Exploring the Data Job Market: An Analysis and Prediction of Job Listings and Salary Trends

Milestone: Data Collection, Data Visualization, Data Exploration and Data Processing

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Problem Setting

The problem setting is as follows: analyze and understand the current job market for Data Scientists, Data Engineers, and Data Analysts, such as identifying:

- The most in-demand skills and qualifications
- The most common industries hiring data scientists/engineers/analysts etc.
- The regions or cities with the highest concentration of data job openings
- The average salary range for various positions
- The most common job titles
- The most common words and phrases used in job descriptions to identify specific tasks and responsibilities that are most sought after by employers.
- Most importantly, to use the job descriptions to develop a model that can predict the job's salary range, given the job description.
- Additionally, it can also be used to build a model that can predict the job industry, given the job description.

A variety of techniques such as data cleaning, data visualization, statistical analysis, and machine learning will be used to understand and provide necessary insights from the dataset.

Problem Definition

The project's goal is to solve the issue of unreported salaries for data scientists, data analysts, and data engineers. Companies can also use this methodology to determine the appropriate starting compensation for new hires. A model is developed based on various criteria to group firms for staff transfers. The projected pay from the model might help employees choose the next ideal position. The project uses job descriptions as input to forecast job attributes such as income range, industry, job title, and other aspects of the work to study and understand the employment market for data scientists, engineers, and analysts. In summary, this model uses machine learning techniques to analyze and understand the job market for data scientists/analysts/engineers by predicting prospective job characteristics.

Data Sources

The datasets for “Data Analyst Jobs”, “Data Scientist Jobs”, and “Data Engineer Jobs” have been taken from https://www.kaggle.com/, an open-source, secure online community, which allows users to browse through numerous datasets. The links for the three datasets are provided below:

i) https://www.kaggle.com/datasets/durgeshrao9993/data-analyst-jobs-datset

ii) https://www.kaggle.com/datasets/andrewmvd/data-scientist-jobs

iii) https://www.kaggle.com/datasets/andrewmvd/data-engineer-jobs

Data Description

After combining the three datasets, the final dataset contains 16 columns (15 attributes and 1 target variable - “Salary Estimate” and 8676 rows. The dataset contains job listings for data scientist roles, data analyst roles, and data engineer roles. It includes several fields such as job title, company name, location, salary, and job description. All the attributes and their descriptions are given below:

No.	Attribute	Description
1.	ID	To identify each record uniquely
2.	Job Title	The title of the job listing
3.	Salary Estimate	The salary range for the job, and this is our response variable

4.	Job Description	A text description of the job responsibilities and qualifications
5.	Rating	Job rating out of 5
6.	Company Name	The name of the company that posted the job listing
7.	Location	The location of the job
8.	Headquarters	Headquarters of the company providing the respective job role
9.	Size	Number of employees working at the company currently
10.	Founded	The year in which the company was founded
11.	Type of Ownership	Type of business [Public, Private, Sports, etc.]
12.	Industry	The industry in which the company operates
13.	Sector	The sector to which the industry belongs to
14.	Revenue	Total income of the company.
15.	Competitors	Other companies that are current competitors to the listed company
16.	Easy Apply	Tells if it is easy to apply or requires specific reference/connections

Table 1: Initial Column Names with their Descriptions

Data Collection (integration of all the three datasets)
To begin our analysis, we initially reviewed the three datasets (pertaining to data analysts, data scientists, and data engineers) independently, with the aim of exploring the distinct columns of each dataset individually. Upon analysing the three datasets, we identified an extraneous column in the Data Analysts dataframe that we dropped, as well as two unnecessary columns in the Data Scientists dataframe that were also removed. However, we did not find any such columns in the Data Engineers dataset.

Next, we merged the three individual dataframes into a consolidated dataframe named "df_comb". Following this, we removed any duplicated rows from the merged dataframe, resulting in the elimination of 16 rows. Ultimately, our final dataframe contained 8674 rows.

Data Cleaning
I. Dropping columns based on number of null values:
To begin with, we computed the number of missing values in each column of the combined dataset. Next, we visualized this data using a horizontal bar chart (Fig 1). The chart allows for an easy comparison of the number of missing values across the different columns.

The column with the highest number of null values is "Easy Apply", with 8286 null values (95.52%). This indicates that a vast majority of the job postings in the combined dataset do not have an easy apply option. Hence, we remove that column. Additionally, we chose to drop the "Competitors" column as well, as it had 71.84% null values (6232). The decision to remove the columns was made based on the understanding that null values may hinder our ability to analyze the data in the columns, and we could obtain useful insights without those columns.

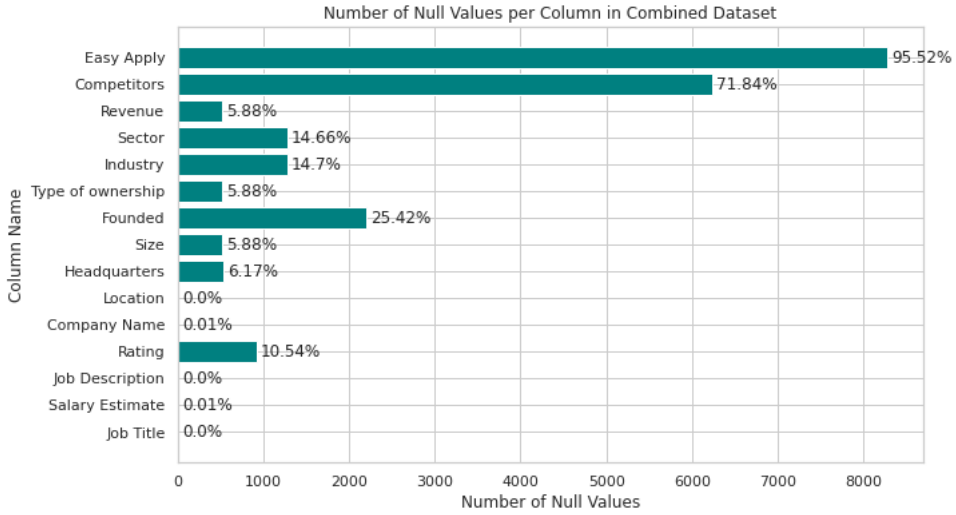


Fig 1: Horizontal Bar Chart to represent number of null values in each column

II. Cleaning "Company Name":

Moving on, we made use of various data cleaning techniques to ensure consistency and reduce redundancy in the columns. In the next step of our data cleaning process, we focused on cleaning the "Company Name" column. Fig 2 represents the state of the "Company Name" column before cleaning, while Fig 3 depicts the state of the column after cleaning.

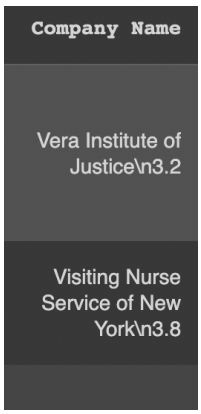


Fig 2: Company Name before cleaning

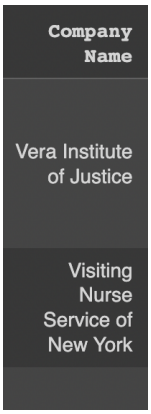


Fig 3: Company Name after cleaning

III. Cleaning "Salary Estimate":

We proceeded to split the "Salary Estimate" column into two separate columns, namely "Starting_Salary" and "Ending_Salary". We also cleaned the column by removing the dollar symbol and "K", multiplying the numerical values by 1000, and converting the values to float type for ease of future analysis. We noticed that in a dataset with nearly 9000 data points, there were only approximately 111 unique values for the starting and ending salaries. To address this, we added a bit of noise, or jitter, to the salary values to improve the diversity of the data. To accomplish this, we utilized the numpy.random.normal() function and generated random numbers from a normal distribution, adding the result to each salary value. The amount of jitter added was equivalent to 10% of the standard deviation of the salary data. By performing these steps, we were able to prepare the salary data for further analysis.

Salary Estimate
$37K-$66K
$37K-$66K

Fig 4: Salary Estimate before cleaning

Starting_Salary	Ending_Salary
39277.0	65008.0
37755.0	62535.0

Fig 5: Salary Estimate after cleaning

Therefore, we have two Response/Target Variables: 1) Starting_Salary 2) Ending_Salary.

IV. Cleaning “Size” Column:

We moved on to cleaning the "Size" column. We started by splitting the column into two separate columns, namely "Min_Size" and "Max_Size." We did this by using the split() function and removing any strings or special characters that could affect the column's quality. Once the column was split, we converted both the columns to numeric datatype.

Size
201 to 500 employees
10000+ employees

Fig 6: Size before cleaning

Min_Size	Max_Size
201	500
10000	NaN

Fig 7: Size after cleaning

V. Cleaning “Revenue” Column:

Now, we clean the revenue column by removing “(USD)”, dollar symbols, any special charactors, replacing “million” or “billion” with the respective number of zeroes, transforming the datatype to numeric, and splitting the column into two: “Minimum_Revenue” and “Maximum_Revenue”.

Revenue
$100 to $500 million (USD)
$2 to $5 billion (USD)

Fig 8: Revenue before cleaning

Minimum_Revenue	Maximum_Revenue
100000000.0	500000000.0
2000000000.0	5000000000.0

Fig 9: Revenue after cleaning

Data Visualization and Exploration

We've visualized the starting salaries and ending salaries through box plots. By creating box plots for the starting and ending salaries, we were able to gain insights into the salary ranges and how they vary across the different job titles in our dataset. The distribution is mostly uniform, with the exception of a couple outliers.

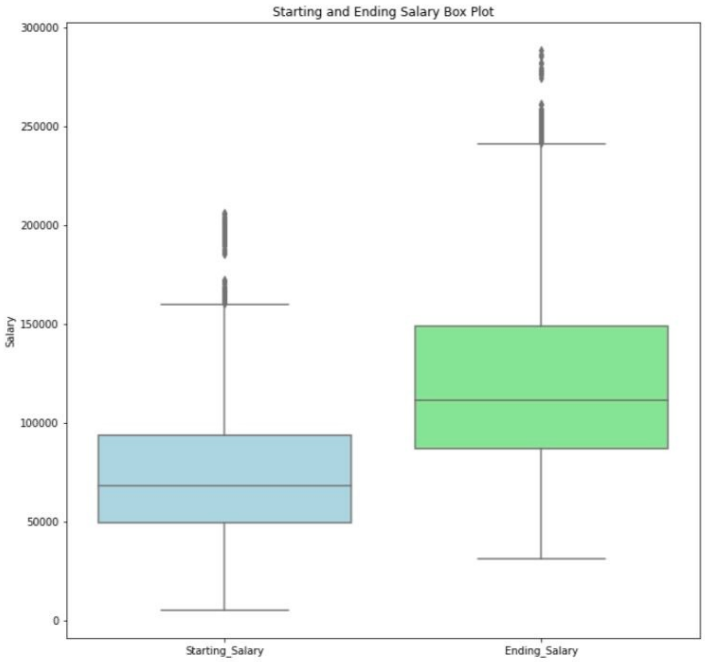


Fig 10: Box Plot visualization of Starting and Ending salaries

A distplot of the "Rating" column would give a graphical representation of the distribution of the "Rating" values in the dataset. It can be observed that the ratings of 1-5 are spread over all the different job postings in an almost normally distributed manner. The slightly left-skewed distribution implies that the median rating is likely higher than the mean rating. This can happen when there are a few companies with very high ratings that pull up the mean but not the median. The skewness can also indicate that there are more companies with lower ratings in the dataset than those with higher ratings. The outlier at rating 5 suggests that there may be some companies that are exceptional in terms of their ratings.

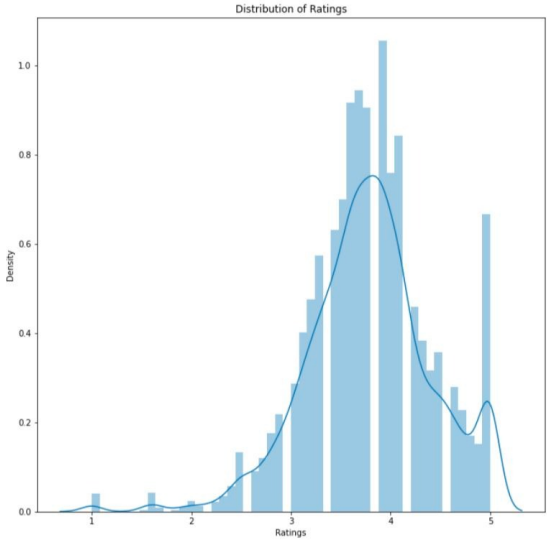


Fig 11: Distplot of Ratings

Next, we've taken mean salary, average size of the company, rating, and average revenue generated by the company each year to create a pairplot, as these are the only numerical columns. We cannot observe any

correlation between these variables as we have many overlapping values. We also observed that we would need to use jittering for better visualization.

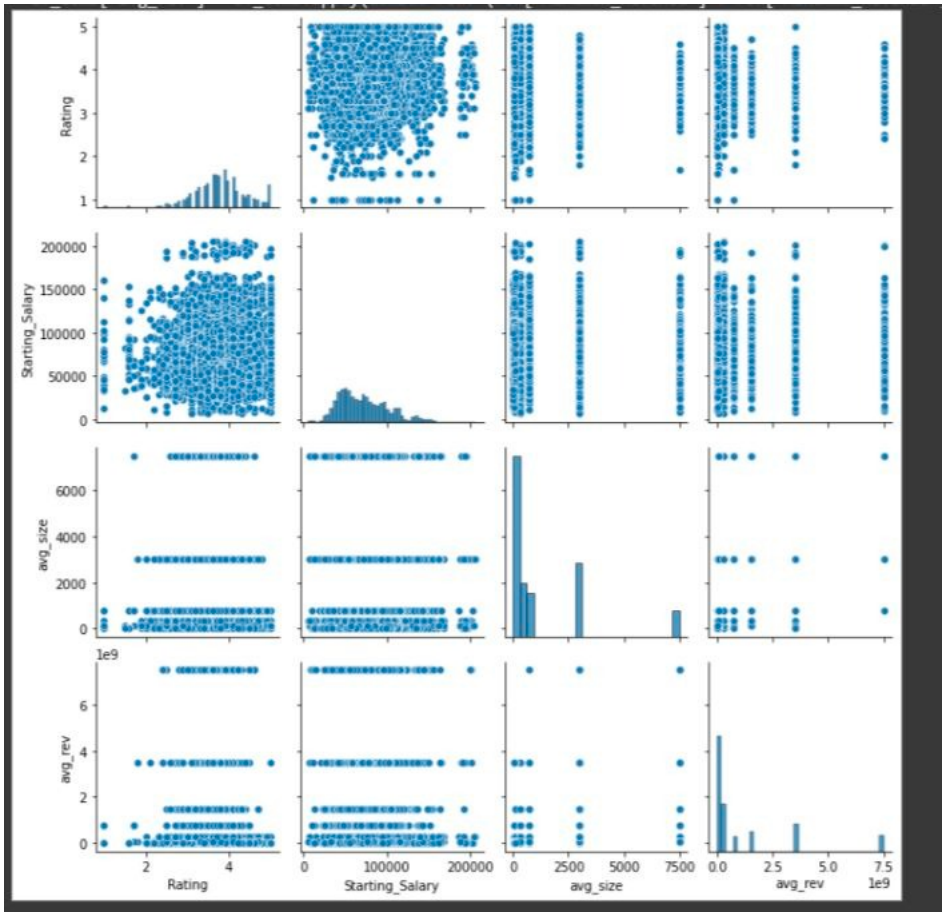


Fig 12: Pairplot among all numerical variables

We have three categories of jobs in our dataset. The below chart shows the names of the top 20 companies that provide these roles in bulk.

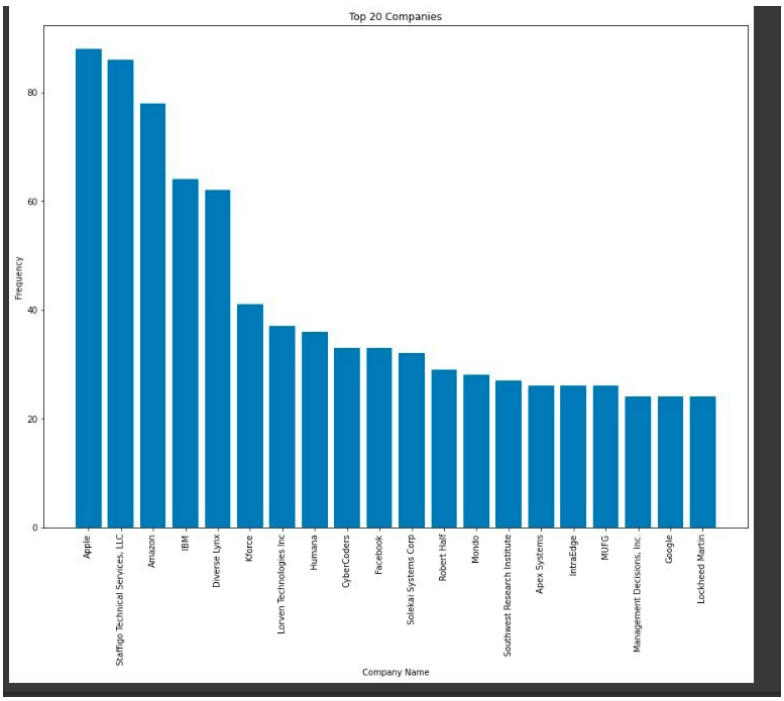


Fig 13: Bar plot for top 20 companies offering DA, DE, and DS roles

Data Processing

I. Sector vs. Mean Salary

We can use a statistical measure called Cramer's V, which is a measure of association between two nominal variables (mean salary and Sector). It ranges from 0 to 1, where 0 indicates no association and 1 indicates a perfect association. After performing a Cramer's V test on the "Sector" column and the mean salary, we obtained a low value of 0.0021. This value suggests that there is no significant association between the Sector that a specific company/job belongs to and our response variables. This means that the salary is independent of sector and vice-versa.

```
import researchpy as rp
import pandas as pd
df_comb["mean_salary"] = df_comb.apply(lambda row: (row["Starting_Salary"] + row["Ending_Salary"])
crosstab, test_results = rp.crosstab(df_comb['Sector'], df_comb['mean_salary'], test='chi-square')
cramers_v = np.sqrt(test_results.iloc[2,1] / (df_comb.shape[0] * (min(crosstab.shape) - 1)))
print(f"Cramer's V: {cramers_v}")

Cramer's V: 0.002140338012218702
```

Fig 14: Cramer's V Test on Sector and Mean Salary

II. Processing "Job Description"

We'll be performing Natural Language Processing (NLP) on the Job Description column. Job description column consists of a string of words in the form of a paragraph. Each paragraph contains information about the job posting, required qualifications and skills. We merged the entire column of Job Descriptions into one big text chunk, and found the frequency of words using NLP. This involves preprocessing the text data, tokenizing the text, converting it into a numerical representation using count vectorization or TF-IDF, and analyzing the frequency of words. We chose 200 such words and then manually filtered 60 skills ['microsoft office', 'oral', 'written','customer service', 'regression', 'classification', 'problem-solving','excel', 'reasoning', 'communication', 'charting', 'python', 'sql', 'management', 'creative', 'dashboards', 'machine learning', 'data visualisations', 'tableau', 'powerbi', 'r', 'etl', 'extract/transform/load', 'nlp', 'nltk', 'natural language processing', 'aws', 'predictive modelling', 'computer vision', 'cloud computing', 'software', 'azure', 'gcp', 'distributed system', 'data reporting', 'cleaning', 'modelling', 'big data', 'deep learning', 'neural network', 'statastical', 'analysis','modeling', 'databases', 'mongodb', 'network', 'cypher', 'hadoop', 'analytics', 'hadoop', 'spark', 'flask', 'florish', 'bachelor','master','data science','computer science','mathematics','statstics']. We then stored the skills in a list and created a data frame with these skills as columns. Now, we go over each row in our original dataframe and check if each job description contains any of the skills, and if it does, then we assign 1 to a particular skill, else 0. Finally, we merge the skills dataframe with our "df_comb".

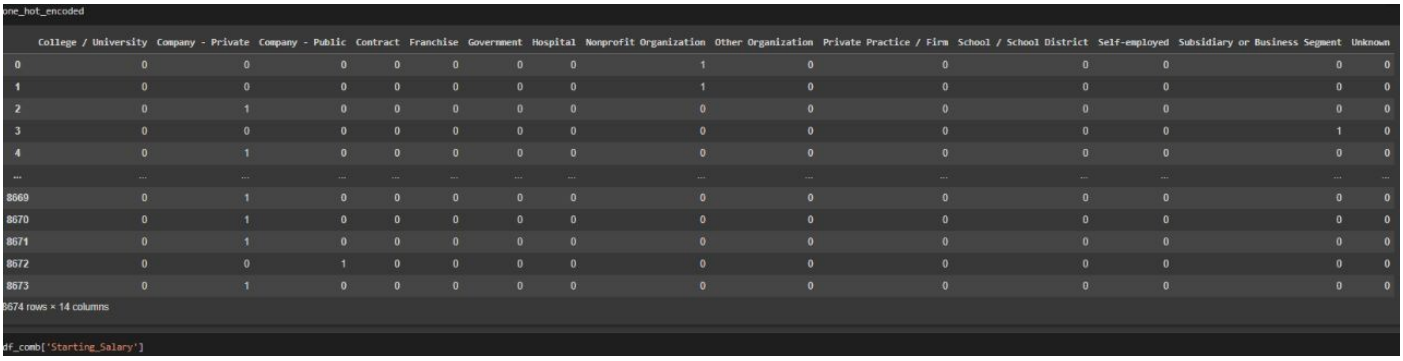
	microsoft office	oral	written	customer service	regression	classification	problem-solving	excel	reasoning	communication	...	hadoop	spark	flask	florish	bachelor	master	data science	computer science	mathematics	statstics
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
669	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
670	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
671	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
672	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
673	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

Fig 15: Pivot form of skills

The number of years of experience in each job description is present in various formats, we're working on its extraction.

III. One-hot encoding of “Type of Ownership” column:

We have converted this categorical variable into a numerical variable using one-hot encoding. We will using the long pivot form of the dataframe for predicting salaries.



one_hot_encoded

	College / University	Company - Private	Company - Public	Contract	Franchise	Government	Hospital	Nonprofit Organization	Other Organization	Private Practice / Firm	School / School District	Self-employed	Subsidiary or Business Segment	Unknown
0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	0	0	0	0	0	0
2	0	1	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	1	0
4	0	1	0	0	0	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
8669	0	1	0	0	0	0	0	0	0	0	0	0	0	0
8670	0	1	0	0	0	0	0	0	0	0	0	0	0	0
8671	0	1	0	0	0	0	0	0	0	0	0	0	0	0
8672	0	0	1	0	0	0	0	0	0	0	0	0	0	0
8673	0	1	0	0	0	0	0	0	0	0	0	0	0	0

8674 rows × 14 columns

df_comb['Starting_Salary']

Fig 16: One-hot-encoded form of “Type of Ownership” column