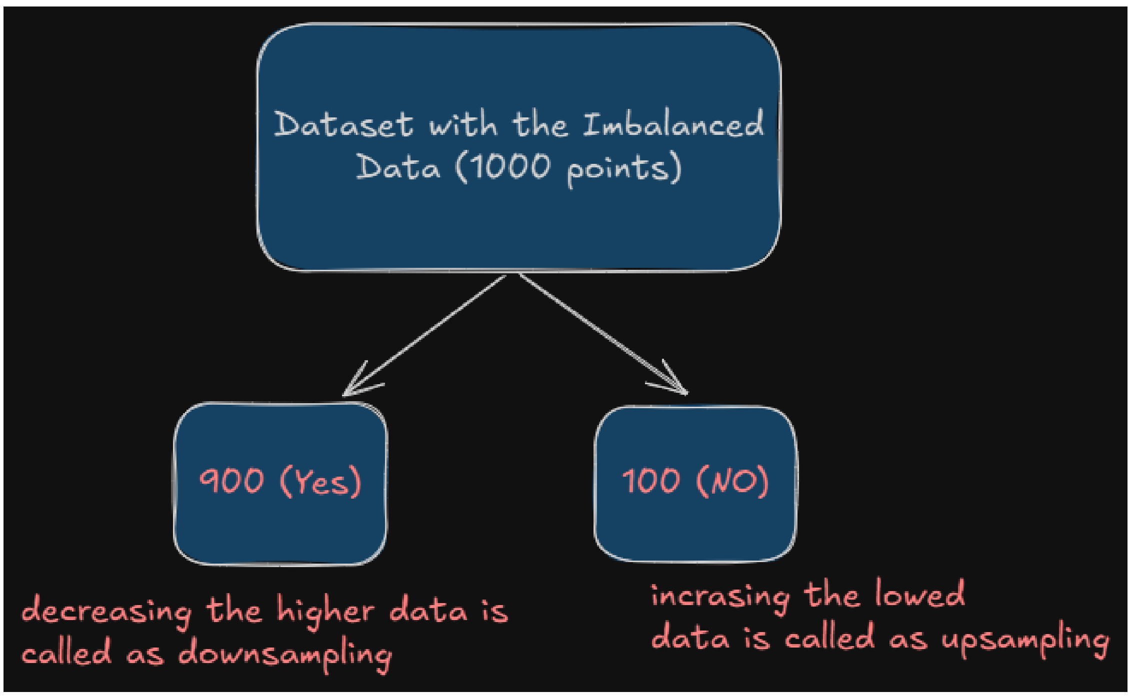
5.2-Handling_Imbalance_dataset

July 15, 2025

0.1 Handling Imbalance Dataset

```
1- Up Sampling
2- Down Sampling
```



[53]:
```python
import numpy as np
import pandas as pd

# Set the random seed for reproducibility
np.random.seed(123)

# create a dataframe with two classes
n_samples  = 1000
class_0_ratio = 0.9
n_class_0 = int(n_samples*class_0_ratio)
n_class_1 = n_samples - n_class_0
```

[54]:
```python
print(f"My Imbalance Dataset with class-0 is {n_class_0} and with class-1 is␣
  ↪{n_class_1}")
n_class_0, n_class_1
```

My Imbalance Dataset with class-0 is 900 and with class-1 is 100

[54]: (900, 100)

0.1.1 Creating Imbalance Dataset

[55]:
```python
class_0 = pd.DataFrame({
        'feature_1': np.random.normal(loc=0, scale=1, size=n_class_0),
        'feature_2': np.random.normal(loc=0, scale=1, size=n_class_0),
        'target': [0]*n_class_0
})

class_1 = pd.DataFrame({
        'feature_1': np.random.normal(loc=0, scale=1, size=n_class_1),
        'feature_2': np.random.normal(loc=0, scale=1, size=n_class_1),
        'target': [1]*n_class_1
})
```

[56]:
```python
df = pd.concat([class_0, class_1]).reset_index(drop=True)
```

[57]:
```python
df.head()
```

[57]:

	feature_1	feature_2	target
0	-1.085631	0.551302	0
1	0.997345	0.419589	0
2	0.282978	1.815652	0
3	-1.506295	-0.252750	0
4	-0.578600	-0.292004	0

[58]:
```python
df.tail()
```

[58]:

	feature_1	feature_2	target
995	-0.623629	0.845701	1
996	0.239810	-1.119923	1
997	-0.868240	-0.359297	1
998	0.902006	-1.609695	1
999	0.697490	0.013570	1

[59]:
```python
df['target'].value_counts()
```

[59]:
```
target
0    900
1    100
Name: count, dtype: int64
```

Upsampling the dataset

[60]:
```
df_minority = df[df['target']==1]
df_majority = df[df['target']==0]
```

[61]:
```
from sklearn.utils import resample

df_minority_upsampled = resample(df_minority, replace=True, # Sample with␣
 ↪replacement
                                 n_samples=len(df_majority),
                                 random_state=42 )
```

[62]:
```
df_minority_upsampled.shape
```

[62]:
```
(900, 3)
```

[63]:
```
df_upsampled = pd.concat([df_majority, df_minority_upsampled])
```

[64]:
```
df_upsampled['target'].value_counts()
```

[64]:
```
target
0    900
1    900
Name: count, dtype: int64
```

0.1.2 DownSampling the dataset

[65]:
```
# Set the random seed for reproducibility
np.random.seed(123)

# create a dataframe with two classes
n_samples  = 1000
class_0_ratio = 0.9
n_class_0 = int(n_samples*class_0_ratio)
n_class_1 = n_samples - n_class_0

print(f"My Imbalance Dataset with class-0 is {n_class_0} and with class-1 is␣
 ↪{n_class_1}")
n_class_0, n_class_1

class_0 = pd.DataFrame({
        'feature_1': np.random.normal(loc=0, scale=1, size=n_class_0),
        'feature_2': np.random.normal(loc=0, scale=1, size=n_class_0),
        'target': [0]*n_class_0
})

class_1 = pd.DataFrame({
```

```
        'feature_1': np.random.normal(loc=0, scale=1, size=n_class_1),
        'feature_2': np.random.normal(loc=0, scale=1, size=n_class_1),
        'target': [1]*n_class_1
})

df = pd.concat([class_0, class_1]).reset_index(drop=True)

# Check the class distribution
df['target'].value_counts()
```

```
My Imbalance Dataset with class-0 is 900 and with class-1 is 100
```

[65]:
```
target
0    900
1    100
Name: count, dtype: int64
```

[66]:
```
df_minority = df[df['target']==1]
df_majority = df[df['target']==0]
```

[67]:
```
df_majority_downsampled = resample(df_majority, replace=False, # Sample with␣
 ↪replacement
                         n_samples=len(df_minority),
                         random_state=42 )
```

[68]:
```
df_majority_downsampled.shape
```

[68]:
```
(100, 3)
```

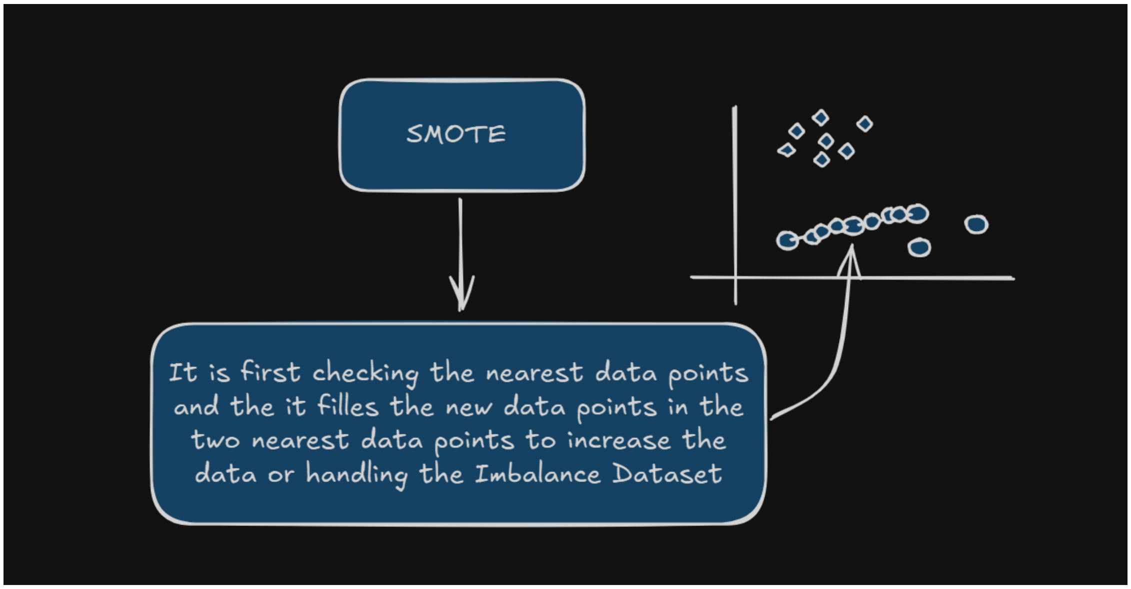
[69]:
```
df_downsampled = pd.concat([df_minority, df_majority_downsampled])
```

[70]:
```
df_downsampled.target.value_counts()
```

[70]:
```
target
1    100
0    100
Name: count, dtype: int64
```

0.1.3 SMOTE(Synthetic Minority Oversampling Technique)

SMOTE is a technique used in machine learning to address imbalanced dataset where the minority class has significantly fewer instances then majority class. SMOTE involves generating synthetic instances of the minority class by interpolating between instances.



[71]:
```python
from sklearn.datasets import make_classification
```

[72]:
```python
X,y = make_classification(n_samples=1000, n_redundant=0, n_features=2,␣
↪n_clusters_per_class=1, weights=[0.90], random_state=12)
```

[73]:
```python
import pandas as pd
df1 = pd.DataFrame(X, columns=['f1', 'f2'])
df2 = pd.DataFrame(y, columns=['target'])
final_df = pd.concat([df1,df2], axis=1)
final_df.head()
```

[73]:

	f1	f2	target
0	-0.762898	-0.706808	0
1	-1.075436	-1.051162	0
2	-0.610115	-0.909802	0
3	-2.023284	-0.428945	1
4	-0.812921	-1.316206	0

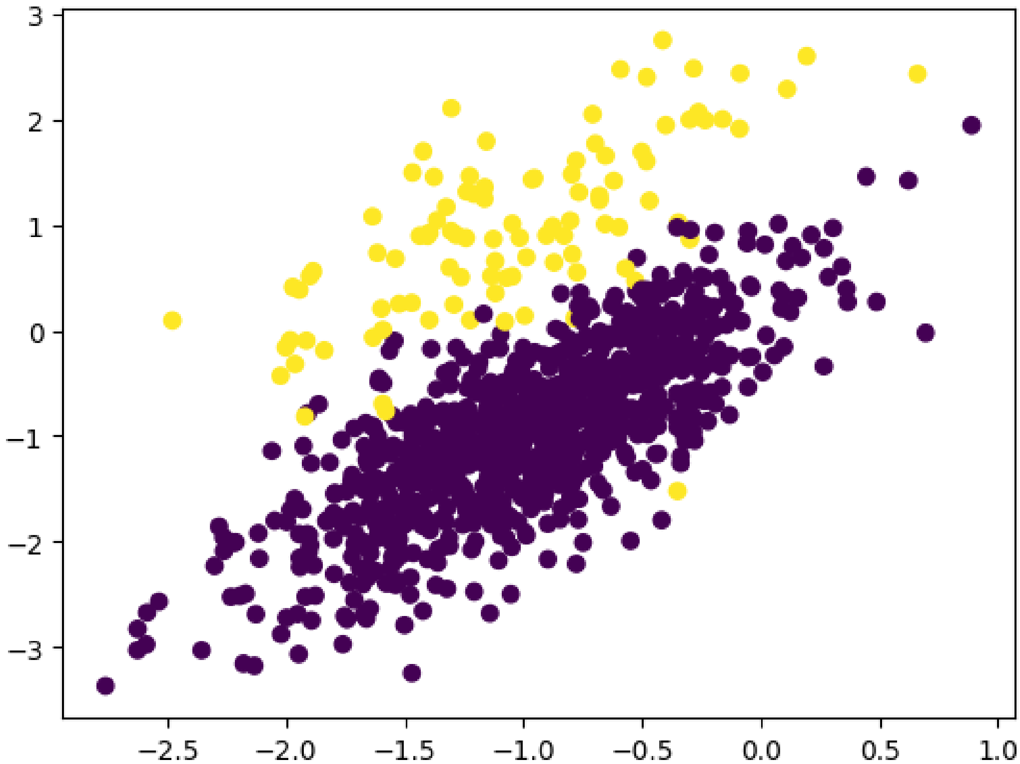
[74]:
```python
final_df.target.value_counts()
```

[74]:
```
target
0    900
1    100
Name: count, dtype: int64
```

[75]:
```python
import matplotlib.pyplot as plt

plt.scatter(final_df['f1'], final_df['f2'], c=final_df['target'])
```

[75]:
```
<matplotlib.collections.PathCollection at 0x132d87affa0>
```



[76]:
```
# !pip install imblearn
```

[77]:
```
from imblearn.over_sampling import SMOTE
```

[78]:
```
## Transform the dataset

oversample = SMOTE()
X,y = oversample.fit_resample(final_df[['f1', 'f2']], final_df['target'])
```

[79]:
```
X.shape, y.shape
```

[79]: ((1800, 2), (1800,))

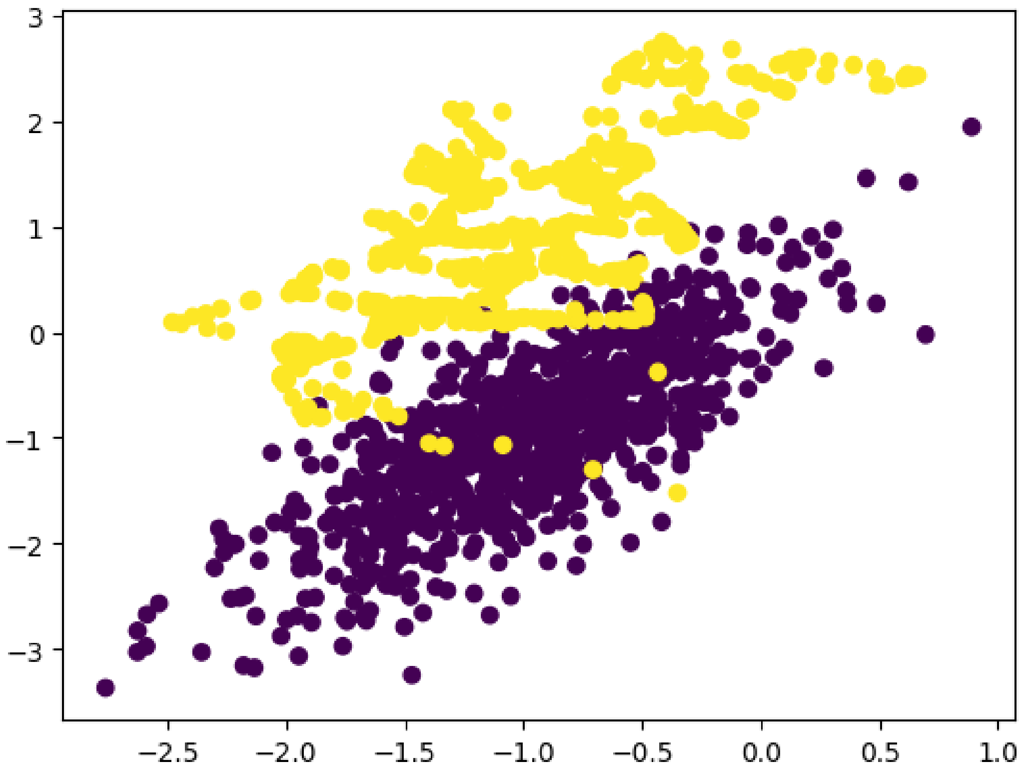
[80]:
```
len(y[y==0]), len(y[y==1])
```

[80]: (900, 900)

[81]:
```
df1 = pd.DataFrame(X, columns=['f1', 'f2'])
df2 = pd.DataFrame(y, columns=['target'])
oversample_df = pd.concat([df1,df2], axis=1)
```

[82]:
```
plt.scatter(oversample_df['f1'], oversample_df['f2'], c =␣
↪oversample_df['target'])
```

[82]: <matplotlib.collections.PathCollection at 0x132d8837070>



The yellow dots are representing the minority data previously now you can see that is the taking the two nearest data points and creating the new data points in between.