Web Traffic Prediction using Echo State Networks

by

Lalit Singh

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Prof. Herbert Jaeger
Bachelor Thesis Supervisor

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With my signature, I certify that this thesis has been written by me using only the indicates resources and materials. Where I have presented data and results, the data and results are complete, genuine, and have been obtained by me unless otherwise acknowledged; where my results derive from computer programs, these computer programs have been written by me unless otherwise acknowledged. I further confirm that this thesis has not been submitted, either in part or as a whole, for any other academic degree at this or another institution.

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Abstract

Consider this a separate document, although it is submitted together with the rest. The abstract aims at another audience than the rest of the proposal. It is directed at the final decision maker or generalist, who typically is not an expert at all in your field, but more a manager kind of person. Thus, don't go into any technical description in the abstract, but use it to motivate the work and to highlight the importance of your project.

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Contents

1 Introduction

1.1 Motivation of Research

The ability to predict the future data, based on past data, makes an important leverage that can push organization forward. Time series forecasting is an important tool under this scenario where the goal is to predict the behavior of complex systems solely by looking at patterns in past data. A time series is a collection of periodic ordered observations that appears in multiple range of domains such as literature, agriculture, finance, media, etc., just to name a few [1]. Time series are very complex because each observation is dependent upon the previous observations and often is influenced by more than one previous observations [2]. Hence, this research mainly focuses on prediction of time series data in web traffic domain.
Information about the potential web traffic that a website might receive in future is essential to the management of server resources and potentially prevent the Denial of Service (DoS) during peak hours. Online advertising business also depends upon predicted web traffic because they need to distribute advertisements to the selected websites based on the predicted web traffic [3]. As the estimation of web traffic is important due to aforementioned purposes, several research works have been done in this sector.

1.2 Prior Works

Traditionally these time series forecasting has been performed using various statistical-based methods [4]. The major drawback of most of the statistical models is that, they consider the time series are generated from a linear process. However, most of the real world time series generated often consists of temporal and/or spatial variability and suffered from nonlinearity of underlying data generating process [5]. In [3], the author used both MLP and RNN for the prediction of web traffic and found out that MLP outperformed RNN. Despite extensive experimentation which involved tuning various parameters, the predictions produced by RNN were consistently poor in terms of prediction accuracy [3]. Work in [6] used Neural Network to forecast prices of flour in three different cities. They compared their results with autoregressive moving average (ARMA) model and found that Neural Network approach outperformed the ARMA model.

In [7], the author uses Recurrent Neural Network sequence to sequence model where he used data features such as days of the week, year to year autocorrelation, quarter to quarter autocorrelation and page popularity to train his model. His model outperformed all the model in a web traffic forecasting competition organized by Google on Kaggle (a platform for predictive modelling and analytics competitions). Another participant of the same competition used Kalman filter to make the prediction [8].

All the methods that have been used before have some sort of disadvantages. ANNs require a complex training process, they may converge to a local minimum, they have difficulty in determining the optimum network structure, and they experience fading memory (FM) [9]. Therefore, it is difficult to create a more accurate web traffic prediction model using ANNs. Echo state networks (ESNs) are a novel type of ANN proposed by Prof. Jaeger in 2001 and are regarded as the closest representation of the learning process of the human brain [10]. ESNs can effectively solve all of the aforementioned problems with

ANNs. In addition, the computational requirement for training ESN is lesser than training ANNs and MLPs because while training ESN the connection weights of the reservoir are not changed and only weights from the reservoir to the output units are adapted, so training becomes a linear regression task [11, 9]. Therefore, we have chosen to use ESNs for the prediction of web traffic.

1.3 Objective

Our main objectives to conduct this research are listed below:

- To evaluate the performance of ESN for the prediction of web traffic.
- To optimize the parameters of ESN for it's best performance.

2 Statement and Motivation of Research

This part should make clear which question, exactly, you are pursuing, and why your project is relevant/interesting. This is the place to cite relevant literature. Where does your project extend the state of the art? What weaknesses in known approaches do you hope to overcome? If you have carried out preliminary experiments, describe them here.

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3 Background Concepts

3.1 Echo State Networks

3.2 Introduction

Echo State Networks (ESNs) are a special kind of Recurrent Neural Networks(RNNs), with an easy to implement training algorithm. Large, sparsely connected RNN with N neurons is used as a ”Dynamic Reservoir”. Each neuron in this reservoir is connected to each other with certain weights. The basic idea of ESN is (i) to drive this network of neurons with K input signals, thereby inducing in each neuron within this reservoir network a nonlinear response signal, and (ii) combine a desired output signal by a trainable linear combination of all of these response signals [12]. The reservoir can be seen as a nonlinear high dimensional expansion of input signal which serves as a memory providing temporal context. Therefore, the reservoir being an input-driven dynamical system should provide a rich and relevant enough signal space such that desired signal can be obtained by linear combination of it [13].

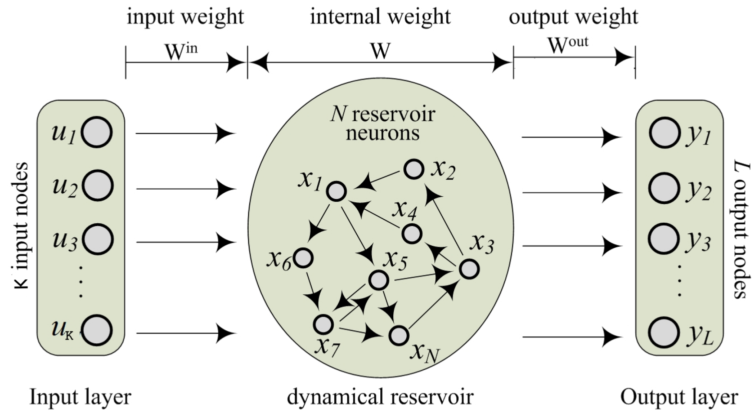

Figure 1: The basic schema of Echo State Network. Image source[14].

3.3 Formalism

We consider discrete time neural networks with K input units, N internal network units and L output units. Each of units at time step n has activation. Activations of input units at time step n are $\mathbf{u}(n) = (u_1(n), \dots, u_K(n))$, of internal units are $\mathbf{x}(n) = (x_1(n), \dots, x_N(n))$ and of output units are $\mathbf{y}(b) = (y_1(n), \dots, y_L(n))$. Real valued connection wights for the input links are collected in the matrix $\mathbf{W}^{in} \in \mathbb{R}^{N\times K}$, for the synaptic links between the neurons in the network are collected in matrix $\mathbf{W} \in \mathbb{R}^{N\times N}$, and for the output weights are collected in matrix $\mathbf{W}^{out} \in \mathbb{R}^{L\times(K+N+L)}$ [15]. The connections from input to output are used and the corresponding connection weights are stored in matrix $\mathbf{W}^{out}$. The output units may optionally project back to internal units with connections however they have not been used in this experiment. A zero weight value can be interpreted as "no connection" [**?**].

The activation of internal units are updated according to the discrete time state update equation given below:

$$\mathbf{x}(n+1) = f(\mathbf{W}\mathbf{x}(n) + \mathbf{W}^{in}\mathbf{u}(n+1) + \mathbf{B}) \tag{1}$$

where $\mathbf{u}(n)$ is the externally given input,$f()$ denotes the the component-wise application of unit output function ($tanh$ used for this experiment), and $\mathbf{B} \in \mathbb{R}^N$ is the bias vector .

The extended system state **z**(n) = [**x**(n) ; **u**(n)] is obtained by the concatenation of system states and input signal at time $\mathbf{n}$. For each time point, $i = 1, \dots, n_{max}$, the extended system state is stacked row-wise in a state collection matrix **S**. This process is known as harvesting reservoir state. The output is obtained from the extended system states by the equation below:

$$\mathbf{y}(n) = \mathbf{g}(\mathbf{W}^{out}\mathbf{z}(n)) \tag{2}$$

$\mathbf{g} = (g_1, \dots, g_L)$ is unit output activation function (in our case identity).[12].

The $\mathbf{W}^{out}$ matrix consisting the weights of links connecting reservoirs to output nodes is obtained by the linear regression of weights of desired outputs **d**(n) on the harvested extended systems states **z**(n). $\mathbf{W}^{out}$ can be computed efficiently by linear regression of **S** and **D** as given by Equation (3) .

$$\mathbf{W}^{out} = (\mathbf{S}'\mathbf{S} + \alpha\mathbf{I})^{-1}\mathbf{S}\mathbf{D}' \tag{3}$$

where α is the regularization coefficient **D** is desired output vector[12].

4 Description of the Investigation

This is the technical core of the thesis. Here you lay out your how you answered your research question, you specify your design of experiments or simulations, point out difficulties that you encountered, etc.

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4.1 Data Description and Preprocessing

The data set used for this experiment was obtained from Kaggle (a platform for predictive modelling and analytics competitions). The data set was provided by Google for a web traffic prediction competition. This data file consists of number of views for 145063 Wikipedia pages on each date starting from 1^{st} of July 2015 to 31^{st} of December 2016. Each time series consists of data for the traffic generated by humans or bots or both from devices like mobile or desktop . For each date, the data contains a single integer value representing the number of views that a particular Wikipedia page received on that date. The total length of each time series is 550. There are some missing values for some of the time series. In this experiment, we have ignored such time series for the sake of convenience. Out of 145063 time series, we have chosen the traffic generated for page named "2002 FIFA World Cup" on english version of Wikipedia i.e `https://en.wikipedia.org/` on desktop devices by all types of agents including humans and bots.

For the preprocessing of the time-series following steps are followed:

4.1.1 Step 1

The time series data used in this experiment has very large values (≈ 7000) as seen in the the Figure 2. Therefore, the time-series data is squeezed component wise such that the maximum value, MAX of the time-series is squeezed to the new maximum value max. This is done by taking small ($<< 1$) power of each component in time series $\mathbf{s}(n) = (s(1), \ldots, s(n))$. The power p that need to be raised to each component of time-series is calculated using Eq. 4.

$$\begin{aligned} max &= MAX^{p} \\ p &= log_{MAX}(max) \end{aligned} \tag{4}$$

4.1.2 Step 2

The resultant time series from step 1 is further rescaled and shifted such that it has zero mean and unit variance. The time-series data is divided component wise by its standard deviation to make its variance unit.

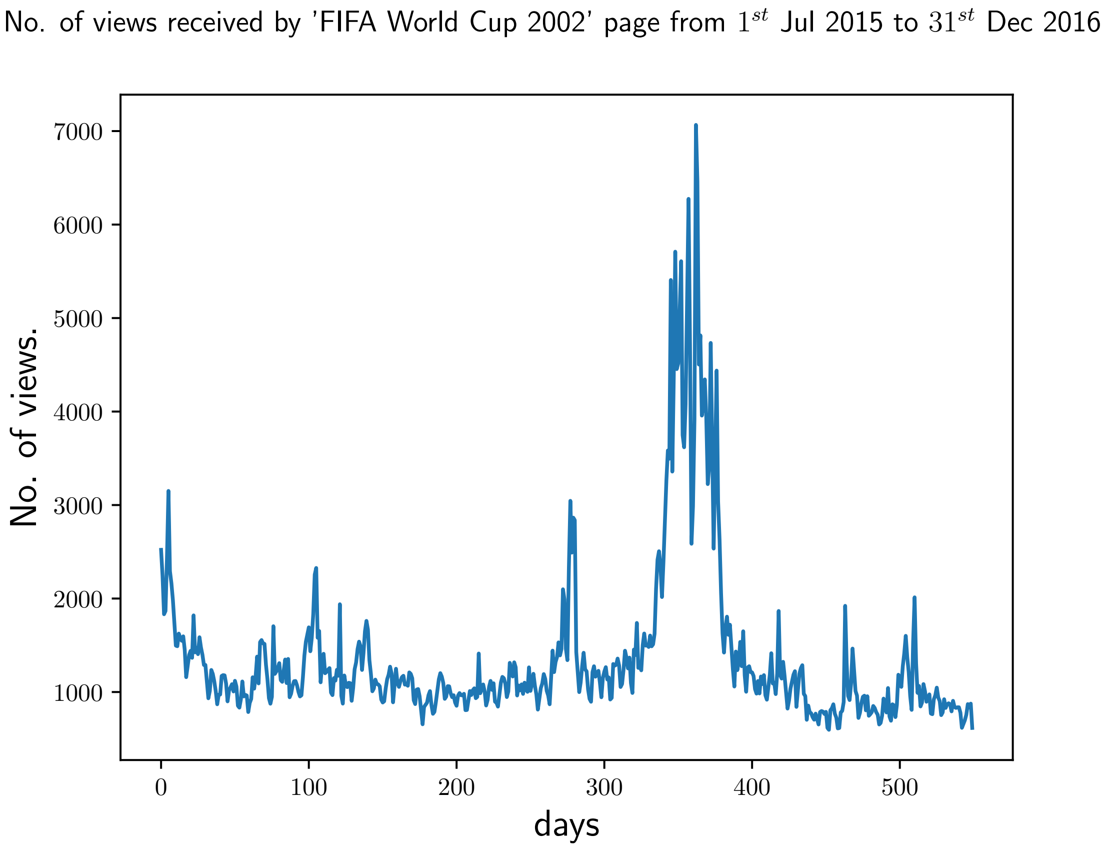
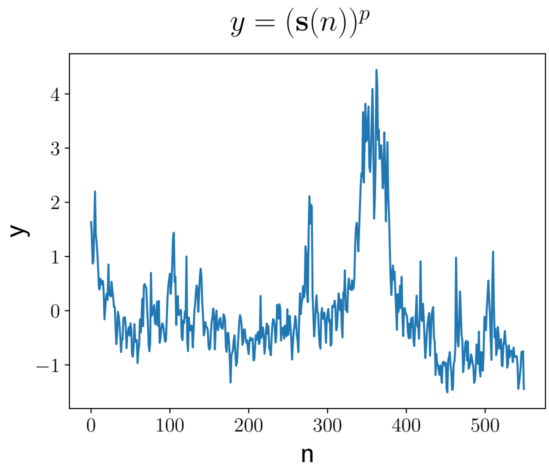


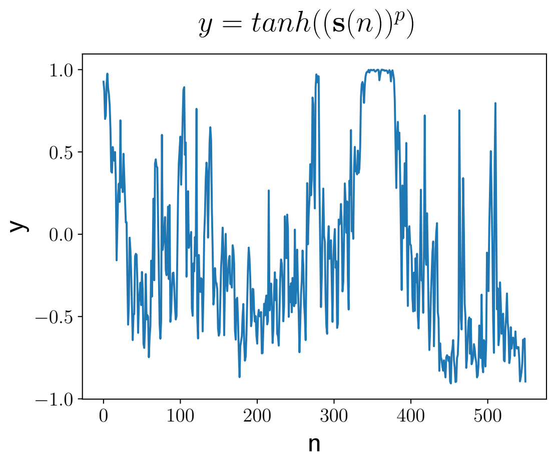
Figure 2: Raw data which has number of views of Wikipedia Pages on each date from 1^{st} of July 2015 to 31^{st} of December 2016.

4.1.3 Step 3

The resultant time series from step 2 is further applied a $tanh$ function component wise. This strictly scales the data points in time series in the range of -1 to 1.



(a) After taking component-wise power



(b) After further taking the $tanh$ of the signal

Figure 3: Preprocessing steps

4.2 Additional Input Signals

By nature, the number of views that a particular Wikipedia Page receives vary according to days in week and months in a year. For instance: A page related to weekend activities might receive a different proportion of views on weekends than on working days. Further, Wikipedia pages that on related subject matters might receives proportional number of views and could follow similar pattern of incoming web traffic. Therefore those related input signals were added to the ESN to improvise the prediction result. In particular we used following approach to find suitable additional input for the network.

1. First of all a sine wave of period 7 was searched which has highest correlation with the main input signal.
2. Then from the data base of about 145 thousand time series top 20 time series are selected with has highest correlation with the main input signal. These signals are further preprocessed using the same preprocessing routines as used for preprocessing the main input signal. To determine the correlation between two time series we have used Pearson's correlation coefficient.

4.2.1 Pearson correlation coefficient

Pearson's correlation coefficient is the measure of the linear correlation coefficient between two variables. It's value is in the range of -1 to 1. Value close to 1 indicate that the variables are highly correlated to each other and values close -1 indicates that the variables are negatively correlated to each other and values close to 0 indicates that the two variables are unrelated. Pearson coefficient between to time series $\mathbf{X} = (x_1, \ldots, x_m)$ and $\mathbf{Y} = (y_1, \ldots, y_m)$ can be computed using the Equation

$$\begin{aligned} \rho X, Y = & \frac{cov(X,Y)}{\sigma_X \sigma_Y} \\ = & \frac{\Sigma_{i=1}^{m}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\Sigma_{i=1}^{m}(x_i - \bar{x}^2)}} \end{aligned} \tag{5}$$

where:

- m is the length of time series
- x_i, y_i are the data points in time series X and Y indexed with i
- $\bar{x_i} = \frac{1}{n}\Sigma_{i=1}^{n} x_i$ and analogously for $\bar{y}$

So to give the insight of weeks and months, two additional input signals with periods 7 and 30 $\pm$ 2 were introduced to the network. These periodic signals were preprocessed (applied log10 and shifted by its mean) before feeding it to the network.

4.3 Network Setup

Under suitable conditions the network state becomes asymptotically independent of initial conditions and depends only on the input history, which is called the "Echo State Property". This means that all desired output signals can be build out of it's own "echos" in the Dynamic Reservoir. [**?**]

We create a reservoir of $N = 99$ neurons. The weights for input links and bias vector are generated randomly from uniform distribution over (-0.5, 0.5) and stored in matrix $\mathbf{W}^{in} \in \mathbb{R}^{N \times K}$ and $\mathbf{B} \in \mathbb{R}^{N \times 1}$ respectively. Then $\mathbf{W}$ matrix is normalized by its maximum eigenvalue. There are $K = 22$ input neurons that receive each of the 21 input signals and $L = 31$ output neurons each of which makes $t = 1, \ldots, 31$ step ahead prediction.

In order to achive good approximation of desired signal, the echo functions should provide a "rich" set of dynamics to combine from. The network should be prepared in a suitably "inhomogeneous" way to meet this demand. One simple method to prepare such a "rich reservoir" echo state network is to supply a network which is sparsely and randomly connected. Sparse connectivity provides for a relative decoupling of subnetworks, which encourages the development of individual dynamics [**?**]. In this experiment, the network weight matrix, $\mathbf{W}$ has different weight regions to create different capability of short term memory so that the network can capture all type of trend (slow, medium and fast trends) in the training signal. The structure of weights matrix used is presented below:

fast	≈ 0	=0
≈ 0	medium	≈ 0
=0	≈ 0	slow

The fast region of matrix $\mathbf{W}$ has values in range 0.7 to 1.0, medium region as values in range 0.4 to 0.7 and the slow region has values in range 0.0 to 0.3 generated randomly from the uniform distribution. The weight matrix $\mathbf{W}_0$ is normalized to $\mathbf{W}_1$ with it's spectral radius by putting $\mathbf{W}_1 = |1/\lambda_{max}|\,\mathbf{W}_0$ where λ_{max} is the spectral radius of $\mathbf{W}_0$. Then the weight matrix $\mathbf{W_1}$ is scaled with a scaling factor sf_W such that $\mathbf{W} = sf_W\mathbf{W_1}$. Then $\mathbf{W}$ has spectral radius of sf_W. The choice of the spectral radius sf_W of the reservoir is crucial for the eventual success of ESN training. This is because sf_W is intimately connected to the intrinsic timescale of the dynamics of the reservoir state. Small sf_W means that one has a fast dynamics reservoir and large sf_W (i.e close to unity) means that one has slow reservoir. Also the input weight matrix $\mathbf{W}^{in}$ and bias vector $\mathbf{B}$ is scaled with a scaling factors sf_Win and sf_B respectively.

4.4 Regularization

In order to access the quality of the prediction produced by the training of ESN, we regularly monitor the actual obtained output weights $\mathbf{W}^{out}$. Large weights indicate that $\mathbf{W}^{out}$ exploits and amplifies tiny differences among the dimension of $\mathbf{x}(n)$, and can be very sensitive to deviations from the exact conditions in with the network has been trained [13]. To counteract this effect the regularization part $\beta\mathbf{I}$ in the ridge regression is used as in Equation (3) .

5 Evaluation of the Investigation

This section discusses criteria that are used to evaluate the research results. Make sure your results can be used to published research results, i.e., to the already known state-of-the-art.

6 Conclusions

Summarize the main aspects and results of the research project. Provide an answer to the research questions stated earlier.

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