Do Internals of Neural Networks Make Sense in the Context of Hydrology?

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ABSTRACT

As of recent times, neural networks have drawn in a lot of attention and popularity because of its application to numerous dimensions, including computer visioning and the processing of natural language. Nevertheless, when it comes to the science applicable to the immediate environment, such as the run-off of rainfall modelling in the field of hydrology, and so being, neural networks have the tendency to have a surprisingly demeaning reputation. This bad record can be blamed on the reality that they are black-boxed in primal nature, as well as to the complication or impossibility to comprehend internals that culminate in a forecast. Neural systems make up a computational technology tailored for hydrological predictions. In spite of being extensively utilized in many other fields of research and application, the number of hydrologists that favor the methodology may be lower than expected. That's as a result of the neural network's data-driven nature for the applied challenges looking to be solved. Also, neural systems make provision for a modelling footprint that comes in handy when there is a sufficiency of raw information to connect X with Y, particularly in the cases where there is a need for real-time results. With this paper, we are introducing neural ecosystem challenges in generality, setting them in a more extensive modelling in relational context with hydrology. This study explores the internals of the learned networks for different basin sets from the sundrily obtainable dataset known as CAMELS. Also, it utilizes local sensing data in symbolism of patterns in alignment with our comprehension of the system of hydrology. Demonstratively, we showcase that internally, LSTMs learned to interpret patterns that align with our comprehension of the hydrological system. For snow-carried catchments, for instance, the network grows specific memory cells with the capacity to imitate conceptual snow memories with yearly dynamics. This is known and accepted for the catchment models based on processes.

Keywords: Neural Networks, Hydrology, Hydroinformatics system

INTRODUCTION

Neural networks, also called NNs, are a complementary as well as alternative category of methods to conventional models. They can be envisaged as a pattern of computational searching and matching processes that allow for predictions in the absence of a rooted understanding of the chemical or physical procedures. For hydrologists, this type of application appeals to a considerable extent, as long as the omission of the explanation into detailed procedures is sustained. Neural networks depend on the provision of enough sets of raw information. But where there is an availability of these datasets, NNs may be designed to scout for the recurrences amongst the data. Based on the pattern-matching school of thought, predictions are carried out on non-dependent datasets, initially, for the validation of the model as well as for operational motives. Neural networks are one section of the wider hydroinformatics system, which came about in the 1990s in the form of an effective manager for information overload. (Govindaraju & Rao, 2000).

Price (2000) acknowledges four strands into the hydroinformatic ecosystem: the understanding of mathematical and physical sciences, handling data and the element that faces human culturalism. One of the major accomplishments of the NN method is that it has the capacity to work with all types of raw information (Fadziso & Manavalan, 2017). The challenge associated with the management of water in its diverse dimensions as well as applications is something which warrants for methods with which a myriad of elements can be connected. This starts from the complex nature of the hydraulics, trickles into the quality of the water itself and on to the monetary planning as well as social schedules (Bynagari, 2016). This move is in the direction of an encompassing or integrated technique for modelling. The methods that are obtainable to hydrologists are numerous and quite varied, each of them with their own upsides and downsides.

Modellers in the 1970s predicting problems (Freeze & Harlan, 1969) have the tendency to crack when computer systems got more power to take on quite complicated equations and extensively arrayed sets of raw information. That vision, though, has started to recede, not quite disappearing by any means. The unique nature of the catchments, the variability in the natural environment, system chaos, the complicatedness of scale integration and the cost of acquiring data all make the prediction task Herculean. When it comes to modelling floods as the basin scale using mesh-based techniques, there is a need for voluminous amounts of computer time. However, it is considered (Beven and Feyen, 2002) that these objectives are in closer proximity given the advancement of visualization and virtual gaming technologies.

As such, the goals for catchment-wide four-dimensional modelling is closer than ever. Neural networks do not, in any way known, look to take the place of such models. However, they can make provision for faster prediction systems operationally obtainable in rather shorter time periods. Neural networks are not in any competition with distributed models. Rather, they offer a complementary as well as alternative way to dealing with prediction challenges. With this study, we intend to use NNs in research for the first time and for the reviewing of recent cases of neural networks; hydrological applications.

Review of Related Literature

The classification pattern of hydrological modelling was proposed by Dooge (1977). The researcher's three-phased black box empirical, physically-based, lumped and distributed distinction model has significant recognition. This culminated into an acceptance of an obvious hierarchy in approach quality using the basic black box taken to be less acceptable compared to the approach that is much theoretically-based, mathematically demanding and distributed. This disparity is valid academically, but it is not often efficient in practice. Using the most basic tool for the task is the more appropriate approach in operational and practical modelling (Bynagari, 2015). Should the raw information be obtainable and the problem linear, it is ideal to employ linear regression.

The rational equations and unit hydrographs scale through due to the fact that they are practical tools designed for the supplication of actionable answers. Though NNs are a relatively novel method for hydrologists, the network has established an antecedence that was acknowledged (Govindaraju and Rao, 2000) from the 1940s onwards. When the concept of neural networks was first proposed (McCulloch and Pitts, 1943), the practical use was however followed by the formulation of the backpropagation NN algorithm, also known as the BPNN algorithm.

The algorithm became the harbinger of a cornucopia of applications in various fields. In the 1990s, a variety of studies generated interests (Masters, 1993; Cruz, 1991), while the first application to the hydrological universe came from Daniell (1991), Hall and Minns (1993), and French et al. (1992). That means, when it comes to hydrologists, it is a relatively new method, one that comes with a brief pedigree. Nonetheless, there has been a significant adoption and positive outcomes in publications as well as conferences (Donepudi, 2014b).

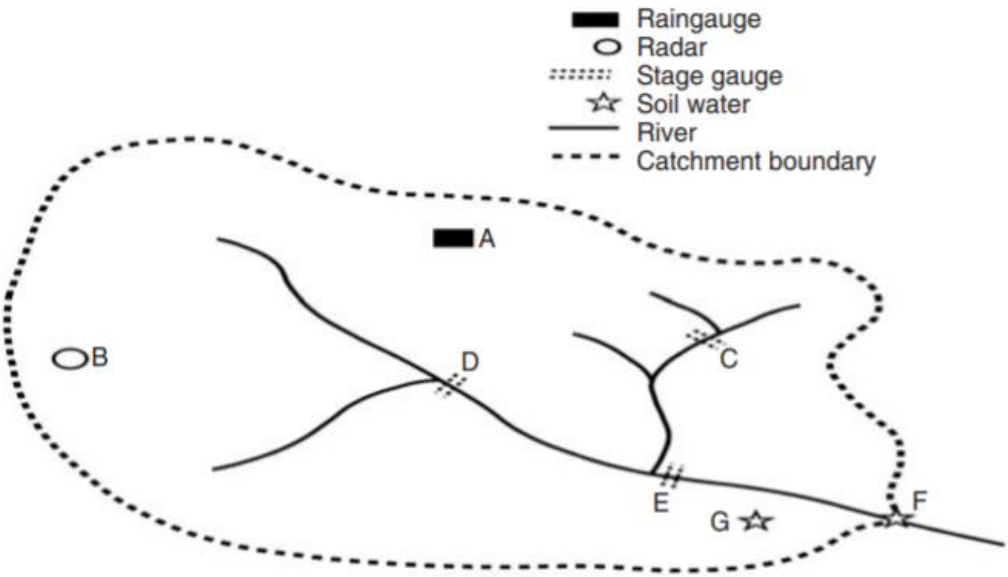
Many other studies describe neural networks as block boxes, dismissing them as empirical. By regarding them empirically, these studies are definitely considerate of NNs as inferior. Surely, the computations are built by the modeller, but the being of the connection that exists between variables is searched for and discovered by the computer. This makes NNs input-output models, effectively, which in turn means they are prone to the problems of insufficient raw information and a predictor that isn't reasonably thoughtful. Still, NNs have the power when juxtaposed with the ARM and regression techniques, for example, where the nonlinear-ness of the connections will be noticed and recorded (Hsu et al., 1995).

Additionally, the black box can be assessed in detail should the predictor wish it to be so (Abrahart et al., 2001; Wilby et al., 2003). Preexisting hydrological research is majorly about the rain-fall-runoff prediction applications, perhaps because these can interpret a conceptually linear point of origin. There are a couple of long-term records for both validation and training variability. The solutions, in question, are obviously not linear.

WHAT ARE NEURAL NETWORKS?

NNs are structures designed to predict via comparison procedures and pattern matching. More often than not, NN tools are not linear adaptive data-processing systems possibly described in mathematical terms (Fischer, 1998). These networks can exist as hard-wired, current-time mechanisms, optical processes, software simulators and specifically tailored neurocomputing chips (Taylor, 1993). Meanwhile, their computational components are inherently generic. NN-based software simulation programs, which are rendered in state-of-the-art high-level learning languages, are the most prevalent forms of the networks (Donepudi, 2014a). There are scores of public and commercial domain simulators from which users can choose, depending on their choice of computer system in addition to the sophistication obtainable in such packages make for substantial attraction (Bynagari, 2014).

There are several catalogues of established shareware and software obtainable on the World Wide Web, for instance NEuroNet (2001) or Sarle (2002). This doubles as an advantage and a possible hurdle that users can download and activate compelling NN products. This also applies to the packaging with little to no actual effort, such as the Stuttgart Neural Network Simulator (SNNS Group, 2003). Learned neural network solutions can also be transformed into committed Third Generation Language (3GL) functions for unification into locally-cultivated software products. Or, they can be connected to commercial use cases with the aid of a run-time connection based on software libraries with standards. This comes as a significant upside for users, especially newbies with intentions to subject the technique to experimentation. Nevertheless, all users need to be well acquainted with the upsides and downsides applicable to this modelling process.



Learning Considerations

The training of NNs is often described as the direct or purposeful modification in the knowledge framework of a system in a way which allows it to carry out operations better or repeat specific tasks or assignments at a later stage (Fischler & Firschein, 1987). Thus, specific information regarding a given topic or assignment will be encoded so that the solution would be able to produce an ideally expected reaction on following scenarios. There are two most common types of learning; the supervised and the unsupervised training. The difference between the two is that, when it comes to supervised learning, there is a requirement to formulate every input pattern in order to achieve a related pattern of output. For supervised learning, the model input has the tendency to output the raw data collected at one or many upstream gauges, wherein the said output is predicted to discharge when it is in a downstream station (Manavalan & Donepudi, 2016).

A study (Cameron et al., 2002) combined river stage at a pair of upstream points with two remote variables to arrive at an estimation for the future river stage at the downstream point. However, for unsupervised learning, the output is more often than not a set of clusters. Case in point, a river-level series can be subjected to partitioning into many groups of events (Abrahart & See, 2000). Similarly, rainfall and records for river series can be divided in order to realize amalgamated clusters spanning the entire input region (Hsu et al., 2002). Also, catchments can be packed into homogenous groups with matching climatological and geomorphological attributes (Hall et al., 2002). Every amalgamation of the input and output-related raw information is called a training pair, while the holistic set of learning pairs is referred to as the training set (Manavalan, 2014).

The learning duration for the presentation of a whole learning group is but a single epoch. The main objective of passing through training is the minimization of the output-related errors. That is realized with the aid of various algorithms whose tasks involve searching the error surface and descending the gradient. Predictors (or inputs) are channelled via the system for them to become the predicatands (output). And, via the training procedure, the weights of the internal connection are changed in response to calculative missteps (Bynagari, 2017). The equation specifying this modification is referred to as the learning rule or the learning law (Manavalan & Bynagari, 2015). There are numerous learning techniques and the process is usually complex, having abundant options, permutations and variables.

MAJOR MODELLING CATEGORIES

More often than not, neural networks are billed as a one-stop-shop. Nevertheless, caveat emptor is applicable because users need to recognize that many important decisions must be taken in the selection of the ideal modelling class (Donepudi, 2015). Certain categories of solutions prove more suited to the modelling of particular hydrological controls or procedures regardless of the notion's novelness and the extensive testing needed for the indicative results can be transformed into clear-cut blueprints. The amount of possible amalgamations and modifications that can be implemented is huge, while carrying out comprehensive and in-depth analysis remains impractical. Nonetheless, for hydrology, there are three more prevalent tools:

- Back propagation neural network (BPNN).
- Radial basis function network (RBFN).
- Self-organising feature map (SOFM).

Back Propagation Neural Network (BPNN)

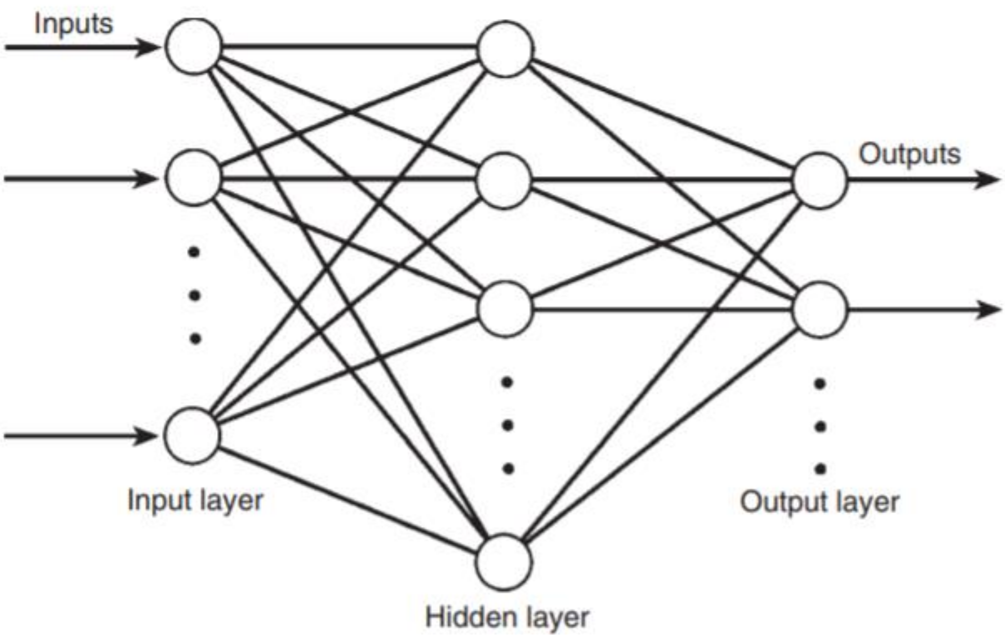
Back propagation is the most prevalent "default" training algorithm (Rumelhart et al., 1986; Tveter, 2003). The approach brings about an effective computational procedure tailored to assess the derivatives of the performance function of the network. This happens with respect to a specific set of parameters and aligns to a propagation of mistakes backwards via the system. However, the term has been adopted into the description of feed-forward multi-layered networks learned with the help of the back propagation algorithm, thus leading to confusion (Manavalan, 2016).

The back propagation neural networks (BPNNs) have surfaced as key workhouses in many fields of commerce and business. These tools form the most widespread mechanism applied to the hydrological modelling problems with more difficulties (Donepudi, 2016). Where trials showed to be insufficient, the non-standard activation functions were adopted by examining various alternatives in terms of the amount of epochs needed to reach a convergence point.

Radial Basis Function Network (RBFN)

The Radial Basis Function Network is the second most prevalent model, one which forms a three-layered network comprising input, hidden and output. The major structural disparities between the RBFN and the BPNN is: in the former, the links between input systems and hidden systems stay unweighted. Moreover, the transfer functions in the hidden system have radial-symmetric attributes, compared to sigmoidal. They (the hidden systems) carry out a non-linear and fixed transformation in the absence of modifiable parameters. Meanwhile, the output layer amalgamates the outcomes linearly with the aid of a simple summation in most cases (Leonard et al., 1992; Donepudi, 2017a).

In the schematics of a Radial Basis Function Network, the activation function in every hidden system does not have a critical role to play in the delivery of the entire network (Chen et al., 1991). Meanwhile, many forms of rudimentary control need to date their considerations. The parameters of the system comprise the centers (represented as Uj), the spread (symbolized as j) of the basis controls in the hidden layer points as well as the synaptic loads of the output layer systems (represented as Ekj). Also, the function centers are points in the input space, which means that the ideal solution is to have a unit at every point of distinction on the input space. However, for most challenges, a couple of input points will be chosen from the entire set of attainable points with the help of the process known as clustering.



Self-Organizing Feature Map

The Self Organizing Feature Map, also the SOFM, is the third most adopted modelling category (Kohonen, 1995). Based on the unsupervised category which comprises processing units that compete with one another, the SOFM network algorithm is used to realize the salient connections existing between datasets. Noteworthily, there is no preexisting understanding to the assistance of the clustering. The conventional framework comprises two processing unit layers, one layer in one-dimensional output form and a 2D competitive layer. The competitive layer, also known as the feature map, is arranged into a consistent grid comprising processing units, each of which is connected to the competitive layer (Manavalan & Bynagari, 2015).

The feature map, in question, possesses connections between the competitive units, wherein each of these units possess one or more additional weights or vector references. These components will be learned to stand for the rudimentary pattern related to each group or class. The learning itself involves the initialization of random weight, followed by the presentation of a data pattern to the system (Donepudi, 2017b). Then, the unit with the closest match is determined, after which the winning unit, as well as those in close proximity to it, are updated.

Potentially Exploitable Benefits

It is impossible for neurocomputing to ever become a universal solution. Meanwhile, there is no question whether it would make traditional computer modelling processes a thing of the past. Not in all cases are these modern tools better performers compared to traditional statistical approaches or well-known mathematical methods. In spite of being often possible for neurocomputing to realize alternatively actionable results in a fast and efficient way, they work with a minimum-sized set of data. However, neural panaceas possess distinctive attributes that should principally allow for these automatic tools to trump the inherent drawbacks involved in standard information processing practices. The strength of the said elements are in more need of full-potential investigation, understanding and exploitation. The major prospect with regards to neural modelling avenues in this scientific field is held to fall within 7 different categories.

- Power to handle complex nonlinear functions.
- Power to perform model-free function estimation.
- Power to learn from training data.
- Power to adapt to changing environments.
- Power to handle incomplete, noisy and fuzzy information.
- Power to effect multi-level generalisation.
- Power to perform high speed information processing.

In essence, neural networks are but one of the numerous tools that are at the disposal of hydrological researchers. The user is at liberty and well equipped to define the non-dependent and dependent variables. NNs also have all the usual modelling challenges, including the location of fitting data, and the testing as well as validation of involved models. A major upside of the neural network-type approach is that it makes less data-related demands. Additionally, dissimilar to multiple regression wherein the limitations of normality in the distribution of data are usually neglected, NNs do not bank on assumptions about the statistical attributes of a set of data. Data earmarked for different variables can come from all types while being obtainable on different times or spatial scales. This way, there is room for a more flexible approach to the collection of raw information and the development of models.

For instance, in management models, information pertaining to the weather, dynamics of the soils, plant development and agro-management can serve as inputs with the help of parameters derived from hourly, weekly and monthly recordings. The second major upside when it comes to NNs is that when they are searching for patterns and links in the sets of data, no assumptions are made regarding linearness. Neural networks are non-linear pattern recognition tools, hence their inherent potential attractiveness when it comes to tackling the un-linear hydrological problems.

The immense prospects of NN-based models for solving extremely complex computational problems, not omitting those where the subsisting ecological relationships are not comprehended (Lek and Guegan, 1999). There is a plethora of understanding for hydrology-related procedures at many scales, from catchment to laboratory and hillslope. Be as it may, it is not often vivid how equations can be written to link the processes comprehend at the m2 scale in order for them to scale up into the basin platform. Neural networks search for the repetitions in the raw information, hence having the capability to formulate the equations that serve as a description of the processes that operate on the catchments being studied.

Observations & Conclusion

Following about a decade of basic groundwork, there may be little doubt that neural solutions are ideal for the demanding task that is hydrological prognostics. The most critical item for successfully implementing each solution will be the acquisition of adequate and symbolistic data (Tokar & Johnson, 1999; Smith & Eli, 1995) as well as the sufficient categorization of the said material into learning, validation and testing sets of data (Bowden et al., 2002). Based on this move, the implementation of an effective technique will be substantially reliant on the skillset as well as experience of the hydrologist in context. The modeller will be presented with a number of possible avenues and optionable mechanisms at every phase of building the modelling process. Thus, the search space needs to be reduced. Also, further advancements will depend on the formulation of detailed working guidelines that comprise objectives for developing and applying every modelling solution. These blueprints need to discern between the circumstances under which a given approach is ideally adoptable as well as the fashion best suited to optimizing the countless processes and parameters that exist inside. Movements also need to be in the direction of identifying specific tasks and scenarios in which some strategies could either under-deliver or even fail to de-constrain the ramifications of the application.

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