Artificial Immune System for Short-Term Electric Load Forecasting

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Abstract. This paper proposes a novel model, based on the artificial immune system, to solve the problem of short-term load forecasting. An artificial immune system is trained to recognize antigens which encode sequences of load time series. The created immune memory is a representation of these sequences. In the forecast procedure a new incomplete antigen, containing only the first part of the sequence, is presented to the model. The second forecasted part of the sequence is reconstructed from activated antibodies. The model was verified using several real data examples of the short-term load forecast.

Keywords: artificial immune system, short-term electric load forecasting, similarity-based method.

1 Introduction

The load demand on an electrical power system varies depending on such factors as seasonal effects, work cycles of industrial plants, meteorological conditions, legal and religious holidays, failures of networks and devices etc. Some of these factors are random. A basic requirement in the operation of power systems is to balance the system load by the system generation at all times. Load forecasting is a very important task for electricity companies in order to manage the production, transmission and distribution of electricity in a secure and efficient way. Accurate load forecasts are essential to optimize unit commitment, economic dispatch, hydro scheduling, hydro-thermal coordination, spinning reserve allocation and interchange evaluation. Moreover, the electricity markets could not function without load forecasts. An accurate load forecast allow a lot of money to be saved, e.g. an increase of only 1% in forecast error caused an increase of 10 million pounds in operating cost per year for one electric utility in United Kingdom [1].

Short-term load forecasting (STLF) is defined as forecasting system load demand from one hour to one week ahead. Many techniques have been investigated to solve the STLF problem in the last tree decades. Conventional STLF methods use smoothing techniques, regression methods and statistical analysis. Regression methods are usually used to model the relationship of load consumption and other factors (weather, day type, customer class) [2]. ARMA and related models are very popular (also known as Box-Jenkins, time series, or transfer function models) [3], where the load is modeled by an autoregressive moving average difference equation.

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These models are based on the assumption that the data have an internal structure, such as autocorrelation, trend and seasonal variation.

In recent years, artificial intelligence methods (AI) have been widely applied to STLF [4]. AI methods for forecasting have shown an ability to give better performance in dealing with non-linearity and other difficulties in modeling the time series. They do not require any complex mathematical formulations or quantitative correlation between inputs and outputs. The AI methods most often used to STLF can be divided as follows:

- Neural networks (NN) – multilayer perceptron [5], RBF NN [6], Kohonen NN [7], counterpropagation NN [8], recurrent NN [9];
- Fuzzy systems [10], [11];
- Expert systems [12], [13].

Expert systems are heuristics models, which are usually able to take both quantitative and qualitative factors into account. A typical approach is to try to imitate the reasoning of a human operator. The idea is to reduce the analogical thinking behind the intuitive forecasting to formal steps of logic. Neural networks, on the other hand, do not rely on human experience but attempt to learn by themselves the functional relationship between system inputs and outputs. Fuzzy logic models map a set of input variables to a set of output variables. These variables need not be numerical and may be expressed in natural language. Most commonly, a fuzzy logic model includes the mapping of input values to output values using IF-THEN logic statements.

In order to overcome some of the limitations of individual methods, hybrid AI models have been constructed, such as neural networks combined with fuzzy systems [14], [15] or neural network-fuzzy expert systems [16], [17].

New STLF methods are still being created. Some of them are based on machine learning and pattern recognition techniques, e.g. regression trees [18], cluster analysis methods [19] and support vector machines [20]. Other original approaches have also been developed, such as a method using fractal geometry [21], the point function method [22] and a canonical distribution of the random vector method [23].

This paper presents an artificial immune system (AIS) as a way of modeling to STLF. The merits of AIS lie in its pattern recognition and memorization capabilities. AIS are being used in many applications such as [24], [25], [26] anomaly detection, pattern recognition, data mining, computer security, adaptive control, and fault detection. Antigen recognition, self-organizing memory, immune response shaping, learning from examples, and generalization capability are valuable properties of immune systems which can be brought to potential forecasting models. In AIS learning occurs through modification of the number and affinities of the antibodies. The cross-reactivity threshold is the parameter which determines the model generalization level. In the proposed method, sequences of the load time series are encoded in antigens. Immune memory after learning is a representation of a set of antigens. When a new incomplete, composed only of the first part of time series sequence, antigen is presented, it is recognized by some antibodies. The second (forecasted) part of the sequence is reconstructed from these antibodies.

2 Forecasting Model Based on the Artificial Immune System

The problem of STLF, considered in this work, is the one-day ahead power system daily load curve forecasting. The daily load curve is represented by the 24-component vector $\boldsymbol{P}$, whose components are the following hourly loads. The input variables are 24 hourly loads of the day preceding the day of forecast. It is assumed that the information about the future realization of the load time series is included in the time series preceding the forecast moment. This assumption for the load time series, which are characterized by annual, weekly and daily cycles due to the changes in industrial activities and climatic conditions, was confirmed by statistical tests [27]. Other factors influencing load (atmospheric temperature, humidity, wind speed, precipitation and cloud cover) are not employed in the proposed model. They are important in the power systems in which electrical heating and air-conditioning are common.

Let $\boldsymbol{P_x}$ be a vector of hourly power system loads in the following hours of the day preceding the day of forecast $\boldsymbol{P_x} = [P_x(1), P_x(2), \ldots, P_x(24)]$, and let $\boldsymbol{P_y}$ be a vector of hourly loads of the day of forecast $\boldsymbol{P_y} = [P_y(1), P_y(2), \ldots, P_y(24)]$. These vectors are preprocessed in order to get rid of the time series trend and seasonality, and simplify the model. The load patterns are introduced: input $\boldsymbol{x} = [x(1), x(2), \ldots, x(24)]$ and output $\boldsymbol{y} = [y(1), y(2), \ldots, y(24)]$, which are vectors with components defined as follows:

$$x(i) = \frac{P_x(i)}{\overline{P}_x} \quad i = 1,2,\ldots,24 \tag{1}$$

$$y(i) = \frac{P_y(i)}{\overline{P}_x} \quad i = 1,2,\ldots,24 \tag{2}$$

where $\overline{P}_x$ is the daily mean load for the day preceding the day of forecast.

The model learns to map $\boldsymbol{x} \rightarrow \boldsymbol{y}$. After learning the input pattern $\boldsymbol{x}$ is presented to the model and the pattern $\boldsymbol{y}$ is obtained as a model output. Formula (2) is used to receive the forecasted load curve $\boldsymbol{P_y}$.

The model is based on the artificial immune system. Concatenated patterns $\boldsymbol{x}$ and $\boldsymbol{y}$ form antigens. Thus each antigen is composed of 48 amino acids (Fig. 1) which are real numbers. It is assumed that the only components of the immune system are antibodies built analogously to antigens. Each antibody has two chains – x to detect the x-chain of the antigens and y to memorize the y-chain of detected antigens.

The task of the immune system is to learn to map the set of antigens into the set of antibodies. The immune memory is an effect of learning. For each day of the week (Monday, …, Sunday) the separate immune memory is created using antigens representing only this day (e.g. for forecasting the Sunday load curve, system learns from antigens which x-chain represents the Saturday pattern and y-chain represents the Sunday pattern). The quality criterion of the immune memory is the forecast error. The forecasting procedure applying the learned immune memory runs in the following order. The new antigen consisting only of the x-chain is presented. It is detected by the antibodies with similar x-chains and the y-chain of the antigen is reconstructed from y-chains of these antibodies.

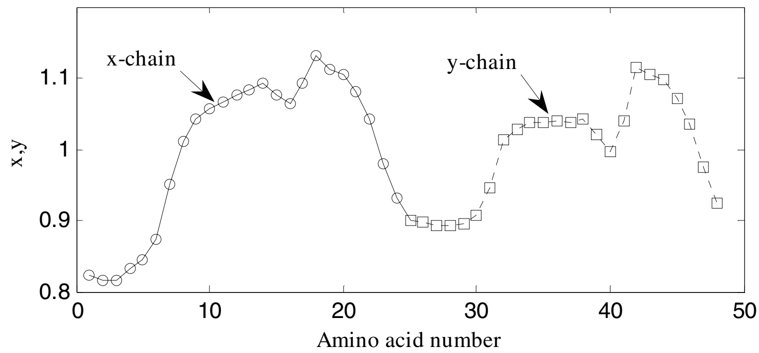

Fig. 1. The antigen and antibody structure

The detailed algorithm of the immune memory creation in the proposed STLF model is described below.

The immune memory creation algorithm in the STLF model

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1. Loading of the training set of antigens
2. Generation of the initial antibody population
3. Calculation of the affinity of antibodies for antigens
4. Activated antibody detection and evaluation
5. Do until the stop criterion is reached
   5.1. Clonal selection
   5.2. Clone hypermutation
   5.3. Antibody affinity calculation
   5.4. Activated antibody detection and evaluation
   5.5. Selection of the best antibodies
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Ad. 1. The whole dataset is divided into two subsets – training one and test one. The first sequences of the time series (typically two thirds of the whole time series) are included in the training set and the latest sequences are included in the test set. Immune memory is trained using the training set, and after learning the model is tested using the test set.

Ad. 2. An initial antibody population is created by copping all the antigens from the training set (antibodies and antigens have the same structure). This way of initialization prevents inserting antibodies in empty regions without antigens.

Ad. 3 and 5.3. The affinity measure is based on the distance between *x*-chains of antigens and antibodies. The Euclidean distance is used:

$$d = \sqrt{\sum_{i=1}^{24} [x_{Ab}(i) - x_{Ag}(i)]^2} \qquad (3)$$

where x_{Ab} and x_{Ag} are the *x*-chains of the antibody and antigen, respectively.

Ad. 4 and 5.4. If the affinity of the antibody for the antigen is smaller than or equal to the cross-reactivity threshold *r*, it means that the antigen lies in the antibody recognition region (the antibody is activated by the antigen). For this antibody the forecast error (MAPE, which is traditionally used in STLF models) is calculated:

$$\delta = \frac{1}{24}\sum_{i=1}^{24}\left|\frac{y_{Ab}(i) - y_{Ag}(i)}{y_{Ag}(i)}\right| \cdot 100\% \tag{4}$$

where y_{Ab} and y_{Ag} are the *y*-chains of the antibody and antigen activating this antibody.

If several antigens lie in the antibody recognition region, the error is calculated for each of them. The mean error $\overline{\delta}$ is applied to evaluate the antibody and is minimized in the following iterations of the algorithm.

Ad. 5. The algorithm stops if the maximum number of iteration L is reached.

Ad. 5.1. Each antibody cases secreting as many clones as many antigens are in its recognition region. Thus most clones are generated in the dense clusters of antigens.

Ad. 5.2. The main goal of hypermutation is to improve the diversity of the immune system in order to effectively recognize new antigens. The hypermutation is realized as follows. Each clone of the antibody is shifted towards different antigen lying in the recognition region of this antibody. The bigger the error δ for the given antigen is, the bigger shift toward this antigen is. The shift is calculated according to the formulae:

$$x_{Ab}(i) = x_{Ab}(i) + \eta(i)[x_{Ag}(i) - x_{Ab}(i)] \quad i = 1,2,...,24 \tag{5}$$

$$y_{Ab}(i) = y_{Ab}(i) + \eta(i+24)[y_{Ag}(i) - y_{Ab}(i)] \quad i = 1,2,...,24 \tag{6}$$

where $\eta \in (0, 1)$ is a learning coefficient calculated from the hyperbolic tangent sigmoid function as follows:

$$\eta(i) = \frac{2}{1 + \exp[-\beta\delta N_i(1,0.1)]} - 1 \quad i = 1,2,...,48 \tag{7}$$

where β is the shape parameter and $N_i(1, 0.1)$ are the independent normally distributed random numbers with mean 1 and standard deviation 0.1.

Random factor in formula (7) is introduced to avoid stagnation of the learning process caused by getting into local minimum trap of the error function**.** For the shape parameter $\beta = 0.04$ and error $\delta = 1\%$ the value of the learning coefficient is minor – $\eta \cong 0.02$, and consequently the shift is minor too. For the higher errors – 2%, 5%, 10%, 100% the η-value is higher – about 0.04, 0.1, 0.2 and 0.96, respectively. This type of hypermutation produces new antibodies only in the regions covered by antigens.

Ad. 5.5. For each antigen from the training set, the set of antibodies activated by this antigen is determined. Only one antibody from this set, with the best evaluation $\overline{\delta}$, is selected to the next population. So the clonal expansion, unnecessary in this model, is halted. The maximum number of antibodies in the next population is equal to the number of antigens, but the real number of antibodies is usually smaller because the same antibody could be selected by the several antigens (it depends on the value of the cross-reactivity threshold r). Outlier, i.e. antigen lying away from other antigens, is represented by the separate antibody.

Forecast procedure. After learning the antibodies represent overlapping clusters of similar antigens. In the forecast procedure new antigen having only x-chain is presented. The Ω set of antibodies, activated by this antigen, is determined. The y-chains of these antibodies storage average y-chains of antigens from the training set with similar x-chains. The y-chain of the input antigen is reconstructed from the y-chains of the antibodies contained in the Ω set (denoted by $\mathbf{y}_{Ab}^{j}$):

$$\hat{y}_{Ag}(i) = \frac{\sum_{j=1}^{|\Omega|} w_j y_{Ab}^{j}(i)}{\sum_{j=1}^{|\Omega|} w_j} \quad i = 1,2,...,24 \tag{8}$$

where $w_j \in (0, 1)$ is the weight which value is dependent on the distance d_j between the input antigen and the j-th antibody from the Ω set:

$$w_j = 1 - \frac{d_j}{r} \quad j = 1,2,...,|\Omega| \tag{9}$$

Antibodies, closer to the antigen, have the higher influence on the forecast forming. If an antigen is not recognized by antibodies, it means that it represents a new shape of the load curve, not contained in the training set. In this case the cross-reactivity threshold r is consistently being increased until the antigen is recognized by one or more antibodies. The level of confidence in the forecast in such a case is low and the forecast should be verified.

3 Application Examples

The described above artificial immune system for STLF was implemented in Matlab and was applied to five real STLF problems. Data are described in Table 1. Usually the smaller power system is, the more irregular and harder to forecasting load time series is. The measure of the load time series regularity could be the forecast error (MAPE) determined by the naïve method. The forecast rule in this case is as follows: the load curve of the day of forecast is the same as seven days ago. The mean forecast errors, calculated according to this naïve rule, are presented in Table 1.

The model parameters – the cross-reactivity threshold r, the shape parameter β and the maximum number of iterations L were determined after the preliminary tests. An increase in the r-value causes an increase in the training set error, but the test set error behavior is rather irregular, especially in the case of irregular time series. So the choice of the r-value is not obvious. The β parameter is not critical. The similar results were received for different values of this parameter. The L-parameter value

Table 1. Description of data used in experiments

Data symbol	Data description	Forecast error of the naïve method, %
A	Time series of the hourly loads of the Polish power system from the period 2002-2006, mean load of the system ~16 GW	4,25
B	Time series of the hourly loads of the Polish power system from the period 1997-2000, mean load of the system ~15,5 GW	4,38
C	Time series of the hourly loads of the local power system from the period July 2001-January 2003, mean load of the system ~1,2 GW	6,59
D	Time series of the hourly loads of the local power system from the period June 1998-July 2002, mean load of the system ~300 MW	7,45
E	Time series of the hourly load demands of the chemical plant from the period 1999-2001, mean load demand of the plant ~80 MW	17,46

should ensure stabilization of the training error at the fixed level. However, the test error is often not stabilized varying in value up and down. The parameter values used in experiments were: $\beta = 0.04$, $L = 50$, r – half of the mean distance between antigens and initial population of antibodies.

Results of forecasting – mean errors for training (MAPE_{trn}) and test sets – are presented in Table 2. Results of test sets include two cases – one where unrecognized antigens are not taken into account (percentage of these antigens is shown in Table 2) and second where the cross-reactivity threshold r increases until recognition of these antigens. The forecast calculated for these untypical antigens is not very reliable and accurate, so the mean errors in the second case (MAPE_{tst2}) are higher than in the first case (MAPE_{tst1}).

More detailed results for the test parts of A (most regular) and E (most irregular) time series are presented in figures. Fragments of the A and E time series and their forecasts – in Fig. 2, MAPE_{tst1} for each day type and hour – in Fig. 3 and percentage error (PE_{tst1}) histograms – in Fig. 4.

For comparison, forecast using the simple nearest neighbor method was calculated. The method applies the following rule: y-chain paired with the input x-chain is the same as the y-chain paired with nearest neighbor (found in the training set) of the input

Table 2. Forecast errors

Data symbol	MAPE_{trn}	MAPE_{tst1}	Percent of unrecognized antigens	MAPE_{tst2}	MAPE_{tst3}	MAPE_{tst4}	MAPE_{tst5}
A	1.56	1.77	5.80	1.88	2.05	-	-
B	1.62	1.82	8.90	2.29	2.63	2.24	2.11
C	2.05	3.16	16.48	4.46	4.76	4.89	4.07
D	2.79	3.55	8.85	4.00	4.17	3.71	3.52
E	3.77	6.41	22.74	8.60	9.47	8.32	8.06

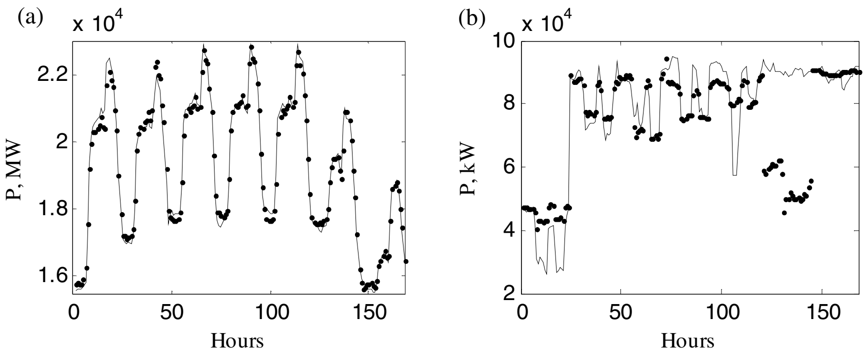

Fig. 2. Fragments (one week) of the test A (a) and E (b) time series (*solid lines*) and their forecasts (*dots*)

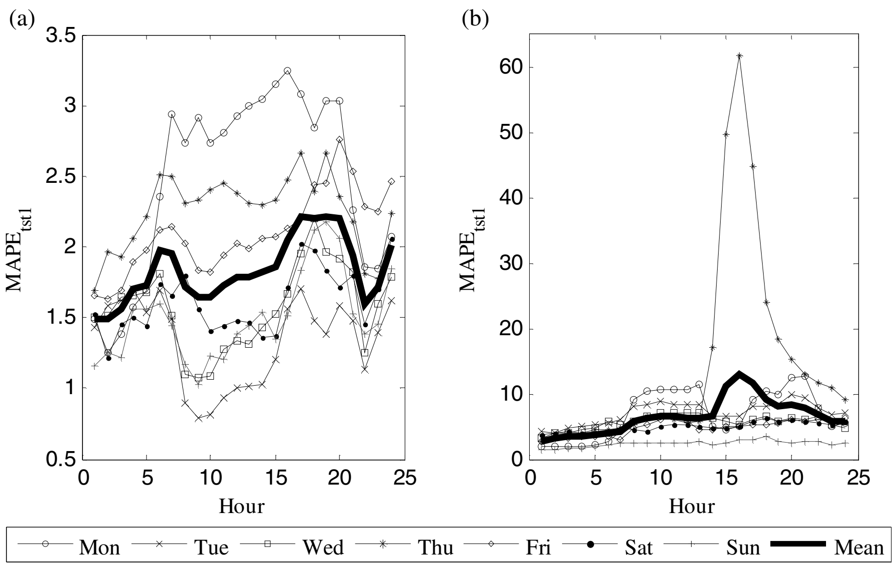

Fig. 3. $\mathrm{MAPE}_{\mathrm{tst1}}$ for each day type and hour for A (a) and E (b) time series

x-chain. The forecast results for this method ($\mathrm{MAPE}_{\mathrm{tst3}}$) are presented in Table 2. In this table the results (taken from [27]) for two other STLF models are also presented: for model based on the neural network ($\mathrm{MAPE}_{\mathrm{tst4}}$) and for model based on the fuzzy clustering ($\mathrm{MAPE}_{\mathrm{tst5}}$). These models are described in [27] and [11].

An example of the antibody and antigens, which activated this antibody, is shown in Fig. 5. The antigens, recognized by the same antibody, have the similar *y*-chains in case of the regular time series (Fig. 5(a)). Thus forecasts are more accurate. It is different in case of irregular series (Fig. 5(b)) – large *y*-chain dispersion causes high errors of forecast.

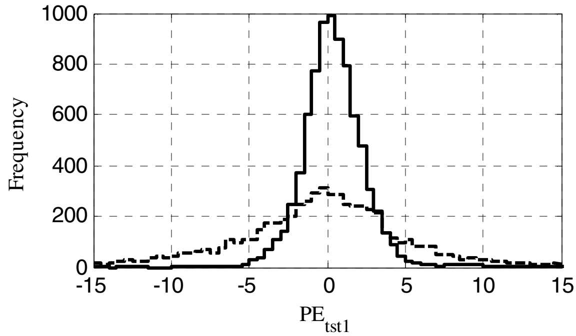

Fig. 4. PE_{tst1} histograms for A (*solid line*) and E (*dashed line*) time series

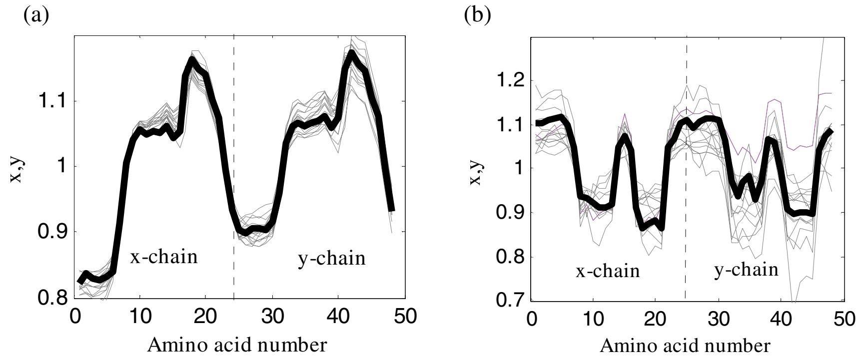

Fig. 5. A group of similar antigens and activated by them antibody (*thick line*) for A (a) and E (b) time series

The peak observed in Fig. 3(a) is a result of the drastic change in load in one day, possibly caused by a failure (load forecast errors of this day reached 2300%; $MAPE_{tst1}$ for the E time series without this day decreased to 5.07%). The prediction of this event was impossible because probable lack of information about this event in the time series sequence before its existence and it was not represented in the training set. For irregular time series, like E series, surely there were many similar situations, e.g. in Fig. 2(b) the forecast for Saturday is completely wrong.

Empirical distributions of errors PE_{tst1} (Fig. 4) are rather symmetrical (skewness close to 0), similar in shape to the normal distribution, but steeper (kurtosis higher than 3).

The proposed AIS has a lot of interesting properties as the forecasting model, but yet it is not developed enough to compete with other AI models such as models using neural networks and fuzzy logic (Table 2), which have been finishing up by many researchers for many years.

4 Conclusions

The proposed STLF model belongs to the class of similarity-based models. These models are based on the assumption that, if patterns of the time series sequences are similar to each other, then following them patterns of sequences are similar to each other as well. It means that patterns of neighboring sequences are staying in a certain relation, which does not change significantly in time. The more stable this relation is, the more accurate forecasts are.

The idea of using AIS as a forecasting model is a very promising one. The immune system has some mechanisms useful in the forecasting tasks, such as an ability to recognize and to respond to different patterns, an ability to learn, memorize, encode and decode information.

The disadvantage of the proposed immune system is limited ability to extrapolation. Regions without the antigens are not represented in the immune memory. However, a lot of models, e.g. neural networks, have problems with extrapolation. But the AIS has a detection mechanism of outliers, i.e. antigens laying outside the recognition regions of antibodies. In the proposed approach for such antigens the cross-reactivity threshold is increasing, and finally these antigens are recognized by antibodies. This solution is not perfect as forecasts in such situation are usually inaccurate. Other solution to this case is to use the other, maybe heuristic, forecasting method.

Another problem is an introduction to the system additional input information which is not homogeneous with time series elements (loads), e.g. wheatear factors.

The further work will be concentrated on the determination of the better antibody receptor structure and on rebuilding the training sets in order to detect and eliminate outliers disrupting the learning process.

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