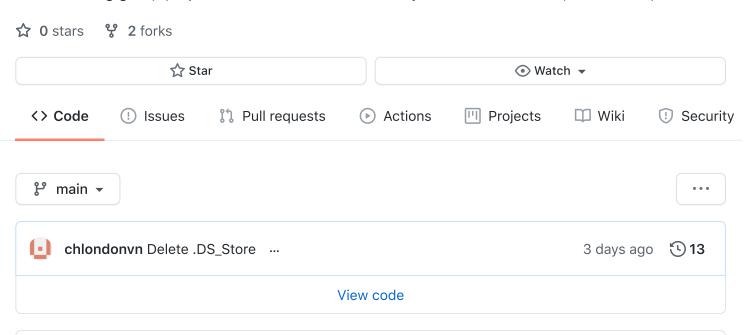
☐ chlondonvn / Messy-Group

Data cleaning group project for the IronHack Data Analytics 10.2020 Cohort, Berlin Campus



README.md



Messy Group

Group Members:

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- -Charlotte Velilla
- -Felix Meier
- -Fred Hatanian
- -Julien Carbonnell
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[DATA ANALYSIS 10-20 Cohort, Berlin]

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Project Description

Working on the 'Data Science Jobs Market' database to clean, analyse and provide interesting and relevant insight into the data and return a final CSV file of cleaned data combined with visualizations. Parts of the requirements of the projects involved:

Questions/ Requirements

- Who gets hired? What kind of talent do employers want when they are hiring a data scientist?
- Which location has the most opportunities?
- What skills, tools, degrees or majors do employers want the most for data scientists?
- Employ string functions + regexp
- Summarise results by job profile, company, location city, area of the country
- Create new columns : employ Boolean T/F logic
- · Handling NULLs in the data

Dataset

Data Scientist Job Market in the U.S.

Link to data: https://www.kaggle.com/sl6149/data-scientist-job-market-in-the-us

The data set used for cleaning is hosted on Kaggle and has been scraped from the web about US data science hires in 2018 (ie pre-covid!).

The dataframe consist of: 6964 rows × 5 columns. A total of 1,682 Null/NaN values were found.

Workflow:

As a group, after a quick review of the data, we were able to locate a number of empty rows to be deleted and discussed how we could further clean each of the columns. For this we used a number of SQL and Python functions, along with some additional libraries for specific tasks, as detailed below:

Data Cleaning/Wrangling:

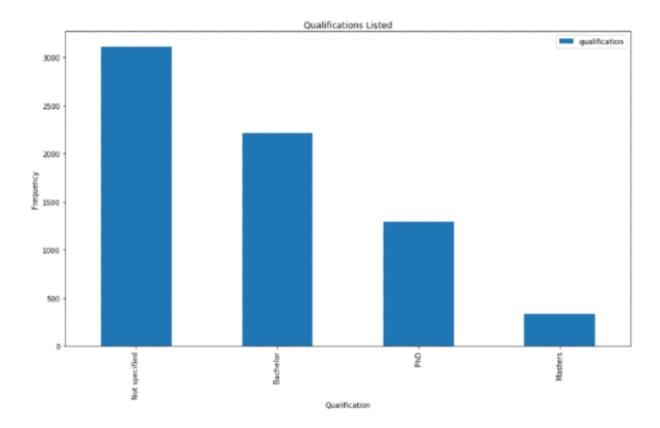
- Company: The data in this column was clear, well formatted and after dropping empty rows, contained no null values, so required no further cleaning.
- Position: We were able to group together roles with similar titles by picking out and linking keywords.
- Location: Split into city, state, zip code. Drop ZIP code and find long and lat coordinates for cities
- Job Description: In order to gain insights on job descriptions such as what skills are needed and what are the keywords that appear most within each of the job descriptions, string functions + regexp was used. Each job description was concatenated, normalized and tokenised to extract keywords and regexp was used to look for 'SQL' and 'Python' skills creating boolean columns with the results.
- Reviews: While the review column could potentially give us some insight into the size of the company, as we are unable to see whether the reviews are positive or negative, we decided to drop the column entirely.

Review

Insights

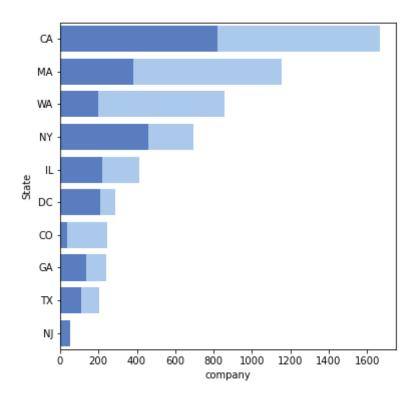
After cleaning and analyzing the data, we were able to find out lots of information about the spread of jobs across the US and the different types of roles available within the Data Science field as well answer the questions and requirements of the project as follow:

1. Who gets hired? What kind of talent do employers want when they are hiring a data scientist?



2. Which location has the most opportunities?





3. What skills, tools, degrees or majors do employers want the most for data scientists?

```
In [19]: df[['position','skills']]
```

Out[19]:

	position	skills
0	Development Director	,,R,
1	An Ostentatiously-Excitable Principal Research	"R,
2	Data Scientist	sql,,R,
3	Data Analyst	sql,,R,
4	Assistant Professor -TT - Signal Processing &	"R,ML
6959	Data Developer / Machine Learning Analyst	sql,,R,ML
6960	Scientist I	"R,
6961	Intern Scientist	sql,,R,ML
6962	Senior Data & Applied Scientist	"R,ML
6963	Principal Data Scientist, Deep Learning	sql,,R,ML

6953 rows x 2 columns

qualification

Not specified	3114
Bachelor	2212
PhD	1295
Masters	332

4. Employ string functions + regexp



5. Summarise results by job profile, company, location city, area of the country

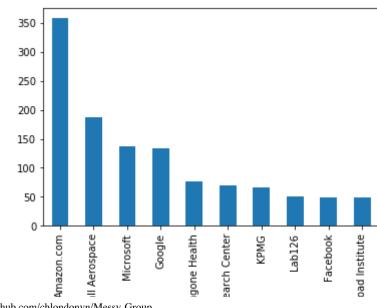
```
In [91]: #Define positions into smaller groups
In [92]: def CleanList (x):
               if 'data scien' in x.lower():
                   return 'Data Scientist'
               elif'data analy' in x.lower():
                   return 'Data Analyst'
               elif'data engineer' in x.lower():
                   return 'Data Engineer'
               elif'research scien' in x.lower():
                   return 'Research Scientist
               elif 'research analy' in x.lower():
                   return 'Research Analyst'
               elif 'scientis' in x.lower():
                   return 'Scientist'
               elif 'developer' in x.lower():
                   return 'Developer'
               elif 'engineer' in x.lower():
                   return 'Engineer'
               elif 'senior analyst' in x.lower():
                   return 'Senior Analyst'
               elif 'customer s' in x.lower():
                   return 'Customer Success'
               elif 'director' in x.lower() or 'executive' in x.lower()or 'head' in x.lower()
                   return 'SeniorRole'
               elif 'analy' in x.lower():
                   return 'Analyst'
               elif 'research' in x.lower():
                   return 'Researcher'
In [34]: #isolating the different levels of seniority
         df.loc[df['position'].str.contains('Junior|Jr|junior|jr', case=False), 'seniority'] = 'junior'
df.loc[df['position'].str.contains('Senior|Sr|senior|sr', case=False), 'seniority'] = 'senior'
         df.loc[df['position'].str.contains('Entry|entry', case=False), 'seniority'] = 'entry level'
         df.seniority.value_counts()
Out[34]: senior
                        1486
         junior
                         49
         entry level
                         17
         Name: seniority, dtype: int64
```

95]: alldata['position_grouped	alldata['position_grouped'].value_counts()		
95]: Data Scientist	1444		
Scientist	1093		
Engineer	1007		
SeniorRole	786		
Analyst	373		
other	359		
Research Analyst	321		
Researcher	298		
Research Scientist	274		
Data Analyst	182		
Data Engineer	177		
Specialist	110		
Developer	110		
Associate	63		
Machine Learning Engineer	61		
Architect	40		
Technician	37		
Programmer	32		
Administrator	32		
Coordinator	26		
Product Specialist	25		
Consultant	24		
Senior Analyst	24		
Designer	19		
Recruiter	12		
Writer	11		
Customer Success	10		
Junior	3		
Name: position_grouped, d	ltype: int64		

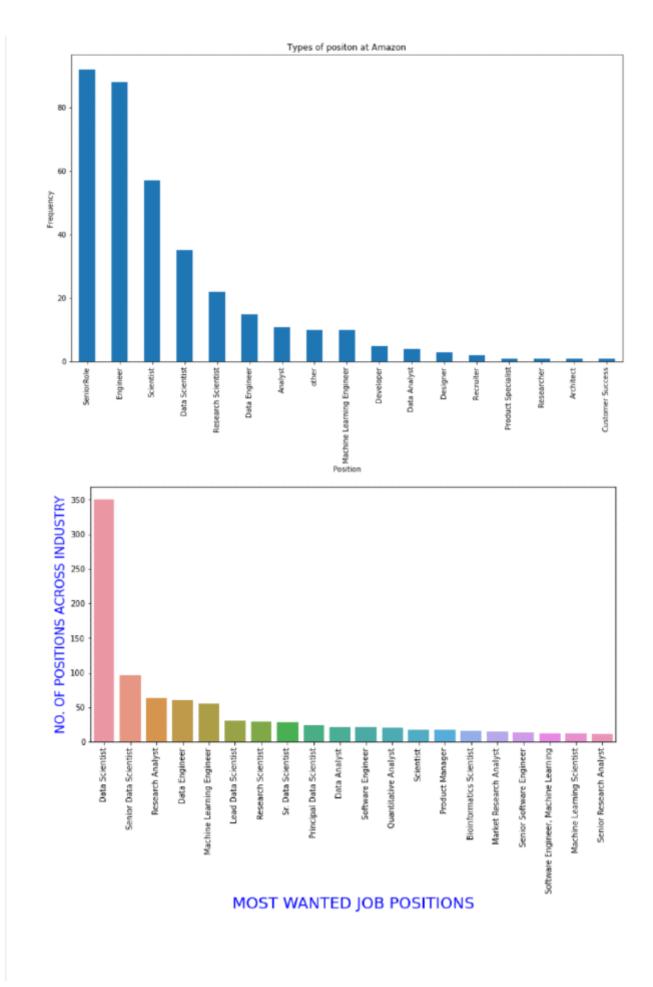
6. Create new columns : employ Boolean T/F logic

seniority	sql	python
Director	False	False
NaN	False	False
NaN	True	True
NaN	True	True
NaN	False	False
NaN	True	True
NaN	False	False
NaN	True	True
Senior	False	False
NaN	True	True

7. Additional Insights



```
Fred Hutchinson Cancer Rese
          # To find the frequency of top 100 words
In [26]:
          from nltk.probability import FreqDist
          fdist = FreqDist(token cleaner)
          fdist100 = fdist.most common(100)
          fdist100
Out[26]: [('data', 37778),
           ('experience', 19441),
           ('work', 16135),
           ('team', 14949),
           ('research', 13582),
           ('development', 11495),
           ('business', 11318),
           ('learning', 9074),
           ('skills', 9042),
           ('new', 8960),
           ('years', 8916),
           ('science', 8793),
           ('including', 8495),
           ('analysis', 7850),
           ('technical', 7573),
           ('machine', 7257),
           ('management', 7239),
           ('software', 7077),
           ('product', 6994),
           ('working', 6925),
           ('support', 6769),
           ('design', 6731),
           ('related', 6557),
           ('engineering', 6512),
           ('ability', 6234),
           ('degree', 6139),
           ('amp', 6115),
           ('systems', 5692),
           ('information', 5479),
           ('opportunity', 5432),
           ('analytics', 5392),
           ('knowledge', 5389),
           ('solutions', 5296),
           ('company', 5243),
           ('teams', 5151),
```



Challenges

We encountered a number of challenges, these included:

- Many crashes before fixing the text mining library on the jupyter notebook.
- Mapping top Tech Hotspots; turns out that most places are the same (e.g. SF bay area) but are grouped differently since city name is different
- Extracting strings from the roles and the description to get seniority and skills and bucket them in meaningful ways.

Further exploration

- Further group columns
- Group the locations more effectively (e.g. combine Manhattan and New York)
- Correlate average salary of position title with location and living cost to get location based purchasing power
- Get review rating, not only number (4 out of 5 stars) to get rating of employer

File structure

In the repository the following files are included:

- alldata.csv
- cleaned_data.csv
- Cleaning_Data_Project_The_Messy_Group.ipynb
- Messy_Graphics directory
- README

Releases

No releases published

Packages

No packages published

Languages

Jupyter Notebook 100.0%