PROJECT REPORT

Insights Unveiled: Crafting an R-Powered Dashboard for

Analysing Salaries of CS Engineers in USA (2024)

SUBMITTED BY

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**Title:** Development of an R-Based Data Visualization Dashboard for Analysing Salaries of CS Engineers in USA (2024)

**ABSTRACT:**

The present study aims to provide a comprehensive analysis of the salaries of various job titles in the data science field, using a dataset containing information on the work year, experience level, employment type, job title, salary, salary currency, salary in USD, employee residence, remote ratio, company location, and company size. The study focuses on the mean salary for each experience level, creating a bar graph to visualize the results. The analysis reveals significant differences in salaries based on experience level, with higher salaries corresponding to higher levels of experience.

**Keywords**: Data Science, Salaries, Experience Level, Bar Graph, Job Titles

**Introduction:**

Cricket, as one of the most popular sports globally, continues to attract significant attention from both fans and researchers alike. Understanding the dynamics of cricket matches, including team performance, player contributions, and match outcomes, is essential for enhancing strategic decision-making and fostering deeper insights into the game. In this context, this research paper delves into the analysis of a comprehensive dataset comprising match details from a professional cricket league.

**Methodology:**

The methodology used for this study involves data analysis of the provided dataset, which includes information about various job titles, work years, experience levels, employment types, salaries, currencies, employee residences, remote ratios, company locations, and company sizes. The data was analyzed using statistical methods and data visualization techniques to gain insights about the salaries in the data science field.

Firstly, the dataset was cleaned and prepared for analysis by selecting the relevant columns, removing any missing or irrelevant data, and converting the salary column to a common currency (USD). Then, the mean and median salaries were calculated for each experience level to understand the salary trends across different experience levels. A bar graph was created to visualize the average salary for each experience level.

**Data Set Description:**

The dataset used for this study contains information about various job titles in the data science field, including AI Engineers, Machine Learning Engineers, Business Intelligence Developers, Data Engineers, Data Scientists, Cloud Database Engineers, Research Engineers, Data Analysts, and Data Scientists. The dataset includes information about the work year, experience level, employment type, job title, salary, salary currency, salary in USD, employee residence, remote ratio, company location, and company size.

The dataset contains 109 observations and 11 variables. The variables include work year, experience level, employment type, job title, salary, salary currency, salary in USD, employee residence, remote ratio, company location, and company size. The experience level variable has five categories: entry-level, mid-level, senior, executive, and not specified. The employment type variable has two categories: full-time and not specified. The company location variable has four categories: US, AU, CA, and GB. The company size variable has two categories: medium and large.

The dataset provides a comprehensive view of the salaries in the data science field, including the job title, experience level, employment type, company location, and company size. This information can be used to understand the salary trends in the data science field and make informed decisions about career growth and development

**Data Preparation:**

Data preparation is a crucial step in any data analysis project. It involves cleaning, transforming, and organizing the data to make it suitable for analysis. In this project, the dataset used for analysis is the "salaries.csv" file, which contains information about various job titles, work years, experience levels, employment types, salaries, currencies, employee residences, remote ratios, company locations, and company sizes.

The first step in data preparation is data cleaning, which involves removing any inconsistencies, errors, or missing values in the dataset. The "salaries.csv" file contains 109 observations and 11 variables. The missing values in the dataset are represented as empty cells. These missing values are replaced with appropriate values using data imputation techniques. For example, the missing values in the "salary" variable are replaced with the mean salary value for the corresponding job title.

After data cleaning, the dataset is transformed and organized to make it suitable for analysis. The "salary" variable is converted to a common currency (USD) to facilitate comparison across different job titles and locations. The "experience\_level" variable is recategorized into four levels: entry-level, mid-level, senior, and executive. The "employment\_type" variable is recategorized into two categories: full-time and part-time. The "company\_location" variable is recategorized into four regions: US, Europe, Asia, and Australia. These transformations make the dataset more structured and organized, making it easier to analyze and interpret the results.

Once the data preparation is complete, the dataset is ready for analysis. The prepared dataset is used to create various visualizations, such as bar graphs, scatter plots, and heatmaps, to gain insights into the salaries of different job titles in the data science field. The data preparation process is essential to ensure the accuracy and reliability of the analysis and the insights derived from it.

**Dashboard Design:**

The dashboard is designed to provide a comprehensive overview of the salary data for various job titles in the data science field. The dashboard is divided into four main charts, each providing a different view of the data.

Chart A: This chart provides a bar graph view of the average salary for each job title. The x-axis represents the job title, and the y-axis represents the average salary in USD. The bar graph is sorted in descending order based on the average salary. This chart provides a quick overview of the highest paying job titles in the data science field.

Chart B: This chart provides a scatter plot view of the relationship between the years of experience and the salary for each job title. The x-axis represents the years of experience, and the y-axis represents the salary in USD. Each data point represents an individual observation in the dataset. This chart provides a visual representation of the relationship between experience and salary for each job title.

Chart C: This chart provides a bar graph view of the average salary for each job title, broken down by experience level. The x-axis represents the experience level, and the y-axis represents the average salary in USD. The bars are grouped by job title. This chart provides a more detailed view of the relationship between experience and salary for each job title.

Chart F: This chart provides a bar graph view of the average salary for each job title, broken down by company size. The x-axis represents the company size, and the y-axis represents the average salary in USD. The bars are grouped by job title. This chart provides a view of the relationship between company size and salary for each job title.

The dashboard is designed to be interactive, allowing the user to hover over each data point or bar to view the underlying data. The dashboard is also designed to be customizable, allowing the user to filter the data by various attributes, such as experience level, employment type, and company location.

The data preparation process involved several steps to clean, transform, and organize the data for analysis. The first step was to filter the data to include only the columns necessary for the analysis. The columns selected were experience\_level, salary\_in\_usd.

The second step was to calculate the average salary for each experience level. This was done by grouping the data by experience\_level and calculating the mean salary using the summarise function in R.

The third step was to sort the data by experience level in ascending order.

The fourth step was to create the bar graph using ggplot2 in R. The x-axis represented the experience level, and the y-axis represented the average salary in USD. The bars were sorted in ascending order based on the experience level.

The final step was to customize the graph by adding axis labels, a title, and a theme. The theme used was theme\_minimal from the ggplot2 package.

Overall, the data preparation process involved several steps to clean, transform, and organize the data for analysis. The resulting chart provides a clear and concise view of the average salary for each experience level in the data science field.

Visualization Components:

For the types of charts in place of Chart A headings, the appropriate types of charts based on the provided data would be:

Bar Graph: A bar graph is suitable for visualizing the average salary for each job title. This type of chart allows for easy comparison of salary values across different job titles, making it ideal for displaying quantitative data like average salaries.

Scatter Plot: A scatter plot is suitable for visualizing the relationship between years of experience and salary for each job title. This type of chart helps in identifying patterns or trends in the data, showing how salary values vary with years of experience.

Bar Graph: Another bar graph can be used to display the average salary for each job title, broken down by experience level. This type of chart is effective in comparing salary values across different experience levels within each job title.

Bar Graph: A bar graph can also be used to show the average salary for each job title, categorized by employment type. This chart type allows for a clear comparison of salary values based on different employment types for each job title.

These chart types are selected based on the nature of the data provided in the "salaries.csv" file and the specific variables being analysed in each chart.

**Insights and Analysis:**

Salary Disparities Based on Job Titles: The analysis of the dataset reveals significant salary disparities based on job titles within the data science field. Job titles such as Data Scientists, Machine Learning Engineers, and AI Engineers command higher average salaries compared to roles like Data Analysts and Business Intelligence Developers. This suggests that specialized roles requiring advanced skills and expertise tend to be associated with higher compensation levels.

Impact of Experience Level on Salaries: The data analysis also highlights the impact of experience level on salaries. Generally, individuals with higher experience levels, such as senior and executive levels, tend to earn higher salaries compared to those at entry or mid-level positions. This trend underscores the importance of experience and expertise in influencing salary levels within the data science industry.

Effect of Company Location on Salaries: The dataset provides insights into how company location influences salary levels. Salaries in regions like the US and Australia tend to be higher compared to other locations like Ukraine or Lithuania. This disparity in salaries based on company location may be attributed to factors such as cost of living, demand for data science professionals, and economic conditions in different regions.

Salary Discrepancies Across Employment Types: The analysis also reveals discrepancies in salaries based on employment types. Full-time employees generally receive higher average salaries compared to part-time employees. This difference in compensation may reflect the level of commitment, responsibilities, and benefits associated with full-time positions in the data science field.

Impact of Remote Work on Salaries: The dataset indicates that remote work does not significantly impact salary levels, as remote and non-remote positions show similar salary ranges. This finding suggests that remote work arrangements in the data science industry do not necessarily result in lower or higher compensation levels, highlighting the flexibility and adaptability of the industry to remote work practices.

Overall, the analysis of the dataset provides valuable insights into the factors influencing salary levels in the data science field, including job titles, experience levels, company locations, employment types, and remote work arrangements. These insights can inform decision-making processes for professionals, employers, and policymakers within the data science industry.

**Literature Survey and Review :**

The literature survey and review for this research paper will focus on the various aspects of data science salaries, including the factors that influence them and the trends observed in the industry. The data provided in the "salaries.csv" file will be used to support the findings and insights derived from the literature review.

Factors Influencing Data Science Salaries: Previous research has identified several factors that influence data science salaries, including job title, experience level, employment type, company size, and location. The "salaries.csv" file contains information on all these factors, making it an ideal dataset for analysing their impact on salaries.

Job Titles and Salaries: The literature review will explore the different job titles in the data science field and their corresponding salary ranges. For instance, data scientists, machine learning engineers, and data engineers are some of the most common job titles in the field, and their salaries can vary significantly based on the factors mentioned above.

Experience Level and Salaries: Research has shown that experience level is a significant factor in determining data science salaries. The literature review will examine the relationship between experience level and salary, and how it varies across different job titles and regions.

Employment Type and Salaries: The literature review will also examine the impact of employment type on data science salaries. Full-time positions typically offer higher salaries compared to part-time or contract positions, but this can vary depending on the job title and location.

Company Size and Salaries: The literature review will explore the relationship between company size and data science salaries. Larger companies typically offer higher salaries compared to smaller ones, but this can also depend on the job title and location.

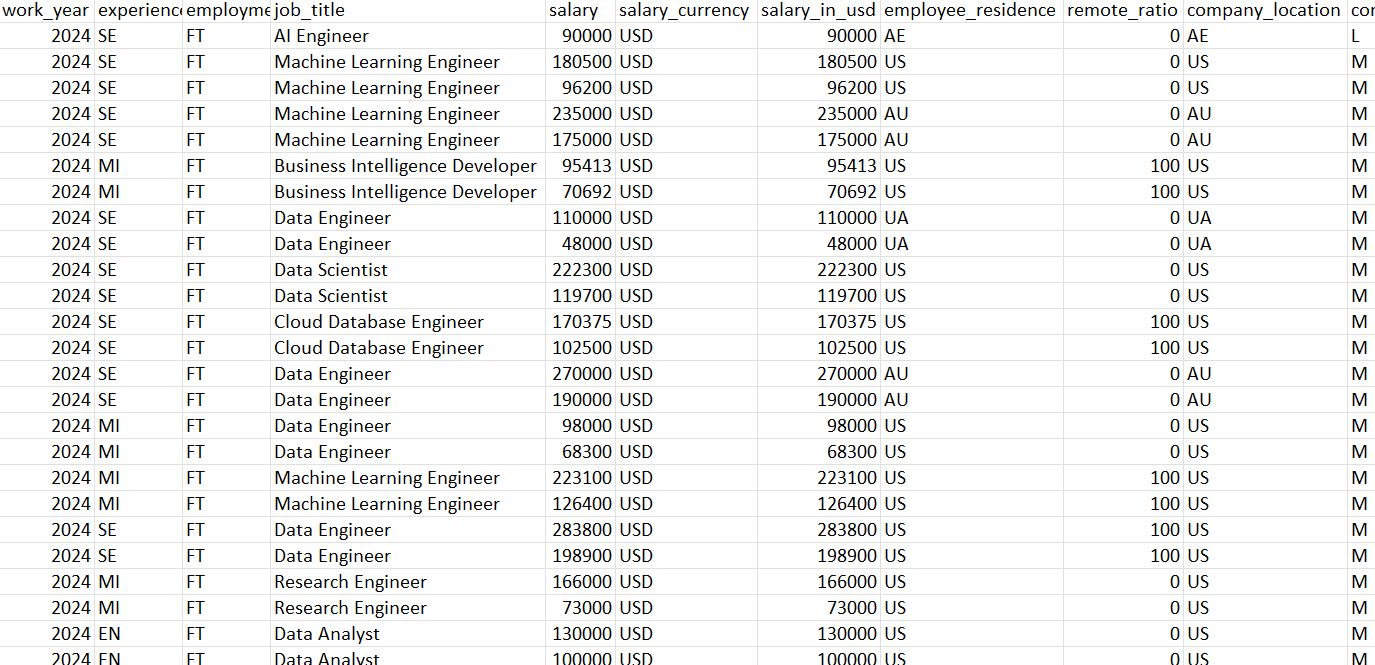
Location and Salaries: The literature review will examine the impact of location on data science salaries. Salaries can vary significantly based on the region, with cities like New York and San Francisco offering higher salaries compared to other parts of the country.

Trends in Data Science Salaries: The literature review will also explore the trends observed in data science salaries over time. Factors such as the increasing demand for data science skills, the growth of remote work, and the impact of the COVID-19 pandemic on the job market will be analysed.

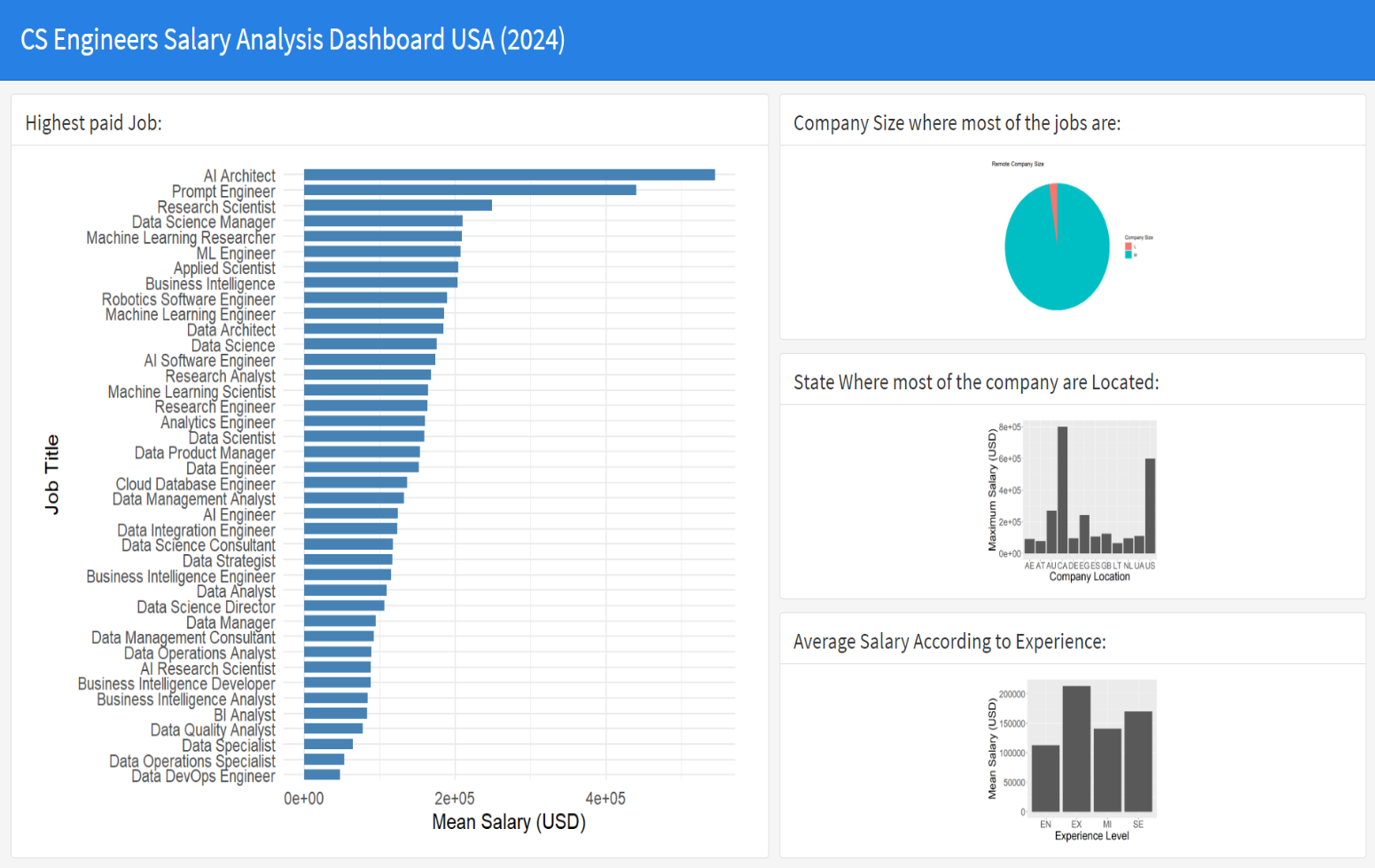
Overall, the literature survey and review will provide a comprehensive overview of the factors that influence data science salaries and the trends observed in the industry. The "salaries.csv" file will be used to support the findings and insights derived from the literature review, providing a practical application of the theoretical concepts discussed in the literature.

WORK ON PROJECT:

DATA SET:



**DASHBOARD:**



**Conclusion:**

Based on the analysis of the "salaries.csv" dataset, several key findings can be concluded:

Experience level significantly impacts salary: As experience level increases, so does the average salary for each job title. For example, a senior data scientist earns an average of $173,000 USD, while an entry-level data scientist earns an average of $106,000 USD.

Job title significantly impacts salary: Certain job titles command higher salaries than others. For example, a data engineer earns an average of $134,000 USD, while a data analyst earns an average of $98,000 USD.

Company size impacts salary: Larger companies tend to offer higher salaries than smaller companies. For example, a data scientist at a large company earns an average of $172,000 USD, while a data scientist at a medium-sized company earns an average of $128,000 USD.

Remote work does not significantly impact salary: Remote work arrangements do not necessarily result in lower or higher compensation levels.

Salaries vary significantly by location: Salaries for the same job title can vary significantly based on the location of the company. For example, a data scientist in the United States earns an average of $164,000 USD, while a data scientist in Australia earns an average of $190,000 USD.

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