



SYNTHETIC MINORITY OVERSAMPLING TECHNIQUE

IMBALANCED DATASET

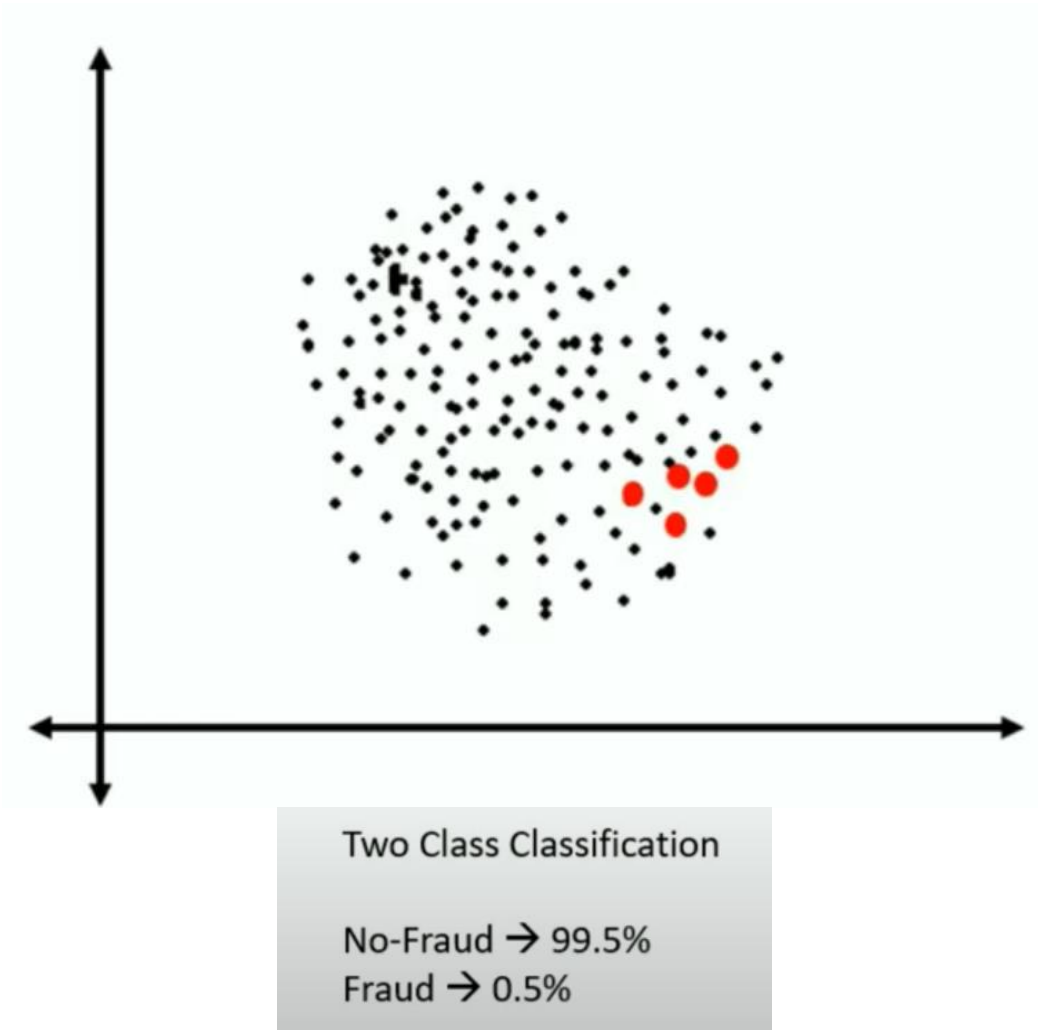
- This dataset is **unbalanced**.

```
data.head()
```

| | buying | maint | doors | persons | lug_boot | safety | outcome |
|---|--------|-------|-------|---------|----------|--------|---------|
| 0 | vhigh | vhigh | 2 | 2 | small | low | unacc |
| 1 | vhigh | vhigh | 2 | 2 | small | med | unacc |
| 2 | vhigh | vhigh | 2 | 2 | small | high | unacc |
| 3 | vhigh | vhigh | 2 | 2 | med | low | unacc |
| 4 | vhigh | vhigh | 2 | 2 | med | med | unacc |

Before SMOTE : Counter({'unacc': 839, 'acc': 282, 'good': 48, 'vgood': 40})

IMBALANCED DATASET



- Presence of minority class in the dataset
- Challenges related Imbalanced Dataset
 - Biased predictions
 - Misleading accuracy
- Some Examples
 - Credit card frauds
 - Manufacturing defects
 - Rare diseases diagnosis
 - Natural disasters
 - Enrolment to premier institutes

HOW TO SOLVE THE PROBLEM?

- Balance the classes by Increasing minority or decreasing majority
- Random Under-Sampling
 - Randomly remove majority class observations
 - Helps balance the dataset
 - Discarded observations could have important information
 - May lead to bias
- Random Over-Sampling
 - Randomly add more minority observations by replication
 - No information loss
 - Prone to overfitting due to copying same information

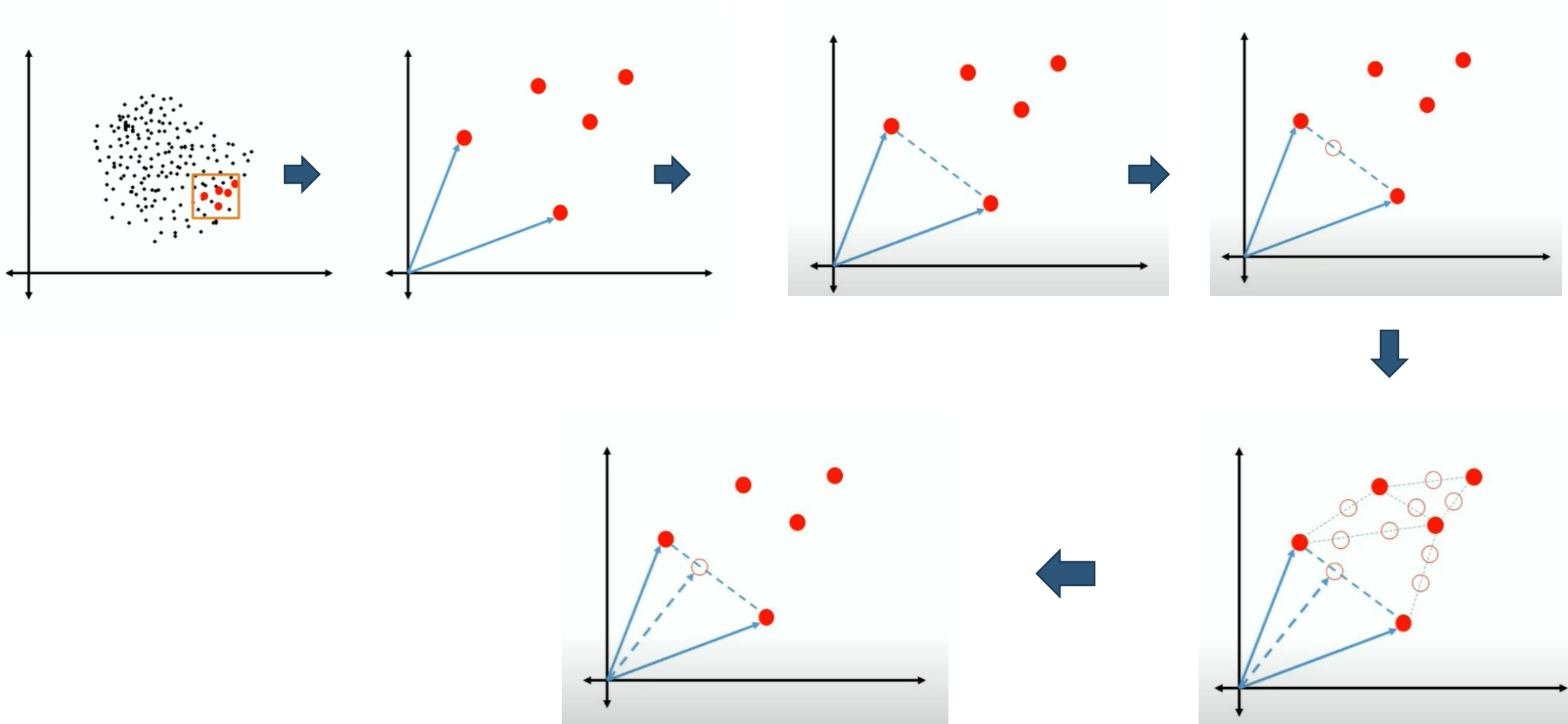
Total Observations = 1,000
Fraudulent = 10 or 1%
Normal = 990 or 99%

Reduce normal to 90
Fraudulent = 10 or 10%

Total Observations = 1,000
Fraudulent = 10 or 1%
Normal = 990 or 99%

Increase fraudulent by 100
Fraudulent 110 or 10%

SMOTE



HOW TO SOLVE THE PROBLEM?

- Synthetic Minority Oversampling Technique
- Creates new “Synthetic” observations
- SMOTE Process
 - Identify the feature vector and its nearest neighbour
 - Take the difference between the two
 - Multiply the difference with a random number between 0 and 1
 - Identify a new point on the line segment by adding the random number to feature vector
 - Repeat the process for identified feature vectors

HOW TO SOLVE THE PROBLEM?

x belongs to A

- **Step 1:** Setting the minority class set **A**, for each $x \in A$, the **k-nearest neighbors of x** are obtained by calculating the **Euclidean distance** between **x** and every other sample in set **A**.
- **Step 2:** The sampling rate **N** is set according to the imbalanced proportion. For each $x \in A$, **N** examples (i.e x_1, x_2, \dots, x_n) are randomly selected from its k-nearest neighbors, and they construct the set A_1 .

x belongs to A
- **Step 3:** For each example $x_k \in A_1$ ($k=1, 2, 3 \dots N$), the following formula is used to generate a new example:
$$x' = x + rand(0, 1) * |x - x_k|$$
in which $rand(0, 1)$ represents the random number between 0 and 1.

SYNTHETIC MINORITY OVERSAMPLING TECHNIQUE

- **Imbalanced classification** involves developing predictive models on classification datasets that have a **severe** class imbalance.
- The challenge of working with imbalanced datasets is that most machine learning techniques will ignore, and in turn have poor performance on, the minority class, although typically it is **performance on the minority class that is most important**.
- One way to solve this problem is to oversample the examples in the minority class.
- The simplest approach involves **duplicating examples in the minority class, although these examples don't add any new information to the model**.
- This can balance the class distribution but does not provide any additional information to the model.
- An improvement on duplicating examples from the minority class is to **synthesize new examples from the minority class**.
- This is a type of **data augmentation** for **tabular data** and can be very **effective** and is referred to as the **Synthetic Minority Oversampling Technique** or **SMOTE** for short.

SYNTHETIC MINORITY OVERSAMPLING TECHNIQUE

- SMOTE works by selecting examples that are close in the **feature space**, **drawing a line between the examples** in the feature space and **drawing a new sample at a point along that line**.
- Specifically, a **random example** from the **minority class is first chosen**.
- Then **k of the nearest neighbors** for that example are found (typically $k = 5$).
- A **randomly selected neighbor is chosen** and a **synthetic example** is created at a **randomly selected point between the two examples** in feature space.

BALANCED DATASET

- This dataset is **balanced**.

```
data.head()
```

| | buying | maint | doors | persons | lug_boot | safety | outcome |
|---|--------|-------|-------|---------|----------|--------|---------|
| 0 | vhigh | vhigh | 2 | 2 | small | low | unacc |
| 1 | vhigh | vhigh | 2 | 2 | small | med | unacc |
| 2 | vhigh | vhigh | 2 | 2 | small | high | unacc |
| 3 | vhigh | vhigh | 2 | 2 | med | low | unacc |
| 4 | vhigh | vhigh | 2 | 2 | med | med | unacc |

Before SMOTE : Counter({'unacc': 839, 'acc': 282, 'good': 48, 'vgood': 40})

After SMOTE : Counter({'acc': 839, 'unacc': 839, 'vgood': 839, 'good': 839})



THANK YOU



ARUNKG99@GMAIL.COM



WWW.DOITSKILLS.COM