Master of Science in Data Science (DS)

# "Mental Health at Workplace"


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# Contents

## Executive Summary

Mental Health is a very important matter that is only now starting to arise in our community. With the development of new data sources and analytical methods, data science has become more and more prevalent in the healthcare industry. In terms of mental health, there is a huge unmet demand in the world. Data science can contribute to our understanding of mental health issues. We may use data science to more fully comprehend and successfully apply treatments for mental health issues.

## Abstract

In this report, we will try to understand the factors that are contributing to the mental health of a person. The dataset used in this project is from Kaggle which is extracted from a 2014 survey that measures attitudes toward mental health and the frequency of mental health disorders in the workplace. From this project, we get to understand mental health in the workplace in a systematic manner.

Topics in CRISP-DM Method (Cross Industry Standard Process)

**Iteration 1:**

The process involved during the first iteration are:

1. Business Understanding
2. Data Understanding
3. Data Preparation
4. Modeling
5. Evaluation and
6. Deployment

**Iteration 2:**

Goal Redefinition

- Data Understanding
- Modeling and Evaluation

**Iteration 3:**

Variable and Instance Selection

## Review of available research

Since the beginning of the covid pandemic, most work institutions around the world have gone to the online model which develops more work pressure and mental pressure due to work and family management.

Mental healthcare itself is a site of stigmatization as many healthcare providers hold stigmatizing notions within mental healthcare settings and have been identified as a major barrier to access treatment and recovery, as well as poorer quality physical care for persons with mental illness. Leaders should encourage fellows to share their psychological distress in safe spaces and validate their concerns. The persistent stigma around mental illness in the medical community, both interpersonal and self-stigma, often deters clinicians from seeking help.

The lack of information about the functioning and effectiveness of the mental health services focused on youth is an obstacle to assessing and, therefore, improving the services.In a healthy society, Manufacturing companies are responsible for more than just producing profitable quantities of goods and services, and their managers are aware that efficient management leads to increased production. However, this crucial goal cannot be achieved without a commitment to and belief in the mental health of the workforce. So, one of the responsibilities of every capable, savvy, and resourceful manager is to look out for the mental health of the team members.

In terms of all mental health problems, bipolar disorder is one of the major forms of depression. Regarding mental health, a survey was conducted among adults and got observations. These observations were used by the machine learning algorithm like systematic fulfillment and argued to enhance the validity of ML approach. With this advancement in the medical field and using the social network in the field to detect in the field. To make it effective it Is necessary to combine the clinical variables using database management tools such as big data. In this MongoDB is one of the tools to handle big data and extract the information and give accurate results in treating several mental disorder problems with low cost and high efficiency.

## Challenge

**How to handle mental health at the workplace**

Mental Health affects mental, psychological, and social well-being. It also affects how we think, feel and act. It also helps us in determining how we handle stress by relating it to others. The impact of mental health on an organization can mean a lot of things: an increase in absent days from work, Decrease in productivity. In the US, approximately 70 percent of adults with depression are in the workforce. Employees with depression will miss a lot of days.

## Solution

This problem can be solved using Mental Health First Aid. It helps participants to notice and support individuals who are suffering from mental health. It teaches employees communication and support skills which can help people suffering from mental health.

Research shows that employees who used first aid have increased awareness of mental health among themselves and their co-workers. It allows them to recognize the signs of someone who is struggling with mental health and teaches them the skills to when and where to reach out.

Moreover, they conduct an Employee Assistance Program that focuses on mental and physical health. These measures can help create a healthy and productive work environment that reduces the stigma associated with mental illness.

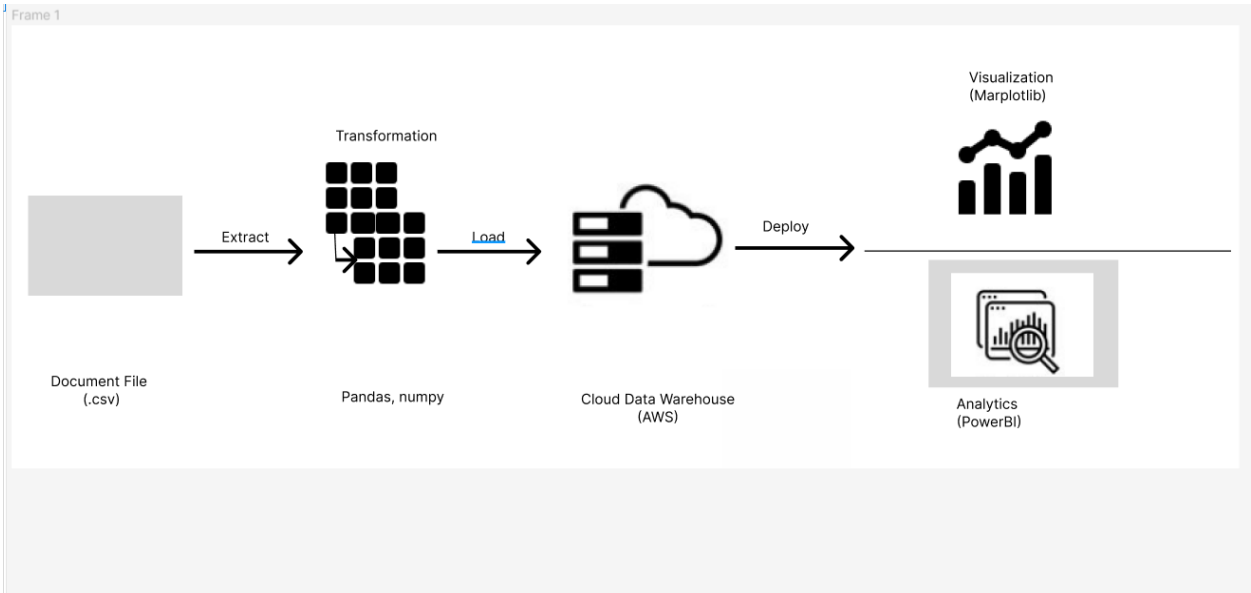
```
df['Country'].value_counts()
```

```
United States              751
United Kingdom             185
Canada                      72
Germany                     45
Ireland                     27
Netherlands                 27
Australia                   21
France                      13
India                       10
New Zealand                  8
Poland                       7
Switzerland                  7
Sweden                       7
Italy                        7
South Africa                 6
Belgium                      6
Brazil                       6
Israel                       5
Singapore                    4
Bulgaria                     4
Austria                      3
Finland                      3
Mexico                       3
Russia                       3
Denmark                      2
Greece                       2
Colombia                     2
Croatia                      2
Portugal                     2
Moldova                      1
Georgia                      1
Bahamas, The                 1
China                        1
Thailand                     1
Czech Republic               1
Norway                       1
Romania                      1
Nigeria                      1
Japan                        1
```

```
df['state'].unique()
```

```
array(['IL', 'IN', nan, 'TX', 'TN', 'MI', 'OH', 'CA', 'CT', 'MD', 'NY',
       'NC', 'MA', 'IA', 'PA', 'WA', 'WI', 'UT', 'NM', 'OR', 'FL', 'MN',
       'MO', 'AZ', 'CO', 'GA', 'DC', 'NE', 'WV', 'OK', 'KS', 'VA', 'NH',
       'KY', 'AL', 'NV', 'NJ', 'SC', 'VT', 'SD', 'ID', 'MS', 'RI', 'WY',
       'LA', 'ME'], dtype=object)
```

## Graphical View of ETL Tools :




## Data

- There are a total of 26 columns in the dataset.
- We see that except the age column, all the columns are of object datatype.
- Comment column seems to contain most number ( 70% ) of null values, which makes sense because it was an optional text box so it's reasonable to expect that many (most) respondents would leave it blank.

- We will be dropping the timestamp column because it's contains date, month, year and time the respondent took this questionnaire, which is irrelevant for us.

The state column also contains a lot of null values. We'll dig deeper into that

| | Timestamp | Age | Gender | Country | state | self_employed | family_history | treatment | work_interfere | no_employees | ... | leave | mental_health_consequence |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 2014-08-27 11:29:31 | 37 | Female | United States | IL | NaN | No | Yes | Often | 6-25 | ... | Somewhat easy | No |
| 1 | 2014-08-27 11:29:37 | 44 | M | United States | IN | NaN | No | No | Rarely | More than 1000 | ... | Don't know | Maybe |
| 2 | 2014-08-27 11:29:44 | 32 | Male | Canada | NaN | NaN | No | No | Rarely | 6-25 | ... | Somewhat difficult | No |
| 3 | 2014-08-27 11:29:46 | 31 | Male | United Kingdom | NaN | NaN | Yes | Yes | Often | 26-100 | ... | Somewhat difficult | Yes |
| 4 | 2014-08-27 11:30:22 | 31 | Male | United States | TX | NaN | No | No | Never | 100-500 | ... | Don't know | No |

| phys_health_consequence | coworkers | supervisor | mental_health_interview | phys_health_interview | mental_vs_physical | obs_consequence | comments |
|---|---|---|---|---|---|---|---|
| No | Some of them | Yes | No | Maybe | Yes | No | NaN |
| No | No | No | No | No | Don't know | No | NaN |
| No | Yes | Yes | Yes | Yes | No | No | NaN |
| Yes | Some of them | No | Maybe | Maybe | No | Yes | NaN |
| No | Some of them | Yes | Yes | Yes | Don't know | No | NaN |

In [4]:
```
# Describing the dataset.
df.head()

print("   ")

df.dtypes

print("   ")

df.isnull().sum()
```

Out[4]:

| | Timestamp | Age | Gender | Country | state | self_employed | family_history | treatment | work_interfere | no_employees | ... | leave | mental_health_consequence |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 2014-08-27 11:29:31 | 37 | Female | United States | IL | NaN | No | Yes | Often | 6-25 | ... | Somewhat easy | No |
| 1 | 2014-08-27 11:29:37 | 44 | M | United States | IN | NaN | No | No | Rarely | More than 1000 | ... | Don't know | Maybe |
| 2 | 2014-08-27 11:29:44 | 32 | Male | Canada | NaN | NaN | No | No | Rarely | 6-25 | ... | Somewhat difficult | No |
| 3 | 2014-08-27 11:29:46 | 31 | Male | United Kingdom | NaN | NaN | Yes | Yes | Often | 26-100 | ... | Somewhat difficult | Yes |
| 4 | 2014-08-27 11:30:22 | 31 | Male | United States | TX | NaN | No | No | Never | 100-500 | ... | Don't know | No |

Out[4]:

```
Timestamp                      object
Age                             int64
Gender                         object
Country                        object
state                          object
self_employed                  object
family_history                 object
treatment                      object
work_interfere                 object
no_employees                   object
remote_work                    object
tech_company                   object
benefits                       object
care_options                   object
wellness_program               object
seek_help                      object
anonymity                      object
leave                          object
mental_health_consequence      object
phys_health_consequence        object
coworkers                      object
supervisor                     object
mental_health_interview        object
phys_health_interview          object
mental_vs_physical             object
obs_consequence                object
comments                       object
dtype: object
```

Out[4]:
```
Timestamp                      0
Age                            0
Gender                         0
Country                        0
state                        515
self_employed                 18
family_history                 0
treatment                      0
work_interfere               264
no_employees                   0
remote_work                    0
tech_company                   0
benefits                       0
care_options                   0
wellness_program               0
seek_help                      0
anonymity                      0
leave                          0
mental_health_consequence      0
phys_health_consequence        0
coworkers                      0
supervisor                     0
mental_health_interview        0
phys_health_interview          0
mental_vs_physical             0
obs_consequence                0
comments                    1095
dtype: int64
```

Comments column have a lot of null values as it's an optional text box and many of them may leave it blank. Timestamp column is also not required because it contains time when the respondent took the questionnaire. State column has lot of null values.¶

It will be really misleading to conclude that one country faces more problems with mental health of employees as 60% of people are from the US.

In [6]:
```
# Let's drop Timestamp,Country,state,comments columns.
df.drop(columns=['Timestamp', 'Country', 'state', 'comments'],inplace=True)
```

# Data Preparation and Feature Engineering :

In [7]:
```
print("Different age groups used in the dataset : ")
df['Age'].unique()
print("Different gender notations used in the dataset :")
df['Gender'].unique()
```

```
Different age groups used in the dataset :
```

Out[7]:
```
array([         37,          44,          32,          31,          33,
                35,          39,          42,          23,          29,
                36,          27,          46,          41,          34,
                30,          40,          38,          50,          24,
                18,          28,          26,          22,          19,
                25,          45,          21,         -29,          43,
                56,          60,          54,         329,          55,
       99999999999,          48,          20,          57,          58,
                47,          62,          51,          65,          49,
             -1726,           5,          53,          61,           8,
                11,          -1,          72])
```

```
Different gender notations used in the dataset :
```

Out[7]:
```
array(['Female', 'M', 'Male', 'male', 'female', 'm', 'Male-ish', 'maile',
       'Trans-female', 'Cis Female', 'F', 'something kinda male?',
       'Cis Male', 'Woman', 'f', 'Mal', 'Male (CIS)', 'queer/she/they',
       'non-binary', 'Femake', 'woman', 'Make', 'Nah', 'All', 'Enby',
       'fluid', 'Genderqueer', 'Female ', 'Androgyne', 'Agender',
       'cis-female/femme', 'Guy (-ish) ^_^', 'male leaning androgynous',
       'Male ', 'Man', 'Trans woman', 'msle', 'Neuter', 'Female (trans)',
       'queer', 'Female (cis)', 'Mail', 'cis male', 'A little about you',
       'Malr', 'p', 'femail', 'Cis Man',
       'ostensibly male, unsure what that really means'], dtype=object)
```

How can age be negative? And how can the age be less than 20? Are they allowed to even work?

Regarding the gender column Males and Females have described themselves in so many different ways. This is what happens when we don't have check boxes or radio buttons while taking surveys.

In [8]:
```
df.drop(df[df['Age'] < 20].index, inplace = True)
df.drop(df[df['Age'] > 100].index, inplace = True)
df['Age'].unique()
```

Out[8]:
```
array([37, 44, 32, 31, 33, 35, 39, 42, 23, 29, 36, 27, 46, 41, 34, 30, 40,
       38, 50, 24, 28, 26, 22, 25, 45, 21, 43, 56, 60, 54, 55, 48, 20, 57,
       58, 47, 62, 51, 65, 49, 53, 61, 72])
```

In [9]:
```
df['Gender'].replace(['Male ', 'male', 'M', 'm', 'Male', 'Cis Male',
                      'Man', 'cis male', 'Mail', 'Male-ish', 'Male (CIS)',
                       'Cis Man', 'msle', 'Malr', 'Mal', 'maile', 'Make'], 'Male', inplace = True)

df['Gender'].replace(['Female ', 'female', 'F', 'f', 'Woman', 'Female',
                      'femail', 'Cis Female', 'cis-female/femme', 'Femake', 'Female (cis)',
                      'woman'], 'Female', inplace = True)

df["Gender"].replace(['Female (trans)', 'queer/she/they', 'non-binary',
                      'fluid', 'queer', 'Androgyne', 'Trans-female', 'male leaning androgynous',
                       'Agender', 'A little about you', 'Nah', 'All',
                       'ostensibly male, unsure what that really means',
                       'Genderqueer', 'Enby', 'p', 'Neuter', 'something kinda male?',
                       'Guy (-ish) ^_^', 'Trans woman'], 'Other', inplace = True)

df['Gender'].value_counts()
```

Out[9]:
```
Male      973
Female    246
Other      16
Name: Gender, dtype: int64
```

From this output we can conclude that the number of males in the tech industry are more when compared to females.

In [29]:
```
# Checking if there are any null-values.
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1235 entries, 0 to 1258
Data columns (total 23 columns):
 #   Column                     Non-Null Count  Dtype 
---  ------                     --------------  ----- 
 0   Age                        1235 non-null   int64 
 1   Gender                     1235 non-null   object
 2   self_employed              1217 non-null   object
 3   family_history             1235 non-null   object
 4   treatment                  1235 non-null   object
 5   work_interfere             978 non-null    object
 6   no_employees               1235 non-null   object
 7   remote_work                1235 non-null   object
 8   tech_company               1235 non-null   object
 9   benefits                   1235 non-null   object
 10  care_options               1235 non-null   object
 11  wellness_program           1235 non-null   object
 12  seek_help                  1235 non-null   object
 13  anonymity                  1235 non-null   object
 14  leave                      1235 non-null   object
 15  mental_health_consequence  1235 non-null   object
 16  phys_health_consequence    1235 non-null   object
 17  coworkers                  1235 non-null   object
 18  supervisor                 1235 non-null   object
 19  mental_health_interview    1235 non-null   object
 20  phys_health_interview      1235 non-null   object
 21  mental_vs_physical         1235 non-null   object
 22  obs_consequence            1235 non-null   object
dtypes: int64(1), object(22)
memory usage: 263.9+ KB
```

In [30]:
```
# Replacing the null-values.
df['work_interfere'] = df['work_interfere'].fillna('Don\'t know' )
print(df['work_interfere'].unique())
```

```
['Often' 'Rarely' 'Never' 'Sometimes' "Don't know"]
```

In [31]:
```
df['self_employed'] = df['self_employed'].fillna('No')
print(df['self_employed'].unique())
```

```
['No' 'Yes']
```

In [32]:
```
df.isnull().sum()
```

Out[32]:
```
Age                          0
Gender                       0
self_employed                0
family_history               0
treatment                    0
work_interfere               0
no_employees                 0
remote_work                  0
tech_company                 0
benefits                     0
care_options                 0
wellness_program             0
seek_help                    0
anonymity                    0
leave                        0
mental_health_consequence    0
phys_health_consequence      0
coworkers                    0
supervisor                   0
mental_health_interview      0
phys_health_interview        0
mental_vs_physical           0
obs_consequence              0
dtype: int64
```

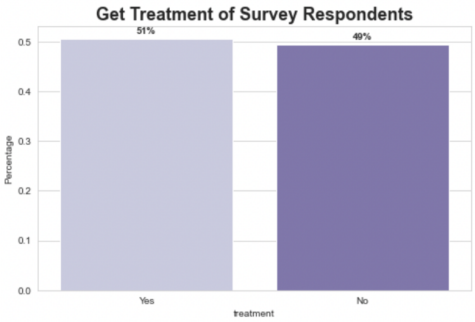
Since most of the columns except Age column are of object type we perform one-hot encoding.

In [34]:
```
# Since most of the columns except Age column are of object type we perform one-hot encoding.
from sklearn.preprocessing import LabelEncoder
object_cols = ['Gender', 'self_employed', 'family_history', 'treatment',
       'work_interfere', 'no_employees', 'remote_work', 'tech_company',
       'benefits', 'care_options', 'wellness_program', 'seek_help',
       'anonymity', 'leave', 'mental_health_consequence',
       'phys_health_consequence', 'coworkers', 'supervisor',
       'mental_health_interview', 'phys_health_interview',
       'mental_vs_physical', 'obs_consequence']
label_encoder = LabelEncoder()
for col in object_cols:
    label_encoder.fit(df[col])
    df[col] = label_encoder.transform(df[col])
```

# Exploratory Data Analysis :

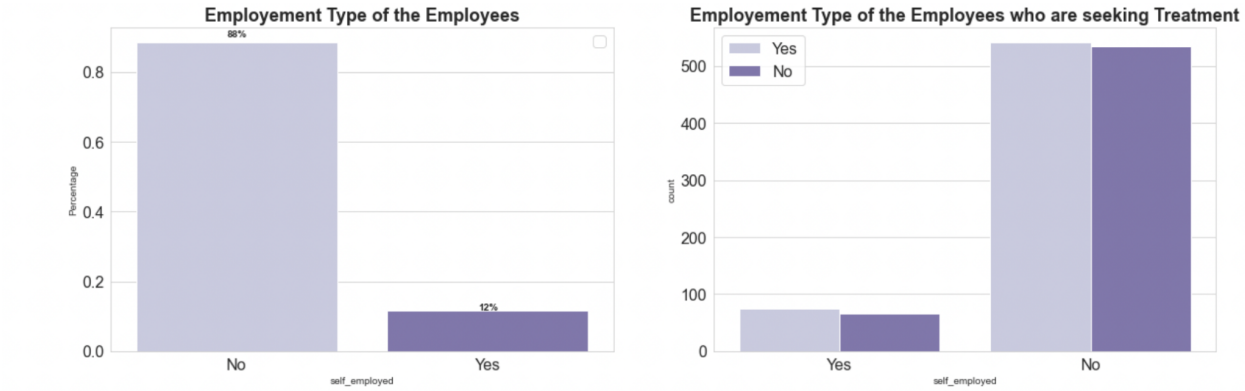
```
In [10]: sns.set_style("whitegrid")
plt.figure(figsize = (8,5))
plt.title('Get Treatment of Survey Respondents', fontsize=18, fontweight='bold')
eda_percentage = df['treatment'].value_counts(normalize = True).rename_axis('treatment').reset_index(name = 'Percentage

ax = sns.barplot(x = 'treatment', y = 'Percentage', data = eda_percentage.head(10), palette='Purples')
for p in ax.patches:
    width = p.get_width()
    height = p.get_height()
    x, y = p.get_xy()
    ax.annotate(f'{height:.0%}', (x + width/2, y + height*1.02), ha='center', fontweight='bold')
```

```
Out[10]: <Figure size 576x360 with 0 Axes>

Out[10]: Text(0.5, 1.0, 'Get Treatment of Survey Respondents')

Out[10]: Text(0.0, 0.5161943319838057, '51%')

Out[10]: Text(1.0, 0.5038056680161943, '49%')
```



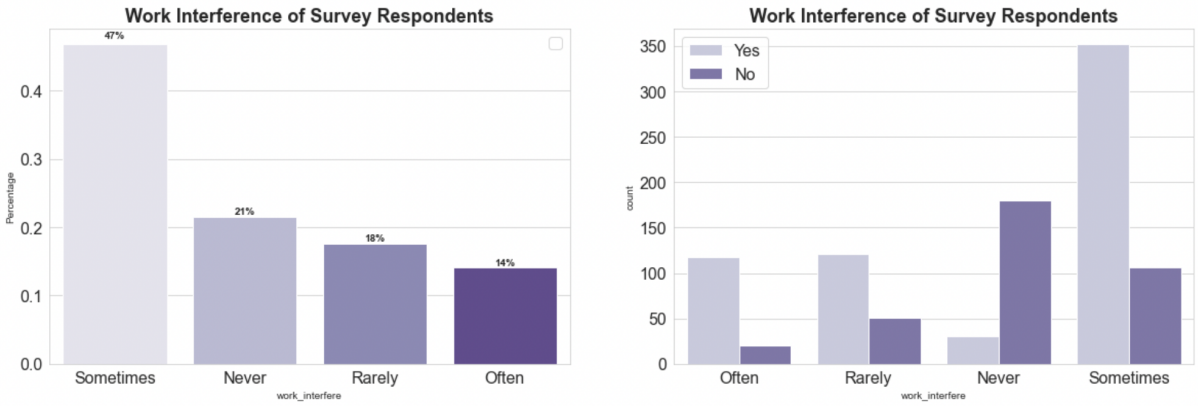

From this graph we can infer the percentage of respondents who want to get treatment is 50%. If employees have good mental health they can : Be more productive, Take active participation in employee engagement activities etc.

```
In [11]: plt.figure(figsize = (20,6))
plt.subplot(1,2,1)
eda_percentage = df['self_employed'].value_counts(normalize = True).rename_axis('self_employed').reset_index(name = 'Pe
ax = sns.barplot(x = 'self_employed', y = 'Percentage', data = eda_percentage, palette = 'Purples')
for p in ax.patches:
    width = p.get_width()
    height = p.get_height()
    x, y = p.get_xy()
    ax.annotate(f'{height:.0%}', (x + width/2, y + height*1.02), ha='center', fontweight='bold')

plt.title('Employement Type of the Employees', fontsize=18, fontweight='bold')
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.legend(fontsize=16)

plt.subplot(1,2,2)
sns.countplot(df['self_employed'], hue = df['treatment'], palette = 'Purples')
plt.title('Employement Type of the Employees who are seeking Treatment',  fontsize=18, fontweight='bold')
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.legend(fontsize=16)

plt.show()
```




Most of the working class employees responded to the survey when compared to working class. But we can observe from the second graph that both classes have the same percentage of people who are seeking treatment.

```
In [13]: plt.figure(figsize = (20,6))
         plt.subplot(1,2,1)
         eda_percentage = df['work_interfere'].value_counts(normalize = True).rename_axis('work_interfere').reset_index(name = '
         ax = sns.barplot(x = 'work_interfere', y = 'Percentage', data = eda_percentage, palette='Purples')
         for p in ax.patches:
             width = p.get_width()
             height = p.get_height()
             x, y = p.get_xy()
             ax.annotate(f'{height:.0%}', (x + width/2, y + height*1.02), ha='center', fontweight='bold')

         plt.title('Work Interference of Survey Respondents', fontsize=18, fontweight='bold')
         plt.xticks(fontsize=16)
         plt.yticks(fontsize=16)
         plt.legend(fontsize=16)

         plt.subplot(1,2,2)
         sns.countplot(df['work_interfere'], hue = df['treatment'], palette = 'Purples')
         plt.title('Work Interference of Survey Respondents', fontsize=18, fontweight='bold')
         plt.xticks(fontsize=16)
         plt.yticks(fontsize=16)
         plt.legend(fontsize=16)
```




Around 70 percent of employees don't work remotely hence most of the mental health issues occur at the workplace. Number of employees seeking treatment in both the categories are more or equal.

# Creating and Evaluating the Models :

In [39]:
```
# Splitting the dataset into train and test datasets.
from sklearn.model_selection import train_test_split
X = df.drop('treatment', axis = 1)
y = df['treatment']

X_train, X_test, y_train, y_test = train_test_split(X,y,
                                                    stratify = y,
                                                     test_size = 0.3,
                                                    random_state = 101)
```

In [40]:
```
%%time
LR = LogisticRegression(solver='lbfgs', max_iter=10000, random_state=555)
RF = RandomForestClassifier(n_estimators = 100, random_state=555)
SVM = SVC(random_state=0, probability=True)
KNC = KNeighborsClassifier()
DTC = DecisionTreeClassifier()
ABC = AdaBoostClassifier(n_estimators = 100)
BC = BaggingClassifier(n_estimators = 100)
GBC = GradientBoostingClassifier(n_estimators = 100)
clf_XGB = XGBClassifier(n_estimators = 100, seed=555,eval_metric='logloss')
clfs = []
print('5-fold cross validation:\n')
for clf, label in zip([LR, RF, KNC, DTC, ABC, BC, GBC, clf_XGB],
                      ['Logistic Regression',
                       'Random Forest',
                       'KNeighbors',
                       'Decision Tree',
                       'Ada Boost',
                       'Bagging',
                       'Gradient Boosting',
                       'XGBoost']):
    scores = sklearn.model_selection.cross_val_score(clf, X_train, y_train, cv=5, scoring="accuracy")
    print("Train CV Accuracy: %0.3f (+/- %0.3f) [%s]" % (scores.mean(), scores.std(), label))
    md = clf.fit(X_train, y_train)
    clfs.append(md)
    print("Test Accuracy: %0.4f " % (sklearn.metrics.accuracy_score(clf.predict(X_test), y_test)))
```

```
5-fold cross validation:

Train CV Accuracy: 0.788 (+/- 0.062) [Logistic Regression]
Test Accuracy: 0.8194
Train CV Accuracy: 0.811 (+/- 0.044) [Random Forest]
Test Accuracy: 0.8275
Train CV Accuracy: 0.753 (+/- 0.034) [KNeighbors]
Test Accuracy: 0.7682
Train CV Accuracy: 0.749 (+/- 0.025) [Decision Tree]
Test Accuracy: 0.7493
Train CV Accuracy: 0.800 (+/- 0.039) [Ada Boost]
Test Accuracy: 0.8248
Train CV Accuracy: 0.803 (+/- 0.036) [Bagging]
Test Accuracy: 0.8167
Train CV Accuracy: 0.800 (+/- 0.034) [Gradient Boosting]
Test Accuracy: 0.8194
Train CV Accuracy: 0.792 (+/- 0.035) [XGBoost]
Test Accuracy: 0.7844
CPU times: user 8.74 s, sys: 1.25 s, total: 9.99 s
Wall time: 3.32 s
```

## Tools that we used to solve this problem :

JUPYTER : We use jupyter to load our dataset , train and test the data using machine learning algorithms to predict the accuracy.

Numpy, Scikit-Learn, Pandas, Matplotlib,

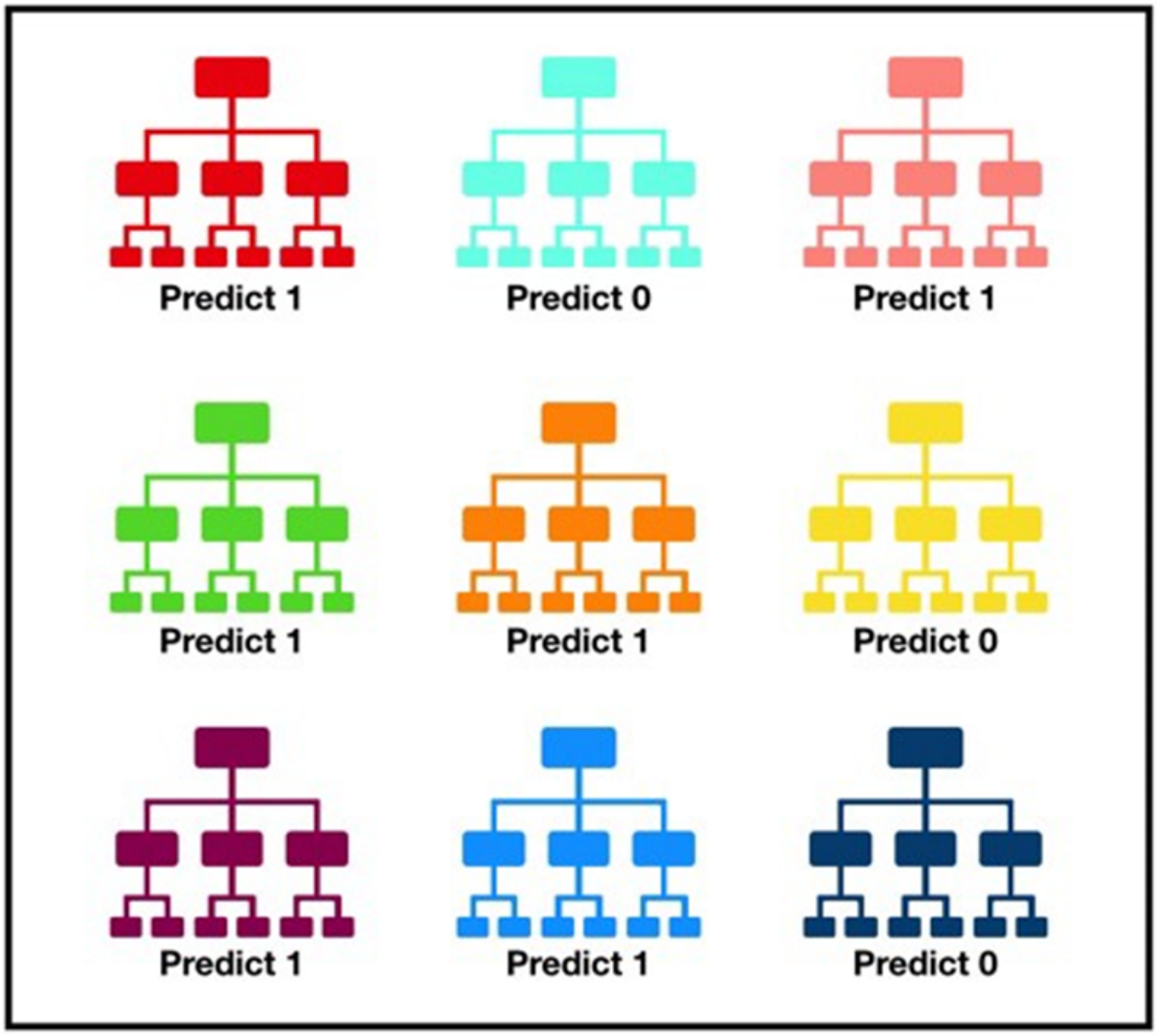
AWS : We use AWS for hosting the web application into a flask server.


## Models that have been used to solve this problem :

We have used Random Forest Classifier,Gradient Boost and AdaBoost Classifier as they give higher accuracy than other models since they are combinations of different models.

### The Random Forest Classifier

Like its name suggests, a random forest is made up of numerous independent decision trees that work together as an ensemble. Every every tree in the random forest spits out a class forecast, and the classification that receives the most votes becomes the prediction made by our model (see figure below).




Tally: Six 1s and Three 0s

**Prediction: 1**

The key is the low correlation between models. Uncorrelated models have the ability to provide ensemble forecasts that are more accurate than any of the individual predictions, just like assets with low correlations (like stocks and bonds) combine to form a portfolio that is greater than the sum of its parts. As long as they don't consistently all err in the same direction, the trees shield each other from their individual errors, which accounts for this lovely result. Many trees will be right while some may be wrong, allowing the group of trees to move in the proper direction. The following conditions must be met for random forest to function effectively

## Gradient Boost

Three factors are involved in gradient boosting

A loss function that must be improved.

A poor predictor of the future.

A model that adds weak learners in order to reduce the loss function

1. Function Loss

The type of problem being solved determines the loss function to be employed. Although several common loss functions are available and you can create your own, it must be differentiable.For instance, classification and regression both sometimes employ logarithmic loss and squared error, respectively.The gradient boosting framework has the advantage that any differentiable loss function can be utilized, hence no new boosting algorithm needs to be developed for each loss function that could be desired to be employed.

2. A slow learner

In gradient boosting, decision trees are utilized as the weak learner.

Regression trees that produce real values for splits and whose output may be added allow for the "correction" of residuals in forecasts by adding the outputs of succeeding models.In building trees, greed is used to select the optimum split points based on purity scores like Gini or to reduce loss.At first, decision stumps—very short decision trees with just one split—were employed, as in the case of AdaBoost. Larger trees can typically be employed with four to eight levels.It is standard practice to impose restrictions on the weaker learners, such as a cap on the number of layers, nodes, splits, or leaf nodes.

3.Additive Model

One tree is added at a time, and the model's already-existing trees are left alone.When adding trees, a gradient descent approach is utilized to reduce loss.

Gradient descent is typically used to reduce a set of parameters, such as the weights in a neural network or the coefficients in a regression equation. The weights are changed to reduce inaccuracy after calculating loss or error.

Weak learner sub-models, or more particularly decision trees, are used in place of parameters. We must incorporate a tree into the model to lower the loss before we can begin the gradient descent technique (i.e. follow the gradient). To achieve this, we parameterize the tree, change its parameters, and then move the tree.

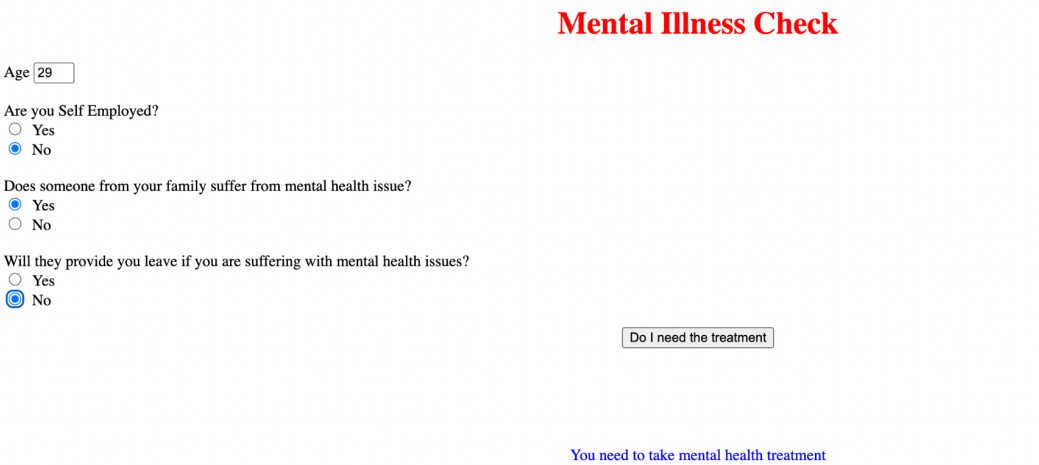
## Ada Boost

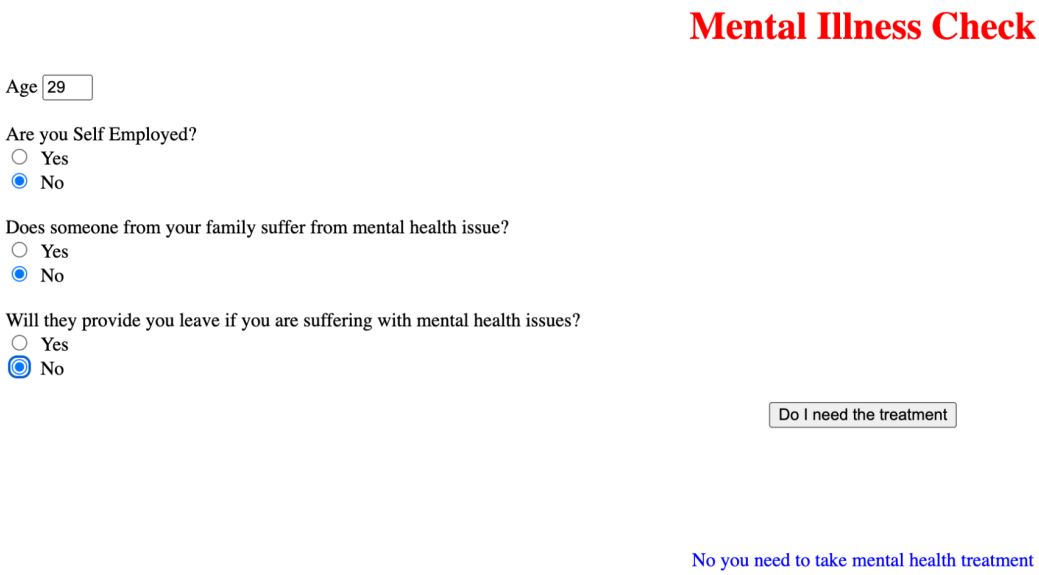
A highly well-liked boosting technique called AdaBoost (Adaptive Boosting) seeks to combine several weak classifiers into one powerful classifier. Yoav Freund and Robert Schapire wrote the first AdaBoost paper.

A single classifier might not be able to predict an object's class with sufficient accuracy, but by grouping several weak classifiers and having each one gradually learn from the incorrectly classified items of the others, we can create one such strong model. The classifier given here could be any of your standard classifiers, including Logistic Regression, Decision Trees (which are frequently the default), and others.

# Results Section

By using flask we created an application which predicts whether an employee needs to take treatment or not

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