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Self-Care : A Case Study on Mental Health in the Tech Industry

Abstract: In this paper we look at a mental health survey conducted for the tech industry and try to analyse and find patterns that characterise participants behaviour with the workplace environment and their mental condition. We then move to identify some correlation between features such as remote working and comfort of discussing mental health issues with their company. Furthermore, we analyse comment words to identify a motive. Finally, we attempt to find whether we can predict a mental health condition based on the participants responses.

Introduction

The tech sector is built on the backs of incredibly bright minds. It's known for its innovation and creation and a culture that fosters high-productivity. It is incredibly broad which makes it attractive to a large number of people coming from different disciplines. Today, the technological improvements have a massive impact in people's behaviour to accommodate their needs for mobility, information and social interaction. Employees in the tech industry work under a very high-stress with tight deadlines while also being constantly available at any time of day. Upon the Pandemic, the tech sector has played an important role in enabling businesses and individuals to keep operating, facilitating the transition to remote working and ensuring that communication and IT platforms can cope with the demand. In recent years, there has been a drawn attention on the importance of mental health in the tech industry and indeed across society more widely. Everywhere around the world, people have mental health problems but not everyone talks about it; one might call the the silent stigma. As a fan of the human mind and a future tech employee, it is worthwhile conducting an analysis on better understanding the attitudes towards mental health in the workplace.

1.Data, Research Questions and Analytical Approach

1.1 Data Source

There are multiple sources for mental health in the workplace environment but we are going to focus in an ongoing survey by Open Source Mental Illness Ltd about mental health in the tech industry. The dataset we are using is from 2014 and includes around 1200 participants. It is focused on examining the frequency of mental health disorders among tech workers as well as the perspective towards mental health. Some questions include:

- Have you sought treatment for a mental health condition?
- Does your employer provide mental health benefits?
- Do you think that discussing a mental health issue with your employer would have negative consequences?

1.2 Research Questions

A famous hypothesis is said that, by improving the comfort level in discussing mental health issues of employees in a workplace, can contribute to improving mental health support for employees in the tech industry. A prescriptive analysis will be done to determine the factors using various questions about personal mental health status and experience with having mental health conversations in the workplace environment, and overall predict whether or not an individual sought treatment for a mental health condition. The survey also includes a question asking participants to briefly describe what the industry can do as a whole to improve mental health support for their employees. The purpose of the analysis is to see whether there are any underlying themes or patterns to the responses. Thus, we derive the below set of questions that aim to unravel in this paper.

- What are some of the qualitative insights for the tech industry to help improve mental health support for employees?
- Can we predict if an individual sought treatment for a mental health condition?
- How do individuals perceive mental health issues and how easy it is for them to express them?

By pursuing these research questions, we should be able to uncover patterns and come to conclusions that can help companies have better understanding of their employees mental health conditions.

1.3 Analytical Approach

Our first objective is to deliver insights and a visual analysis to see if we can detect some patterns about employees. On the other hand, the classification model will be used for the prediction of a treatment. Thus, the following plan will help to guide us through our work:

1. Import and data from Kaggle, provided by OSMI.
2. Clean data: combine responses, impute missing values, handle outliers
3. Visualise data: exploratory data analysis
4. Feature engineer with feature selection
5. Perform classification modeling
6. Results and concultions

2.Finding and Discussion

2.1 Findings

2.1.1 Age and treatment

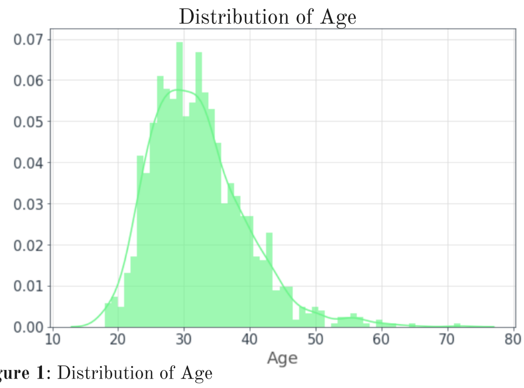

Figure 1: Distribution of Age

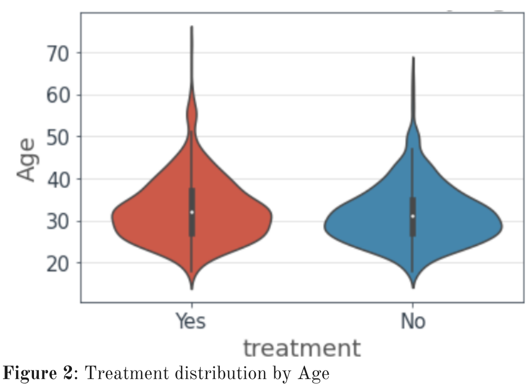

Figure 2: Treatment distribution by Age

One of the first thing we looked at is the distribution of age and the the distribution of treatment by age. while this might be higher than expected for the tech industry, it is important to understand in which age group mental health conditions are taking place. We also see that most participants are between the ages of mid-20 and 40, which is rather young comparing this to age ranges in other industries.

Additionally, the survey received many different responses for gender which we chose to group into three, male, female and other , for better visualisation of the distribution of gender. The responses add up and identify broadly as men with an 80%, which is common of the gender imbalance in the tech industry.

2.1.2 Support of Employees

Figure 3: WordCloud visualisation of employees support comments

Words with bigger fonts in the WordCloud are ones that occur more frequently. Looking at the figure 3 above, it seems like words like "depression", "time", "insurance" and "feel" are a big motive of the responses. While the finding does not directly back up any concrete, prosecutable solution that raise the state of mental health in the tech industry, it supports the need of looking deeper into factors that involve comfort level in discussing mental health in the workplace environment.

2.1.3 Comfort and Knowledge

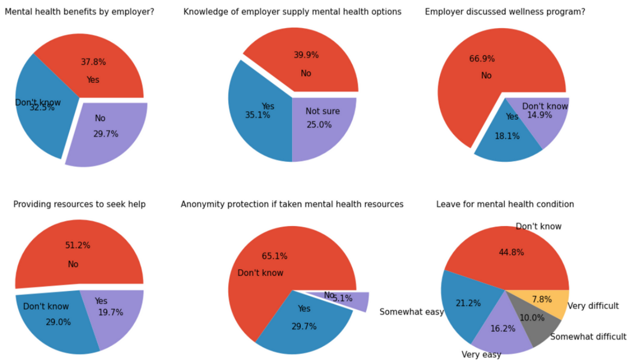

Figure 4: Showing Knowledge and comfort of discussing mental health

In figure 4 above, we visualise the knowledge of the participants in the corresponding factors. We can see that many companies are not discussing or embedding a wellness program for the employees which may result to not knowing the benefits they provide. Furthermore, the majority of the graph show that employees are not so well informed about the mental health benefits as well as if they are allowed to leave for a mental health condition which includes nearly half of our participants.

According to Dr. Darnell Motley[1] who is a researcher at the University of Chicago and specialises in the development of structural and behavioural interventions, says that "the feelings our jobs cultivate in us can have major impacts on our mental health, especially when you consider how much time we spend at work and how as a country we put so much value into our career achievements." Jobs can have massive impact on an individual mental health but hopefully with more and more companies taking this into consideration, mental health will be prioritised as few countries have done.

2.1.3 Negative Consequences, Mental vs Physical

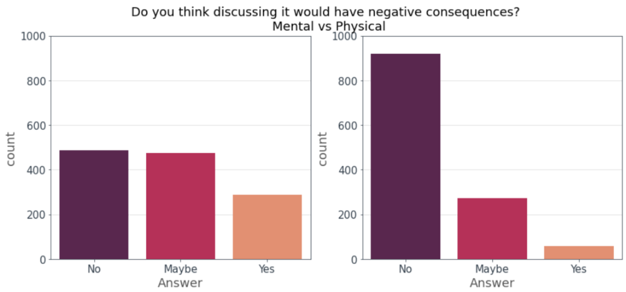

Figure 5: Discussing negative consequences, mental vs physical health

Demonstration in figure 5 show that employees are not afraid to discuss a physical health condition with their employer and they believe it will not have negative consequences. On the other hand, there is a significant difference about how they feel about mental health.

People shouldn't be afraid to talk about their mental health especially to someone there are working with everyday. In terms for the employer, it may be more efficient to apply some mental health anonymity program which will help the silent one's to talk about their mental issues. Mental health is as important as physical health and should be treated the same.

2.Modeling

2.1 Correlation

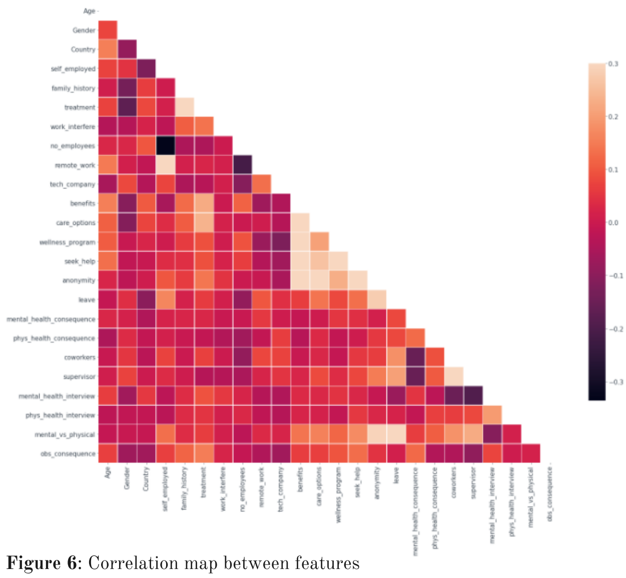

Figure 6: Correlation map between features

A correlation map was constructed to identify any multi-collinearity between the features. As seen from the graph in figure 6, there seems to be a high correlation between the wellness_program and seek_help. This might affect the our predictions on the treatment target. Further analysis is taken to identify also how features correlate with the target variable, if employees sought treatment.

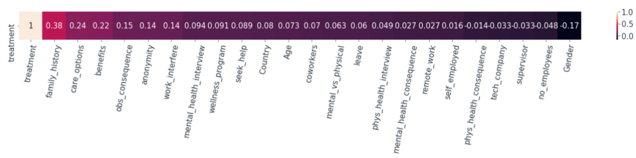

Figure 7: Correlation for treatment

In figure 7 we can see that the correlation detected in the previous figure might affect the prediction in our model but not so much as expected. We can carry by implementing our model and reflecting again after the feature importance.

2.2 Feature Importance

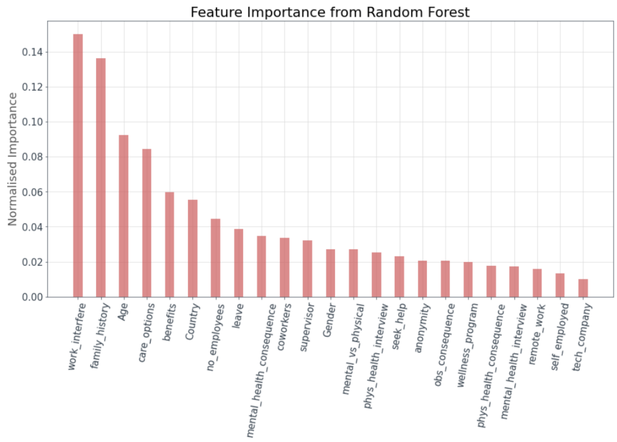

Figure 8: Feature Importance for the classification model

The graph in figure 8 is ranked by the feature importance as been constructed with the random forest classification model. The features are normalised and shown a ratio of importance of the predictor. One surprising finding is the relationship between the impact of one's observation of other mental health discussions in the workplace has and one's comfort level in remote working. Although the feature is ranked low in feature importance, people who feel less inclined to reveal a mental health issue due to their observations of similar discussions at work are 70% more likely to be comfortable with mental discussions. This may indicate a fragility to the comfort level in a sense that the workplace environment and attitude towards mental health can greatly affect their likelihood in opening up at work.

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----------Classification Report---------------------
              precision    recall  f1-score   support

         0.0       0.71      0.75      0.73       176
         1.0       0.77      0.73      0.75       200

    accuracy                           0.74       376
   macro avg       0.74      0.74      0.74       376
weighted avg       0.74      0.74      0.74       376
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Figure 9: Classification report

2.Discussion

The thorough visual analytic and modeling leads to interesting insights about the work environment in the tech industry. Considering the amount of time spent high-stressed and always on the spot someone should be careful about their mental health. Many companies can benefit from this analysis and better understand their employees.

However, when we fit this model on our inference dataset, we see that we are predicting 74% of the diagnoses correctly. Our model didn't performed so well in the accuracy sector as expected for a random forest model. Some tuning approach and further feature selection might have assisted for better precision.

Finally, the analysis concludes that there should be an improvement of the accessibility to medical leave requests due to mental illness and create a positive attitude and atmosphere in a way that mental health issues are discussed to encourage those who are more hesitant in opening up and share their thoughts and feelings.

3.References

1. Monique Wingard, 2019, Working In Tech Can Have a Big Impact On Your Mental Health. This Founder Is Building a Community To Help, AFROTECH, Available at: https://afrotech.com/working-in-tech-can-have-a-big-impact-on-your-mental-health-this-founder-is-building-a-community-to-help, [10 December 2020]