

Original Research Paper

Toward a Good Decision to Improve the Weight of Control of Expenditure for Local Communities

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Abstract: In order to improve the weight control of local government spending, we have developed a technique to supervise the classification of local authorities according to their expense ratios. This aims to develop the repository of rules and decision-making skills of business leaders of local communities and enabling to detect frauds in expenditure ratios that cause weakness of the Current Flow margin (CCF).

Keywords: Datamining, Unsupervised Classification, Supervised Classification, Decision Tree, Knowledge, Clustering Algorithms, Separation Distance, Categorical Data

Introduction

Projections of future finance laws require a reflection on the sustainability of public finances face a continuing global economic crisis. Decisions are already taken by several countries on fiscal austerity and fiscal consolidation, to reduce deficits and debt levels of countries. However, expenditure rationalization will be effective at the national level that when established at the regional level (MDFEDLP, 2004; Riad Solh and El Belkacemi, 2015).

As part of the optimization of expenses of CL, we have developed a new classification technique to compare communities according to control their expenditure on the basis of current cash flow (MAC) (MDFEDLP, 2004; Riad Solh and El Belkacemi, 2015).

But the comparison of communities according to their MAC values is relative and does not produce reliable results for financial analysts because of the diversity of their ways and their revenue ratios. It why we introduce segmentation techniques to group communities that share the same levels of revenue ratios (MDFEDLP, 2004; Riad Solh and El Belkacemi, 2015).

For each community, we measured the distance between the value of the CCF and the value of the largest CCF cluster to which it belongs.

Depending on the value of this distance, we can determine the classification of this community in the cluster to inform about its weight-control spending.

Indeed, a short distance is a significant weight and a significant distance results in a low weight (MDFEDLP, 2004; Riad Solh and El Belkacemi, 2015).

In order to improve the weight control spending of the LCs and to weaken the distance between its CCF and the highest CCF of its cluster (center of gravity of the cluster), we used techniques of supervised classification of CCF values of communities according to their expense ratios. This aims to develop the repository of rules and decision-making skills of business leaders of local communities and enabling the detect frauds in expenditure ratios that cause weakness of the margin of current flow.

On the basis of those techniques, we can deduce the measures to be applied at the expense ratios of the community to increase its CCF and minimize the distance between the CCF and the center of gravity of the cluster.

The Limits of the Basic Classification

In order to standardize and categorize the value of the CCF, we defined for each community LC_i the following report of its CCF categorization (Riad Solh and El Belkacemi, 2015) ($NCCF$):

$$NCCF(LC_i) = \frac{CCF(LC_i)}{MAX(CCF)}$$

where, $CCF(LC_i)$ is the CCF value of community LC_i and $MAX(CCF)$ is the maximum value of CCF same types of communities.

This ratio which is less than or equal to '1', tells us about the CCF value of LC_i over most CCF communities of the same type (Riad Solh and El Belkacemi, 2015). For example:

- $CCF(PR6) = 32715$ MMDH
- $MAX(CCF) = CCF(PR13) = 71185$ MMDH
- $NCCF(PR6) = CCF(PR6) / MAX(CCF)$
- $NCCF(PR6) = 32715$ MMDH / 71185 MMDH
- $NCCF(PR6) = 0,460$
- $NCCF(PR13) = CCF(PR13) / CCF(PR13) = 1$

To make the correspondence between the $NCCF$ report and the weight of expenditure control (category CCF (Table 1)) (Chang and Ding, 2005; Solh and

El Belkacemi, 2015; Hanumantha *et al.*, 2011), we proposed the following categorization.

The more the CCF report categorization ($NCCF$) is closed to '1', better is the weight-control spending and vice versa (Riad Solh and El Belkacemi, 2015).

The result of the traditional classification of 16 provinces (previous example) according to CCF allows developing the following (Table 2).

So it is clear that this classification has deficiencies and weaknesses due to the different levels of revenue ratios (Riad Solh and El Belkacemi, 2015).

The classification will be relevant when the LC have the same means and the same reference point. That is why we introduce a segmentation technique (Sivaram and Ramar, 2010; Antonellis *et al.*, 2007; Riad Solh and El Belkacemi, 2015) to group and classify LC who share the same level of revenue ratios (Fig. 1).

Table 1. Correspondence between the $NCCF$ report and the category of the CCF (Riad Solh and El Belkacemi, 2015)

Indicator	Operator	Margin	Category CCF	Situation of control spending
NCCF	<	0	Category 6	Critical state
	In	[0, 0.2]	Category 5	very low
	In	[0.2, 0.4]	Category 4	Low
	In	[0.4, 0.6]	Category 3	Average
	In	[0.6, 0.8]	Category 2	Well
	>=	0.8	Category 1	Very well

Table 2. The result of the traditional classification of 16 provinces (Riad Solh and El Belkacemi, 2015)

LC	NCCF	Category CCF	Situation of control spending
PR 10	[0, 0.2]	Category 5	Very low
PR 7	[0, 0.2]	Category 5	Very low
PR 15	[0.2, 0.4]	Category 4	Low
PR 1	[0.2, 0.4]	Category 4	Low
PR 11	[0.2, 0.4]	Category 4	Low
PR 14	[0.2, 0.4]	Category 4	Low
PR 5	[0.4, 0.6]	Category 3	Average
PR 16	[0.4, 0.6]	Category 3	Average
PR 6	[0.4, 0.6]	Category 3	Average
PR 2	[0.4, 0.6]	Category 3	Average
PR 4	[0.4, 0.6]	Category 3	Average
PR 3	[0.4, 0.6]	Category 3	Average
PR 12	[0.4, 0.6]	Category 3	Average
PR 9	[0.4, 0.6]	Category 2	Well
PR 8	[0.8, 1]	Category 1	Very well
PR 13	[0.8, 1]	Category 1	Very well

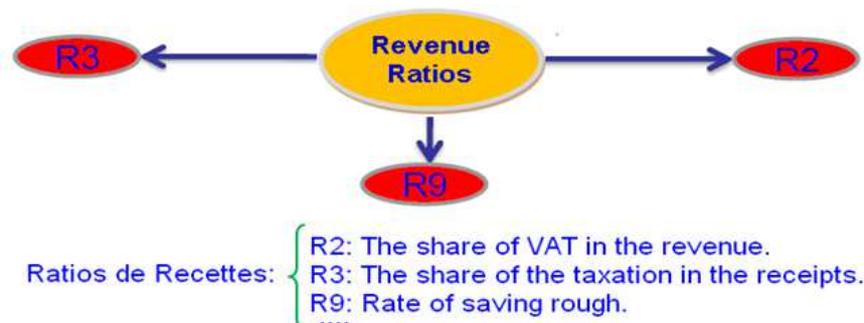


Fig. 1. Revenue ratios

Setting the Points of Reference and Ensuring a Relevant Classification of LC According to their Means

In order to make a relevant and accurate classification, we segmented first the LC (Sivaram and Ramar, 2010; Antonellis *et al.*, 2007; Riad Solh and El Belkacemi, 2015) according to their local revenue ratios (MDFEDLP, 2004; Riad Solh and El Belkacemi, 2015) by producing a set of clusters (Shih *et al.*, 2010; Ayesha *et al.*, 2010; Ivancsy and Kovacs, 2006; Riad Solh and El Belkacemi, 2015) (Fig. 2).

As a result, for each community, we measured the distance between the value of the CCF and the value of the largest CCF cluster to which it belongs (Sarangi and Murthy, 2010; Holmes, 2005; Riad Solh and El Belkacemi, 2015) (Fig. 3).

At the cluster level 'C₁', the community LC₁ has the largest CCF which is 'CCF₁'.

Dist_k(C₁): It's the distance between the CCF community LC_k of cluster C₁ 'CCF_k(C₁)' and the highest CCF 'CCF₁(C₁)' of cluster C₁.

What are the precautions to be taken by the manager of CL tops to achieve the best of its category CCF cluster?

Secondly, we classified (supervised classification) (Hanumantha *et al.*, 2011; Adeyemo and Kuye, 2006) CCF Communities according to their expense ratios from (Fig. 4) (Riad Solh and El Belkacemi, 2015): Financial autonomy, the share of expenses in spending the weight of debt service in operating expenses and the rate of indebtedness (Fig. 7).

The following chart describes the layout of NCCF for a sample of 16 provinces (previous example) in relation to their expense ratios for 2002 (Fig. 5).

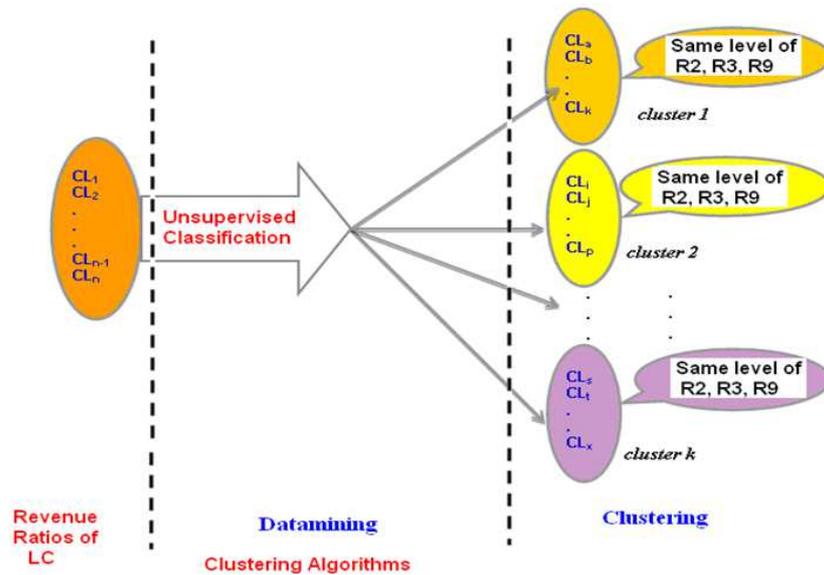


Fig. 2. Segmentation of LC according to their revenue ratios by clustering algorithms

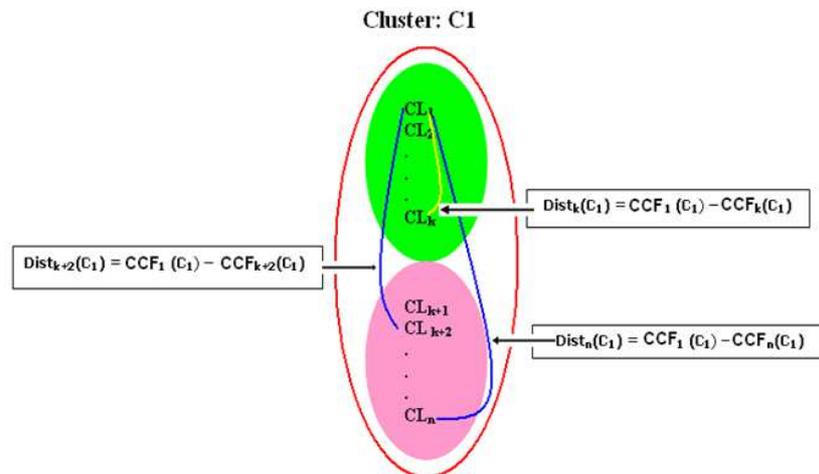


Fig. 3. Calculating distances in a cluster



Fig. 4. Expense ratios

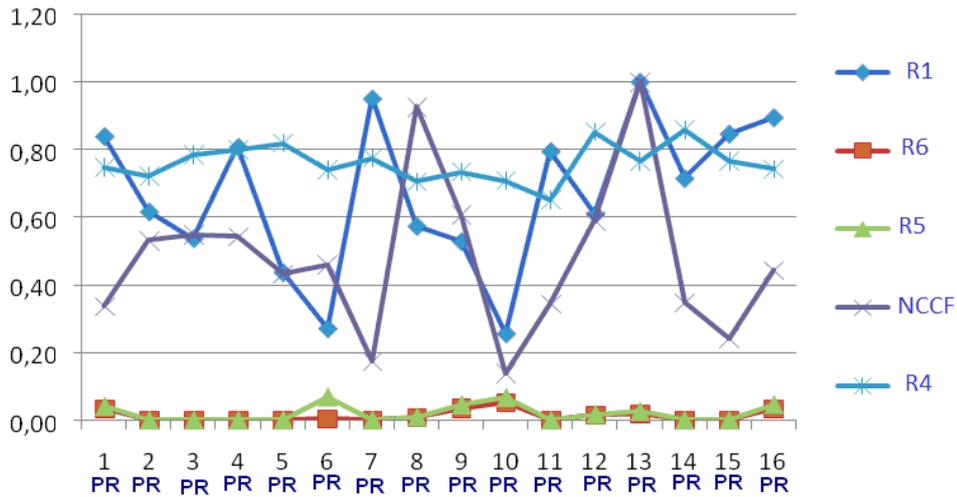


Fig. 5. Knowledge generation by type of CCF and depending on expense ratios

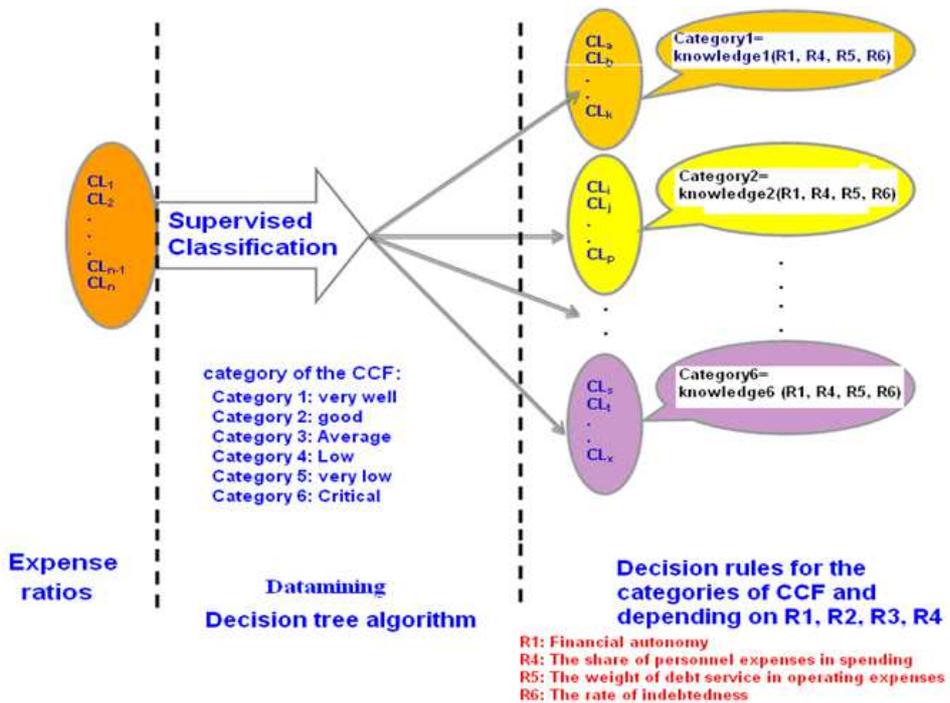


Fig. 6. Knowledge generation by type of CCF and depending on expense ratios

Our objective is to generate knowledge and decision rules (Adeyemo and Kuye, 2006; Anyanwu and Shiva, 2013; Vasantha and Bharathy, 2010; Hall and Holmes, 2003; Ganesh and Chandrasekar, 2011) type of CCF (Fig. 6).

According to this knowledge, the manager of a CL tops may have a look on the values of expense ratios (MDFEDLP, 2004; Riad Solh and El Belkacemi, 2015) in order to reduce the distance between the CCF and the best CCF of its cluster.

Result: Evolution of the grade level of CCF in the same cluster.

Description of the Method

The procedure of the clustering of communities is discussed in our article reference (Riad Solh and El Belkacemi, 2015; Hee-Jung and Kim, 2009)

Improving the Weight-Control Spending

We try to classify CLs according to their CCF based on their expense ratios (MDFEDLP, 2004; Riad Solh and El Belkacemi, 2015). For this, we use decision tree algorithms (Anyanwu and Shiva, 2013; Vasantha and Bharathy, 2010; Hall and Holmes, 2003; Ganesh and Chandrasekar, 2011) to develop the repository of rules and decision-making skills.

Based on these standards, we can deduce the measures to be implemented at the expense ratios for

the leaders of a CL to increase the level of CCF (moving from a lower to a higher level in its class of CCF level).

Let n be the number of communities in the cluster (C_c) that has k categories (CAT) of CCF with $k \leq 6$.

We note that the best CCF of a cluster is its center of gravity.

The concern of the leader of a CL is how to converge its class CCF to that of the center of gravity of the cluster, chasing all communities in a cluster share the same level of revenue ratios.

In our case, the community with the best CCF in a cluster ensures good control and rationalization of expenditures over revenues.

For each category i of CCF we generate the decisional knowledge (Anyanwu and Shiva, 2013; Vasantha and Bharathy, 2010; Hall and Holmes, 2003; Ganesh and Chandrasekar, 2011) adequately according to their expense ratios by decision trees algorithms (data mining algorithms).

Thus, Knowledge (i) on the category (i) is based on expense ratios R_1, R_4, R_5, R_6 , etc (Fig. 7).

CCF category desired by the leaders of a local authority is that of the center of gravity of the cluster. To ensure good control of expenses and to have that desired CCF type, we must respect the decision rules for its knowledge (Anyanwu and Shiva, 2013; Vasantha and Bharathy, 2010; Hall and Holmes, 2003; Ganesh and Chandrasekar, 2011).

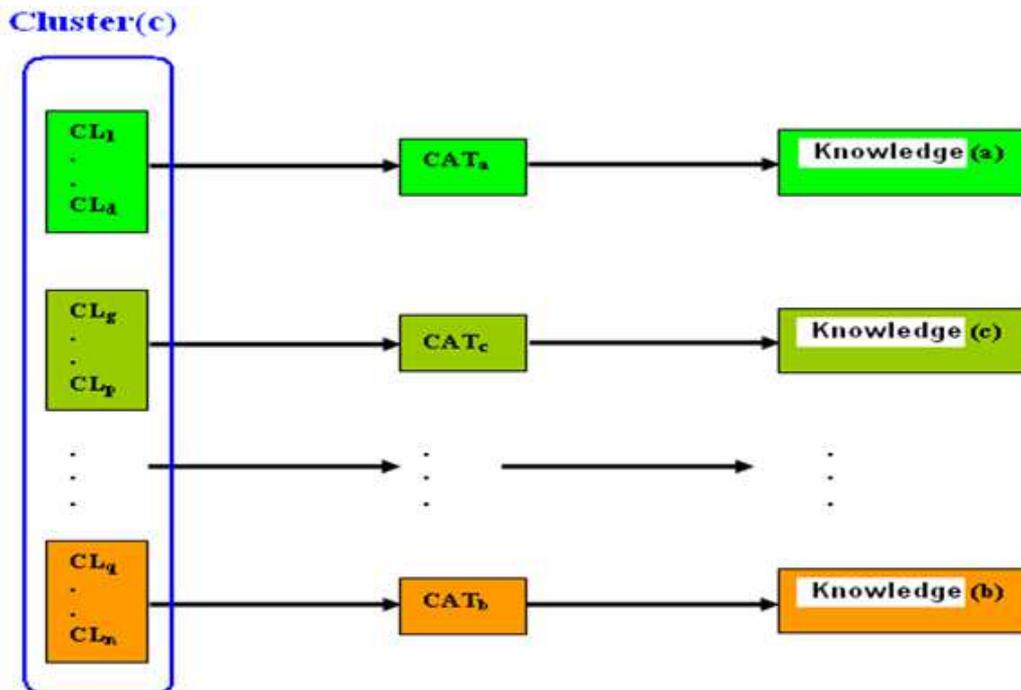


Fig. 7. Segmentation of LA by their category of CCF

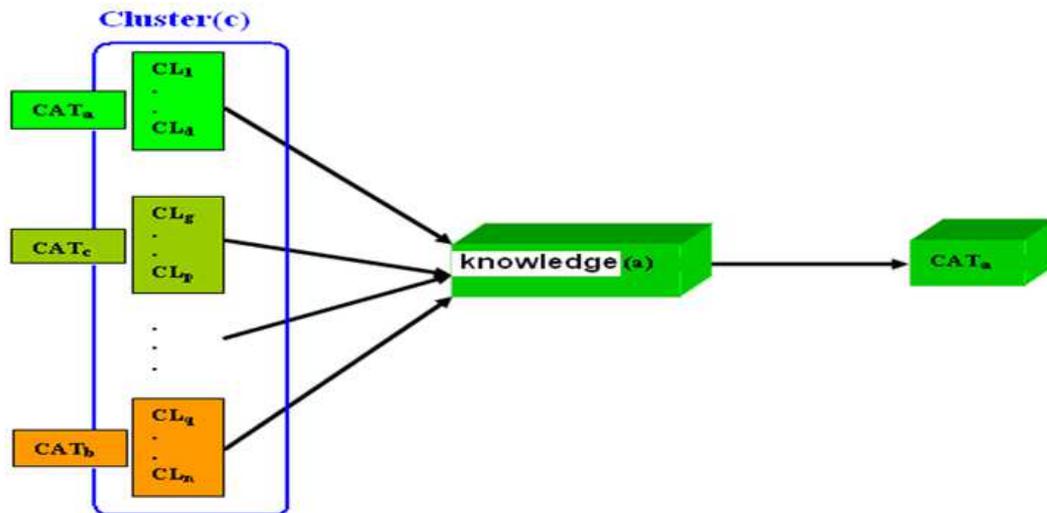


Fig. 8. Respect the knowledge: 'Knowledge (a)' returns to respect the rule R1, the rule R4, the rule R5 and R6 rule on 'Knowledge (a)'

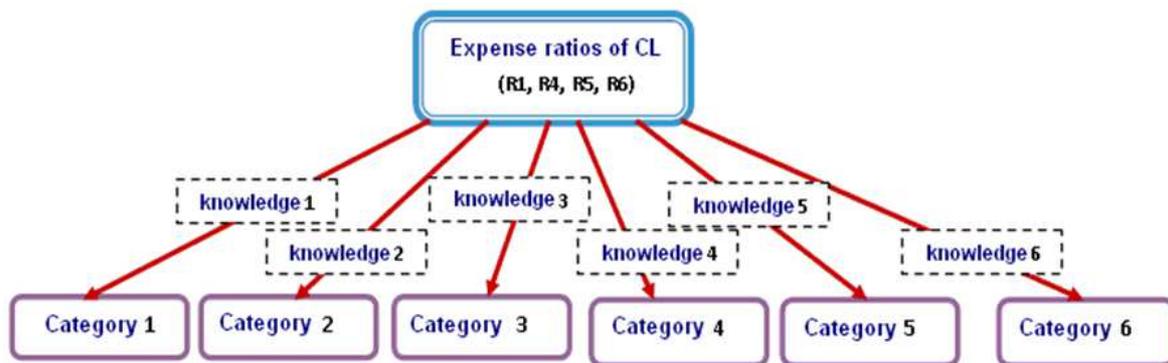


Fig. 9. The figure shows the decision tree generating categories of CCF according to local government spending ratios

If we assume that the class of CCF: 'CAT_a' is the best class of the cluster, the local community leaders in the cluster must meet the knowledge on this class of CCF: 'Knowledge (a)' to ensure good rationalization and tight control of expenses.

Respect the knowledge: 'Knowledge (a)' returns to respect the rule R1, the rule R4, the rule R5 and R6 rule on 'Knowledge (a)' with (Fig. 8):

- R1: Financial autonomy
- R4: The share of staff expenses in spending
- R5: The weight of debt service in operating expenses
- R6: The rate of indebtedness

List of knowledge (Fig. 9):

- Category1 = knowledge1 (R1, R4, R5, R6)
- Category2 = knowledge2 (R1, R4, R5, R6)
- Category3 = knowledge3 (R1, R4, R5, R6)
- Category4 = knowledge4 (R1, R4, R5, R6)

- Category5 = knowledge5 (R1, R4, R5, R6)
- Category6 = knowledge6 (R1, R4, R5, R6)

Evolution of CCF'S Category of a Local Community

The evolution of the CL MAC category is explained at our article reference (Riad Solh and El Belkacemi, 2015).

The more the CCF category of a community is away from the center of gravity of the cluster, the more streamlined procedure applied by these leaders will be rigorous.

Some Results

The following Fig. 10 shows the necessary changes in the categories of the CCF for a sample of 16 provinces (LC) in order to ensure the rationalization of expenditures based on the (two-step algorithm) segmentation of their financial data (revenue ratios and CCF) for 2002.

category \ LC	category1	category2	category3	category4	category5	category6
PR1				X		
PR2			X			
PR3	Y		Z			
PR4			X			
PR5		Y	Z			
PR6			X			
PR7		Y			Z	
PR8	X					
PR9		X				
PR10			Y		Z	
PR11				X		
PR12		Y	Z			
PR13	X					
PR14	Y			Z		
PR15				X		
PR16	Y		Z			

Fig. 10. X: The community belongs to the same category of CCF that the center of gravity of the cluster (balanced management of expenses over revenue); Z: Given these recipes, the community is poorly placed in this category because of the mismanagement of expenses over revenue; Y: Given these recipes, the community needs this type of CCF to avoid difficult financial and critical situations and to ensure proper rationalization of spending (the category of the center of gravity of the cluster where it belongs)

It is based on the decision tree algorithm (C&RT Algorithms) to develop rules to apply in order to have the desired Category CCF.

For the Community PR10:

- The weight-control spending of the community PR10 is very low 'Category 5', however, the center of gravity of the cluster has a weight average expense control (Category 3)
- For the weight-control spending means, the community PR10 must respect the decision knowledge on the category of the center of gravity of the cluster 'Category 3'
- Respect the knowledge on the 'Category 3' returns to respect the R1, R4, R5 and R6 on that 'knowledge 3'

The Ratios Unmanaged by the Community PR10:

- Financial autonomy (R1 = 0.022290) is very low due to the increase in operating expenses compared to specific recipes, it must be at least greater than the value 0.023618
- The weight of debt service in operating expenses and the rate of indebtedness are very high (annuities related to expenses and operating revenues are high) so that the average of these two ratios should not

exceed the 0.039497 value (the value of its average equal 0.059349)

Ratios Controlled by the Community PR10

The ratio on the part of staff expenses in operating expenses is controllable by this community, its value: 0.707374, normally it can go up to the value 0.852094. So, during this period, the CL PR10 can ensure premiums for its staff or proceed to a new recruitment.

Conclusion

Rationalization of local government spending is a major project that requires goodwill of the government and the use of new technologies by adopting appropriate algorithms to develop strategic dashboards and alerts. That is why we tried to develop this decision support system that carries business assistance to community leaders to avoid difficult financial situations and to ensure good governance as a result of their spending.

This publication has a dual purpose: First, we proposed a new approach that presents an objective classification of local authorities by controlling their spending over their means. Secondly, the development of a knowledge repository, which allows the deduction of measures to be implemented at the expense ratios by

community leaders to improve their rankings and the level of control of their expenses.

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Author's Contributions

Anouar Riad Solh: Participated in all experiments, coordinated the data-analysis and contributed to the writing of the manuscript.

Mourad El Belkacemi: Participated in all experiments, coordinated the data-analysis and contributed to the writing of the manuscript.

Ethics

No ethical conflicts will arise after publication of the manuscript.

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