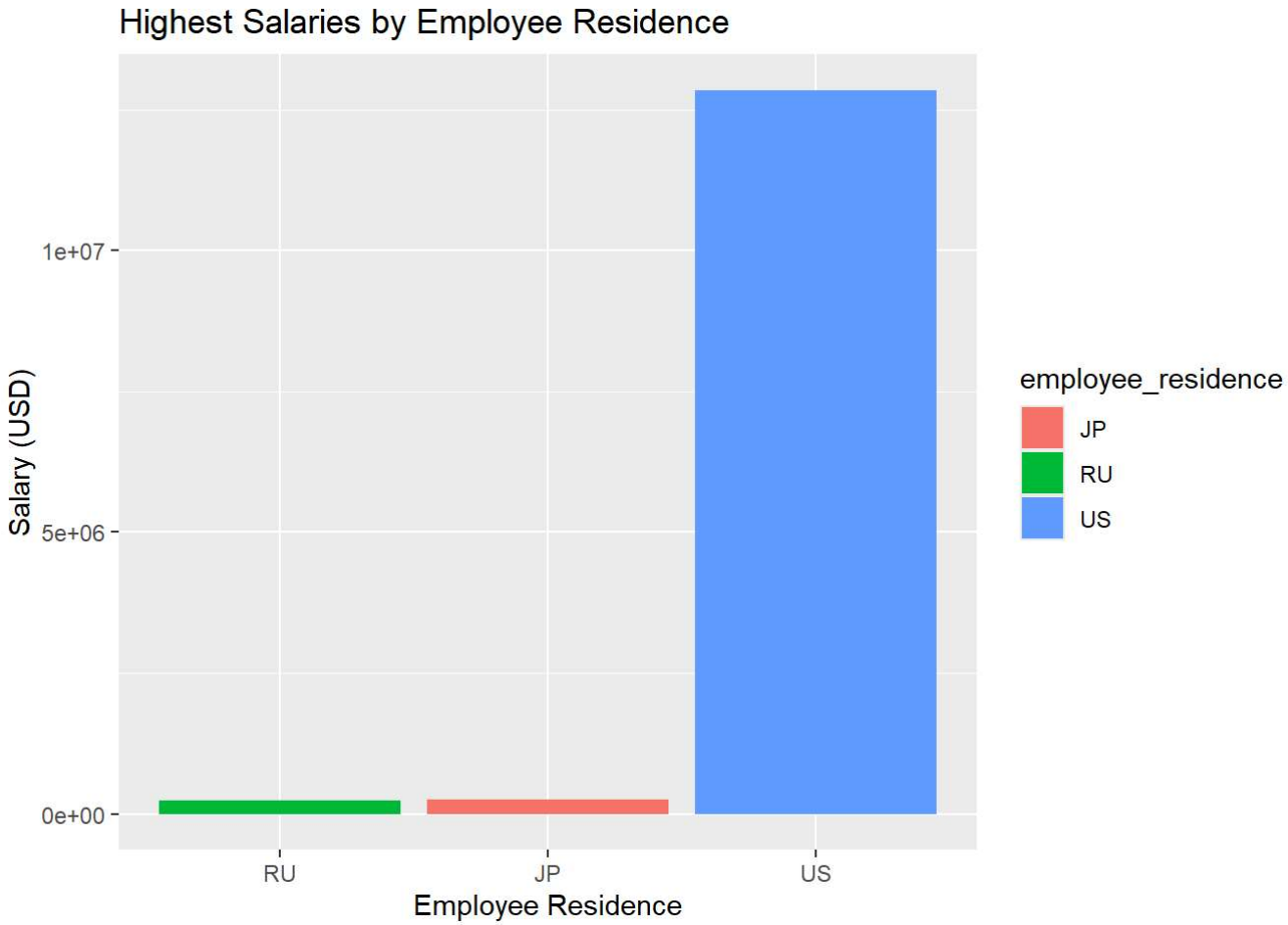
```
## # A tibble: 57 × 5
##    employee_residence avg_salary median_salary min_salary max_salary
##    <chr>                   <dbl>         <dbl>      <int>      <int>
##  1 AE                    100000        115000      65000     120000
##  2 AR                     60000         60000      60000      60000
##  3 AT                     76739.        74130      64849      91237
##  4 AU                    108043.        87425      86703     150000
##  5 BE                     85699         85699      82744      88654
##  6 BG                     80000         80000      80000      80000
##  7 BO                     75000         75000      75000      75000
##  8 BR                     54635.        21454.     12000     160000
##  9 CA                     97085.        85000      52000     196979
## 10 CH                    122346        122346     122346     122346
## # ℹ 47 more rows
```

```
ggplot(salary_by_residence, aes(x = employee_residence, y = avg_salary, fill = employee_residenc
e)) +
  geom_col() +
  labs(title = "Average Salary by Employee Residence",
       x = "Employee Residence",
       y = "Salary (USD)")
```




```
#This is an overwhelming plot. I'm going to try something else.
```

```
# Can I see the top 50 highest-paid people and where they happen to reside, instead?

top_50_salaries <- ds_salaries %>%
  arrange(desc(salary_in_usd)) %>%
  head(50)

ggplot(top_50_salaries, aes(x = reorder(employee_residence, salary_in_usd), y = salary_in_usd, f
ill = employee_residence)) +
  geom_bar(stat = "identity") +
  labs(title = "Highest Salaries by Employee Residence",
       x = "Employee Residence",
       y = "Salary (USD)")
```




```
#I don't think I gleaned anything useful from this, but I'll keep it in here, just the same.
```

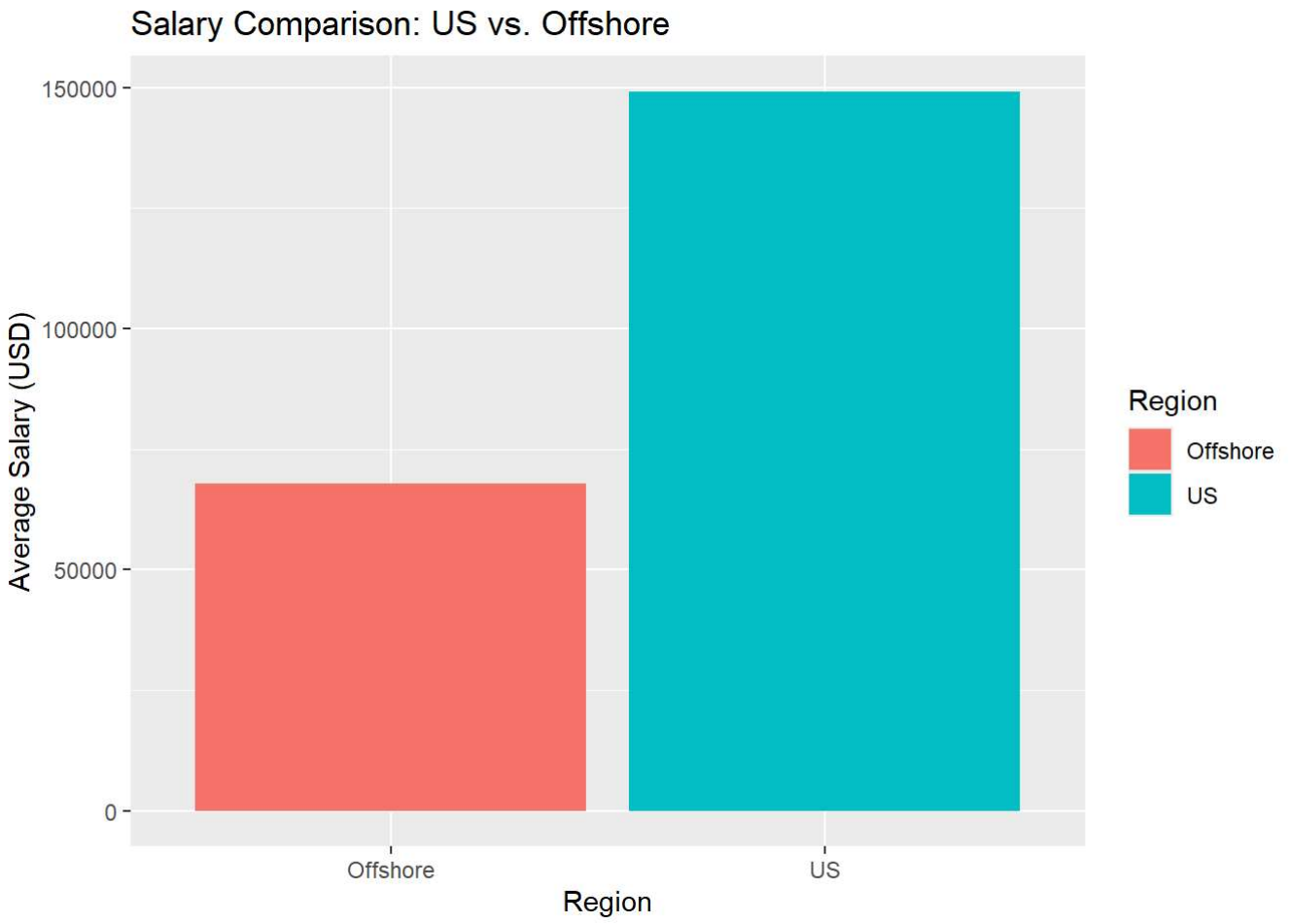
```
# I want to see how US salaries compared with non-US salaries overall

us_data <- ds_salaries %>% filter(employee_residence == "US")
offshore_data <- ds_salaries %>% filter(employee_residence != "US")

us_salary_avg <- mean(us_data$salary_in_usd)
offshore_salary_avg <- mean(offshore_data$salary_in_usd)

print(us_salary_avg)
```

```
## [1] 149194.1
```

```
print(offshore_salary_avg)
```

```
## [1] 67754.04
```

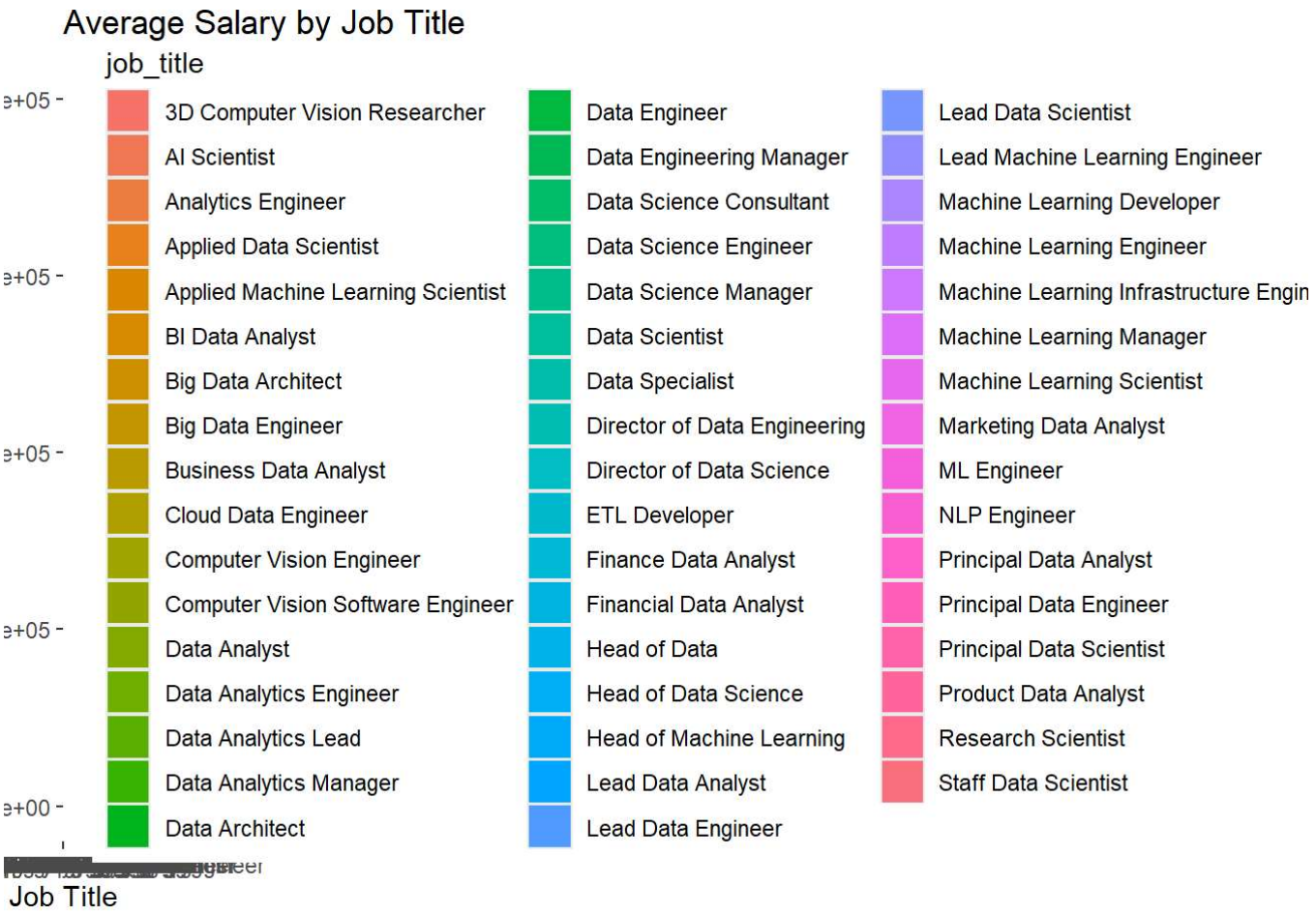
```
salary_comparison <- data.frame(
  Region = c("US", "Offshore"),
  Avg_Salary = c(us_salary_avg, offshore_salary_avg)
)

ggplot(salary_comparison, aes(x = Region, y = Avg_Salary, fill = Region)) +
  geom_bar(stat = "identity") +
  labs(title = "Salary Comparison: US vs. Offshore",
       x = "Region",
       y = "Average Salary (USD)")
```




```
# Does job title make a difference?

salary_by_job_title <- ds_salaries %>%
  group_by(job_title) %>%
  summarize(
    avg_salary = mean(salary_in_usd),
    median_salary = median(salary_in_usd),
    min_salary = min(salary_in_usd),
    max_salary = max(salary_in_usd)
  )

print(salary_by_job_title)
```

```
## # A tibble: 50 × 5
##    job_title                     avg_salary median_salary min_salary max_salary
##    <chr>                              <dbl>         <dbl>      <int>      <int>
##  1 3D Computer Vision Researcher       5409          5409       5409       5409
##  2 AI Scientist                       66136.        45896      12000     200000
##  3 Analytics Engineer                175000        179850     135000     205300
##  4 Applied Data Scientist            175655        157000      54238     380000
##  5 Applied Machine Learning Scie…    142069.        56700      31875     423000
##  6 BI Data Analyst                    74755.        76500       9272     150000
##  7 Big Data Architect                 99703         99703      99703      99703
##  8 Big Data Engineer                  51974         41306.      5882     114047
##  9 Business Data Analyst              76691.        70912      18442     135000
## 10 Cloud Data Engineer               124647        124647      89294     160000
## # ℹ 40 more rows
```

```
ggplot(salary_by_job_title, aes(x = job_title, y = avg_salary, fill = job_title)) +
  geom_col() +
  labs(title = "Average Salary by Job Title",
       x = "Job Title",
       y = "Salary (USD)")
```



```
#I can't really tell by this graph
#Also didn't realize there were so many job titles
#I think cleaning this data is a little beyond my scope at the moment
```

```
# I asked ChatGPT for alternative ways to display this data

library(knitr)
kable(salary_by_job_title, caption = "Average Salary by Job Title")
```

Average Salary by Job Title

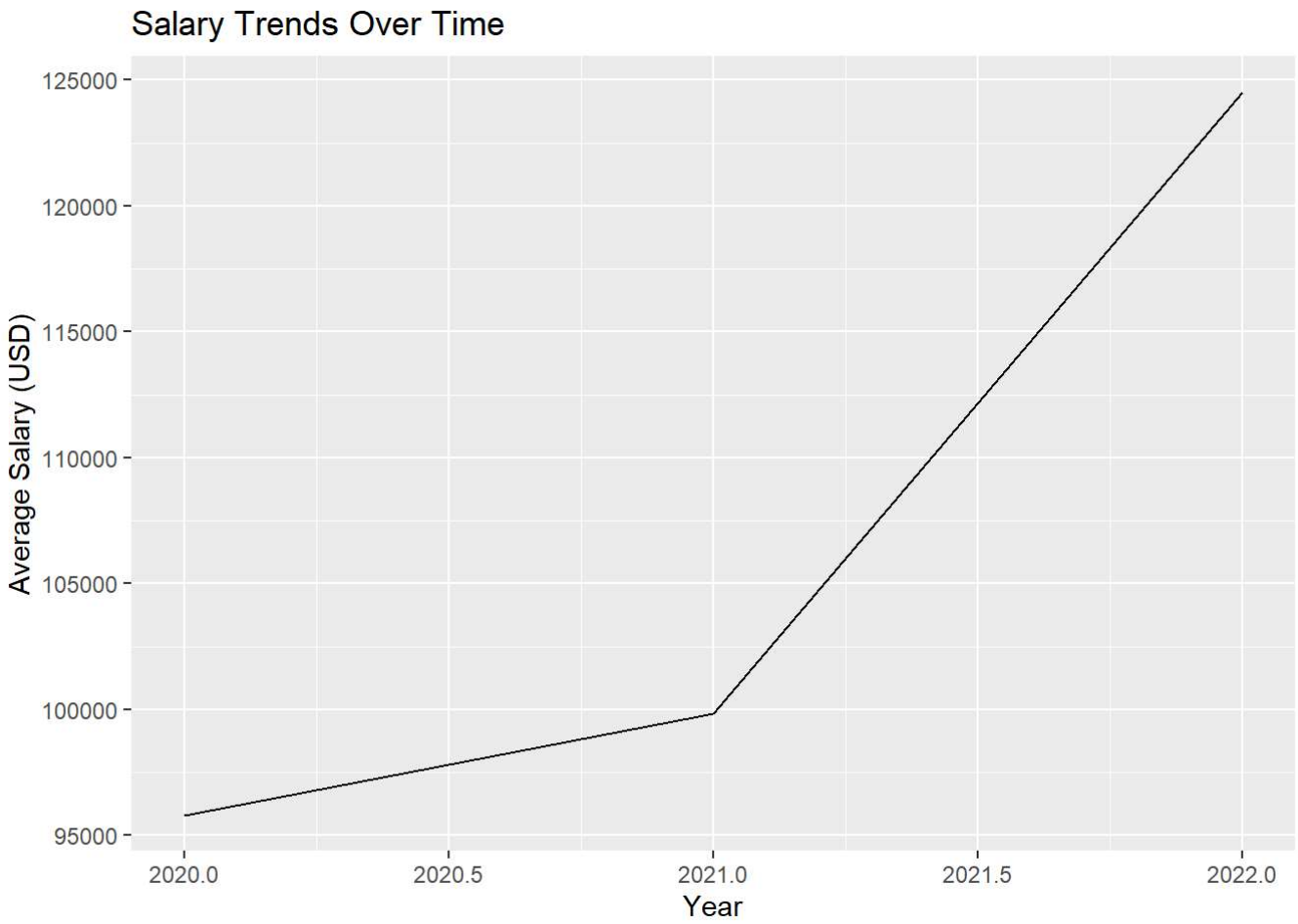
| job_title | avg_salary | median_salary | min_salary | max_salary |
|---|---|---|---|---|
| 3D Computer Vision Researcher | 5409.00 | 5409.0 | 5409 | 5409 |
| AI Scientist | 66135.57 | 45896.0 | 12000 | 200000 |
| Analytics Engineer | 175000.00 | 179850.0 | 135000 | 205300 |
| Applied Data Scientist | 175655.00 | 157000.0 | 54238 | 380000 |
| Applied Machine Learning Scientist | 142068.75 | 56700.0 | 31875 | 423000 |
| BI Data Analyst | 74755.17 | 76500.0 | 9272 | 150000 |
| Big Data Architect | 99703.00 | 99703.0 | 99703 | 99703 |
| Big Data Engineer | 51974.00 | 41305.5 | 5882 | 114047 |
| Business Data Analyst | 76691.20 | 70912.0 | 18442 | 135000 |
| Cloud Data Engineer | 124647.00 | 124647.0 | 89294 | 160000 |
| Computer Vision Engineer | 44419.33 | 26304.5 | 10000 | 125000 |
| Computer Vision Software Engineer | 105248.67 | 95746.0 | 70000 | 150000 |
| Data Analyst | 92893.06 | 90320.0 | 6072 | 200000 |
| Data Analytics Engineer | 64799.25 | 64598.5 | 20000 | 110000 |
| Data Analytics Lead | 405000.00 | 405000.0 | 405000 | 405000 |
| Data Analytics Manager | 127134.29 | 120000.0 | 105400 | 150260 |
| Data Architect | 177873.91 | 180000.0 | 90700 | 266400 |
| Data Engineer | 112725.00 | 105500.0 | 4000 | 324000 |
| Data Engineering Manager | 123227.20 | 150000.0 | 59303 | 174000 |
| Data Science Consultant | 69420.71 | 76833.0 | 5707 | 103000 |
| Data Science Engineer | 75803.33 | 60000.0 | 40189 | 127221 |
| Data Science Manager | 158328.50 | 155750.0 | 54094 | 241000 |
| Data Scientist | 108187.83 | 103691.0 | 2859 | 412000 |

| job_title | avg_salary | median_salary | min_salary | max_salary |
|---|---|---|---|---|
| Data Specialist | 165000.00 | 165000.0 | 165000 | 165000 |
| Director of Data Engineering | 156738.00 | 156738.0 | 113476 | 200000 |
| Director of Data Science | 195074.00 | 168000.0 | 130026 | 325000 |
| ETL Developer | 54957.00 | 54957.0 | 54957 | 54957 |
| Finance Data Analyst | 61896.00 | 61896.0 | 61896 | 61896 |
| Financial Data Analyst | 275000.00 | 275000.0 | 100000 | 450000 |
| Head of Data | 160162.60 | 200000.0 | 32974 | 235000 |
| Head of Data Science | 146718.75 | 138937.5 | 85000 | 224000 |
| Head of Machine Learning | 79039.00 | 79039.0 | 79039 | 79039 |
| Lead Data Analyst | 92203.00 | 87000.0 | 19609 | 170000 |
| Lead Data Engineer | 139724.50 | 121593.5 | 56000 | 276000 |
| Lead Data Scientist | 115190.00 | 115000.0 | 40570 | 190000 |
| Lead Machine Learning Engineer | 87932.00 | 87932.0 | 87932 | 87932 |
| ML Engineer | 117504.00 | 70537.5 | 15966 | 270000 |
| Machine Learning Developer | 85860.67 | 78791.0 | 78791 | 100000 |
| Machine Learning Engineer | 104880.15 | 87932.0 | 20000 | 250000 |
| Machine Learning Infrastructure Engineer | 101145.00 | 58255.0 | 50180 | 195000 |
| Machine Learning Manager | 117104.00 | 117104.0 | 117104 | 117104 |
| Machine Learning Scientist | 158412.50 | 156500.0 | 12000 | 260000 |
| Marketing Data Analyst | 88654.00 | 88654.0 | 88654 | 88654 |
| NLP Engineer | 37236.00 | 37236.0 | 37236 | 37236 |
| Principal Data Analyst | 122500.00 | 122500.0 | 75000 | 170000 |
| Principal Data Engineer | 328333.33 | 200000.0 | 185000 | 600000 |
| Principal Data Scientist | 215242.43 | 173762.0 | 148261 | 416000 |
| Product Data Analyst | 13036.00 | 13036.0 | 6072 | 20000 |
| Research Scientist | 109019.50 | 76263.5 | 42000 | 450000 |
| Staff Data Scientist | 105000.00 | 105000.0 | 105000 | 105000 |

```
# I want to look at salary trends over time, now that I have a basic idea of how various factors have influenced average salaries
# This chart calculates the average, median, minimum, and maximum salaries for all individuals in the data frame by the year each salary was paid

salary_by_year <- ds_salaries %>%
  group_by(work_year) %>%
  summarize(
    avg_salary = mean(salary_in_usd),
    median_salary = median(salary_in_usd),
    min_salary = min(salary_in_usd),
    max_salary = max(salary_in_usd)
  )

print(salary_by_year)
```

```
## # A tibble: 3 × 5
##   work_year avg_salary median_salary min_salary max_salary
##       <int>      <dbl>         <dbl>      <int>      <int>
## 1      2020     95813          75544       5707     450000
## 2      2021     99854.         82528       2859     600000
## 3      2022    124522.        120000      10000     405000
```

```
ggplot(salary_by_year, aes(x = work_year, y = avg_salary)) +
  geom_line() +
  labs(title = "Salary Trends Over Time",
       x = "Year",
       y = "Average Salary (USD)")
```




```
# and that is a massive leap from 2021 to 2022!
```