STREAM VOLUME PREDICTION IN TWITTER WITH ARTIFICIAL NEURAL NETWORKS

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Abstract: Twitter is one of the most important social network, where extracting useful information is of paramount importance to many application areas. Many works to date have tried to mine this information by taking the network structure, language itself or even by searching for a pattern in the words employed by the users. Anyway, a simple idea that might be useful for every challenging mining task - and that at out knowledge has not been tackled yet - consists of predicting the amount of messages (*stream volume*) that will be emitted in some specific time span. In this work, by using almost 180k messages collected in a period of one week, a preliminary analysis of the temporal structure of the stream volume in Twitter is made. The expected contribution consists of a model based on artificial neural networks to predict the amount of posts in a specific time window, which regards the past history and the daily behavior of the network in terms of the emission rate of the message stream.

1 INTRODUCTION

Twitter has become one of the main communication medias on the Internet. Users employ this media to share ideas, news or simply feelings about anything, producing in this way a valuable footprint about what is happening at every second and what people think or feel about it. Nowadays Twitter has become one of the most popular microblogging services, having hundreds of millions of messages posted everyday by more than 50M of users. In Twitter, users post short messages with a 140 characters length at most - which are called tweets - commenting about their thoughts, feelings, recent actions or even discussions about recent news. Every posted message has associated its creation timestamp, the message content, some user information and also georeferential information if there is any.

The massive information content generated in Twitter has become an interesting source of research and application. Briefly, some areas and works where the reader could find a more detailed insight are: *Event detection* (Mathioudakis and Koudas, 2010; Petrovic et al., 2010; Lee et al., 2011), *Credibility Analysis* (Mendoza et al., 2010; Castillo et al., 2011) and *Marketing in Social Networks* (Domingos, 2005; Banerjee et al., 2010). The high frequency generation of the data poses important challenges in terms of storage and processing, given the inherent online characteristic of this context. It is in this sense that the stream volume would be a useful information for every task of the aforementioned, specially those tasks that involve important computation processes executed in an online fashion.

Time series analysis over streaming data probably dates back to (Datar et al., 2002), where the authors propose the sliding window model for computation in data streams and also tackle the problem of maintaining aggregates statistics of a data stream using this approach. Several works have follow this path for computing aggregate estimates over streaming data (Zhu and Shasha, 2002; Guha et al., 2006; Lee and Ting, 2006; Pan et al., 2010), although at our knowledge no one pointed out to twitter or social network data. Moreover, the main focus of current works consisted in enabling the support of selected queries over the stream instead of the prediction task.

The aim of this preliminary work is to study the feasibility of forecasting the stream volume of tweets in certain time span. To accomplish this task we pro-

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pose to model the streaming data as an nonlinear autoregressive time series (NAR) by using a semiparametric model based on a well-known multilayer perceptron. This model will considers the daily behavior of the stream and allows a parametric prediction horizon. Then, the main goal pursued is to demonstrate that the temporal structure of the data might be useful for stream volume prediction regarding its seasonal behavior. Spite of the simplicity of the idea, we think that the stream volume prediction using non-linear models without considering expensive computations such as fourier or wavelet synopsis, text or network analysis in data, may fit quite well in the steaming environment.

This work is organized as follows. In next section we deliver the fundamental concepts related to non-linear time series forecasting with artificial neural networks. In section 3 we stipulate the proposed methodology to be able to predict the stream volume. In section 4 we show preliminary results related to test the artificial neural network models with different configurations for the input structure. Finally, some concluding remarks and future work are given in the last section.

2 BACKGROUND

2.1 Artificial Neural Networks

Artificial Neural Networks (ANN) have received a great deal of attention in many fields of engineering and science. Inspired by the study of brain architecture, ANN represent a class of non-linear models capable of learning from data. The essential features of an ANN are the basic processing elements referred to as neurons or nodes; the network architecture describing the connections between nodes; and the training algorithm used to estimate values of the network parameters.

Artificial Neural Networks (ANN) are seen by researches as either highly parameterized models or semiparametric structures. ANN can be considered as hypotheses of the parametric form $h(\cdot;\mathbf{w})$, where the hypothesis h is indexed by the parameter $\mathbf{w}$. The learning process consists in estimating the value of the vector of parameters $\mathbf{w}$ in order to adapt the learner h to perform a particular task.

The Multilayer Perceptron (MP) is the most popular and widely known artificial neural network. In this network, the information is propagated in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. Figure 1 illustrates the architecture of this artificial neu-

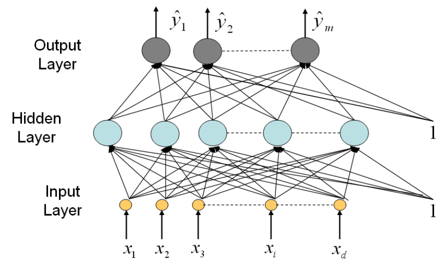


Figure 1: Network architecture of the Multilayer Perceptron.

ral network with one hidden layer. Furthermore, this model has been deeply studied and several of its properties have been analyzed. One of the most important theorem is about its universal approximation capability (see (Hornik et al., 1989) for details), and this theorem states that *every bounded continuous function with bounded support can be approximated arbitrarily closely by a multi-layer perceptron by selecting enough but a finite number of hidden neurons with appropriate transfer function*.

The non-linear function $h(\mathbf{x},\mathbf{w})$ represents the output of the multilayer perceptron, where $\mathbf{x}$ is the input signal and $\mathbf{w}$ being its parameter vector. For a three layer MP (one hidden layer), the output computation is given by the following equation

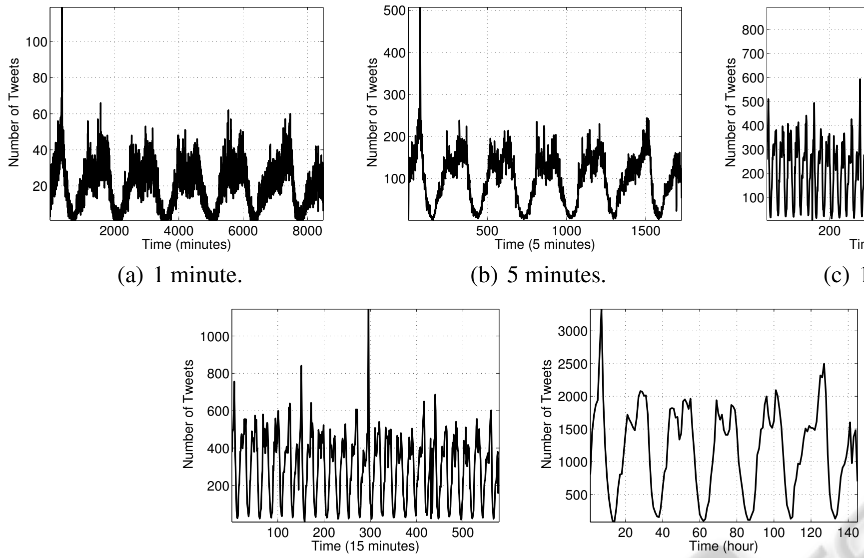
$$g(\mathbf{x},\mathbf{w}) = f_2\left(\sum_{j=1}^{\lambda} w_{kj}^{[2]} f_1\left(\sum_{i=1}^{d} w_{ji}^{[1]} x_i + w_{j0}^{[1]}\right) + w_{k0}^{[2]}\right) \tag{1}$$

where λ is the number of hidden neurons. An important factor in the specification of neural models is the choice of the transfer function, these can be any non-linear function as long as they are continuous, bounded and differentiable. The transfer function of the hidden neurons $f_1(\cdot)$ should be nonlinear while for the output neurons the function $f_2(\cdot)$ could be a linear or nonlinear function.

The MP learns the mapping between the input space $\mathcal{X}$ to the output space $\mathcal{Y}$ by adjusting the connection strengths between the neurons $\mathbf{w}$ called weights. Several techniques have been created to estimate the weights, where the most popular is the backpropagation learning algorithm, also known as generalized delta rule, popularized by (Rumelhart et al., 1986).

2.2 Non-linear Time Series Prediction

The statistical approach to forecasting involves the construction of stochastic models to predict the value of an observation x_t using previous observations. This is often accomplished using linear stochastic differ-



(a) 1 minute. (b) 5 minutes. (c) 10 minutes.

(d) 15 minutes. (e) 1 hour.

Figure 2: Aggregated time series of the Chilean tweets stream sampled between 20th through 26th of July 2011. The selected windows size are (a) 1 minute, (b) 5 minutes, (c) 10 minutes, (d) 15 minutes, and, (d) 1 hour.

ence equation models. By far, the most important class of such models is the linear autoregressive integrate moving average (ARIMA) model.

An important class of Non-linear Time Series models is that of non-linear Autoregressive models (NAR) which is a generalization of the linear autoregressive (AR) model to the non-linear case. A NAR model obeys the equation $x_t = h(x_{t-1}, x_{t-2}, ..., x_{t-p}) + \varepsilon_t$, where h is an unknown smooth non-linear function and ε_t is white noise, and it is assumed that $E[\varepsilon_t | x_{t-1}, x_{t-2}, ...] = 0$. In this case the conditional mean predictor based on the infinite past observation is $\hat{x}_t = E[h(x_{t-1}, x_{t-2}, ...) | x_{t-1}, x_{t-2}, ...]$, with the following initial conditions $\hat{x}_0 = \hat{x}_{-1} = ... = 0$.

Artificial Neural Networks have been successfully applied as a NAR model in time series forecasting. Refer to the work of (Balestrassi et al., 2009) for further details.

3 METHODOLOGY

3.1 Data Collection and Processing

In this work we obtain preliminary results with a little collection of Tweets obtained in a region encompassing the central part of Chile during the period of time covered between the 20th and 26th of July, 2011, where the amount of post sum up to 171.991 tweets obtained in a time span of almost 6 days (8488 minutes). In previous work, we have characterized the tendency based on the most frequent terms, number of tweets per user, amount of link references, among others descriptive results.

The collected messages was accomplished by using the *streamming* API of Twitter using the Python language, together with the Json (module to process data in JSON format) toolkit. The collected Tweets messages are in a JSON format (JavaScript Object Notation) that is a lightweight data-interchange format with the characteristic that it is easy to parse and generate. With Json, the tweets messages were exported to several formats as XML and TXT. The *streamming* API allows to access in near-realtime to a random sub-set of publicly available Twitter data, we configured the API with the statuses/sample method to have a feed of 1% of real volume of Tweets, this mode is called Spritzer.

The Tweet structure has a timestamp at the *created_at* field. We have sorted the post according this timestamp, and then we proceeded to aggregate the information by counting the number of Tweets generated in a time-window defined by the user. In this work we have selected the windows of size *1-minute*, *5-minutes*, *10-minutes*, *15-minutes* and *1-hour*. Figure 2 graphically shows the summary of the aggregated time series with different windows size.

3.2 Stream Volume Forecasting

To forecast the volume of messages we model the stochastic process as a non-linear autoregressive (NAR) time series. However, a difficult issue in time series forecasting is the structural identification of the model, where the relevant lags are hard to find. However in this preliminary work we exhaustively test some configurations with the aim of knowing if we are able to make one step prediction based on past information. The selected configurations are shown in table 1, where configurations $C1$, $C2$ and $C3$ were tested for all windows size. On the other hand the configurations $C4$, $C5$, $C6$, $C7$ and $C8$ wer tested for the windows of size *1-minute*, *5-minutes*, *10-minutes*, *15-minutes*, *1-hour* respectively, in order to elucidate if there exist any seasonal contribution.

The multilayer perceptron with three layers was applied to model de NAR process. The architecture of the neural network consists in three layers of neurons, where the number of input neurons depends on the number of lags of each selected configuration, the number of output neurons was set in one (1-step prediction), and we arbitrarily decided to test with two hidden neurons to maintain a low complexity of the model. We selected the *log sigmoid* transfer function,

$$f_1(z) = \frac{1}{1+e^{-z}}$$

for the hidden neurons and the linear transfer function, $f_2(z) = z$, for the output neurons. The parameters were estimated with the training function that updates weight and bias values according to Levenberg-Marquardt optimization. For this study we have used the Neural Nework toolbox of Matlab.

4 RESULTS

For the experiments, we have partitioned the data sets, structured according to the selected configurations given in table 1, in three sets: Training (70% of the data), Validation (15% of the data) and Test (15% of the data). In this section we report the best performance result obtained after 5 runs for each model. We have computed the mean square error (MSE)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (2)$$

and the correlation coefficient (R)

$$R = \frac{\sum_{i=1}^{n}(y_i - \overline{Y})(\hat{y}_i - \overline{P})}{\sqrt{\sum_{i=1}^{n}(y_i - \overline{Y})^2}\sqrt{\sum_{i=1}^{n}(\hat{y}_i - \overline{P})^2}} \quad (3)$$

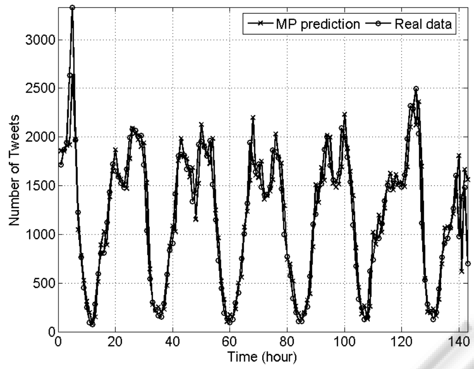


Figure 3: Multilayer perceptron prediction with configuration 2 for the 1-hour time window.

for the predictions in the Test set. Tables 2(a), 2(b), 2(c), 2(d) and 2(e) show the performance of the MP and an autoregressive model (*baseline*) for the stream volume prediction task with different window size and by testing several configurations (shown in table 1). In bold are highlighted the best results for each time-window (Two decimals approximation was made over the results).

In all the simulations we have a correlation coefficient higher than 80% and with a relatively low error, with this results we have shown that it is feasible to forecast the stream volume with the multilayer perceptron. Although the identification of the best lags configuration remains as an open issue, the performance are similar among them. We were not able to detect the seasonal component in almost all cases with the exception of the *10-minutes* and *15-minutes* windows size. In general the best results were obtained for the third configuration that it is characterized by containing more lags with recently past information than the other configurations. Figure 3 qualitatively shows the prediction performance of the best resulting configuration for the multilayer perceptron in modeling the stream volume with a 1-hour time-window.

5 CONCLUSIONS

In this paper we were able to give a solution to the problem of stream volume prediction in Twitter, where a non-linear autoregressive time series model, based on artificial neural networks, is used to predict the amount of posts in a specific time window. This model will considers the recently past history together with a seasonal component to improve the prediction of the amount of messages that will arrive during the upcoming time period.

Furthermore, regarding the performance values pre-

Table 1: Selected configurations of the autoregressive structure of the time series data.

(a)

Configuration	Lags
C1	x_{t-1}
C2	x_{t-1}, x_{t-2}
C3	$x_{t-1}, x_{t-2}, , x_{t-3}$
C4	$x_{t-1}, x_{t-1440}, x_{t-1441}$

(b)

Configuration	Lags
C5	$x_{t-1}, x_{t-288}, x_{t-289}$
C6	$x_{t-1}, x_{t-144}, x_{t-145}$
C7	$x_{t-1}, x_{t-96}, x_{t-97}$
C8	$x_{t-1}, x_{t-24}, x_{t-25}$

Table 2: Summary of the results for the prediction performance obtained by the MP for the 1-minute (table 2(a)), 5-minutes (table 2(b)), 10-minutes (table 2(c)), 15-minutes (table 2(d)) and 1-hour (table 2(e)) time window.

(a)

	ANN		AR	
Config.	MSE	R	MSE	R
C1	30.80	0.86	38.42	0.86
C2	27.10	0.89	31.15	0.89
C3	**24.07**	**0.90**	28.58	0.90
C4	35.60	0.88	33.34	0.88

(b)

	ANN		AR	
Config.	MSE	R	MSE	R
C1	417.14	0.92	571.48	0.92
C2	317.48	0.94	464.10	0.93
C3	**271.44**	0.94	434.57	0.94
C5	412.46	**0.94**	394.42	0.94

(c)

	ANN		AR	
Config.	MSE	R	MSE	R
C1	2764	0.86	3802.65	0.85
C2	2167	0.88	3647.86	0.86
C3	**1976**	0.89	3504.11	0.86
C6	2264	0.92	2017.84	**0.92**

(d)

	ANN		AR	
Config.	MSE	R	MSE	R
C1	11605	0.87	8044.59	0.86
C2	12455	0.86	7571.96	0.87
C3	11791	0.90	7346.80	0.87
C7	**4154**	0.88	5885.25	**0.90**

(e)

	ANN		AR	
Config.	MSE	R	MSE	R
C1	53628	0.90	93505.67	0.89
C2	**28545**	0.94	67112.10	0.93
C3	30043	0.94	66873.07	0.93
C8	79056	0.92	38874.10	**0.95**

sented in table 2, it results interesting to notice that even when the R achieved by both models under evaluation are comparable in every time window, the MSE value attained by the MP is substantially lower. This observation may suggests that the last mentioned model could be an acceptable choice for data containing outliers and high frequency observations, common features found in the streaming context. Anyway, a more thorough validation is required given the random initialization of the ANN. Finally, by observing fig. 2, a change in the shape pattern presented by the first two plots is noticed in comparison to the two next plots. After that, the first shape pattern is repited for the 1-hour plot. More data is needed to outline a conclusion about this point.

Future works are needed in order to determine the best lags that elucidate the time-structure of the autoregressive model. Several applications in Twitter analysis can be supported by our proposed model as for example event detection. Due to the noise and the presence of outliers in the data, in specific at lower levels of aggregation, robust procedures are needed to better estimate the model parameters and enhance the prediction. We are planing to collect data for a longer period of time and maybe by considering a higher encompassing spatial region in order to better validate the proposed model.

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