Methods to handle Imbalanced Datasets

Imbalanced Datasets

- Imbalanced datasets are a special case for classification problem where the class distribution is not uniform among the classes. Typically, they are composed by two classes: The majority (negative) class and the minority (positive) class

Imbalanced datasets can be found for different use cases in various domains:

- **Finance:** Fraud detection datasets commonly have a fraud rate of ~1–2%
- **Ad Serving:** Click prediction datasets also don't have a high clickthrough rate.
- **Transportation/Airline:** Will Airplane failure occur?
- **Medical:** Does a patient has cancer?
- **Content moderation:** Does a post contain NSFW content?

Import Necessary Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Data Ingestion to perform different sampling techniques

In [2]:
```
df = pd.read_csv('/content/drive/MyDrive/Projects/Credit Card Defaulter/creditcard.csv')
```

In [3]:
```
df = df.sample(n = 10000)
df.head()
```

Out[3]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26	V27	V28	Amou
151880	96431.0	-3.013289	-0.063993	-0.477127	-0.518490	0.504245	-0.606251	0.347949	0.895879	1.040650	...	-0.258792	-0.987856	-0.226383	0.512856	0.819863	-0.136745	-0.039184	-0.343886	133.4
67417	52524.0	1.256197	0.382598	0.314188	0.689831	-0.336645	-1.063868	0.113954	-0.226451	-0.027626	...	-0.282913	-0.797489	0.124441	0.356244	0.229427	0.093052	-0.020515	0.031711	1.9
241448	151031.0	1.871320	0.856649	-3.099026	3.048466	3.450256	3.715127	-0.170953	0.935592	-1.238025	...	-0.421857	-1.325685	0.344396	0.381318	-0.223819	-0.321475	0.013652	0.012921	15.0
248934	154163.0	-0.770565	0.761731	0.618994	1.010775	0.019008	0.807681	0.246049	0.633583	-0.066220	...	-0.368574	-0.915945	0.324773	-0.883694	-0.708756	-0.977528	0.055889	0.092501	68.0
231398	146745.0	-0.208718	0.706677	-0.501664	-0.446124	0.183556	-1.163360	0.927933	0.097723	-0.219148	...	-0.048686	-0.370857	0.342134	-0.152432	-0.617539	-0.733923	-0.063031	-0.021223	79.4

5 rows × 31 columns

In [4]:
```
df['Class'].value_counts()
```

Out[4]:
```
0    9990
1      10
Name: Class, dtype: int64
```

Segregating Independet and Dependent Variables

In [5]:
```
X = df.iloc[ : , : -1]
y = df.iloc[ : ,-1]
```

Observation:

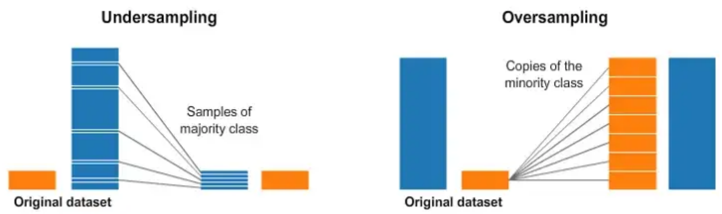
- Highly imbalanced dataset

1. Random Undersampling and Oversampling

- A widely adopted and perhaps the most straightforward method for dealing with highly imbalanced datasets is called resampling. It consists of removing samples from the majority class (under-sampling) and/or adding more examples from the minority class (over-sampling)

In [6]:
```
from PIL import Image
im = Image.open("/content/drive/MyDrive/FSDS_Job_Gurantee/Machine_Learning/Cheat Sheet/Handle Imbalanced Dataset/Random Undersampling and Oversampling.jpeg")
im
```

Out[6]:



In [7]:
```
num_0 = len(df[df['Class'] == 0])
num_1 = len(df[df['Class'] == 1])
print(num_0,num_1)
"""Random Undersampling"""
undersampled_data = pd.concat([df[df['Class'] == 0].sample(num_1) , df[df['Class'] == 1] ])
print(len(undersampled_data))
"""Random Oversampling"""
oversampled_data = pd.concat([ df[df['Class'] == 0] , df[df['Class'] == 1].sample(num_0, replace=True) ])
print(len(oversampled_data))
```

```
9990 10
20
19980
```

In [8]:
```
undersampled_data['Class'].value_counts()
```
Out[8]:
```
0    10
1    10
Name: Class, dtype: int64
```
In [9]:
```
oversampled_data['Class'].value_counts()
```
Out[9]:
```
0    9990
1    9990
Name: Class, dtype: int64
```

Observation:

- After random sampling data is equally distributed

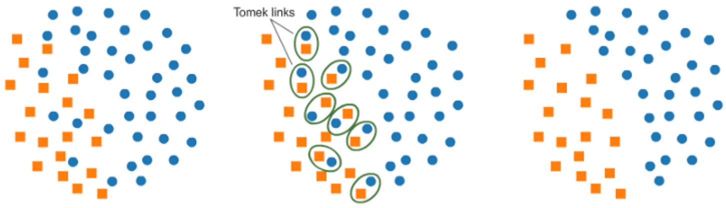
2. Undersampling and Oversampling using imbalanced-learn (SMOTE and TomekLinks)

- imbalanced-learn(imblearn) is a Python Package to tackle the curse of imbalanced datasets
- It provides a variety of methods to undersample and oversample

a. Undersampling using Tomek Links:

- One of such methods it provides is called Tomek Links. Tomek links are pairs of examples of opposite classes in close vicinity
- In this algorithm, we end up removing the majority element from the Tomek link, which provides a better decision boundary for a classifier

In [10]:
```
from PIL import Image
im = Image.open("/content/drive/MyDrive/FSDS_Job_Gurantee/Machine_Learning/Cheat Sheet/Handle Imbalanced Dataset/TomekLinks.jpeg")
im
```
Out[10]:



In [11]:
```
from imblearn.under_sampling import TomekLinks
tl = TomekLinks(sampling_strategy = 'majority')
X_tl, y_tl = tl.fit_resample(X, y)
```
In [12]:
```
pd.DataFrame(y_tl).value_counts()
```
Out[12]:
```
Class
0        9986
1          10
dtype: int64
```

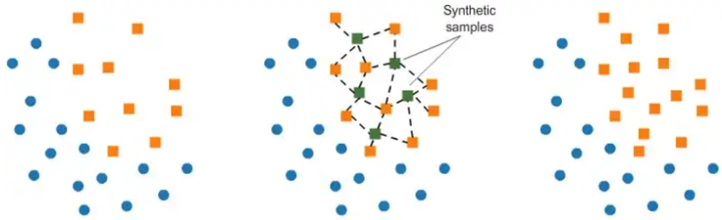
Observation:

- Only 5 data points from majority class was in close vicinity with minoriy class and and those are reduced from the majority class

b. Oversampling using SMOTE:

- In SMOTE (Synthetic Minority Oversampling Technique) we synthesize elements for the minority class, in the vicinity of already existing elements

In [13]:
```
from PIL import Image
im = Image.open("/content/drive/MyDrive/FSDS_Job_Gurantee/Machine_Learning/Cheat Sheet/Handle Imbalanced Dataset/SMOTE.jpeg")
im
```
Out[13]:



In [14]:
```
from imblearn.over_sampling import SMOTE
smote = SMOTE(sampling_strategy = 'minority')
X_sm, y_sm = smote.fit_resample(X, y)
```
In [15]:
```
pd.DataFrame(y_sm).value_counts()
```
Out[15]:
```
Class
0        9990
1        9990
dtype: int64
```

Observation:

- Both the class is equally distributed now

Note:

- There are a variety of other methods in the imblearn package for both undersampling(Cluster Centroids, NearMiss, etc.) and oversampling(ADASYN and bSMOTE) that you can check out

3. Class weights in the models

- Most of the machine learning models provide a parameter called class_weights. For example, in a random forest classifier using, class_weights we can specify a higher weight for the minority class using a dictionary

In [16]:
```
from PIL import Image
im = Image.open("/content/drive/MyDrive/FSDS_Job_Gurantee/Machine_Learning/Cheat Sheet/Handle Imbalanced Dataset/class_weight.jpeg")
im
```

Out[16]:

Example:

```
from sklearn.linear_model import LogisticRegression
clf = LogisticRegression(class_weight={0:1,1:10})
```

But what happens exactly in the background?

In logistic Regression, we calculate loss per example using binary cross-entropy:

```
Loss = −ylog(p) − (1−y)log(1−p)
```

In this particular form, we give equal weight to both the positive and the negative classes. When we set class_weight as class_weight = {0:1,1:20}, the classifier in the background tries to minimize:

```
NewLoss = −20*ylog(p) − 1*(1−y)log(1−p)
```

So what happens exactly here?

- If our model gives a probability of 0.3 and we misclassify a positive example, the NewLoss acquires a value of -20log(0.3) = 10.45
- If our model gives a probability of 0.7 and we misclassify a negative example, the NewLoss acquires a value of -log(0.3) = 0.52

That means we penalize our model around twenty times more when it misclassifies a positive minority example in this case

Note:

- How can we compute class_weights?
  - There is no one method to do this, and this should be constructed as a hyperparameter search problem for your particular problem

4. Change your Evaluation Metric

- Choosing the right evaluation metric is pretty essential whenever we work with imbalanced datasets. Generally, in such cases, the F1 Score is what I want as my evaluation metric
- The F1 score is a number between 0 and 1 and is the harmonic mean of precision and recall

$$F_1 = 2 * \frac{precision * recall}{precision + recall}$$

Example:

- How does it help?
- Let us start with a binary prediction problem. We are predicting if an asteroid will hit the earth or not
- So we create a model that predicts "No" for the whole training set
- What is the accuracy(Normally the most used evaluation metric)?
  - It is more than 99%, and so according to accuracy, this model is pretty good, but it is worthless.
- what is the F1 score?
  - Our precision here is 0. What is the recall of our positive class? It is zero. And hence the F1 score is also 0.
  - And thus we get to know that the classifier that has an accuracy of 99% is worthless for our case. And hence it solves our problem.
- Simply stated the F1 score sort of maintains a balance between the precision and recall for your classifier. If your precision is low, the F1 is low, and if the recall is low again, your F1 score is low.

5. Miscellaneous

- Various other methods might work depending on your use case and the problem you are trying to solve:
- **Collect more Data**
  - This is a definite thing you should try if you can. Getting more data with more positive examples is going to help your models get a more varied perspective of both the majority and minority classes
- **Treat the problem as anomaly detection**
  - Anomaly detection is the identification of rare items, events or observations which raise suspicions by differing significantly from the majority of the data
  - You can use Isolation forests or autoencoders for anomaly detection.
- **Model-based**
  - Some models are particularly suited for imbalanced datasets.
  - For example, in boosting models, we give more weights to the cases that get misclassified in each tree iteration

Conclusion

- There is no fixed methods to handle imbalanced datasets. Choose the methods depends on the problem statement
- In this notebook, I have listed all the widely used methods to handle imbalanced datasets with practical