Artificial-Int-Sravan (/github/sravanatmoon/Artificial-Int-Sravan/tree/3eedb466a48a7c548a109188d00f95d0a4f18199)
/
Exploratory_Data_Analysis_.ipynb (/github/sravanatmoon/Artificial-Int-Sravan/tree/3eedb466a48a7c548a109188d00f95d0a4f18199/Exploratory_Data_Analysis_.ipynb)

Open in Colab
(https://colab.research.google.com/github/sravanatmoon/Artificial-Int-Sravan/blob/master/Exploratory_Data_Analysis_.ipynb)

# EDA of Haberman dataset

In [1]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force
```

## Haberman dataset

The dataset contains cases from a study that was conducted between 1958 and 1970 at the University of Chicago's Billings Hospital on the survival of patients who had undergone surgery for breast cancer.

- Objective: Classify a new Candidate as belonging to one of the 2 classes given the 3 features.

In [2]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np


df = pd.read_csv("/content/drive/My Drive/Colab Notebooks/haberman.csv")
df.head(2)
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.testing is de
  import pandas.util.testing as tm
```

Out[2]:

| | age | year | nodes | status |
|---|---|---|---|---|
| **0** | 30 | 64 | 1 | 1 |
| **1** | 30 | 62 | 3 | 1 |

In [3]:

```
df.shape    #(number of points, numer of features),
```

Out[3]:

```
(306, 4)
```

In [4]:

```
df.columns    # Names of Features
```

Out[4]:

```
Index(['age', 'year', 'nodes', 'status'], dtype='object')
```

In [5]:

```
#number of classes
df["status"].unique()
```

Out[5]:

```
array([1, 2])
```

In [6]:

```
df["status"].value_counts()  # data-points per class
# distorted dataset upto some extent (as 74% of Examples belong to a single class while only 26% on other)
```

Out[6]:

```
1    225
2     81
Name: status, dtype: int64
```

balancing the dataset by resample method

In [7]:

```
# learnt from an article from towardsdatascience.com
from sklearn.utils import resample

# separate minority and majority classes
class_1 = df[df['status']==1]
class_2 = df[df['status']==2]

# upsample minority
class_2_upsampled = resample(class_2, replace=True, # sample with replacement
                          n_samples=len(class_1), # match number in majority class
                          random_state=27) # reproducible results

# combine majority and upsampled minority
df = pd.concat([class_1, class_2_upsampled])
df["status"].value_counts()
```

Out[7]:

```
2    225
1    225
Name: status, dtype: int64
```

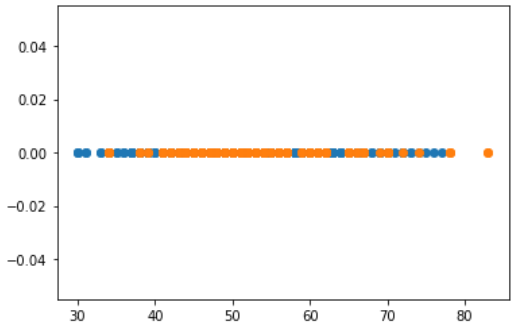
Observations:

1. As the data was imbalanced, balanced with resampling technique

# Histogram, PDF, CDF

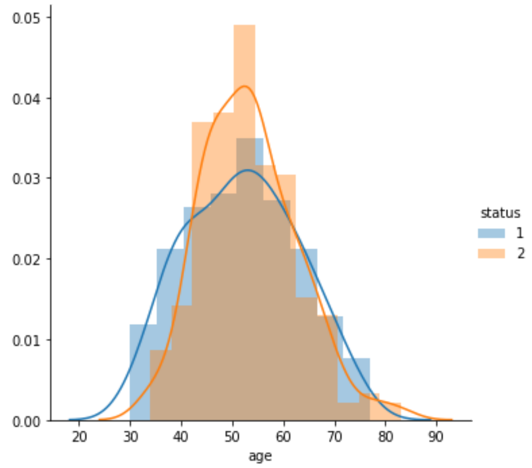
In [8]:

```
df_class1 = df[df["status"] == 1];
df_class2 = df[df["status"] == 2];
plt.plot(df_class1["age"], np.zeros_like(df_class1["age"]), 'o')
plt.plot(df_class2["age"], np.zeros_like(df_class2["age"]), 'o')
plt.show()
```



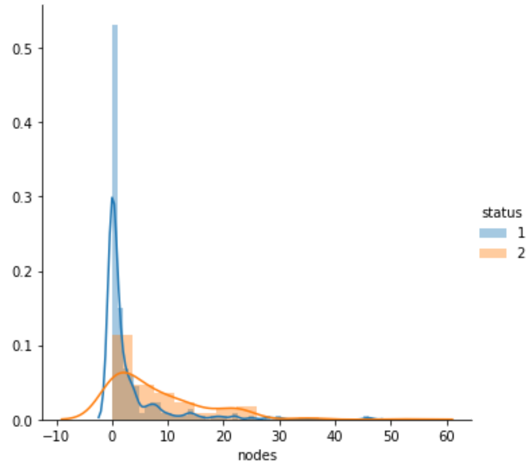
In [9]:

```
sns.FacetGrid(df, hue="status", height=5) \
   .map(sns.distplot, "age") \
   .add_legend();
plt.show();
```



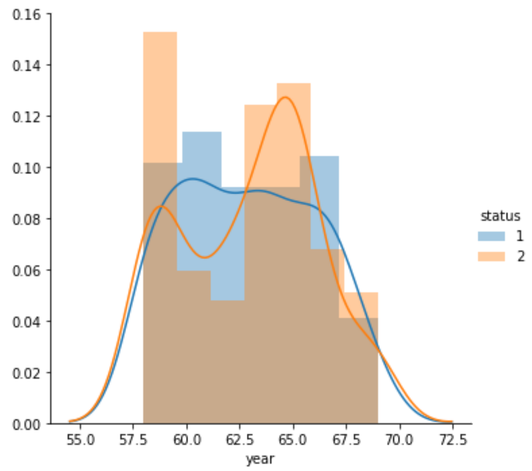

In [10]:

```
sns.FacetGrid(df, hue="status", height=5) \
   .map(sns.distplot, "nodes") \
   .add_legend()
plt.show()
```




In [11]:

```
sns.FacetGrid(df, hue="status", height=5) \
   .map(sns.distplot, "year") \
   .add_legend()
plt.show()
```

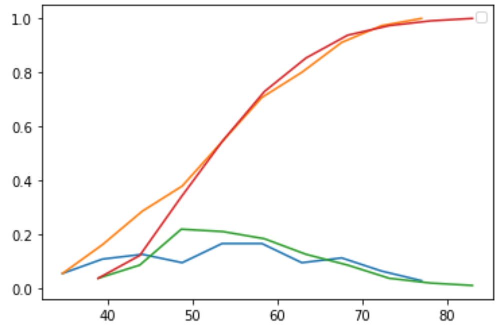


In [12]:

```
#class_1
frequency, age_groups = np.histogram(df_class1['age'], bins=10, density = True)
pdf = frequency/(sum(frequency))
plt.plot(age_groups[1:], pdf)
plt.plot(age_groups[1:], np.cumsum(pdf))  # cdf direct inside plot

# class_2
frequency, age_groups = np.histogram(df_class2['age'], bins=10, density = True)
pdf = frequency/(sum(frequency))
plt.plot(age_groups[1:], pdf)
plt.plot(age_groups[1:], np.cumsum(pdf))   # cdf direct inside plot
plt.legend()
plt.show()
```

```
No handles with labels found to put in legend.
```




**Obsevation:**

Nothing SIgnificant to conclude anything

## Mean, Variance and Std-dev

In [13]:

```
#Mean, Variance, Std-deviation,
print("Means:")
print("Age :",np.mean(df_class1["age"]), np.mean(df_class2["age"]))
print("Nodes :",np.mean(df_class1["nodes"]), np.mean(df_class2["nodes"]))
print("Year :",np.mean(df_class1["year"]), np.mean(df_class2["year"]))

print("\nStd-dev:");
print("Age :",np.std(df_class1["age"]), np.std(df_class2["age"]))
print("Nodes :",np.std(df_class1["nodes"]), np.std(df_class2["nodes"]))
print("Year :",np.std(df_class1["year"]), np.std(df_class2["year"]))
```

```
Means:
Age : 52.017777777777778 53.382222222222225
Nodes : 2.7911111111111113 7.7555555555555555
Year : 62.86222222222222 62.96

Std-dev:
Age : 10.98765547510051 9.282990152576891
Nodes : 5.857258449412131 8.372854433108504
Year : 3.2157452144021956 3.215683787660443
```

## Median, Percentile, Quartile, IQR, MAD

In [14]:

```
print("Medians:")
print("Age :",np.median(df_class1["age"]), np.median(df_class2["age"]))
print("Nodes :",np.median(df_class1["nodes"]), np.median(df_class2["nodes"]))
print("Year :",np.median(df_class1["year"]), np.median(df_class2["year"]))
```

```
Medians:
Age : 52.0 53.0
Nodes : 0.0 5.0
Year : 63.0 64.0
```

In [15]:

```
print("90th Percentiles:")
print("Age : ", np.percentile(df_class1["age"],90), np.percentile(df_class2["age"],90))
print("Nodes : ", np.percentile(df_class1["nodes"],90), np.percentile(df_class2["nodes"],61))
print("year : ", np.percentile(df_class1["year"],90), np.percentile(df_class2["year"],90))
```

```
90th Percentiles:
Age :  67.0 65.0
Nodes :  8.0 8.0
year :  67.0 67.0
```

Observations:

1. 90% of the Persons of class_1 are under the age of 67, where are 90% of the members of class_2 are above 43.
2. 90% of the Persons of class_1 were having nodes under 8 while that is only 61% for class_2

In [16]:

```
print("Quartiles:")
print("Age : ", np.percentile(df_class1["age"],np.arange(0, 100, 25)), \
      np.percentile(df_class2["age"],np.arange(0, 100, 25)))
print("Nodes : ", np.percentile(df_class1["nodes"],np.arange(0, 100, 25)), \
      np.percentile(df_class2["nodes"],np.arange(0, 100, 25)))
print("year : ", np.percentile(df_class1["year"],np.arange(0, 100, 25)), \
      np.percentile(df_class2["year"],np.arange(0, 100, 25)))
```

```
Quartiles:
Age :  [30. 43. 52. 60.] [34. 47. 53. 60.]
Nodes :  [0. 0. 0. 3.] [ 0.  1.  5. 13.]
year :  [58. 60. 63. 66.] [58. 60. 64. 65.]
```

In [17]:

```
print("IQRs:")
def IQR(series):
    Q1, Q3 = np.percentile(series, [25 ,75])
    return (Q3 - Q1)

print("Age : ", IQR(df_class1["age"]), IQR(df_class2["age"]))
print("Nodes : ", IQR(df_class1["nodes"]), IQR(df_class2["nodes"]))
print("year : ", IQR(df_class1["year"]), IQR(df_class2["year"]))
```

```
IQRs:
Age :  17.0 13.0
Nodes :  3.0 12.0
year :  6.0 5.0
```

In [18]:

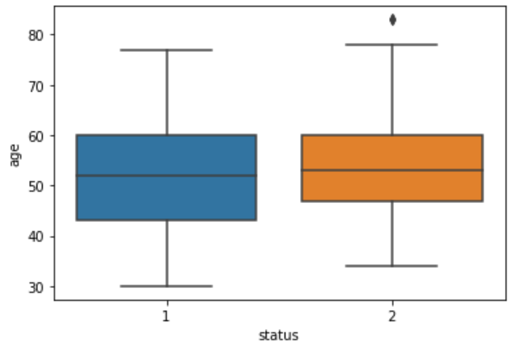
```
# Mean Absolute Deviation (or MAD)
from statsmodels import robust
print ("Median Absolute Deviation")
print("Age : ",robust.mad(df_class1["age"]), robust.mad(df_class2["age"]))
print("Year : ",robust.mad(df_class1["year"]), robust.mad(df_class2["year"]))
print("Nodes : ",robust.mad(df_class1["nodes"]), robust.mad(df_class2["nodes"]))
```

```
Median Absolute Deviation
Age :  13.343419966550417 10.378215529539213
Year :  4.447806655516806 2.965204437011204
Nodes :  0.0 7.41301109252801
```

# Box plot and Whiskers

In [19]:

```
sns.boxplot(x='status',y='age', data=df)
plt.show()
```

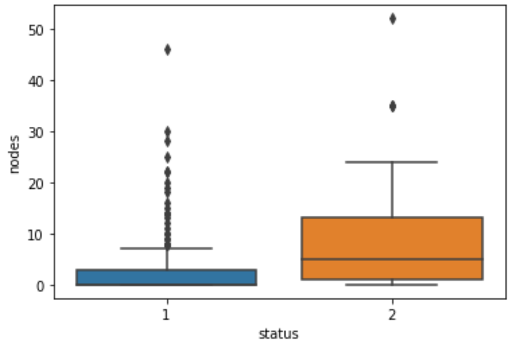


In [20]:

```
sns.boxplot(x='status',y='nodes', data=df)
#plt.show()
```

Out[20]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f10713bf278>
```

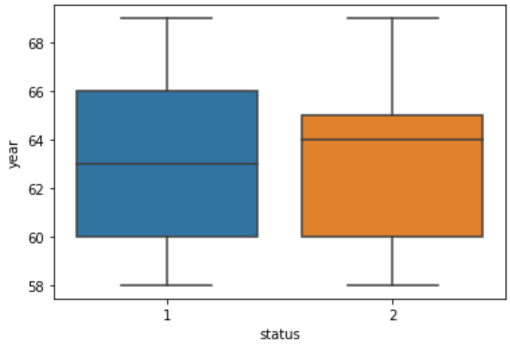



Obsrvations

1. 75% of the class_1 persons had nodes less than 3
2. 75 % of the class_2 persons had notes more than 1

In [21]:

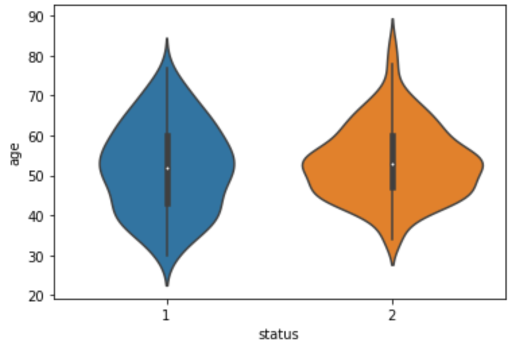
```
sns.boxplot(x='status',y='year', data=df)
plt.show()
```




# Violin plots

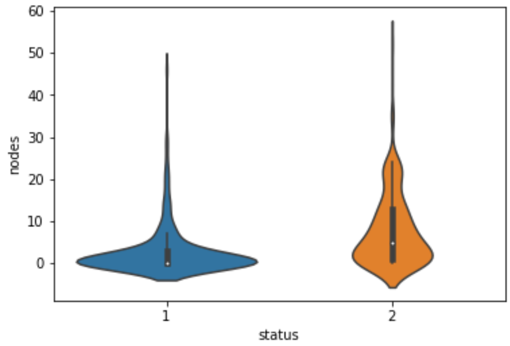
In [22]:

```
sns.violinplot(x="status", y="age", data=df, size=8)
plt.show()
```



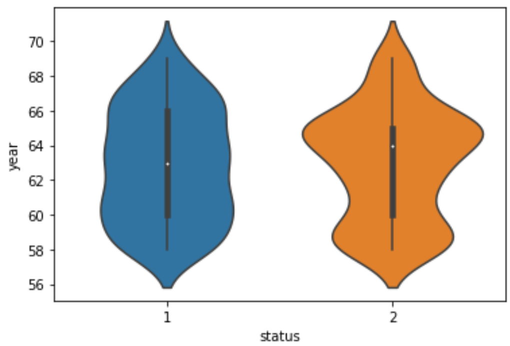
In [23]:

```
sns.violinplot(x="status", y="nodes", data=df, size=8)
plt.show()
```




In [24]:

```
sns.violinplot(x="status", y="year", data=df, size=8)
plt.show()
```




## 2-D Scatter Plot

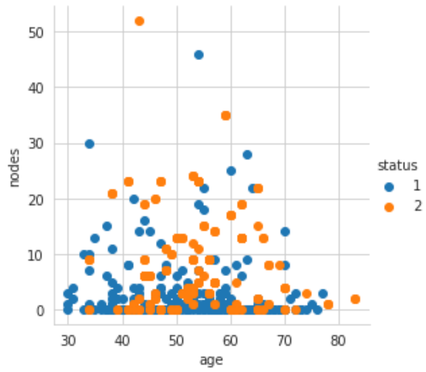
**Observation(s):**

1. all the 3 combinations doesn't give any specific info of classification.

In [25]:

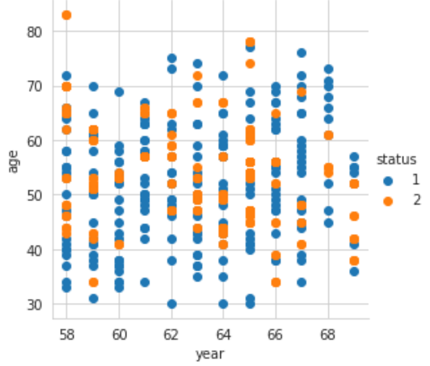
```
sns.set_style("whitegrid");
sns.FacetGrid(df, hue="status", height=4) \
   .map(plt.scatter, "age", "nodes") \
   .add_legend();
plt.show();

# data points cannot be easily seperated.
```



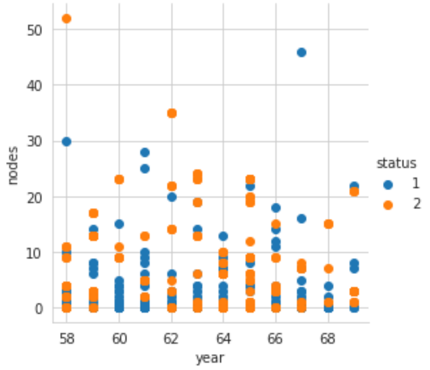
In [27]:

```
sns.set_style("whitegrid");
sns.FacetGrid(df, hue="status", height=4) \
   .map(plt.scatter, "year", "age") \
   .add_legend();
plt.show();
```




In [29]:

```
sns.set_style("whitegrid");
sns.FacetGrid(df, hue="status", height=4) \
   .map(plt.scatter, "year", "nodes") \
   .add_legend();
plt.show();
```




# Pair-plot

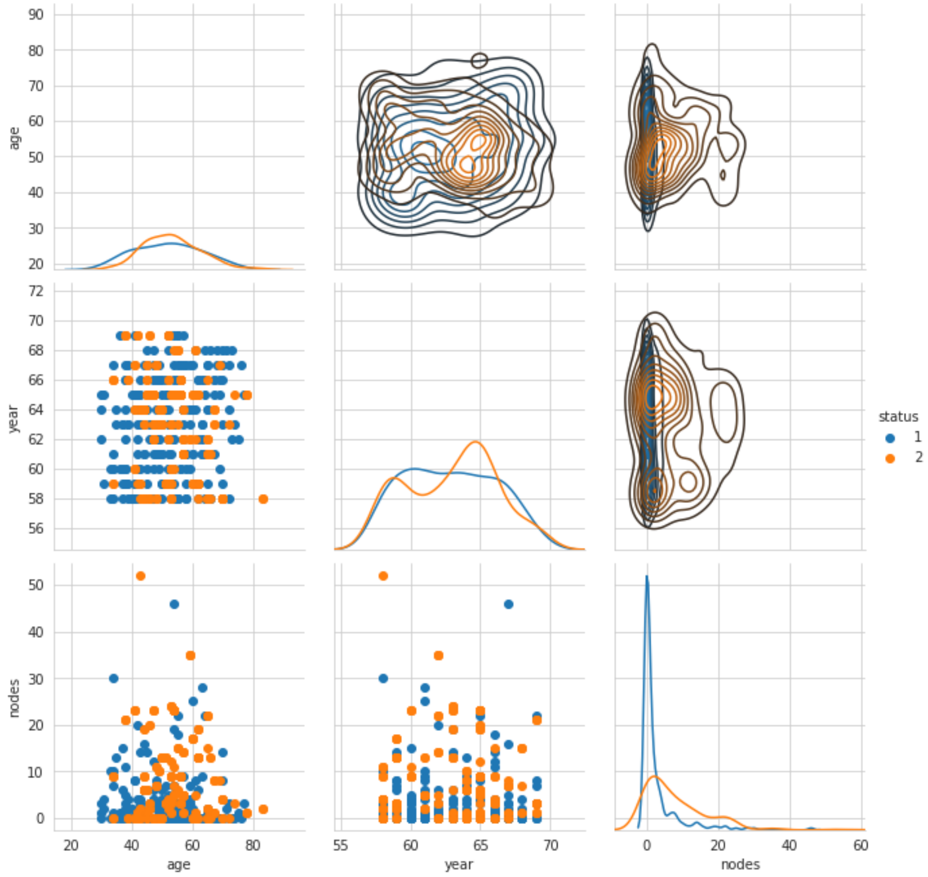
In [31]:

```
sns.set_style("whitegrid");
Grid = sns.PairGrid(df, hue="status", height=3)

Grid.map_upper(sns.kdeplot)
Grid.map_lower(plt.scatter)
Grid.map_diag(sns.kdeplot)
Grid.add_legend()
#Grid.show()
```

Out[31]:

```
<seaborn.axisgrid.PairGrid at 0x7f1070e36f98>
```




**Observations**

1. None of the feature individually give insight about the required class classificatin, we have to further explore

# 3D-Plot

In [32]:

```
import plotly.express as px
fig = px.scatter_3d(df, x='age', y='year', z='nodes', color='status')
fig.show()
```