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ARTIFICIAL NEURAL NETWORKS FOR MATERIAL CLASSIFICATION IN PURCHASING PORTFOLIO MANAGEMENT

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Abstract. *Strategic sourcing is an important technique within supply chain management area that allows companies to understand their purchasing portfolio and to better take advantage of their bargain power versus key suppliers, reducing supply risks to an acceptable minimum. The Kraljic portfolio matrix is an important model for evaluating materials and services categories in two main aspects: the importance of a particular purchasing and the complexity of the supply market. Although, the classification phase can present a hard task depending on the number of materials and the complexity of a specific portfolio. In this context, the present work proposes the application of machine learning classifiers – artificial neural network, extreme learning machine and K-nearest neighbors – for material grouping in a data set of 1,560 active items composing the electric and electronic portfolio components of a large Brazilian transportation company. Eight features are used for classifying material purchase and maintenance criticality. The artificial neural network presented an accuracy of 94.77% for purchase and 60.41% for maintenance classification.*

Keywords: *strategic sourcing, kraljic portfolio matrix, supervised learning, classification problem, artificial neural network*

1 INTRODUCTION

Purchasing is becoming supply management, as every day more companies are rethinking their processes and chains in order to create shared value to respond rapidly to their customers requirements and gaining competitiveness. In this conditions, the purchase portfolio model is an important approach that allows companies to analyze their expenditure profile and to define action plans based on the relationship required for each of their suppliers. The first portfolio analysis model, proposed by Kraljic (1983), has become routine in many purchase departments around the globe, due to its simplicity and easiness to implement. Many modifications and improvements have been proposed for the original model so far, in agreement with specific industries and situations needs.

Within large enterprises, where thousands of different items are bought every year, grouping and classifying various materials can present a complex task, requiring a higher degree of analysis then achievable by a human specialist. On the other hand, the latest advances in the artificial intelligence field permitted the development of statistical algorithms for pattern recognition in large set of quantitative data, providing useful insights for assessing decision-making in many different areas.

This paper proposes an expert system for purchase material classification based on machine learning classifiers (MLC) and presents the case study of electric and electronic components arrangement in MRS Logistica (https://www.mrslogistica.com.br/), a Brazilian company in railway industry.

The major contributions of this paper are stated as follows:

- Achievement of 94.77% accuracy and 60.41% for maintenance criticality classification;
- Performance evaluation of three different MLC: artificial neural network, extreme learning machine and K-nearest neighbors on the specific problem.

The major conclusions are as follows:

- The 8 selected attributes presented great results in purchase classification, however they failed in classifying the maintenance aspect;
- All methods presented satisfactory results, whereas the artificial neural network achieved best performance scores;
- A single hidden layer of neural network with 5 neurons adopting logistic activation functions presented a sufficient complexity to address the problem.

This paper is organized in 5 sections. Following this Introduction, Section 2 provides an analysis of published articles concerning purchase portfolio models proposed so far. Section 3 provides a background of some learning classifiers, training methods through grid search and cross-validation and performance measurements indexes. Section 4 describes the application of the selected classifiers in electric and electronic components purchase database, followed by Section 5, in which the results and discussions are presented. Finally, Section 6 concludes this paper and includes some future works recommendations.

2 LITERATURE REVIEW

In a prior study, Kraljic (1983) introduced a method for strategic purchase portfolios evaluation, that became widely disseminated and applied in business so far. The method is composed by four phases: (1) classification, (2) market analysis, (3) strategic positioning and (4) action plans development. It became known as Kraljic Portfolio Matrix (KPM), as purchase categories are positioned in a 2x2 matrix shown in Fig. 1 and labeled into four categories: strategic, bottleneck, leverage and noncritical items, such that each category is associated with a particular relationship approach.

Several improvements were proposed since then: positioning categories can be treated dynamically rather than statically in case the action plans for managing these changes within a supply chain are developed in a medium-long term scheme (Gelderman & Weele, 2002). A new portfolio model is proposed which, taking into account final market features, indicates both the level of right buyer-supplier integration and the evaluation parameters to assess when choosing the supplier for that relationship (Brun & Pero, 2011). The matrix dimensions can be extent according to the application requirement: a quality axis is adjoined to the original matrix for classifying aircraft material, therefore items are labeled in $2^3 = 8$ different categories (Cai et al., 2014).

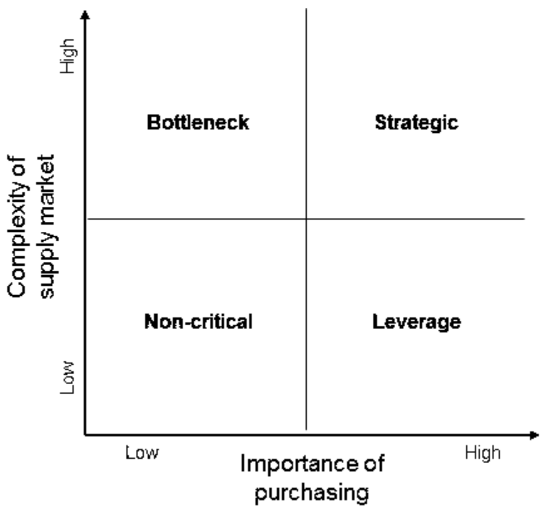


Figure 1 – Kraljic Portfolio Matrix (Kraljic, 1983)

Although KPM contributed by transforming many purchase areas into supply chain departments within companies of all around the world, the original method depends on the subjective judgment of several specialists and executives of the firm, along the support of consultant firms assessing its application. Several quantitative methods were applied along Kraljic's matrix by many other researchers. A multi-criteria approach was adopted for composing each of the utility scales composing the two axes "importance of purchasing" and "complexity of supply market" from the several sub attributes (Lee & Drake, 2010). A fuzzy multi-attribute scoring is proposed for better handling the linguistic judgments of the original method (Pahdi et al., 2012) and applied to assign performance ratios to different commodities.

A different approach for composing the scales was proposed from the application of two independent artificial neural network (Osiro et al., 2013), one for each of KPM axes, considering

3 attributes in "importance of purchasing": quality impact, share in total cost, social and environment impact; and 4 attributes in axis "complexity of supply market", the four attributes were considered: concentration of companies in supply market, entry barriers in supply, possibility of substitution, specification of integration level.

3 MATERIALS AND METHODS

3.1 Artificial neural network – ANN

An artificial neural network (ANN) is a biologic inspired algorithm considered presenting intelligent-behaviors, as they have the capacity of learning new tasks, through errors and discoveries, interpreting and conceiving generalizations. They are commonly applied to solve complex problems of interest by producing complex linear or non linear models and producing outputs for inputs not encountered direct during its training (Haykin, 1999).

Figure 2 shows a multi-layered feedforward network dopted in the present work, also known as multi-layered perceptron (MLP) which provides a general ANN representation. The MLP has one or more non-linear layers – known as hidden layers – and can learn a non-linear function $f(\cdot) : R^m \rightarrow R^o$, where m is the number of dimensions for input and o is the number of dimensions for output, from a given set of features $X = x_1, x_2, ..., x_m$ and a target y for prediction (Pedregosa et al., 2011).

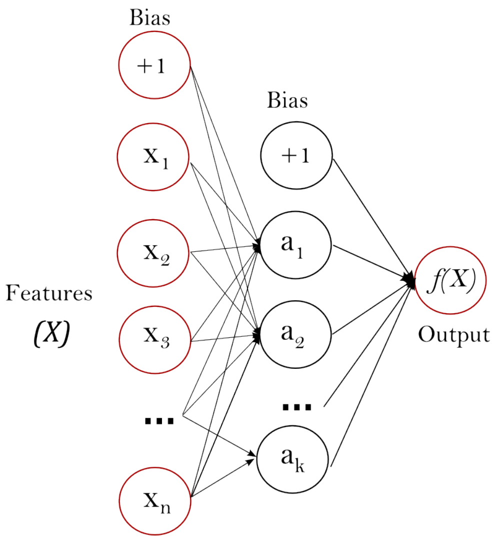


Figure 2 – General MLP with a single hidden layer (Pedregosa et al., 2011)

The input layer is composed by a set of neurons $\{x_i | x_1, x_2, ..., x_m\}$ which are modified by a non-linear activation function $g(\cdot) : R$ set by the user – such as logistic or hyperbolic tangent – and incorporated to the weighted linear summation $\sum_m^i w_i x_i$ that generates the subsequent hidden layers and output values.

The main advantage of MLP is their capability to learn non-linear models in real-time. On the other hand, some drawbacks of these kinds of network are the loss of function in problems with more than one local minimum, its sensitivity to feature scaling and the requirement of hyper-parameters tuning.

3.2 Extreme learning machine – ELM

The extreme learning machine (ELM) is a special case of an artificial network with one single-hidden layer, which randomly chooses hidden nodes and analytically determines output weights of the network (Huang et al., 2006). Thus, the network is reduced to a linear problem, lowering the computation cost of the learning process. Compared to an ANN though, the number of neurons in the intermediate layer of a network of this nature is generally higher.

The randomness in this approach occurs in three different levels: (Huang, 2015)

1. the hidden nodes, which are randomly generated;
2. the connections, as seen that not all input nodes are connected to a particular hidden one;
3. the sub-networks, formed by several nodes resulting in learning local features.

ELM is known for providing a good generalization performance for classification problems in most cases, learning thousands of times faster than the conventional learning algorithms, which is contributing to the popularization of the particular approach. This machine is implemented for the purpose of performance comparison.

3.3 K-nearest neighbors – KNN

K-nearest neighbor (KNN) is a simple and intuitive classifier, in which points are classified based on the class of their nearest k neighbors, where k is an integer value specified by the user. It is considered a lazy learning technique, since induction is delayed to run-time and classification is directly related to the training examples (Cunningham & Delany, 2007).

KNN assigns a class to each point according to the category of their surrounding aspects, simply computed from the majority of votes of the nearest neighbors of the particular point. Since it does not intend to build a general internal model, but to store instance of the dataset, the method is considered to be of a particular kind of instance-based or non-generalizing learning. Larger values set for k may mitigate noise effects, however it makes classification bounds less specific, what causes a trade-off to be faced when implementing this particular method (Pedregosa et al., 2011). The KNN classifier is also used for performance comparison purpose.

3.4 Parameter estimation using grid search with cross-validation

Learning classifiers models often present parameters which are not directly learnt during its training, also known as hyper-parameters. A technique usually applied in such cases is the grid search, which exhaustively searches a parameter configuration for the best cross-validation within a predefined range (Pedregosa et al., 2011). The hyper-parameters and ranges defined for model selection in this work is shown in Table 1.

Cross-validation is an important concept used to estimate how accurate is a classifier for a new set of data, avoiding a common problem known as overfitting, in which a particular model becomes excessively complex and unable to classify other dataset but the training one. The k-fold cross-validation, one of the most applied along with grid search, randomly splits a dataset D into k mutually exclusive subsets (or folds) of practically equal size (Kohavi, 1995).

Figure 3 exemplifies the iterative procedure of cross-validation through data division into $k = 5$ subsets, preserving the percentage of samples of each class, used for training the selected

Table 1 – Hyper-parameters and range adopted for grid search

Method	Hyper-parameters	Parameters range
ANN	alpha (α)	10^{-1}, 10^{-2}, 10^{-3}
	Activation function (ρ)	Logistic, hyperbolic tangent, relu
	Hidden layers	[5], [10], [20], [10,10], [5,5], [5,5,5]
ELM	Activation function	Sigmoid, hyperbolic tangent, gaussian, multiquadric, inverse multiquadrics, relu
	Neurons in the hidden layer (L)	10, 30, 50, 80, 100, 120, 150, 200
KNN	N Neighbors	1, 2, 3, 4, 5, 6, 10

classifiers. Finally, the trained models are tested in a group of unseen data and have their comparison metrics computed.

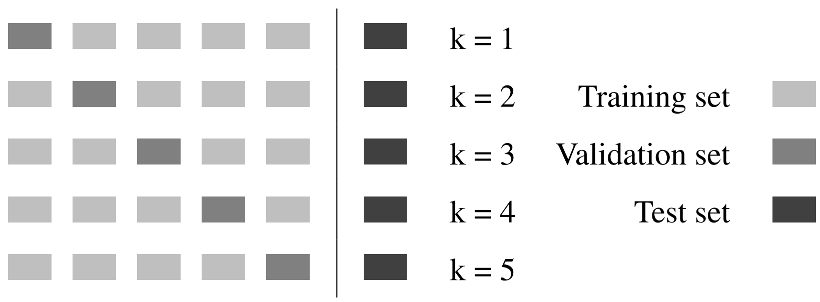


Figure 3 – Division of the dataset into $K = 5$ folds

3.5 Performance metrics

For assessing the methods classification performance, it was applied the evaluation metrics accuracy score (AS) and precision score (PS). The AS computes are the fraction of correct predictions, while the PS is the ability of the classifier not to label as positive a sample that is negative (Pedregosa et al., 2011).

These criteria are given by:

$$AS = \frac{1}{N}\sum_{i=0}^{N-1} 1(y_i - \hat{y}_i)^2$$

$$PS = \frac{t_p}{t_p + f_p}$$

where N is the number of samples, $\hat{y}_i$ is the estimated target output, y_i is the corresponding (correct) target output, $1(x)$ is the indicator function, t_p is the number of true positives and f_p the number of false positives.

4 CLASSIFICATION IN PURCHASE PORTFOLIO OF A RAILWAY OPERATOR

The supply chain department of a Brazilian freight operator, MRS Logistica, is responsible for managing materials and services of outsourcing processes, which together represents over 70% of the total cost of the company. In a particular purchase category of electric and electronic components, over than 1,000 materials are bought every year. To aid the procurement and inventory management processes, items are classified by technical and administrative specialists according to its purchase and maintenance criticality.

Purchase orders and material master data reports were exported from company's enterprise resource management system, regarding four years of operation. From this database, 8 features were adapted conforming the criteria suggested by Kraljic (1986): cost of materials/total costs, value-added profile, profitability profile, supply, monopoly or oligopoly conditions, pace of technological advance, entry barriers, logistic costs, complexity, among others.

- x_1: Number of suppliers
- x_2: Number of warehouses receiving the item
- x_3: Purchase frequency
- x_4: Unit price
- x_5: Total bought yearly
- x_6: Delivery lead time
- x_7: Supplier predisposition for agreement
- x_8: Imported or locally sourced

The criticality of each component was determined by the company's executives, according to the following scale:

- y_1: Purchase criticality. 0 for "non-critical", 1 for "low", 2 for "medium" and 3 for "high" criticality;
- y_2: Maintenance criticality. *NA* for "not applicable", *X* for "low", *Y* for "medium" and *Z* for "high" criticality.

Table 2 – Electric and electronic category composition

		Maintenance crit.				
		X	Y	Z	NA	
Purchase crit.	3	54	5	80	29	168
	2	346	41	212	98	697
	1	381	43	145	60	629
	0	-	-	-	66	66
		781	89	437	253	1560

A descriptive data analysis is shown in Table 2. This simple data visualization fashion assesses the understanding of some particular characteristics of the ’electronic and electric components portfolio’, which are responsible for purchasing critical items for railway systems, such as signaling, communication and traffic management components, among others. None of the items labeled as critical for maintenance are considered critical for purchase. Even though around half of the items were considered low maintenance impact (781 in 1560), the particular category presented a relevant parcel of critical items (437, or 28%).

Finally, the learning algorithms were implemented using the *scikit-learn* library in Python (Pedregosa et al., 2011). From the original data, 30% of the database was cleaved for composing the test set. Each model was trained exhaustively for 65 iterations, using the procedure described in Subsection 3.4.

5 RESULTS AND DISCUSSION

The difference between the accuracy achieved in the training and test sets are shown in Fig. 4. The higher is the difference, more likely is that the model achieved an overfitted solution. This is specially noticed in maintenance criticality classification through KNN model, in which the model accuracy average in the training data set was around 7% superior when compared to its application in test data set. For purchase criticality, the difference between training and test set errors were lesser for all models applied.

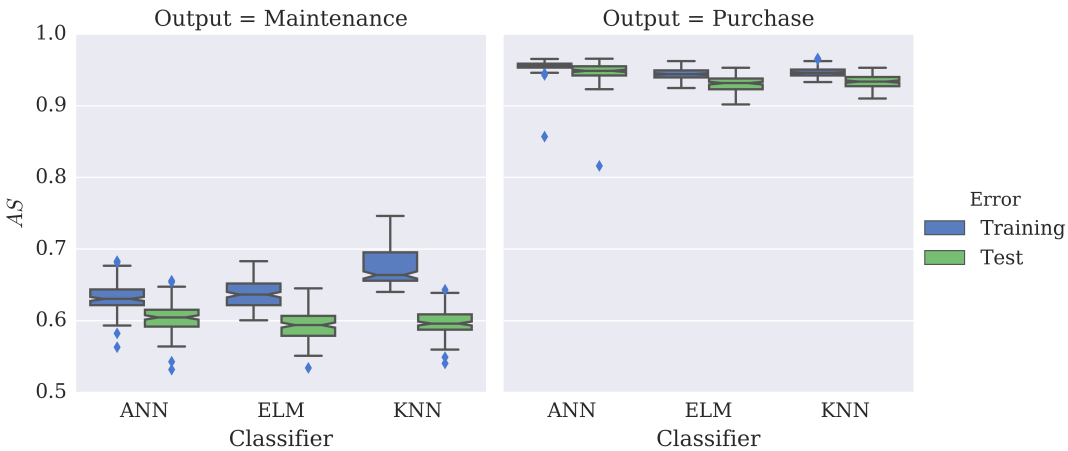
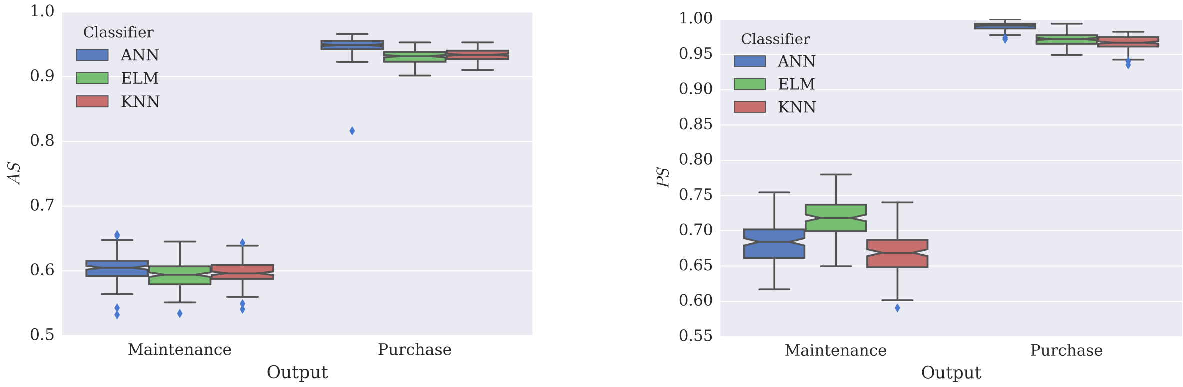


Figure 4 – Training and test errors comparison

Fig. 5, Table 3 and 4 present the performance metrics computed in each model applied. The ANN presented the best accuracy average compared to the other methods when classifying items as purchase criticality (94.8%). ELM had the lowest (93.0%) accuracy, 1.8% lower than the ANN, but it is still a satisfactory approximation, since the main goal of this particular model is achieving a proper approximation at a much lower computational cost. KNN presented an intermediate AS of 93.3% and the lowest standard deviation, presenting a suitable model as well. When comparing the models regarding its precision, ANN presents once more the highest value (99.0%), followed by ELM (97.2%) and KNN (96.6%).

The values achieved on maintenance criticality were quite lower, above 60.5%, which indicates that features selected from the database are not enough for categorizing materials in



(a) Accuracy Score (AS) **(b)** Precision Score (PS)

Figure 5 – Boxplot of performance metrics adopted

Table 3 – Accuracy score (*AS*) comparison

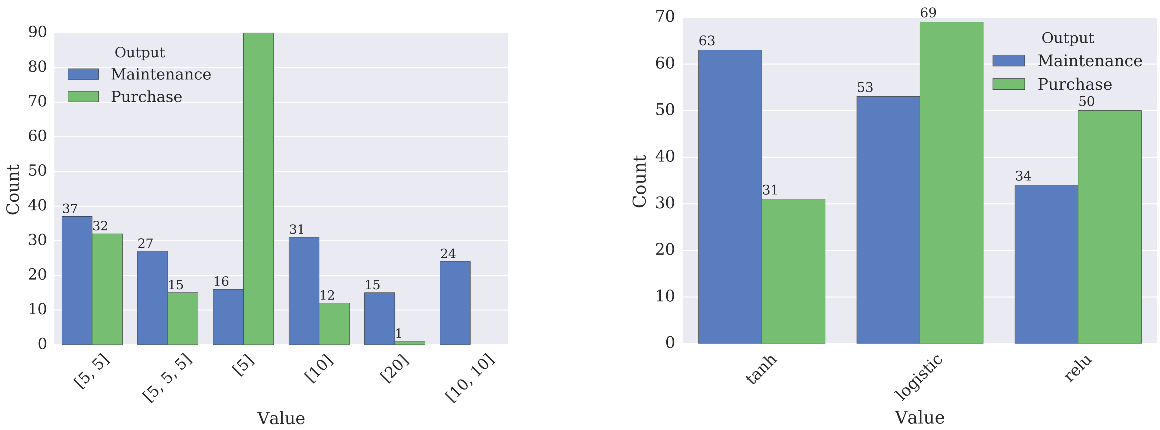
Output (Criticality)	Classifier	Average	Max	Median	Min	Std Dev
Purchase	ANN	0.9477	0.9658	0.9487	0.8162	0.0136
	ELM	0.9297	0.9530	0.9316	0.9017	0.0106
	KNN	0.9336	0.9530	0.9338	0.9103	0.0098
Maintenance	ANN	0.6041	0.6560	0.6047	0.5321	0.0203
	ELM	0.5933	0.6453	0.5940	0.5342	0.0191
	KNN	0.5984	0.6432	0.5962	0.5406	0.0174

Table 4 – Precision score (*PS*) comparison

Output (Criticality)	Classifier	Average	Max	Median	Min	Std Dev
Purchase	ANN	0.9903	1.000	0.9911	0.9715	0.0054
	ELM	0.9716	0.9936	0.9717	0.9493	0.0091
	KNN	0.9658	0.9822	0.9667	0.9352	0.0106
Maintenance	ANN	0.6820	0.7545	0.6842	0.6170	0.0289
	ELM	0.7182	0.7798	0.7181	0.6496	0.0263
	KNN	0.6680	0.7402	0.6688	0.5905	0.0262

such aspect, which may be related to other technical attributes that were not available in the purchasing database, so they could not be taken into account in the research.

According to Fig. 6, within the configurations adopted, a single layer network with 5 neurons was, in more than half of the cases, able to predict item purchase criticality, mostly applying logistic function as activation function parameter. For item maintenance criticality, none of the models presented a satisfactory performance, both configuration and activation functions were more equitably distributed between the approaches adopted, characterization of the model's randomness.



(a) Distribution of hidden layer sizes **(b)** Distribution of activation functions

Figure 6 – ANN hyper-parameters distribution along simulations

6 CONCLUSION

The MLC are powerful tools when analyzing and classifying large volume of purchase items, rather than qualitatively done by specialists as required in original KPM procedure. In this fashion, it is possible to achieve an advanced analysis capability, required in companies with large amounts of transactions and materials.

In this study, 3 different models – ANN, ELM and KNN – were applied for classifying materials criticality from 8 features in 2 aspects: purchase and maintenance. Cross-validation and grid search were also applied in this procedure, with regard to explore different network parameters and configuration whilst avoiding the overfitting problems. ANN presented the best accuracy for classifying the materials: 94.77%, in average. The model failed meeting a satisfactory performance for classifying the maintenance aspect, so it is concluded that the chosen features are not adequate to perform the proposed task, that may be related to other technical aspects not considered in the presented model.

Future works include exploring the relative importance of each attributes in material classification, identifying new dimensions for KPM, applying clustering methods for grouping similar materials and developing new frameworks for categories positioning.

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