# **Random Forest from scratch**

interpreting the Math behind the 'Black Box'

## Motivation

Random Forest Ensembles are widely used for real-world machine learning problems, **Classification** as well as Regression. Their popularity can be attributed to the fact that practitioners often get **optimal results** using a Random Forest algorithm with **minimal data** cleaning, and no feature scaling.



## Motivation

Widely believed to be a black box, a quick walkthrough of the algorithm will prove it is actually quite interpretable, apart from being a powerful technique leveraging the **'power of the majority** vote'.



#### Introduction

- Random Forest Ensembles are a divide-and-conquer approach used to improve performance of individually weak Decision Tree models.
- The main principle behind this is that a group of "weak learners" can come together to form a "strong learner". Each classifier, individually, is a "weak learner," while all the classifiers taken together are a "strong learner".





### Random Forest Ensemble

- At the heart of the Random Forest concept is averaging the results from a number of Decision Trees.
- Decision Trees are often handy tools to explain the intuition behind a prediction to people unfamiliar with Machine Learning. But explaining how a Random Forest arrived at a prediction, and using which features or independent variables, can be quite a task. Random Forests are often misinterpreted as 'Black Boxes' or difficult to understand.





initial dataset

bootstrap samples + selected features deep trees fitted on each bootstrap sample and considering only selected features



## What is a Decision Tree?

- Decision tree is a simple, deterministic data structure for modelling decision rules for a specific classification problem.
- At each node, one feature is selected to make separating decision. We can stop splitting once the leaf node has optimally less data points.
- Such leaf node then gives us insight into the final result (Probabilities for different classes in case of classfication).

#### How does it split?

- The most decisive factor for the efficiency of a decision tree is the efficiency of its splitting process. We split at each node in such a way that the resulting **purity** is maximum.
- Well, purity just refers to how well we can segregate the classes and increase our knowledge by the split performed. An image is worth a thousand words. Have a look at the image below for some intuition:

#### Low Gini Coefficient (bad split) High-Risk upping Low-Risk Low-Risk Indicator 1 Known Low-Risk Customer High-Risk Indicator 2 Known High-Risk Customer



### Visualization

- Each split leads to a straight line classifying the dataset into two parts. Thus, the final decision boundary will consist of straight lines (boxes).
- Each split leads to a straight line classifying the dataset into two parts. Thus, the final decision boundary will consist of straight lines (or boxes).

## Easy use of Random Forest Classification

#### dzetsaka : Classification tool

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Fast and Easy Classification plugin for Qgis

Plugin for semi-automatic classification with Gaussian Mixture Model, Random Forest\*, and SVM\* classifiers. Very easy and fast to use. \*You need to install scitkit-learn library to use these algorithms. For more information on this tool check our github : https://github.com/lennepkade/dzetsaka/

 $\uparrow \uparrow \uparrow \uparrow \uparrow \uparrow \uparrow$  35 rating vote(s), 43805 downloads

Category	Raster					
Tags	classification,semi-automatic,gaussian,mixture,model,random forest,svm,knn,forest,processing					
More info	homepage bug tracker code repository					
Author	Nicolas Karasiak					
Installed version	3.4.8					
vailable version 3.4.8						
Changelog	<ul> <li>3.4.8</li> <li>* Fix errors when number of classes &gt; 44 (problem of datatype in sample extraction).</li> <li>3.4.7</li> <li>* Support more than 255 classes to predict (if n &gt; 255, raster datatype will be set to uint16)</li> <li>3.4.6</li> <li>* Minor fixes and remove SLOO training due to error in code</li> <li>3.4.5</li> <li>* Fix bug when predicting a raster with a previous model and no vector loaded in Qgis.</li> <li>3.4.4</li> </ul>					

Initially based on Gaussian Mixture Model classifier developped by <u>Mathieu Fauvel</u> (now supports Random Forest, KNN and SVM), this plugin is a more generalist tool than <u>Historical Map</u> which was dedicated to classify forests from old maps. This plugin has by developped by <u>Nicolas Karasiak</u>.

## Dzetsaka

• After plugin instalation

etsaka : classification tool	
	ATA
Photography by Guillaume Feuillet. PAG	
2	✓ or □ Load mod
3	✓ Model
Classification. Leave empty f	or temporary file
Perform the	classification
• Optional	
🕏 🗆 Mask	Automatic find filena
Confidence map	Map of confidence
🌢 🗆 Save model	To use with another
	Save confusion matri
Split (?)	100% 🗧

🔇 dzetsaka	: settings panel —	×			
Classifier :	Random Forest	`			
Temp suffix :	Gaussian Mixture Model Random Forest				
Temp prefix :	Support Vector Machines K-Nearest Neighbors				
Mask suffix :	_mask				
Providers :	Standard	``			

0, %

### Dzetsaka

#### • To install Random Forests



1. Open OsGeo shell in admin

#### 2. Run command: py3\_env.bat

Administrator: OSGeo4W Shell

run o-help for a list of available commands C:\Windows\System32≻py3\_env.bat\_

#### 3. Run command: pip install scikit-learn



### How to run Dzetsaka tool

- You need 1 raster and 1 shapefile
- So you need to create a **shapefile with a numeric column** where you save your classification number for each polygon. Here's a example

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		🥪 🥼 💽 ү 🖏 📲 🏹		
Class 1 2	Type Forest Rock	<ul> <li>✓ I training novi_sad</li> <li>✓ 1</li> <li>✓ 2</li> <li>✓ 3</li> <li>✓ 4</li> <li>✓ 5</li> <li>✓ ●</li> <li>✓ ■</li> <li>✓ sample_novi_sad</li> </ul>		
3	Water			
4	clouds			
5	Shadow			



