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A SELF-ORGANIZING MAP OF THE ELECTIONS IN PORTUGAL

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ABSTRACT

As (artificial) neural networks are simulations of the supposed biological neurons work, the structure of human brains - where processing units, the so-called neurons, are connected by synapses - is approximated by (artificial) neural networks. As most of neural networks, self-organizing maps are trained through a learning process. By the use of a neighborhood function in this learning process, self-organizing maps (SOMs) thus allow to visualize which (and how) democratic elections were more similar/distinct. For Portugal the SOM identifies two clusters of elections: one made of those corresponding to a re-election of the incumbent, i.e. in 1987, 1995, 1999 and 2009; and another made of elections that led to a change in the party in power, i.e. 1991, 2002, 2005 and 2011.

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[I] INTRODUCTION

The electoral cycle literature has developed in two clearly distinct phases. The first one, which took place in the mid-1970s, considered the existence of non-rational (naive) voters. In accordance with the rational expectations revolution, in the late 1980s the second phase of the models considered fully rational voters. In terms of the electorate rationality, an intermediate approach, i.e. one that considers learning voters, which are bounded rational, may be more appropriate.

Generally speaking, learning models have been developed as a reasonable alternative to the unrealistic informational assumption of rational expectations models. Moreover, through learning models it is possible to study the dynamics of adjustment between equilibriums which, in most rational expectations models, is ignored. Although a number of different studies modeling learning have been presented, two main classes of models can be distinguished: rational learning and bounded rational learning models (Sargent [1]). In rational learning models, it is assumed that agents know the true structural form of the model generating the economy, but not some of the parameters of that model. In bounded rational learning models, it is assumed that agents, while learning is taking place, use a 'reasonable' rule, e.g., by considering the reduced form of the model. Salmon [2] is, to the best of our knowledge, one of the few references where an innovative bounded rationality approach such as neural networks learning has been applied in a policy-making problem.

Despite the vastness of the literature on the economic importance of the elections and on neural networks, the fact is that there are even fewer references that combine these two aspects. In Caleiro [3] it is proposed to use a kind of neuroeconomics approach within a political business cycles context. Specifically, Caleiro [3] showed how a particular neural network, i.e. a perceptron would classify policies and outcomes as 'electoralist' or not, using Nordhaus [4]' model. In Caleiro [5] it is also explored the problem of how to classify a government showing in which, if so, circumstances a perceptron can resolve that problem. This was done by considering a model recently considered in the literature, i.e. one allowing for output persistence, which is a feature of aggregate supply that, indeed, may turn impossible to correctly classify the government. Following a different objective, but also using a perceptron, Gill [6] addressed the problem of forecasting the result of general elections in India. Given the ability of fuzzy sets to represent vagueness and neural network ability to learn – see Chen [7] – Jiao et al. [8] considered a fuzzy adaptive network to model and also forecast national presidential elections.

Owing the number of relevant variables in any political-economic structure it could be considered a dimension associated with each of these variables. As a matter of fact, it is generally considered that structure to be a system in which the existence of causal relations between the variables which compose it allows the same to be characterized by a smaller number of dimensions. This reduced number of dimensions is, however, limited in view of the existence of random elements. These make causal relationships, although detectable, inaccurate. From this standpoint, it is important, especially when dealing with empirical data, the use of methods which allow the reduction of the multi-dimension of data.

Plainly, the reduction in the multi-dimension of the data is an issue that obviously received a substantial attention in the

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literature. As is known, when the transformation is linear, the principal component analysis (Pearson [9]) is particularly suitable in converting a set of observations of possibly correlated *n* variables into a set of values of their principal components, understood as (linearly) uncorrelated variables, which are to be in a number smaller than *n*.[1] [[1] As well known, the principal component analysis relates to the factorial analysis. The first is concerned essentially with the variance, while the second is concerned essentially with the covariance.] When the transformation is non-linear in nature, there are other techniques for dimension reductions such as principal curves (Hastie and Stuetzle [10]), multidimensional scaling (Kruskal and Wish [11]) or self-organizing maps (SOMs) (Kohonen [12, 13, 14]).

Self-organizing maps are intended not only to reduce the dimensions of data but also as a visualization technique that produces a map (usually in one or two dimensions) which plots the similarities on the data by clustering similar data objects. In doing so, self-organizing neural networks are used. As most of the neural networks, SOMs are trained through a learning process. By the use of a neighborhood function in this learning process, self-organizing maps thus allow to visualize which (and how) democratic elections were more similar / distinct. Notably, by the use of the SOM methodology, Niemelä and Honkela [15] explored the relationship between parliamentary election results and socio-economic situation in Finland between 1954 and 2003.

The use of a SOM methodology is indeed appropriate given the importance of the expected distinction of incumbents and of their performances in democracies. For instance, in accordance to the political version of the electoral business cycles, ideological aspects are not important whereas in the partisan version the ideology of the incumbent is indeed relevant. From this point of view, it is accepted that the evolution of the economy and the consequent election results will be different depending on the type (left-right; conservative-liberal) of the incumbent. The existence of distinct parties in power in Portugal after the restoration of democracy allows, therefore, studying these issues. In this chapter such a study is done using a particular type of neural network, self-organizing maps, which, by their characteristics, are particularly suited in accomplishing the task of checking for how the different democratic elections (in Portugal) were similar or distinct in terms of their results.

In consequence, the remaining of the chapter is structured as follows. In a succinct way, Section II presents the neural network general methodology and, in particular, the method of SOMs. The results of the application of this methodology to the elections in Portugal are analyzed in Section III. Section IV concludes.

[II] MATERIALS AND METHODS

Generally speaking, (artificial) neural networks are simulations of how biological neurons are supposed to work, i.e. the structure of human brains, where processing units, the so-called neurons, are connected by synapses, is approximated by (artificial) neural networks. As such, the interconnected network of processing units describes a model which maps a set of given inputs to an associated set of outputs values.[2] [[2] A more formal definition would consider a neural network < P,< > to be a directed graph over the set P of processors (neurons), where a processor is a mapping from an input to an output space.] As the number of inputs does not have to be equal to the number of outputs, a neural network can, alternatively, be described as mapping one set of variables onto another set of a possibly different size.

The knowledge of the values for the input and output variables constitutes, then, the major part of the information needed to implement a neural network. Despite the minimal information requirement, this constitutes no motive for questioning the results obtained; see Salmon [2]. In fact, this characteristic makes neural networks particularly appropriate for cases where the structure connecting inputs to outputs is unknown.[3] [[3] Take, for instance, Wall [16], which intends to bridge the gap between substantive rationality and procedural rationality. The fact that it is considered that the exact form of the objective function is unknown is what makes this bounded rationality model a good example of a possible application of neural networks.] In this sense, neural networks can be classified as 'non-structural' procedural models. Furthermore, they are in good agreement with a typical characteristic of bounded rationality: the adaptive behavior. Indeed, the adaptation to the environment as a crucial characteristic of a neural network makes it distinct from many (standard) models of learning.[4] [[4] In particular, neural networks relax the constant linear reduced form assumption of least squares learning by considering a time varying possibly non-linear stochastic approximation of that form.]

Neural networks are used mainly to learn two types of tasks; see Swingler [17]:

1. Continuous numeric functions - When the task is to approximate some continuous function, as in the case of a signal extraction;
2. Classification - When the input is a description of an object to be recognized and the output is an identification of the class to which the object belongs. The most common kind of neural network for classification purposes are the so-called perceptrons, see Rosenblatt [18].[5] [[5] For a clear explanation of the link between perceptrons and the statistical discriminant analysis see Cho and Sargent [19].] In this sense, one may consider perceptrons as learning mechanisms used by voters to perform a classification of the incumbent in order to distinguish opportunistic

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(electorally motivated) from benevolent (non-electorally motivated) behavior of the government, Caleiro [3] and Caleiro [5].

Let us then clarify the *modus operandi* of neural networks by a simple formalization as follows.[6] [6 For a clear mathematical presentation see Ellacott and Bose [20], among others. More advanced references include White [21]. Given an input vector, *x*, the neural network determines a particular parameterization, say β, which, in conjunction with a function *g* – also possibly determined by the neural network – leads to an output vector *y* = *g* (*x*,β) 'closest' to some target *y**. In other words, the output units *y*(*k*), (*k* = 1, ..., *t*), process, using a function *g*, the inputs *x*(*i*), (*i* = 1, ..., *r*), previously amplified or attenuated by the connection strengths $\beta(i,k)$.[7] [7 Implicitly assumed is a feedforward model, where signals flow only from x(i) to y(k). It is, nevertheless, also possible to consider feedback effects.]

The simplest neural network structure described above is usually relaxed to obtain flexibility by considering a layer of, so-called, hidden units. In this case, the transformation of inputs into outputs includes an intermediate processing task performed by the hidden units. Each hidden unit, then, produces, by the consideration of an activation or transfer function *f* (·), an intermediate output *s* (*j*), *j* = 1, ..., *s*, which is finally sent to the output layer.[8] [8 It is also (and generally) possible to consider a bias node shifting the weighted sum of inputs by some factor b(j). See **Figure–1**.] This situation is illustrated in **Figure–1**.

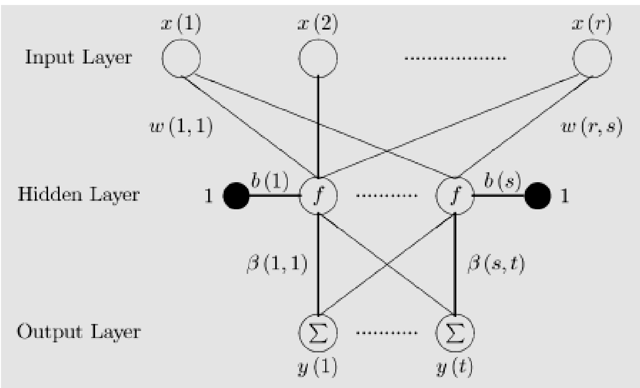

Fig: 1. A neural network representation

The neural network then computes:

1. The input(s) to the hidden layer

$$h(j) = b(j) + \Sigma_i\, w(i,j)\, x(i) \qquad i = 1,\ldots,r;\ j = 1,\ldots,s;$$

2. The output(s) of the hidden layer ≡ the input(s) to the output layer

$$s(j) = f(h(j)),$$

where *f* is the so-called activation function;

3. The output(s) of the output layer:[9] [9 It is possible to consider an activation function and/or a bias before the determination of the final outputs.]
4.
$$y(k) = \Sigma_j\, \beta(j,k)\, s(j) \qquad j = 1,\ldots,s;\ k = 1,\ldots,t.$$

As pointed out in White [21], the output vector *y* = *g* (*x*,θ) can be viewed as generating a family of approximations (as θ ranges over the set Θ, say) for the unknown relation between inputs *x* and their corresponding outputs *y*. The best approximation can be determined by a recursive learning procedure known as back-propagation. The learning process – training – is then an iterative procedure of processing inputs through the neural network, determining the errors and back-propagating the errors through the network to adjust the parameters in order to minimize the error between the predicted and observed outputs. This method of learning is referred to as gradient descent as it involves an attempt to find the lowest point in the error space by a process of gradual descent along the error surface.[10] [10 Two factors are used to control the training algorithm's adjustment of the parameters: the momentum factor and the learning rate coefficient. The momentum term, which is quite useful to avoid local minima, causes the present parameter changes to be affected by the size of the previous changes. The learning rate dictates the proportion of each error which is used to update parameters during learning.]

Back-propagation is a supervised training technique in the sense that the training data consists of an input vector and a target vector such that the weights (and bias) of the network are changed during the learning process in order to reduce the difference between the output and the target vectors. This learning technique is common in most neural networks but, however, does not apply in the case of self-organizing maps, making them a very special case of a neural network.

Given its main objectives, the architecture of a SOM is different from the traditional structure. It usually consists on a 2D lattice of nodes, each being connected to the input layer. Each node is properly positioned in the lattice (for example, by coordinates *x*, *y*) and has an associated vector of weights with the same size of the input vectors.

The training process is iterative and follows the steps described below:

1. Each node's weights are initialized;
2. An input vector is chosen at random from the set of training data and confronted to the lattice;
3. Every node is examined in order to determine the so-called *best matching unit*, i.e. the one with weights that are the most similar to the input vector;
4. Starting with the value of the lattice – in order to include all nodes – and making it smaller in every iteration, the radius

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of the best matching unit's neighborhood is calculated. Any nodes found within this radius are considered to be inside the best matching unit's neighborhood;

5. The weights of all neighboring nodes determined in step 4 are adjusted to make in order to make them more similar to the input vector;
6. Step 2 is repeated for *n* iterations.

[III] RESULTS

Constitutional governments have ruled in Portugal after the establishment of democracy in 1974.[11] [[11] The 3rd, 4th and 5th constitutional governments, which were in power between August 1978 and January 1980, were actually governments of presidential initiative.] In any legislative election that took place after 1974, the winning party has always been the Social Democratic Party (PSD) or the Socialist Party (PS), resulting in the formation of governments supported by one of those two parties.[12] [[12] The only exception was the 9th constitutional government, supported by a post-election coalition between the two parties, which was in power between June 1983 and November 1985.] Still, third parties in Portugal have been representing a fairly important role, even in terms of parliamentary seats.

Those facts lead us to consider the following classification in what follows: taking the parties with parliamentary seats, we consider the results of those two main parties, i.e. PSD and PS, and the results of the parties to their left – basically the Democratic Unity Coalition (CDU)[13] [[13] A coalition between the Communist Party and the ecologist party "Os Verdes".] and the Left Bloc (BE) – and to their right – basically the Social Democratic Centre/People's Party (CDS/PP). This classification has the advantage of not introducing distortions because, in time period under consideration, there were parties with parliament seats that have now been extinguished – the case of the Democratic Renewal Party (PRD) – and others that meanwhile were created as is the case of BE.

In what concerns the remaining data,[14] [[14] The source of the data is the Bank of Portugal] ever since the seminal paper of Nordhaus [4], inflation and unemployment have been considered to be the most important economic variables explaining the electoral results, (Caleiro and Guerreiro [22]). More recent literature has shown that the existence of persistence in real variables, such as unemployment, may invert the political business cycle optimal pattern (Gärtner [23], Caleiro [24]). By respecting these facts, it will be considered the average value of monthly inflation and of monthly unemployment in the first and second halves of the mandate ending with each election. The same division of the mandate is also considered in terms of another variable that recently have been associated with election results (in Portugal), i.e. consumer confidence (Ramalho et al. [25]). Finally, a dummy variable taking the value 1 in case of a re-election and 0 in case of an electoral defeat of the (previous) incumbent is also considered. Taking into account the availability of the data, the legislative elections of July 1987,[15] [[15] The previous election took place in October 1985.] October 1991, October 1995, October 1999, March 2002, February 2005, September 2009, and June 2011 are to be considered. **[Table-1]** summarizes the data (all data, except confidence and the dummy are in percentage).

Table: 1. The data

Election	Left	PS	PSD	Right	Inflat_i	Inflat_f	Unemp_i	Unemp_f	Conf_i	Conf_f	Dummy
1987	17.05	22.24	50.22	4.44	0.9691	0.7182	9.1	7.8	-13.750	-9.800	1
1991	8.80	50.60	29.13	4.43	0.9331	0.9473	5.9	4.6	-8.423	-5.654	0
1995	8.57	43.76	34.12	9.05	0.6321	0.3617	4.6	6.9	-20.917	-28.500	1
1999	8.99	44.06	32.32	8.34	0.2000	0.2154	7.1	5.4	-18.917	-8.250	1
2002	9.68	37.79	40.21	8.72	0.3293	0.2753	4.5	4.6	-10.600	-18.600	0
2005	13.89	45.03	28.77	7.24	0.2933	0.1694	6.4	7.5	-32.889	-29.000	0
2009	17.68	36.55	29.11	10.43	0.2689	0.0364	8.7	9.2	-29.536	-37.821	1
2011	13.08	28.06	38.65	11.70	0.1918	0.2945	11.6	12.4	-33.818	-47.091	0

Starting with the minimum x-y neural network configuration, i.e. a 2x2 (hexagonal) topology, the obtained SOM is shown in **Figure 2**.[16] [[16] The results were modeled by Spice-SOM 2.1, written by Cao Thang, available at http://www.spice.ci.ritsumei.ac.jp/~thangc/programs/ (accessed on June 12, 2012).]

Notably, the SOM identifies two clusters of elections: one made of those corresponding to a re-election of the incumbent, i.e. in 1987, 1995, 1999 and 2009; and another made of elections that led to a change in the party in power, i.e. 1991, 2002, 2005 and 2011. This kind of map is remarkable given that, in what concerns economic variables, a re-election or a defeat of the (previous) incumbent happened after a typical, as well as an atypical, pattern of electoral business cycle.

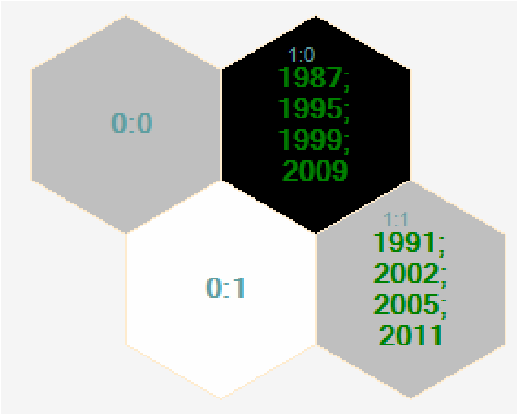

Fig: 2. Elections in Portugal organized by the SOM

Plainly, increasing the x-y neural network configuration would lead to a clearer separation of the elections. As a matter of fact, for instance considering a 8x8 (the number of elections) neural network, the pairs (1995-1999), (1987-2009), (1991-2005), (2002-2011) seem to emerge (see **Figure–3**) but, in general, the same conclusion is achieved.

From the political science point of view the results are interesting from the outset because they provide evidence supporting that (in Portugal) the political version of electoral cycle models cycles prevail over the partisan one. As a matter of fact, the clustering of elections is not based on the winning party, therefore on the alleged difference between the two major parties, which have supported all governments under study. Whilst the, so-called, third parties play a far from negligible role (see Caleiro [26]) in Portugal, the fact is that the convergence of political propaganda towards the position of the median voter has made those two major parties to become very similar in terms of their major decisions - not so much in terms of their political intentions. Thus, it makes sense that the clustering of the SOM does not consider sufficiently significant the remaining partisan differences.

[IV] CONCLUSION

The electoral cycle literature has developed in two clearly distinct phases. The first one, which took place in the mid-1970s, considered the existence of non-rational (naive) voters. In accordance with the rational expectations revolution, in the late 1980s the second phase of models considered fully rational voters. In any of these two phases a distinction between the political and the partisan versions was also made. In accordance to the political version the ideological aspects are not important whereas in the partisan version the ideology of the incumbent is indeed relevant. From this point of view, it is accepted that the evolution of the economy and the consequent election results will be different depending on the type (left-right; conservative-liberal) of the incumbent.

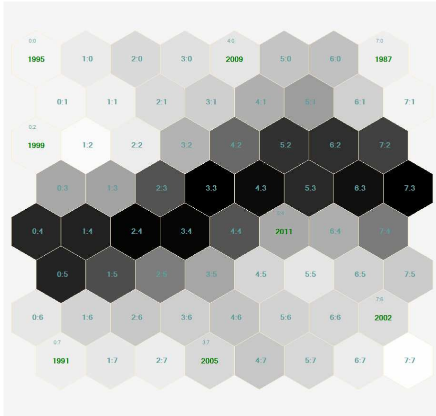

Fig: 3. Elections in Portugal organized by the SOM

The existence of distinct parties in power in Portugal after the restoration of democracy allows, therefore, studying those issues. In this article this study is done using a particular type of neural network, SOMs, which, by their characteristics, are particularly suited in accomplishing the task of checking for how the different democratic elections (in Portugal) were similar or distinct. A SOM of the electoral results combined with some relevant economic variables allows visualizing that the legislative elections that took place in Portugal in 1987, 1995, 1999, and 2009 were similar, the same happening with the 1991, 2002, 2005, and 2011 elections. The clustering is made in terms of the elections that corresponded to an electoral victory or to an electoral defeat of the previous incumbent.

From a political science standpoint, the results are essentially of political nature, given that they are in accordance to the fact that, despite some partisan differences between the two major parties in Portugal, which have being the support of all incumbents, those are not sufficiently clear to emerge in the clustering of the elections obtained by the SOM. This is a result that may as well be valid for other countries and/or future elections. A casual observation of recent episodes has been showing that the implementation of contractionary measures at the beginning of the mandate is more easily justifiable by the incumbent after a substitution of the party in power, i.e. after an electoral defeat of the previous incumbent. From this point of view, if the electoral cycles are to be important, the clustering of the elections in terms of the defeat or victory of the (previous) incumbent seems to be the expected result.

Given the apparent importance of space in the explanation of electoral results (Caleiro and Guerreiro [22], Caleiro [27]) a promising avenue for further research is the combination of the SOM methodology and of spatial clustering and/or GIS (Kaski and Kohonen [28], Skupin and Hagelman [29], Pablo-Martí and Arauzo-Carod [30]).

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CONFLICT OF INTERESTS

None

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