There are two data generators as below: a) Guassian Quantiles b) Make_classification

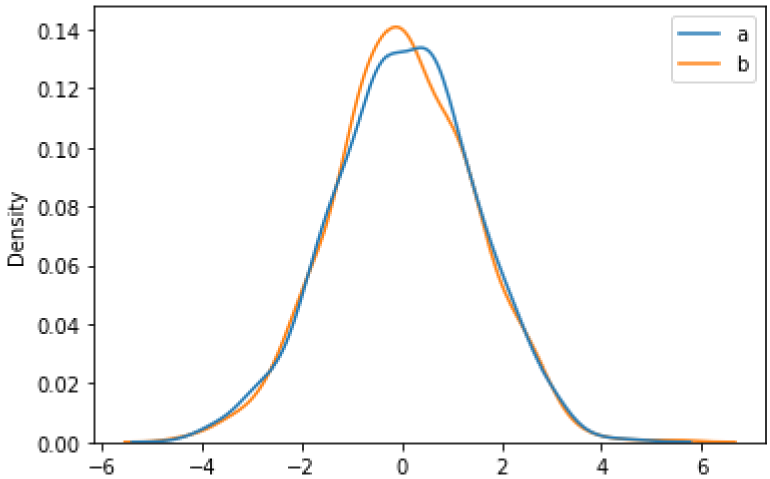
GAUSSIAN QUANTILES

```
import warnings
warnings.filterwarnings("ignore")
from sklearn.datasets import make_gaussian_quantiles
import pandas as pd
x,y=make_gaussian_quantiles(cov=2,n_samples=1000,n_classes=2,n_features=2,random_state=1)
#If you are aware of gaussian distribution, it takes the data that way. It assumes the cor
df=pd.DataFrame(x)
y1=pd.Series(y)
df.head(7)
#The below shows the data dispersed between the features
```

	0	1
0	-1.140108	0.069384
1	1.533599	-0.155701
2	-1.559834	1.074086
3	1.239134	0.174310
4	-2.794104	-0.832874
5	1.600366	2.149346
6	-1.794438	2.487261

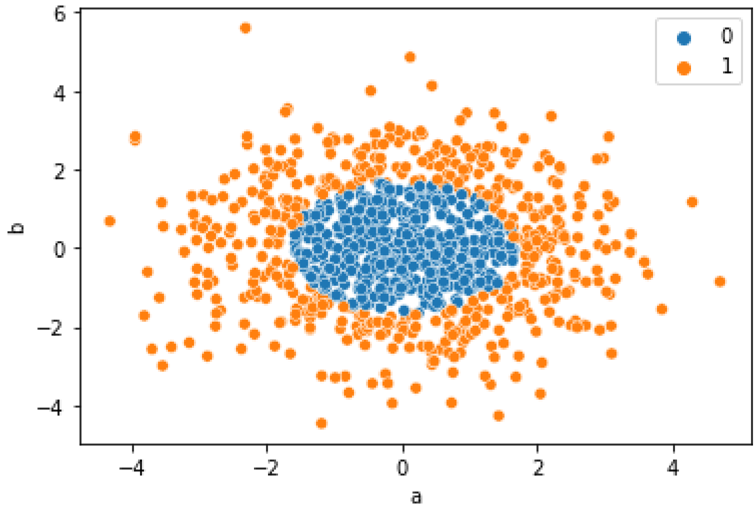
```
#PDF's for the features
import seaborn as sns
x1=pd.DataFrame(x,columns=['a','b'])
sns.kdeplot(data=x1)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fb03bf9cc10>

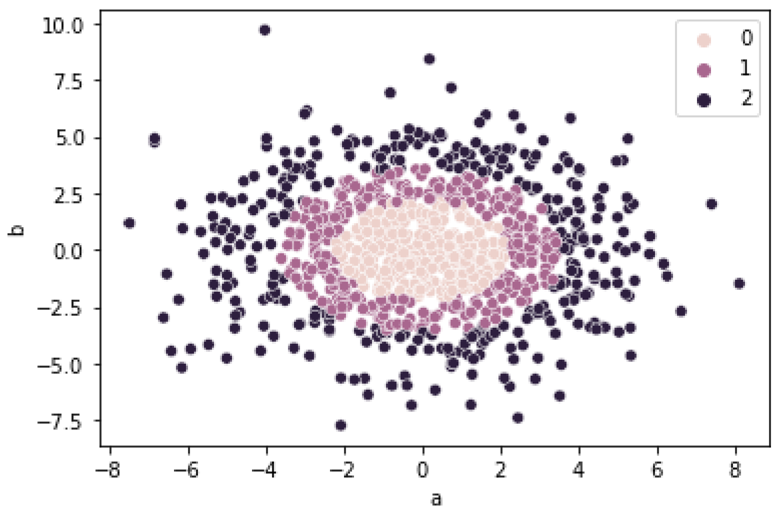



```
#Lets visualise it more better
```

```
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt
vis_obj=TSNE(n_components=2,random_state=47,n_iter=400,angle=0.6)
vis_obj.fit_transform(x1)
sns.scatterplot(x1.iloc[:,0],x1.iloc[:,1],hue=y1)
plt.show()
```



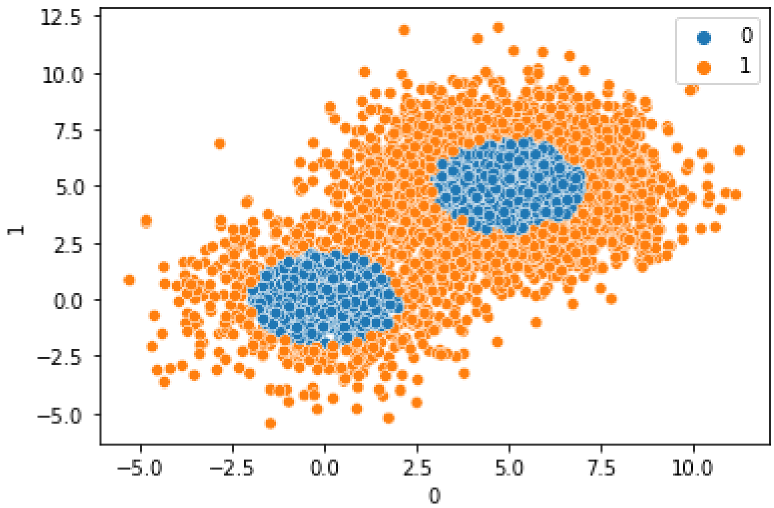

```
#Now lets add more classes and see the gaussian quantile visually
xz,yz=make_gaussian_quantiles(cov=6,n_samples=1000,n_features=2,n_classes=3,random_state=1
xz1=pd.DataFrame(xz,columns=['a','b'])
yz1=pd.Series(yz)
vis_obj=TSNE(n_components=2,random_state=47,n_iter=400,angle=0.6)
vis_obj.fit_transform(xz1)
sns.scatterplot(xz1.iloc[:,0],xz1.iloc[:,1],hue=yz1)
plt.show()
```



COMBINING THE ABOVE TWO GAUSSIAN QUANTILES

```
import numpy as np
#Gaussian 1
xz,yz=make_gaussian_quantiles(cov=3,n_samples=1000,n_features=2,n_classes=2,random_state=1
xz1=pd.DataFrame(xz,columns=['a','b'])
```

```
xz1=pd.DataFrame(xz,columns=['a','b'])
yz1=pd.Series(yz)


#Gaussian 2: Locating at mean= 5.This critically displaces the quantile.
x,y=make_gaussian_quantiles(mean=(5,5),cov=3,n_samples=5000,n_features=2,n_classes=2,rando
x1=pd.DataFrame(x,columns=['a','b'])
y1=pd.Series(y)

#Concatenate above Gaussians
X = pd.DataFrame(np.concatenate((x1,xz1)))
Y = pd.Series(np.concatenate((y1,yz1)))
vis_obj=TSNE(n_components=2,random_state=47,n_iter=400,angle=0.6)
vis_obj.fit_transform(X)
sns.scatterplot(X.iloc[:,0],X.iloc[:,1],hue=Y)
plt.show()
```



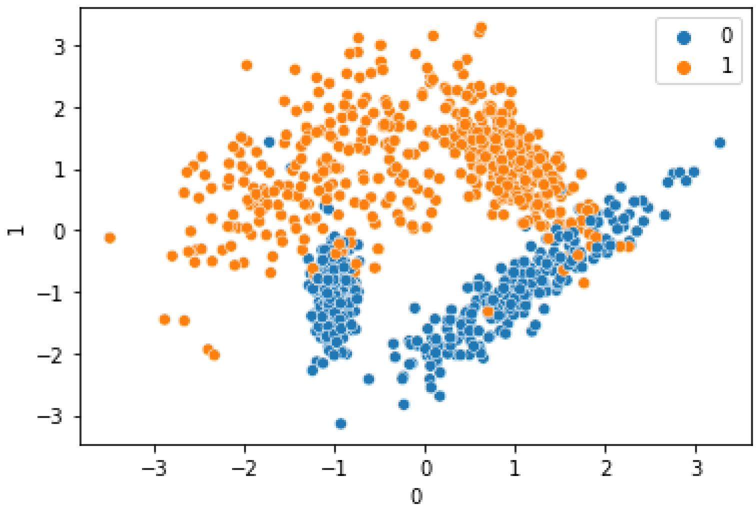
MAKE_CLASSIFICATION

POINTS TO PONDER:

```
1) make_classification can help us adding noise by adding random classes

2) It helps to easy the classification by using class seperators

3) You can also adjust the redundant features and compare the sensitivity of ML algorithms

4) n_informative is the dimension or the number of features through which your cluster is we
```

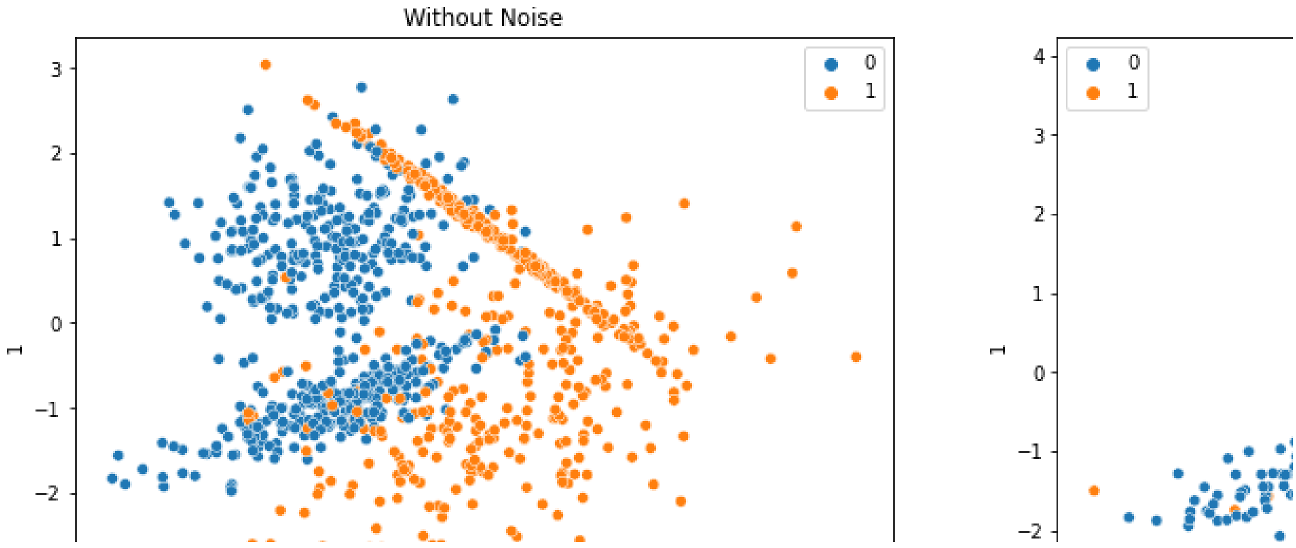
```
from sklearn.datasets import make_classification
import seaborn as sns
x,y=make_classification(n_samples=1000,n_classes=2,n_features=2,n_redundant=0)
X = pd.DataFrame(x)
Y = pd.Series(y)
vis_obj=TSNE(n_components=2,angle=0.6,n_iter=400,random_state=47)
```

```
vis_obj.fit_transform(X)
sns.scatterplot(X.iloc[:,0],X.iloc[:,1],hue=Y)
plt.show()
```



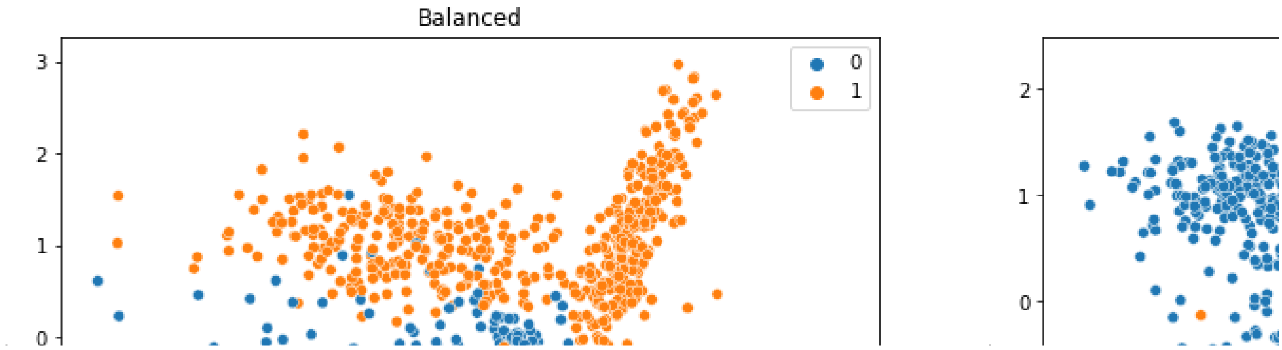
Lets add Noise to the data

```
from sklearn.datasets import make_classification
import seaborn as sns
x,y=make_classification(n_samples=1000,n_classes=2,n_features=2,n_redundant=0)
X = pd.DataFrame(x)
Y = pd.Series(y)
vis_obj=TSNE(n_components=2,angle=0.6,n_iter=400,random_state=47)
vis_obj.fit_transform(X)
f, (ax1,ax2) = plt.subplots(nrows=1, ncols=2,figsize=(17,6))
sns.scatterplot(X.iloc[:,0],X.iloc[:,1],hue=Y,ax=ax1)
ax1.set_title('Without Noise')


#Noise data
from sklearn.datasets import make_classification
import seaborn as sns
x,y=make_classification(n_samples=1000,n_classes=2,n_features=2,n_redundant=0,flip_y=0.2)
X = pd.DataFrame(x)
Y = pd.Series(y)
vis_obj=TSNE(n_components=2,angle=0.6,n_iter=400,random_state=47)
vis_obj.fit_transform(X)
sns.scatterplot(X.iloc[:,0],X.iloc[:,1],hue=Y,ax=ax2)
ax2.set_title('With Noise')
plt.show()

#Noise data is hard to classify, so you can see some regions classes overlap
```



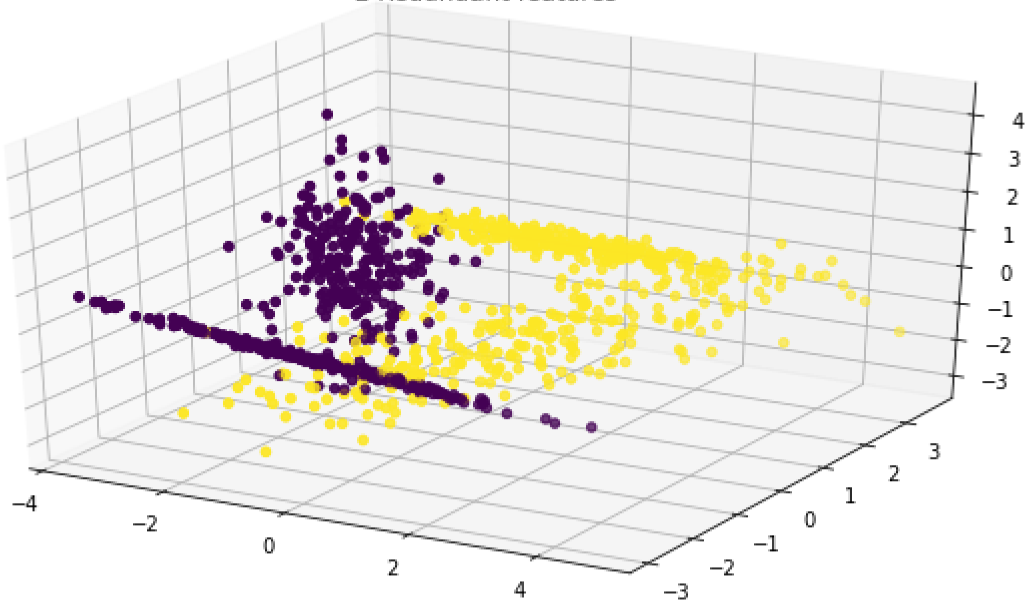
DEALING WITH BALANCED DATASET AND UNBALANCED DATASET

```
from sklearn.datasets import make_classification
import seaborn as sns
x,y=make_classification(n_samples=1000,n_classes=2,n_features=2,n_redundant=0,weights=[0.5
X = pd.DataFrame(x)
Y = pd.Series(y)
vis_obj=TSNE(n_components=2,angle=0.6,n_iter=400,random_state=47)
vis_obj.fit_transform(X)
f, (ax1,ax2) = plt.subplots(nrows=1, ncols=2,figsize=(17,6))
sns.scatterplot(X.iloc[:,0],X.iloc[:,1],hue=Y,ax=ax1)
ax1.set_title('Balanced')


#Unbalanced data
from sklearn.datasets import make_classification
import seaborn as sns
x,y=make_classification(n_samples=1000,n_classes=2,n_features=2,n_redundant=0,weights=[0.9
X = pd.DataFrame(x)
Y = pd.Series(y)
vis_obj=TSNE(n_components=2,angle=0.6,n_iter=400,random_state=47)
vis_obj.fit_transform(X)
sns.scatterplot(X.iloc[:,0],X.iloc[:,1],hue=Y,ax=ax2)
ax2.set_title('Unbalanced')
plt.show()
```



DEALING WITH REDUNDANT FEATURES

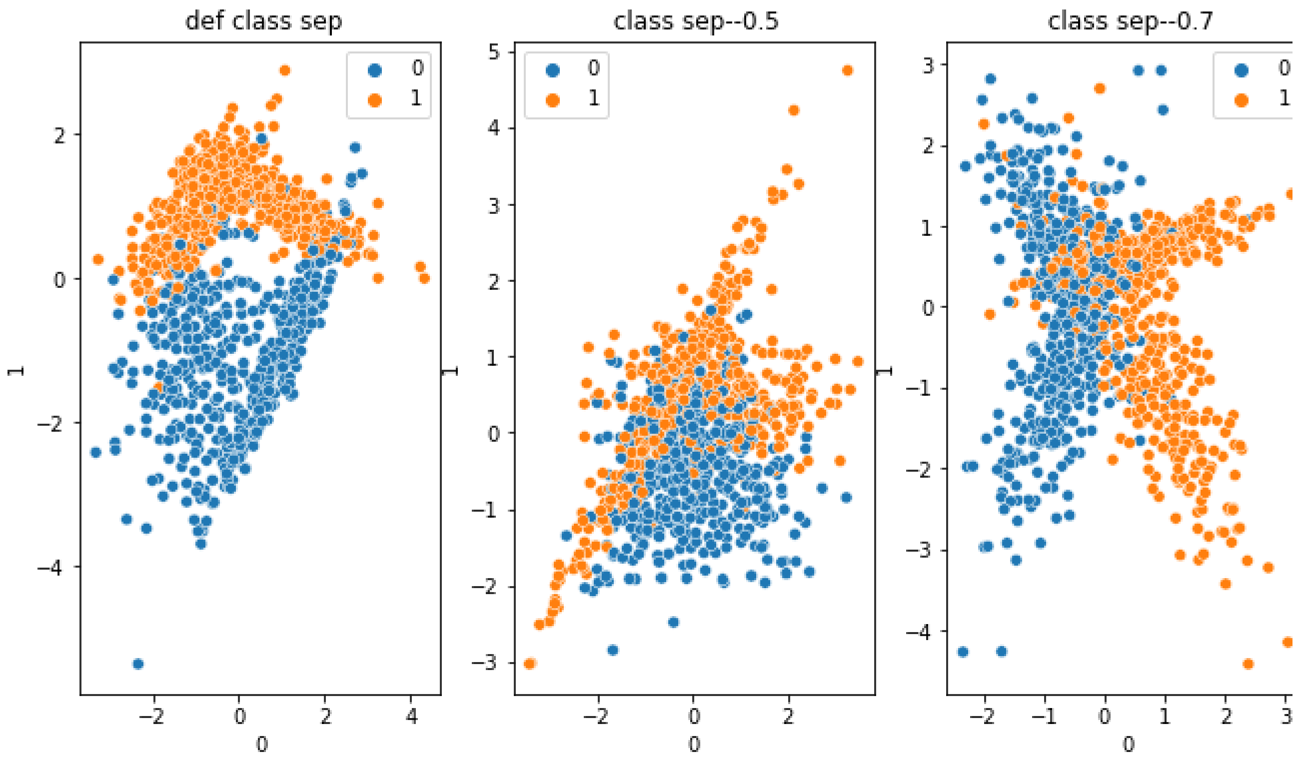
```
import matplotlib.pyplot as plt
from mpl_toolkits import mplot3d
from sklearn.datasets import make_classification
x,y=make_classification(n_samples=1000,n_classes=2,n_features=4,n_redundant=2)
X=pd.DataFrame(x)
Y=pd.Series(y)
f,ax1=plt.subplots(nrows=1,ncols=2,figsize=(11,6))
ax1 = plt.axes(projection ="3d")
for i in Y.unique():
  ax1.scatter3D(X.iloc[:,0],X.iloc[:,1],X.iloc[:,2],c=Y)# the color comes out with the bin
ax1.set_title(' 2 Redundant features')

plt.show()
#Redundant features degrade the performance and will be difficult to classify
```



IF WE NEED THE CLASSES TO BE WELL SEPERATED

```
import matplotlib.pyplot as plt
from mpl_toolkits import mplot3d
from sklearn.datasets import make_classification
x,y=make_classification(n_samples=1000,n_classes=2,n_features=2,n_redundant=0)
X=pd.DataFrame(x)
```

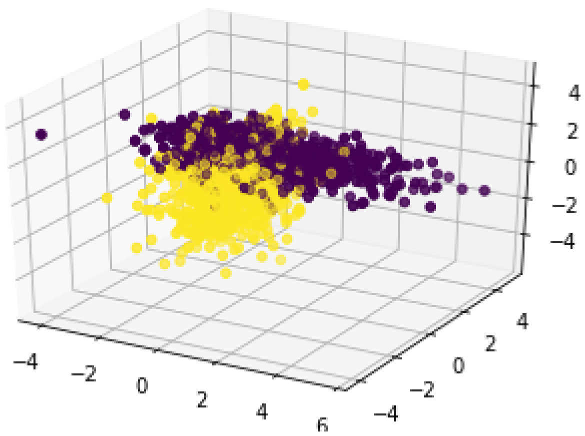
```
X=pd.DataFrame(x)
Y=pd.Series(y)
f,(ax1,ax2,ax3)=plt.subplots(nrows=1,ncols=3,figsize=(11,6))

sns.scatterplot(X.iloc[:,0],X.iloc[:,1],hue=Y,ax=ax1)# the color comes out with the binary
ax1.set_title(' def class sep')

#With class seperator as 0.5
x,y=make_classification(n_samples=1000,n_classes=2,n_features=2,n_redundant=0,class_sep=0.
X=pd.DataFrame(x)
Y=pd.Series(y)
sns.scatterplot(X.iloc[:,0],X.iloc[:,1],hue=Y,ax=ax2)# the color comes out with the binary
ax2.set_title(' class sep--0.5')


#With class seperator as 0.7
x,y=make_classification(n_samples=1000,n_classes=2,n_features=2,n_redundant=0,class_sep=0.
X=pd.DataFrame(x)
Y=pd.Series(y)
sns.scatterplot(X.iloc[:,0],X.iloc[:,1],hue=Y,ax=ax3)# the color comes out with the binary
ax3.set_title(' class sep--0.7')
plt.show()
#easy classification for high class seperator
```



n_clusters per class

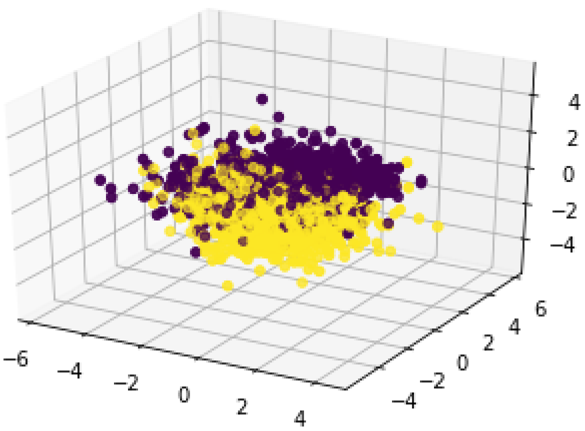
```
from sklearn.manifold import TSNE
from mpl_toolkits import mplot3d
x,y=make_classification(n_samples=2000,n_classes=2,n_clusters_per_class=2,n_features=4,n_r
X=pd.DataFrame(x);Y=pd.Series(y)
vis_obj=TSNE(n_components=2,angle=0.7,random_state=47)
vis_obj.fit_transform(X)
ax = plt.axes(projection ="3d")
```

```
ax = plt.axes(projection ="3d")
for i in Y.unique():
  ax.scatter3D(X.iloc[:,0],X.iloc[:,1],X.iloc[:,2],c=Y)
plt.figure(figsize=(70,11))
plt.show()
```




```
<Figure size 5040x792 with 0 Axes>
```

```
#No Of Clusters taken as 3
from sklearn.manifold import TSNE
from mpl_toolkits import mplot3d
x,y=make_classification(n_samples=2000,n_classes=2,n_clusters_per_class=3,n_features=4,n_r
X=pd.DataFrame(x);Y=pd.Series(y)
vis_obj=TSNE(n_components=2,angle=0.7,random_state=47)
vis_obj.fit_transform(X)
ax = plt.axes(projection ="3d")
for i in Y.unique():
  ax.scatter3D(X.iloc[:,0],X.iloc[:,1],X.iloc[:,2],c=Y)
plt.figure(figsize=(70,11))
plt.show()
```




```
<Figure size 5040x792 with 0 Axes>
```

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