Methods

#### Topics

1. Multiclass classification
2. One-class classification
3. Multi-Label Classification
4. Ensemble Learning

* Boosting and Bagging
  + Random Forest
  + Gradient Boosting

1. Learning to Label Sequences
2. Sequence-to-Sequence Learning
3. Active Learning
4. Semi-Supervised Learning
5. One-Shot Learning
6. Zero-Shot Learning

# 1. Multiclass Classification

For multiclass classification problems, we extend the logistic regression to **softmax regression algorithm.** This is done by replacing sigmoid function in logistic regression with softmax function.

The loss function in softmax regression is typically the cross-entropy loss (also known as log-loss). Given a set of training examples, the cross-entropy loss measures the dissimilarity between the predicted probabilities and the true class labels.

- log a1, if y == 1

- log a2, if y == 2

L = :

:

- log an, if y == n

Where aj = ezj / ΣNk=1 = P(y = j | x) , where N is the number of classes

# 2. One class classification

One-class classification, also known as unary classification or class modeling, tries to identify objects of a specific class among all objects, by learning from a training set containing only the objects of that class. The most widely used in practice are one-class Gaussian, one-class k-means, one-class kNN, and one-class SVM.

# 3. Multi-Label Classification

In some situations, more than one label is appropriate to describe an example from the dataset. In this case, we talk about the multi-label classification. The only difference with the usual multiclass problem is that now we have a new hyperparameter: **threshold**. If the prediction score for some label is above the threshold, this label is predicted for the input feature vector. In this scenario, multiple labels can be predicted for one feature vector.

# 4. Ensemble learning

Ensemble learning is a learning paradigm that, instead of trying to learn one super-accurate model, focuses on training a large number of low-accuracy models and then combining the predictions given by those weak models to obtain a high-accuracy **meta-model.**

Low-accuracy models are usually learned by weak learners, that is, learning algorithms that cannot learn complex models, and thus are typically fast at the training and at the prediction time. The most frequently used weak learner is a decision tree learning algorithm in which we often stop splitting the training set after just a few iterations. The obtained trees are shallow and not particularly accurate, but the idea behind ensemble learning is that if the trees are not identical and each tree is at least slightly better than random guessing, then we can obtain high accuracy by combining a large number of such trees. To obtain the prediction for input x, the predictions of each weak model are combined using some sort of **weighted voting**. Two principal ensemble learning methods are boosting and bagging.

#### Boosting and Bagging

**Boosting** consists of using the original training data and iteratively creating multiple models by using a weak learner. Each new model would be different from the previous ones in the sense that the weak learner, by building each new model tries to “fix” the errors which previous models make. The final ensemble model is a certain combination of those multiple weak models built iteratively.

**Bagging** consists of creating many “copies” of the training data (each copy is slightly different from another) and then apply the weak learner to each copy to obtain multiple weak models and then combine them. A widely used and effective machine learning algorithm based on the idea of bagging is random forest.

#### Random Forest

Random Forest is a **specific implementation of bagging that is tailored for decision trees** and **incorporates feature randomness** to further enhance its performance and robustness. In a Random Forest, multiple decision trees are trained on different subsets of the data using sampling with replacement and with random feature subsets. The predictions from these individual trees are then combined to make a final prediction, typically through a majority vote for classification tasks or averaging for regression tasks.

Random forest is one of the most widely used ensemble learning algorithms. The reason is that by using multiple samples of the original dataset, we reduce the variance of the final model, lowering overfitting.

#### Gradient Boosting

Gradient boosting is a modified boosting algorithm that implements a gradient descent (in a non traditional way) to calculate the error caused by the ensemble trees. This error is used to update the trees, training the model and reducing the error. However, instead of getting the gradient directly, we use its proxy in the form of residuals: they show us how the model has to be adjusted so that the error (the residual) is reduced. It reduces underfitting, but can lead to overfitting. So careful selection of hyperparameters is adviced.

Gradient boosting is one of the most powerful machine learning algorithms—not just because it creates very accurate models, but also because it is capable of handling huge datasets with millions of examples and features. It usually outperforms random forest in accuracy but, because of its sequential nature, can be significantly slower in training.

# 5. Sequence-to-Sequence Learning

**Sequence Labeling** is the problem of labelling a sequence of data. For eg, classifying each word in a string to {‘noun’, ‘verb’, ‘adjective’}.

Sequence-to-Sequence learning (seq2seq learning) is a generalisation of the sequence labeling problem. The crux of the problem is to take in a sequence and output another sequence (of different length) according to the situation. Eg: text generation, machine translation, etc.