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Scheduler for SANN Analysis of U.S. Supreme Court Network Based on Markov-Shannon Entropy

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Abstract: Many complex systems may be represented as complex networks of ith parts or nodes (ni) interconnected by some kind of bonds, ties, relationships, links (Lij). For instance, Fowler *et al.* represented all case citations (Lij) in the U.S. Supreme Court as a network of nj cases citing and/or cited by other. These huge collections of nodes/links are impossible to remember and rationalize by a single person in order to assign correct links in new situations. Fortunately, Artificial Neural Networks (ANNs) can help us in this task. If we want use ANNs to predict links in complex networks, first we need to transform all the information into numerical input parameters to feed ANNs, second: we need to find the best ANN to predict our network. We can solve the first problem quantifying the structural information of the complex system (Brain, Ecological, Social, *etc.*) with universal information measures known as Shannon entropy (Sh). We can quantify topological (connectivity) information of both the complex networks under study and a set of ANNs trained using Shannon measures. Then using both sets of information parameters as inputs we can develop a dual QSPR model to discriminate between SANNs and not efficient ANN topologies. Here we used this QSPR method to develop potential HPC schedulers for complex systems. We studied 663072 citations to majority opinions in 43 sub-networks; each one with 5,000 (5K) citations to U.S. Supreme Court decisions (5KCNs). The overall accuracy of the ANN found was of >85% for 5KCNs; in training and validation series.

Keywords: SANN Scheduler; Markov-Shannon Entropy; U.S. Supreme Court; Social Network Analysis.

1. Introduction

Many important systems, in center of attention of modern science, may be approached as complex networks of ith parts or nodes (*ni*) interconnected by some kind of links (*Lij*), bonds, ties, or relationships [1-7]. The diversity of systems susceptible to be studied by complex networks is very high; e.g.,: Human brain [8], Ecosystems [9-11], or the citations to U.S. Supreme Court decisions [12]. All these collections of nodes and links are so large that it is impossible for a person to remember and rationalize all possible connections. We can solve this problem using Quantitative Structure-Activity/Property Relationships (QSAR/QSPR) models [13-18]. In QSAR/QSPR modeling we can represent the system as a graph of interconnected nodes and use as inputs theoretic-information parameters that quantify information about the structure of the graph. In this context, Shannon entropy quantifies the information contained in a message, usually in units such as bits [19-36]. The software MARCH-INSIDE (Markov Chains Invariants for Network Simulation and Design) has become a very useful tool for QSAR/QSPR studies [37-45].

In this occasion we selected the dataset of Fowler *et al.* [12], represented all case citations (Lij) in the U.S. Supreme Court as a network of nj cases citing and/or cited by other. Fowler used a complex network approach to quantify links in citations between cases and unravel the most relevant precedents. The work opens the door to the use of complex network structural parameters like topological indices and/or information measures to predict the future citation behavior of state courts, the U.S. Courts of Appeals, the U.S. Supreme Court, as well as other legal systems [45, 60-62].

The number of nodes and connections in complex systems is very large and the problem of prediction of correct links may become a computationally expensive task for large collections of complex systems. Artificial Neural Networks (ANNs) can help us in this task. ANNs are powerful bio-inspired algorithms able to learn/infer large datasets. There many examples of applications of ANNs to seek QSPR-like models [63-66]. ANNs can mange, for example, to learn to discriminate the correct collections of nodes (nj) and links present in complex systems (Lij) from other connectivity patterns not correct and/or distributed at random. We have at least two major problems if we want use ANNs to predict links in bio-systems and complex other networks. First, we need to transform all the information into numerical input parameters to feed ANNs. Next, we have to train many ANNs to detect which topology is better learning the structure of the system under study.

In this work, we introduce a new type of algorithm to solve this problem. The idea is simple: if ANNs are networks with nodes (neurons) and links (functions) we should treat them as such. In so doing, we can quantify topological (connectivity) information of both the complex networks under study and a set of ANNs trained using Shannon measures. Using both sets of information parameters as inputs we can develop a dual Quantitative Structure-Property Relationship (QSPR) model to discriminate between SANNs and not efficient ANN topologies. Here we used this QSPR method to develop potential HPC scheduler for complex systems. We studied 663072 pairs in 43 sub-networks; each one with 5,000 (5K) citations to U.S. Supreme Court decisions (5KCNs). The overall accuracy of the SANN-HPC schedulers found was of >81% for 5KCNs; in training and validation series (see Figure 1). This report of QSPR models potentially useful as task schedulers for HPC or Cloud Computing of ANNs with the subsequent can help to safe time and computational resources in the prediction of Complex Networks.

Linear Discriminant Analysis (LDA) models: Once the values of the Markov-Shannon entropies were obtained, we carried out a Linear Discriminant Analysis (LDA) by means of the STATISTICA software [76]. Let be qS(Lij) the output variable of a HPC schedule model used to score the ability of a given ANNq to predict correctly the link Lij between two nodes i-th and j-th (Lij = 1). We can use LDA to seek a linear equation with coefficients aik, bjk, cqk, dijqk, and e0. These are the coefficients of the Shannon entropies for the first node (Shik), for the second node (Shjk), and for the ANN graph (Shk(ANNq)), used as input for the LDA model. The k subindex indicates that this Shk value codify information for all nodes placed at least at topological distance d = k from the node of reference. We can use different statistical parameters to evaluate the statistical significance and validate the goodness-of-fit of LDA equation: n = number of cases, $\chi2$ = Chi-square, p = the error level, as well as the Accuracy, Specificity, and Sensitivity of both train and external validation series [77]. We can write the LDA equation with the parameters mentioned above in the following form, see also **Figure 1**.

2. Results and Discussion

Social Network Analysis (SNA) emerged in 1930 to become one of the more powerful tools in socials sciences [80]. With the rise of network search, commerce, consume, and socialization companies like Google, Facebook, Twitter, LinkedIn, Amazon, and others, SNA have become a very important tool for the analysis of the high amount of information of users interactions in the web [refs]. However, the application of these methods in legal studies is still at the beginning [81, 82]. Network tools may illustrate the interrelation between the different law types/judicial cases and help to understand law/judicial cases effect in the legal system and its effectiveness to regulate aspects of necessity in society or not. We have applied the present methodology the design new schedulers for HPC of ANN models useful to predict one important legal network. The example selected was the USSCC network and the best model found was:

Where Shk(Lti) and θk(Lti+1) are the entropy parameters that quantify information about the Legal norms (Laws) of type L introduced in the Spanish legal system at time ti and ti+1 with respect to the previous or successive kth norms approved. The model behaves like a time series embedded within a complex network. This is because it predicts the recurrence of the Spanish law system to a financial norm of class c when socio-economical conditions change at time ti+1 given that have been used a known class of norm in the past at time *ti*. The model correctly re-constructed the network of the historic record for the Spanish financial system with high Accuracy, Specificity, and Sensitivity (**Table 1**).

Table 1. Results of models for USSC network.

Model	Training Series				Model	Cross-Validation Series			
Param.[a]	%	Class	$L_{ij} = 0$	$L_{ij} = 1$	Param.[a]	%	Class	$L_{ij} = 0$	$L_{ij} = 1$
Sp	92.8	$L_{ij} = 0$	**219919**	17161	Sp	92.8	$L_{ij} = 0$	**74552**	5780
Sn	73.8	$L_{ij} = 1$	41449	**116831**	Sn	73.0	$L_{ij} = 1$	13817	**37391**
Ac	85.2	Total			Ac	85.1	Total		

Rows: Observed classifications; Columns: Predicted classifications; C_{ij} = Calculation with high priority; NC_{ij} = No C_{ij}.

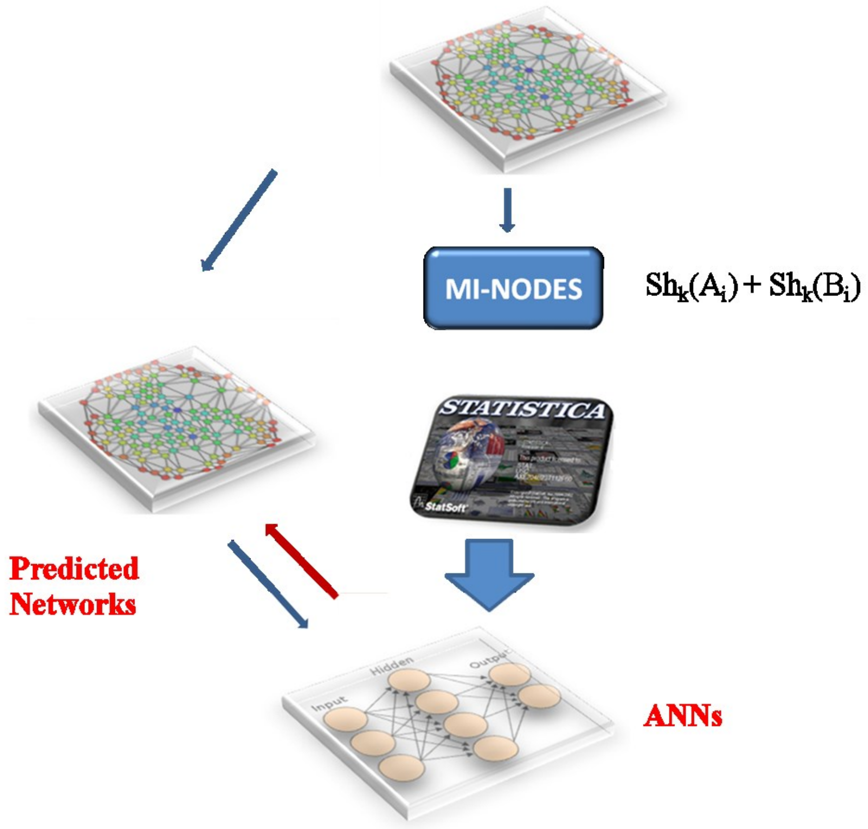

Figure 1. General workflow used in this work to develop new ANN for USSC network.

3. Materials and Methods

Datasets: U.S. Supreme Court (USSC) Network. We used a complex network constructed by Fowler et al. [75]. The authors included 26,681 majority opinions written by the U.S. Supreme Court. The dataset contains all cases that cite this U.S. Supreme Court decisions from 1791 to 2005. In this network each case is represented by a node. The links between two nodes Ai and Bj (arcs) express that the case jth cites the ith case previous to it (precedent). In order to both make more tractable the dataset for computation of Shk(Ai) and Shk(Bj) values and focused on specific intervals of time we split the data in 43 sub-networks. Each one represent one slot of 5000 (5K) citing cases, 5K-Citations Network (5KCNs) for > 22,000 cases of the U.S. Supreme court.

Computational Methods: Markov-Shannon Entropy Centralities for nodes.

We construct the classical Markov matrix (1Π) for each network as follows. First, we download from public resources the connectivity matrix L or obtain the data about the links between the nodes to assemble L (n by n matrix, where n is the number of vertices). Next, the Markov matrix Π is built. It contains the vertices probability (pij) based on L. The probability matrix is raised to the power k, resulting (1Π)k, and multiplied by the vector of the initial probabilities (0pj). The resulting vectors contain the absolute probabilities to reach the nodes moving throughout a walk of length k from node ni (kpj) for each k and are the base for the entropy centrality (Shk) calculation:

4. Conclusions

In this work we confirm that it is possible to combine Markov Chains and Shannon Entropy in order to calculate higher order entropy parameters. We also show that these parameters can be used to quantify information about local and global node-node connections in different types of complex networks. For it, we have used MI-NODES, a new tool for the study of complex networks which is an upgrade of the software MARCH-INSIDE, classically used to study drugs and proteins.

Conflicts of Interest

The author declares no conflict of interest.

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