Importance of class balance in training a classification model

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Table of contents

When building a **classification model**, one of the most important — and often overlooked — aspects is **class balance**. Class balance refers to how evenly distributed the categories (or classes) in our dataset are. Getting this wrong can cause our model to fail silently, producing high accuracy but poor performance in practice.

## What is Class Balance and Why Does it Matter?

Imagine you’re training a model to detect credit card fraud. Out of 100,000 transactions, maybe only 500 are fraudulent — that’s **0.5% fraud cases vs. 99.5% normal cases**. This dataset is **imbalanced**, because one class (normal transactions) dominates the other. On the other hand, if you had 50,000 fraud cases and 50,000 normal cases, the dataset would be **balanced**, meaning each class contributes equally to training.

1. **Misleading Accuracy**
	* If 99.5% of your data is “normal,” a model that predicts *everything as normal* would be **99.5% accurate** — but it’s useless for catching fraud.
2. **Biased Learning**
	* Machine learning algorithms tend to optimize for the majority class, learning little to nothing about the minority class.
3. **Real-World Risks**
	* In fraud detection, medical diagnosis, or spam filtering, the minority class is usually the one we *care about most*. Missing these cases can have huge consequences.

## Strategies to Handle Class Imbalance

### 1. **Resampling Techniques**

* **Oversampling minority class** (e.g., SMOTE — Synthetic Minority Oversampling Technique)
* **Undersampling majority class** to reduce dominance

Useful when we want to directly modify the training dataset.

### 2. **Algorithmic Approaches**

* Use models that handle imbalance better, like **tree-based models** (Random Forest, XGBoost) with class weights.
* Adjust **class weights** in algorithms (e.g., class\_weight='balanced' in scikit-learn).

### 3. **Evaluation Metrics Beyond Accuracy**

Accuracy isn’t enough. We use:

* **Precision & Recall** (focus on the minority class)
* **F1-score** (balance between precision & recall)
* **ROC-AUC / PR-AUC** (good for imbalance scenarios)

### 4. **Data Collection & Domain Knowledge**

Sometimes the best solution is **collecting more samples of the minority class** or applying **domain-specific rules** to aid the model.

## Randomization

Another desirable characteristic we want in the data is the randomization of all classes. If your dataset is ordered (e.g., first all “Class 0” rows, then all “Class 1” rows), most machine learning algorithms will process it sequentially. Without randomization (shuffling), we risk:

* The model learning from only one class at the start, delaying convergence.
* Batch-based algorithms (like stochastic gradient descent, mini-batch training) seeing batches with only one class implies poor updates.

Solution: We should shuffle our data before splitting into train/test and before feeding into training.

* In *scikit-learn*: train\_test\_split(..., shuffle=True) (default).
* In *PyTorch / TensorFlow*: DataLoader(..., shuffle=True).

Randomization is crucial before splitting, otherwise we may end up with:

* Train set = only majority class
* Test set = only minority class

leading to meaningless evaluation. So, we should always shuffle, and in imbalanced data, consider stratified splitting (preserves class ratios in both sets: train\_test\_split(X, y, stratify=y))

## Example

Let’s explain everything with the famous *IRIS* dataset from the seaborn library.

import torch
import torch.nn as nn
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model\_selection import train\_test\_split
iris = sns.load\_dataset('iris')
data = torch.tensor(iris[iris.columns[0:4]].values).float()
labels = torch.zeros(len(data), dtype=torch.long)
labels[iris.species=='versicolor']=1
labels[iris.species=='virginica']=2
sns.countplot(x="species", data=iris)
print(labels)

tensor([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
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 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
 2, 2, 2, 2, 2, 2])



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| --- |
|  Important |
| As we can see that the number of observation is 150. So, if we just directly split this data into 70-30 or 80-20 training-test ratio then the training data will be an imbalanced data. |

trainProp = 0.8
numTrainData = int(len(labels)\*trainProp)
trainTestB = np.zeros(len(labels), dtype=bool)
trainTestB[range(numTrainData)] = True
trainTestB

array([ True, True, True, True, True, True, True, True, True,
 True, True, True, True, True, True, True, True, True,
 True, True, True, True, True, True, True, True, True,
 True, True, True, True, True, True, True, True, True,
 True, True, True, True, True, True, True, True, True,
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 True, True, True, True, True, True, True, True, True,
 True, True, True, True, True, True, True, True, True,
 True, True, True, False, False, False, False, False, False,
 False, False, False, False, False, False, False, False, False,
 False, False, False, False, False, False, False, False, False,
 False, False, False, False, False, False])

Let’s check if the dataset is balanced

print('Class average in full dataset')
print(torch.mean(labels.float()))
print('')
print('Class average in the training proportion')
print(torch.mean(labels[trainTestB].float()))
print('')
print('Class average in the test proportion')
print(torch.mean(labels[~trainTestB].float()))

Class average in full dataset
tensor(1.)

Class average in the training proportion
tensor(0.7500)

Class average in the test proportion
tensor(2.)

|  |
| --- |
|  Note |
| Note that the average in all cases should be either 1 or very close to one, as we have 0,1, and 2 classes. |

actualTrain = np.random.choice(range(len(labels)), numTrainData, replace=False)
trainTestB = np.zeros(len(labels), dtype=bool)
trainTestB[actualTrain] = True
print('Class average in the training proportion')
print(torch.mean(labels[trainTestB].float()))
print('')
print('Class average in the test proportion')
print(torch.mean(labels[~trainTestB].float()))

Class average in the training proportion
tensor(0.9917)

Class average in the test proportion
tensor(1.0333)

Modeling

iris\_classifier = nn.Sequential(
 nn.Linear(4, 64),
 nn.ReLU(),
 nn.Linear(64,64),
 nn.ReLU(),
 nn.Linear(64,3)
)
loss\_fun = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(iris\_classifier.parameters(), lr=0.01)

Data Structure

print('Full data shape')
print(data.shape)
print(' ')
print('Training data shape')
print(data[trainTestB, :].shape)
print(' ')
print('Test data shape')
print(data[~trainTestB, :].shape)

Full data shape
torch.Size([150, 4])

Training data shape
torch.Size([120, 4])

Test data shape
torch.Size([30, 4])

Next, train and test the model

nEpochs = 1000
losses = torch.zeros(nEpochs)
accuracy\_track = []

for epoch in range(nEpochs):
 # forward pass
 yHat = iris\_classifier(data[trainTestB,:])
 # compute accuracy
 accuracy\_track.append(
 100\*torch.mean(
 (torch.argmax(yHat, axis=1)==labels[trainTestB]
 ).float())
 )
 # compute loss
 loss = loss\_fun(yHat, labels[trainTestB])
 losses[epoch] = loss

 # back propagation
 optimizer.zero\_grad()
 loss.backward()
 optimizer.step()

After training, now we can use our model to compute train and test accuracies

pred = iris\_classifier(data[trainTestB, :])
training\_accuracy = 100 \* torch.mean(
 (torch.argmax(pred, axis=1)==labels[trainTestB]).float()
)
pred = iris\_classifier(data[~trainTestB, :])
test\_accuracy = 100 \* torch.mean(
 (torch.argmax(pred, axis=1)==labels[~trainTestB]).float()
)
print('Accuracy on training data: %g%%' %training\_accuracy)
print('Accuracy on test data: %g%%' %test\_accuracy)

Accuracy on training data: 98.3333%
Accuracy on test data: 100%

Instead of manual splitting, we could also use sklearn library and obtain similar results

def modeling():
 iris\_classifier = nn.Sequential(
 nn.Linear(4, 64),
 nn.ReLU(),
 nn.Linear(64,64),
 nn.ReLU(),
 nn.Linear(64,3)
 )
 loss\_fun = nn.CrossEntropyLoss()
 optimizer = torch.optim.SGD(iris\_classifier.parameters(), lr=0.01)
 return iris\_classifier, loss\_fun, optimizer

nEpochs = 200
X\_train, X\_test, y\_train, y\_test = train\_test\_split(
 data, labels, train\_size=trainProp
 )
def model\_training():
 losses = torch.zeros(nEpochs)
 training\_accuracy = []
 test\_accuracy = []
 for epoch in range(nEpochs):
 # forward pass
 yHat = iris\_classifier(X\_train)
 loss = loss\_fun(yHat, y\_train)

 # back propagation
 optimizer.zero\_grad()
 loss.backward()
 optimizer.step()

 # compute training accuracy
 training\_accuracy.append(
 100\*torch.mean((torch.argmax(yHat, axis=1)==y\_train).float()).item()
 )
 # compute test accuracy
 predtest = torch.argmax(iris\_classifier(X\_test), axis=1)
 test\_accuracy.append(
 100\*torch.mean((predtest==y\_test).float()).item()
 )
 return training\_accuracy, test\_accuracy

Now we re-train the model

iris\_classifier, loss\_fun, optimizer = modeling()
train\_acc, test\_acc = model\_training()
plt.plot(train\_acc, 'r-', label='train')
plt.plot(test\_acc, 'b-', label='test')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()



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