

Web service workload prediction using deep learning - Report 3

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1 State of the art

Calheiros et al. [5] apply the ARIMA model to cloud workload prediction. The model was evaluated using a trace of English Wikipedia resource requests spanning a duration of four weeks. The first three are used for training and the fourth for prediction using a time window of 1 hour. The MAPE varies from 9% to 22% depending on the confidence interval chosen, from 80 to 95 which is meant to limit the occurrences of underestimations.

Other classic timeseries models have also been applied for this task, like Brown Exponential Smoothing by Mi et al. [17] obtaining a Mean Relative Error of 0.064 on the France World Cup 1998 web server trace. Another classic model is Weighted Moving Average, applied by Aslanpour et al. [1] in which recent observations are given more weight based on the Fibonacci rule, and was tested on a NASA server 24h trace achieving a 5% improvement in response time on a cloud scaling simulator.

Kumar and Singh [13] applied artificial neural networks for workload prediction on a seven month log of traffic from a Saskatchewan University web server and a two month one from the NASA Kennedy Space Center web server. They use a classic ANN architecture : one input layer(size 10), one hidden and one output, and the model is trained through the SaDE technique, which means learning its weight through evolutionary algorithms. The results of this model were compared to an ANN trained through backpropagation: 0.013 and 0.001 for D1 and D2 vs 0.265 and 0.119, using the RMSE metric over normalized data.

CloudInsight [12] is one of the most complex models for workload prediction. It uses a technique called "council of experts", meaning an ensemble of different models, in this case: classic timeseries (autoregressive, moving average, exponential smoothing), linear regression, and machine learning (SVM). Each model has a different prediction weight which is also learned real-time through a SVM based on their accuracy on the dataset. The evaluation was done on a subset of the wikipedia trace [20], on google cloud data and on some generated workloads. An indicator of performance is normalized RMSE, meaning how much better it performs than other models. On average it was 13% to 27% better than baselines (ARIMA, FFT, SVM, RSLR).

A review of how deep learning methods can be applied to time series problems was created by Gamboa [8]. The paper distinguishes between three types of problems: classification, forecasting and anomaly detection, presents methods for modelling them and guidance for selecting appropriate models. It also shows an improvement in performance over the previously existing techniques. Brownlee [4] published a comprehensive guide on applying MLPs, CNNs and LSTMs on various real datasets and discussed their advantages over classic methods, which were used as baselines for the experiments.

Lin et al [15] proposed a hybrid CNN LSTM architecture for learning trend in time series. It relies on on CNN to extract important features from raw timeseries data and

LSTM to find long range dependencies in historical data. The model was shown to outperform both CNN and LSTM with around 30% lower RMSE on 3 real world datasets.

2 Approach

The main goal is to find a performant model for web application workload prediction, which can be later used by a proactive microservice scaler. The methods used are different architectures of deep learning models: MLP, CNN, CNN-LSTM hybrid. The main contribution of this research is the application of deep learning to this specific problem and the comparison with a classic timeseries approach (ARIMA).

The problem design has been influenced by the goal of integrating this model into a proactive microservice scaler. First of all, the choice of the workload measure is number of requests. The idea is that the scaling prediction should not influence the predicted value, as would be the case with CPU or memory usage. Also this is in line with research done by Jindal et al [10] who propose a metric for measuring microservice performance based on number of satisfied requests. Another consideration is the prediction interval. Taking into account the experience of Netflix [7], who run a microservice architecture in production, the time window should be in the order of minutes, so you can predict spikes and have time to deploy new service instances.

A realistic workload has been used for this experiment, a wikipedia trace for 12 days in september 2007. From this a subset of requests was extracted (all requests for Japanese wikipedia). The subset was selected in order to compare results with Kim et al. [12] which used the same dataset. In order to turn a web request log file into a supervised dataset the following steps were taken: create buckets which contain the number of requests in a time interval, iterate over the buckets using the sliding window technique [2]. Basically we generate training instances with input $(t, t-1, \dots, t-n)$ and output $(t+2)$. The predicted value is $t+2$ instead of $t+1$ because a scaler using this model would need to have a buffer window during which to deploy the services.

After preparing the dataset two baseline models were prepared: the naive approach (predict traffic in window $t+2$ to be traffic in t) and a classic timeseries model (ARIMA). The next step was to experiment with different deep learning architectures and measure the results.

3 Evaluation of the approach

3.1 Validation and tuning

Model tuning and validation was done on the Japanese wikipedia trace because although presenting some patterns it also has some interesting irregularities, like a huge spike which

is not repeated. The selected time window for tuning is 10 min. todo plot of dataset

The dataset is split into a training and testing with a ratio of 0.9. The validation method is k-fold Cross-Validation [18] with $k = 3$, which means splitting the training dataset into k equal parts, perform training on $k - 1$ and evaluation on the part left out. This process is repeated k times. The main idea is to not touch the testing data while tuning the model, so the model will not be influenced by it.

3.2 Performance metrics

The error metrics selected for this experiment are: Mean squared error(MSE), Mean absolute error(MAE) and Mean absolute percentage error(MAPE) as described in [3] and defined in equation 1. MSE was used as the loss function for training because it tends to penalize big deviations in prediction, which is desirable for our problem as we want to accurately predict traffic spikes. MAE is similar, but conceptually simpler, given that each prediction error contributes in proportion to its absolute value.

MAPE is independent of the problem scale and can be interpreted intuitively, herefore can be used to give a general impression of how well a model performs across different datasets. According to [16] a highly accurate forecast would have MAPE lower 10%, and a good forecast between 10 and 20%.

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad MAE = \frac{1}{n} \sum_{i=1}^n |Y_i - \hat{Y}_i| \quad MAPE = \frac{1}{n} \sum_{i=1}^n \frac{Y_i - \hat{Y}_i}{Y_i} \quad (1)$$

3.3 Baseline

3.3.1 Naive baseline

A naive baseline is set, to get an idea if the models are useful at all. The naive predictor simply states that traffic in window $t+2$ will be the same as in the last measured window. The prediction is plotted in figure 1 and achieves MSE: 20233320.341, MAE: 3577.844, MAPE: 7.106.

3.3.2 ARIMA

ARIMA [9], which stands for autoregressive integrated moving average, is a classic approach to modelling timeseries. In order to apply this model we need to find appropriate values for its parameters: p , q , d .

The value of d means the number of times the series needs to be differentiated in order to make it stationary. The series stationarity was checked using the augmented Dickey-Fuller test [6] which found the p-value to be $1.0902496274664773e-08$. This is lower than 0.05, the commonly used threshold, meaning we can set d to 0.

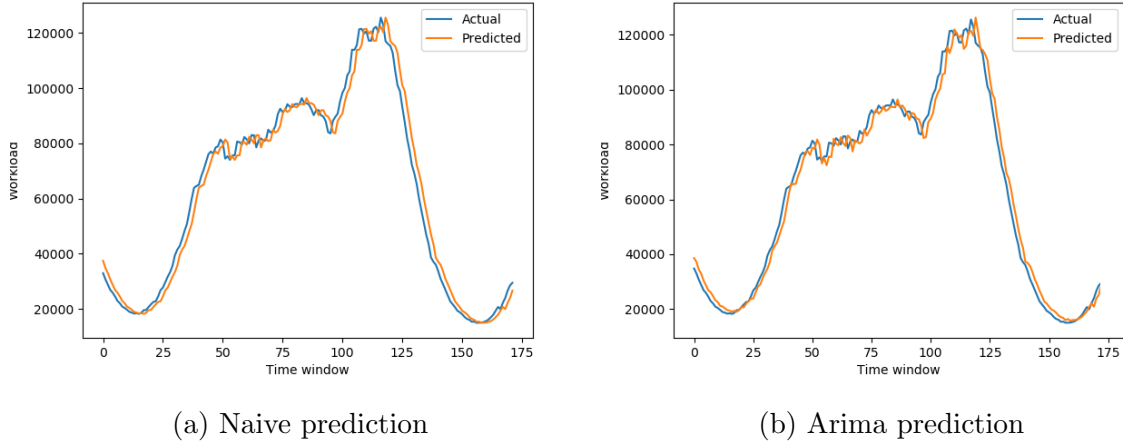


Figure 1: Baseline predictions

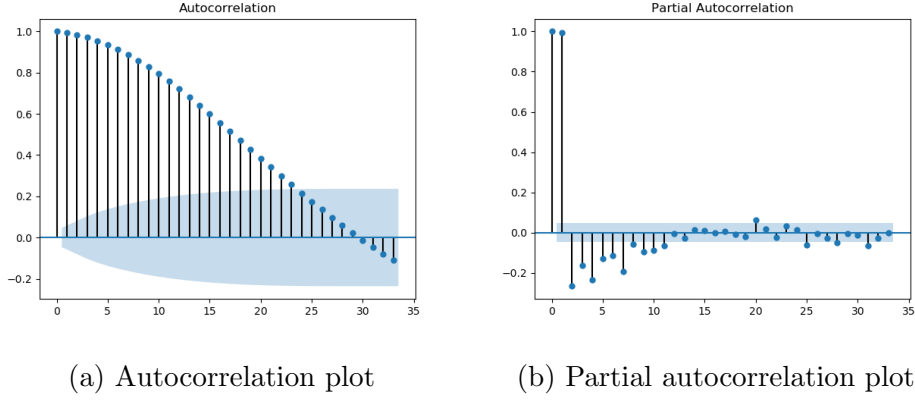


Figure 2: ARIMA params

The partial autocorrelation plot was analyzed to set the autoregression parameter (p). From figure 2 we can see that the significance region is confidently passed at 1, with a steep decline afterwards. The moving average parameter (q) is approximated from the autocorrelation plot. It suggests a value of around 20 would be a good start. After fitting ARIMA(1,0,20) the final 2 layers had P-value of 0.547 and 0.758 which meant that they were not significant. After trying some values for q : 5,10,15,18 the best results were obtained on ARIMA(1,0,15) with 14263566.564, MAE: 3056.765, MAPE: 6.349.

3.4 Deep learning models

3.4.1 MLP

After some manual experiments started with a MLP with 2 hidden layers (150, 100 neurons) and sliding window size of 24 (input size).

To find an optimal combination of batch size and epoch no a 2d grid search was performed 3. Batch size should ideally be a power of 2 for extra performance on GPU

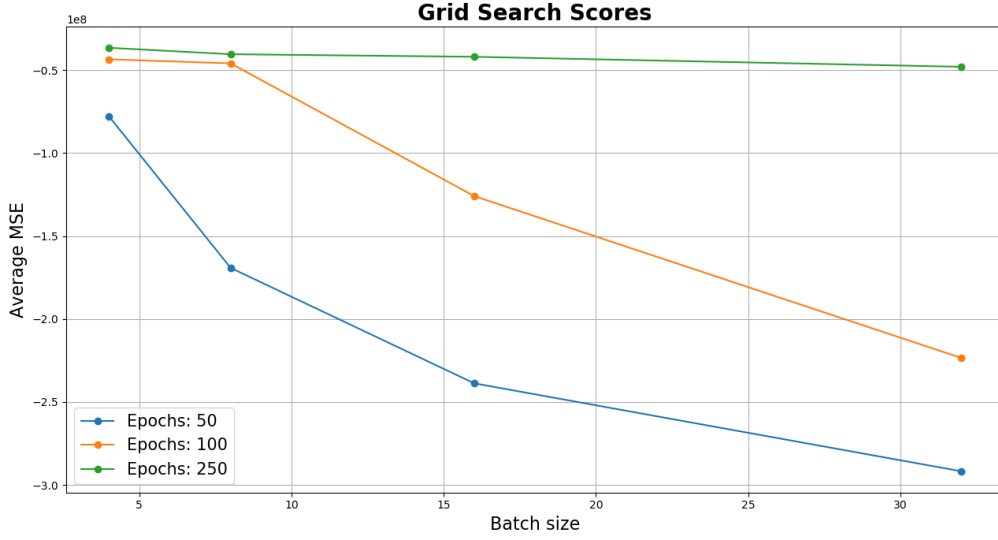


Figure 3: 2d grid search for epoch no and batch size

architectures, as some experiments were ran on Google Colab. Lower batch size is more accurate but training is slower [11]. As expected the best MSE is obtained for the lowest batch size(4) however it does not drop significantly at 8, regardless of epochs no. The selection of epoch no is again a tradeoff between speed and accuracy. We see a smaller no of epochs(50) performs poorly, while the difference between 100 and 250 is not that great, meaning that we can get a good approximation of a model using a batch size of 100.

Some experiments were done with adding Dropout layers on different values (0.2, 0.1, 0.05) however it did not improve performance. These are generally used to prevent overfitting, when the network is too big, the data is scarce or training is done for too long [19], which was not the case for this experiment.

Various optimizer and activation functions were tested. The Adadelata optimizer and the relu activation were selected. A comprehensive grid search was performed for sliding window size and number and content of hidden layers, of around 90 combinations. Some of the best performing are presented in table 2.

3.4.2 CNN

Firstly, a baseline model was selected through manual experimentation. This had the following structure: input of size 20, a 1d convolutional layer, a maxpooling layer, a flatten layer, a dense layer of size 150 and the output layer. The same batch size, epoch no grid search was performed and it yielded similar results to 3. This was followed by iterating the same optimizers and activation function in order to select Adadelata and softplus.

The main idea behind using a CNN model for this task is to pass a larger history

Table 1: Selecting optimizer and activation. Scores are averaged MSE.

Optimizer		Activation function	
RMSprop	24734800	softmax	4875804739
Adadelata	19291753	softplus	20314197
Adagrad	190604349	softsign	4034049993
Adam	25828119	relu	19571788
Adamax	29578706	tanh	4175933232
Nadam	20400557	sigmoid	3055609656
		linear	20661311

Table 2: MLP layers and size tuning

Sliding window	Layers	MSE
4	(100, 50, 25, 20, 10)	18889414
4	(10, 10, 10, 10, 10, 10)	18935098
4	(100, 50, 50, 20, 10)	18847516
8	(100, 50, 25, 20, 10)	17044955
8	(150, 50, 50, 50, 50, 10)	17216134
8	(50, 50, 50, 50)	18394493
16	(10, 20, 30, 40, 50)	18116299
16	(100, 20, 20, 20, 10)	18466524
16	(10, 10, 10, 10, 10, 10, 10)	18311036

Table 3: CNN layers and size tuning

Sliding window	Layers	MSE
8	(25, 10, 5)	35385451
64	(100, 20, 10, 5)	35012864
128	(100, 20, 10, 5)	21086942
128	(300, 50)	22287266
128	(10, 10, 10)	23441869
256	(100,20,10,5)	23783826

Table 4: CNN-LSTM layers and size tuning

Sliding window	LSTM layers	MSE
144	(20, 10, 5)	51700082
todo	todo	todo

window as input. CNN layers build different filter that learn certain characteristics of the input data. They are well suited for data which has a spatial relationship (like timeseries) [14].

3.4.3 CNN-LSTM Hybrid

This model was applied on a range of timeseries tasks by Lin et al. [15]. The starting values for some parameters were influenced by this research: 32 cnn filters, 1 lstm layer with a couple hundred units.

3.5 Experiment Results

Each of the most promising models were then trained again on all training data, for a larger number of epochs and repeated multiple times to account for the random weight initialization. The best results were then compared to baselines and to each other as seen in table 5.

Table 5: Final results

Dataset	Naive	ARIMA	MLP	CNN	CNN-LSTM
Jp10	20233320	15289199	8591086	11709317	7252806
Jp15	87883950	56662039	31042348	35069911	57719162
De10	16789198	10318406	5180340	10526800	todo
De15	77481580	43398336	17276322	35485149	todo

4 For article - REMOVE ME

4.1 Data preparation

The raw data used for this experiment is a wikipedia trace for 12 days in september 2007 [20]. From this a subset of requests was extracted as separate datasets: all requests to Japanese and German wikipedia respectively. The subsets were selected in order to compare results with Kim et al. [12] which used the same data. Another reason for

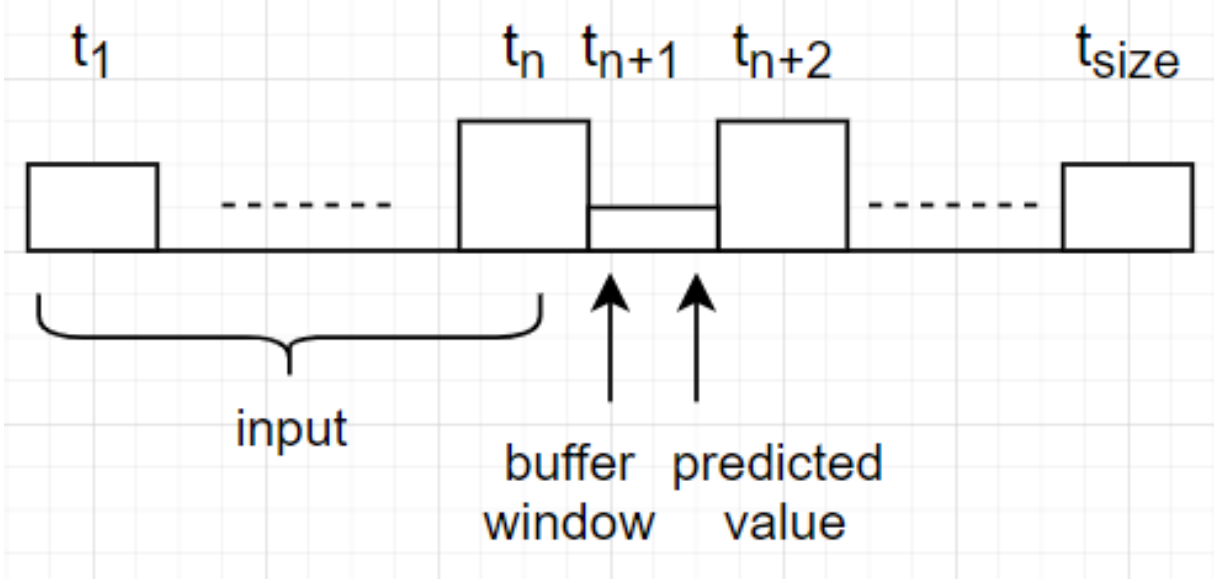


Figure 4: Sliding window technique

extracting subsets it's that the amount of data after preparation is the same as what we would extract from the global trace, given it's the same time range, but processing is much faster.

In order to turn a web request log file into a supervised dataset the following steps were, taken:

- extract timestamps of all requests for a country (e.g. all lines matching ja.wikipedia)
- create buckets which contain the number of requests in a time interval
- iterate over the buckets using the sliding window technique [2], described below

The starting point for the sliding window is a time series $(t_1, t_2, \dots, t_{size})$ where t_i is the number of requests in the i -th bucket. Training instances are then generated with input $(t_i, t_{i+1}, \dots, t_{i+n-1})$ and output (t_{i+n+1}) , where n is the size of the sliding window. This process starts at $i = 1$ and is incremented by 1 until $i = size - n + 1$. The predicted value is t_{i+n+1} instead of t_{i+n} because a scaler using this model would need to have a buffer window during which to deploy the services.

The size of the datasets before applying the sliding window are 111316009 requests for ja.wikipedia and 101917920 for de.wikipedia.

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