A STUDY OF ARTIFICIAL NEURAL NETWORKS HYPERPARAMETER TUNING FOR DATA DRIVEN DECISION SYSTEMS

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Abstract. *Targeted marketing based on data mining techniques can help the companies to understand their current and future customers in their efforts to deliver them best products and services. Artificial Neural Networks as universal approximators have the capability to find patters in data for delivering benchmark results in various domains for various classification or regression problems. Considering the digital transformation, available data and available communication channels between suppliers and customers it is becoming easier to identify the right customers and more cost effective to target then only. Technology advance and competition creates the premises for both success and failure to be just a matter of tuning the models in the best way for the selected use case. Moreover, it is not only about the industry. It is about the Artificial Neural Networks understanding added to the subject matter experts knowledge and experience. Moreover, Artificial Neural Networks can be applied with success in many other areas rather than marketing. Usually the limitations are not given by Artificial Neural Networks intrinsic characteristics but by the use case itself. This paper may engage marketing analysts or enthusiasts in using Artificial Neural Networks in their real-world use cases. Covering a wide range of knowledge from Artificial Neural Networks fundamentals to hyperparameter fine tuning and model evaluation being a guide for marketing practitioners in deploying their own solutions for data driven marketing campaigns.*

Keywords: Artificial Neural Networks, Hyperparameter Tuning, Data Mining, Data Driven Decision

JEL classification: Model Evaluation, Artificial Neural Networks, Customer Data

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1. Introduction

Targeted marketing identifies a group of people who are likely to buy a service or product, and then the service or product is promoted only to the group previously identified for purchase. In this way the promotion messages are transmitted directly to the members of the identified groups with great potential to purchase, instead of being sent to a large mass of people who can buy or not. This allows the efforts to be concentrated towards groups for which the services or products to be promoted have relevance, leading to an increase in the rate of transformation of potential customers into actual customers. Nowadays mass marketing impact on customers is not meeting the expectations [1]. If 20 years ago marketing meant TV ads, magazines or newspapers, currently marketing campaigns are conducted by a large proportion in the online environment, an environment unavailable on such a scale in the past. Innovation in the field of information technology such as large-scale adaptation of high-speed internet, cheap internet

services and mobile smart devices, the emergence of social networks, all have led through digital transformation [2], to the creation of new rules in marketing. Marketing facilitates the relationship between customers and suppliers by mapping customers behaviors, expectations and experiences, transmitting them to the suppliers who can shape their services and products accordingly. From the point of view of digital marketing development, so far, 3 important roles have been identified in 3 different periods of time, approximately 5 years each: facilitator of individual expression, decision support tool, marketing intelligence [3]. On the other hand, advertising messages unsolicited or unwanted by the potential customers represent what is generally known as spam [4]. This topic has been included in European law as part of the protection of electronic communication (2002/58/EC) and only e-mail messages were included. The multitude of communication channels available have created the premises to reinforce the law across EU and to add the EU General Data Protection Regulation (GDPR) in 2018. Going further and understanding the impact of the new technologies on the way marketing is made a new type of communication was been developed, two-way communication between customers and suppliers, both groups sharing same virtual space [5]. Through social media companies can share with their customers and future customers content about products driving in a new way marketing initiatives. Moving to Big Data conventional methods can start to lose the capability of making the right prediction. Moreover, taking advantage of the new data that is now available it is allowing to perform deep dives for data insights that were never revealed before Big Data. RFM is covering 3 dimensions in customer analysis: Regency, Frequency and Monetary Value. Basically, this method is analyzing how recently a customer completed a purchase, how often is purchasing and how much is the amount of money spent [6].

Artificial Neural Networks can be used to solve one of the most commune targeted marketing use case, classification of potential customers as buyers or non-buyers. Multilayer perceptron can be deployed with very good results in direct marketing and fraud detection [7]. Moreover, the algorithm can be customized to be profit-driven by selecting an objective function that is maximizing the profit. This is possible by associating a different weight to each instance based on the importance. In this way the misclassification of each instance is impacting in a different way the result. The difference between this approach and the approach in which each class is having same importance is not big but, in some cases, the first one is performing slightly better. Direct-marketing campaigns represents one of the marketing pillars [8]. For a model aiming to provide optimum way to select the right clients to receive one or multiple offers during a marketing campaign the studied problem can become strongly NP-hard and finding the optimum based on a constant-factor approximation algorithm can become impossible. Multiple heuristics were developed based on integer programming. Conducting activities associated with direct-marketing in the right way can generate profit in two ways: customer acquisition, when new customers are targeted and transformed from potential customers into actual customers and customer retention, when existing customers are kept by selling them new services or products based on their customer profile [9]. Artificial Neural Networks can be used to map and model the relationship between customer and supplier based on the attributes that are creating and increasing loyalty [10]. Indonesian coffee market growth it is generated by the Indonesian customers which started to include drinking coffee in their daily lifestyle. A Multilayer perceptron is used to classify the customers based on their level of loyalty, 1, for higher preference, and 0, for lower preference. A high preference is considered when customers have consumed repeatedly same instant coffee brands. The conclusion based on the research is that the most influencing variables in this analysis are related to the product appearance like size, package, design, product information on the package, coffee differentiation. Proposed ANN predicted well the customers preferences in 58.2% of the cases. An interesting use case

is represented by the marketing strategy built based on Artificial Neural Networks, Decision trees and Support Vector Machine [11]. The aim is to identify locations for educational events organized for healthcare professionals using data analytics. Support Vector Machines and Artificial Neural Network models performed better than Decision trees in classifying if an event should be scheduled or not in a certain location. Another dimension in the relationship between suppliers and customers is that one related to the emotional responses generated by the marketing campaigns [12]. Multiple Feedforward Neural Networks are used to model data gathered from the customers through surveys. The results are meaningful for the two companies involved in the study giving insights about both slogans used in marketing campaigns and customers emotional responses. Same data set used in this research paper has been analyzed using Artificial Neural Networks, Decision Trees, Support Vector Machine, Logistic Regression [13] and a hybrid approach called Neuro-fuzzy approach. The Neuro-fuzzy systems are used to substitute the lack of transparency of the Artificial Neural Networks considered to be black boxes. The mathematics and intrinsic fuzzy rules represent the domain knowledge [14]. In 1957 Frank Rosenblatt presented an improved version of McCulloch and Pitts work called perceptron. By modifying the absolute inhibition and unit equal synaptic weights constrains his model was actually able to learn from data. The way model was learning was called further supervised learning. The values of the synaptic weights were adjusted based on the training data feed into the model. Another adding on the first proposed model it is the bias, a constant input value with a similar role as a synaptic weight.

2. Artificial Neural Networks

In biology a neuron has the main function to process information. In the brain neurons are building blocks which are communicating with other cells using special connections. The dendrites receive signals (impulses) from other neurons and are send them to the cell body where the information is processed. Signals generated by the cell body are transmitted further along axon which it is branching into strands. The region between an axon of a neuron and a dendrite of another one is called synapse. This functional unit releases certain chemicals (neurotransmitters) based on the electrical impulse received from the cell body via axon. Based on the nature of the receptor neuron those neurotransmitters can enhance or inhibit further electrical impulses. The synapse behavior can be changed in time based on the signals passing through it. This process and its explanation can be transposed into what we are calling learning in both biology and Artificial Neural Network theories.

Warren McCulloch and Walter Pitts published in 1943 for the first time a paper where they explained their concept about neural networks [15].

Figure 1. Mathematical representation of the neuron model proposed by Rosenblatt

Each neuron is having its own input $(x_1, x_2, x_3, \dots, u_n) \in R^n$. Transformation f is applied on the weighted sum of the input variables. The output of a neuron can be calculated as following:

$$y = f(z) \quad (1)$$

$$z = \sum_{i=1}^n u_i w_i + b \quad (2)$$

Where b is the bias and $w = (w_1, w_2, \dots, w_m) \in R^m$ represents the weights vector.

Most simple calculation for the output:

$$y = f(z) = \begin{cases} 1, & \text{if } wu + b \geq \tau \\ 0, & \text{if } wu + b < \tau \end{cases} \quad (3)$$

Where τ represents the threshold.

Artificial Neural Networks are learning by adjusting the synaptic weights during the training process. A major role is represented by the loss function which is saying how close is the prediction to the actual values. This function can be named cost function or error function as well. Loss function selection is a matter of studied problem. For classification cross-entropy is preferred. A maximum likelihood loss function as Binary Cross-Entropy is making an estimation of the closeness between predicted values and actual values. Therefore, the final objective of the network is to provide answers (predictions) as close as possible to the actual values.

$$Loss = -(y \log(p) - (1 - y) \log(1 - p)) \quad (4)$$

Where here y is 1 or 0 if the class label is correct or not correct classified and p is the predicted probability of an observation to be part of the class in which was predicted.

Cross-entropy is used to measure the error between two probability distributions under maximum likelihood. Aim is to find best synaptic weights combination to minimize the difference between predicted and actual probability distributions.

3. Hyperparameters

Batch size can be defined as the numbers of samples that are propagated through the neural network. Gradient Descent it is a first order optimization algorithm considering first derivative only when parameters update is made. Synaptic weights are updated to minimize the model error over the training set. Neural network parameters are update in the opposite direction of the objective function's gradient. Learning rate is determining the size of the step on each iteration.

Over the last years due to the increase of data available for analysis an increase of the research activities for finding optimization algorithms scalable based on the use case [16]. Stochastic gradient descent become one of the popular choices of the practitioners. Gradient descent is one of optimization algorithms used for synaptic weights calculation and update. Let's consider

a function $y = f(x)$, y and x both real numbers. The derivative of $f(x)$, $f'(x)$ or $\frac{dy}{dx}$, gives

the slope of it in a certain point x [17]. The derivative provide information about how to change x to minimize y . Reducing $f(x)$ by moving x in the opposite of the derivative is called gradient descent. The point in which derivatives does not provide anymore the direction where to move the value x is called critical point, $f'(x) = 0$. For use cases with multiple inputs partial

derivatives $\frac{df}{dx_i}$ will measure how x_i is impacting the function f in a certain x points. $\nabla_x f(x)$

represents the vector of all partial derivatives. Extending the logic of the above-mentioned critical point in case of multiple dimensions for each gradient element must be 0. Using the intuition explained above Gradient descent method for finding a new point is the following:

$$\omega_{t+1} = \omega_t - \eta \nabla_{\omega} J(\omega) \quad (5)$$

where η represent the learning rate $\in (0,1)$, $J(\omega)$ represent objective function and model parameters are represented by ω , ω_{t+1} is the future state of the model parameters and ω_t is the current state.

In the Batch Gradient Descent, the error is calculated, as for the Stochastic Gradient Descent, for each example of the training set but the model parameters are updated after all training examples are passing through the network. One passing through the network is called epoch. Therefore model parameters are updated after an epoch is completed. This approach can decrease the computational power and training time and could enable parallel processing since error calculation and model parameters update are separated. Over large batches the advantage of faster training could disappear. Batch size is equal to the size of the training set. Batch Gradient Descent method update equation:

$$\omega_{t+1} = \omega_t - \eta \nabla_{\omega} J(\omega; x^{(i)}; y^{(i)}) \quad (6)$$

Stochastic Gradient Descent represents an instance of the Gradient Descent algorithm that calculates error and the synaptic weights updates after each example of the training set. This approach could insure for some use cases faster learning, better generalization capability by avoiding local minimum. On the other hand, same upsides can lead to slow convergence, longer training time and costly computation since the model is updated for each training set example. Batch size is equal to 1.

Mini-Batch Gradient descent represents a solution that is aiming to deploy in the same time Batch Gradient Descent and Stochastic Gradient Descent. Small batches of training data are feed into the neural network, over each mini-batch the mean gradient is calculated and further the synaptic weights are updated. Batch size is equal to a value bigger than 1 and smaller than training data set size. Mini-Batch Gradient Descent method update equation:

$$\omega_{t+1} = \omega_t - \eta \nabla_{\omega} J(\omega; x^{(ii+n)}; y^{(ii+n)}) \quad (7)$$

Parameters are updated after every mini-batch containing n training examples is passed through the network.

Adagrad (Adaptive Gradient Algorithm) is part of the Adaptive stochastic gradient descent methods. It is known and demonstrated that can perform well for non-convex stochastic optimization [18]. Adagrad algorithm is adapting all learning rates of the model parameters. This is possible by scaling the learning rates based on the partial derivative of the loss, the greater the derivative the faster the decrease of the associated learning rate. For the parameters having small partial derivative of the gradient the decrease of the associated learning rate is also smaller [19].

$$\omega_{t+1} = \omega_t - \frac{\eta}{\sqrt{G_t + \varepsilon}} \nabla_{\omega} J(\omega) \quad (8)$$

$$G_t = G_{t-1} + [\nabla_{\omega} J(\omega)]^2 \quad (9)$$

And where ε is a constant included to avoid possible scenarios in which the division would have been possible to be made by zero. Based on (8) learning rate is divided by the square root of the sum of past and current squared gradients. Due to the way that the squared gradients are used iteration by iteration the cumulative value of the denominator is growing as the number of iterations is increasing. The consequence is that the learning rates are becoming smaller and smaller until the point where the algorithm is no longer acquiring knowledge.

RMSProp or Root Mean Square Prop as Adagrad is an adaptive learning rate optimization algorithm [20]. This solution was proposed to solve Adagrad's shortcoming on diminishing

learning rates. Taking the exponential moving average of the gradients instead of cumulative sum of squared gradients it will overcome this weakness of the Adagrad algorithm. The update equation remains the same as in (8) the difference is made on the denominator term G_t .

$$G_t = \beta G_{t-1} + (1 - \beta) [\nabla_{\omega} J(\omega)]^2 \quad (10)$$

Adam is a method for stochastic optimization based on adaptive estimates of low-order moments [21]. The name of this method is come from adaptive moment estimation. Is combining the advantages of Adagrad and RMSProp working well for sparse gradients, under on-line and non-stationary framework, being computationally and memory efficient. Adam is using exponential moving average of gradient (m_t - the estimate of the first moment (mean) of the gradient) for scaling the learning rate instead of the simple average used in Adagrad and squared gradient (v_t the second raw moment (the uncentered variance) of the gradient) as in RMSProp.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) \nabla_{\omega} J(\omega) \quad (11)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) [\nabla_{\omega} J(\omega)]^2 \quad (12)$$

β_1 and β_2 represents hyper-parameters $\in [0,1)$ used for controlling the exponential decay rates of the moving averages (m_t) and (v_t).

During the initial time steps due to the initialization as vectors of 0 and for values of β_1 and β_2 are close to 1 then m_t and v_t are biased towards 0. To avoid this drawback bias-corrected estimates of m_t and v_t are proposed

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t} \quad (13)$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t} \quad (14)$$

And in this case the update method is the following:

$$\omega_{t+1} = \omega_t - \frac{\eta}{\sqrt{\hat{v}_t} + \varepsilon} \hat{m}_t \quad (15)$$

Adamax is an evolution of the Adam optimizer deploying a p-norm based update rule. For the use cases in which $p \rightarrow \infty$ then the algorithm become simple and stable.

Update steps for Adamax:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) \nabla_{\omega} J(\omega) \quad (16)$$

$$u_t = \max(\beta_2 u_{t-1}, |\nabla_{\omega} J(\omega)|) \quad (17)$$

Where u_t represents the update of the exponentially weighted infinity norm.

Finally, the update for all network parameters:

$$\omega_t = \omega_{t-1} - \frac{\eta}{(1 - \beta_1^t)} \frac{m_t}{u_t} \quad (18)$$

Weights initialization is paying an important role in the overall network training. A proper initialization proved to be critical in having a network that is converging to the desired minima in a reasonable amount of time or in the opposite scenario the training could spread on bigger time frame with even less performance. For an initialization with a constant value all neurons will have an identical impact on the cost which leading to identical gradients. Further during

the training, neurons will evolve symmetrically, restricting neurons in acquiring different knowledge. Moreover, having initial values too big or too small will lead to enlarging or vanishing gradients. Both cases generating poor performance of the network. Randomly selecting small numbers out of a normal distribution will drive to a variance of the weights as function of the number of inputs. The initialization strategies deployed were chosen to overcome the weaknesses presented above. LeCun initialization methodology suppose drawing the initial synaptic weights values from a distribution with zero mean and a certain variance [22]. Two instances of this methodology are widely deployed, both solving the dependence of variance on number of inputs. LeCun Normal Initialization is taking a truncated normal distribution centered in zero and with a standard deviation σ_w described by:

$$\sigma_w = \sqrt{\frac{1}{input_dim}} \quad (19)$$

Where $input_dim$ is the number of connections feeding into the neuron. LeCun Uniform Initialization is drawing the samples out of a distribution bounded lower and superior:

$$lower\ bound = -\sqrt{\frac{3}{input_dim}} \quad (20)$$

$$upper\ bound = \sqrt{\frac{3}{input_dim}} \quad (21)$$

Xavier initialization is an evolution of LeCun's work but instead of taking into consideration only the number of input units in the weight tensor is taking also the number of output units in the weights tensor [23]. Xavier Normal Initializer is using samples drawn from a truncated normal distribution centered on 0 with the standard deviation σ_w :

$$\sigma_w = \sqrt{\frac{2}{input_dim + output_dim}} \quad (22)$$

Where $input_dim$ is the number of inputs units in the weight tensor and $output_dim$ is the number of output units in the weight tensor. Xavier Uniform Initializer is drawing the samples from a uniform distribution bounded lower and upper.

$$lower\ bound = -\sqrt{\frac{6}{input_dim + output_dim}} \quad (23)$$

$$upper\ bound = \sqrt{\frac{6}{input_dim + output_dim}} \quad (24)$$

Activation functions are triggering neuron to transfer or to not transfer the signal further. In literature activation functions are known also as transfer functions. Activation functions can be divided in two categories: linear activation functions and non-linear activation functions. Without activation functions the neural network model is just a linear regression model. Linear activation function is one of the simplest solutions:

$$y_i = mz_i = f(z_i) \quad (25)$$

The derivative of the function with respect to z_i is m . This means there is no relation to the input z_i .

Sigmoid or logistic activation function is one of the most used in feedforward neural networks due to some of its advantages like being nonlinear and computational simplicity of its derivative [24]. It is continuously differentiable function satisfying the relation:

$$y_i = \frac{1}{1 + \exp(-z_i)} = f(z_i) \quad (26)$$

The output of the sigmoid activation function is always bounded in the range (0,1). Most important pitfall while using the sigmoid functions are the extreme ends, almost horizontal regions in which where the responses on the changes in z are diminished. It is used for the models where the output is represented by a probability, like classification problems. A more general logistic activation function is Softmax and is used for multiclass classification.

Tanh is an activation function similar with sigmoid being a scaled sigmoid function, existing in the range (-1,1).

$$\tanh(z_i) = 2\text{sigmoid}(z_i) - 1 \quad (27)$$

$$f(z_i) = \tanh(z_i) = \frac{2}{1 + \exp(-2z_i)} \quad (28)$$

Tanh as sigmoid is exposed as well on diminished responses for the close to horizontal regions. Relu or Rectified linear unit is one of the most popular activation functions among deep learning practitioners. Relu is more computationally efficient than sigmoid and tanh activation functions by activating only some of the neurons at same time.

$$f(z_i) = \max(0, z_i) \quad (29)$$

On the other hand, this can become a weakness since could lead to a situation in which a large percentage of the neurons will not be activated anymore during the training. Being less expensive than sigmoid and tanh in terms of computation is enabling a faster convergence [26]. An Artificial Neural Network architecture should provide a robust solution for studied use case. Robustness can be evaluated through the network performance. An architecture that is providing minimal error indicate that the network can generalize [26]. The number of neurons on the hidden layer can be fixed using existing knowledge based on trials or can be adapted based on the use case [27]. One approach for the number of neurons on the hidden layer of an MLP is specified by Kolmogorov, 1957. In this theory the number of neurons on the hidden layers should be $2n+1$, where n is the number of neurons of the input vector.

When the number of hidden layers is analyzed, and the exact number of layers must be chosen it is important to know the type of problem that the ANN will deal. For applications where, linear separable functions need to be represented, a single layer perceptron can be enough to make a split. An example of application can be in this case the binary classification. For high-dimensional use cases where linear separability is not enough to split certain classes, where separability plane is needed MLP is used.

Underfitting and overfitting can be explained also by analyzing the number of neurons inside hidden layers [28]. When the number of neurons is not big enough to capture the complexity of the relations between variables inside the data set under fitting may appear. On the other hand, when the number of neurons inside hidden layers is bigger than the number of neurons needed to map the relations between variables this might generate over fitting.

4. Methodology

CRISP-DM (Cross-Industry Standard for Data Mining) is a standard that is defining step by step data mining process. SAS institute proposed before CRISP-DM their own data mining framework called SEMMA (Sample, Explore, Modify, Model, Assess). In 1996, SPSS,

Teradata, Daimler AG, NCR and OHRA joined their forces to build what the data mining standard that become nowadays Cross Industry Standard for Data Mining. In 2015 IBM published its own instance of CRISP-DM. A refined standard called ASUM-DM (Analytics Solutions Unified Method for Data Mining/ Predictive Analytics). CRISP-DM is a living document being updated and refined multiple times in the last 20 years and based on the dynamics inside analytics ecosystem it looks like CRISP-DM will continue to evolve.

The main phases of CRISP-DM framework are the following: Business Understanding, Data understanding, Data Preparation, Modeling, Evaluation and Deployment. For this paper just the first five phases will be followed, deploying the model being out of scope. The framework can be customized and shaped on the user's goals and resources.

5. Data overview

The data set used in this analysis was generated during a marketing campaign based on phone calls made available by University of California at Irvine (UCI). S. Moro, R. Laureano and P. Cortez collected the data and built the data set. Moreover, they built their own predictive analysis and their results will be the base line for this analysis [29]. Used data set contains 41188 records, 20 independent variables and 1 dependent variable. Data set variables are split in numerical (Age, Duration, Campaign, Pdays, Previous, Employment variation rate, Consumer price index, Consumer confidence index, Euribor 3-month rate, Number of employees) and categorical (Job, Marital, Education, Default, Housing, Loan, Contact, Month, Day of week, Poutcome, Output).

Taking into consideration the learning scenario and based on the data available this research is falling in the supervised learning category. Supervised learning is a paradigm in which the algorithm is feed with labeled data as training data and must make predictions for unseen data. This means the algorithm will need to identify patterns inside the training data that will allow it to predict the correct label of the unseen data [30]. To be more specific for this analysis a binary classification is requested.

Before feeding the data into the neural network one crucial step is to transform the categorical data using one-hot encoding [31] since neural networks are not capable deal with categorical variables. New features are built for day of week and month using the date variable. At the end of this step 19 out of 81 independent variables are removed due to multicollinearity. Data set split between training and testing is 80% for training and 20% for testing during the entire study.

6. Evaluation

To find the best architecture multiple optimization scenarios are performed. First step is to select the metrics and to set the baseline. Once the baseline is set the optimization can start. In terms of performance understanding Confusion matrix represents the starting point when a classification model performance is assessed. Confusion matrix it is a 2D "Actual" and "Predicted" table. Inside confusion matrix are the following values: True Positives (TP) – Actual class of the point to be predicted as True (1), True Negatives (TN) - Actual class of the point to be predicted was False (0), False Positive (FP) – Actual class of the point to be predicted was True (1) but the prediction was False (0), False Negative (FN) – Actual class of the point to be predicted was False (0) but the prediction was True (1) [32].

In an ideal case it is desirable to minimize both False Positive and False Negative. Based on use case in real world problems it is needed to minimize False Positive Rate or False Negative Rate. False Positive Rate (FPR) or Type I error represents represent the fraction of alerts when a point was predicted to be true put the actual value was false.

$$FPR = \frac{FP}{FP + FN} \quad (30)$$

False Negative Rate or Type II error represents fraction of the data points for which we missed to predict the False (0).

$$FNR = \frac{FN}{TP + FN} \quad (31)$$

For highly imbalanced data sets FPR or FNR tend to be low or high based on which class of the data set is imbalanced.

For this use case Type II errors count is higher than Type I errors because the TN class is bigger than TP class and Type II errors are calculated using TN as part of the denominator.

Specificity or True Negative Rate measures how well the False (0) observations were classified as False (0).

$$TNR = \frac{TN}{TN + FP} \quad (32)$$

True Positive Rate or Recall or Sensitivity represents it's a measure of observations classified as positive out of all possible positive observations

$$FPR = \frac{TP}{TP + FN} \quad (33)$$

Positive Predictive Value or Precision represents how well the True (1) points are predicted as True (1).

$$PPV = \frac{TP}{TP + FP} \quad (34)$$

Accuracy is a measure of both True and Positive points classified correctly

$$ACC = \frac{TP + TN}{TP + FP + TN + FN} \quad (35)$$

Overcoming this issue F1 Score combines the Recall and Precision into a single Metric by making the harmonic mean between these two.

$$F_1 = 2 \frac{Sensitivity \cdot Precision}{Sensitivity + Precision} \quad (36)$$

AUC (Area Under the Curve) – ROC (Receiver Operating Characteristics) curve is a measure of how good is the model in distinguishing classes based on predicted probability. False Positive Rate is on the X- axis and True Positive Rate is on the Y-axis in most typical approach. Higher the AUC, better the model is making the predictions, distinguishing between classes. Considering the multitude of metrics available for this type of classification and the use case in this paper AUC it is selected for measuring the performance of the tested algorithms while F1 Score and Accuracy are used to decide for closer AUC values which combination of hyperparameters it is performing better. There is no rule on how many combinations of hyperparameters will continue after every optimization, it is a matter of how promising the results are.

7. Results

The neural network deployed initially to set the baseline is a Multi-layer Perceptron with 61 input variables, Xavier uniform weights initialization and Adam optimizer. Hidden layer consists of 123 neurons ($2n+1$, where n is the number of input variables) with Relu activation

function. Output layer is represented by a single neuron with Sigmoid activation function. Baseline metrics for are: AUC=0.9377, F1 Score= 0.5174, Accuracy=0.9124.

Table 1. Epochs and Batch optimization

	e1	e10	e20	e30	e40	e50	e60	e70	e80	e90	e100
AUC b10	0.9406	0.9414	0.9351	0.9312	0.9238	0.9228	0.9175	0.9120	0.9168	0.9161	0.9138
AUC b30	0.9408	0.9419	0.9371	0.9348	0.9304	0.9275	0.9199	0.9197	0.9202	0.9151	0.9142
AUC b50	0.9387	0.9436	0.9393	0.9377	0.9332	0.9306	0.9251	0.9247	0.9204	0.9205	0.9154
F1 Score b10	0.5915	0.5770	0.5571	0.5867	0.5479	0.5420	0.5503	0.5295	0.5570	0.5338	0.5506
F1 Score b30	0.5637	0.5627	0.5468	0.5807	0.5432	0.5405	0.5570	0.5454	0.5804	0.5494	0.5540
F1 Score b50	0.5525	0.5798	0.5649	0.5960	0.5515	0.5450	0.5636	0.5701	0.5617	0.5511	0.5497
Accuracy b10	0.9182	0.9153	0.9120	0.9101	0.9054	0.9034	0.8980	0.8965	0.8996	0.8961	0.8997
Accuracy b30	0.9156	0.9149	0.9119	0.9108	0.9096	0.9104	0.8996	0.9008	0.9047	0.8999	0.8982
Accuracy b50	0.9156	0.9178	0.9142	0.9134	0.9096	0.9104	0.9013	0.9081	0.9017	0.9051	0.8988

In the Table 1. where b stands for batch and e stand for epochs biggest AUC value is obtained after training the initial architecture over 10 epochs and using mini-batches of 50. Bigger the number of epochs, lower the AUC. Regarding the mini-batch size, no significant improvement appears for values bigger than 50.

Table 2. Optimization algorithm optimization

	Adagrad b10 e10	Adagrad b30 e10	Adagrad b50 e10	Adam b10 e10	Adam b30 e10	Adam b50 e10	Adamax b10 e10
AUC	0.9456	0.9455	0.9450	0.9416	0.9424	0.9426	0.9430
F1 Score	0.5978	0.5854	0.5947	0.5857	0.5696	0.5803	0.5667
Accuracy	0.9206	0.9187	0.9198	0.9155	0.9171	0.9166	0.9144
	Adamax b30 e10	Adamax b50 e10	RMSProp b10 e10	RMSProp b30 e10	RMSProp b50 e10	SGD b1 e10	
AUC	0.9439	0.9445	0.9358	0.9403	0.9414	0.9428	
F1 Score	0.5757	0.5840	0.5831	0.5672	0.5769	0.5860	
Accuracy	0.9181	0.9185	0.9193	0.9155	0.9161	0.9170	

Adagrad and Adamax are performing better than Adam. Based on the theoretical aspects of these 3 optimizers highlighted above the expectation was to have both Adam and Adamax performing better than Adagrad. Additionally, the impact of the mini-batch size is limited for Adagrad and Adamax. Moreover, SGD or Stochastic Gradient Descent it is performing better than Adam and RMSProp even the last two are taking the advantage of adaptive learning.

Table 3. Learning Rate Optimization

	Adamax b50 e10 lr=0.0001	Adamax b50 e10 lr=0.001	Adamax b50 e10 lr=0.01	Adamax b50 e10 lr=0.1	Adamax b50 e10 lr=0.2	Adagrad b10 e10 lr=0.0001	Adagrad b10 e10 lr=0.001	Adagrad b10 e10 lr=0.01
AUC	0.9309	0.9449	0.9422	0.9392	0.9346	0.7315	0.9271	0.9449
F1 Score	0.4986	0.5897	0.5686	0.5977	0.6351	0.1149	0.4836	0.5950
Accuracy	0.9206	0.9165	0.9153	0.9139	0.9116	0.9101	0.9156	0.9195
	Adagrad b10 e10 lr=0.1	Adagrad b10 e10 lr=0.2	Adam b50 e10 lr=0.0001	Adam b50 e10 lr=0.001	Adam b50 e10 lr=0.01	Adam b50 e10 lr=0.1	Adam b50 e10 lr=0.2	
AUC	0.9421	0.9386	0.9390	0.9436	0.9392	0.8707	0.4989	
F1 Score	0.5765	0.5911	0.5592	0.5852	0.6067	0.0399	nan	
Accuracy	0.9172	0.8878	0.9176	0.8831	0.9188	0.8884	0.9164	

Adamax and Adagrad become flat starting with the learning rate equal to 0.001 staying flat for learning rates up to 0.2. Adam proved to be more sensitive on the learning rate variation. For the next optimizations the learning rate lr=0.001 is kept as unique learning rate over all other optimizations.

Table 4. Weights initialization optimization

	ln Adagrad b10 e10	ln Adamax b50 e10	lu Adagrad b10 e10	lu Adamax b50 e10	One Adagrad b10 e10
AUC	0.9318	0.9438	0.9222	0.9453	0.7323
F1 Score	0.4783	0.5909	0.4691	0.5775	0.3606
Accuracy	0.9094	0.9205	0.9082	0.9183	0.9023
	One Adamax b50 e10	xn Adagrad b10 e10	Xn Adamax b50 e10	xu Adagrad b10 e10	xu Adamax b50 e10
AUC	0.8077	0.9313	0.9448	0.9298	0.9456
F1 Score	0.3532	0.4969	0.6050	0.4832	0.5784
Accuracy	0.9026	0.9122	0.9217	0.9104	0.9177

Where ln= LeCun normal, lu= Lecun uniform, xn= Xavier Normal, xu= Xavier Uniform. Out of all five possible initialization strategies the one consisting of initial weights equal to 1 (One Adagrad and One Adamax) proved to be the worst. The difference between this one and the other four being around 10% less for all metrics considered. For F1 Score the difference it is even bigger going up to 40%.

Table 5. Activation Function Optimization

	relu xn	relu ln	relu xu	relu lu	linear xn	linear ln	linear xu	linear lu
AUC	0.9448	0.9438	0.9456	0.9453	0.9349	0.9351	0.9349	0.9351
F1 Score	0.6050	0.5909	0.5784	0.5775	0.5243	0.5259	0.5259	0.5247
Accuracy	0.9217	0.9205	0.9177	0.9183	0.9121	0.9122	0.9122	0.9122
	sigmoid xn	sigmoid ln	sigmoid xu	sigmoid lu	tanh xn	tanh ln	tanh xu	tanh lu
AUC	0.9423	0.9429	0.9425	0.9428	0.9448	0.9433	0.9430	0.9435
F1 Score	0.5805	0.5858	0.5898	0.5942	0.6019	0.5860	0.6012	0.5977
Accuracy	0.9181	0.9192	0.9193	0.9202	0.9204	0.9182	0.9211	0.9198

Only the activation function of the hidden layer is part of this optimization. After the weights initialization optimization was performed ln, lu, xn and xu weights initialization strategies were selected to be part of the activation function optimization step due to the metrics closeness. Linear activation function it is outperformed by the other three activation functions. Even both LeCun normal and uniform initialization strategies are scoring very good in terms of AUC, the other metrics have lower values than Xavier strategies. Considering this, relu xn, relu xu and tanh xn are selected to be part of the next optimization.

Table 6. Number of neurons on the hidden layer optimization

	relu xn $h(2n-1)$	relu xn $h(2n+1)$	relu xn $h(4n-2)/(n-3)$	relu xn $h(6n+2)/(n-3)$
Neurons	h121	h123	h4	h6
AUC	0.9452	0.9448	0.9361	0.9380
F1 Score	0.6075	0.6050	0.5656	0.5967
Accuracy	0.9222	0.9217	0.9151	0.9193
	relu xu $h(n/2-1)$	tanh xu $h(2n-1)$	relu xu $h(4n-2)/(n-3)$	relu xu $h(6n+2)/(n-3)$
Neurons	h29	h121	h4	h6
AUC	0.9404	0.9442	0.9357	0.9343
F1 Score	0.5769	0.5974	0.5192	0.5790
Accuracy	0.9165	0.9205	0.9134	0.9137
	relu xu $h(2n-1)$	relu xu $h(2n+1)$	tanh xu $h(4n-2)/(n-3)$	tanh xu $h(2n+1)$
Neurons	h121	h123	h4	h123
AUC	0.9462	0.9456	0.9413	0.9430
F1 Score	0.6037	0.5784	0.6014	0.6012
Accuracy	0.9211	0.9177	0.9199	0.9211
	tanh xu $h(n/2-1)$	relu xn $h(n/2-1)$	tanh xu $h(6n+2)/(n-3)$	
Neurons	h29	h29	h6	
AUC	0.9432	0.9403	0.9427	
F1 Score	0.6072	0.5851	0.5839	
Accuracy	0.9209	0.9181	0.9166	

Where h represents the hidden layer, n the number of input variables and inside the brackets the formula for number of neurons on the hidden layer. The best results are provided by the networks with the neurons on the hidden layer var varying around $(2n+1)$ and $(2n-1)$.

Table 7. Number of layers optimization

	relu xn $h(2n-1)$	relu xn $h(n/2-1)$	relu xu $h(2n-1)$	relu xu $h(4n-2)/(n-3)$	relu xu $h(6n+2)/(n-3)$
Neurons	h121,hh241	h29,hh13	h121,hh241	h4,hh14	h6,hh12
F1 Score	0.5769	0.5901	0.5919	0.5718	0.5446
Accuracy	0.9172	0.9172	0.9192	0.9087	0.9101
AUC	0.9435	0.9397	0.9432	0.9323	0.9332
	relu xu $h(2n+1)$	relu xu $h(n/2-1)$	tanh xu $h(n/2-1)$	tanh xu $h(4n-2)/(n-3)$	tanh xu $h(6n+2)/(n-3)$

Neurons	h123,hh247	h29,hh13	h29,hh13	h4,hh14	h6,hh12
F1 Score	0.5869	0.6019	0.5924	0.6052	0.6033
Accuracy	0.9187	0.9149	0.9183	0.9173	0.9184
AUC	0.9436	0.9398	0.9422	0.9417	0.9421
	relu xn h(2n+1)	tanh xu h(2n-1)	tanh xu h(2n+1)	relu xn h(4n-2)/(n-3)	relu xn h(6n+2)/(n-3)
Neurons	h123,hh247	h121,hh241	h123,hh247	h4,hh14	h6,hh12
F1 Score	0.5925	0.5896	0.6002	0.6055	0.5661
Accuracy	0.9195	0.9160	0.9192	0.9081	0.9124
AUC	0.9438	0.9424	0.9419	0.9323	0.9367

Notation convention made for a single hidden layer it is kept for the second layer optimization and additionally hh stand for second hidden layer. The number of neurons of the second hidden layer is calculated considering the first hidden layer input for it. Adding the second hidden layer is not adding any improvement on the metrics, but it is adding computational power and time for the training. For the studied use case the best architecture it is a Multi-layer perceptron with one hidden layer consisting of 121 neurons, Relu activation function for the hidden layer, Sigmoid for output layer and Adamax optimizer. Weights initialization it is made using Xavier uniform strategy.

Table 8. Comparison between baseline and final selected model

	baseline model	relu adamax b50 e10 xu h(2n-1) model
Neurons	123	121
AUC	0.9377	0.9462
F1 Score	0.5174	0.6037
Accuracy	0.9124	0.9211

8. Conclusion

Technological advance it is creating the premise for gathering more and more. Setting the right skill set in terms of data mining and subject matter is essential to bring value into and to remain competitive. This study fills the gap in the data driven decision systems for marketing campaigns presenting an end-to-end approach for increasing effectiveness. The deep dive made on both theoretical and experimental aspects of hyperparameter tuning give right image over how much the right setting can make the difference between benchmark performance and poor performance. Weights Initialization and Activation function proved to impact most the performance of the neural network. The negative impact on the selected hyperparamters can go up to 40%. The best hyperparameters configuration improved some of the existing work done on the same data set. However, the baseline model proved to be competitive even without optimization and this fact is only highlighting again one of the premises of this research, Artificial Neural Networks can act like universal approximators being able to find patters in the data for benchmark results.

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