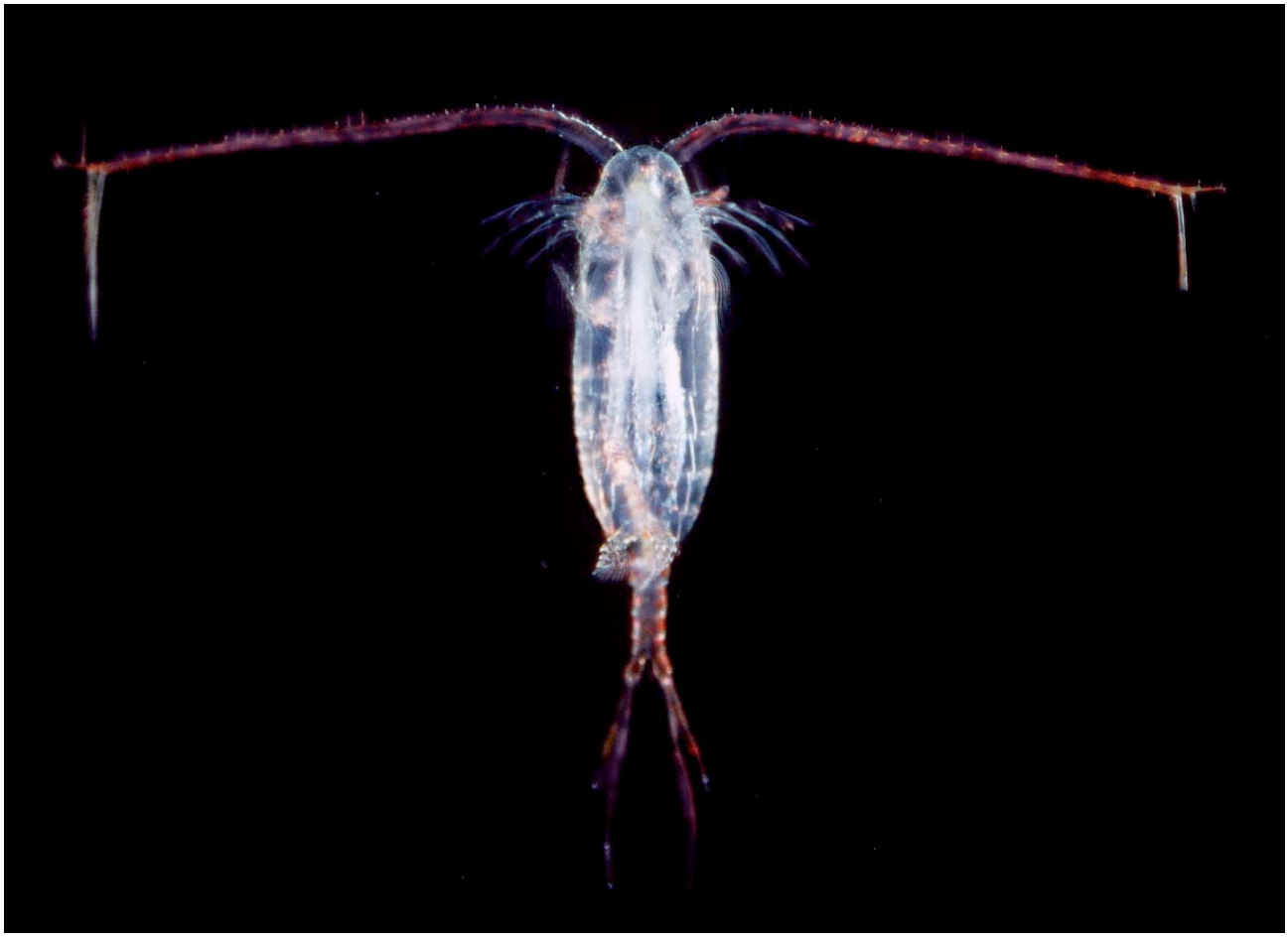


Gaiasavers - Ocean group

2020

Group members:

Model selection :
Michel Dit Ferrer Paul
Bournet Raphaël
Preprocessing :
Coquisart Jérôme
Garcia Pierre
Visualisation:
Dahalani Luqman
Marchment George (Leader)

Our GitHub repository
Project link, we've worked on the preprocessed data at first
Link to our Youtube video
Link to Visualisation notebook

Background and motivation

This semester, we're participating in a data science challenge. The goal of this project is to learn data science, including the fields of data visualisation, data preprocessing and model comparison.

This is also a great thing since we are learning how to work as a group of six. Especially learning tools such as Github, which is the first time for some of the members of the group.

Data and problem description

The goal of this project is to classify plankton (7 different types of plankton!) based on photographs using machine learning. We have a bank of 10752 images of plankton to train our algorithm on. We also have some previously extracted data of these photographs at disposal. It's a classification problem using pictures (pixel matrices) or feature with no restriction on model.

We will create what's called a classifier which goal is to learn given data (plankton images here) to be able to identify them from features which makes these data identifiable. Features can be anything like the length of a plankton on a given image, its shape, it's only defined as something which make an object identifiable.

Brief description of the classes

We splitted work in three tasks : preprocessing the data, select a proper classifier, extracting results from our algorithm. We assigned three separated teams for each of these tasks.

Before doing anything, we need to work on our data themselves before training our classifier. This is the objective of the preprocessing. This is a crucial part in any data science work since it will make our data features more significant by reducing the number of

useless ones. Hence, the preprocessing will increase the score of our model, which means that it will increase the proportion of properly identified data. Preprocessing will also reduce the execution time since there will be less useless features to work on for the classifier. Our images are extracted data from the raw-data set instead of the preprocessed set.

The selection team has to find the best classifier to work on the data preprocessed by the preprocessing team. There isn't a best classifier fitted for all sets of datas. Their objective is is to train the best classifier possible to return the best score and to find the best hyperparameters for this classifier with our given data.

The visualisation team must produce interesting graphs and models, to be able to extract valuable information from the algorithm or the results. Training a classifier is good but we also need to be able to visualize our results in order to see where our work is going. Science needs results to progress, this is where the visualisation team comes in.

Preprocessing

This section is about the Preprocessing work on the project.

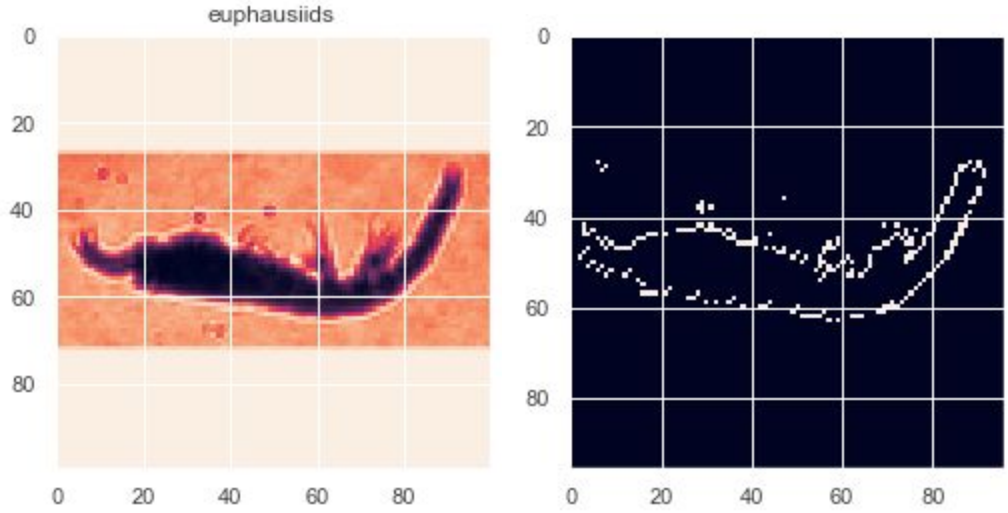
For the preprocessing we remove outliers using Local Outlier Factor. We are also extracting features from raw data images.

To work on these images, we need a classifier optimized for our set of data. We compare the performances of several classifier on our data to keep the best models. With these classifiers, we are able to create a more effective models called a Voting classifier which is able to make all of our submodels work at the same time and vote on each data to classify it.

We have to collect data on our algorithm. To do so, we've drawn different graphs using different algorithms, such as the learning curve showing the score based on the quantity of data to work with, the confusion matrix giving the score of each class of our data, and the clustering of the data, which mean we clustered data with common features together.

Feature extraction 1: derivatedImage: When applied twice to an image this algorithm extracts the plankton's border, and allow us to get it's perimeter, other data could be extracted as well. This is the first algorithm we used to extract.

This first extraction is important since we extracted a crucial feature on our data : the shape of the plankton.



graph A

This algorithm is a kind of adaptation of the sobol border extract algorithm.

This derivation algorithm works by giving to each pixel in the image the sum of the 4 surrounding (left right, down & up) pixel's brightness divided by the center pixel one's.

The first the derivation function comes, it gets the texture intensities close to zero and homogenised it. The second time, the division gets the resulting image pixel to be high if the pixel which divides is less bright than the ones around it.

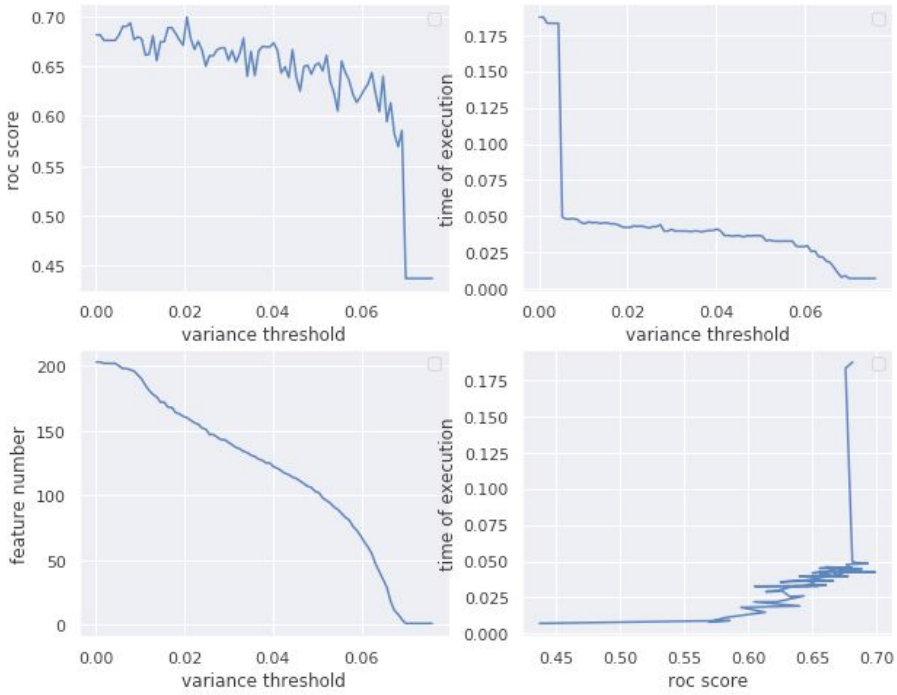
We plan to adapt the real sobol perimeter extraction algorithm and to try to implement so it runs on the GPU which will make feature extraction faster.

Variance threshold algorithm helped us to decide how many features to select.

So it made various feature selection changing the variance parameter on variance threshold selection algorithm. Then we trained a model on the various sets given. We then measured how many features it kept, how much time the model took to fit, finally how well it predicted.

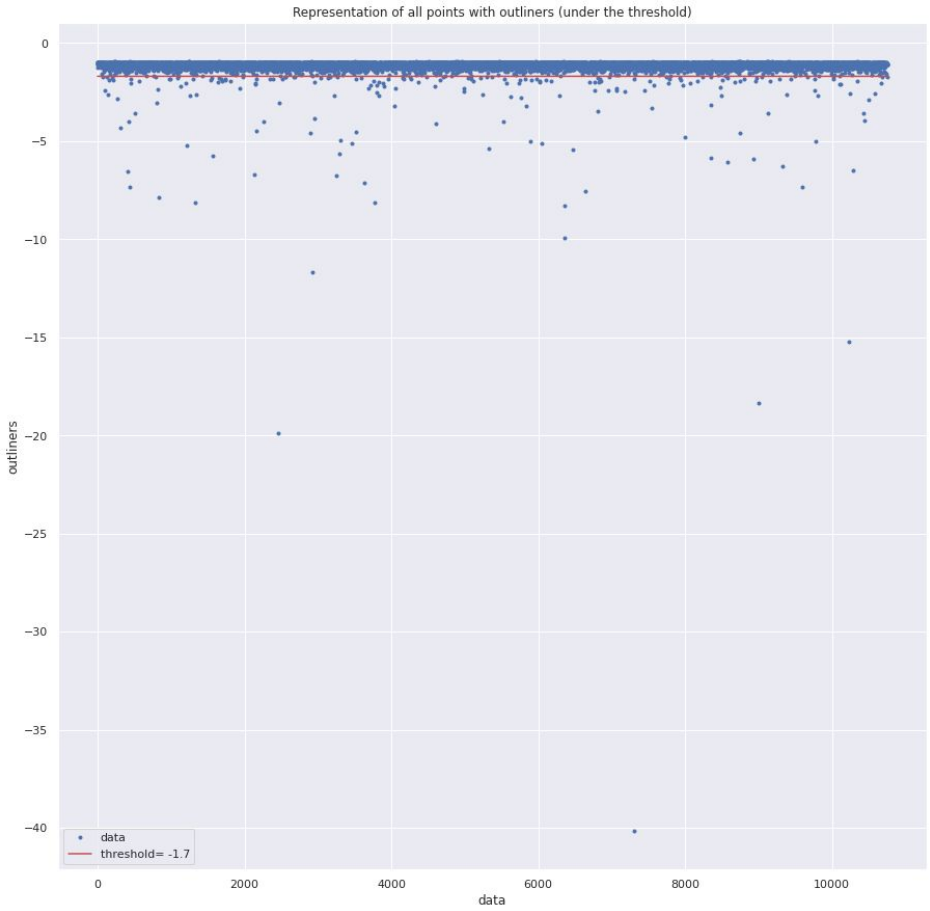
So we chose to represent it on 4 different curves (cf. graph B):

And we concluded we should use 175 feature as it got the best result and a big execution time loss.



graph B

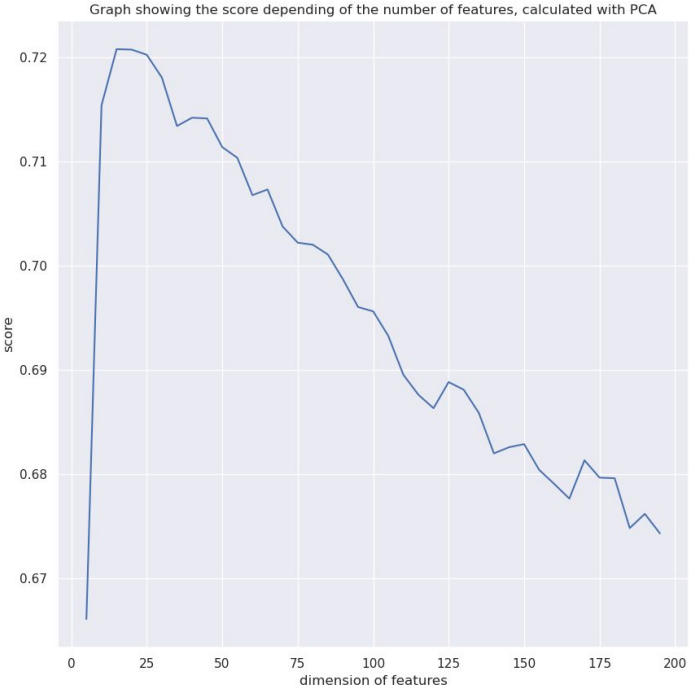
Let's look at the **LocalOutlierFactor** algorithm. The last step of preprocessing is to remove unnecessary data. Now that our database size is reduced, we can apply this function that will look at the neighbors of each data to determine if the data is isolated or not. Eventually, the algo gives a score to each data (cf. graph D).



graph D

We've manually set a threshold (in red in the graph) and every data under the threshold, which means every data isolated, will be deleted afterwards.

We have also tried some PCA algorithm. To select the best number of features, we tested the score for different feature dimension but the score was always worse than without PCA. Since the time of execution is not too long, we can forget PCA on this project.



graph E

This graph E shows that the best dimension for our features is around 25. It may be useful if we want to improve performance.

Model Selection

This section is about the Model Selection work on the project.

Even if the preprocessing team has done great work, we decide to stay on the originals features to begin with. Our objective is to find the best classifier for our problem. Firstly we looked on SKlearn on all the classifier we could use.

5 models captured our attention : Perceptron, GaussianNB, KNeighbors, DecisionTree and RandomForest.

It is possible to set these models with their best parameters to work on our set of data by using a library named GridSearchCV which will search the best hyperparameters for us.

We proceeded to compare their respective performances on our set of data using cross-validation.

We divided our data into to separated sets : a training set of data, and a testing set of data. The objective is to train our models on the training set, then, to test their performances on the testing set, this is very important to avoid overfitting.

The performance value evaluate the rate for successful predictions on the data of the model. As we can see GaussianNB, KNeighbors and RandomForest are the best models (cf Table 2 below).

As our models have low performances, we tried a voting system where our best models would be set as voters. For each evaluation on the data, each voter would give a prediction, the prediction with the highest vote would be the one chose by the model.

Modèle	Performances
Voting	0.2589

This model has mediocre performances. Even if it certainly has high potential, this one might be hard to use to set its parameters. We realised that it was harder than juste put all the model we wanted in the voting classifier. So we chose to focus on finding the best parameter for the RandomForestClassifier, which already has more than decent performances, than try to understand how the voting classifier works.

The **Random Forest Classifier** consists in a forest of decision trees. Each of these trees are composed of branch taking decision to decide the class of each data. Each tree is submitting a vote on the class of the datum to decide how to classify it.

The particularity of the random Forest is that if you don't fix the randomSeed, each fit is different.

In order to show how precise our algorithm is, we need to show the result of many tries.

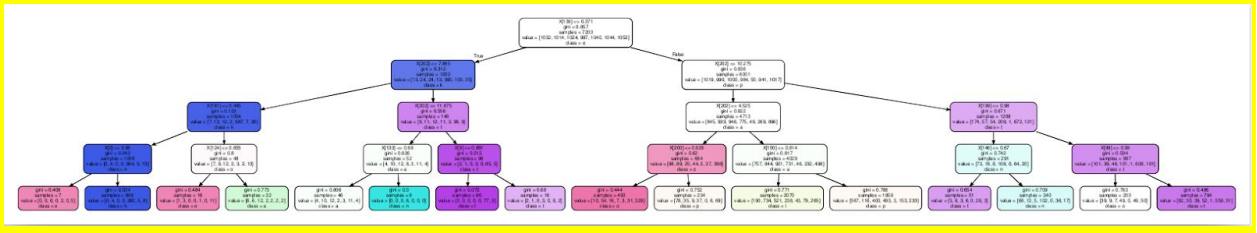
We launch our program 5 times and here are the results :

Try 1	0.7804262090167626
Try 2	0.7742394916470391
Try 3	0.7784480441540652
Try 4	0.7803140758097683
Try 5	0.781021546560843

The average is 0.77889 and the standard deviation is 0.00248, this show that our algorithm is quite precise

A DecisionTree works by asking question, in which there is a binary response (yes/no). Depending on the result, the classified image go in one of the two child branch. And after a certain number of question, the decision tree can determine which class the image came from.

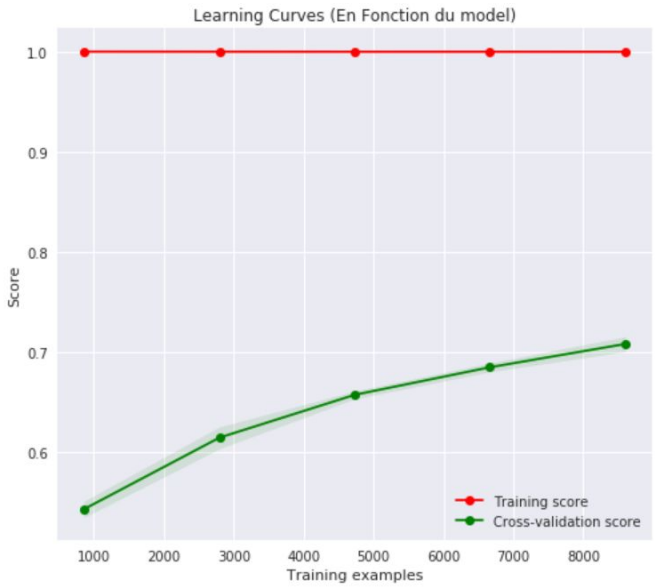
There is a little and none accurate example :



We chose for the exemple to go to a max depth of 5 so it's stay readable. But in our algorithm each Decision Tree is too deep to be shown.

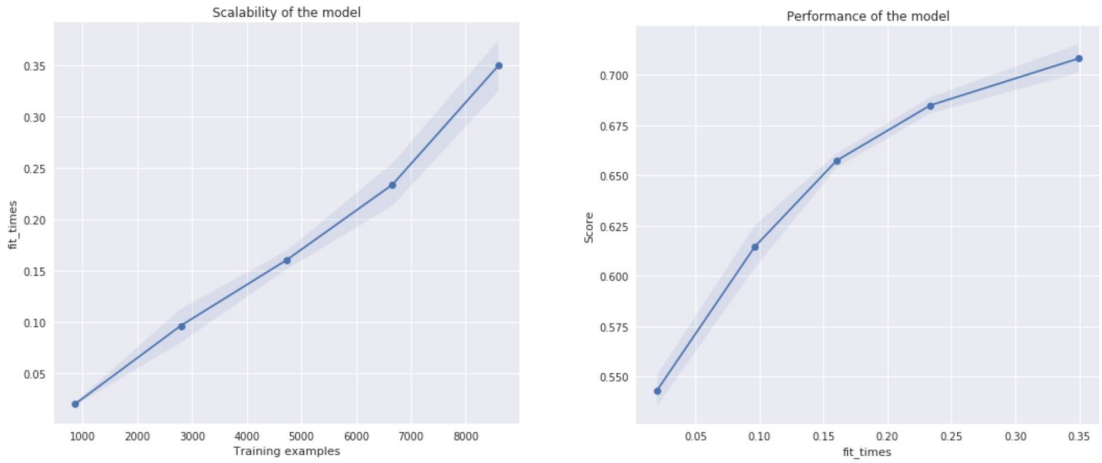
Graphs to show our results

The learning curve graphs (cf. graph F) shows the score (training score and cross-Validation score) of the model as a function of the size of the training set.



graph F

We also have 2 other graphs: one that shows the time of execution as a function of the training set (cf. graph G), and the other the score as a function of the time of execution (cf. graph G).



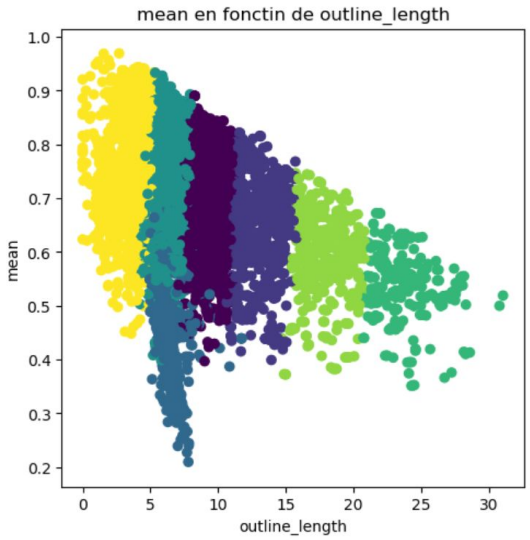
graph G

One of the best advantage of RandomForest is that it's hard to overfit. So during the research of the best parametres we also looked on which size of data we need to use for the best training. We realised that we can use the all data set without overfit.

Visualisation

This section is about the Visualisation work on the project.

The goal of the **clustering** of the data, is to be able to see different patterns in the data to ease the prediction of the model to hopefully get a smaller error rate, which means a better score. To do this we use K Means (cf. graph H).

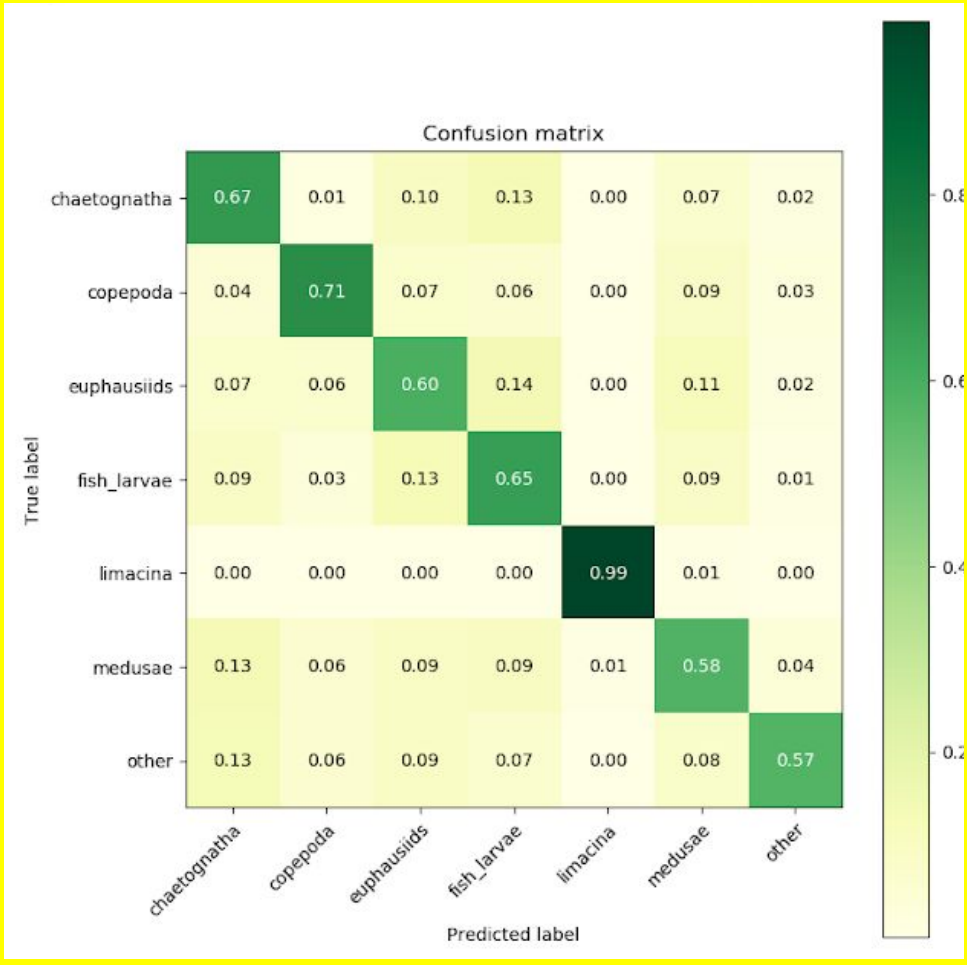


graph H

Here we have the clustering of the data (mean as a function of outline_length), when we actually looked at the labels in the 7 different clusters, we saw that the purple cluster was able to identify the 90% limacina plankton, with an error rate of 7%. This is something that we can use later on to be able to get a better score.

We can also make a **confusion matrix** showing the performances of our models on the different data (cf. graph I).

Each column represents the result of the model for one species , and each Line represents what the model identified for that species. The diagonal hence represents the frequency of the correct identifications.



graph U

The diagonal always shows the best scores by far. This shows our model has good performance.

Python classes

This section explains what we have done after testing each part (Preprocessing & Model Selection) separately.

Our code is now under the form of Python classes instead of notebook pages. This allow more flexibility on the usage of our functions. It's now easier to deploy and use our algorithm as we only have to import our classes. Our 'model.py' file is able to both call the preprocessing of the datas and to train the model on preprocessed data.

We can preprocess our datas with the preprocessing class. Our BestClf and BestParam classes are able to find the best classifier with the best parameters in a given list. The best model is then initialized with the model class. We also have a class to test our model in 'model.py'.

Tests are verifying our model is working properly. We first test our scoring_function supposed to return the score of our model. Then, we use it to verify our parameters are relevant and are increasing the score of our model.

Conclusion

As we can see we are first on the leaderBoard (cf graph H) with a score of 0.73, which means we can correctly identify the right species of a given plancton 73% of the time.

RESULTS

#	User	Entries	Date of Last Entry	Prediction score ▲	Duration ▲	Detailed Results
1	OCEAN	22	03/07/20	0.7349 (1)	0.00 (1)	View
2	PLANKTON	15	03/21/20	0.7241 (2)	0.00 (1)	View
3	greenforce	20	03/29/20	0.7229 (3)	0.00 (1)	View
4	ECOLO1	7	03/21/20	0.7227 (4)	0.00 (1)	View
5	guyon	11	03/23/20	0.5689 (5)	0.00 (1)	View
6	pavao	11	10/14/19	0.5689 (5)	0.00 (1)	View
7	gaiasavers	2	10/12/19	0.5689 (5)	0.00 (1)	View
8	xporters	3	10/08/19	0.5463 (6)	0.00 (1)	View

Graph H

Since we don't have a score of 1 (which is equivalent to 100%), we can always make upgrades such as, making RandomForest better, improving the preprocessing, and the classifiers (better voting classifier).

Pseudo-code

This sections is showing some of our algorithm to go further.

Here is a function used to extract features.

Elongation

```
n = length(imageDataSet)
extractedFeatures = list of length (n*ImageDataSet[0][0])
for i in (0, n-1), do
      for x in ImageDataSet[i]:
            max = 0
            min = 0
            for y in ImageDataSet[i][x]:
                        if ImageDataSet[i][x][y] < min and
ImageDataSet[i][x][y] = 1 then min = ImageDataSet[i][x][y]
                        if ImageDataSet[i][x][y] > min and
ImageDataSet[i][x][y] = 1 then max = ImageDataSet[i][x][y]
            end for
            extractedFeaturesX[i][x] = max - min
      end for
      for y in ImageDataSet[i]:
            max = 0
            min = 0
            for x in ImageDataSet[i][y]:
                        if ImageDataSet[i][x][y] < min and
ImageDataSet[i][x][y] = 1 then min = ImageDataSet[i][x][y]
                        if ImageDataSet[i][x][y] > min and
ImageDataSet[i][x][y] = 1 then max = ImageDataSet[i][x][y]
            end for
```

```
            extractedFeaturesY[i][y] = max - min
      end for
end for
return (extractedFeaturesY, extractedFeaturesX)
```

Model Selection

```
For each Classifier:
      Find Best Param (using GridSearchCV)
      Fit with best param
      Print( Training score)
      Print( Cross Validation score)
Compare and if necessary :
      Find more precise parameters
```

REFERENCE PAGE

"Sklearn.feature_selection.chi2." *Scikit*, scikit-learn.org/stable/modules/generated/sklearn.feature_selection.chi2.html#sklearn.feature_selection.chi2.

"Sklearn.feature_selection.SelectKBest." *Scikit*, scikit-learn.org/stable/modules/generated/sklearn.feature_selection.SelectKBest.html

"Sklearn.decomposition.PCA.", *Scikit,* scikit-learn.org/stable/modules/generated/sklearn.decomposition.PCA.html

"Sklearn.neighbors.LocalOutlierFactor.", *Scikit,* scikit-learn.org/stable/modules/generated/sklearn.neighbors.LocalOutlierFactor.html#sklearn.neighbors.LocalOutlierFactor

"Principal component analysis", *Wikipedia,* en.wikipedia.org/wiki/Principal_component_analysis

"Sklearn.ensemble.RandomForestClassifier.", *Scikit,* scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html

Josh Starmer, "StatQuest: Random Forests Part 1 - Building, Using and Evaluating", *YouTube,* www.youtube.com/watch?v=J4Wdy0Wc_xQ