BigOrganics Business Case

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Introduction

This project is made for the Data & Machine Learning Visualisation course followed for the Applied MSc in Data Analytics at DSTI.

The statement is the following:

- Try to find the best model with Model Studio!
- Explain variables you try to add
- Explain the process
- Use and compare result from regressions, neural network, Forest, GB etc.
- Justify choice with screenshot.

Exploring the dataset

Dataset:

Name : BIGORGANICS

- Columns : 13 - Rows : 111,115

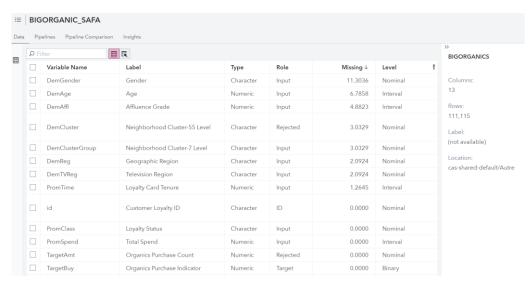
Variable roles:

- 9 inputs
- 2 rejected
- 1 ID
- 1 target

Target variable:

Label: "Targetbuy"

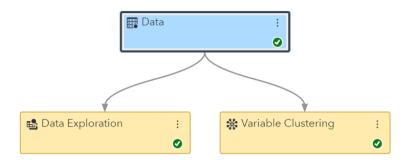
- Type: Binary



Pipelines

1- Exploration

We begin our analysis with the first pipeline named Exploration. It has three nodes as shown below:



Those nodes allow us to explore the data to see if some preprocessing is needed (about outliers or missing values or negative values for example). It also allows us to know if we will need to do some transformations / imputations on the data or some feature selection.

The results of the data exploration node are shown below. Only some of the useful plots and tables will be shown.

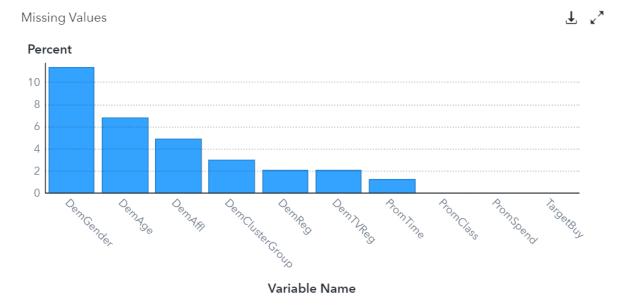
Partition used for the exploration:



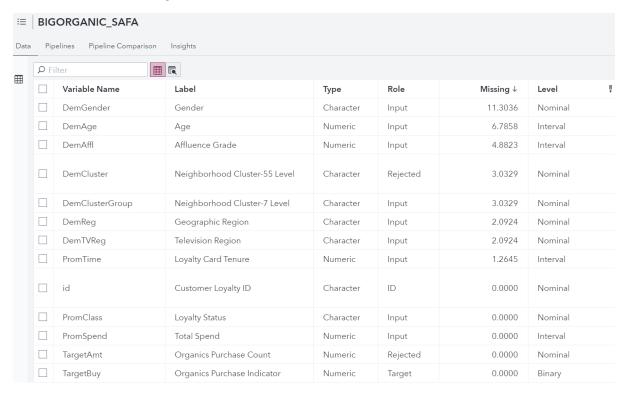
Looking for missing values:

Displaying results of the Data Exploration node we notice that they're some important missing values.

The chart below shows variables ranked by the percentage of missing values they have. Here, for example: Demographic Gender has the most missing values ...



We can also see that using the Data Tab:



We will need to manage the missing values using the Imputation node in the next pipelines for the models that can't handle Missing values.

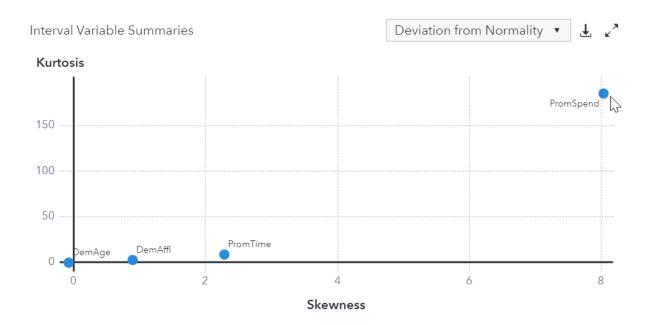
Looking for Skewness:

Interva	Variable N	loments

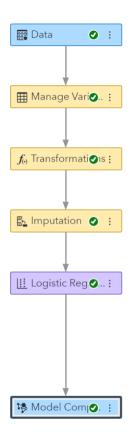
Variable Name	Minimum	Maximum	Mean	Standard De	Skewness ↓
PromSpend	0.0100	296,313.8500	4,420.5900	7,558.9115	8.0368
PromTime	0	39	6.5647	4.6570	2.2827
DemAffl	0	34	8.7119	3.4211	0.8916
DemAge	18	79	53.7972	13.2058	-0.0798

The variable PromSpend has a very high level of skewness so we will probably have to transform it (Log for example) to use it properly.

The chart below shows this as well:

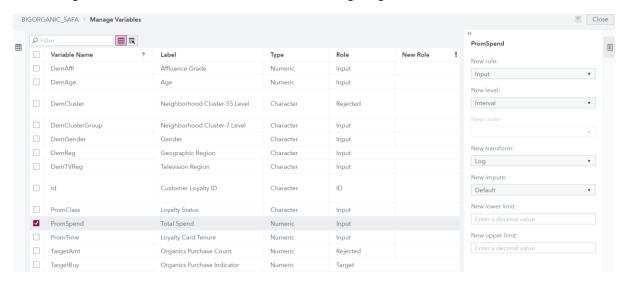


2- Starter Template



Nodes used are:

- Manage Variables: to select the variable to transform. Here, it's the PromSpend that has high level of skewness. We will transform it using "Log".



- Transformation: apply the Log transformation made at the manage variable node

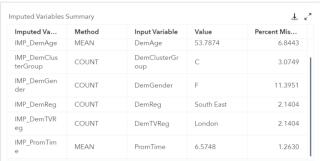
Transformed Variables Summary



Transforme	Method	Input Variable	Formula	Variable Level
LOG_PromSpe nd	LOG	PromSpend	log('PromSpen d'n + 1)	INTERVAL

- Imputation: to replace missing values





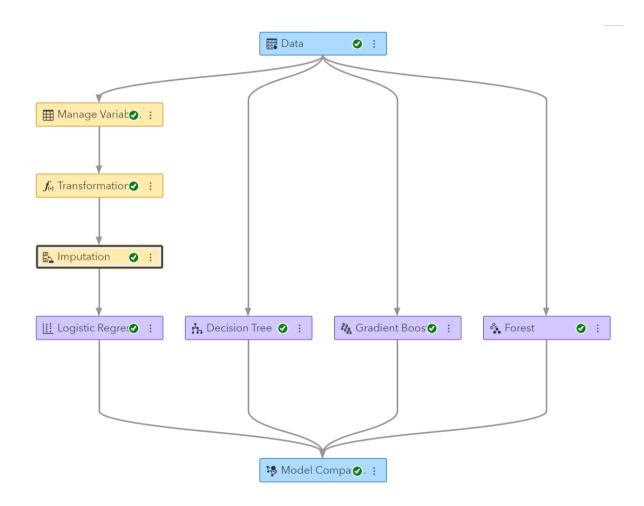
Results of the pipeline:



The logistic regression model has a KS of 0.4296 in this pipeline.

3- Tree based Default models

This pipeline contains 4 models to compare: Tree based models such as Decision tree, Gradient Boosting and Forest that don't need any data preparation and the logistic regression for which we added the pre-processing defined earlier. Here, we run the models with their default settings.



Results of the pipeline:



As we know, the Model Comparison node chooses the Champion model based on the default KS (Youden).

Consequently, in this pipeline, the champion model is Forest.

We can also check other parameters:

- If we are interested in Decision prediction, we can used Misclassification Rate to choose the Champion model. Here also, the smaller the better → Forest also the champion.
- If we want to predict a probability or an estimate, we look at the average squared error (expanding the window). Smaller is Better and Forest is again the champion model
- Finally, if we are interested in ranks, we can look at the area under the Curve (ROC chart) where bigger is better and here also Forest is the best model.

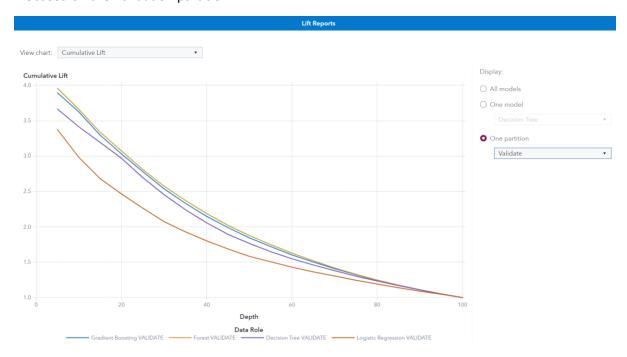


Thus, Forest model is the best according to this pipeline and according to the numerical analysis of the models.

We can also have a graphical analysis to confirm this result:

- Lift Reports and choosing the "Cumulative Lift"

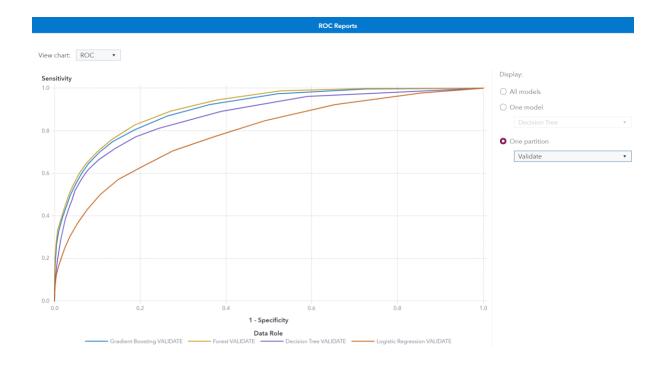
I focused on the Validation partition:



No matter how depth we are in the horizontal axis, the line representing Forest is always on the top, giving the highest cumulative lift so Forest is the best model.

ROC chart : choosing ROC

Also here, focusing on the validation data:

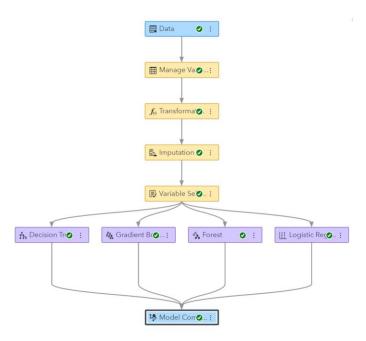


It's similar to the chart before: based on different cutoffs, no matter what cutoff we're at, the yellow line (Forest model) is always the one that's closest to the upper left hand corner of the graph.

Therefore, for this pipeline, numerically & graphically, Forest model is the winner.

4- Tree based Improved models

This pipeline has the same models to compare but I optimized them, improving their efficiency by changing some parameters and by pre-processing the data before applying the tree based models also.



Changes made to the Decision Tree:

- Changes in the structure parameters of the Decision tree:
 - o Increase the maximum depth (to grow a larger tree)
 - o Increase minimum leaf size (helps prevent overfitting)
 - o Increase number of interval bins
- Changes in Recursive Partitioning parameters :
 - Change the grow criterion
 - Class target criterion to Gini
- Changes in the Pruning parameters:
 - Subtree method to Reduced Error

Changes made to improve the Gradient boosting:

- Increase the number of trees
- Increase the maximum depth in the tree splitting options
- Increase the minimum leaf size
- Increase the number of interval bins

Changes made to the Forest model:

- Decrease the number of trees
- Change the class target criterion to Entropy
- Decrease the maximum depth
- Increase the minimum leaf count
- Increase the number of interval bins

Results of the pipeline:

Numerically:

Model Comparison									
Champion	Name	Algorithm Name	KS (Youden)	Misclassification Rate					
•	Forest	Forest	0.5875	0.1602					
	Gradient Boosting	Gradient Boosting	0.5625	0.1645					
	Decision Tree	Decision Tree	0.5379	0.1603					
	Logistic Regression	Logistic Regression	0.4293	0.1984					

The model with the best KS is the Forest model so it's the champion model again in this pipeline.

	Model Comparison											
Champi	Name	Algorith	KS (You	Misclas	Misclas	Root Av	Averag	Sum of	Multi-Cl	Gini Co	Area Un	Gain
*	Forest	Forest	0.5875	0.1602	0.1602	0.3363	0.1131	33,334	0.3598	0.7553	0.8777	2.5533
	Gradient Boosting	Gradient Boosting	0.5625	0.1645	0.1645	0.3422	0.1171	33,334	0.3721	0.7340	0.8670	2.4322
	Decision Tree	Decision Tree	0.5379	0.1603	0.1603	0.3467	0.1202	33,334	0.3948	0.6925	0.8463	2.4232
	Logistic Regressio n	Logistic Regressio n	0.4293	0.1984	0.1984	0.3777	0.1427	33,334	0.4473	0.5722	0.7861	2.0012

We can notice that different models have improved:

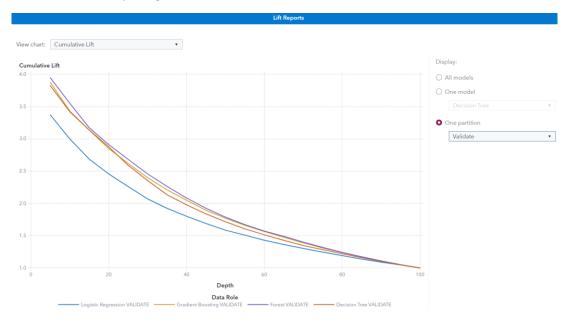
- Decision tree model:
 - o KS went from 0.4683 to 0.5379
 - o Average squared error went from 0.1343 to 0.1202.
- Gradient Boosting model:
 - o KS went from 0.5149 to 0.5625
 - o Average squared error went from 0.1275 to 0.1171

On the other hand, the *Forest model*, even if it's still the champion model didn't improve :

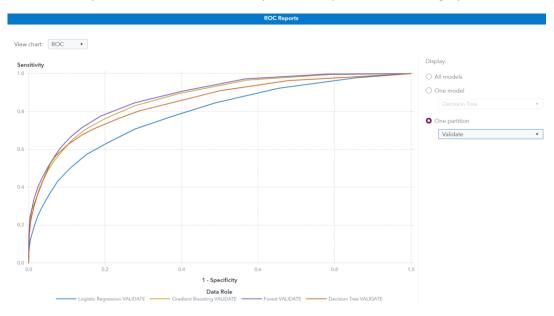
- o KS went from 0.6357 to 0.5875
- o Average squared error went from 0.1010 to 0.1131

Graphically:

Cumulative Lift report : On the validation partition, the line representing the Forest model is on the top no matter how deep we go.



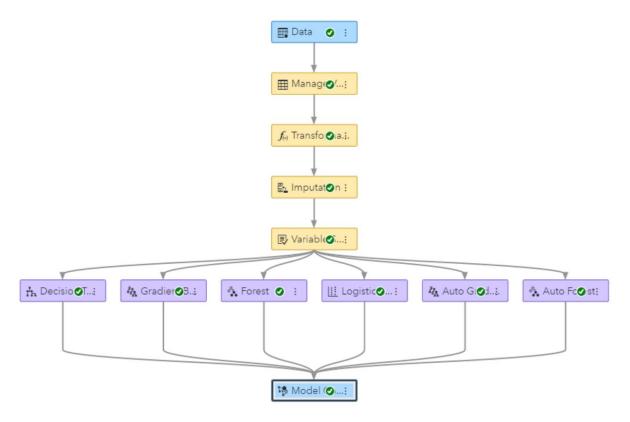
ROC chart: Similarly, Forest model's line is always on the top left hand of the graph.



We can clearly see that Forest model is the best graphically also.

Performing Autotuning on this pipeline

I added several nodes to this pipeline to perform autotuning and see if the champion model would change.



Results after autotuning:

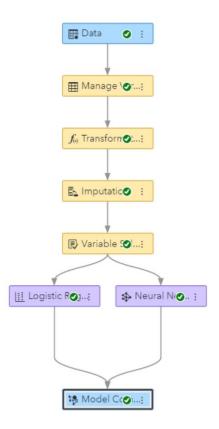


After performing autotuning on Gradient Boosting model and Forest we can see that the champion model has changed. The new one is the *Autotuned Gradient Boosting model*.

5- Neural Networks

In this pipeline, I added two models: Neural Network and Logistic Regression.

I left the Neural Network to its default settings.



Results of the pipeline:



In this pipeline, according to the Misclassification rate or the Average squared error, the champion model is the Logistic Regression.

Improving the model:

Changes made to the Neural Network model:

- Change the input standardization to "Z score"
- Clear the checkbox for "Use same number of neurons on hidden layers"
- Decrease Custom Hidden Layer 1

Change the Learning and Optimization Parameters :

- Increase the L1 weight decay
- Decrease the L2 weight decay

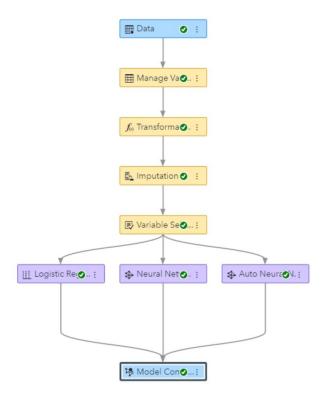
Results of the improved pipeline:



The champion has changed! The new one is the improved Neural Network model (according to the Misclassification rate: went from 0.2477 to 0.1981 and its Average squared error really improved also!)

Performing Autotuning on this pipeline

I added a new node to this pipeline to perform autotuning and see if the champion model would change.

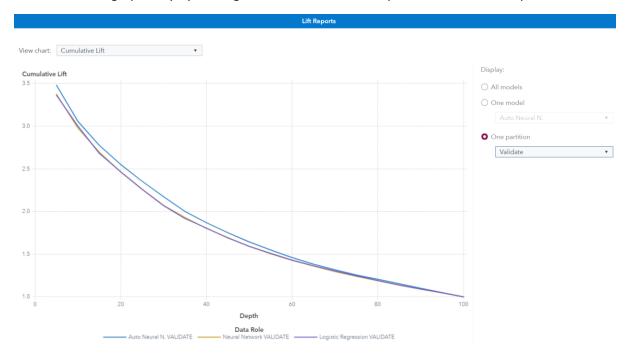


Results after autotuning:

	Model Comparison												
Champi	Champi Name Algorith KS (You Misclas Misclas Root Av Averag Sum of Multi-Cl Gini Co Area Un Gain												
*	Auto Neural N.	Neural Network	0.4684	0.1916	0.1916	0.3700	0.1369	33,334	0.4296	0.6133	0.8066	2.0579	
	Neural Network	Neural Network	0.4331	0.1981	0.1981	0.3785	0.1433	33,334	0.4494	0.5715	0.7857	1.9793	
	Logistic Regressio n	Logistic Regressio n	0.4303	0.1984	0.1984	0.3778	0.1427	33,334	0.4474	0.5741	0.7871	2.0023	

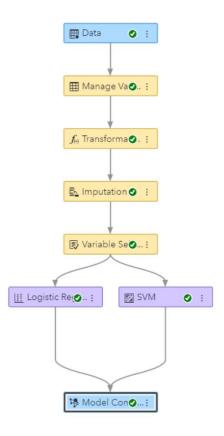
The champion model in this pipeline after performing autotuning is the Auto neural network.

We can check it graphically by looking at the Cumulative lift Report on the validation partition :



The line representing the Autotuned Neural Network model is, at any depth, on the top.

6- Support Vector Machine



Results of the pipeline:



In this pipeline, the champion model is the Logistic Regression according to the KS or the Misclassification rate.

Improving the model:

Changes made to the SVM model:

- Decrease the Penalty / to change the methods of solution parameters
- Change the Kernel setting to Polynomial
- Increase the tolerance to avoid overfitting
- Decrease the maximum iterations

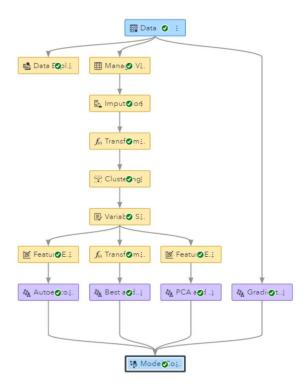
Results of the improved pipeline:



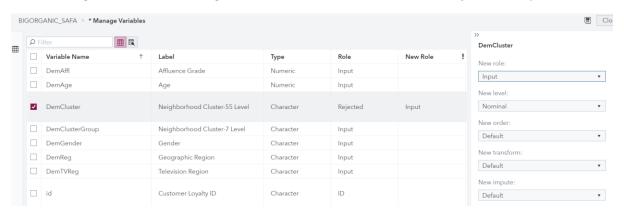
After modifying the parameters of the SVM model, the KS and the Misclassification rate improved but not the Average squared error which is higher than before. But still, even with this general improvement, the champion model is the Logistic Regression.

7- Feature Engineering

This pipeline is based on the feature engineering template available in Model Studio.

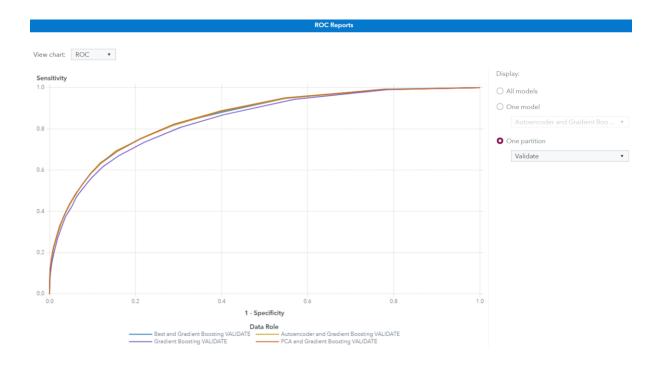


In the manage variable node I assigned a new role to "DemCluster" from Rejected to Input:



Results of the pipeline:

	Model Comparison											
Champi	Name	Algorith	Misclas	Misclas	Root Av	Averag	Sum of	Multi-Cl	KS (You	Gini Co	Area Un	Gain
*	PCA and Gradient Boosting	Gradient Boosting	0.1730	0.1730	0.3499	0.1224	33,334	0.3862	0.5420	0.7100	0.8550	2.3087
	Best and Gradient Boosting	Gradient Boosting	0.1736	0.1736	0.3503	0.1227	33,334	0.3876	0.5405	0.7063	0.8531	2.2990
	Autoenco der and Gradient Boosting	Gradient Boosting	0.1744	0.1744	0.3505	0.1229	33,334	0.3879	0.5400	0.7059	0.8530	2.2930
	Gradient Boosting	Gradient Boosting	0.1783	0.1783	0.3571	0.1275	33,334	0.4013	0.5149	0.6794	0.8397	2.2094



In this pipeline, the champion model is the PCA and Gradient Boosting model.

Pipeline Comparison

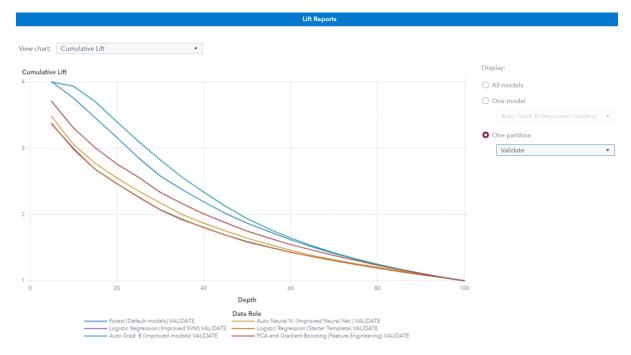
Now that we have the champion model for each pipeline, we can run a comparison of all these champions using the Pipeline Comparison Tab.

Here are the results:

	Pipeline Comparison											
Champion	Champion Name Algorithm Name Pipeline Name KS (Youden) Sum of Frequencia											
*	Auto Grad. B	Gradient Boosting	Improved models	0.728	33,334							
	Forest	Forest	Default models	0.636	33,334							
	PCA and Gradient Boosting	Gradient Boosting	Feature Engineering	0.542	33,334							
	Auto Neural N.	Neural Network	Improved Neural Net.	0.468	33,334							
	Logistic Regression	Logistic Regression	Improved SVM	0.430	33,334							
	Logistic Regression	Logistic Regression	Starter Template	0.430	33,334							

The champion model, all pipelines combined, is the *Gradient Boosting performed with autotuning*. It has a KS of 0.728.

We can confirm that by looking at the Cumulative Lift report, on the Validation partition:



CONCLUSION

Our target variable is of type binary so we could process several models to analyse it and model it.

When choosing a model for a specific dataset, it is important to consider some points like the size and the nature of the data. Some models are more efficient with a specific size of the dataset, but overall they apply from small to large datasets (even if tree based models and neural network are better with mid sized to large datasets).

We need to know what we are trying to achieve with the model, how accurate it has to be, how much time do we have to train it and most of all how interpretable it needs to be.

In this analysis, after running several pipelines with their own models and modifying parameters to improve them, the best model of the whole project is the Gradient Boosting performed with autotuning. It is important to notice that the Gradient boosting model has a Moderate level of interpretability and is instable with small training sets. Therefore, even if the pipeline comparison chose this champion model for us, it is up to business needs to define which model to go on with.