

# PROJECT-1

## EXPLORATORY ANALYSIS

### **DATASET: CITIES WITH BEST WORK-LIFE BALANCE**

Cities with best work-life balance in 2022 Dataset :  
Cities with the Best Work-Life Balance 2022, This dataset consists of 24 attributes each of them contributing for the study of Work-life fit in various cities. The dataset consists of columns: 24 , rows : 100 , out of which 13 are of datatype float64, 2 are of int64 datatype and 9 are of object type data. 24 different columns are namely : 2022, Minimum Vacations Offered (Days), Unemployment, Covid Impact, Covid Support, Healthcare, Access to Mental Healthcare, Inclusivity & Tolerance, Affordability, Happiness-Culture & Leisure, City Safety, Outdoor Spaces, Air Quality, Wellness and Fitness, TOTAL SCORE, Paid Parental Leave (Days), Inflation, Multiple

Jobholders, Vacations Taken (Days), Overworked Population, 2021, City, Remote Jobs, Country etc...  
Cities with the Best Work-Life Balance 2022  
1. Three aspects of work-life balance  
2. Work Intensity  
3. Society and Institutions  
4. City Liveability.

Work-life balance entails to a balanced state, where one adequately balances work or professional demands and those of their personal life. An individual who lacks a work-life balance has more obligations with respect to work and home, works longer hours, and experiences shortfall in personal time. Some utilize work-life balance as an opportunity to work no more than 8 hours a day and still have time to hit the gym, run some other works, and spend time with family and friends. Here we get to see which cities best aid work-life balance.

Not maintaining proper work-life blend can lead to mental health issues such as depression, anxiety,

and insomnia, as well as physical health issues including chronic aches and pains, heart troubles, and hypertension. Burnout happens when an employee suffers too much stress over a long period of time.

## Data preparation :

Replacing the irrelevant data in the dataset.

```
In [7]: df['Covid Support']=df['Covid Support'].replace('-', '0')
In [8]: df['Remote Jobs']=df['Remote Jobs'].replace('%', '', regex=True).astype(float)
In [9]: df['Overworked Population']=df['Overworked Population'].replace('%', '', regex=True).astype(float)
In [10]: df['Minimum Vacations Offered (Days)']=df['Minimum Vacations Offered (Days)'].replace('%', '', regex=True).astype(float)
In [11]: df['Vacations Taken (Days)']=df['Vacations Taken (Days)'].replace('-', '0')
df['Vacations Taken (Days)']=df['Vacations Taken (Days)'].replace('%', '', regex=True).astype(float)
In [12]: df['Inflation']=df['Inflation'].replace('%', '', regex=True).astype(float)
In [13]: df['Multiple Jobholders']=df['Multiple Jobholders'].replace('%', '', regex=True).astype(float)
```

Removing the null values from the dataset

```
In [55]: df1 = df.mask(df == '0.0', np.nan)
In [17]: df1 = df.dropna()
```

However the prevalent null values and the irrelevant data is hardly about 2-5% of the dataset as a whole which does not effect the further analysis.

## Getting the information of the attributes and their statistical report respectively

```
In [52]: df1.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 24 columns):
 #   Column                                          Non-Null Count  Dtype  
---  --
 0   2022                                           100 non-null    int64   
 1   2021                                           100 non-null    object  
 2   City                                           100 non-null    object  
 3   Country                                       100 non-null    object  
 4   Remote Jobs                                   100 non-null    float64  
 5   Overworked Population                         100 non-null    float64  
 6   Minimum Vacations Offered (Days)             100 non-null    float64  
 7   Vacations Taken (Days)                       100 non-null    float64  
 8   Unemployment                                 100 non-null    float64  
 9   Multiple Jobholders                           100 non-null    float64  
10  Inflation                                     100 non-null    float64  
11  Paid Parental Leave (Days)                   100 non-null    object  
12  Covid Impact                                 100 non-null    float64  
13  Covid Support                                 100 non-null    float64  
14  Healthcare                                    100 non-null    float64  
15  Access to Mental Healthcare                   100 non-null    float64  
16  Inclusivity & Tolerance                       100 non-null    float64  
17  Affordability                                100 non-null    float64  
18  Happiness, Culture & Leisure                  100 non-null    float64  
19  City Safety                                   100 non-null    float64  
20  Outdoor Spaces                               100 non-null    float64  
21  Air Quality                                  100 non-null    float64  
22  Wellness and Fitness                         100 non-null    float64  
23  TOTAL SCORE                                  100 non-null    float64  
dtypes: float64(19), int64(1), object(4)
memory usage: 18.9+ KB
```

```
In [15]: df.describe()

Out[15]:
```

	2022	Remote Jobs	Overworked Population	Minimum Vacations Offered (Days)	Vacations Taken (Days)	Unemployment	Multiple Jobholders	Inflation	Covid Impact	Covid Support	Healthcare	Access to Mental Healthcare	In T
count	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	
mean	50.500000	37.841600	12.645000	14.410000	14.647000	93.292000	5.016000	8.548400	77.875000	84.953000	88.753000	72.143000	
std	29.011492	5.083966	1.866146	6.313518	8.044641	5.888556	1.758944	10.310558	6.959949	6.918230	8.483537	8.688286	
min	1.000000	16.840000	8.600000	6.000000	0.000000	50.000000	1.100000	0.890000	50.000000	50.000000	50.000000	50.000000	
25%	25.750000	36.237500	11.875000	10.000000	8.700000	92.675000	3.800000	6.260000	74.150000	81.100000	86.000000	66.600000	
50%	50.500000	37.775000	12.500000	10.000000	9.400000	94.850000	4.800000	7.735000	78.350000	84.900000	89.000000	67.500000	
75%	75.250000	41.180000	13.200000	20.000000	24.025000	95.950000	6.000000	9.050000	82.350000	89.450000	94.800000	78.600000	
max	100.000000	52.060000	23.400000	30.000000	30.000000	100.000000	10.000000	107.410000	100.000000	100.000000	100.000000	100.000000	

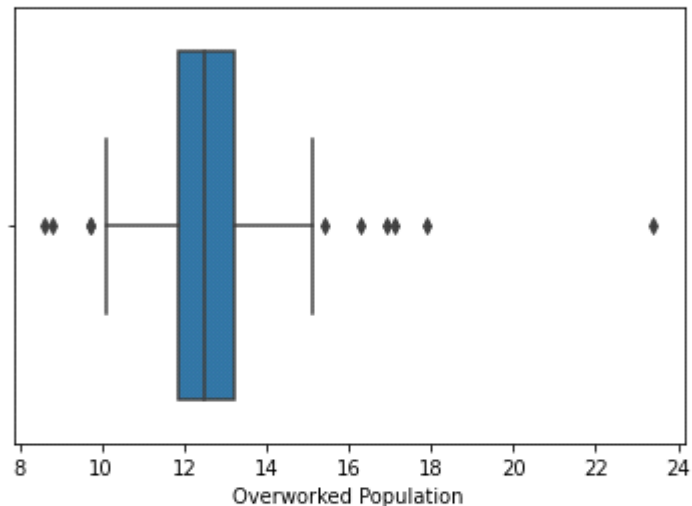
## Doing the outlier analysis

Outlier analysis is performed by plotting a boxplot. In spite of having the outliers it does not make significant changes to the analysis. As the attributes in the dataset we chose have varied behaviour i.e. they are not set to behave a certain

way , removing the outliers is not considered in this case.

```
In [45]: #plotting a boxplot for outliers  
sns.boxplot(df['Overworked Population'])
```

```
Out[45]: <AxesSubplot:xlabel='Overworked Population'>
```



```
In [46]: #identifying the outliers  
np.where(df['Overworked Population']<10)
```

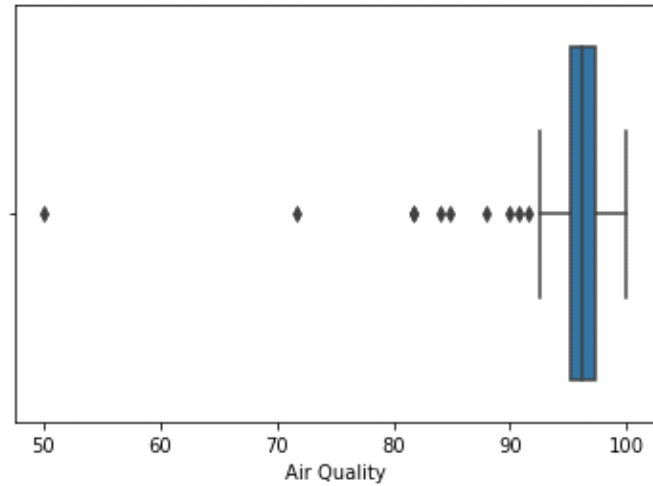
```
Out[46]: (array([ 7, 11, 12, 94], dtype=int64),)
```

```
In [47]: #identifying the outliers  
np.where(df['Overworked Population']>15)
```

```
Out[47]: (array([13, 44, 92, 93, 95, 97, 98], dtype=int64),)
```

```
In [36]: #plotting a boxplot for outliers  
sns.boxplot(df['Air Quality'])
```

```
Out[36]: <AxesSubplot:xlabel='Air Quality'>
```

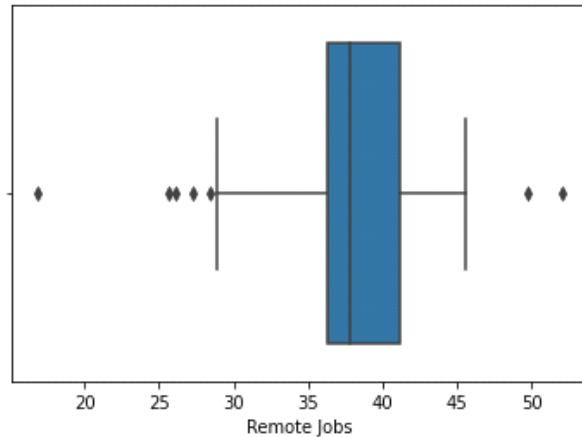


```
In [37]: #identifying the outliers  
np.where(df['Air Quality']<91)
```

```
Out[37]: (array([13, 44, 87, 90, 92, 95, 96, 97, 98], dtype=int64),)
```

```
In [42]: #plotting a boxplot for outliers  
sns.boxplot(df['Remote Jobs'])
```

```
Out[42]: <AxesSubplot:xlabel='Remote Jobs'>
```



```
In [43]: np.where(df['Remote Jobs']<28)  
  
#identifying the outliers
```

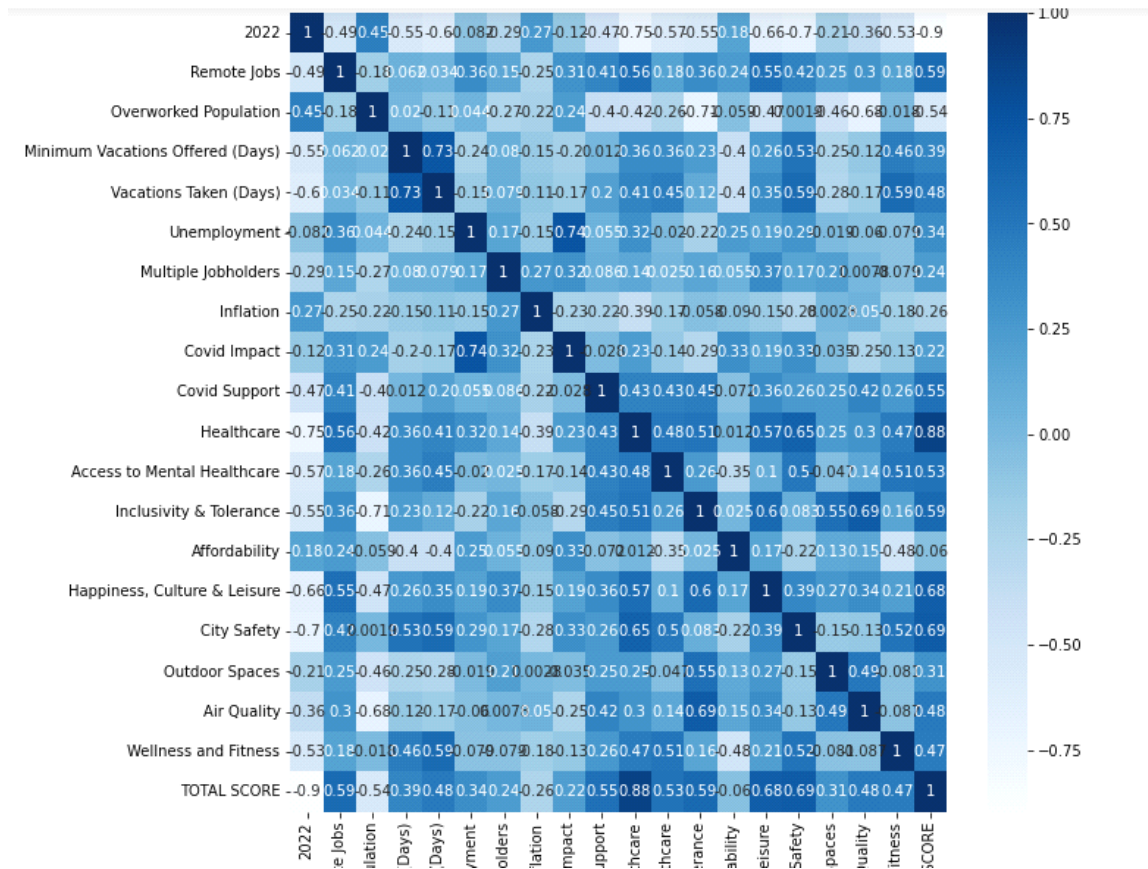
```
Out[43]: (array([93, 95, 96, 99], dtype=int64),)
```

```
In [44]: #identifying the outliers  
np.where(df['Remote Jobs']>45)
```

```
Out[44]: (array([40, 44, 61], dtype=int64),)
```

## Exploratory analysis

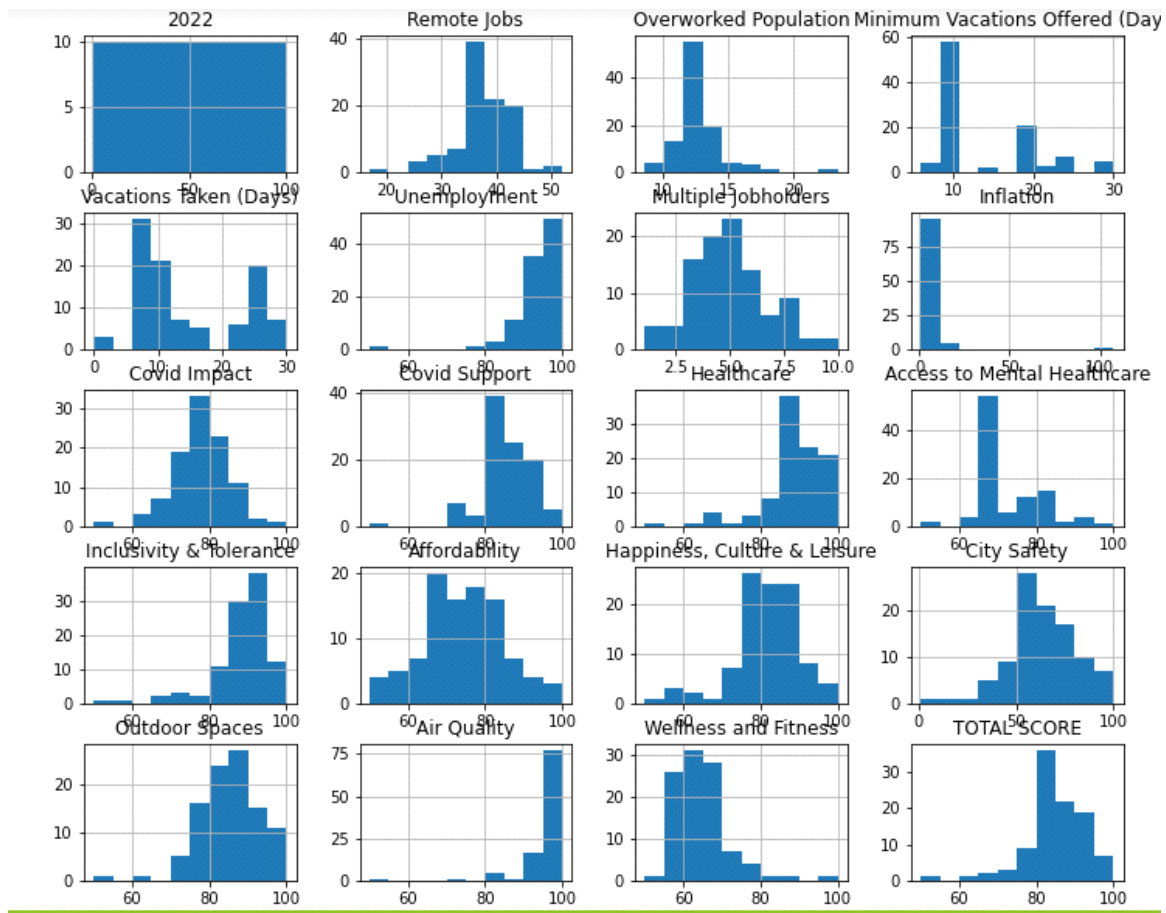
\*Plotting a heatmap showing the correlation between the attributes .



We see high correlation between Healthcare and TotalSCORE, and Unemployment with Covid Impact

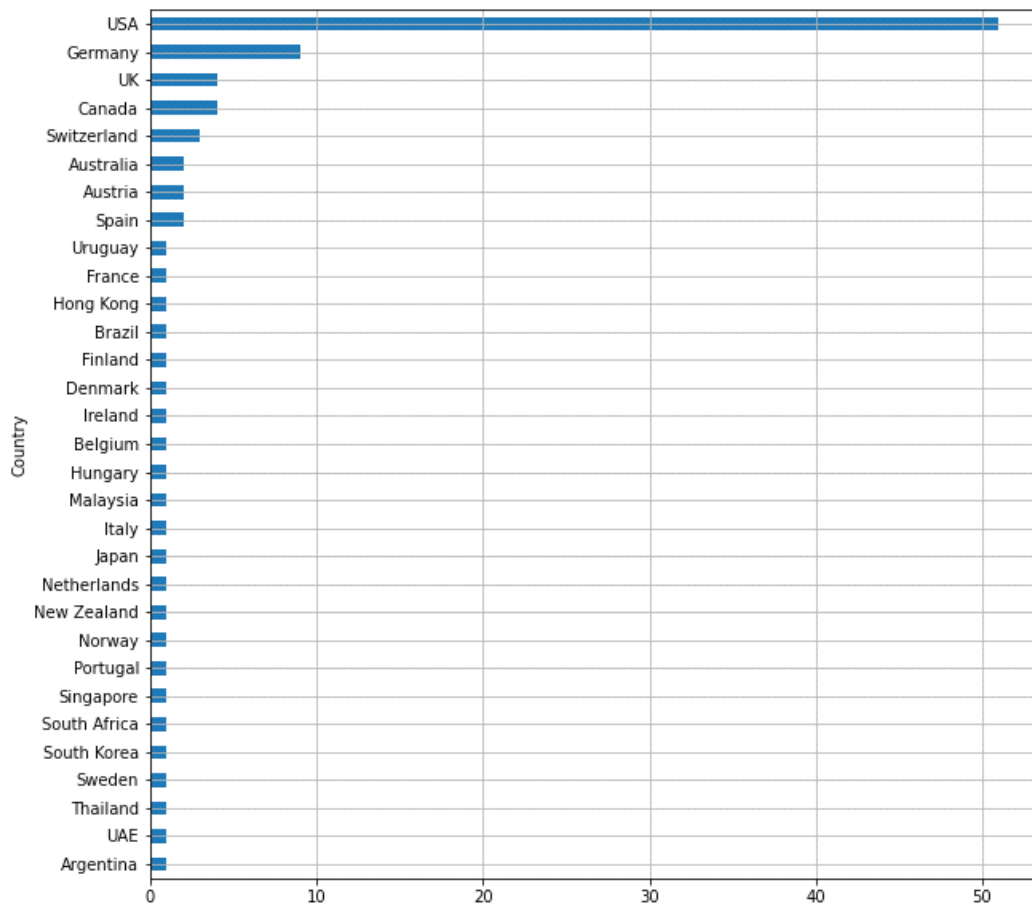
\*Plotting and visualizing the data in the form of a histogram.



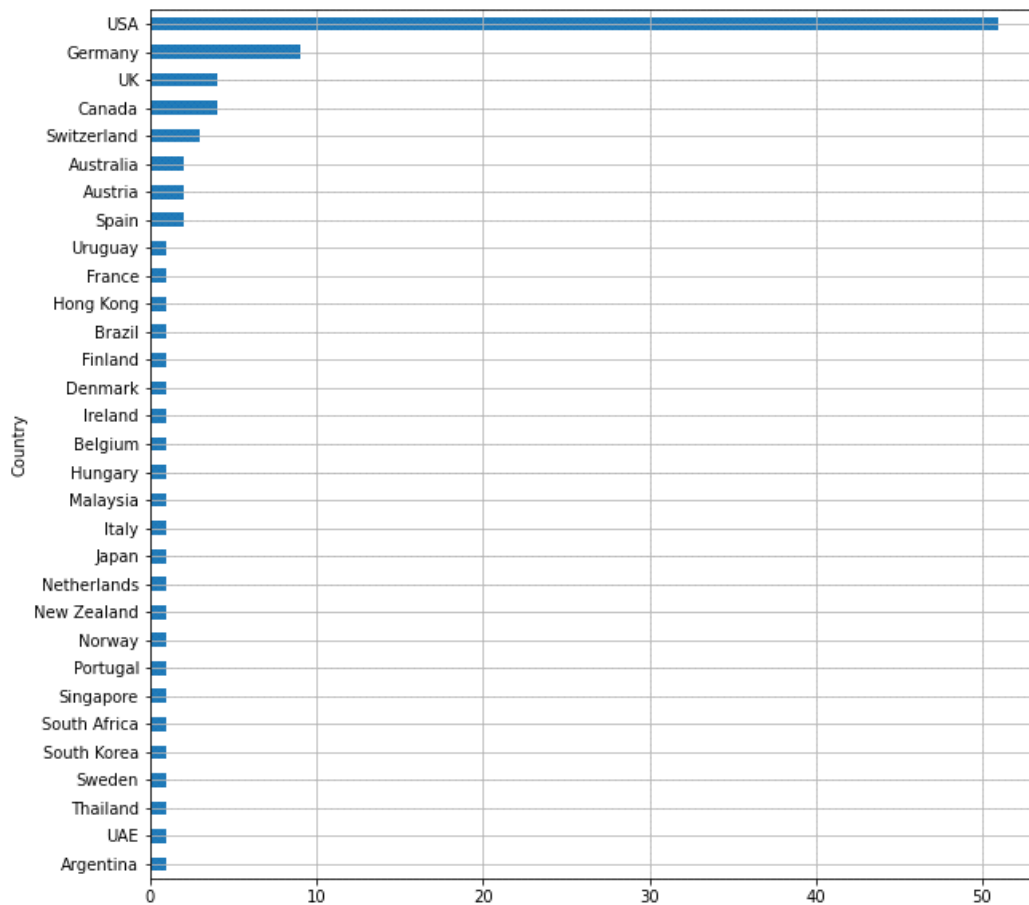


By performing analysis between various attributes the following inferences are made.

\* Most number of cities for the survey are considered from the U.S , Germany , and Canada respectively according to the graph below.

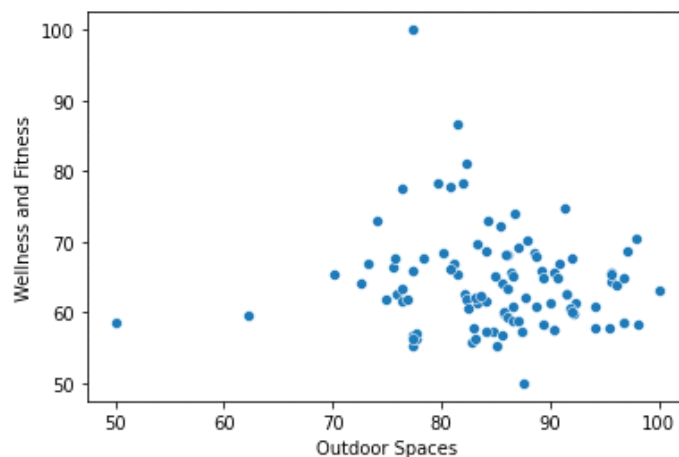


\*It is also seen that U.S has most of the remote jobs then Germany UK,Canada and so on.



\*Wellness and fitness of people are not highly affected by the availability of outdoor spaces.

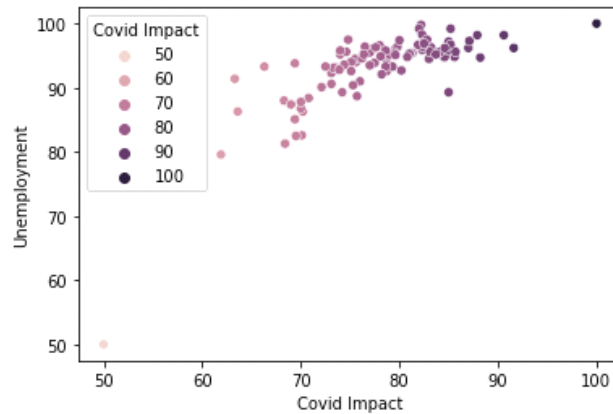
Out[13]: <AxesSubplot:xlabel='Outdoor Spaces', ylabel='Wellness and Fitness'>



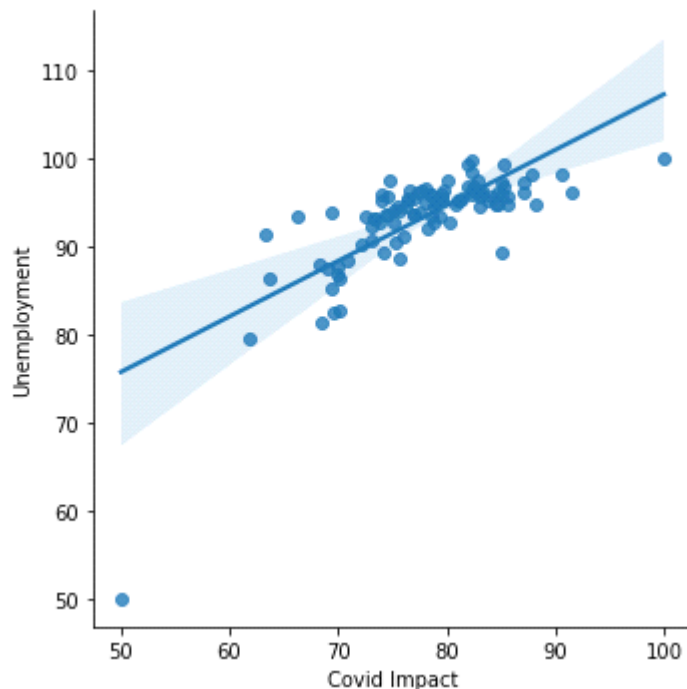
\*It is evident that covid impact has great influence on

unemployment,there is a direct impact of covid on employment .

```
Out[5]: <AxesSubplot:xlabel='Covid Impact', ylabel='Unemployment'>
```

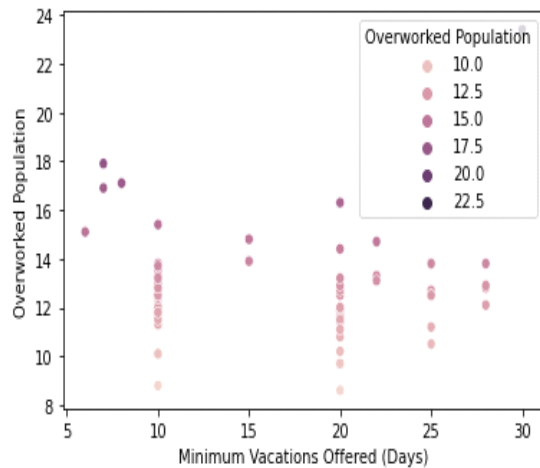


```
Out[50]: <seaborn.axisgrid.FacetGrid at 0x1e3e8325d90>
```



\*Minimum Vacations Offered (Days) are hardly more than 20 days for the population who are considered overworked.

```
Out[48]: <AxesSubplot:xlabel='Minimum Vacations Offered (Days)', ylabel='Overworked Population'>
```



\*As the percentage of Overworked population increases the count in the Happiness, Culture & Leisure subsequently decrease.

```
Out[51]: <AxesSubplot:xlabel='Overworked Population', ylabel='Happiness, Culture & Leisure'>
```

