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1 Hypothysis testing Algerian Forest Fire Dataset

[5]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pylab as plt
%matplotlib inline
```

[ ]:
```
data = pd.read_csv(r"../Algerian_forest_fires_dataset_UPDATE.csv",header=1)
data
```

[ ]:
```
data[data.isna().any(axis=1)]
data.iloc[121:125,:]
data.drop([122,123],inplace=True)
data.reset_index(inplace=True)
data.drop(['index',"day","month","year"],axis=1,inplace=True)
data["region"] = None
data.iloc[:122,-1] = "Bejaia"
data.iloc[122:,-1] = "Abbes"
data
```

2 Data cleaning operations

[ ]:
```
data.info()
```

Getting unique values from y data column:
* Getting unique values from a column involves identifying and selecting only the distinct or unique values in that column.

[ ]:
```
data["Classes  "].unique()
```

Apply `str.strip()` to clean the data:
* As we can see y data has some blank spaces so we need to remove then before use.
* I have used the `.strip()` method in Python to remove the leading and trailing spaces from the data in a column.

[10]:
```
data["Classes  "] = data["Classes  "].str.strip()
```

[12]:
```
data["Classes  "].unique()
```

[12]:
```
array(['not fire', 'fire'], dtype=object)
```

Convert data type of all data column:
* In below code I am selecting all data which are intiger and making the column data type as float64

[ ]:
```
columns = data.columns[:-2]
for i in columns:
    data[i] = data[i].astype("float64")
data.info()
```

3 Hypothysis testing

What is a Mann-Whitney U test?

- The Mann-Whitney U test, also known as the Wilcoxon rank-sum test, is a non-parametric statistical test used to compare two independent groups of data that are not normally distributed. It is a useful alternative to the t-test, which assumes that the data is normally distributed.

[14]:
```
from scipy.stats import ttest_ind
ttest_ind(data[data["Classes  "] == "fire"]["Temperature"],data[data["Classes ␣
↪"] != "fire"]["Temperature"])
```

[14]:
```
Ttest_indResult(statistic=9.423536449577796, pvalue=3.665914717669193e-18)
```

- there is a significant difference in distributions for `Temperature` when fire and not fire

[15]:
```
from scipy.stats import mannwhitneyu
mannwhitneyu(data[data["Classes  "] == "fire"][" RH"],data[data["Classes  "] !=␣
↪"fire"][" RH"])
```

[15]:
```
MannwhitneyuResult(statistic=3700.5, pvalue=3.7651087930605746e-11)
```

- there is a significant difference in distributions for `RH` when fire and not fire

[16]:
```
mannwhitneyu(data[data["Classes  "] == "fire"][" Ws"],data[data["Classes  "] !=␣
↪"fire"][" Ws"])
```

[16]:
```
MannwhitneyuResult(statistic=7148.0, pvalue=0.7601300563655673)
```

- there is no significant difference in distributions for `Ws` when fire and not fire

[17]:
```
mannwhitneyu(data[data["Classes  "] == "fire"]["Rain "],data[data["Classes  "] !
↪= "fire"]["Rain "])
```

[17]:
```
MannwhitneyuResult(statistic=2013.0, pvalue=3.0087110412485163e-26)
```

- there is a significant difference in distributions for `Rain` when fire and not fire

[18]:
```
mannwhitneyu(data[data["Classes  "] == "fire"]["FFMC"],data[data["Classes  "] !
↪= "fire"]["FFMC"])
```

[18]: MannwhitneyuResult(statistic=14604.0, pvalue=1.3687976313621596e-40)

- there is a significant difference in distributions for `FFMC` when fire and not fire

[19]:
```
mannwhitneyu(data[data["Classes  "] == "fire"]["DMC"],data[data["Classes  "] !=␣
↪"fire"]["DMC"])
```

[19]: MannwhitneyuResult(statistic=13419.5, pvalue=5.619625810682857e-29)

- there is a significant difference in distributions for `DMC` when fire and not fire

[20]:
```
mannwhitneyu(data[data["Classes  "] == "fire"]["DC"],data[data["Classes  "] !=␣
↪"fire"]["DC"])
```

[20]: MannwhitneyuResult(statistic=13012.5, pvalue=1.8727139327610821e-25)

- there is a significant difference in distributions for `DC` when fire and not fire

[21]:
```
mannwhitneyu(data[data["Classes  "] == "fire"]["ISI"],data[data["Classes  "] !=␣
↪"fire"]["ISI"])
```

[21]: MannwhitneyuResult(statistic=14610.0, pvalue=1.1675868001492136e-40)

[22]:
```
mannwhitneyu(data[data["Classes  "] == "fire"]["BUI"],data[data["Classes  "] !=␣
↪"fire"]["BUI"])
```

[22]: MannwhitneyuResult(statistic=13398.0, pvalue=8.749537975061532e-29)

[23]:
```
mannwhitneyu(data[data["Classes  "] == "fire"]["FWI"],data[data["Classes  "] !=␣
↪"fire"]["FWI"])
```

[23]: MannwhitneyuResult(statistic=14481.5, pvalue=2.615638636647991e-39)

- We can validate the findings in Hypothysis testing with below `pairplot`
- `Ws` has almost same distribution for `fire` and `non-fire` data

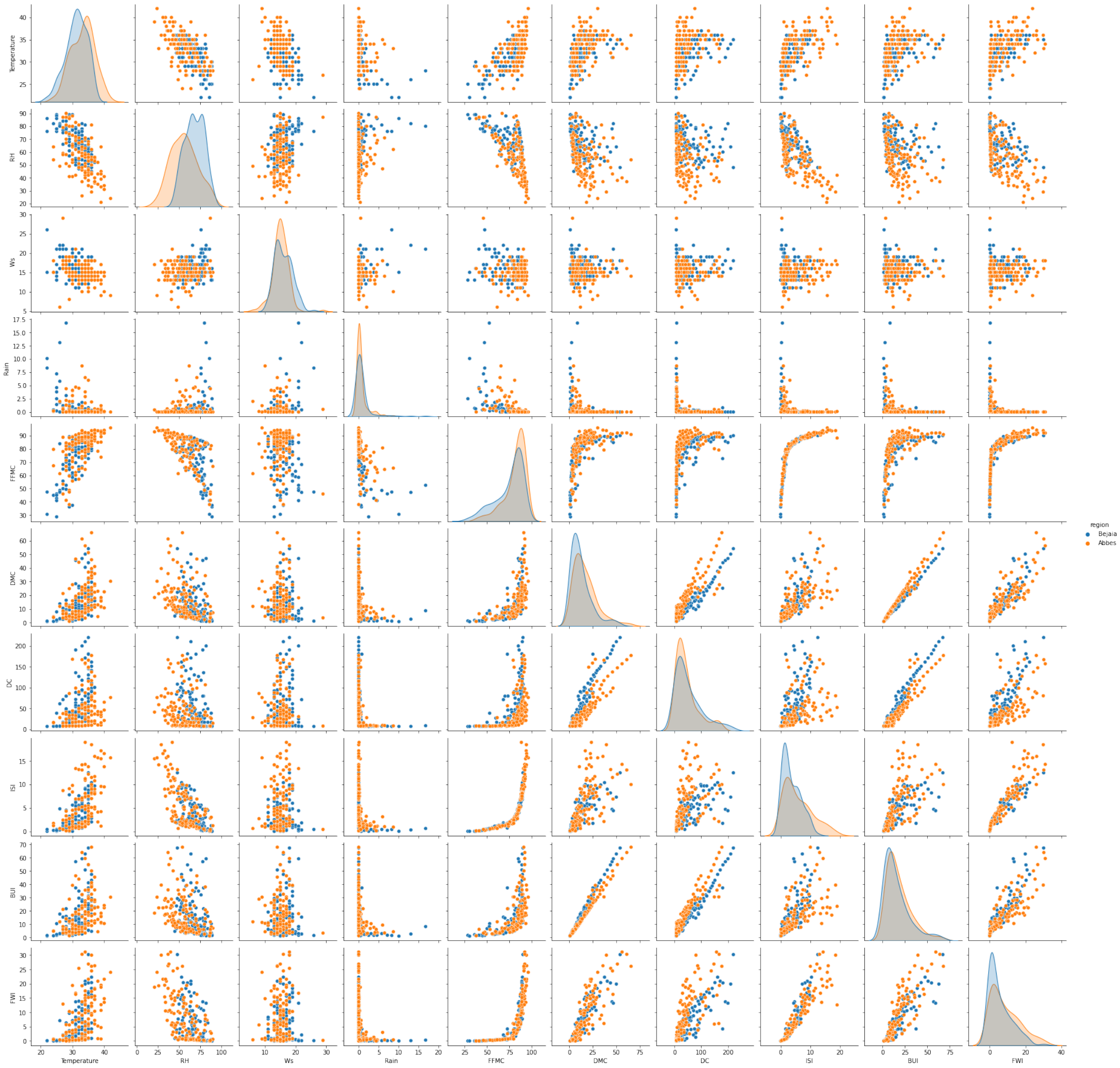
[24]:
```
sns.pairplot(data,hue="Classes  ")
```

[24]: <seaborn.axisgrid.PairGrid at 0x7f4e55f67f40>

- Now we are need to test `Region` has any impact on `fire` or not
- since `Region` and `Classes` both are categorical data so I am using `fisher_exact` for testing

[25]:
```
sns.pairplot(data,hue="region")
```

[25]: <seaborn.axisgrid.PairGrid at 0x7f4e26f08610>




```python
[26]: data_crosstab = pd.crosstab(data["Classes  "],data["region"],margins = False)
      print(data_crosstab)
```

```
region     Abbes  Bejaia
Classes
fire          79      59
not fire      43      63
```

what is a fisher_exact?

- The output of the Fisher's exact test includes the odds ratio, the confidence interval for the odds ratio, and the p-value. If the p-value is less than the significance level (usually 0.05), the null hypothesis of independence is rejected, and it is concluded that there is a significant association between the two categorical variables. Conversely, if the p-value is greater than the significance level, the null hypothesis cannot be rejected, and it is concluded that there is no significant association between the two categorical variables.

[27]:
```python
from scipy.stats import fisher_exact
fisher_exact(data_crosstab)
```

[27]: (1.9617658651951124, 0.013954999729002686)

[28]:
```python
fisher_exact(data_crosstab,alternative="greater")
```

[28]: (1.9617658651951124, 0.006977499864501343)

- The P-value for `fire` and `region` is `0.006977499864501343` which is less then 0.05 to we reject the null hypothesis.

- i.e there is a significant association between the two categorical variables.

I am converting Rain from numerical to categorical data.
Reason is While analysing the data I found that rain has 52-56% zero values.

And from EDA for rain, we can see where is rain change for fire is very less,

So I am changing this dataset from numerical to categorical data.

I will put `rain` if rain > 0 else `not rain`

[29]:
```python
data["Rain "] = data["Rain "].apply(lambda x: 'not rain' if x == 0 else 'rain')
```

[30]:
```python
data_crosstab = pd.crosstab(data["Classes  "],data["Rain "],margins = False)
print(data_crosstab)
```

```
Rain        not rain  rain
Classes
fire             114    24
not fire          19    87
```

[31]:
```python
fisher_exact(data_crosstab)
```

[31]: (21.75, 7.112449017362336e-25)

[32]:
```python
fisher_exact(data_crosstab,alternative="greater")
```

[32]: (21.75, 3.8242593558010855e-25)

- The P-value for `fire` and `Rain` is `3.8242593558010855e-25` which is less then 0.05 to we reject the null hypothesis.

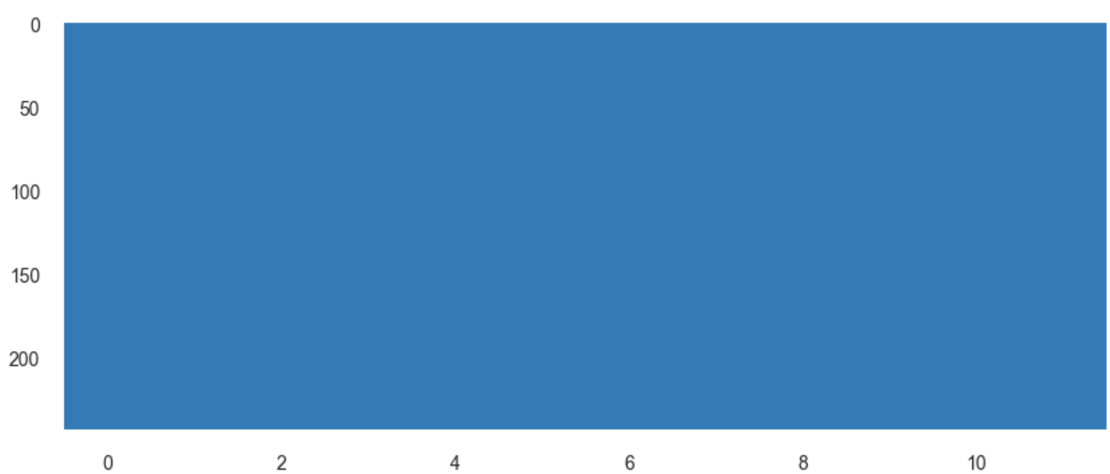
- i.e there is a significant association between the two categorical variables.

[50]:
```python
from pandas_profiling import ProfileReport
profile = ProfileReport(data, explorative=True)

#Saving results to a HTML file
```

```python
profile.to_file("pandas_profiling.html")
```

```
Summarize dataset:  95%|      | 101/106 [00:08<00:00,  8.41it/s, Missing
diagram matrix]         /home/sanjiv/anaconda3/lib/python3.9/site-
packages/pandas_profiling/model/missing.py:89: UserWarning: There was an attempt
to generate the Matrix missing values diagrams, but this failed.
To hide this warning, disable the calculation
(using `df.profile_report(missing_diagrams={"Matrix": False}`)
If this is problematic for your use case, please report this as an issue:
https://github.com/ydataai/pandas-profiling/issues
(include the error message: 'keyword grid_b is not recognized; valid keywords
are ['size', 'width', 'color', 'tickdir', 'pad', 'labelsize', 'labelcolor',
'zorder', 'gridOn', 'tick1On', 'tick2On', 'label1On', 'label2On', 'length',
'direction', 'left', 'bottom', 'right', 'top', 'labelleft', 'labelbottom',
'labelright', 'labeltop', 'labelrotation', 'grid_agg_filter', 'grid_alpha',
'grid_animated', 'grid_antialiased', 'grid_clip_box', 'grid_clip_on',
'grid_clip_path', 'grid_color', 'grid_dash_capstyle', 'grid_dash_joinstyle',
'grid_dashes', 'grid_data', 'grid_drawstyle', 'grid_figure', 'grid_fillstyle',
'grid_gapcolor', 'grid_gid', 'grid_in_layout', 'grid_label', 'grid_linestyle',
'grid_linewidth', 'grid_marker', 'grid_markeredgecolor', 'grid_markeredgewidth',
'grid_markerfacecolor', 'grid_markerfacecoloralt', 'grid_markersize',
'grid_markevery', 'grid_mouseover', 'grid_path_effects', 'grid_picker',
'grid_pickradius', 'grid_rasterized', 'grid_sketch_params', 'grid_snap',
'grid_solid_capstyle', 'grid_solid_joinstyle', 'grid_transform', 'grid_url',
'grid_visible', 'grid_xdata', 'grid_ydata', 'grid_zorder', 'grid_aa', 'grid_c',
'grid_ds', 'grid_ls', 'grid_lw', 'grid_mec', 'grid_mew', 'grid_mfc',
'grid_mfcalt', 'grid_ms']')
  warnings.warn(
Summarize dataset: 100%|      | 106/106 [00:08<00:00, 11.84it/s, Completed]
Generate report structure: 100%|      | 1/1 [00:04<00:00,  4.29s/it]
Render HTML: 100%|      | 1/1 [00:01<00:00,  1.21s/it]
Export report to file: 100%|      | 1/1 [00:00<00:00, 47.38it/s]
```



[51]:
```python
import sweetviz as sv

#EDA using Autoviz
sweet_report = sv.analyze(data)

#Saving results to HTML file
sweet_report.show_html('sweet_report.html')
```

```
Done! Use 'show' commands to display/save.   |          | [100%]   00:00 ->
(00:00 left)

Report sweet_report.html was generated! NOTEBOOK/COLAB USERS: the web browser
MAY not pop up, regardless, the report IS saved in your notebook/colab files.
```