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Classification of Household Appliances by Smart Meter Readings -- Based time series classification model

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Abstract

This paper considers the time series classification problem of "identifying the type of household appliances through daily power monitoring", and uses the ElectricDevices data set provided by UCR to build a DNN model to obtain the classification results of the test set: the accuracy rate is 79%, of which The F1 scores of categories 2, 3, 5, and 7 are higher than 0.8, and the classification effect is better; the classification effect of categories 1, 4, and 6 is poor due to the similar electricity consumption, which proves that although some electrical appliances can be identified with a high degree of accuracy , but it is difficult for the remaining appliances to be accurately classified with this granularity of data .

Keywords

Time series classification, DNN, household appliances classification.

1. Introduction

With the deterioration of the global environment, all countries are mobilizing and calling on the whole people to improve the environment and save resources. A project in the United Kingdom hopes to use smart meters to monitor household appliances, collect electricity usage data, and allow smart meters to notify users when they detect equipment failure or exceed the required power, so that users can reduce electricity and money. cost. However, a prerequisite for a smart meter to identify faults or inefficient behaviors is to know the type of the detected device and a description of the normal behavior under that type, in order to avoid consumers manually identifying each detected electrical appliance.

The data in this article is one of the time series datasets provided by UCR: ElectricDevices, developed by GEO in the UK in order to provide communities and households with fair, accurate and independent advice on how to reduce carbon emissions and save the cost of energy bills. After the smart meters, they installed monitoring devices in 187 homes in East England , recording the usage of a single device every 15 minutes for each home for about a year. Since the government hopes to provide an effective way to significantly reduce electricity consumption by installing smart meters in every household, and collecting electricity usage data itself is obviously unlikely to change users' long-term behavior , they are preparing to increase the function of electricity meters, so that the electricity meter can be used in While monitoring the power consumption, if it is found that the monitored electrical appliance fails or uses more power than necessary , the user can be notified in time to avoid unnecessary energy consumption.

A prerequisite for identifying faults or inefficient behavior is the classification of the type of appliance being monitored. For the user, it would be too cumbersome for the user to manually identify each monitored electrical appliance. Therefore, it is considered to automatically identify the electrical appliance type based on the daily electricity consumption, so that the electrical appliance is more friendly and easy to use for consumers.

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2. Data collection and analysis

For the ElectricDevices dataset, there are 8926 pieces of data in the training set and 7711 pieces of data in the test set. The first column of the data is the corresponding category, and there are 7 categories in total. The length of each time series is equal to 96, and there is no missing data in the data.

By consulting the literature [1], we know that the data is the result of measuring the electrical representation of the household appliances of 187 British households at 15-minute intervals, and each time series represents a certain electrical appliance recorded every 15 minutes in one day the meter reading. And according to the literature, since the goal is to be able to identify the type of appliances for new users who have no label usage history , the splits for testing and training consist of different families , that is, there is no data from the same family that exists in both the test set and the training set. The seven categories represent: TV (computer and TV), dishwasher, refrigeration (refrigerator, freezer, etc.), electric hot water rod, kettle, oven cooker, washing machine. Figure 1 shows an example of the electricity consumption of appliances in 7 categories:

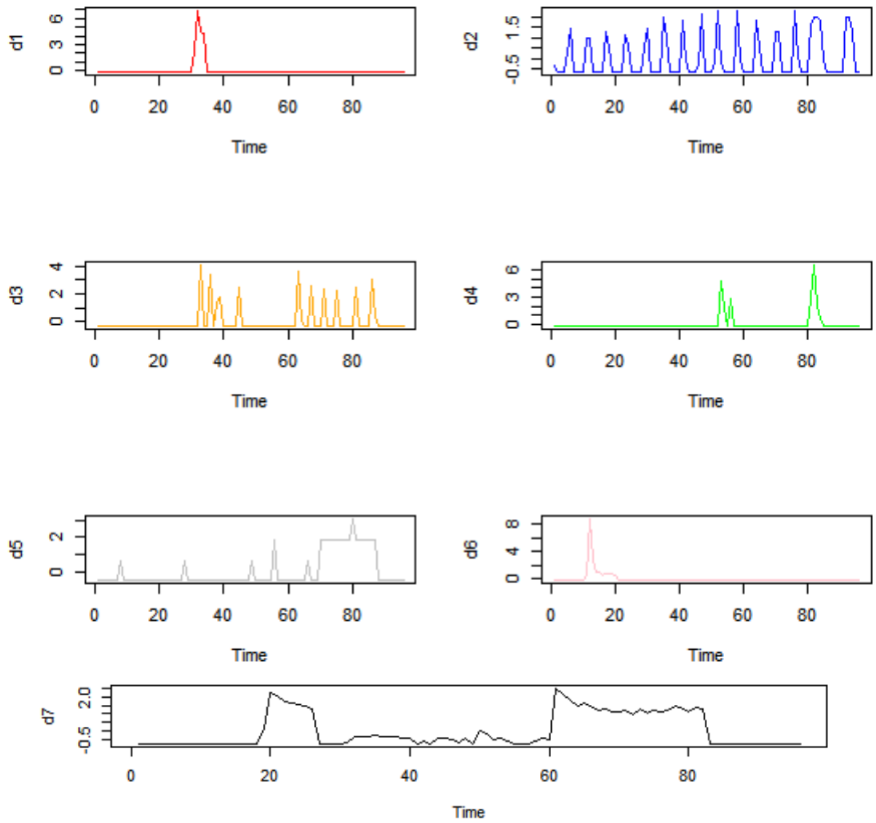

Figure 1. Example of electricity usage for appliances in 7 categories

It is found that 7 types of electrical appliances have their own characteristics in the electricity consumption in one day. Since neither the data set compression package nor the cited references explain the types of electrical appliances corresponding to the classification numbers, we can only compare the power consumption examples of different electrical appliances in Figure 1 and literature [1] (attached to the appendix), and it is preliminarily inferred that category 2 corresponds to " "Refrigeration category", category 4 corresponds to "oven cooker", and the remaining categories cannot be determined, but this does not affect the subsequent time series classification.

Table 1 shows the sample size of each category of test set and training set:

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Table 1 Sample size of test set and training set

	1	2	3	4	5	6	7	total
test set	667	1956	755	1165	1869	742	556	7710
Training set	726	2231	851	1474	2406	509	728	8926

Since the given data is a Z-standardized data set, it is impossible to obtain practical average statistical data of various types of electrical appliances through this data set.

3. Model building

In this paper, a deep neural network (DNN) model is used to solve the time series classification problem of electrical appliances.

3.1. Model principle

The neural network is based on the extension of the perceptron, and DNN can be understood as a neural network with many hidden layers. The multi-layer neural network and the deep neural network DNN actually refer to the same thing. DNN is sometimes called a multi-layer perceptron (Multi-Layer). perceptron, MLP). [2]

From DNN is divided according to the position of different layers, the neural network layer inside DNN can be divided into three categories, input layer, hidden layer and output layer, as shown in the following figure, generally speaking, the first layer is the input layer, and the last layer is the output layer , and the middle layers are all hidden layers. [2]

Different from the general structure diagram, the last layer uses the softmax function to obtain a set of numbers from 0 to 1, which is regarded as the probability that the data is classified into each category, and the largest is most likely to be the category to which it belongs, so as to classify the data.

3.2. Construction of the model

This paper uses the Keras package of python to construct the DNN model. The established DNN model consists of input layer, hidden layer, loss layer, output layer and softmax function. In this model, cross-entropy is chosen as the loss function and Adam as the iterative optimizer. First build a three-layer base layer:

First layer: input layer (batch normalization).

In the process of training the neural network, the fully linked neural network is used to extract features from the original sequence, and the extracted features may be of a large order of magnitude, which will cause the activation function to prematurely saturate when processing these feature values. Specifically, if the activation function is used to process these eigenvalues, they will all be mapped to the vicinity of 1, so the work done by the activation function will fail, and the feature extraction effect cannot be achieved. On this basis, this paper uses the batch normalization optimization strategy to map the original feature map to the normalized interval before entering the activation function, so that the activation function can play the function of feature extraction.

The second layer: the full link layer

The full link layer (Dense) , the full link is the hidden layer of a basic neural network. In the first layer, the hidden layer of the neural network is set to 128 hidden layer units. The parameters of the initialized weight matrix are 12288, the bias unit is 128, and a total of 12416 parameters are used for learning. The output layer of the last layer is also the structure of the

fully connected layer, but unlike other fully connected layers, the activation function of the last layer is the softmax function.

The third layer: dropout layer (dropout)

For the hidden layer of the neural network, due to more parameters and less training data, it is easy to over-fit. Therefore, this paper uses the Dropout mechanism to randomly lose some nodes of the neural network without training. The Dropout value is set in this project. It is 50%, which means that in each training, 50% of the parameters will be randomly selected to not participate in the training. This approach can effectively prevent the network from excessively memorizing the training data and lacking the ability to draw inferences from one case.

Table 2 shows the model structure of the constructed DNN model. The subsequent layers are superimposed on the base layer above, and the last full link layer is the output layer.

Table 2. Model structure

Layer(type)	OutPut Shape	Param
Batch_normalization 3	(None,96)	384
Dense 5	(None,128)	12416
Dropout 4	(None,128)	0
Batch_normalization 4	(None,128)	512
Dense 6	(None,256)	33024
Dropout 5	(None,256)	0
Dense 7	(None,128)	32896
Dropout 6	(None,128)	0
Dense 8	(None,7)	903

Total params : 80135
Trainable params : 79687
Non-trainable params : 448

Figure 2 , in the process of gradient descent, if the learning rate is kept too high, it will cause the training process to drop to the lowest point and then rise in reverse due to the learning rate being too large; if the learning rate is too low, it will cause the gradient during training The slow decline has not been able to converge to the lowest point.

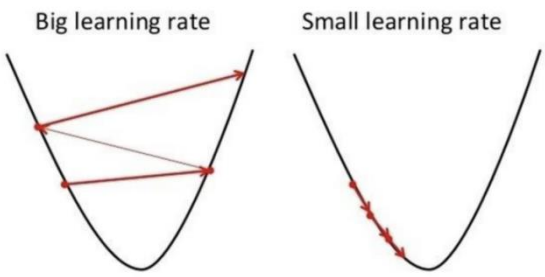

Figure 2. The effect of learning rate on gradient descent

Therefore, we also added the ReduceLROnPlateau learning rate decay in the training process: this paper uses the ReduceLROnPlateau function provided by Keras to automatically adjust the learning rate. At the beginning of the training process, a larger learning rate is used for training. By judging the accuracy index of the test set, if the index remains unchanged or increases continuously for many times, the strategy will be activated to adjust the learning rate. Perform automatic decay.

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3.3. Analysis of results

Use 8600 pieces of data in the training set for training.Then use the trained model to classify a total of 7710 samples in the test set, and get the classification results: Table 3 is the resulting confusion matrix, and Table 4 is the indicators of each classification (precision rate, recall rate, F1 score)

Table 3. Confusion matrix

actual predict category	1	2	3	4	5	6	7
1	389	17	2	93	8	158	0
2	54	1796	3	6	93	1	3
3	11	6	689	11	1	29	8
4	109	5	53	849	72	71	6
5	131	85	5	80	1499	31	38
6	106	1	36	121	25	451	3
7	8	7	2	29	73	10	427

Table 4 Evaluation indicators

	pricision	recall	f1-score	support
1	0.48 _	0.5 8	0.53	667
2	0.94 _	0.9 2	0.9 3	1956
4	0.71 _	0.7 3	0.72	1165
5	0.8 5	0.80 _	0.8 2	1869
6	0.6 0	0.61 _	0.6 0	743
7	0.88	0.77 _	0.82 _	556
accuracy			0.7 9	7711
macro avg	0.7 6	0.7 6	0.7 6	7711
Weighted avg	0.80 _	0.7 9	0.7 9	7711

in:

Accuracy is the ratio of correctly classified samples to all samples

The precision is the ratio of the number of correct classifications to class i to all classifications to class i.

The recall rate is the ratio of the number of classes classified to class i to the total number of samples of class i.

F1 score (f1-score) is the harmonic mean of precision and recall [4] , the formula is as follows:

$$F1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

In this paper, the accuracy rate is used to evaluate the overall pros and cons of the model, and the F1 score is used to evaluate the pros and cons of each category of the model.

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The final accuracy rate obtained in Table 3 is 79%, which is higher than the 0.7737 finally obtained by the random forest method in [1] (see Appendix 1, calculated by the confusion matrix given in [1]). It can be seen that for the overall In terms of accuracy, compared with the random forest method, the classification results obtained by using the DNN model established in this paper are more accurate; but according to the information given on the official website [3] , the optimal algorithm for this data set is ST, which is accurate The rate reaches 85%, indicating that the accuracy of the algorithm in this paper has not yet reached the optimum.

In addition, it can be found from Table 4 that the F1 scores of categories 2, 3, 5, and 7 are all higher than 0.8. Combining with Figure 1, it can be seen that the electricity consumption of electrical appliances in these categories has obvious characteristics, especially the category 2, so the F1 score for category 2 is also the highest 0.93.

The F1 scores of categories 1 and 6 are lower, 0.53 and 0.60, respectively. Combined with the confusion matrix in Table 3,

It can be seen that 158 (23.6%) of the 667 samples that actually belong to category 1 were misclassified as category 6; 106 (14.3%) of the 742 samples that actually belonged to category 6 were misclassified as category 1, and 121 (16.3%)) was misjudged to category 4, and it can be seen from Figure 1 that the sequence diagrams of electrical appliances in category 1 and category 6 are similar.

According to the above results combined with the confusion matrix obtained in [1] (see appendix), we can infer that categories 1 and 6 are "oven cookers" and "washing machines", and category 4 is "dishwashers", thus we can conclude: oven cookers, washing machines, Dishwashers have similar daily electricity usage, making classification based on time series poor and indistinguishable.

Figure 3 shows the overall accuracy of the visualization (Accuracy), and the horizontal axis is the number of traversals (epoch)

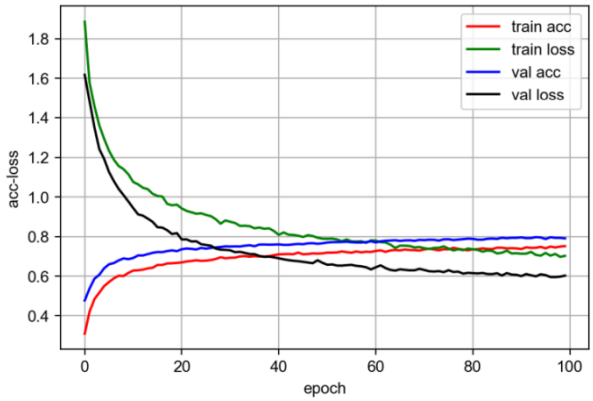

Figure 3. Model accuracy and loss

As shown in Figure 3, the accuracy of the training set is always lower than that of the test set. This may be because we set the loss layer in the process of training with the training set. There is a 50% dropout, and the training set is completed. The model is used on the test set without a dropout layer.

4. Conclusion

In this paper, the DNN model is used to classify the data set of household appliances, and the accuracy rate reaches 79%, indicating that the overall model classification effect is good; using the F1 score as an indicator, it can be seen that the F1 scores of categories 2, 3, 5, and 7 are all greater than 0.8 , it is believed that the model can be used to classify these four categories in

practical applications. However, the F1 scores of categories 1, 4, and 6 are lower than 0.75, and the daily electricity consumption of these three types of electrical appliances is similar.

This paper conjectures that the sequence diagrams of categories 1, 4, and 6 are similar because the time interval of smart meter measurement is too long (15 minutes). To improve the accuracy of 1, 4, and 6 classification, you can shorten the time interval and collect data before trying .

References

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