Team Name: Algo Warriors

Members: Rahul Basak, Aden Zhao, Arnav Kaul

PM: Samara Silverman

Oakley Reading Insights: Set boundaries early, be firm in our expectations, and do not enable

dysfunctional behavior

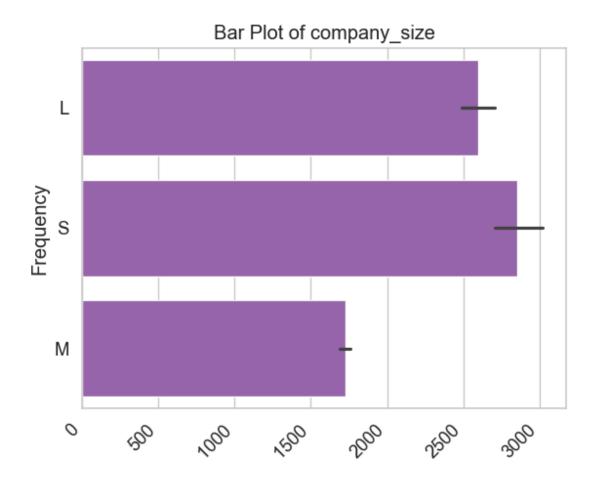
PM Meeting insights: We had not started the project upon meeting her, but it was nice to formally introduce ourselves.

Summary Statistics for Dataset:

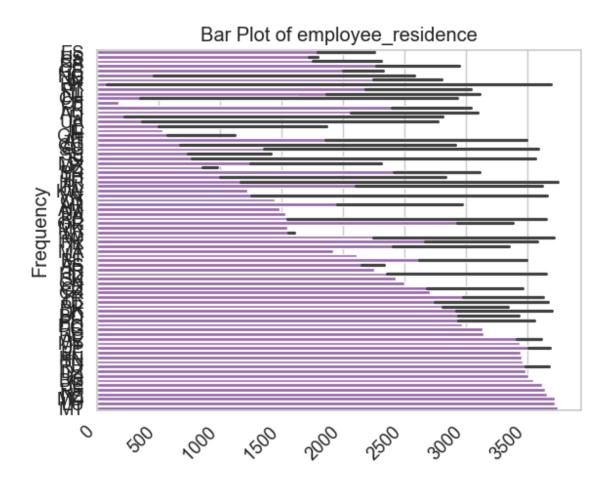
(work; wear): ("mean: np.float64(2022.378551531233), median': np.float64(2022.0), "mar: np.in64(2020), "mar: np.in64(2020), "sar: np.float64(606442342671899)), experience, "wear): ("minux-yalves"; ISF, "Nalves, Mr. 805, Mr.

Plots and descriptions:

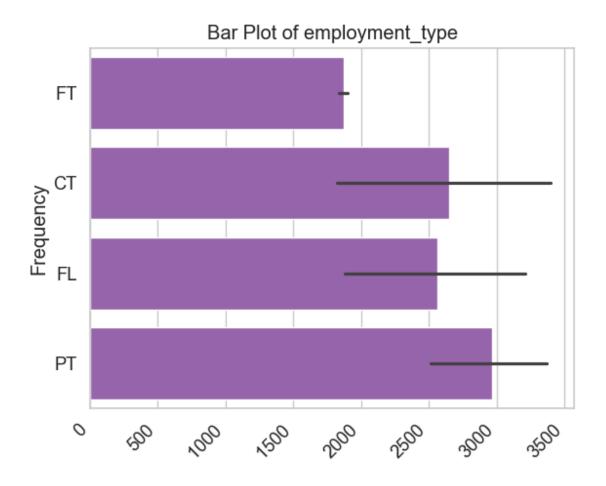
The plot below tells us the relative frequencies of company sizes in our data set. There are less medium companies.



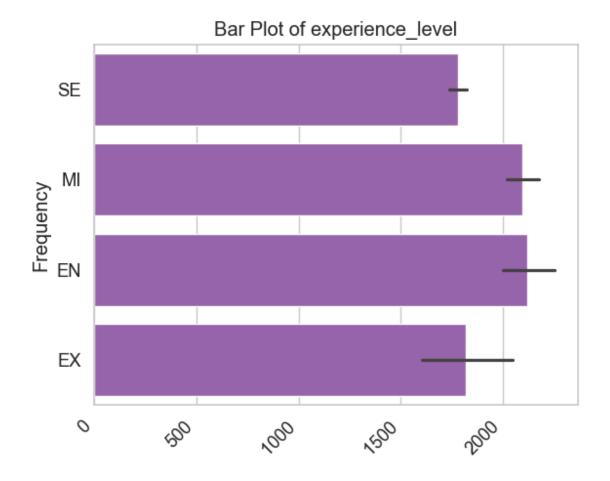
The plot below tells us the relative frequencies of employee residences. It's not very useful since the plot is so cluttered. Maybe a different plot would be better suited for this particular column.



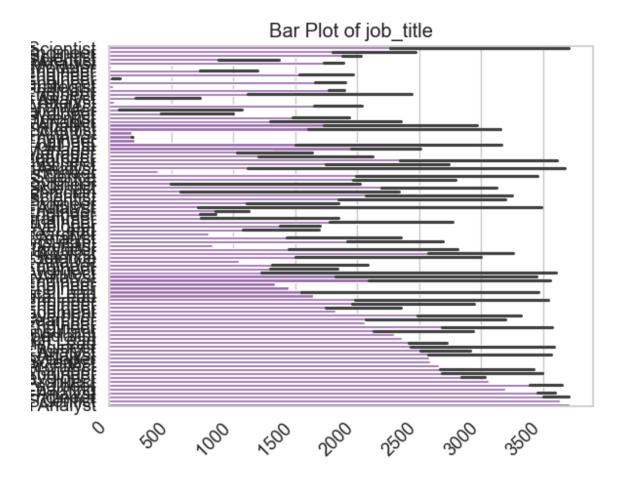
The plot below tells us about the relative frequencies of employment_type. There are a lot of part time workers.



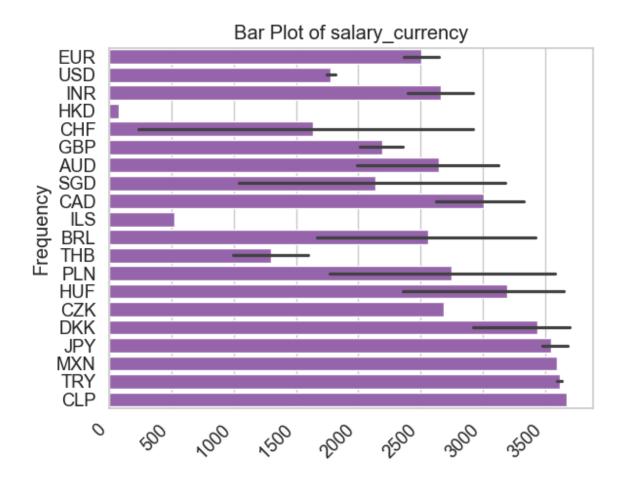
The plot below tells us about the relative frequencies of experience level. It's pretty even.



The plot below tells us about the relative frequencies of job title. Again, it's not very useful because of how cluttered it is, which tells us that a different plot would perhaps be better suited.



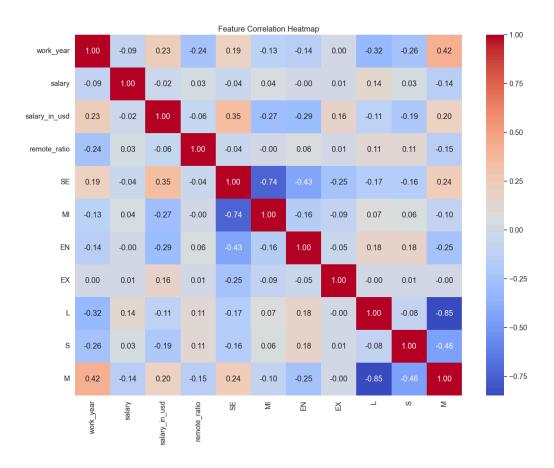
The plot below tells us about the relative frequencies of salary currency. Again, it's fairly even with outliers on the lower end like HKD.



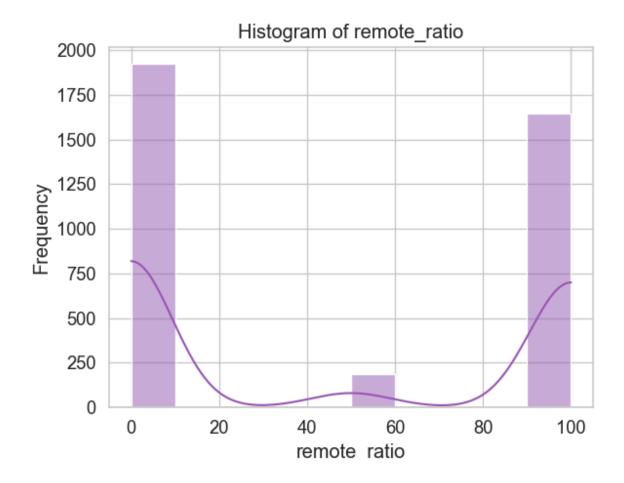
The plot below tells us about the distribution of salaries by remote work ratio. (the title is a typo). Strangely, 50% remote work jobs earn noticeably less money.



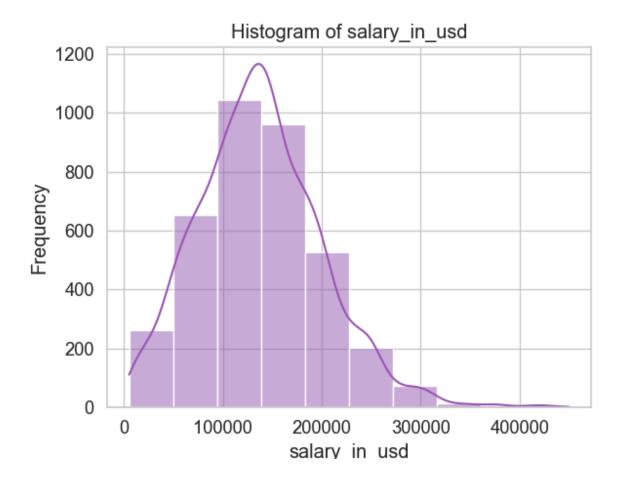
The plot below is a feature correlation heat map of the features: work year, salary, salary_in_usd, remote_ratio, job title, and company size. The plot tells us a lot of things, like remote ratio and work year are negatively correlated, suggesting that as the number of years someone has been working increases, the proportion of remote work decreases. Strange.,



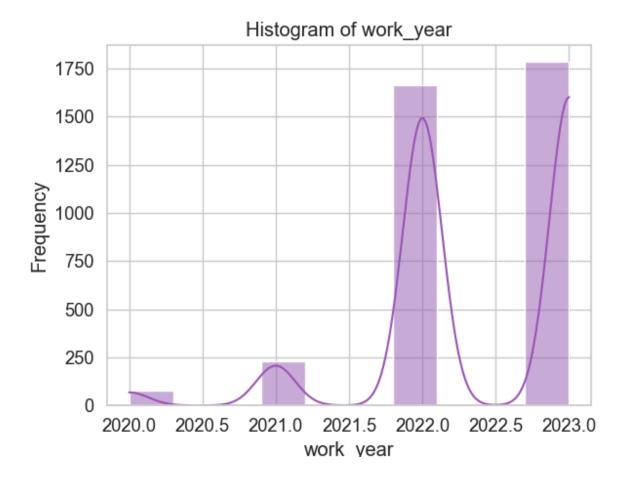
The histogram below tells us the frequencies of remote ratios. In person and remote are pretty equal.



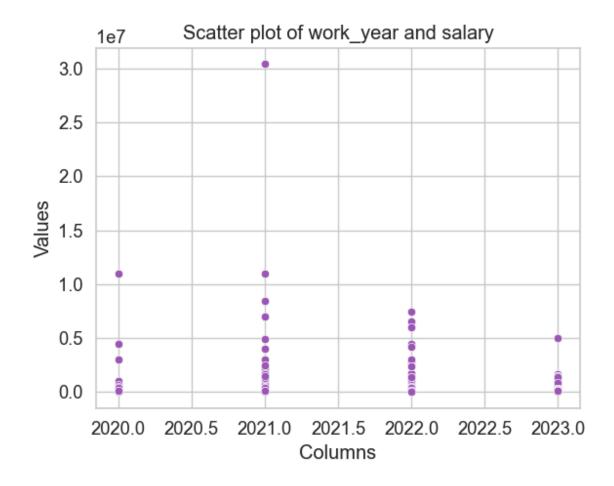
The histogram below tells us about the frequency of salaries. The most common salary seems to be \$150k.

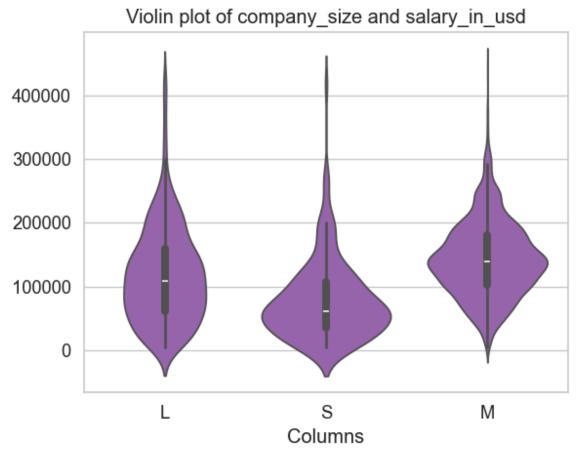


The histogram below tells us about the frequency of work years. 2022 and 2023 are very common.



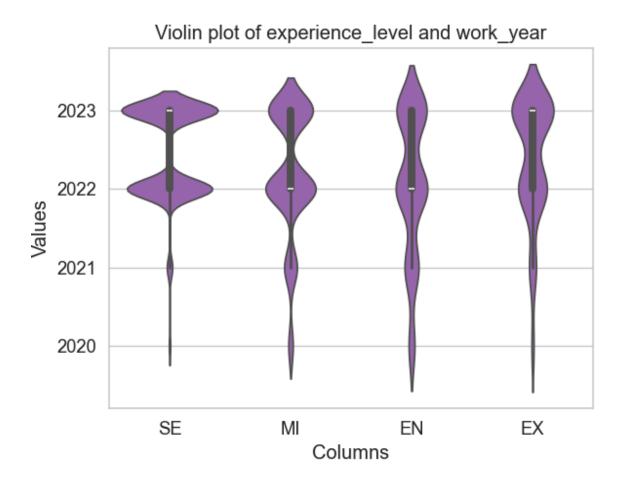
This scatter plot tells us how correlated wrk_year and salary are. There doesn't appear to be much of a correlation though





This violin plot illustrates how company size and salary are correlated. Small companies pay less, which makes sense.

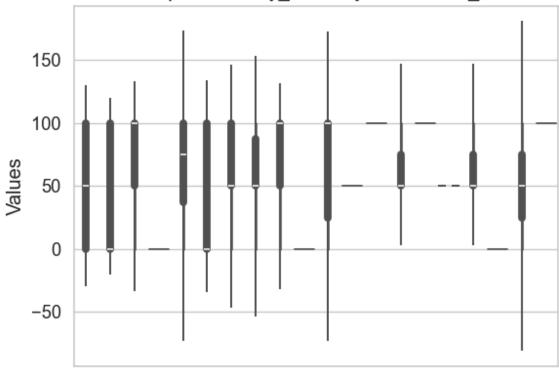
The violin plot illustrates how experience level and work year are related. The results make sense.



This violin plot illustrates how remote work ratio and salary distribution are related (the title is a typo). Remote and in person work do not have much of a difference.



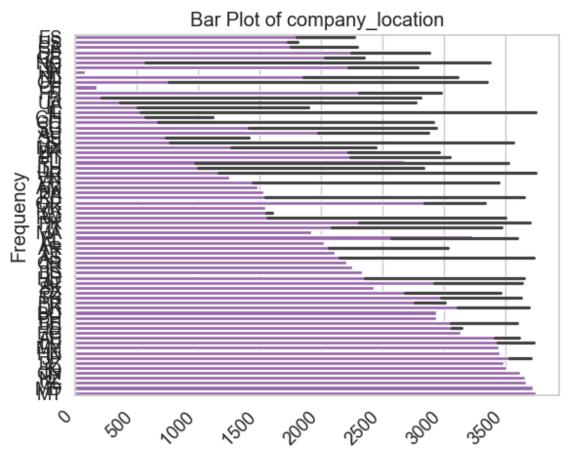




EURSIDNRIKICHGBRUBGOADLSBRITHBLINUEZIOKKIPMIXINRYCLP Columns

This violin plot is too crowded, which suggests that a different plot would represent this data better.

This bar plot is too crowded to be useful, unfortunately. Maybe rotating the axis labels would help.



Interesting patterns:

Remote work did not seem to have an effect on salary compared to full-time, but half remote saw a significant salary drop.

There were data science jobs all around the world, which was cool to see visualized.

Insights:

It's very easy for categorical column plots to become too crowded. I wonder what methods there are to solve this problem.

Questions: none

Signatures: Rahul Basak, Arnav Kaul, Aden Zhao