Data Job Posting Analysis

Introduction

As a job seeker, browsing through hundreds or even thousands of job postings is a demanding task. An applicant can spend 5-8 hours a day on searching and applying for positions. As a modern day computer science student interested in data science, automating the searching process can be a lifesaver, increasing both the efficiency and quality of job searching. In this project, I aim to build a pipeline to collect job postings, extract information using advanced AI tools, clean the data, and analyze them to gain deep insight of the job market. Once built, it will save me a lot of time searching for a perfect match on the job market.

Methods

Data is collected using web scraping techniques, key words of Data Analyst and Data Scientist are used to collect web information of job postings, including, applicationsCount, applyType, applyUrl, benefits, companyId, companyName, companyUrl, contractType, description, experienceLevel, jobId, jobUrl, location, postedTime, posterFullName, posterProfileUrl, published date, salary, sector, title, and workType. Data is saved as .csv file and is processed in Visual Studio 2019 with anaconda environment, python version 3.11. OpenAI API and ChatGPT 4o-mini is called to extract more information from the description column for skills, salary and whether it’s a remote work. Even though the salary is already in the scraper response, some job postings don’t have that information under the salary section but in the description. Several libraries are adapted to match similar words together, such as K-means clustering from SKlearn and fuzzymatch. Seaborn and Matplotlib are used to plot the visualizations.

Data Cleaning and Pre-Processing

A weeks’ posting, about 1515 entries of data related job postings are scraped from Linkedin using existing actors on Apify and saved as one .csv file. Due to the nature of online postings and the imperfect of AI generative models, there are a significant amount of work to clean the dataset. Job titles have all kinds of descriptions in it, salaries are either missing or contain typos. Locations are not standardized with different names for the same location. At last but not least, the scripts generated by OpenAI have many variations for the same thing. Data cleaning is challenging in this manner.

Data Preprocessing

Description Information Extraction

The information extraction is done by OpenAI API and ChatGPT 4o-mini. A code calling the API, a concatenated prompt with the job description and my customized prompt is send to the server. The server returns a response with a python dictionary data structure with key names of min\_years\_of\_experience, min\_hourly\_salary, max\_hourly\_salary, min\_yearly\_salary, max\_yearly\_salary, required\_degree, remote\_work, required\_skills. Each row of description is processed this way, and each response is saved into a new column, then each key is separated and saved into a new column.

Due to the variation of job titles, it will be impossible to plot data against job titles. So I simplified them into four categories: Intern, Data Analyst, Data Scientist and Business Intelligence. These four categories consist of the majority of the posting.

Salary Cleaning

First the dataset is randomly sampled with a sample size 20, the salary column is compared with the hourly and yearly salary extract by ChatGPT. If salary is not None but no information is obtained from the description, then use the clean\_salary helper defined in utils.ipynb to fill the empty cells. Average hourly salary and yearly salary are calculated from the min and max salary columns. The statistics are described in Table 1 data description of average salary. It’s clear that some outliers exist, there should be no hourly salary of $140,000, nor yearly salary of 67.5. A closer look at the outliers shows that there are typos in several entries where hr and yr are misplaced. After these are fixed, the statistics become normal (Table 2). Many entries are empty in both salary and description of the scraped data, there is no way to get these information so they are left to None data type.

Table 1 data description of average salary

Table 2 data description of average salary after cleaning

Skills Cleaning

Due to the inconsistency between responses, the skill list obtained from ChatGPT often have different names for the same skill, such as SQL vs Advanced SQL, analytics vs analytical, Excel, MS excel or Microsoft Excel. Standardize thousands of inconsistent strings is super labor intensive and challenging in the old times. The advancement of machine learning techniques have made this much easier. Still some tuning and testing are needed to find out the best solution for this problem. In this project, I tested three methods to standardize the skill names: word count, KMeans-clustering and Fuzzymatch. Before applying these methods, the strings are first standardized by converting them to lower cases and removing all special characters.

Word count

Word count is a classic method to deal with inconsistent strings. The phases are break down to single words, counted and displayed. Common words with minimal information are removed, such as ‘skill’, ‘skills’, ‘tools’ and ‘etal’. It’s obvious that some words have similar counts and recombine words like ‘machine’ with ‘learning’, ‘power’ with ‘bi’.

KMeans-clustering

KMeans-clustering group similar elements together by calculating their distance in a map. It can not be used on words directed so the words are first vectorized using TfidfVectorizer library in python, then fitted by KMeans model from SKlearn library, the result is a cluster index label for each skill. The model is tuned by testing nine values of clusters, ranging from the total unique values of the skills to a 10th of that value. The most frequent word in each cluster is used as the representatives in the final top skill list. One problem arising from this test is some simple words like ‘r’ can be randomly grouped into many clusters. For example, ‘r’ is the most frequent word in a cluster, however there are 100 words in it and ‘r’ only counts for 10, but counted as 100 when counting the skill frequency. So it end up have ridiculous high count in the top skill list. Two adjustment were added to the algorithm to minimize the effect: 1. A context specific qualifiers are added to those simple words like ‘r language’ or ‘C++ language’; 2. A threshold is added to the clusters when counting skill names, only count the skill name when it consist of more than 50% of the cluster.

Fuzzymatch

This method utilize the Fuzzywuzzy library. A fuzzy match compare words with similarity defined by a threshold. A 80% threshold is used in this project.

Cleaning Result

The cleaning result is shown in Figure 1. All three methods generated similar skill list, although the order can be slightly different. Among the three methods, Fuzzymatch works the best with minimum human input while the other two need close examination of the skill list for data preparation and fine tuning. It also loss the least amount of data during the process.

Figure 1 Comparison of Three Cleaning Method

Location Name Cleaning

I faced similar problems with the location data as in the skill cleaning. Many location entries are the same places with different name, like ‘New York, NY’, ‘NY, United State’, ‘New York Metropolitan Area’ and ‘New York City Metropolitan Area’. However, same techniques produce much worse results. It’s probably due to the long words like ‘Metropolitan Area’ stops clustering and fuzzymatch to work. Fortunately, there are limited variation of the location names, I end up creating a map that mapping variations into one location name.

Suspicious Companies and Duplicates Cleaning

Many companies spam multiple postings for the job. Some are remote jobs created for different locations, some are shady companies try to increase their exposure to attract more applicants. There are two companies stand out, one is Outlier which is a crowed sourcing company for AI training, the other is Synergistic IT which is not a legitimate company who will charge applicants for ‘training’, but write their postings like a paying job. These two companies post a lot of jobs at all times, so they need to be removed for any analysis work. In the meantime, other jobs with the same company, title and publish date are also removed except one copy of that job. In the end, 749 job postings are removed, leaving 766 data entries for further analysis.

Analysis

Posting Trend

After removing the non-legit companies and duplications, there are 766 postings left from the original 1515. The majority (>90%) are Data Analyst and Data Scientist jobs, the rest are intern and other Data related work, such as Business Intelligence Analyst. Data Analyst and Scientists opportunities are almost 50-50 (Figure 2 ). Top company which posted the most are Intuit, Meta and Walmart (Figure 3). Figure 4 and Figure 5 shows the job posting number trend over date and weekdays, respectively. There is only one week’s data so no meaningful information can be seen here. One interesting observation is that the postings peak on Tuesday and gradually decline to Monday. The reason is unknown, my theory is HR need to prepare the postings on Monday, and start to post them start from Tuesday.

Location

As shown in Figure 6, about 39% of the postings are remote job so they don’t have a exact location. After location names are cleaned, the postings are grouped based on names and counted. The result is plotted in Figure 7. It can be seem that NYC hosts the most data jobs, far above the rest of cities. San Fransisco is the close second if combined with Mountain View CA which is also near Bay Area. Washington DC and Atlanta holding the third place with above the same number of jobs. Chicago is only city with decent data job postings in the central US.

Experience Requirements

Most data jobs require some level of experience, even for entry level positions. This requirement makes the data field somewhat hard to break in. Figure 8 shows the histogram of experience level and years distribution. As we can see, mid-senior level is the most in demand level, followed by entry level. There is almost no job has no experience requirement, most require 1-5 years of experience in the industry. 3 years and 5 years are most common requirements.

Figure 8 Experience level and required years of experience

Salary Analysis

Table 3 Salary statistics by job title

Figure 9 Boxplot of hourly and yearly salary by job title

Figure 10 Companies paying the highest salary

Only 432 job postings out of the 766 included salary information, 89 are hourly rate due to the contract nature of the work. The rest are yearly salaries. The distribution is plotted in Figure 9 and the numbers are shown in Table 3 Salary statistics by job title. It’s clear that the Data Scientist jobs pay the most with an average salary of $160K and max of $300K. Data Analyst and Business Intelligence Analyst have similar salary of around $100K. However, the highest paid Data Analyst job also pays about $300K. The top paying companies are shown in Figure 10 for reference.

Top Skills

All three methods mentioned in the data preprocessing section provide similar results. Due to the fact that the fuzzy match needs the least human input, and less computation power than KMeans, it’ s chosen for this analysis. The top skills are listed in Figure 11. The overall skill list is about the same, all jobs have skills like data analysis, SQL, communication, data visualization and Python on the top. However, the importance is slightly different on different titles. Analyst jobs emphasize more on the data analysis and visualization and Data Scientists need more advanced modeling techniques like Python and Machine Learning.

Figure 11 top skills by job title

Conclusion

This project provides valuable insights into the trends in the job market, including job opportunities, locations, salary expectations, and skill to learn. These information will help tremendously in my job search. The key take aways are:

Nearly a thousand unique job posted in a near holiday week

39% of the jobs are remote opportunities. NYC and the Bay Area offer the best chances for on-site jobs..

Data Scientist positions provide decent pay, which is about 60% more than Analysts.

The most in demand experience level are mid-senior level, and then entry level. Companies usually requires 1-5 years of experience.

Top skills are Data Analysis, SQL, Python, Communication, and Data Visualization using Tableau and Power BI. If I want to apply for Data Scientist positions, Machine Learning is also a top skill.

Developing and leveraging advanced AI tools such as ChatGPT, unsupervised machine learning tool like KMeans-clutering, and word matching algorithm like fuzzywuzzy are proven to be valuable assets. They can quickly convert messy web scraped information into insights of the job market to speed up job applications tremendously.

Future Work

This project only analyzed a week’s job posting on Linkedin. To understand the long-term trend of the industry, more data is needed. I will keep collecting job posting data while searching and applying for jobs.

I also learned a lot in the project by the healthy cycle of encounter problems, to search and test solutions, and eventually solve the problem. Learning is a continuous process with no end, I will keep learning more AI and language processing tools to improve this project, both for demonstration my data analysis skills and speeding up my job searching.

Finally, after discussions with the administration of nearby universities, they showed some interest in providing funding for long term data service. I will collect and compile job posting information for their students to use. In the future, this project will not just include data-related work, more fields of study, such as Finance, Accounting, or Chemistry will be added. User feedback will also be collected to further improve the quality and usability of this project.