

Data Science Jobs Salary Analysis

Ri-on Kim

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Intro

Data science-related jobs have become increasingly prominent across all industries. Analyzing these roles by experience level, specific job titles, and salaries can provide valuable insights, particularly for individuals studying computer science, statistics, and data science. This project will focus primarily on salary, as it represents a clear and significant index for differentiation.

Questions

- How do salaries differ by specific jobs?
- How is salary distributed across company sizes?
- How does salary change based on experience level?
- Overall, which specific job offers the highest salary?

Importing the Data & Libraries

```
data <- read.csv("ds_salaries.csv")
library(ggplot2)
library(dplyr)
library(scales)
```

For Data Science job salary analysis, importing data set is essential. The 'ds_salaries.csv' data is sourced from Kaggle (<https://www.kaggle.com/datasets/arnabchaki/data-science-salaries-2023/data>). This project will use the library ggplot2 and dplyr mainly.

Understanding the Data

```
head(data, 7)
```

```
##   work_year experience_level employment_type      job_title salary
## 1      2023              SE             FT Principal Data Scientist 80000
## 2      2023              MI             CT      ML Engineer 30000
## 3      2023              MI             CT      ML Engineer 25500
## 4      2023              SE             FT      Data Scientist 175000
## 5      2023              SE             FT      Data Scientist 120000
## 6      2023              SE             FT Applied Scientist 222200
## 7      2023              SE             FT Applied Scientist 136000
##   salary_currency salary_in_usd employee_residence remote_ratio
## 1              EUR       85847                ES           100
## 2              USD       30000                US           100
## 3              USD       25500                US           100
## 4              USD      175000                CA           100
```

```
## 5          USD      120000          CA      100
## 6          USD      222200          US        0
## 7          USD      136000          US        0
##   company_location company_size
## 1                ES           L
## 2                US           S
## 3                US           S
## 4                CA           M
## 5                CA           M
## 6                US           L
## 7                US           L
```

The imported dataset comprises 11 columns and 3,755 rows. It includes crucial variables like `experience_level`, `job_title`, `salary_in_usd`, and `company_size`. Initial inspection reveals several issues that need addressing through data cleaning:

- The abbreviations in the `experience_level` column (e.g., “MI”, “SE”) are not intuitive.
- Since salaries can vary significantly based on employee residence, analyzing data without filtering by location may lead to confusion.
- The `job_title` column contains an overly broad array of titles. (Beside the data shown in the head, there are too many different job titles like AI engineer, data science consultant.)

Cleaning the Data

```
data_cleaned <- data %>%
  filter(employee_residence == "US") %>%
  mutate(
    job_title = case_when(
      grepl("Data Scientist", job_title, ignore.case = TRUE) ~ "Data Scientist",
      grepl("Data Engineer", job_title, ignore.case = TRUE) ~ "Data Engineer",
      grepl("Analyst", job_title, ignore.case = TRUE) ~ "Data Analyst",
      grepl("Machine Learning", job_title, ignore.case = TRUE) ~ "Machine Learning Engineer",
      grepl("Manager", job_title, ignore.case = TRUE) ~ "Data Science Manager",
      grepl("Director", job_title, ignore.case = TRUE) ~ "Data Science Manager",
      grepl("Architect", job_title, ignore.case = TRUE) ~ "Data Architect",
      TRUE ~ "Other"
    )
  )

data_cleaned <- data_cleaned %>%
  mutate(
    experience_level = case_when(
      experience_level == "EN" ~ "Entry",
      experience_level == "MI" ~ "Midium",
      experience_level == "SE" ~ "Senior",
      experience_level == "EX" ~ "Executive",
      TRUE ~ as.character(experience_level)
    ),
    experience_level = factor(experience_level, levels =
      c("Entry", "Midium", "Senior", "Executive"))
  )

head(data_cleaned, 7)
```

```
##   work_year experience_level employment_type   job_title salary
```

```
## 1      2023      Midium      CT      Other 30000
## 2      2023      Midium      CT      Other 25500
## 3      2023      Senior      FT      Other 222200
## 4      2023      Senior      FT      Other 136000
## 5      2023      Senior      FT Data Scientist 147100
## 6      2023      Senior      FT Data Scientist 90700
## 7      2023      Senior      FT Data Analyst 130000
## salary_currency salary_in_usd employee_residence remote_ratio
## 1      USD      30000      US      100
## 2      USD      25500      US      100
## 3      USD      222200      US      0
## 4      USD      136000      US      0
## 5      USD      147100      US      0
## 6      USD      90700      US      0
## 7      USD      130000      US      100
## company_location company_size
## 1      US      S
## 2      US      S
## 3      US      L
## 4      US      L
## 5      US      M
## 6      US      M
## 7      US      M
```

```
table(data_cleaned$job_title)
```

```
##
##      Data Analyst      Data Architect      Data Engineer
##      554      98      908
##      Data Science Manager      Data Scientist Machine Learning Engineer
##      102      679      266
##      Other
##      397
```

After cleaning, notable adjustments include:

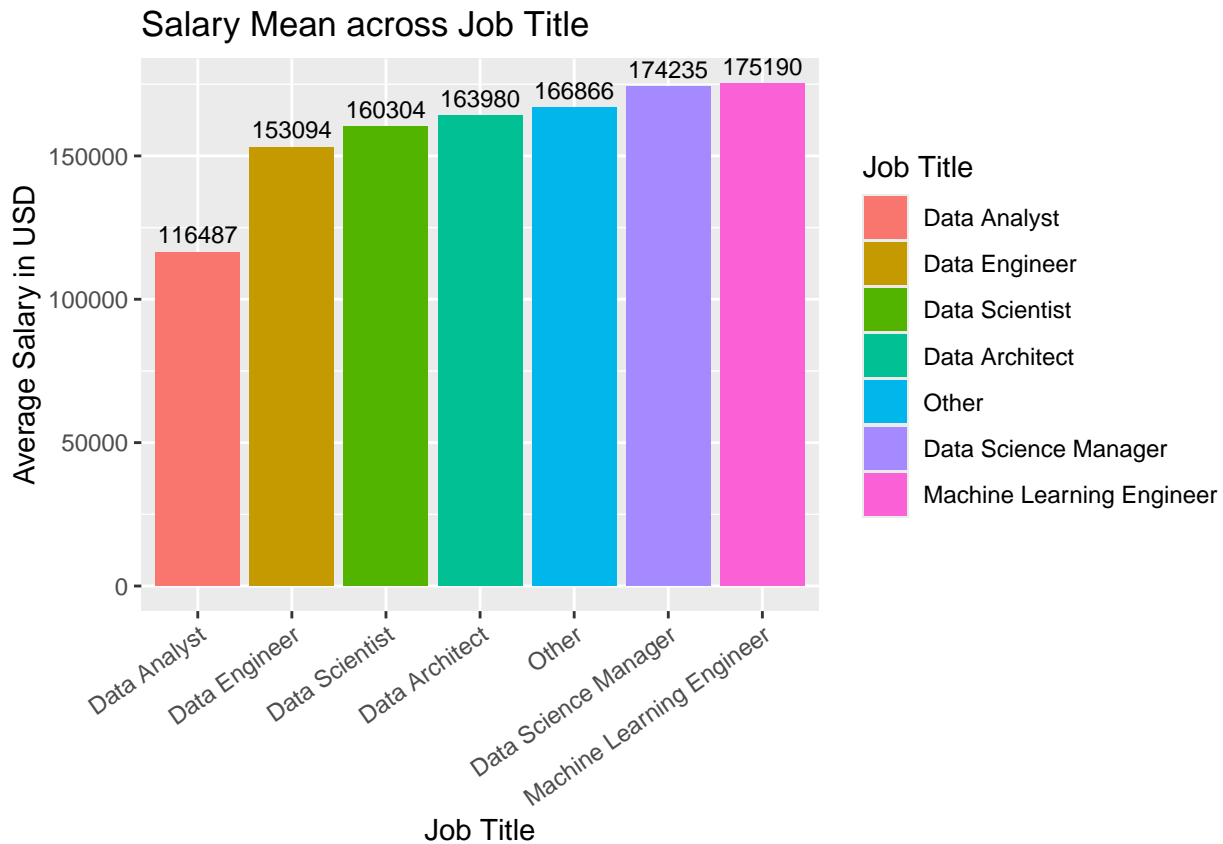
- For clarity, the `experience_level` column now uses intuitive labels: “Entry”, “Mid”, “Senior”, and “Executive”.
- To avoid confusion, the dataset has been filtered to only include employees residing in the US.
- To make the graph clear, similar elements in `job_title` is merged and minor elements are classified as “Other”. The “Other” variable contains the job like “Applied Scientist”, “Data Modeler”, “AI Engineer”, “Computer Vision Engineer”, etc. Finally, there are only 7 elements in `job_title`.

Salary Mean and Median across Job Title

```
avg_salary_by_title <- data_cleaned %>%
  group_by(job_title) %>%
  summarise(average_salary = mean(salary_in_usd, na.rm = TRUE)) %>%
  arrange(desc(average_salary))

ggplot(avg_salary_by_title, aes(x=reorder(job_title, average_salary), y=average_salary, fill = reorder(
  geom_bar(stat="identity") +
  geom_text(aes(label = round(average_salary, 0)),
    vjust = -0.5,
```

```
size = 3) +
theme(axis.text.x = element_text(angle = 35, hjust = 1)) +
labs(title="Salary Mean across Job Title",
x="Job Title", y="Average Salary in USD", fill = "Job Title")
```



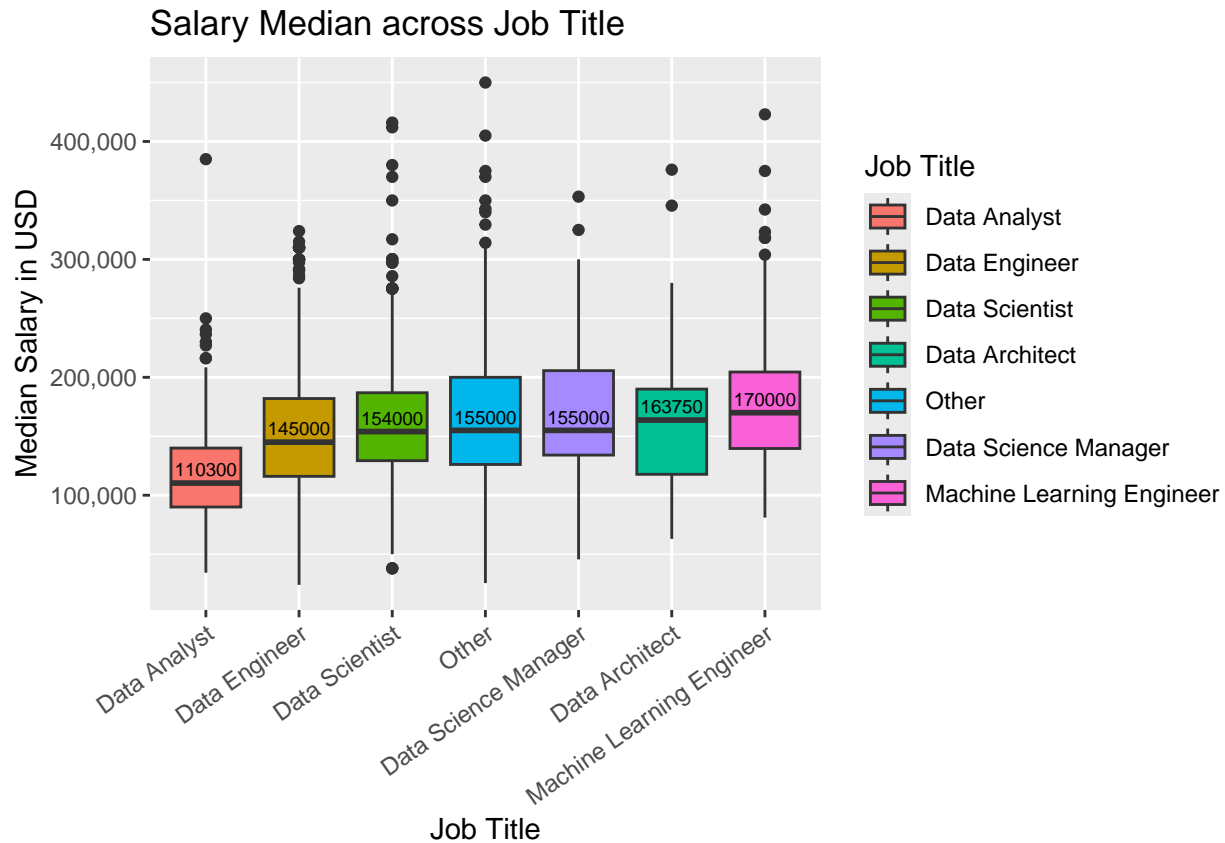
Analysis reveals:

- Data Analysts have the lowest average salary among the roles examined, with a significant gap to Data Engineers.
- Machine Learning Engineers and Data Science Managers emerge as the highest earners, showcasing the narrow salary gap between these two positions.

For consistency, the same color scheme used in the average salary graph will be applied to the median salary graph for clear comparison.

```
data_cleaned$job_title <- factor(data_cleaned$job_title, levels = rev(avg_salary_by_title$job_title))

ggplot(data_cleaned, aes(x = reorder(job_title, salary_in_usd, FUN = median), y = salary_in_usd, fill =
  geom_boxplot() +
  scale_y_continuous(labels = scales::comma) +
  theme(axis.text.x = element_text(angle = 35, hjust = 1)) +
  labs(title = "Salary Median across Job Title",
    x = "Job Title", y = "Median Salary in USD", fill = "Job Title") +
  stat_summary(fun=median, geom="text", aes(label=..y..), vjust=-0.5, color="black", size = 2.5)
```



Analysis reveals:

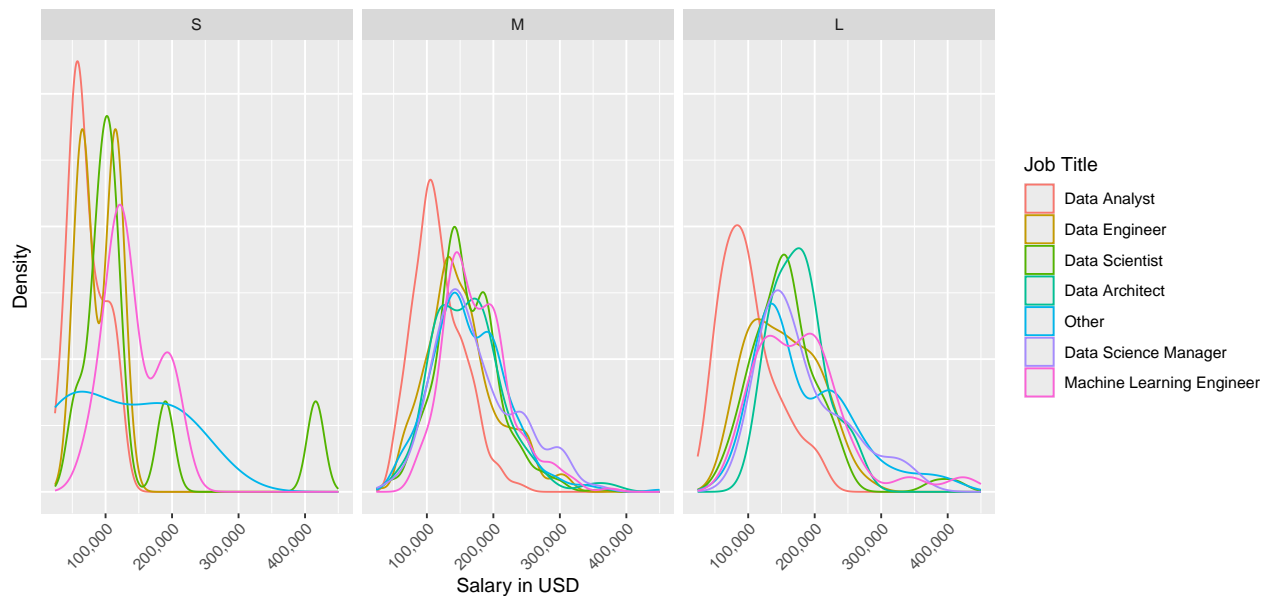
- Although there are some differences, the median salary across job titles is quite similar to the average salary.
- One point to note is that the Data Science Manager role shows a significant difference between the average and median salaries. The box plot displays a large range in the Q1 to Q2 quartile, indicating that high 25% of Data Science Managers are paid way more than the median salary data science manager compared to other jobs.

Salary Distribution across Job Titles and Company Size

```
data_cleaned$company_size <- factor(data_cleaned$company_size, levels = c("S", "M", "L"))

ggplot(data_cleaned, aes(x = salary_in_usd, col = job_title)) +
  geom_density(alpha = 0.8) +
  scale_x_continuous(labels = label_comma()) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        axis.text.y = element_blank(),
        axis.ticks.y = element_blank()) +
  labs(title = "Salary Distribution across Job Titles and Company Size",
       x = "Salary in USD", y = "Density", col = "Job Title") +
  facet_wrap(~company_size)
```

Salary Distribution across Job Titles and Company Size



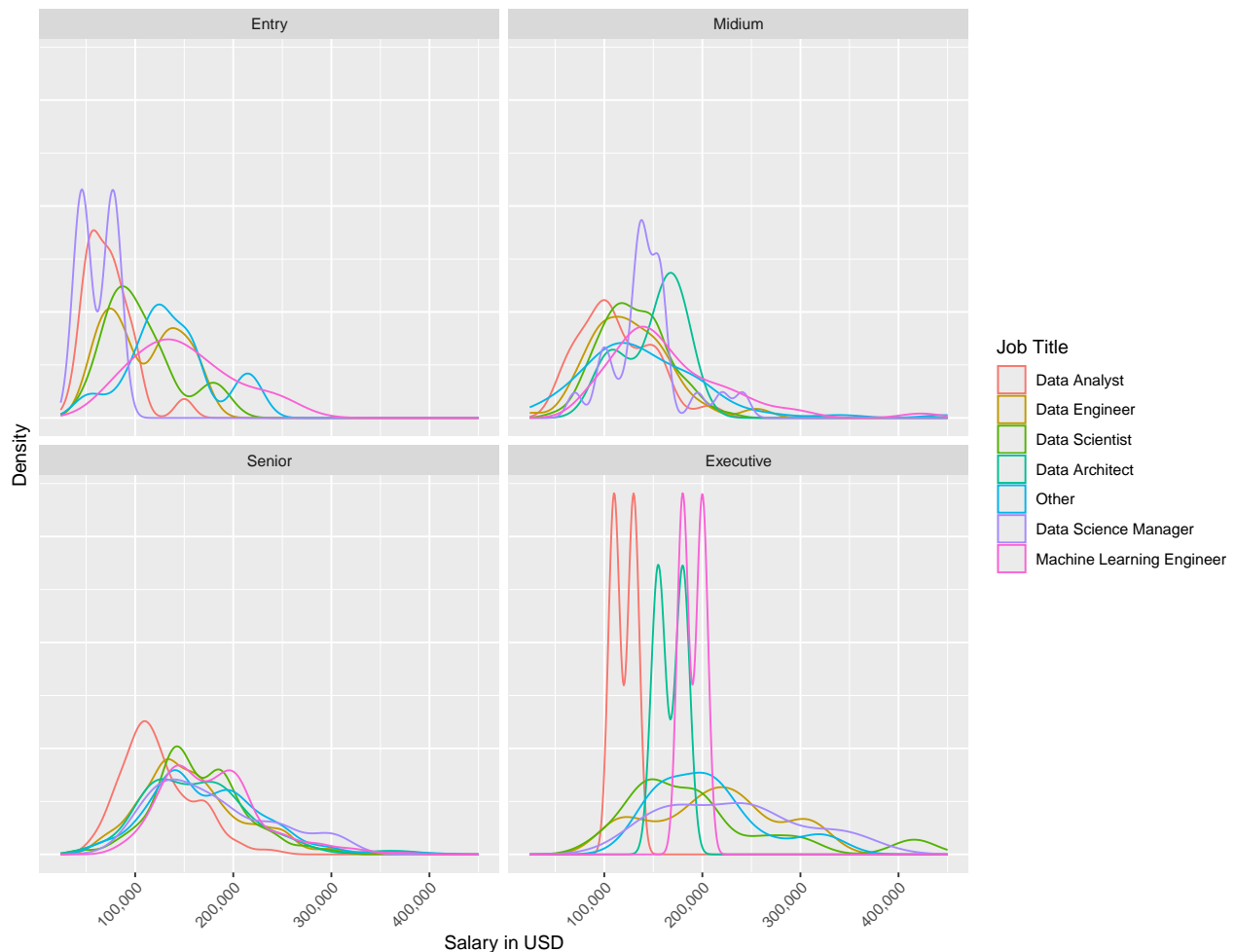
Now, we can examine the salary distribution based on company size. I utilized the `facet_wrap` function to display three company sizes simultaneously. From examining the graph, we can observe the following:

- As company size increases, the overall salary across all job titles tends to increase as well. Notably, the difference between small and mid-sized companies is larger compared to the difference between mid-sized and large companies.
- An interesting observation in the graph for small-sized companies is that some data scientists are receiving exceptionally high salaries (over \$400,000). This suggests that data scientists may perform particularly well in small-sized companies compared to other jobs.
- Additionally, it's intriguing that mid-sized companies tend to offer higher salaries to data analysts than large-sized companies.

Salary Distribution across Job Titles and experience level

```
ggplot(data_cleaned, aes(x = salary_in_usd, col = job_title)) +
  geom_density(alpha = 0.8) +
  scale_x_continuous(labels = label_comma()) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        axis.text.y = element_blank(),
        axis.ticks.y = element_blank()) +
  labs(title = "Salary Distribution across Job Titles and experience level",
       x = "Salary in USD", y = "Density", col = "Job Title") +
  facet_wrap(~experience_level)
```

Salary Distribution across Job Titles and experience level



Given that experience level can significantly impact salary, it's crucial to examine the salary distribution by experience level. To facilitate this analysis, I utilized the `facet_wrap` function once more to compare across different experience levels. The following observations can be made:

- As one might expect, the overall salary distribution curves shift to the right, indicating that higher experience levels correlate with higher salaries across all job titles.
- Interestingly, Data Science Managers have the lowest salaries at the entry level. This could be attributed to the role typically requiring more extensive experience than other positions.
- Although Machine Learning Engineers and Data Architects have high average and median salaries compared to other roles, at the executive level, Data Scientists, Data Engineers, Data Science Managers, and others can get higher salaries than both Machine Learning Engineers and Data Architects.

App for Data Science Job Salary Distribution Comparisons

<https://1minute99.shinyapps.io/shiny/>

- The shiny app is designed for comparing salary distribution more interactively. It can help to focus on comparing two jobs' salary.

Conclusion

- Data Analysts generally earn the lowest salaries.

- Salary difference between small size company and medium size company is significant compare to the difference between mid size company and large size company for most of jobs.
- Machine Learning Engineers rank among the highest earners.
- At the executive level, several roles can surpass salary of Machine Learning Engineers and Data Architects, indicating the value of experience across job titles.