

The machine learning in the prediction of elections

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Abstract: This research article, presents an analysis and a comparison of three different algorithms: A.- Grouping method K-means, B.-Expectation a convergence criteria, EM and C.- Methodology for classification LAMDA, using two software of classification Weka and SALSA, as an aid for the prediction of future elections in the state of Quintana Roo. When working with electoral data, these are classified in a qualitative and quantitative way, by such virtue at the end of this article you will have the elements necessary to decide, which software, has better performance for such learning of classification.

The main reason for the development of this work, is to demonstrate the efficiency of algorithms, with different data types. At the end, it may be decided, the algorithm with the better performance in data management.

Keywords: Automatic Learning, fuzzy logic, grouping, Weka, SALSA, LAMDA, state elections, prediction.

El aprendizaje automático en la predicción de las elecciones

Resúmen: Este artículo de investigación presenta el análisis y comparación de tres algoritmos diferentes: A.- método de agrupamiento K-media, B.- expectativa de criterios de convergencia y C.- metodología de clasificación LAMDA usando dos softwares de clasificación, Weka y SALSA, como auxiliares para la predicción de las futuras elecciones en el estado de Quintana Roo. Cuando se trabaja con datos electorales, éstos son clasificados en forma cualitativa y cuantitativa, de tal virtud que al final de este artículo tendrá los elementos necesarios para decidir que software tiene un mejor desempeño para el aprendizaje de dicha clasificación. La principal razón para hacer este trabajo es demostrar la eficiencia de los algoritmos con diferentes tipos de datos. Al final se podrá decidir sobre el algoritmo con mejor desempeño para el manejo de información.

Palabras clave: aprendizaje automático, lógica fuzzy, agrupamiento, Weka, SALSA, LAMDA, elecciones estatales, predicción.

1. Introduction

The fascination for predict the future, is one of the intents and desires that man still insists on getting. Much effort have individuals and companies to predict various aspects, for example, climate and product prices in the market. For example: Toro (2006) Forecast stock market using intelligent techniques, Matamoros (2006) Methodology for predicting oil prices based on fractal

dynamics and Weron (2007) Modeling and forecasting electricity loads and prices: A statistical approach. Other works are to: Matamoros (2005) Methodology oil price prediction based on fractal dynamics; calculated logarithmic returns, tracing methods, average values in time series to generate probabilistic scenarios.

There are many works prediction Data mining, a variant is research on the prediction and treatment of disease, alcohol use in adolescents, Vega (2009) Data Mining Applied to Prediction and Treatment of Diseases. Another perspective is: Jungherr (2012) Why the pirate party won the German election of 2009 or the trouble with predictions. A response to Tumasjan, A, Sprenger, TO, Sander, PG, & Welpe, IM predicting elections with Twitter : What reveal 140 characters reveal political sentiment.

There are studies on predicting elections that have been made in countries such as:

Spain, where Dellte (2012) Conducted prediction political tendency Twitter: Andalusian elections 2012; For Holland, Tumasjan (2010), Predicting Elections with Twitter. What about 140 Characters Reveal Political Sentiment; Germany, Sang (2012) Predicting the 2011 senate election results with Dutch twitter. In Proceedings of the Workshop on Semantic Analysis in Social Media. Jungherr (2012) Why the pirate party won the German election of 2009 or the trouble with predictions: A response to Tumasjan, A, Sprenger, TO, Sander, PG, & Welpe, IM "predicting elections with Twitter. What reveal 140 characters about political sentiment "; and Canada, where Sidorov (2013) did an Empirical study of machine learning based approach for mining review in tweets. In Advances in Artificial Intelligence.

According to (Becerra-Fernandez, 2003), the discovery of knowledge in databases has made the computational procedures in automatic programming are increasingly sophisticated. Say Berry (1997), the data mining aims to uncover patterns and relationships to make predictions.

First, the classification of the data, by a process of unsupervised learning as the grouping clustering, brings the find of groups that are different but the individuals are equal among themselves as noted (Vega, 2012) In the methodology of data mining.

We select the use of the data mining software called Weka, because it is an easy tool, and where different jobs are chose: like, Empirical studies of machine learning based approach for opinion mining in tweets, (Sidorov, 2013), The comparison of different classification techniques using Weka for breast cancer (Bin, 2007) and the compared in Data Mining Applied to Prediction and Treatment of Diseases (Vega, 2012) and the different software products for data mining.

Also we chose a hybrid model, see table 1, as clustering techniques for better results, some work related are, for example: The Data Mining applied to prediction and treatment of diseases (Arango, 2013) and Methods for predicting stock market indices. Echoes of Economics, (García, 2013).

Table 1.Description of prediction models (Garcia, 2013) and (Arango, 2013).

Technique	Model type
Multiple Regression	Linear
Neural networks (Radial Basis Function, RBF and Backpropagation)	Nonlinear
Methods K-nearest neighbor	Nonlínear
Probabilistic neural network (PNN)	Nonlínear
Genetic algorithm	Nonlinear
Neuro-fuzzy networks	Nonlinear e Hybrid
Neural networks MPL	Nonlinear

Table 1. Description of prediction models (Garcia, 2013) and (Arango, 2013).

Technique	Model type
SVM support vector machine	Nonlinear

With comparative purposes, this work shows the results of the classification performed into two applications of software: Weka and SALSA, with different techniques of clustering. Also are shown and detailed the experiment on the preparation of the data. In the first part it explains our intention of predicting state elections with qualitative and quantitative data as well as briefly describing of the three techniques of clustering: Expectation-Maximization, k-means and describe the methodology of classification LAMDA. Was made, a comparison of the techniques and software used with the results obtained, finally, we show the performance of each software tool.

2. Background

2.1 References

To analyze the decision-making of the citizens, it is necessary to have instruments of measurement with respect to its electoral behavior, such as surveys and projections. In Mexico in the first part there is something written, but on the second there is very little.

The literature on electoral projections is basic, because studies should nourish it, as in the case of statistical analysis, which are scarce (Torres, 2000). The lack of specialized bibliography, is due to the fact that since 1993, are disseminated by the Federal Electoral Institute IFE, and the state electoral bodies, the overall results and with some levels of disaggregation; what has meant is that there are no historical series of voting, nor criteria to build units of comparison.

With the practice, of presenting the basic statistics disaggregated to the level of electoral section and even casilla, have been ameliorated some of the described

shortcomings, however, there remains the need to analyze and interpret the data; setting criteria for the construction and use of statistical aggregates; and finally, to make attempts of predictions.

The literature on individual electoral behavior, has underlined the existence of stable predispositions to vote, sustained in the long term, on the basis of which the decision be finalized, except that they act on the individual circumstances of a particular choice: candidates, issues, and so on, all forces of short-term.

2.2 Prediction of state elections

The prediction of the 2009 elections in Germany, using the techniques referenced, as shown in (Jungherr, 2012) Why the party won the German election of 2009 or the trouble with predictions: was done by taking into account the frequency of mentions and to get the total mentions, replication of mentions and percentages of mentions. The sample is less than a month, and takes representative days. It also takes into account the progression of the followers. The analysis of the results is quantitative.

On the other hand, the classification in the Empirical study of machine learning is based in approach for opinion mining in tweets. Sidorov (2013), through automatic learning, shows the possible classifications of classes and Support Vector Machine SVM as the best binder driving records 3393 as the best data set of training.

In this case, we take the elections in the state of Quintana Roo in the years 1998, 2004 and 2010.

3. Theoretical framework

3.1 Automatic learning

Today's Data Mining can be defined in terms of three easy concepts:

Statistics with emphasis on exploratory data analysis proper, big data and machine learning.

Samuel (1959) say, the definition of machine learning, was given to the field of study that assigns to the computers the ability to learn without being explicitly programmed. In other words, machine learning investigates ways in which the computer can acquire knowledge directly from data and thus learn to solve problems. The automatic learning is the acquisition of new knowledge, the development of a motor and cognitive skills through instruction or practice, the organization of new knowledge, effective representation and discovery of new facts and theories through observation and experimentation. The types of knowledge acquired are parameters in algebraic expressions, decision trees, formal grammar, production rules, logic-based formal expressions, graphs and networks, frameworks and diagrams and other procedural encodings and computer programs.

This learning is applied to many areas such as chemistry, education, computer programming, expert systems, video games, mathematics, music, natural language processing, robotics, speech recognition and image, and sequences of prediction example: An overview of machine learning, in Machine learning, by (Carbonell, 1983) among others.

3.2 Techniques of grouping or clustering

The Clustering techniques, is referred in English as grouping, are procedures which are used to group a series of items. Clustering is used in statistics and science. The methods to deal with are: the hierarchical method because it is an exploratory tool designed to reveal the natural groups within a set of data that would otherwise is not clear. It is useful when you want to group a small number of objects, may be cases or variables, depending on if you want to classify cases or examine relationships between the variables.

A review of clustering algorithms, can be referenced by (Xu, 2005) and discuss different algorithm. The hierarchical method is built by a cluster of trees or hierarchical clusters. Each node contains clusters children. Categorized in agglomerative and divisive. The first begins with a cluster and after two or more similar clusters. The second begins with a cluster containing all the data points and recursively divides the group most appropriate. The process continues and stops until the criterion is improved.

Table 2.Classification of clustering algorithms (Berkhin, 2006).

Method	Category
Hierarchical method	Agglomerative algorithms y divisive algorithms
Method partition and relocation	Clustering probabilistic, K-medoids y K-means.
Partitioning method based on density	Clustering connectivity clustering based on density and density functions.
Network-based method	
Based on co-occurrence of categorical data Method	
Other clustering techniques	Constraint-based clustering, graph-partitioning, clustering algorithms with supervised learning and clustering algorithms with machine learning
Scalable clustering algorithms	
Algorithms for high dimensional data	Subspace clustering and co-clustering techniques

3.1.1 K-means

K-means (MacQueen, 1967) is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. k-means is one of the

simplest unsupervised learning algorithms that solve the well known clustering problem. This algorithm is classified, as a method of partitioning, and relocation of each of its clusters, represents the average of their points centroid. The advantage of using this is by the quick view graph and statistics. The target function, is the sum of the errors between the centroid and their points, i.e. the total variance within the cluster.

Although it can be proved that the procedure will always terminate, the k-means algorithm does not necessarily find the most optimal configuration, corresponding to the global objective function minimum. The algorithm is also significantly sensitive to the initial randomly selected cluster centres. The k-means algorithm can be run multiple times to reduce this effect. K-means is a simple algorithm that has been adapted to many problem domains, it is a good candidate for extension to work with fuzzy feature vectors.

Finally, this algorithm aims at minimizing an objective function, in this case a squared error function.

3.1.2 Expectation Maximization EM

The algorithm of Expectation Maximization, EM, belongs to the family of finite mixture models, used for segmenting multivariable data. It is a probabilistic clustering algorithm, where it seeks to know the target function of the unknown probability to which the data set belongs. Each cluster is defined by a normal distribution, the problem is, that the distribution is not known to which the data and parameters corresponds. Specifically, the algorithm is divided into two stages: expectation and a convergence criteria.

The first with unknown underlying variables, using parameter estimation up to the observation. The second provides a new estimation of the parameters, as shown in the papers: The algorithm of expectation-maximization (Moon, 1996) and unsupervised learning of finite mixture models (Figueiredo, 2002). Iterate both, until converge. In other words, the calculation of the probabilities or the expected

values is performed and the value of the parameters of the distributions, is calculated for maximizing the probability of distributions of the data. The estimation of the parameters is considered to be the probability that the data belongs or does not belong to a cluster.

3.1.3 Fuzzy Logic

The fuzzy logic deals when imprecise or subjective terms is handled, where an element can belong to multiple sets of partial form. Fuzzy logic was defined in this work by membership functions of campaign by the functions mean and standard deviation.

The characteristic function μ_S commonly used to define if a member belongs or not to a member, or a set of members (S), $\mu_S(x) = 1$, if x is a member of S and $\mu_S(x) = 0$, if x is not a member of S.

$$\mu_S(x) \begin{cases} 1, & x \in S \\ 0, & x \notin S \end{cases}$$

Formula 1. Feature.

The operations to be performed on fuzzy sets are shown in table 3.

Table 3. Operations on fuzzy sets.

Operation
Inclusion or subassembly
Union. Zadeh logical OR operator (max)
Intersection. Zadeh logical AND operator (min)
Denial or supplement
Cartesian product

Table 3.Operations on fuzzy sets.

Operation

Cartesian co-product

3.1.4 LAMDA classification methodology

The LAMDA algorithm, Learning Algorithm for Multivariate Data Analysis, is a classification method developed by N. Piera and J. Aguilar (Aguilar, 1982), (Desroches, 1987), (Piera, 1989). It is created by a principle to categorize data, where there may be many variables, however, classified in both numeric and symbolic, quantitative data and qualitative data.

LAMDA enters the classification within the theory of networks of radial basis function, which is a method to improve the generalization of new data. The learning of radial basis can be given supervised or not supervised. Supervised, when it seeks to minimize the error between the output value of the network and the desired output value, using least squares. Non-supervised, where it allows to divide the space of input patterns into classes. The number of classes, is the number of hidden neurons in a radial basis network.

An object X, is represented by a vector that contains a set of features, in this case it can be the votes of party1, party 2 or party 3, called descriptors. In the classification, each object X is assigned to a class. A class is defined as the universe of descriptors that is characterized as a set of objects.

LAMDA, performs classification according to criteria of similarity in two stages: first, the similarity criteria of each descriptor object corresponding, to the descriptor of a given class measured, this is also known as the obtaining or calculation of the degree of marginal adequacy MAD (Marginal Adequation Degree). Second, when the measurement of the relevance of an object is added to a particular class, this is also known, as the obtaining or calculation of the degree of overall adequacy GAD (Global Adequation Degree).

The calculation of GAD, deals with the concept of diffuse connective, which is explained by the aggregation function as linear interpolation of t-norm with t-conorma. The total diffuse intersection and the total diffuse union respectively. These aggregation operators get the GAD an individual data added to a class.

$$GAD = \beta T(MAD) + (1 - \beta) S(MAD) \quad (1)$$

$$GAD(x|C) = \alpha \cdot \gamma[MAD(x_1|C), \dots, MAD(x_P|C)]$$

$$+ (1 - \alpha) \cdot \beta[MAD(x_1|C), \dots, MAD(x_P|C)]$$

The connectors used in GAD are, the intersection, t-norm and union, t-conorma. The role of aggregation (Piera and Aguilar, 1991) is a linear interpolation between t-norm (α) and t-conorma (β).

$$\gamma(a, b) = a.b(t\text{-norm}) \text{ and } \beta(a, b)$$

$$= a + b - a.b(t\text{-conorm})$$

$$\gamma(a, b) = \min(a, b)(t\text{-norm}) \text{ and } \beta(a, b)$$

$$= \max(a, b)(t\text{-conorm})$$

Finally the global maximum of similarity of an object in a class allows the definition of a class that best describes the object.

In other words MAD is a related term of how similar a descriptor object is, to the same descriptor of a given class and GAD is defined as the degree of relevance of an object at a given class given, as a function of relevance diffuse.

$$MAD_{c,d} = \rho_{c,d}^{X_{i,d}} (1 - \rho_{c,d})^{1-X_{i,d}} \quad (1)$$

Where:

$\rho_{(c,d)}$ =Learning Parameter (Rho) for class c and the descriptor d.

$X_{(i,d)}$ =The Descriptor d of object i.

The implementation of LAMDA, includes a probability function for estimating the distribution of descriptors based on fuzzification, the process of converting an element in a value of each class to which it belongs.

The main features and that makes difference of LAMDA are the NIC, Not Information Classified, which allows you to perform supervised classifications and non-supervised, learning functions are based on arithmetic, they can modify the parameters representative of each class. NIC accepts all objects contained in the universe of description with the same degree of appreciation GAD. For more information about the learning algorithm for the analysis of multivariate data, refer (Aguado-Chao, 1998), a mixed qualitative quantitative self-learning classification technique applied to situation assessment in industrial process control.

4. Methodology

It is important to study the relationship between the historical trend of the vote and the electoral results of a specific process; it is important because it allows us to make predictions, which can, in good measure, sensitizing political actors and citizens about the possible results of the electoral process.

It is pertinent to note, that the research was carried out, by ordering the results of the processes of local governor 1998, 2004 and 2010 of the state of Quintana Roo, to develop historical series of votes, which were necessary to carry out the projections.

The election results are not entirely accidental events, fully relieved by past events, and that much of what happens in local processes allows us to contemplate the possible scenarios of the local process.

Thus, in the case of the local executive, it incorporates data from the last three elections for governor 1998, 2004 and 2010, data were analyzed from municipal presidents and local deputies, the above are for every 3 years; due to the

difficulties to normalize the data and the lack of the data themselves; it was determined to use the data for governorship.

The historical evolutions that have had the political parties in the State of Quintana Roo, clearly shows how diversity have emerged from these political actors , but with the passage of time it have been terminated. The political parties which, with the passage of time have subsisted alone or coalitions are: the PAN, PRI and the PRD, for the case study.

To obtain the data already standardized, was made a historical analysis of the evolution of political parties and their coalitions; it concluded: in the case of the state of Quintana Roo, in all elections for governor all three major political parties in Mexico were present or were coalitions.

First, and for not having bias or trend, it was taken, in the order they appear registered in the State electoral unit, in such a way that they appear in the following way: PAN, PRI and PRD or their respective coalitions. In that sense we started to take the year of election 1998, 2004 and 2010 as data, being the data that was obtained from State Electoral Body and taking into account that the major election is performed every 6 years.

The data are then classified by electoral district of the years: 1998, 2004 and 2010 for these years there have been 15 districts; in such a way that the division was carried out by electoral district and for each electoral district it disaggregated by casilla, for every casilla there was a need to standardize the information; for each casilla is divided by type of casilla, in such a way that it was the unbundling of the most basic data form.

The record is as follows: year of the election, the electoral district, casilla, political 1, political 2 and 3. Leaving 2 types of data: qualitative data and the others quantitative.

5. Experiments

5.1 Salsa

The generated file of the data, must include the header, a, according to the format that handles the tool for this case SALSA, subsequently the data is standardized; file, b, is saved. It is appropriate to perform the loading of the data through the file in text format, c.

Once it has been proceeded to load the data in SALSA, ii proceeds to process them d.

5.1.1 File Header

The format of the header of the file that will be used to process the data in the tool is the one shown in table 4, the tool asks that at the beginning of the file exists & and the other columns should be separated by a Tab.

Table 4.File header.

&ANIO	DIST	CAS	PAN	PRI	PRD
					.

5.1.2 Standardized Data year 1998- 2010

The data were grouped by years 1998, 2004 and 2010, the electoral district to which corresponds I. XV, the number and type of polling station Basic, contiguous, special or extraordinary and finally the vote for the party.

Table 5.SALSA dataset file.

&ANIO	DIST	CAS	PAN	PRI	PRD
1998	I	300B	83	149	45
...					
1998	XV	297B	11	235	236

Table 5.SALSA dataset file.

&ANIO	DIST	CAS	PAN	PRI	PRD
...					
2004	I	300B	206	161	20
...					
2004	XV	297B	3	35	127
2010	I	300B	47	153	58
...					
2010	XV	297B	73	137	79

5.1.3 Data loaded

In figure 1, it is seen as if the tool has already grouped and sorted all 100 % the data, in a quantitative and qualitative manner, if we are to observe the previous point, the file is a set of unsorted and unclassified data, where there are numbers and alphanumeric.

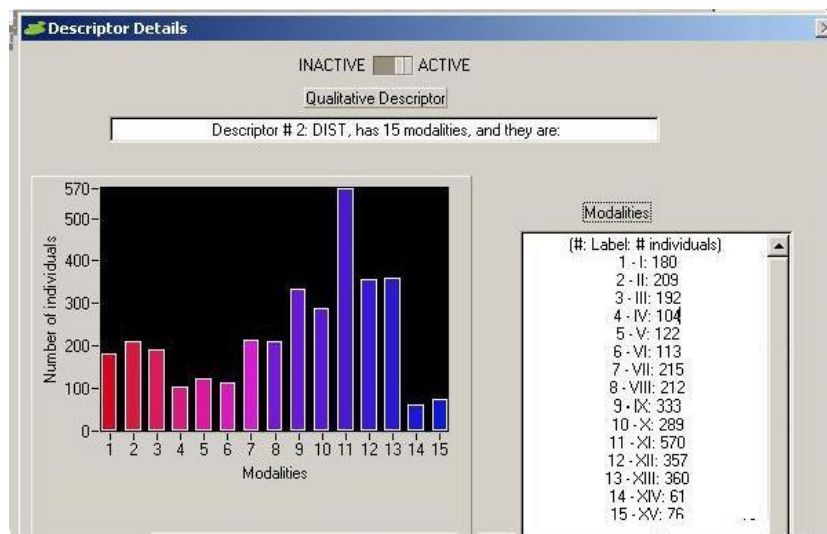


Figura 1. Details of descriptors.

5.1.4 Processed data

The historical data processed contain 3390 samples and 15 descriptors or physical variables obtained by the normalization done to the election data. Through a standardization of data, it shows the representation of the behavior of the variables. The minimum and maximum values that are used in each descriptor helps homogenize the influence of its dimensions.

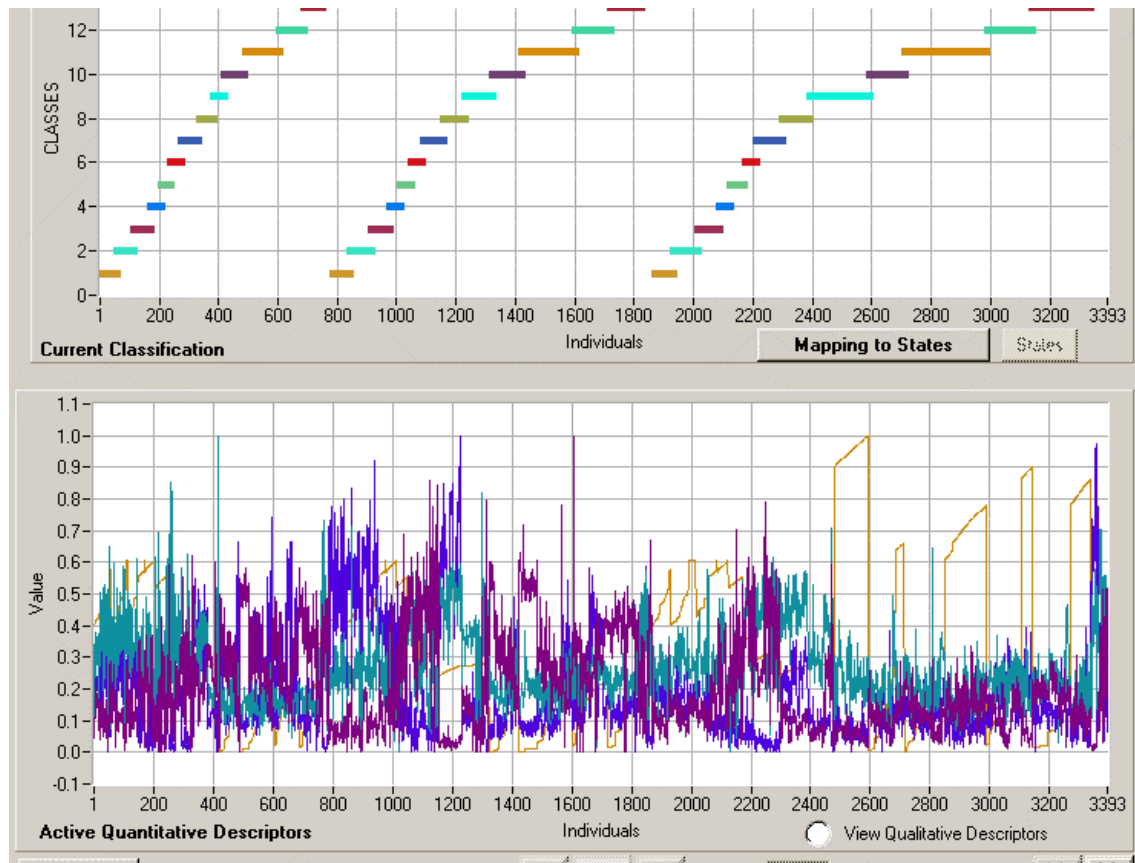


Figura 2. Profiles.

As a last step the profile of the class e is obtained.

5.1.5 Descriptors

This context has 6 descriptors with the current state of the active descriptor:

Table 6. Descriptors of the dataset.

No.	Nombre	Tipo	Max	Min
1	Anio	CUANTITATIVO	2010	1998
2	DIST	CUALITATIVO	Label no. 1 Label no. 15	Valor I Valor XV
3	CASILLA	CUANTITATIVO	741	1
4	PAN	CUANTITATIVO	248	0
5	PRI	CUANTITATIVO	491	0
6	PRD	CUANTITATIVO	491	0

5.2 WEKA

A procedure is performed similar to that made with *salsa*. As a first step it generates a data file, the file generated from the data, must include the header a, according to the format the tool handles, for this case *Weka*, after such data is standardized, the file is saved. It is appropriate to perform the loading of the data through the file in text format b.

5.2.1 File Header

In the case of the EM algorithms and K-means using the software *Weka*, the attribute *polling station* had to be removed, due to both *grouping* classifiers does not allow qualitative data.

@relation 'datos'

@attribute anio numeric

@attribute distrito {I, II, III, IV, V, VI, VII, VIII, IX, X, XI, XII, XIII, XIV, XV}

@attribute pan numeric

@attribute pri numeric

@attribute prd numeric

Figura 3. File Weka Dataset.

5.2.2 Data loaded

It is noted how Weka does the classification in the form of a table and in the form of bars, in the case of the table it makes a classification by district and the result of the grouping of the data for each district. For the graphs it only shows its concentration and one would have to deduce that each bar is an electoral district.

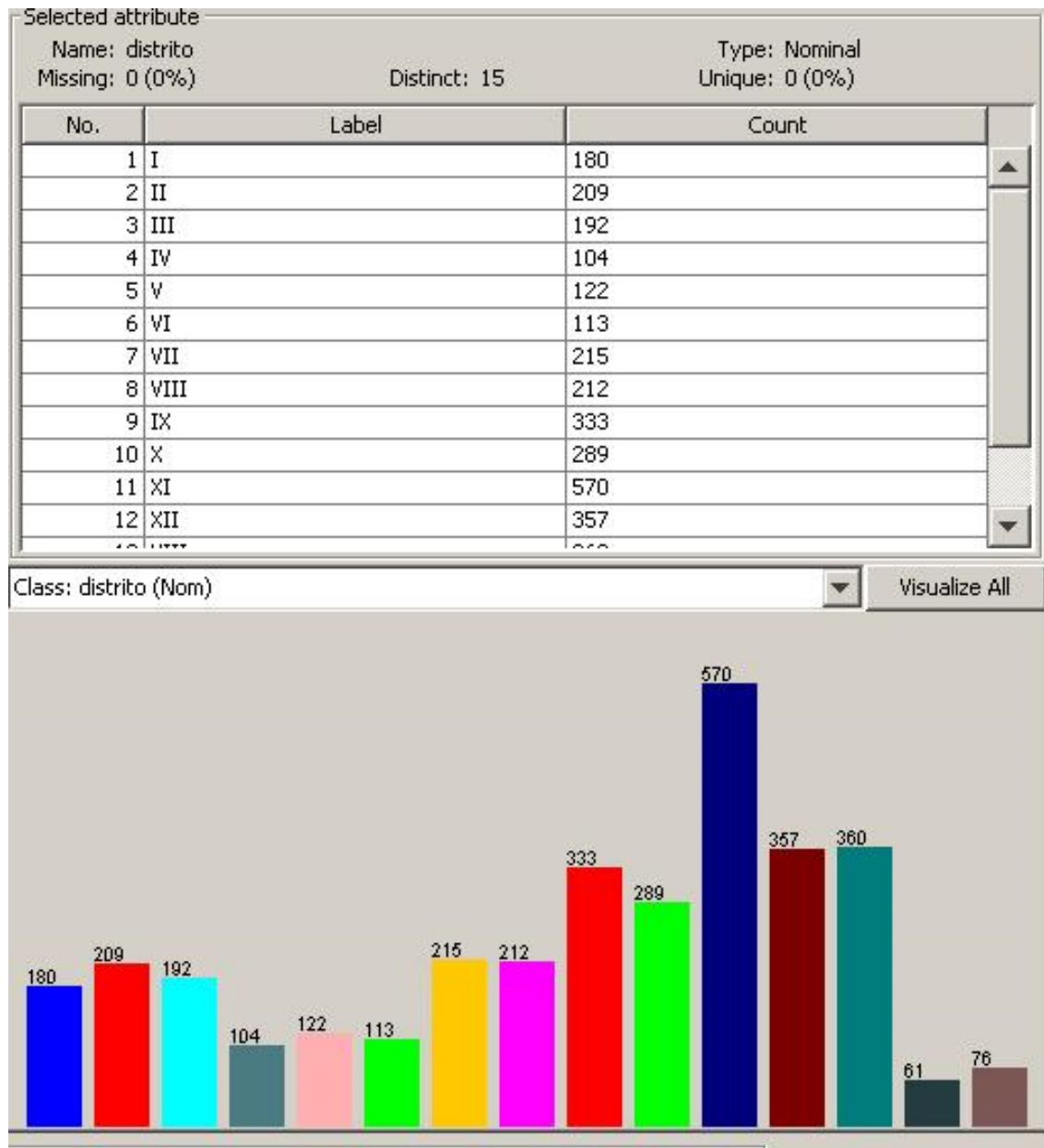


Figura 4. Classification.

5.2.3 Data processed by K-means

As how it can be observed in the circles in Figure 3, the tool generates two Cluster Centroids turns the display XI and XIII and it handles them as if they were the most distant and from that first the adjustment is made.

```

Clusterer output

Clusterer Model

kMeans
*****

Number of iterations: 22
Within cluster sum of squared errors: 2635.438902787142
Missing values globally replaced with mean/mode

Cluster centroids:

Attribute      Full Data      Cluster#
              (3393)        0          1
-----
distrito       XI            XIII       XI
pen            51.3118      81.3363   29.1205
pri            129.104     148.432   114.8186
prd            88.0899     65.9341   104.4654

Time taken to build model (full training data) : 0.36 seconds

--- Model and evaluation on training set ---

Clustered Instances

0      1442 ( 42%)
1      1951 ( 58%)

```

Figura 5. Cluster Model - K-means.

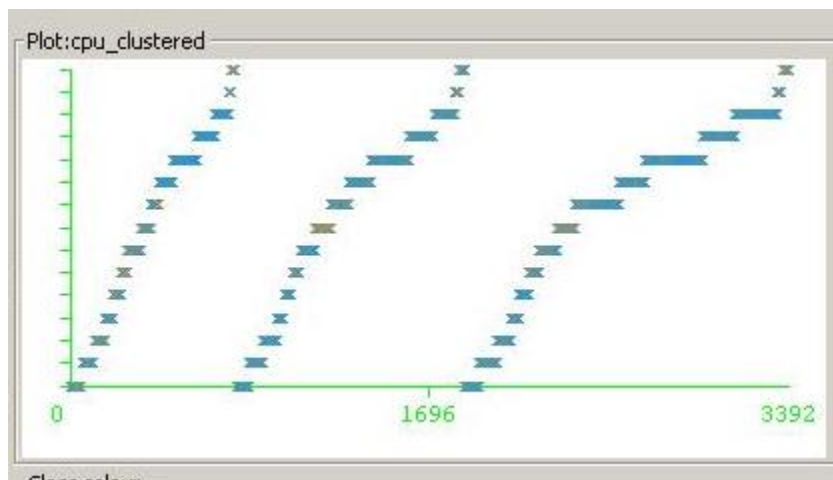


Figura 6. Cluster Plot.

Generation of results through the Weka methods.

6. Advantage

Proper use of data classification algorithms, has several advantages. With this work, we have concluded that there are the following advantages:

In an investigation of qualitative nature, these algorithms serve to validate the data, because they are based on mathematical models. Once the system has been trained, within the domain that is done, the manipulation of data, interpretation of the results is often simple. Because, using the mathematical methods, experiments can be repeated and provide the same results for verification.

The clustering techniques, have significant advantages in terms of time. The quality of the results depends on the similarity measure used. Further the quality is measured by its ability to discover hidden patterns.

The cost of learning is null. No need to make any assumptions about the concepts to learn. You learn complex concepts using simple functions such as local approximations. You can extend the mechanism to predict continuous values.

7. Results and future work

Although Weka is a software that allows you to make automated classifications by different methods and forms, in this analysis only the methods proposed at the beginning of the article were used, in such a way that it shows, the results that were more adjusted or approximated the classifications long awaited by the expert. This is due to the fact that there are qualitative data, not all of the tools have the ability to properly classify and on the other hand the behavior cannot be explained under some statistical method. The software that best made the classifications was SALSA, see section 5.1, C and D, due to the fact that it included in the right way, the qualitative data along with the quantitative data.

With the data that has already been processed in both Weka and in SALSA, an analysis and comparison was carried out. The analysis was performed with respect to its performance to the clustering of quantitative and qualitative data, on the other hand, is made with respect to the efficiency when performing such data. In this point, it can be seen that the 3393 data 100 %, were classified properly in SALSA, unlike Weka which could not reach its classification in this same percentage.

The application of these algorithms in state elections is very efficient. The algorithms to predict the future, can be used in real time, like an option for the process electoral. It would be very useful and efficient to determine trends in state election by electoral districts in real time. For this case it is very useful to use the larger districts. With the bases shown in this work, on the future, a forecast can be done for any mathematical methodology as well as the correlations between the data of the districts and the casillas, and completing the corresponding analyzes by experts; for the work or the purposes to be used. The application of these algorithms in state elections is very efficient. The algorithms to predict the future, can be used in real time, like an option for the process electoral. It would be very useful and efficient to determine trends in state election by electoral districts in real time. For this case it is very useful to use the larger districts.

Based on the article and with the base shown in this work, in the future, you can make projections for a forecast, to be classified with new data and clustering algorithms; and we will make an analysis, a correlations between the data of the districts and the casillas. Our work will be done, for the purposes that the political groups consider relevant.

8. Conclusions

This article, find the current state of the art, related to the prediction of elections, using automatic programming. In particular of three algorithms: A.- Grouping method K-Means, B.- EM and C.- Methodology for classification LAMDA, through

the use and application of the Weka and SALSA, as support tools for the processing of standardized set of data, to make electoral predictions, for the election of governor in the state of Quintana Roo. Due to the set of data that were analyzed qualitative and quantitative as a whole, it was determined that the algorithm of LAMDA that used implicitly the SALSA software is the one that best returned the results, and is adjusted to the criteria of a more accurate form.

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